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SURVEY

Indoor Autonomous Multi-UAVs: A Review of Current Research, Enabling Technologies and Open Challenges

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ABSTRACT The utilization of autonomous uncrewed aerial vehicles (UAVs) has increased in recent years for various tasks in indoor environments, including inventory management, rapid emergency response, underground inspections, warehouse monitoring, payload delivery, surveillance, and real-time mapping. Robust control systems are essential for reliable and safe operation in indoor environments. The use of these systems in the indoor environment requires autonomy, scalability, and efficiency to perform the assigned tasks with robustness. At present, a large number of researchers and scholars have shown growing interest in various key research factors for indoor multi-UAV operations. However, multi-UAV operations pose critical challenges in indoor environments owing to congested spaces, dynamic obstacles, and static hindrances such as walls. These challenge areas include a range of various factors, including sensing, communication, obstacle avoidance, control systems, networking, mission planning, and computational complexities. This paper presents a review of research on indoor autonomous multi-UAV systems and synthesizes existing work on obstacle avoidance, sensing capabilities, networking, and mission planning. This research systematically reviews the current methodologies in each area, benchmarks performance in each domain, and highlights the key contributions, challenges addressed, strengths, and limitations of existing solutions. In addition, this study explores the potential of emerging technologies, such as edge computing and machine learning, to enable advanced solutions for research challenges and their integration into future systems. Finally, the paper identifies key research challenges that can be addressed through the utilization of emerging technologies to develop effective autonomous multi-UAV systems for indoor environments.

INDEX TERMS Uncrewed aerial vehicles (UAVs), indoor autonomy, indoor environment, autonomous multi-UAVs, mission planning, indoor localization, UAVs networking, machine learning, edge computing, intelligent UAVs.

I. INTRODUCTION

In recent years, the deployment of advanced and lightweight embedded systems in Uncrewed Aerial Vehicles (UAVs) has progressed significantly, enabling the production of a wide range of indoor UAVs. Academic research groups and technology companies have developed lightweight, low-power, and reliable indoor UAV platforms with varying capabilities, including semi-autonomous operation, precise navigation, and localization. The operation of these systems in indoor environments offers a controlled and contained environment, making it a feasible option for the deployment of these systems for various indoor missions. The potential for indoor UAV teams, known as multi-UAV systems, to operate effectively, safely, and agilely is a key opportunity. These systems help overcome critical limitations in areas

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where human operation is unsafe. This potentially reduces both the time and risk associated with task completion [1]. Therefore, this review focuses on the enabling aspects of multi-UAV systems in indoor environments.

Multi-UAV systems involve some form of coordination for safe and efficient operation. Effective coordination is constrained by limited onboard resources, including energy, computing power, and communication capacity [2]. These constraints become even more critical in GPS-denied or resource-constrained environments, where reliance on networked coordination, edge computing, and intelligent control mechanisms is essential. The development of multi-UAV systems has increased owing to advanced technological development in lightweight embedded electronics, which has enabled the production of various indoor UAV types, including bicopters, helicopters, quadcopters, tricopters, hexacopters, and bio-inspired UAVs [3]. The number of research publications related to multi-UAV systems has increased significantly in recent years. Modern technology companies are producing indoor UAVs equipped with advanced autopilot features that support real-time processing and onboard intelligence [4]. The design of these systems includes safety concerns and often has protected rotors to avoid mishaps. These systems have key features, such as indoor autonomy, precise mobility, hovering capability, vertical takeoff and landing, affordability, adaptability, and low manufacturing cost, which make them well-suited for applications that pose safety risks to humans, such as oil and gas pipeline inspection, chemical tank monitoring, underground tunnels, and warehouse exploration [5]. The use of such systems enhances flexibility, expands operational coverage, and improves system reliability [6]. Additionally, their maneuverability helps reduce production costs by optimizing logistics operations, including transportation, inspection, monitoring, and surveillance [7]. Ongoing research on multi-UAV autonomy is actively pursued by institutions such as the MRS Group [8], GRASP Lab [9], and GRVC [10], which are establishing experimental laboratories in collaboration with the industry. Achieving indoor autonomy for UAVs is difficult, particularly because of the absence of GPS signals. Accurate localization and flight stability rely on various sensors, including Inertial Measurement Units (IMUs), LiDAR, stereoscopic cameras, proximity, and ultrasonic sensors. Furthermore, resources such as power, computational ability, reliable communication, and robust control are limited. The advent of Industry 4.0 has led to significant advances in aerial automation, with a strong focus on optimizing performance and production [11], [12], [13]. Current indoor aerial operations are semi-autonomous and often require human intervention in areas such as UAV charging, power management, 3D mapping and navigation. With the progress of advanced research, it will continue to evolve and address the current research gaps. Given these challenges and rapid industrial adoption, there is a growing need for a comprehensive survey that consolidates the existing research on indoor multi-UAV autonomy. Such a survey helps identify the state-of-the-art, highlights open research problems, and provides a roadmap for advancing fully autonomous, scalable, and safe indoor UAV systems.

A. PREVIOUS SURVEY PAPERS RELATED TO INDOOR UAVs

Several survey papers have covered different aspects of multi-UAV teams. For example, Coppola et al. presented the research challenges of indoor micro-aerial vehicles (MAVs) for the formation of swarms [14]. In a recent literature review, Awasthi et al. highlighted emerging trends in the autonomy of indoor multi-UAV systems. This study emphasized advancements in path planning and computational strategies for enabling efficient indoor operations [15]. Croon and Wagter presented hardware and other challenges for tiny indoor UAVs [16]. Additionally, Perez et al. conducted a survey on indoor UAVs, focusing on localization aspects [17]. Li et al. did comprehensive survey and explored obstacle avoidance techniques for indoor UAVs [18]. Sandamini et al. presented a review article and discussed various indoor positioning technologies, including Wi-Fi, UWB, vision, and RFID, for UAV location in environments denied GPS [19]. Recently, Chang et al. presented a survey paper and examined autonomous UAV navigation methods in scenarios denied by GPS, covering visual SLAM, LiDAR-based mapping, and sensor fusion [20]. Table 1 presents an overview of previous review articles on multi-UAVs in indoor environments.

B. RESEARCH GAPS AND CONTRIBUTIONS

While prior surveys have primarily focused on specific aspects of indoor autonomous multi-UAV systems, such as navigation, networking, and mission planning, an integrated and comprehensive review remains absent. Most existing studies either emphasize outdoor scenarios or address isolated challenges, leaving key dimensions underexplored. In particular, current studies are fragmented: obstacle avoidance is often limited to single-UAV scenarios, networking research overlooks indoor-specific issues such as congestion and multipath interference, and there is limited attention to scalable coordination and benchmarking. Moreover, critical trade-offs between onboard and edge computing, as well as the need for integrated frameworks that balance energy, computation, and communication, are rarely addressed. To bridge these gaps, this study presents the first holistic review of indoor autonomous multi-UAV systems, synthesizing research on navigation, localization, networking, mission planning, and computation. Beyond summarizing past work, this research paper analyzes the evolution of methodologies, identifies unresolved challenges, and explores how emerging technologies, such as machine learning and edge computing, can enable future advancements. Moreover, this review addresses the following research questions:

1) What are the published methodologies and current research on obstacle avoidance, networking, mission

TABLE 1. Overview of review survey papers for indoor multi-UAVs.

Authors, Ref.	Contribution Overview	Research Domain
Coppola et al., [14]	A survey on swarming with micro air vehicles	Navigation and Challenges
Awasthi et al., [15]	Review on micro UAV swarm for industrial applications in indoor environment	Navigation and Planning
G. Croon and C. De Wagter, [16]	Presented hardware design open problems and challenges for indoor UAVs	Navigation and Planning
Perez et al., [17]	Survey on indoor UAVs covering the localization factor	Indoor Localization
Junlin Li et al., [18]	Survey on indoor UAV obstacle avoidance research	Obstacle Avoidance
Sandamini et al., [19]	A review of indoor positioning systems for UAV localization with machine learning algorithms	UAV Localization
Chang et al., [20]	A review of UAV autonomous navigation in GPS-denied environments	Autonomous Navigation

planning, sensing, localization, and navigation for multi-UAV operations in indoor environments?
2) How are advanced technologies—such as machine learning and edge computing—being deployed to enhance the scalability, autonomy, and collaboration of indoor multi-UAV systems?

The contributions of this survey are as follows.

1) This research presents an in-depth survey of the autonomous UAVs in indoor environments, and explores the relationship between different key functionalities such as obstacle avoidance, networking, path planning computations, localization, and sensing ability. The paper explores methodologies utilized in each factor in detail and classifies the reviewed papers based on their contributions. Each section includes a summary of key contributions along with performance benchmarking of the reviewed approaches.
2) The paper explores the applications and potential of advanced technologies, including machine learning and edge computing, to support the required functionalities of multi-UAV systems. It identifies the application and potential of machine learning and edge computing to support the required functionalities of indoor multi-UAV systems.
3) Finally, he paper identifies research challenges and addresses open issues in obstacle avoidance, networking, localization, sensing, mission path planning, and the incorporation of AI and edge computing required to enable full-scale development of multi-UAV systems in indoor environments.

This review consolidates scattered and diverse research efforts into a single structured article, providing researchers with a unified reference for the key aspects of indoor multi-UAV systems. By integrating mixed research findings across navigation, communication, mission planning, sensing, and autonomy, this paper serves as a comprehensive foundation for advancing future work in indoor UAV technologies.

C. REVIEW METHODOLOGY

To ensure a systematic and reproducible literature survey, this article adopts a structured review methodology, as outlined below and in the PRISMA flow diagram presented in Figure 1.

- **Databases Searched:** IEEE Xplore, MDPI, Elsevier, Web of Science, Scopus, Springer, Google Scholar, and arXiv.org.
- **Keywords Used:** '"indoor UAVs", "'Indoor multi-UAVs", "Indoor UAVs autonomy", "indoor UAVs navigation and Localization", "Indoor UAV swarms", "Indoor UAVs mission planning", "Indoor UAVs Networking", and "Indoor UAVs Obstacle Avoidance".
- **Time Frame:** 2013–2025
- **Initial Papers Retrieved:** 280
- **Inclusion Criteria:** Peer-reviewed journal and conference papers focusing on indoor UAVs in the contexts of multi-UAVs, swarm coordination, obstacle avoidance, mission planning, networks/communication, sensing, and navigation.
- **Exclusion Criteria:** Outdoor-only UAVs, hardware-only studies without software/system relevance, military-exclusive work
- **Final Papers Included in Survey:** 160

D. STRUCTURE OF THE RESEARCH PAPER

The rest of the survey paper is structured as follows. Section II presents the operating context for autonomous UAVs, challenges, and applications. Section III presents a systematic review of the literature for key functional aspects of multi-UAVs in indoor missions: networking, collision avoidance, autonomous mission planning, and sensors. This section also reviews key research technology trends and benchmarking analysis. Section IV explores the opportunities to enhance autonomy by applying edge computing and AI. Section V discusses the open research questions, gaps, and potential challenges. Finally, Section VI presents the conclusion. The detailed pictorial structure of the paper is presented in Figure 2.

II. THE CONTEXT FOR AUTONOMOUS MULTI-UAVs

A. INDOOR ENVIRONMENTS AND CHALLENGES

Indoor environments have confined and enclosed spaces characterized by various static and mobile obstacles. Multi-UAV systems in such environments are subject to limitations in their behavior, including height restrictions due to ceiling clearance and low speeds required to maintain safe distances from humans and floor obstructions. Under such conditions,

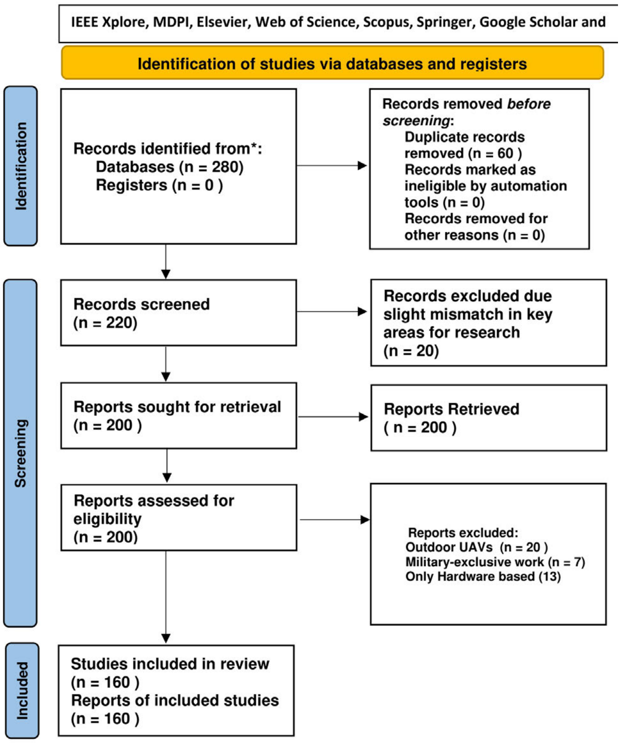


FIGURE 1. PRISMA flow diagram of screening.

UAVs rely on localization techniques, such as SLAM, which utilize onboard sensors to simultaneously map the environment and determine the position [21]. Indoor UAVs operate under different radio communication conditions than outdoor environments, including a higher density of communicating devices and the presence of reflective surfaces that cause signal absorption, multipath interference, and reduced communication reliability. Table 2 compares the operational differences between indoor and outdoor UAVs. The flights of multiple UAVs in indoor environments face a different set of challenges compared to outdoor operations [16]. The risk of collision is increased by near-wall turbulence caused by the UAVs' own rotors, which can destabilize the flight [22]. Communication and network reliability are major concerns for these systems. Radio frequency signals, UAV-to-UAV, and UAV-to-ground station communication are typically disrupted by walls, ceilings, and electronic devices, leading to signal attenuation, multipath interference, and non-line-of-sight limitations. Mission planning and computations are other key elements of these systems, which are difficult to handle. UAVs typically rely on GPS for navigation and localization. However, in indoor conditions, the absence of GPS signals necessitates the use of alternative methods for localization, such as visual odometry, LiDAR, Wi-Fi, SLAM, or ultra-wideband systems. Similarly, sensing capabilities and localization become difficult for navigation, such as cameras, barometers, IMUs, and proximity sensors, which may produce erroneous or unreliable data owing to variable inaccurate calibration, lighting, environmental clutter, or signal reflections. Overall, addressing these challenges requires an integrated approach that combines precise obstacle avoidance, resilient communication, intelligent mission planning, and robust localization tailored to the complexities of indoor environments.

B. UAVs APPLICATIONS IN THE INDOOR ENVIRONMENT

Indoor UAVs are being deployed across various technological sectors, including oil and gas, construction, entertainment, and medicine, with representative application examples illustrated in Figure 3. This trend has grown rapidly and is expected to continue growing [23]. Their use in aerial photography, indoor security patrols (e.g., in museums and factories), target tracking, underground inspections, and inventory automation is becoming popular because of their ability to execute tasks with greater time efficiency and less risk than humans [24], [25]. Multi-indoor UAVs are widely used for infrastructure monitoring, rescue operations, and ensuring environmental safety. Their use includes the inspection of underground tunnels, detection of gas leaks, monitoring of electrical faults, and fires [26]. In emergency scenarios, these UAVs can form collaborative groups to perform 3D aerial mapping and assist in locating victims inside buildings. For instance, the work of McGuire et al. demonstrated UAV-based victim identification in indoor fire emergencies [27]. As large-scale industries demand higher levels of automation, multi-UAV systems are leveraged to enhance their operational efficiency. They can autonomously perform tasks such as inventory management, product location, barcode scanning, and load delivery, while supporting emergency response workflows [28]. The field remains active and evolving, with ongoing efforts to overcome the current limitations and fully realize the potential of multi-indoor UAVs [29]. Additionally, multi-UAV autonomy is increasingly being applied to cooperative source-seeking tasks, such as locating hazardous leaks or emission hotspots in confined environments. Swarm-scale deployments of micro flying robots have demonstrated the feasibility of distributed sensing in unstructured spaces, reducing reliance on heavy onboard computation and centralized mapping. Recent approaches also introduce gradient-free cooperative strategies that enable quadrotors to track sources under disturbances and intermittent communication constraints [30]. Furthermore, self-triggered distributed formation control reduces communication burden and energy consumption during exploration, offering scalable multi-UAV operation in cluttered or GPS-denied environments [31]. These advances highlight the potential of multi-UAV swarms for efficient indoor source localization while raising future challenges related to sensing robustness, scalability in dense swarms, and safe deployment in constrained indoor settings.

C. RESEARCH EFFORTS AND INDUSTRIAL INITIATIVES

Several companies and research institutions have established dedicated centers to advance autonomous multi-UAV

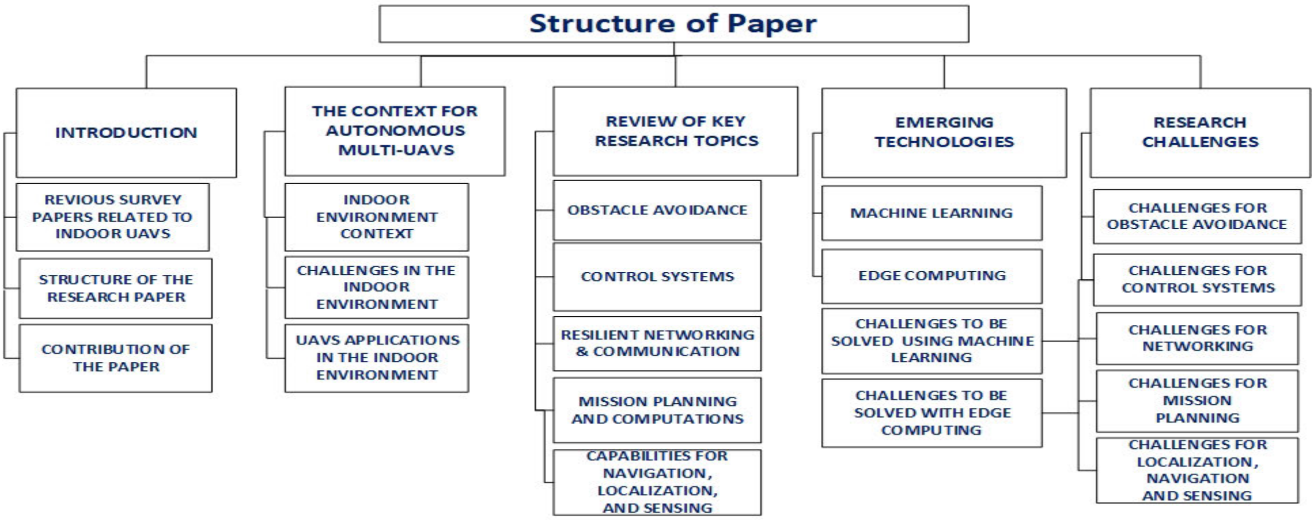


FIGURE 2. Structure of the research paper.

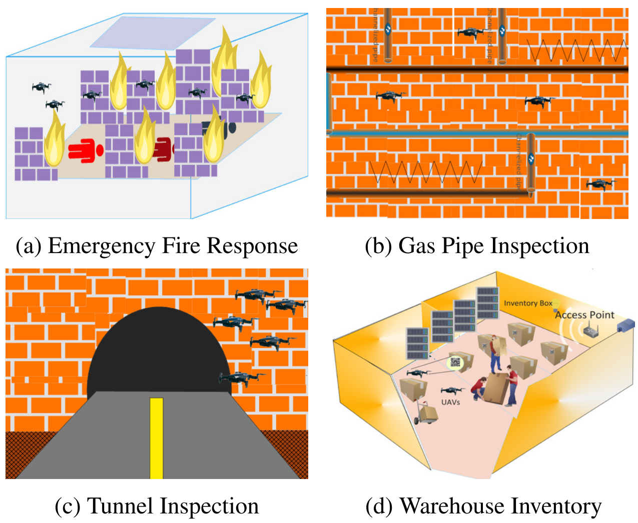


FIGURE 3. Representative Multi-UAV Applications in Indoor Environments.

TABLE 2. Comparison between indoor and outdoor UAV operational characteristics.

Aspect	Indoor	Outdoor
Navigation	Relies on sensors	GPS-based
Signals	Blind spots exist	Mostly line of sight
Environment	Limited indoor space	Open spaces
Communication	Short-range (Wi-Fi)	Long-range
Common Sensors	Ultrasonic, vision-based, LiDAR, infrared, proximity	GPS, barometers, LiDAR, long-range sensing
Weather	Stable wind	Wind present
Obstacle Avoidance	High priority (walls/structures)	Lower priority, fewer obstacles
Localization	Vision/LiDAR-based (UWB, VICON, SLAM)	GPS/RTK GNSS-based
Lighting Conditions	Often low or artificial light	Natural light, sunlight
Flight Altitude	Restricted (low ceilings)	Regulated by aviation authority
Legal Constraints	Fewer, private facilities	Heavily regulated by aviation authorities
Collision Risk	High (close obstacles)	Lower, unless urban areas

technologies. For example, Flyability [32], Modal-AI [33], Indoor Robotics [34], and Nexxis [35] are actively conducting high-end research to enable the integration of multi-UAV systems in indoor environments. These companies are developing advanced solutions, including indoor swarm systems utilizing 5G technology for high throughput, as proposed by the GSM Association [36]. ETH Zurich, in collaboration with industry partners, is leading efforts to design next-generation autonomous indoor drones for industrial applications [37]. Similarly, other research institutions are pursuing innovative strategies to support autonomous UAV exploration and operations in indoor environments.

III. REVIEW OF KEY RESEARCH TOPICS FOR INDOOR AUTONOMOUS MULTI-UAVs

In this section of the survey paper, a synthesis of the current research on multi-UAV autonomy in indoor environments is presented, along with a critical analysis of existing approaches. paper presents a taxonomy for multi-UAV research to demonstrate the links between the core topics of obstacle avoidance, control systems, resilient networking, communication, mission planning, localization, navigation, and sensing.

On Simulation-Only vs. Experimentally Validated Studies: Across the research domains reviewed in this section—obstacle avoidance, resilient networking, control systems, mission planning and computation, and indoor localization/sensing—this study indicated that a substantial portion of prior work relies primarily on simulation tools such as Gazebo, MATLAB, AirSim, and ROS-based virtual environments. Although these studies are valuable for algorithm development and controlled benchmarking, solutions supported by real-world indoor experiments, hardware-in-the-loop (HIL) testing, or multi-UAV deployment trials provide a stronger indication of practical applicability. In Section III greater weight is given to papers that demonstrate their methods on physical UAV platforms inside realistic indoor spaces, particularly when they incorporate sensing noise, communication impairments, occlusions, or resource limitations inherent to actual deployment. Simulation-only results are discussed for their conceptual contribution, but their performance claims are interpreted cautiously, unless accompanied by some level of physical validation. This distinction is also reflected in the Evaluation Method entries of Tables 3–6, which differentiate between simulation-only, HIL-based, and real experimental evaluations to help readers identify the methods that are closest to deployment.

A. OBSTACLE AND COLLISION AVOIDANCE

Obstacle avoidance in multi-UAV systems is a crucial factor for successful mission execution. Unlike a 2D simulation environment, 3D space introduces additional freedom of movement, requiring UAVs to navigate along the x, y, and z axes. Indoor environments comprise both static and dynamic objects, as well as confined pathways and limited space for navigation. These systems are programmed to maintain safe distances and control formation to avoid collisions with each other and nearby obstructions. When multiple UAVs operate simultaneously, integrating collision avoidance into the control system is essential to prevent damage to the drones and the infrastructure. The computations become hard to process due to challenges in decision-making and prediction inaccuracies. In such situations, UAVs perceive and respond to dynamic surroundings with high precision and low latency. This makes them highly effective in cluttered indoor spaces, where rapid and autonomous decision-making is essential to prevent collisions and ensure coordinated swarm behavior. The need for advanced obstacle avoidance research is evident, as mission planning and control systems rely on its accuracy. The need for advanced obstacle avoidance research is evident, as mission planning and control systems rely on its accuracy. Perception, control, and planning are closely linked to obstacle avoidance and must adapt to environmental conditions. To improve autonomy and reliability in indoor missions, advanced obstacle avoidance methods must be explored. These techniques support optimized mission planning, lower energy consumption, and enhanced flight performance in multi-UAV operations. The typical flow of obstacle detection algorithms is depicted in Figure 4. The standard methodologies utilized for indoor obstacle avoidance are presented in Figure 5. As a significant amount of research has been published on this topic, however, as detailed in the previous section, our selection process focused specifically on studies relevant to indoor autonomous UAVs and multi-UAV systems. The following subsections provide a structured review of recent research contributions, categorized into sensor-based methods, learning-based, coordination-based, and reactive approaches.

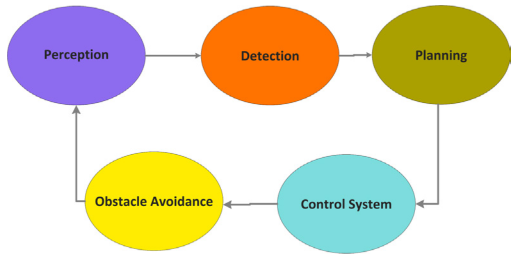


FIGURE 4. Obstacle avoidance control flow diagram.

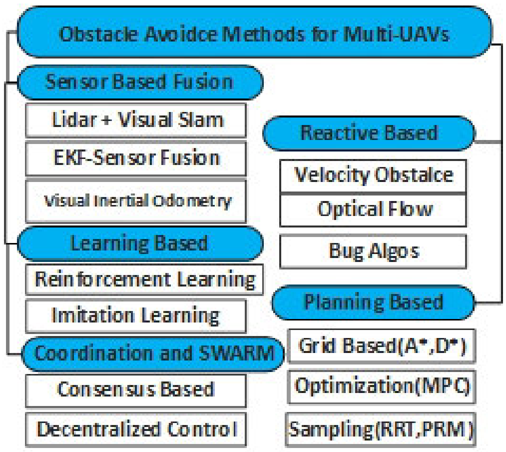


FIGURE 5. Overview of obstacle avoidance methods for multi-UAVs.

1) CLASSICAL/REACTIVE METHODS

Reactive obstacle avoidance methods for UAVs have shown progress across different scales of operation and usage. These methods for UAVs have evolved from simple single-UAV incorporation to more advanced multi-UAV systems. Early approaches, such as basic Artificial Potential Field (APF) methods with static obstacle avoidance, offered lightweight algorithms but were prone to local minima and lacked the dynamic adaptability of indoor UAVs [38]. Bio-inspired methods, particularly those modeled on the locust LGMD visual pathway, introduced real-time reactions to dynamic obstacles but struggled with robustness under visual noise, and integration with global planning was missing [39]. Recent research extended this methodology to multi-UAV contexts by incorporating multi-UAV spacing and collaborative repulsion mechanisms, improving coordination but facing challenges in scalability and real-time performance [40]. With advanced research in this methodology, hybrid models that combine the APF with curl-free vector fields show promise in mitigating formation jamming and maintaining safety using Lyapunov-based guarantees [41]. Overall, these studies presented the progress of classical obstacle avoidance algorithms from basic single-UAV navigation in static environments to more advanced multi-UAV and multi-UAV frameworks, with limited extensions to dynamic and practical experimental scenarios. However, despite these advancements, most approaches remain confined to simulation environments and rely primarily on qualitative evaluations. This highlights the ongoing need for comprehensive benchmarking, real-world testing, and robust performance under dynamic and uncertain conditions indoors.

2) SENSOR BASED METHODS

Sensor-based navigation techniques for indoor UAV obstacle avoidance have incorporated lightweight monocular and ToF-based systems to fuse multi-sensor algorithms that offer spatial understanding and robustness. Early research proposed a 3D LiDAR-based method using point cloud geometry to detect static and dynamic obstacles, paired with online trajectory optimization for safe navigation in structured indoor spaces [42]. The main gaps include real-world validation, uncertainty handling, and comparative baselining. Similarly, nano-UAV platforms have strict power and computational limitations, as in *Niculescu* et al. developed an onboard depth-sensing and perception pipeline that enabled reliable autonomous exploration in office-like indoor environments, achieving efficient real-time obstacle avoidance within a constrained flight envelope [43]. This sets a strong bar for future fusion/planning work on miniature platforms. Building on these ideas, *Tang and Niu* introduced a stereo vision and 2D LiDAR fusion approach, improving indoor state estimation by combining depth, visual geometry, and flight control feedback [44]. This integration addressed the weaknesses of single-sensor methods, such as limited field-of-view or poor texture, although scalability and robustness across varied lighting and layouts remained untested. Overall, these research contributions illustrate a transition from minimal perception to multimodal sensing for indoor multi-UAVs. However, there is a continued need for robust benchmarking, hardware-in-the-loop (HIL) testing, and generalization to dynamic obstacles and cluttered environments.

3) SWARM & COORDINATION-BASED METHODS

The work on multi-UAV coordination and collaborative avoidance methods has progressed over time. Early approaches incorporated distributed algorithms using velocity obstacles and information fusion from sensors. The authors proposed a solution for faster formation convergence and addressed local minima and inter-UAV collision avoidance. However, their research methods were sensitive to local sensing errors, and the solution was locally optimal and lacked robustness in indoor or noisy environments [45]. To address congestion in dense UAV traffic, subsequent studies introduced deadlock prevention mechanisms, ensuring progress but sometimes sacrificing efficiency through conservative stop–resume strategies [46]. Building on this, a more advanced method incorporated chance-constrained nonlinear model predictive control (NMPC) to explicitly handle uncertainty and dynamic obstacles, advancing theoretical safety guarantees [47]. The authors presented a useful real-time (NMPC) with a tighter collision probability bound, which is empirically safer and more efficient than the prevalent baselines and offers scalability. The main gaps in this research are prediction realism, trajectory-level risk, and formal feasibility of recovery. Parallel efforts have been made to integrate formation control with obstacle avoidance to maintain group structure in dynamic environments. The authors presented a pragmatic enhancement of APF that empirically resolves classic pitfalls and integrates well with consensus formation [48]. However, research requires stronger experimental depth, formal guarantees, sensing realism, and comparative benchmarking. Trajectory smoothing under kinematic constraints has also been explored using Spline-based VO techniques, improving motion quality but still facing limitations in scaling and highly cluttered indoor scenes [49]. Notably, recent studies have begun to emphasize real-world swarm testing to validate practicality, although often without proposing novel control algorithms [50]. Hybrid approaches that combine consensus control with potential fields augmented through parameter tuning with particle swarm optimization (PSO)have been attempted to resolve local minima issues; however, they still depend heavily on fine-tuned parameters and lack formal robustness guarantees [51]. Nonetheless, key challenges remain in balancing real-time feasibility, scalability in complex environments, and robustness to sensing uncertainties, and communication constraints.

4) LEARNING-BASED METHODS

The reviewed work on indoor multi-UAVs advances autonomy by tackling indoor navigation, obstacle avoidance, and multi-UAV coordination using machine learning, reinforcement learning, and neuromorphic approaches. Early efforts Devos et al. [52] proved adaptive obstacle avoidance in real-world setups, while later studies Singla et al. [53], Lo et al. [54] and Zhang et al. [55]) applied DRL for robust decision-making under uncertainty and lightweight inference on resource-constrained drones. Su et al. [56] extended path planning with hybrid Voronoi–Q-learning, and Ahmadvand et al. proposed neuromorphic digital-twin controllers for scalable multi-UAV deployment [57]. Despite these advances, challenges remain, including high training costs, limited generalization, and real-time constraints on nanodrones. DRL still requires large datasets and is impractical for safety-critical indoor trials, whereas swarm coordination under dynamic obstacles and delays remains unsolved. Many studies remain simulation-heavy, with gaps in validation, energy efficiency, and explainability issues. Future work should unify DRL, lightweight onboard inference, swarm-level planning, and neuromorphic computing for robust and scalable indoor UAV autonomy. Huang et al. [58] provide a comprehensive review of collision avoidance strategies for multi-UAV systems. Their work synthesizes the sensing, coordination, and control techniques, highlighting the strengths and limitations of the major algorithmic families.

a: BENCHMARKING, KEY TAKEAWAYS AND DISCUSSION

Table 3 provides a comprehensive benchmark of obstacle avoidance approaches for indoor UAV navigation, highlighting a wide spectrum of techniques ranging from simple static modeling to complex dynamic and learning-based systems.

Key Takeaways and Discussion:

Obstacle Sensing and Modeling: Research has explored a variety of obstacle sensing modalities—including LiDAR, stereo vision, ultrasonic, and time-of-flight (ToF) sensors—to detect and estimate the distance of obstacles. Obstacle representative shapes vary from simple static shapes (e.g., cylinders, boxes, and static items) to complex dynamic entities. Current research effectively handles simple and limited cases; however, robust sensing and modeling of dynamic indoor scenarios remain open research challenges.

Learning-Based Approaches: Reinforcement learning methods have demonstrated improved obstacle handling and adaptability. However, ML-based approaches face significant challenges, including high computational demands and the difficulty of transferring models trained in simulations to real-world scenarios.

Multi-UAV Coordination: Research on multi-agent scenarios or inter-UAV collision has been increasing due to demand in industries. Coordinated methodologies (such as heartbeat message exchange or distributed LTS) would enable scalable multi-agent operations but still require refinement in handling communication losses and shared navigation spaces.

Simulation vs. Real-World Testing: Current published studies evaluated and compared their proposed methodology in simulation environments such as MATLAB, ROS, V-REP, or AirSim etc. Real-world experiments with practical hardware platforms and embedded controllers remain limited, but they are critical for validating reliability and robustness in practical deployments.

Real-Time Capabilities: Recent research focused on detection algorithms that can be implemented with low computational overhead makes them suitable for deployment on resource-constrained UAV hardware. Lightweight computation is essential for obstacle avoidance in multi-UAV systems. Balancing algorithmic complexity with real-time execution on resource-constrained onboard hardware is essential for practical indoor multi-UAV autonomy.

B. GROUP CONTROL AND COORDINATION PARADIGMS

Control systems are central to autonomous multi-UAV operations, ensuring stable flight, coordinated behavior, and reliable task execution in constrained indoor settings. As missions increase in size and complexity, the control architecture must support accurate trajectory tracking, disturbance tolerance, formation coherence, and adaptation to environmental uncertainty. Unlike single-UAV control, multi-UAV coordination requires continuous state synchronization, shared situational awareness, and distributed decision making to maintain safety and reliability. To meet these requirements, the literature includes classical feedback control, potential-field methods, distributed consensus, optimization-based formulations, and emerging learning-driven techniques. This section consolidates and classifies these control paradigms to clarify their core principles and respective contributions to indoor multi-UAV autonomy. Figure 6 illustrates the paradigms that dominate multi-UAV group control research:

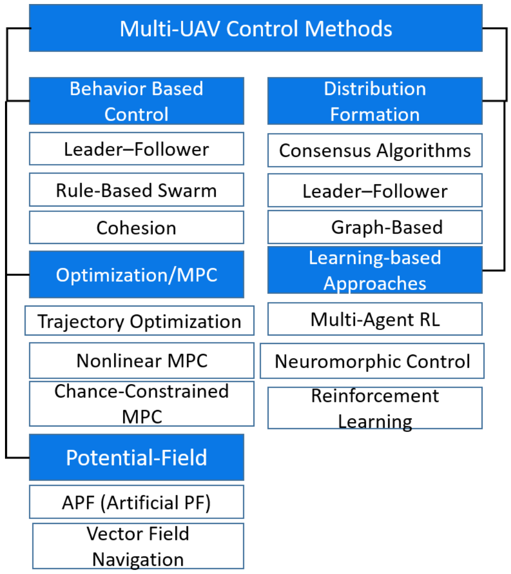


FIGURE 6. Overview of categories of control system methods for multi-UAVs.

1) BEHAVIOR-BASED CONTROL

Recent work on rule-based multi-UAV control has largely drawn from biologically inspired flocking behaviors to achieve distributed and collision-free motion coordination. One study introduced flocking and foraging rules to maintain formations, addressing stability but leaving scalability in dense spaces unresolved [59]. Another set of authors proposed a distributed flocking controller with guaranteed velocity convergence and collision avoidance, though fixed interaction parameters limit adaptability in rapidly changing indoor environments [60]. Follow-up research incorporated individualized behavioral properties to better handle UAV heterogeneity, yet robustness under strong disturbances remained an open challenge [61]. A separate approach extended rule-based flocking to constrained environments using a virtual-tube structure, but tube generation becomes increasingly complex in cluttered layouts [62]. Additional work applied probabilistic fuzzy-logic rules for indoor navigation in dynamic collaborative environments, improving uncertainty handling at the cost of significant tuning overhead [63]. A recent survey emphasized that although

TABLE 3. Summary of obstacle avoidance approaches in UAV systems.

Research Method/Author	Research Challenge Addressed	Evaluation Method	Research Strengths	Limitations/Tradeoffs
Reactive Methods/ Salau, 2018 [38]	Multi obstacle avoidance for Indoor UAVs with Artificial Navigation Potential	MATLAB	Simple and lightweight algorithm, works for static obstacle mapping, effective in simulated UAV navigation	Only static obstacles tested; no hardware integration; Empirical Validation Future Work
Zhao, 2019 [39]	Addressed the collision avoidance with LGMD-Based competitive collision avoidance	MATLAB/Real Exp	Lightweight, fast, and efficient; real-time escape; suitable for embedded systems; doesn't require mapping	Visual-only reliance; no learning or prediction; limited performance in clutter or low-light areas; No quantitative benchmarking
L. Dongcheng et al., 2020 [40]	3D multi-UAV APF that solves unreachable-target and local-minimum issues via modified potential functions	3D Simulated Environment	Solves local minima; Avoids jitter via dynamic step method ;Maintains inter-UAV distances; Simulated success in 3D space	No hardware implementation;High dependency on tuning parameters; Only static obstacles handled; Heuristic sensitivity
T. Muslimov et al., 2023 [41]	Multiple UAVs safe motion in cluttered spaces where standard Artificial Potential Field (APF) methods can "jam" at local minima;	Simulation Unity 3D using physics-based modeling	Lightweight, distributed control logic,Scalable, Does not rely on global path planning	Only tested in simulation, No consideration for dynamic obstacles; Real dynamic will be explored in future work
Sensors Based/ Aldao et al., 2019 [42]	Real-time obstacle avoidance with both static and moving obstacles (Sensor-Based Hybrid Approach (uses LiDAR + stereo vision)	Simulation tests	Lightweight, real-time, computationally efficient, embedded implementation; direction-aware collision response based on competitive spiking neurons	Single-UAV system; performance may be affected in visually cluttered or low-light environments
Niculescu et al., 2023 [43]	Fully onboard obstacle avoidance for resource-constrained UAVs; Sensor-Based (Depth camera + onboard microcontroller for efficient processing)	Emulated real-world navigation and verified with real flights in lab-like test environments	Fully embedded and real-time; Ultra-low power and memory-efficient; Adapted for very small drones	No dynamic obstacle handling; Relies on depth-only sensing (Single front sensor)
Tang and Niu, 2024 [44]	Achieving robust GPS-denied indoor UAV flight and obstacle avoidance where single-sensor (vision or laser) methods fail under lighting, scale, or geometry ambiguities	Real Testbed Trails	Combines benefits of both sensors; Real-time responsive adjustments; Good spatial accuracy	Requires sensor calibration and alignment; Limited quantitative rigor; Scalability no adressed; Unclear generalization to unseen layouts
Co-ordinated Based/ S. Huang et al., 2017 [45]	Real-time collision-free navigation for multi-UAVs with mixed obstacles and low on-board compute	4 case simulations + Hardware-in-the-Loop (HILS)	Robust Decentralized Collision Avoidance, real-time SLAM + path planning, Support for Complex Obstacles; Practical and lightweight approach	Locally optimal, not globally optimal, Increases geometric complexity; Empirical scale is modest
Zhou et al., 2017 [46]	Prevent collisions and physical deadlocks in multi-robot systems	MATLAB Simulated	Distributed, scalable, deadlock-free, low overhead	Assumes ideal communication, static paths
Zhu , 2019 [47]	Real-time navigation for MAVs in cluttered, dynamic spaces (robots + humans) under state-estimation and motion uncertaint	Simulated dynamic environment + real MAV flight tests	Explicitly handles moving obstacles with probabilistic guarantees; Real-time; Tested on physical MAVs	Global optimality & deadlocks; Model mismatch sensitivity; Requires accurate motion prediction of obstacles
Cheng Ma, 2022 [48]	Distributed multi-UAV UAVs to avoid static and dynamic obstacles in real time	2D Software Simulation	Solves local minima and unreachable target issues; Dynamic obstacle handling; Maintains UAV formation; Considers velocity constraints	No real-world validation;High tuning requirement for coefficients; Sensing & estimation gap; only planar tests
Peng and Meng, 2022 [49]	Real-time collision avoidance for multiple UAVs against dynamic UAVs and irregular static obstacles	2D simulation in a 300 m × 300 m area;Five UAVs navigating from start to target point	-Proposes a lightweight cooperative algorithm suitable for real-time use; Handles both dynamic and irregular static (polygonal) obstacles	No real-world or hardware-in-the-loop testing; purely simulation-based; Assumes ideal GPS and perfect communication, without modeling packet loss, latency, or interference
Chuhao Qin et al., 2024 [50]	Build a low-cost, testbed that integrates collision avoidance for Indoor UAVs	Testbed with Crazyflie Drones	Realistic collision avoidance with 3 types,Low-cost drones, Accurate energy modeling, Open-source, reproducible and Real-world dataset used	Small number of drones tested (4); Static priorities for APF; Limited sensor diversity (no LiDAR, etc.); Offline-only EPOS planning; Evaluations use a small 2×3 grid and slow speed (0.1 m/s)
Zhang et al., 2024 [51]	Multi-UAV Obstacle Avoidance with Optimal Consensus Control and Improved APF	Custom simulation	Fast convergence, avoids local minima, smooth collision-free trajectories with PSO-optimized control	Limited to 2D simulation, lacks real-world dynamics, not tested beyond 6 UAVs
ML Based/ A. Devos et al.,2018 [52]	Enable autonomous, adaptive obstacle avoidance in complex environments without heavy sensors or compute	V-REP, ROS + C++	Lightweight, memory-driven neural control, low-power, deadlock escape	No real hardware test yet; performance sensitive to configuration; low speed only
Singla et al.,2018 [53]	Enabling UAVs with only monocular RGB vision to perform real-time obstacle avoidance in partially observable indoor environments	Simulated 2D and 3D environments	Learns optimal navigation policy via exploration, long-term obstacle context, robust learning	No real-world validation, high training cost, sim-to-real gap
Chun Lo et al.,2023 [54]	Fast, safe obstacle avoidance in narrow spaces and L-shaped turns using only onboard vision + DRL.	Simulation only	Learns effective avoidance policies, real-time reactive and memory-based	High memory/computational demand, Limited sensor modeling realism
Wenjia et al., 2024 [55]	Build paths for safe amid obstacles while enforcing inter-UAV safety distance constraints	Simulated 2D and 3D	Efficient multi-UAV planning, Optimizes energy and distance	No real-world testing, Accurate modeling required
Zhang et al., 2024 [56]	Enable vision-only obstacle avoidance on nano-drones with severely limited compute/memory)	Simulated training in photorealistic engine (AirSim); tested in real-world indoor environment	Purely end-to-end with minimal manual tuning; Operates on constrained nano-drones; Effective in cluttered spaces	Model generalization limited by synthetic training; No explicit mapping or SLAM; May struggle in drastically different lighting
Ahmadvand et al., 2025 [57]	Scalable collision-free multi-UAV control in indoor environments, robust to intermittent cloud connectivity	Yes (MATLAB + 3D environment)	Highly adaptable in dynamic environments, multi-agent coordination, better convergence and success in complex terrain	Sim-only, not tested on real UAVs, lacks onboard processing validation; No network-layer benchmarks

rule-based flocking is attractive for its simplicity and decentralization, persistent gaps remain in adaptability, situational awareness, and real-time integration with learning-based methods [64].

2) POTENTIAL-FIELD AND VECTOR-FIELD METHODS

Recent work applying artificial methods to multi-UAV control has advanced formation stability and obstacle avoidance under uncertain and dynamic environments. One approach employed negative-imaginary systems theory to improve formation robustness, though scalability to large teams remains challenging [65]. Another combined consensus control with artificial potential fields to achieve coordinated motion, yet performance can degrade when potential fields introduce local minima [66]. A hybrid IAAPF–SMC formulation strengthened obstacle avoidance and tracking accuracy but still depends on careful tuning for aggressive maneuvers [67]. Further studies focused on formation planning in unknown dynamic environments using artificial decision mechanisms, addressing adaptability while leaving real-time responsiveness as an open issue [68].

3) DISTRIBUTED CONSENSUS AND FORMATION CONTROL

Research on distributed and consensus-based control has focused on enabling scalable coordination without centralized dependence. One study applied consensus formation control to mixed crewed–uncrewed systems, addressing cooperative stability but leaving open issues related to communication delays and battlefield uncertainty [69]. Experimental work demonstrated a low-cost testbed for decentralized UAV control, advancing real-world validation yet constrained by limited swarm size and sensing fidelity [70]. A comprehensive review highlighted that consensus implementations offer robustness and modularity, but performance still degrades under intermittent links and dynamic task switching [71]. More recent preprint work extended negative-imaginary consensus properties to formation-containment control with experimental results, improving disturbance resilience while still facing challenges in complex, cluttered 3D environments [72].

4) OPTIMIZATION AND MPC-BASED CONTROL

Studies applying control optimization and MPC to multi-UAV systems have focused on achieving precise, collision-free trajectories in constrained and cluttered environments. One trajectory-optimization framework addressed multi-UAS path planning in enclosed spaces, improving safety and efficiency but remaining sensitive to computational load in densely obstacle-rich scenarios [73]. Decentralized MPC approaches have demonstrated strong capability for formation deployment and reconfiguration with multiple outgoing agents, enhancing flexibility and distributed decision-making [74]. However, real-time feasibility becomes challenging as the number of UAVs increases, and performance depends heavily on accurate prediction models and reliable inter-UAV communication.

5) LEARNING-BASED AND NEUROMORPHIC CONTROL

Machine-learning-driven control, particularly multi-agent reinforcement learning, has emerged as a powerful tool for enabling adaptive and resilient multi-UAV coordination in uncertain environments. Recent work has integrated joint communication–motion decision-making to mitigate jamming, improving swarm robustness but remaining dependent on extensive training and high-dimensional state representations [75]. Other studies introduced adaptive DRL navigation frameworks for unknown indoor environments, enhancing autonomy while still struggling with sample efficiency and real-time deployment [76]. DRL-based formation controllers demonstrated effective static and dynamic obstacle avoidance, though generalization across different environments remains limited [77]. Learning-based MPC has also been applied to tight quadrotor formations, improving precision at the cost of increased computational demand [78]. A recent survey emphasized that while MARL methods offer strong adaptability and decentralized coordination, practical challenges persist in scalability, safe exploration, and hardware–simulation transfer [79].

a: BENCHMARKING, KEY TAKEAWAYS AND DISCUSSION

Table 4 provides a comprehensive benchmark of control system approaches for indoor UAVs.

Key Takeaways and Discussion:

- **Control Architectures:** Multi-UAV control approaches span behavior-based flocking, potential-field methods, consensus schemes, MPC, and learning-based controllers. Each provides partial benefits, but no single framework fully satisfies the constraints of dense, GPS-denied indoor environments.
- **Distributed Coordination:** Most coordination methods rely on idealized communication or perfect neighbor sensing. Robust formation-keeping under packet loss, latency, and partial observability remains an open challenge for scalable indoor swarm deployments.
- **Robustness and Stability:** NI-based control, sliding-mode variants, and hybrid APF–consensus approaches improve disturbance tolerance and convergence. However, their underlying assumptions simplify UAV dynamics and are not fully validated in cluttered indoor settings.
- **MPC and Optimization-Based Control:** MPC enables structured, constraint-aware control but remains computationally intensive, limiting real-time performance and scalability to large teams in dynamic indoor environments.
- **Learning-Based Control:** DRL and learning-enhanced MPC offer strong adaptability and can jointly handle formation and interaction with obstacles. Key limitations include high training cost, weak sim-to-real transfer, and heavy computational demands on embedded UAV hardware.
- **Simulation vs. Real-World Validation:** Most studies rely primarily on simulation platforms, with limited physical multi-UAV experiments. Real-world testing is

TABLE 4. Summary of multi-UAV control and coordination methods.

Research Method/Author	Challenge Addressed	Evaluation	Strengths	Limitations
Behavior-Based Control/ Zhang, [59]	Bio-inspired flocking and formation cohesion	Simulations + stability analysis	Distributed flocking rules; stable and simple implementation	No real indoor tests; simplified UAV dynamics
Liu & Qiu, [60]	Distributed flocking in GPS-denied settings	Simulations + small indoor tests	Uses only relative vision; stable flocking indoors	Limited UAV count; basic obstacle modeling
Shen & Wei, [61]	Heterogeneous flocking with individual UAV traits	Simulations	Handles heterogeneity; ensures cohesion	No experiments; simplified sensing assumptions
Lei et al., [62]	Hierarchical swarm flight in constrained "virtual tube"	3D simulation	Strong coherence; good for corridor navigation	Narrow application; no dense clutter evaluation
Agrawal et al., [63]	Fuzzy-logic navigation in dynamic indoor spaces	Simulations in collaborative environments	Good uncertainty handling; interpretable control rules	Rule tuning complexity; not validated at scale
Ali et al., [64]	Survey of flocking and collective-motion strategies	Literature review	Good taxonomy; identifies research gaps	No experiments; high-level indoor insights
Potential-Field and Vector-Field Methods/ Tran et al., [65]	Formation + obstacle avoidance via NI systems	Simulations + experiments	Robust NI-based stability; unified design	NI model constraints; small-scale demos
Wang et al., [66]	Consensus + improved APF for formation safety	Simulations	Avoids local minima; maintains relative spacing	Simulation-only; limited sensing realism
Zhang et al., [67]	IAAPF-SMC robust formation control	Custom simulations	Fast convergence; disturbance resilient	Requires tuning; lacks hardware validation
Chen et al., [68]	Formation planning in unknown dynamic areas	Simulation preprint	Handles dynamic obstacles; leader–follower logic	Early-stage; simplified environment models
Distributed Consensus and Formation Control/ Ma & Cao, [69]	Consensus-based formation for mixed UAV–manned teams	Numerical simulations	Flexible topology; coordinated maneuvers	No communication delay modeling; sim-only
Sahebsara et al., [70]	Low-cost decentralized multi-UAV testbed	Indoor experimental testbed	Enables practical validation; cheap hardware	Few UAVs; limited test area
Lizzio et al., [71]	Survey of consensus-based UAV implementations	Review	Summaries real deployments; highlights challenges	No unified benchmarks; high-level analysis
Su et al., [72]	NI formation–containment control	Theory + experiments	Formal NI guarantees; modular structure	Linear NI assumptions; limited-scale tests
Optimization- and MPC-Based Control/ Barlow et al., [73]	Trajectory optimization in enclosed spaces	Constrained simulations	Generates feasible indoor-safe paths	Offline optimization; limited experiments
Chevet et al., [74]	Decentralized MPC for formation deployment	2D MPC simulations	Distributed; handles agents joining/leaving	2D-only; computation grows with team size
Learning-Based and Neuromorphic Control/ Guo et al., [75]	MARL planning under jamming	Simulations	Joint communication–motion planning; scalable	Simplified radio model; no indoor tests
Zhou et al., [76] (DRAL)	DRL indoor navigation using monocular vision	Simulations	Lightweight sensing; adaptive control	Sim-to-real gap; limited multi-UAV scenarios
Xie et al., [77]	RL formation + obstacle avoidance	Two-stage RL simulations	Handles moving obstacles; unified formation policy	High training cost; preprint stage
Chee et al., [78]	Learning-based MPC for tight formations	Sim + real UAV flights	Very tight spacing; improved tracking	Complex tuning; assumes mild clutter
Ekechi et al., [79]	Survey of MARL for UAV control	Literature survey	Strong taxonomy; identifies open problems	No new algorithms; heterogeneous comparisons

essential to evaluate reliability under turbulence, sensor noise, and indoor multipath communication effects.

- **Environmental Complexity:** Many control strategies assume static formations or moderately cluttered scenes. Methods that model dynamic obstacles, airflow variations, and sensing uncertainty indoors are still emerging.
- **Scalability:** Current research typically evaluates only small groups (2–6 UAVs). Larger indoor swarms require scalable communication, lightweight coordination logic, and efficient resource management, which remain largely unresolved issues.

C. COMMUNICATION AND RESILIENT NETWORKING

Effective obstacle avoidance in multi-UAV systems depends on reliable communication, which allows UAVs to share detected hazards, coordinate maneuvers, and prevent conflicts in dynamic indoor spaces. Indoor environments are typically GPS-denied and characterized by severe signal attenuation from walls, metal structures, and cluttered layouts, which makes communication a central challenge. Therefore, UAVs rely on either a central server or peer-to-peer links to maintain coordination, as illustrated in Figures 7. Ensuring connectivity requires resilient network topologies that support real-time data exchange and fault tolerance under intermittent links, power constraints, and non-line-of-sight (NLoS) conditions. Growing performance demands have driven research into advanced indoor UAV networking, with major contributions to network architecture, communication protocols, learning-based communication, and integration with modern 5G and Wi-Fi systems. The following subsections review recent developments across these core categories.

1) TAXONOMY OF COMMUNICATION

Indoor multi-UAV networking in indoor environments can be systematically classified across three fundamental research

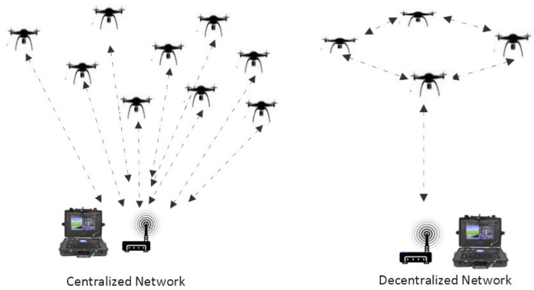


FIGURE 7. Central vs decentralized architecture for multi-UAVs.

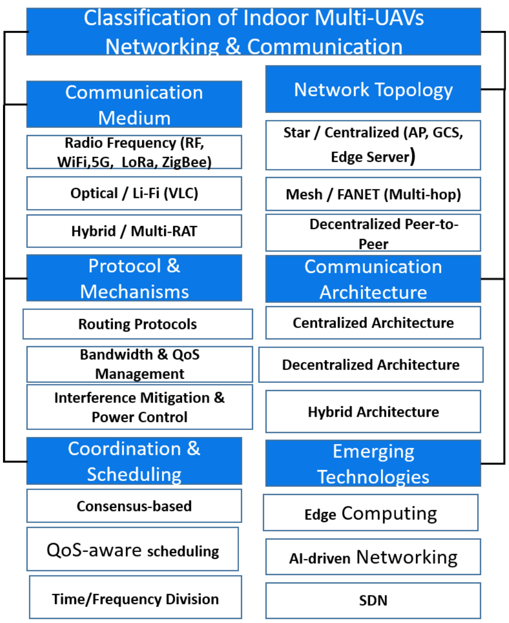


FIGURE 8. Overview of communication and networking taxonomy for multi-UAVs.

dimensions: (1) the communication medium used for wireless transmission, (2) the network topology that defines how UAVs and infrastructure are interconnected, and (3) the protocol-layer mechanisms that govern routing, interference mitigation, bandwidth management, and coordination. This taxonomy provides a unifying structure that organizes the diverse approaches in the literature and clarifies how each technique addresses reliability, latency, scalability, and robustness challenges in constrained indoor environments.

2) COMMUNICATION MEDIUM

Indoor UAV communication relies on several wireless media. Radio frequency (RF) links include Wi-Fi(5/6/7), sub-GHz technologies, and cellular (4G/5G) systems that offer reliable connectivity and wide compatibility. Optical or Li-Fi systems provide high-speed, interference-free communication but are sensitive to alignment and line of sight. Hybrid and multi-RAT approaches combine Wi-Fi with 5G or UWB to enhance localization accuracy, redundancy, and signal robustness in complex indoor layouts.

3) NETWORK TOPOLOGY

Different mission requirements motivate different multi-UAV topologies. Centralized star topologies rely on AP/GCS/edge servers for coordination, whereas multihop FANET/MANET mesh topologies support decentralized communication and redundancy. Peer-to-peer and cluster-based structures enable local coordination between nearby UAVs and support scalability, load distribution, and robustness in dynamic environments or link failures.

4) PROTOCOL-LAYER MECHANISMS

Protocol design plays a central role in maintaining reliability, low latency, and efficient bandwidth usage. Key mechanisms include mobility-aware routing (e.g., OLSR, GPSR), interference and transmit-power control, TDMA/FDMA/OFDMA resource scheduling, and QoS-aware bandwidth allocation. Modern studies increasingly employ SDN for centralized flow control and learning-based methods (RL/FL) for adaptive routing, channel selection, and congestion avoidance in multi-UAV swarms. Figure 8 presents the complete taxonomy that guides the integration of the architectural, protocol, learning-based, and 5G/Wi-Fi approaches reviewed in the subsequent subsections.

5) COMMUNICATION AND NETWORKING REVIEW

The following paragraphs—Architecture, Protocols, Learning-Based Approaches, and 5G/Wi-Fi Integration—fit directly into the taxonomy introduced above. Architecture corresponds primarily to the topology dimension; Protocols span both communication media and protocol-layer mechanisms; Learning-Based techniques operate at the protocol/mechanism layer; and 5G/Wi-Fi Integration focuses on hybrid media with strong implications for reliability, localization, and indoor coverage.

a: ARCHITECTURE

Early research on multi-UAV architecture identified major networking challenges, such as intermittent links, small UAV size, poor link quality, non-line-of-sight (NLoS) conditions, power issues, and lack of GPS support for multi-UAVs [80]. It identified major gaps, including the absence of UAV-specific routing protocols, limited SDN deployment, immature handover and DTN mechanisms, and insufficient focus on energy efficiency. Subsequent studies proposed a hybrid architecture leveraging cellular (4G/5G) networks to enable distributed, autonomous UAV-to-UAV communication [81]. This study highlighted the limitations of existing indoor protocols and advocated for 5G adoption to enhance communication efficiency. It also introduces planning frameworks and a functional swarm coordination testbed. However, challenges such as regulatory hurdles, scalability, security, energy constraints, and real-world 5G validation persist. To support heterogeneous applications, researchers have proposed flexible communication designs that handle diverse ranges, support star and mesh topologies, and integrate multiple wireless standards and data rates [82]. However, issues remain regarding scalability, security, energy efficiency, and the lack of AI-driven optimization or edge computing. Similarly, a self-organizing multi-UAV swarm architecture was introduced to unify networking and computation [83]. This highlights the need for high throughput, low latency, and reliability in multi-formation coordination. However, most existing studies treat networking and computation separately, lack scalable and secure designs, and fail to support dynamic in-network function execution under resource constraints.

b: PROTOCOLS

Covering the architecture and topology design for protocols, and reliability for UAVs. Early researchers highlighted the unique networking requirements of indoor UAV operations and discussed the limitations of applying traditional routing protocols, such as those used in vehicular ad hoc networks (VANETs) [84]. These protocols often fall short of meeting critical needs, such as cooperation, security, and adaptability, in dynamic indoor environments with mobile obstacles. To address this, the author proposed the development of Light Fidelity (Li-Fi)-based transmitter and receiver circuits for more advanced and reliable communication links. With progress, researchers have investigated the operational behavior of distributed indoor UAV swarms forming ad hoc networks in unknown environments [85]. Their study focused on the energy consumption challenges of UAV swarms, supported by theoretical modeling, simulation, and experimental validation. Similarly, an advanced study presented a comprehensive review of collaborative communication in multi-UAV systems [86]. The authors discussed the characteristics of intelligent UAVs and emphasized the communication and control requirements necessary for autonomous coordination and real-time collaboration. To address the challenge of adaptive channel allocation of a power-constrained communication protocol framework tailored to indoor UAV networks, the authors introduced adaptive power and channel allocation strategies designed to meet energy efficiency goals [87]. Through simulations, they demonstrated methods for minimizing power consumption and optimizing the computational load per UAV to support large-scale multi-UAV deployments.

c: LEARNING-BASED

Advancement in emerging technologies like ML have been utilized in networking. Early research proposed a solution for optimizing the movement of multiple UAVs to maximize the downlink capacity by ensuring the coverage of all ground terminals [88]. They formulated the problem as a constrained Markov decision process (CMDP) and evaluated the proposed algorithm using simulations. However, the authors noted that practical implementation requires further research. Similarly, further studies developed a deep reinforcement learning (DRL)-based framework for quality-of-experience (QoE)-driven deployment and dynamic control of multi-UAV systems. Their model addressed the non-convex 3D movement of UAVs with the goal of maximizing the aggregate Mean Opinion Score (MOS) of ground users [89]. A federated learning-based system for multi-UAV networking was utilized [90]. The authors utilized UAVs to collect image data using onboard cameras and performed local classification tasks. The local model updates from each UAV were then transmitted to a ground fusion center over fading wireless channels, thereby enabling collaborative model training without direct data sharing.

d: 5G / WI-FI INTEGRATION

Recently, research has progressed to utilize indoor 5G and Wi-Fi technologies for UAV networking. Researchers have addressed the critical challenge of accurate indoor localization for drones using a hybrid 5G and Wi-Fi infrastructure [91]. The key contribution lies in optimizing Wi-Fi (Wi-Five) router placement using evolutionary algorithms to minimize the geometric dilution of precision (GDOP), particularly improving the Z-axis (height) accuracy, which is often neglected. The integration of Wi-Fi with 5G enhances signal coverage in areas affected by attenuation. However, a remaining gap is the lack of real-world deployment or large-scale experimental validation beyond simulations and limited consideration of dynamic drone movement patterns and environmental interference in realistic indoor environments. Moreover, advanced research has introduced the concept of Wi-Fi-based 6-DoF tracking for indoor drone flights, addressing the challenge of accurate indoor positioning. The system employs 6-DOF tracking and fuses position data with flight control inputs to enable reliable navigation in indoor environments [92]. However, remaining gaps include scalability to larger multi-drone systems, robustness under dynamic interference or heavy multipath conditions, and generalization across diverse indoor topologies or Wi-Fi configurations. Further work is required to extend the performance in high-density or collaborative UAV scenarios.

e: ZIGBEE-BASED MULTI-UAV COMMUNICATION AND FORMATION CONTROL

The authors in [93] develop a distributed formation-control strategy based on onboard sensor information sharing, a concept that can be adapted to indoor environments where GPS is unavailable and cooperative sensing is essential for stable formation. Similarly, the ZigBee-based communication framework in [94] demonstrates a lightweight, low-power networking approach that can be repurposed for short-range indoor UAV swarms, where limited bandwidth is acceptable and energy efficiency is advantageous. These studies therefore provide foundational methods that, with appropriate modifications, can support indoor multi-UAV coordination and communication. Although this work primarily designed for outdoor multi-UAV operations, their core techniques offer transferable value for indoor systems.

TABLE 5. Summary of communication and network in UAV systems.

Research Method/Author	Research Focus	Evaluation Method	Research Strengths	Limitations/Tradeoffs
Architecture Gupta et al., 2017 [80]	Architectural, routing, control, and QoS issues in UAV communication networks	UAV Ad Hoc Networks (UAANETs), Wireless Mesh Networks; Infrastructure-based UAV systems; SDN-based UAV control; Delay/Disruption Tolerant Networks	Highlighted stability needs for UAV networks, Introduced SDN for UAVs, Comparative analysis of routing protocols	Lacks practical implementation or testbed validation, Lacks integration with modern tech like 5G or edge computing
Campion et al., 2019 [81]	WiFi-based Mesh Communication, UAV swarm communication and control architectures, emphasizing autonomy, cellular networking, and swarm decision-making	Wi-Fi Mesh, Hybrid SWARM	Prototype using Raspberry Pi + Pixhawk; Uses existing cellular infrastructure (scalable, reliable)	Latency concerns and cellular dependency
Sanku et al., 2021 [82]	UNET: Multi-UAV communication for heterogeneous applications	Infrastructure (4G/LAN) + Infrastructure-less (adhoc mesh)	Generic, protocol-agnostic, real implementation, GCS remote control, scalable	No security layer, limited AI, 5 UAVs only tested
Asaamoning et al., 2024 [83]	Topologies, control architectures, and integration strategies	Ad hoc, cluster-based, and multi-hop UAV-to-UAV communication	Integration of networking and computing as a unified control architecture; Introduced Named Function Networking (NFN) to support function-based data forwarding.	Conceptual; NFN and in-network computing proposals are not validated via experiments; limited performance data
Protocols Sadiq et al., 2017 [84]	Li-Fi for indoor UAV communication	FANET (Flying Ad Hoc Network) with Li-Fi	Novel light-based links for indoor UAVs; High bandwidth via visible light (300 THz); Secure, high-throughput, interference-free networking	No hardware implementation; Scalability not quantified, No testbed
Aznar et al., 2018 [85]	Energy-efficient, pheromone-based swarm behavior for indoor UAV ad-hoc network deployment	Ad-hoc UAV-based MANET via landed beacons	Decentralized, energy-efficient, and robust swarm behavior	Requires tuning, Needs virtual pheromone sensor hardware
Javaid et al., 2023 [86]	Protocols for Coordination	Protocol Review Wi-Fi, UHF, FSO, LoRaWAN, Satellite	Comprehensive review of protocols, Multi-Domain Perspective	Limited discussion on security and privacy
Salameh et al., 2022 [87]	Power-aware communication: Minimizing transmit power, channel assignment, QoS in dense indoor settings	Indoor Beyond 5G/6G UAV communication systems; Cognitive radio (CR)-enabled UAVs	Designed for realistic indoor constraints; Highly energy-efficient; Convex optimization; Supports multi-antenna UAVs (MIMO)	Focuses only on uplink; no downlink analysis; Lacks real-time or hardware validation
Learning Based Q. Wang et al., 2019 [88]	Real-time UAV movement optimization using Dueling Deep Q-Networks (DDQN) to maximize downlink capacity and coverage	Multi-UAV downlink wireless communication to multiple ground terminals (GTs)	Real-time adaptation, Improved DQN with dueling structure; Scalable framework	High Training Overhead; Simplified Channel Assumptions; No Real-World Testing
X. Liu et al., 2019 [89]	3D deployment and dynamic movement of UAVs using Q-learning to maximize QoE	QoE-driven multi-UAV assisted communication framework	Adaptive 3D UAV deployment and movement; low post-training complexity	Relies on offline training; Complex for real-time UAV dynamics
Zhang and Hanzo, 2020 [90]	Efficient image classification in multi-UAV networks using federated learning	Multi-UAV coordination via federated learning over wireless uplink to GFC	Reduces communication cost via FL; Preserves data privacy; Handles imperfect CSI; High classification accuracy (95%)	Simulation-based only, no real-world test; Limited by single-antenna UAVs; GFC still a central bottleneck
5G / Wi-Fi Integration A. Famili et al., 2023 [91]	3D indoor localization for drones using optimized Wi-Fi router placement in multi-RAT 5G network	Multi-RAT (5G + Wi-Fi)	Combines 5G/Wi-Fi for accurate UAV tracking; Effectively minimizes 3D localization error by optimizing Wi-Fi router placement using a GDOP-aware evolutionary algorithm.	Early-stage testbed; Lacks real-world deployment and scalability testing beyond a fixed 4-router setup in simulation
Guoxuan et al., 2022 [92]	Standalone 6-DoF indoor drone tracking using commercial Wi-Fi signals	Wi-Fi CSI-based	6-DOF tracking via existing Wi-Fi signals; Achieved accurate, real-time 6-DoF tracking using only Wi-Fi, robust to lighting and texture conditions.	Performance may degrade in complex multi-path environments and requires careful hardware calibration.
ZigBee Based Park et al., 2015 [93]	Distributed formation-flight control using onboard sensor information sharing (adaptable to indoor cooperative navigation)	Simulation and real-world outdoor flight tests; evaluation of formation stability, inter-UAV spacing, and cooperative response to disturbances	Eliminates reliance on centralized control; enables robust formation through distributed sensing and information sharing; concept transferable to GPS-denied indoor environments	Designed primarily for outdoor conditions; not optimized for indoor constraints such as multipath interference, tight spaces, or limited communication bandwidth
Pereira et al., 2020 [94]	ZigBee-based low-power communication architecture for multi-UAV networking (applicable to short-range indoor swarms)	Experimental ZigBee communication tests; throughput, packet loss, link reliability, and power consumption measurements	Lightweight and energy-efficient protocol suitable for compact UAVs; feasible for short-range indoor communication where low-data-rate control messages dominate	Limited bandwidth and scalability; ZigBee unsuitable for high-rate sensing tasks; originally validated outdoors and requires adaptation for dense indoor radio conditions

6) MECHANISMS SUPPORTING RELIABILITY, LATENCY, AND QoS

Across the surveyed literature, the performance requirements of indoor multi-UAV networking—low latency, high reliability, robustness under mobility, and efficient bandwidth use—are achieved through concrete technical mechanisms. Reliability is supported by multi-hop mesh redundancy, hybrid 5G/Wi-Fi failover, robust modulation/coding, and delay-tolerant networking for intermittent links. Low-latency operation is achieved via OFDMA scheduling, spatial reuse enhancements in Wi-Fi 6/7, edge-assisted computation, and SDN-based fast rerouting. Bandwidth and QoS are improved through interference-aware power control, cognitive radio channel allocation, and optimization-based scheduling tailored for dense UAV deployments. These mechanisms provide the operational basis for the architectural and protocol-level designs discussed in the preceding subsections. subsubsectionBENCHMARKING, KEY

TAKEAWAYS AND DISCUSSION Table 5 presents a benchmarking comparison of the selected studies.

Key Takeaways and Discussion:

Diverse Network Types: In published studies, indoor multi-UAV systems employed ad hoc networks (FANET, MANET), mesh, infrastructure-based (Wi-Fi 5/6/7, 4G/5G), and hybrid networks based on flexibility, coverage need, and performance choice.

Networks for Localization and Tracking : Wi-Fi CSI and multi-RAT methods offer accurate, real-time 6-DoF tracking and improved UAV localization.

Role of ML in advanced Control Methods : Research on software defined networking (SDN), centralized networking, and reinforcement learning (DQN, FL) is currently increasing and progress for scalable and intelligent UAV coordination is being in demand for multi-UAVs.

Integration with Modern Tech: Recent research incorporated 5G/6G, and Named Function Networking (NFN) to build adaptive and customized communication systems.

Energy and Efficiency Focus: Networking solutions (e.g. Li-Fi and CR-enabled UAVs) emphasize energy efficiency and interference-free communication.

Prototype Implementations Vary: Published work (e.g., Campion 2019, Kumar 2021) implemented the algorithms on real-world testbeds. The simulation of practical implementation has gaps that need to be reduced by developing practical prototypes.

Need for Standardized Testbeds: Absence of hardware-based validation and benchmarks impedes practical deployment and comparison.

D. MISSION PLANNING AND COMPUTATIONS

The data exchanged through communication channels (e.g., obstacle maps, attitude, UAV positions, and task updates) directly influence path planning. Coordinated planning relies on shared knowledge to optimize routes, avoid congestion at specific locations, and balance workloads among UAVs. One of the key research factors in autonomous multi-UAV systems is mission planning, along with ensuring sufficient computing power to support the real-time execution of complex algorithms in indoor environments, as shown in Figure 9. Path planning requires significant processing resources, and the need for optimization becomes critical as the number of operational UAVs increases. To reduce the computational load, UAVs must follow efficient paths when navigating between locations. Based on published research, an overview of the methodologies is presented in Figure 10 and Figure 11. Research in this area focuses on multi-UAV coordination, path optimization, and the integration of onboard intelligence within a limited processing capacity. This section provides an overview of existing studies on mission planning and computational strategies, highlighting the difficulties posed by hardware and resource constraints in indoor settings.

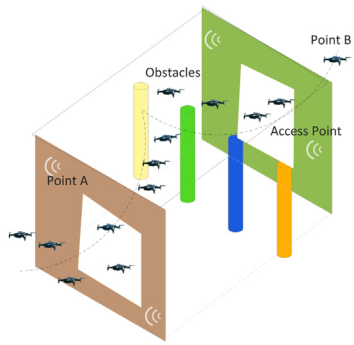


FIGURE 9. Indoor UAVs moving from Point A to Point B with algorithms.

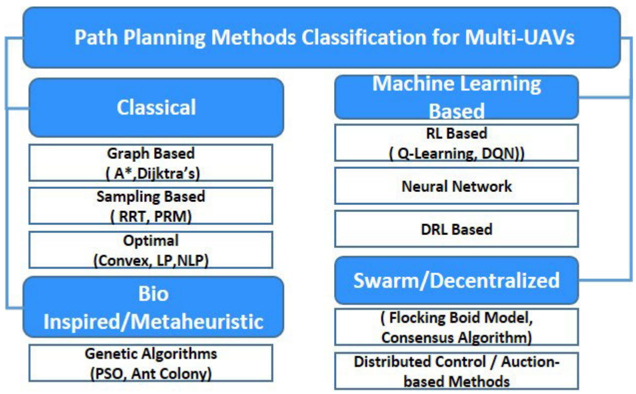
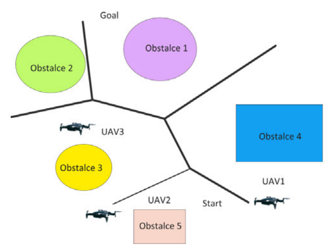
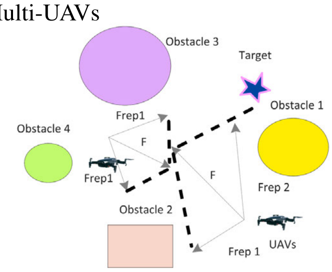


FIGURE 10. Overview of path planning methods for multi-UAVs.



(a) A* Algorithm Path Planning for Multi-UAVs



(b) Potential Field Path Planning for Multi-UAVs

FIGURE 11. Common path planning algorithms: (a) A* algorithm and (b) Potential field algorithm.

1) TASK ASSIGNMENT AND PLANNING ALGORITHMS

Recent research has focused on developing task planning and scheduling algorithms for multi-UAV operations in GPS-denied indoor environments. To address real-time mission coordination challenges, early work proposed a two-level architecture with a Global Mission Planner (GMP) that partitions mission zones, distributes tasks, and dynamically re-plans missions [95]. This framework decomposes high-level objectives into low-level tasks, enabling continuous UAV operation, but still faces challenges such as managing failures and optimizing trajectories. Building on this, a task scheduling system tailored for indoor UAV operations was introduced [96], featuring a formal mathematical model and a PSO-integrated heuristic evaluated using realistic datasets. The remaining issues include dynamic uncertainty handling, fine-grained collision avoidance, and sensor integration. A voxel-based mission planning approach using the 3D Propagating Approximate Euclidean Distance Transformation (3D PAEDT) was proposed in [97], effective for static environments but limited in handling dynamic obstacles. Reinforcement learning has also been applied to indoor multi-UAV path planning, with a two-stage curriculum strategy to improve navigation in obstacle-rich spaces [98]. Similarly, a grid-optimized A*-based planner was developed to enhance mission planning accuracy in simulated 3D indoor spaces using Gazebo [99], although real-world validation remains an open area for future work.

2) OPTIMIZATION TECHNIQUES AND SWARM COORDINATION

This body of work centers on optimization strategies and swarm coordination for indoor UAV operations, addressing challenges such as mission planning complexity and coordination in GPS-denied environments. A multi-objective genetic algorithm design was presented to optimize swarm-based mission planning involving UAVs and ground control stations [100]. Using a hybrid fitness function, the approach effectively balanced fuel consumption and travel distance across diverse mission datasets. Furthermore, this research was advanced in this direction by introducing a bi-level framework for indoor reconnaissance with heterogeneous UAVs [101]. This method integrates iterative search algorithms and solution-space compression to allocate tasks efficiently while meeting strict mission constraints, significantly improving planning scalability in complex environments. Further emphasizing swarm intelligence, the authors reviewed hierarchical formation control strategies, detailing algorithms for obstacle avoidance, path planning, and communication models that enable both centralized and decentralized swarm configurations [102]. Complementing these efforts, recent developments have focused on a decentralized system for target detection in cluttered, GPS-denied indoor settings [103]. This methodology combines onboard sensing with collaborative exploration to maximize area coverage and minimize redundant paths, achieving high performance in real-world tests. Overall, this study advances the field by addressing key challenges, such as efficient multi-agent coordination, constraint-aware task assignment, and real-time exploration in constrained indoor settings. However, open challenges remain, particularly in achieving robust scalability for large swarms, adapting to dynamic mission objectives in real time, and ensuring reliable inter-UAV communication in obstructed indoor environments.

3) VISION-BASED PLANNING

Focusing on perception-aware architectures and semantic navigation frameworks for indoor UAVs, these studies addressed key challenges such as vision-based obstacle avoidance, semantic scene understanding, and autonomous path planning in unknown indoor environments. A perception-aware framework for vision-based target recognition and collision avoidance was proposed for indoor UAV missions [104]. The system enables safe navigation in enclosed indoor spaces with unknown regions, random obstacle placements, and target distributions. Simulations conducted using Gazebo software assessed the performance based on multiple Key Performance Indicators (KPIs). The framework supports both centralized and decentralized communication models, allowing UAVs to operate in swarm configurations and execute coordinated tasks. This study also highlighted the limitations of existing indoor path-planning methods, particularly in handling low-altitude flights, autonomy, complexity, and convergence speed. In a related contribution, an indoor navigation module for autonomous UAV and robot movement across defined zones within unknown environments was presented in [105]. This method relies on segmenting indoor areas into semantic regions derived from environmental contours. The system incorporates advanced sensing and semantic reasoning to facilitate autonomous navigation. The authors suggested that using the probabilistic distribution of semantic network data could further improve planning accuracy and system efficiency. These studies advance the field by enabling more intelligent, perception-driven indoor navigation. However, challenges persist in scaling semantic reasoning to dynamic multi-UAV scenarios, reducing computational overhead for onboard processing, and ensuring robustness under uncertain or sensor-degraded conditions.

4) HARDWARE-CONSTRAINED EXECUTION

This group of research addresses hardware-related constraints in indoor UAV path planning and mission execution, focusing on issues such as computational limits, sensor reliability, energy constraints, and scheduling efficiencies. Early authors examined the optimization of UAV systems under constraints such as control latency, sensor accuracy, and platform responsiveness [106]. By testing various hardware setups, including ASICs, FPGAs, and Raspberry Pi, they evaluated the trade-offs in cost, performance, and autonomous capability using open-source platforms. This research was advanced by enhanced indoor navigation by integrating semidirect visual odometry with ORB-SLAM2, improving localization robustness under low-light conditions [107].

Similarly, authors contributed a collaborative path-planning approach for UAVs operating in tight indoor spaces, and researchers combined global and local planners to boost obstacle avoidance and reduce collisions [108]. Regarding resource scheduling, advanced research proposed a heuristic–PSO-based task scheduler that considers UAV energy limits, recharge cycles, task dependencies, and collision avoidance [109]. Collectively, this review mitigates hardware-induced limitations through software–hardware co-optimization, efficient scheduling, and robust localization. However, challenges remain in achieving real-time processing on constrained platforms, extending battery life for prolonged missions, and ensuring scalability in hardware-aware-swarm coordination.

a: BENCHMARKING, KEY TAKEAWAYS AND DISCUSSION

Although various studies have addressed indoor navigation, significant challenges remain in mission planning, particularly in complex multi-UAV scenarios. Successful mission execution requires reliable indoor localization and efficient onboard computations. Accurate positioning and real-time processing are essential for effective coordination of UAVs. The review concludes that future research should integrate cutting-edge technologies to overcome the current limitations and further enhance the autonomy and scalability of indoor UAV systems. Table 6 presents an overview of mission planning contributions for indoor multi-UAVs.

Key Takeaways and Discussion:

Classical Methods: Classical methods (e.g., voxel, A*) offer low complexity but lack dynamic adaptability.

Swarm and Decentralized Methods:
Sensor fusion and decentralized exploration improve resilience in GPS-denied settings but require an increased number of stable communication links. The complexity of managing these links increases when the density of UAVs increases.

Role of ML : Learning-based approaches (e.g., DQN, PPO) yield better convergence but demand computations. The solutions require accurate datasets and training models to obtain better results for convergence. Region-based and learning-based semantic planners allow efficient navigation, although few integrate uncertainty modeling or dynamic replanning for multi-UAVs.

Role of Edge Computing: Edge computing can offload computation from UAVs and enables the gate for faster planning and coordination. When the number of UAVs increases, the edge offers better computational performance for complex tasks and scalability.

Energy Constraints: Performing indoor UAV missions requires more energy and computations when uncertain conditions arise or the number of UAVs increases. Owing to this requirement, the energy increased. Currently, the flight time of UAVs is limited by the nature of the battery power source.

E. CAPABILITIES FOR NAVIGATION, LOCALIZATION, AND SENSING

Accurate localization and sensing are essential for reliable path planning and real-time adjustments in indoor multi-UAV systems, particularly in GPS-denied environments. UAVs rely on onboard sensors, such as cameras, LiDAR, ultrasonic sensors, and IMUs, for navigation; however, sensor limitations, such as noise, latency, or failure, can hinder autonomy and increase collision risks in multi-UAV operations. As shown in Figure 12, maintaining situational awareness becomes more challenging with swarm-scale deployments. Researchers continue to explore robust and cost-effective alternatives to high-end sensors. This section highlights the key contributions in sensing, localization, and navigation strategies, categorized in Figure 13, including SLAM, UWB, vision-based navigation, acoustic methods, sensor fusion, and decentralized autonomy.

1) SLAM-BASED APPROACHES

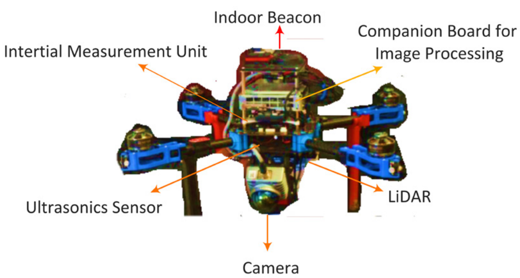
Several studies have explored low-cost SLAM techniques for UAV indoor sensing and navigation. Early researchers developed a lightweight feature-based SLAM approach using cameras and particle filtering, which was validated through real-world testing [110]. Further advances in research used a multicopter to generate accurate 2D floor maps, emphasizing decision-making variables for indoor flight [111]. By applying simulated annealing and IMU data for pose estimation on a low-cost drone, minimal error was achieved in indoor navigation [112]. Advanced researchers have enhanced monocular SLAM with EKF-filtered IMU data but faced challenges in localization accuracy [113]. To advance this field of study, researchers proposed an ultrasonic sensor-based mapping system that showed comparable accuracy to Gmapping and Hector SLAM while reducing the cost [114]. By combining ORB-SLAM with IMU fusion via EKF for improved pose accuracy, researchers advanced this methodology and verified it through trajectory tracking [115]. By utilizing an ROS-based system integrating 2D LiDAR and an IMU for reliable low-cost localization, the authors simulated SLAM for indoor UAVs to address the challenge of navigation [116]. The key challenges addressed include reducing the computational burden, achieving real-time localization with limited sensors, and improving pose estimation through sensor fusion. The remaining challenges involve enhancing robustness in dynamic indoor environments, improving fusion accuracy, and achieving consistent performance across diverse real-world scenarios.

2) UWB-BASED NAVIGATION

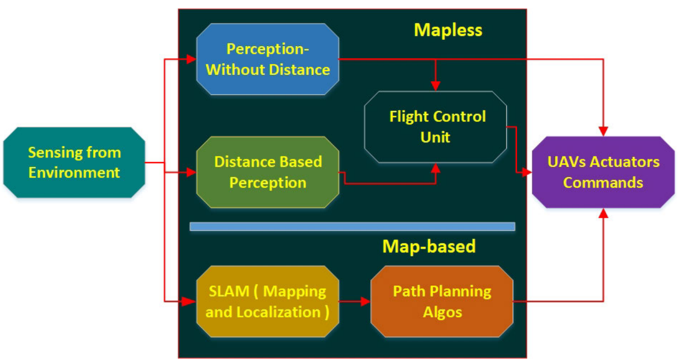
UWB-based navigation has gained traction in enhancing indoor UAV localization. Initial studies used nRF905 modules and motion capture systems to provide 3D coordinates for UAVs, leveraging advances in sensing and computation [117]. Building on this, UWB technology was explored for multi-UAV localization to address autonomous navigation

TABLE 6. Benchmarking of mission planning and computation strategies for indoor multi-UAV systems.

Research Method/Author	Research Focus	Performance	Research Strengths	Limitations/Tradeoffs
Task/Planning Algos Sampedro et al., [95]	Global Mission Planner (GMP) for multi-drone task decomposition and scheduling	Good coordination	Dynamic mission replanning in real time	No quantitative metrics (e.g., mission time, energy)
Khosiawan et al., [96]	Hybrid heuristic-based scheduling under energy and priority constraints	Improved energy use	Hybrid heuristic + optimization	Deterministic environment, no real-time replanning; assumes homogeneous UAVs
Fangyu Li et al., [97]	Voxel-based PAEDT for universal indoor path planning and obstacle avoidance	Accurate static planning	Voxel-based precision in known maps	No dynamic obstacle support
Jongmin and Kwansik, [98]	Multi-agent reinforcement learning with curriculum learning for dense indoor spaces	Improved convergence	Curriculum learning efficiency	High training cost; limited UAVs; no hardware validation
Bing Han et al., [99]	Grid-optimized A* algorithm for structured 3D indoor airspace planning	Fast: GO-APP 1.2s for 2D planning	Grid-based A* enhancement	Not tested in hardware; longer paths in GO-LBPP due to backtracking; assumes static environment
Optimized/SWARM Cristian et al., [100]	Multi-UAV mission planning using hybrid MOGA + CSP	Multi-objective optimization	Flexible GA with hybrid fitness	High complexity for scaling
Zhang et al., [101]	Indoor multi-UAV task assignment and path planning (ARIRTP) using bi-level optimization	Efficient task sequencing	Bi-level optimization framework	Heavy computation; ignores UAV communication losses, real-world uncertainties
Y. Zhou et al., [102]	Swarm coordination using hierarchical body structure model	Theoretical scalability	Layered swarm structure	No real implementation
Zhu et al., [103]	Sensor-fused, decentralized UAV target search in GPS-denied indoor spaces	Robust in GPS-denied areas	Sensor fusion + decentralization	Requires reliable communication; no dynamic role switching; only tested with 3 UAVs
Learning Based Farooq et al., [104]	KPI-based visual system for safe payload navigation indoors	Safe obstacle navigation	Perception-aware planning	Limited to 2D mapping (fixed altitude); no real-world deployment; no multi-UAV collaboration
Akbari et al., [105]	Semantic reasoning for intelligent autonomous navigation in confined spaces	Faster execution, greater explored volume	Region-based planning logic	No real-world deployment; no uncertainty modeling; single-agent only
Hardware- Constrained R. Hadidi et al., [106]	Compute–energy–weight tradeoffs for UAVs; SLAM optimization on various platforms	Hardware-level benchmarking	Realistic latency insights	Focus mainly on SLAM; no multi-UAV coordination
Basiri et al., [107]	Fusing SVO and ORB-SLAM2 with Adaptive Complementary Filter for localization	Improved indoor SLA	SVO + ORB-SLAM2 fusion	Lacks real-world validation; struggles in feature-poor/dynamic environments
Feng et al., [108]	Collaborative path planning for UAVs in cluttered indoor environments	Smooth, conflict-free paths for up to 60 UAVs; 14.5% shorter avg. paths	Realistic modeling (downwash, 3D collisions); supports up to 60 UAVs; public dataset/code	Assumes static environment; no real-time replanning or physical UAV validation
Khosiawan et al., [109]	Three-layer UAV system architecture for multi-UAV indoor scheduling	Architectural framework	Modular scheduling structure	Conceptual only; lacks detailed performance evaluation



(a) Indoor UAVs Sensors



(b) Overall Navigation Flow for Indoor UAVs

FIGURE 12. Illustrations of (a) onboard sensor configurations and (b) the overall navigation process used in indoor UAV systems.

challenges [118]. However, the experiments were limited in scope, and odometer calibration and sensor inaccuracies remain a concern. Hybrid methods that combine motion capture with UAV control hardware have shown good performance in hover and waypoint tests [119]. UWB-based localization using two-way time-of-flight (TW-TOF) and maximum likelihood estimation (MLE) also demonstrated high precision in simulations with optimized anchor placement [120]. Multi-sensor fusion approaches that integrate UWB, IMU, sonar, SLAM, and markers further improve 2D and 3D localization [121] and [122]. Dead reckoning using lightweight UAVs and virtual 3D maps based on IMU data also contributed to the position estimation. The remaining challenges include limited scalability and persistent issues with sensor inaccuracy and odometer calibration. Accurate localization still heavily depends on ideal anchor placement and incurs a high computational load from multisensor fusion. Moreover, achieving real-time robust performance in

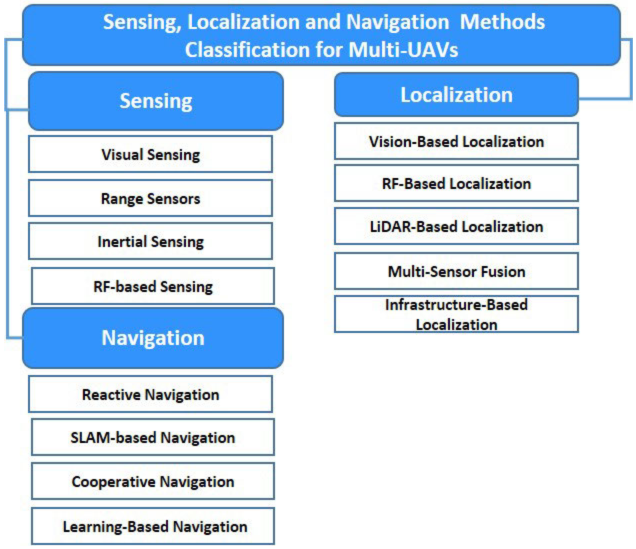


FIGURE 13. **Sensing, Localization and Navigation Methods Classification for Multi-UAVs.**

dynamic environments while reducing reliance on external systems, such as motion capture, remains unresolved.

3) VISION BASED NAVIGATION

Moving forward with vision-based navigation for indoor UAVs, a novel autonomous flight method using onboard relative positioning sensors was introduced [123]. A decentralized algorithm enabled goal-directed multi-UAV flights and large-area indoor searches without external sensors or special lighting. The simulation results showed successful navigation with dynamic beacon switching and ceiling attachment. Vision-based self-stabilization using fast image processing and feedback control for UAV groups was demonstrated in [124], which maintained stable operation even during temporary visual link loss. An autonomous UAV with onboard visual intelligence, requiring no operator or offloading, was proposed for indoor inspection tasks [125], and validated using Gazebo and ROS in 3D oil field scenarios. Visual-inertial odometry, markers, UWB, and SLAM were also used to address inventory management challenges such as path planning [126], alongside low-cost acoustic systems for UAV localization in confined spaces. The key challenges addressed include the removal of GPS dependency, enabling decentralized control, and achieving visual self-stabilization and autonomous indoor inspection. The remaining issues involve improving the accuracy in low-visibility areas, enhancing the robustness in tight and dynamic environments, and optimizing onboard processing for real-time performance.

4) ACOUSTIC SENSING

The localization methodology for indoor UAVs, PILOT (High-Precision Indoor Localization for Autonomous Drones), was presented in [127]. PILOT uses ultrasonic sound signals to determine locations. Utilizing a frequency-hopping spread spectrum (FHSS), it mitigates the effects of multipath fading. Similarly, researchers have presented Acoustic Inertial Measurement (AIM), a method for tracking and locating drones indoors. The AIM estimated the drone location and calculated its movement using acoustic signals and their characteristics [128]. The authors tested non-line-of-sight conditions, and the Interquartile Range Rule (IQR) and Kalman filter were used to reduce location estimation errors. An off-the-shelf microphone array was used to implement the AIM, and its performance was assessed using a commercial drone in various environments. In the same line of research, advanced research has described how to use ultrasonic sensors to create a mapping system for indoor UAVs in unknown indoor environments [129]. The core platform was the DJI Mini Tello UAV, a lightweight 80 g drone with limited capabilities. The mission was completed using a distributed-system approach without exceeding the system constraints. The remaining challenges include improving accuracy under multipath and non-line-of-sight conditions, enhancing system reliability with low-cost hardware, and overcoming the range and resolution limits of acoustic sensors in complex indoor environments.

5) SENSOR PLACEMENT

Sensor placement plays a critical role in enabling autonomous indoor UAV flights, supported by advances in processing, precision, and compact embedded systems. For hazardous environments, a novel aerial sensor deployment technique was introduced using impulsive launching and a micro-SMA-based trigger to enhance the precision of action [130]. Indoor and outdoor tests revealed placement uncertainties but validated the deployment approach. In [131], Marvelmind beacons, a PX4 controller, and ESP8266 were used to bridge the simulation-to-reality gaps in localization. A Multi-Sensor Fusion Factor Graph (MSF-FG) method combining IMU, odometry, and LiDAR was proposed in [132] to reduce complexity via factor graph theory and optimize sensor parameters. SPIN, developed in [133], integrated LiDAR, IMU, and WiFi for GPS-free indoor multi-UAV navigation, using optimization algorithms for effective sensor placement in large three-dimensional (3D) spaces. Despite this progress, achieving full autonomy in complex indoor environments still requires further refinement of sensor integration and placement strategies.

6) DECENTRALIZED AUTONOMY

Focused on decentralized autonomy in indoor environments, the implementation of a multi-UAV system with reliable operation was enabled through wireless network support. A decentralized architecture was presented using Decentralized Partially Observable Markov Decision Processes (Dec-POMDPs) to manage decision-making under uncertainty in known environments [134]. The authors used ROS and Gazebo to test their system in GPS-denied, cluttered settings that included wall barriers, multiple UAVs, and various

TABLE 7. Benchmarking of indoor multi-UAV Sensing, Localization, and Navigation research.

Author(s),[Ref.]	Research Focus	Computation	Efficiency	Strengths	Limitations
SLAM Based Buonocore , [110]	Low-cost SLAM with camera and particle filter integration	Onboard CPU	High accuracy (<2–3.5% error), consistent maps	Affordable + Real tested	Limited scalability
Alpen et al., [111]	Custom-built UAV for orthogonal SLAM	Microcontroller based	Moderate	Simplicity, cost-effective, Autonomous	SLAM limited to 2D mapping; Prototype-only validation
Hussein et al., [112]	Low-cost autonomous UAV using simulated annealing and IMU data	Embedded system	High navigation accuracy	Low-cost, accurate, modular, scalable, robust, validated.	No dynamic obstacle handling, IMU drift not corrected
Garcia et al., [113]	EKF-based Visual SLAM with IMU fusion	Moderate	Effective fusion of low-cost sensors	LSD-SLAM sensitive to low-light and rotations	
Zheng, [114]	SLAM using inexpensive ultrasonic and visual sensors	Lower than visual SLAM and GMapping	Comparable scan accuracy to costly SLAM techniques	Low hardware cost	Tested only in simulation, No real-world deployment, Limited obstacle handling
Haddadi, [115]	Visual-inertial fusion with ORB-SLAM for quadrotors	ORB-SLAM onboard; Intensive	High; Vertical stability is strong (Z axis)	Low-cost drone compatibility; Real-time visual-inertial fusion	Relies on off-board ROS processing; Sensor Drift is sensitive
Irwansyah et al., [116]	ROS-based integration using LiDAR, IMU, odometry for SLAM	ROS-based CPU	Moderate; Error: 3.25–5.50%	ROS modular design	Limited validation; IMU-only localization prone to drift
UWB Localization Zou et al., [117]	Motion capture with 3D telemetry via nRF905	Low complexity	Moderate	Accurate, practical	Not scalable; Expensive; Way Point Following
Tiemann, [118]	Ultra-Wideband for precise localization indoors	Real Time	High	Real-time ROS based and Low Cost	Vertical Error; Packet loss
Dai et al., [119]	Indoor UAV control using low-cost Motion Capture System	Moderate: Integral Backstepping	Moderate	Affordable system	Single UAVs; Less Scalable
Yang et al., [120]	High-precision UWB with TW-TOF and MLE	TW-TOF unit; Iterative	High	High-resolution location	Metal-sensitive, Limited-range, Offboard-computation
Gerwen et al., [121]	Multi-sensor fusion with UWB, IMU, SLAM, sonar	Multi-sensor fusion board	High	Practical Impact	Sensor dependency; EKF constraints
Putra, [122]	Indoor autonomous drone navigation using virtual 3D map	Lightweight Computations	Moderate	3D planning ability	Error accumulates; Less accurate
Vision-Based Stirling et al., [123]	Relative positioning using onboard vision	Low Computations	Low	Fully onboard and decentralized	Limited obstacle handling
Saska et al., [124]	Visual-based stabilization for swarm UAVs	Optimized	High	Fully onboard sensing	Limited range; Processing load
Grando et al., [125]	Visual drone with onboard computation for inspection	Onboard vision SoC	Moderate	Full autonomy, open-source, Accurate	Light-sensitive vision; Limited compute
Lin et al., [126]	AprilTag + Visual-Inertial Odometry for tracking	Visual-Inertial CPU	Moderate	Comprehensive integration	Computational load
Acoustic Based Famili et al., [127]	PILOT: Ultrasonic localization using FHSS	Acoustic processing node	Moderate	Centimeter-level 3D accuracy	Beacon-dependent; Environment-sensitive
Sun et al., [128]	AIM: Tracking via acoustic signature and IMU	Acoustic signature processor	Moderate	Low cost and power	Signal Dependency; Delay + drift in NLoS
Basiri et al., [129]	Distributed mapping with ultrasonic sensors	Low onboard computation	Moderate	Lightweight, low-cost, and energy-efficient	Low-resolution; Rotation-sensitive
Sensors Placement Zufferey et al., [130]	Impulsive aerial sensor placement in hazards	Lightweight	Low	Enables safe, precise sensor deployment	Accuracy Constraints; Environmental Dependence
Cabrita, [131]	Marvelmind beacons for closed-loop localization	Beacon controller Lightweight	Sub-centimeter accuracy	Low-Cost and Accessible	Limited Testbed Size
Zhang et al., [132]	Factor graph fusion (IMU, LiDAR, odometer)	EKF2 state estimator	Moderate	Sensor graph theory	Complex tuning
Famili et al., [133]	SPIN: Sensor placement strategy with optimization	Optimized sim node	Moderate	Efficient, scalable, and cost-effective	High sim. dependency
Decentralized Systems Zhu et al., [134]	Decentralized Partially Observable MDPs (Dec-POMDPs)	Dec-POMDP CPU	Moderate	Decentralized, robust to noise	Sensitive to clutter; No SLAM degradation modeling
Li et al., [135]	WiFi + IMU Kalman filter fusion for positioning	Kalman fusion CPU (High Cost)	High Accuracy	Robust indoor fusion; Accurate	IMU drift; Noise susceptibility
Hybrid Fusion Godio et al., [136]	Stereo vision-based SLAM for planning and control	High Cost	High	Robust SLAM and visual odometry	VIO drift; Latency
James et al., [137]	ZED2i, LiDAR, IMU integration with ROS	ZED2i + LiDAR CPU	High Accuracy Mapping	Navigation	Range Sensitivity; High Computational Cost
Map-Merging M. Basso et al., [138]	Distributed 3D occupancy grid map merging for multi-UAV cooperative navigation	Heavy multi-stage pipeline	High	Fully distributed	High Cost; sensitive to noise
Resource Constraints M.Artal et al., [139]	Visual SLAM for monocular, stereo, and RGB-D cameras	CPU-based Intensive	Highly optimized ORB feature pipeline	Robust tracking, Open Source	No Dynamic Support, High Sensitivity
Qin et al, [140]	Robust monocular visual–inertial state estimation	High Cost(Optimization-based)	Real-time: 20–30 Hz VIO, 100 Hz IMU	High VIO accuracy; robust initialization	Highly Sensitive; Computationally heavy
Lichtsteiner et al., [141]	128×128 asynchronous temporal contrast vision sensor	High Cost	Ultra-low latency; sparse output	120 dB dynamic range; 15 µs latency	Bottleneck in dense scenes
NI SLAM Wang et al., [142]	Non-iterative visual-inertial SLAM framework using depth camera	O(n log n) due to FFT-based kernel regression	High	First non-iterative, online-trainable SLAM with dense mapping	No loop-closure, Requires strong frame-to-frame overlap

obstacles for system and performance evaluations. Similarly, a positioning technique that fuses WiFi and IMU data using a Kalman filter. Probability models have been employed to assess the performance of multiple UAVs [135]. However, testing was limited to a small number of drones, and further research is required to validate the proposed fusion algorithms on a larger scale.

7) HYBRDI FUSION SYSTEMS

Using hybrid fusion system techniques, authors addressed innovative approaches to indoor drone autonomy [136]. The drone system enables autonomous navigation in GNSS-denied environments using VIO and sensor fusion techniques. Loop closure and custom corrections improved the localization accuracy despite the limitations of the T265 camera. SITL simulations played a key role in testing and validating the proposed system. In future work, we aim to introduce a ground agent to enhance the 3D mapping capabilities. A stereo camera (Intel RealSense™D455) was used to test visual odometry, tracking, state estimation, multi-task planning, and software-in-the-loop simulations. A multi-sensor integration system involving a depth sensor from the ZED 2i camera, IMU data, and LiDAR readings was utilized, facilitated by ROS [137]. The authors conducted simulations using the ROS and RTAB maps. The research methodology achieved promising results with navigation accuracy, with errors of 0.4 m, and mapping quality characterized by a Root Mean Square Error (RMSE) of just 0.13 m.

8) MAP-MERGING APPROACHES

Recent advances in multi-UAV cooperative navigation have demonstrated that merging three-dimensional occupancy grid maps (3D-OGMs) is an effective way to improve global situational awareness during indoor operations. A relevant example of map-merging for multi-UAV systems is the 3D occupancy-grid fusion method proposed by Basso et al. [138]. Their approach aligns and merges voxel-based maps from multiple UAVs and demonstrates reliable performance in indoor environments with varying obstacle density. These methods highlight key implications for cooperative navigation: (i) UAVs must exchange local map segments or compressed 3D data, increasing the communication load; (ii) timely sharing of pose and map updates is essential to maintain global consistency; and (iii) dense or cluttered indoor areas amplify the need for efficient data-sharing strategies. These considerations reinforce that map-merging is tightly coupled with communication constraints and should be treated as an integral component of multi-UAV coordination.

9) QUANTITATIVE RESOURCE CONSTRAINTS IN LOCALIZATION AND SENSING

To contextualize the trade-off between accuracy and onboard resource limitations, this study explicitly reports computational, memory, and power metrics from highly pertinent techniques. ORB-SLAM2, a widely used baseline for visual SLAM, requires approximately 1.2–1.6 GFLOPS and a memory footprint of 250–300 MB to sustain 20–30 Hz operation on embedded processors [139]. Similarly, VINS-Mono, one of the most influential visual–inertial odometry (VIO) frameworks, reports 70–90% CPU load on an Intel i5-class embedded computer at 30 Hz, with memory usage exceeding 150 MB during extended trajectories [140]. These requirements exceed the capabilities of nano- and micro-UAV platforms, which often rely on microcontroller-class processors. By contrast, UWB localization designed for micro aerial vehicles—such as the TDOA-based Crazyflie implementations—consumes only tens of milliwatts per anchor and requires less than 10 kB of RAM for real-time state estimation while achieving 10–20 cm accuracy at 50–100 Hz as discussed eariler in [118]. Event-based vision further illustrates low-power sensing options: the seminal DVS sensor operates at 150–200 mW total power while supporting sub-millisecond asynchronous updates [141].These quantitative differences clarify why dense visual SLAM and high-capacity learning-based mapping remain restricted to larger UAVs, while UWB, ultrasonic, feature-light vision, and event-driven sensing dominate in resource-constrained indoor platforms.

10) NI SLAM RESEARCH

In addition to recent advances in research on this category, NI-SLAM has demonstrated mature and highly robust SLAM technology for GPS-denied indoor and outdoor environments [142]. This technology combine visual–inertial fusion, tightly coupled estimation, and deployment-scale experimentation, achieving high-precision localization under motion blur, illumination changes, and complex environmental dynamics. This body of work represents one of the earliest and most comprehensive demonstrations of operational SLAM in real-world conditions and therefore serves as a critical benchmark for evaluating newer solutions. Quantitatively, NI-SLAM provides superior localization accuracy (0.11 m on an Intel i7, representing a 39% improvement over ORB-SLAM) and substantially higher update rates (79.7 Hz, nearly double that of ORB-SLAM and several times higher than OKVIS and ElasticFusion). These performance gains, combined with reduced hardware requirements, position NI-SLAM as an attractive solution for emerging applications demanding rapid, dense mapping and high-frequency pose estimation, including autonomous mobility, industrial automation, consumer robotics, and resource-constrained domains such as underwater and space robotics.

Liu et al. reviewed sensing technologies for mobile autonomous robots in indoor environments, analyzing single and multi-sensor systems and comparing key algorithms [143]. They evaluated the limitations of IMU, LiDAR, infrared, ultrasonic, RF, and vision-based sensors. Similarly, Choutri et al. [144] highlighted current sensor methods, their constraints, and proposed future directions, including high-rate sensors, AI-driven vision, advanced DSP, and improved sensor fusion techniques.

a: BENCHMARKING AND COMPARATIVE DISCUSSION OF LOCALIZATION AND MAPPING TECHNOLOGIES

Table 7 provides a comprehensive benchmarking of state-of-the-art research in indoor multi-UAV sensing, localization, and navigation, evaluating existing studies across criteria such as computational strategies, efficiency, technical strengths, and practical limitations. Complementing this detailed review, indoor localization and mapping solutions today draw upon several technology families, including visual and LiDAR-based SLAM, visual odometry (VO), visual–inertial odometry (VIO), radio-based approaches (UWB and Wi-Fi CSI), and acoustic systems. While Table 7 organizes individual contributions within these domains, practitioners often require a higher-level comparison to select the most suitable technology for specific indoor conditions or multi-UAV deployment constraints. To address this need, Table 8 summarizes the characteristic performance of these technology classes along key dimensions such as accuracy, scalability for multi-UAV operation, onboard computational complexity, robustness to environmental factors, and associated cost or hardware requirements.

Key Takeaways and Discussion:

Computation and Deployment: Mostly research utilized onboard or embedded controllers for real-time processing of algorithms. Onboard lightweight approaches enabled high-accuracy systems and cost-effective deployment, which required computational hardware and often utilized offloading via ROS or edge nodes.

Efficiency vs. Accuracy Trade-off: High precise frameworks like sensor fusion and SLAM come with the expense of computation and power. Simpler, low computational methods trade accuracy for scalability and resource efficiency.

Sensor Fusion and Modularity: Fusion of sensors—visual, acoustic, inertial— are emerging concept to enhance 6-DOF accuracy, supported by modular robotics middleware like Gazebo and ROS.

Role of Edge Computing and ML: Recent solutions and frameworks benefit from edge computing by offloading intensive visual SLAM or fusion-based complex tasks to nearby ground stations or edge servers. This offloading increases processing power and improves latency. ML is being utilized for robust perception, adaptive control, and noise resilience.

IV. EMERGING RESEARCH TECHNOLOGIES FOR INDOOR UAVs

A. MACHINE LEARNING

Researchers are actively conducting experiments to use machine learning technologies in indoor autonomous UAVs.

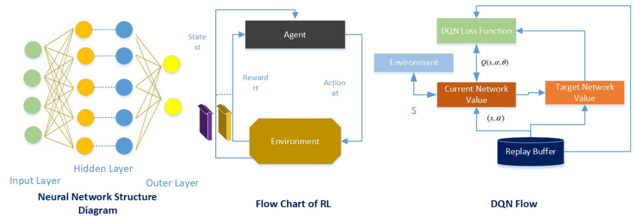


FIGURE 14. Overview Common ML Methods for Multi-UAVs.

Machine learning algorithms offer more robust prediction and performance capabilities by developing and training models. To improve indoor autonomy, machine learning models for indoor autonomous drones focus on crucial areas such as perception, navigation, control, and task execution, as conceptual illustration is shown in Figure 14. Indoor UAVs collect sensor data, machine learning models, and computational hardware resources to perform their tasks. The choice of services manages energy and is crucial for its execution.

1) VISION BASED ML NAVIGATION

The first category is research on vision-based machine learning for navigation and perception. An informative method for real-time autonomous navigation using tiny quadcopters was introduced in [145], employing a monocular camera and a convolutional neural network (CNN) with Hierarchical Structured Learning (HSL). Similarly, research conducted in [146] used computer vision to address indoor drone navigation, creating a 3D map via visual scanning and onboard camera input. The advent of fast-processing embedded devices and innovations has simplified the integration of machine learning and vision algorithms in real time. Using machine learning algorithms, a study developed collision avoidance methods for indoor UAVs to pass through tight gates [147]. The authors estimated the center of a gate through which indoor MAVs could pass reliably using a convolutional neural network. The authors used deep learning for vision and navigation to construct real-time gate-identification networks on embedded computers with NVIDIA Jetson hardware. A Siamese deep convolutional neural network was presented as a unique, resilient, and efficient deep learning indoor navigation system [148]. This study investigated a multi-stage transfer learning strategy by gathering several datasets from drones and training. Artificial landmarks were used to determine the position of an indoor drone for autonomy using machine learning techniques [149]. Using machine learning algorithms, the authors created artificial landmarks based on QR codes that could be recognized by flight vision. Similarly, the authors in [150] introduced MR-iFLY, a modular framework for indoor UAV autonomy that uses GPU power and machine learning approaches for collision avoidance and depth estimation. The integration of deep learning and vision in autonomous indoor UAVs for navigation has been examined. The article highlighted path

TABLE 8. Comparative assessment of indoor localization and mapping technologies for multi-UAV systems.

Technology Class	Typical Indoor Accuracy	Scalability to Multi-UAVs	Onboard Computational Complexity	Robustness to Environmental Factors	Cost / Hardware Requirements
Visual SLAM (mono/stereo)	*cm–decimeter level* in feature-rich environments, accuracy degrades in texture-poor or repetitive areas	Moderate: scales with careful scene management and loop-closure handling; inter-UAV map fusion still challenging	High: real-time feature extraction, matching, and pose graph optimization required, especially for dense 3D mapping	Sensitive to lighting changes, motion blur, glass/reflective surfaces; robust in static, well-lit indoor scenes	Low–medium: cameras and embedded GPU/CPU required; no external infrastructure but calibration and mounting are critical
LiDAR-based SLAM	*cm-level* for range-based maps in structured environments; stable over long trajectories	High: supports multiple UAVs sharing consistent geometric maps if communication bandwidth is sufficient	High: scan matching and 3D registration are computationally intensive, but real-time is achievable with optimized libraries	Robust to illumination and texture; performance can degrade in heavy smoke, dust, or sparse geometry	Medium–high: 2D/3D LiDAR sensors add mass and cost, plus a capable onboard computer; no external anchors required
Visual / Visual–Inertial Odometry (VO/VIO)	Local *cm–decimeter* accuracy over short horizons; drift accumulates over time without loop closures	Moderate: suitable as a local odometry backbone for each UAV with occasional global corrections	Medium–high: lighter than full SLAM (reduced mapping overhead), but still demanding for nano-UAVs	Sensitive to lighting and texture; IMU fusion improves robustness to short-term occlusions and fast maneuvers	Low–medium: camera + IMU are standard onboard sensors; additional compute required for real-time VIO
UWB-based Ranging / Localization	*decimeter–cm level* in well-calibrated anchor setups; accuracy degrades with NLoS and multipath	High: many UAVs can share the same anchor infrastructure; performance limited by channel access and packet collisions	Low–medium: ranging and simple multilateration are lightweight; more complex fusion (e.g., EKF) adds modest overhead	Robust to lighting; sensitive to metallic structures, NLoS, and radio interference; anchor placement strongly affects performance	Medium: requires deployment and calibration of UWB anchors; lightweight tags on UAVs; infrastructure cost increases with coverage area
Wi-Fi CSI / RSSI-based Localization	*meter–sub-meter level* depending on environment, calibration, and antenna configuration	High: reuses existing indoor Wi-Fi infrastructure; well suited for large-scale or multi-floor deployments	Low–medium: CSI/RSSI fingerprinting and learning-based estimators can run on modest embedded platforms	Sensitive to multipath, human motion, and interference; robust to lighting; performance depends on AP density and placement	Low–medium: leverages commercial Wi-Fi APs and radio chips; additional calibration and data collection required
Acoustic / Ultrasonic Systems	*cm–decimeter level* in small/medium spaces with controlled noise conditions	Moderate: multiple UAVs possible, but interference between acoustic sources and microphones must be managed	Low–medium: time-of-flight and angle-of-arrival estimation are lightweight; robust filtering adds some overhead	Sensitive to ambient noise, airflow, and obstacles; performance degrades in highly reverberant or very large spaces	Low–medium: inexpensive transducers and microphone arrays; requires careful placement and sometimes dedicated beacons
Hybrid Sensor Fusion (e.g., SLAM + UWB / Wi-Fi / IMU)	*cm-level* achievable by compensating individual sensor weaknesses and reducing drift	High: well suited for multi-UAV teams where shared maps are fused with global ranging or infrastructure-based cues	High: requires multi-sensor synchronization, calibration, and probabilistic fusion (EKF, factor graphs)	Most robust: combines resilience to lighting changes (radio/acoustic) with geometric consistency (SLAM/VIO)	Medium–high: combines multiple sensing modalities (cameras, LiDAR, UWB/Wi-Fi, IMU), increasing hardware and integration effort
NI-SLAM (Non-Iterative SLAM)	*cm–decimeter level* with high-frequency pose updates; demonstrated accuracy of 0.11 m on high-performance processors	Moderate–high: suitable for multi-UAV deployments due to low latency and fast update rates enabling synchronized mapping	Low–medium: avoids iterative optimization through closed-form estimation and Kernel Cross-Correlation; achieves 79.7 Hz on Intel i7 and 30.9 Hz on Intel Atom	Robust to moderate illumination changes and dynamic motion; performance depends on visual depth quality and IMU reliability	Low–medium: requires RGB-D or depth camera + IMU; computational efficiency allows deployment on low-power processors without high-end GPUs

planning and perception and discussed the challenges [151]. In a similar vein, researchers [152] used this approach to assess machine learning algorithms in various interior environments, such as buildings and garages. The authors concentrated on employing UAVs to observe humans as subjects of various morphologies. A multitask deep network was recently proposed by [153]. The technique used feature map region division, which made use of monocular interior cameras for UAV autonomous navigation, to visualize and execute precise navigation.

2) DRL BASED SOLUTIONS

The second category focuses on research involving deep reinforcement learning (DRL) and decision-making for UAVs. In [154], a framework was simulated in which UAVs equipped with LiDAR, IMU, and cameras used DRL techniques for autonomous decision-making based on sensory data. To address indoor drone mobility, researchers in [155] employed DRL to enable navigation and exploration in unknown environments. They built a 3D virtual model using spatial data, visualized as stacked color-coded maps, and applied a two-stage reinforcement learning strategy with a DQN agent to select the final actions. However, this study lacked detailed training and implementation. In a study presented by authors in [156], a DRL-based framework for autonomous indoor UAV navigation using Markov decision processes was proposed, tackling challenges such as uncertainty and limited visibility. The simulation results demonstrated effectiveness in cluttered and dynamic environments, with future work planned for real-world

TABLE 9. Benchmarking of machine learning contributions for indoor multi-UAV systems.

Author Name and Reference	Research Focus	Computational Cost	Performance	Strength	Limitations
Vision Based / Vishakh, [145]	CNN and HSL-based monocular vision for flight planning	Moderate (HSL is CPU-based, CNN requires 0.2s/prediction; whole pipeline 0.4s/frame)	Effective in monocular vision tasks; 92.66% CNN classification accuracy for flight planning	Simple integration using HSL	Limited to simulated settings; (hierarchical error propagation)
Horvath, [146]	Indoor autonomous drone navigation using high-definition point cloud maps, computer vision, and AI for obstacle avoidance	High-resolution point clouds (18 GB) required significant storage	Accurate 3D map reconstruction; 91.2% successful flight rate in early tests	GPS-free indoor navigation; Real-world tested mapping	No real-time sensory input during testing; High Compu tation Cost
S. Jung, [147]	Indoor autonomous drone racing using deep learning for gate detection and line-of-sight (LOS) navigation on embedded platforms	High (Jetson TX2)	28.95 FPS on Jetson TX2 with 0.755 AP; Reliable navigation Error < 0.1m	High-speed real-time detection	Power-hungry platform
Yeboah, [148]	Siamese CNN and multi-stage transfer learning for navigation	High (deep + transfer learning)	Improved navigation accuracy; 99.25% (Variant 1)	High classification and segmentation accuracy; strong generalization via transfer learning	Needs large labeled datasets; pre-defined control strategies
Chie, [149]	QR-code-based artificial landmarks for indoor UAVs	Low	Effective in visual marker-based guidance; Landmark Detection Accuracy: 86.25% with SSD Inception v2	Low-cost and simple setup using QR codes	Reliant on artificial landmarks; Sensitive to camera view angle
Nicholas, [150]	MR-iFLY: Modular ML framework for collision avoidance	Reduced via model distillation + TensorRT; uses classical CV + optimized ML; real-time with 25ms inference	Up to 15× speedup; successful flight tests; robust depth estimation and obstacle avoidance	Low-SWaP, modular, hybrid ML + CV	Lacks dynamic adaptation; limited to monocular input
Aditya, [151]	Integration of deep learning with UAV vision perception	N/A (review)	Theoretical insights	Integration potential with DL tools	No implementation or benchmarks
Kucukayan, [152]	Proposed YOLO-IHD, a real-time human detection system tailored for indoor drone environments	Moderate; Significantly lower than full YOLOv4	High accuracy; Robust detection	Real-time execution; Adapted YOLOv4-Tiny	Limited generalization
Zhang X, [153]	Monocular camera with feature map division for navigation	Reduced Complexity	Achieved 96.96% accuracy and F1-score of 0.9645	Efficient; Real-time; feature map division	Lack of Depth Estimation; Over-prediction Risk
DRL Based/ A. Seel, [154]	Deep RL with sensor fusion (LiDAR, IMU, Camera)	High (sensor fusion DRL)	Robust navigation	Fully onboard sensors (IMU, LiDAR); Modular	No real-world validation; LiDAR can miss visual features
Hang, [155]	DQN-based map generation and mobility control	Moderate	Precise mapping with mobility control	Adaptive with DQN for planning	No physical robot or real-world deployment
Walker, [156]	DRL with MDP and cluttered environment handling	Moderate to high	Sparse reward PPO agent converges successfully	MDP formulation boosts learning; Offers better generalization	Lacks validation on physical UAVs
Position Tracking / Sandamini, [19]	ML with radio signal-based indoor positioning	Low	Theoretical model validated	Focused radio-based positioning	Limited real-world validation
A. Safa, [158]	FMCW radar + unsupervised learning	Moderate	FMCW radar effective indoors	First large-scale indoor drone FMCW dataset (with raw ADC, RGBD, and pose)	High dependency on radar fidelity
Rodriguez, [159]	Visual navigation using dual-camera placement	Moderate	Achieved under 6% error in distance estimation, 90% success in indoor target visitation	Cost-effective, GPS-free setup; Real field-tested dual camera setup	Sensitive to drift and lighting conditions; Lacks SLAM or LiDAR precision
Hsieh, [160]	YOLOv4-Tiny + carrot-chasing for tracking/avoidance	Low (YOLOv4-tiny)	Uses YOLOv4-Tiny + TensorRT; Achieves 23 FPS; CPU: 30–70%, GPU: 75–99%, RAM: 3.3 GB	Low-cost, real-time vision-based system; Lightweight DL model	Not robust for unstructured environments

testing. In addition, advanced research in [157] presents a comprehensive review of reinforcement learning applications for autonomous multi-UAV wireless networks, covering areas such as resource allocation, mobile-assisted edge computing, path planning, and localization.

3) ML BASED POSITIONING/TRACKING

The remainder of this section presents the use of machine learning for positioning, tracking, and sensor fusion in indoor UAV systems. The research presented in [19] reviewed indoor positioning systems and discussed the application of machine learning techniques combined with radio signal-based methods for accurate localization. Similarly, the authors in [158] explored the use of unsupervised learning with FMCW radar data, built a model based on radar principles, and represented it with low-dimensional data. In GPS-denied environments, [159] proposed a visual navigation method using front and rear UAV cameras to collect data for positioning. An indoor drone tracking and obstacle avoidance system was introduced in [160], which was specifically designed for nano-embedded processors. The system employed depth image processing for obstacle detection and YOLOv4-Tiny for object classification. The model performance was evaluated on both straight and curved paths using an enhanced carrot-chasing algorithm. Finally, the research highlights frameworks, system-level reviews, and future trends. Recent research has highlighted emerging technologies such as machine learning, cloud computing, and 5G, which are being integrated into indoor drone target tracking [161]. Although ML plays a vital role in perception and control, achieving full autonomy for multi-UAV indoor systems remains a challenge. Future research should focus on hybrid approaches, real-world deployment, and improving computational efficiency on embedded platforms to bridge the existing gaps.

Key Takeaways and Benchmarking Discussion for Machine Learning in Indoor UAVs: Tables 9 present the overview of the contributions of research papers in different techniques of machine learning for indoor UAVs.

1) ML approaches for utilization in navigation, object detection, localization, and sensing showed better performance and reached classification accuracies reaching over 99%.
2) Real-time optimized models were trained on platforms (e.g., YOLOv4-Tiny, TensorRT), with frame rates exceeding 20 FPS on low-SWaP platforms.
3) Deep learning with transfer learning enhanced generalization, but required exhaustive labeled datasets and training. Sensor fusion and reinforcement learning models demonstrated modular adaptability, but practical deployment in reached is in early stages.
4) Lightweight solutions (e.g., Hsieh, Chie) enabled cost-effective and simple solutions with implementation using QR codes or simplified CNNs, but are sensitive to environmental conditions.
5) Hybrid methods, which integrated classical CV and ML (e.g., Nicholas, 2022), improved robustness and speed for tasks like obstacle avoidance and mission planning.
6) High-performance ML solutions trade off latency or accuracy for computational cost, often requiring GPU-based systems.

B. EDGE COMPUTING

In indoor UAV flights, edge computing utilization plays an important role in simplifying the calculations required for complex missions. When it comes to tackling difficult calculations, edge computing offers fast computations and reduces the latency, as shown in Figure 15, which presents multi-UAV scenarios in which data traffic is being offloaded to the edge servers. It demonstrates how indoor multi-UAVs can be integrated in numerous situations and offload complicated computing tasks.

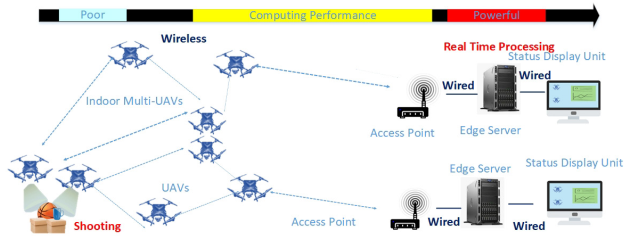


FIGURE 15. Example of UAVs computation offloading in UAV-Edge- Server Model.

1) COMPUTATIONAL OFFLOADING

The first focus is on computational offloading frameworks for indoor UAVs, where edge computing plays a key role. An edge offloading system was presented in [162], which used an online environment to connect multiple indoor drones into a network. To maximize offloading, the authors applied a Markov approximation-based method with multihop scheduling aided by edge servers and simulated algorithms for multi-indoor UAVs. In [163], the authors evaluated edge computing for UAVs by integrating autonomous drones with server offloading. Based on optical and inertial data, UAVs perform 3D mapping and navigation, with the architecture deciding whether to offload data to servers or process it onboard. Similarly, in article [164], the authors assessed the role of edge computing with 5G for UAV navigation, where drones offloaded image processing tasks to servers. Three methods were compared for vision navigation: partial offloading, onboard processing, and full offloading. Finally, in study [165], the authors proposed a platform for deploying ML algorithms on low-power embedded systems using edge computing. Real-time deep learning was demonstrated using optimized models with TinyML tools, such as TensorFlow and CMSIS-NN, and experiments on obstacle detection evaluated the latency, power, and accuracy of lightweight devices.

2) RESOURCE ALLOCATION

Second, we present research in the category of resource allocation and optimization. In [166], a resource allocation methodology for multi-UAV-assisted edge computing was proposed to address user mobility and wireless base station coverage limitations in indoor environments. By jointly optimizing the bandwidth, trajectory, and processing capability, this study suggests an effective approach to enhance the energy efficiency of MEC systems. The study in [167] further examined the challenges of edge computing and its impact on UAV operations, including communication, navigation,

TABLE 10. Benchmarking of edge computing contributions in indoor multi-UAV systems.

Author Name and Reference	Research Focus	Computational Cost	Performance	Strength	Limitations
Computation Offloading Zhang, [162]	Joint computation offloading and traffic routing for UAV swarms in a hybrid edge–cloud computing architecture	Moderate	Improved offloading efficiency	Markov approximation with multi-hop scheduling; Distributed algorithms	Assumes ideal network models
Messous, [163]	Visual-inertial integration with adaptive offloading	Edge and ground stations have higher CPU frequencies (10× and 5× drone CPU, respectively)	Adaptive offloading outperforms full local or remote execution	Flexible offloading strategy (local, edge, or ground)	No real-world deployment tested
S. Hayat, [164]	5G-enabled offloading comparison: onboard vs edge	High (5G testbed)	Selective offloading (first layers onboard, rest offloaded) yields best trade-off between accuracy and latency	Practical 5G-enabled experiments; Low Latency; Improved Performance	Infrastructure dependent; no modeling of mobility-induced variation
Andrea, [165]	Development of a low-power, modular, edge-computing platform for real-time deep learning inference on small UAVs	High (embedded + edge)	Best Config: Raspberry Pi 4 + LeNet + NCS; 0.246 J/frame, 45 ms, 22.26 FPS	Edge-accelerated learning and deployment	Altitude Constraint; Model Complexity; Performance Bottleneck
Resource Optimization Chen, [166]	Optimized bandwidth, trajectory and MEC resources for UAVs	High	Proposed method reduces system delay significantly (up to 30%) compared to benchmarks	Joint optimization approach for trajectory, association, and resource allocation	Theoretical model assumptions
McEnroe, [167]	Integration of Edge Computing and Artificial Intelligence (AI) for UAVs	Balancing energy, latency, and computation load for deep learning tasks	Conceptual resource guidance	Security and comms considerations addressed	Lacks quantitative benchmarks
Asiful, [168]	Computation offloading in UAV-enabled Mobile Edge Computing (MEC) systems	N/A (survey)	Comparative offloading strategies	Classifies offloading modes systematically	Limited multi-UAV practical deployments
F. Zhou, [169]	UAV-based offloading architecture and edge design challenges	Moderate	UAV edge design insights	Architecture-level focus on UAV edge networks	Does not cover deployment/validation
Edge-Enabled Sensing Zhu H, [170]	Integration of edge computing with UAV swarm operations to enhance sensing, communication, and trajectory planning	Offloading to edge servers reduces onboard UAV computation	Efficient edge-based mapping	Synergistic use of sensing, communication, and planning	Lacks real-world validation or simulations
Koubaa, [171]	Onboard AI edge computing for UAV-based remote sensing, object detection, and tracking using YOLOv4/YOLOv7 with DeepSORT and TensorRT acceleration	Moderate to High	Accuracy: Precision 99.3%, Recall 73%, F1 84%	Reduced latency, increased autonomy; Scalable	Requires reliable multi-layer infrastructure
Mihir, [172]	Lightweight, low-cost autonomous drone systems leveraging edge computing to enable real-time visual processing tasks like tracking and obstacle avoidance	Moderate; Real-time edge offloading of 720p video frames at constrained rates (0.7–3 FPS)	Optimized; Object Detection Precision/Recall at 5m: 0.99/0.85	Fully COTS-based solution; Practical	Limited Onboard Processing; High end-to-end latency (≥1s)

formation control, security, and power management. This study also discusses the key difficulties, lessons learned, and potential directions for applying edge AI to UAVs. A detailed investigation of computation offloading in indoor UAV-enabled edge computing was presented in [168], where algorithms were classified into binary, load-relaying, and partial offloading, and the current challenges and open issues were highlighted. Similarly, in [169], the authors proposed methods and architectures for multi-UAV edge computing, emphasizing deployment concerns and unresolved challenges in autonomous indoor applications.

3) EDGE-ENABLESD SENSING

We present research focusing on edge-enabled sensing for indoor UAVs to address the challenges of managing the computational complexity. In [170], UAVs were employed for mapping, where sensor data were offloaded to edge stations for real-time environmental reconstruction. Edge computing has emerged as a key enabler of indoor autonomy by combining hybrid cloud–edge frameworks with AI to manage computational complexity. A novel edge-based remote sensing approach was proposed in [171], which enables UAVs with embedded processors to execute complex AI tasks. The framework, called AERO, integrates GPU-powered edge devices with TensorRT, YOLOv4/YOLOv7 for object detection, and DeepSort for tracking, efficiently processing, and transmitting target information to the cloud without overloading UAV resources. Although the accuracy could be further enhanced by integrating thermal and LiDAR sensors, the framework also opened research directions in security and resilience against cyber-attacks. Complementary work in [172] applied edge computing to optimize the energy efficiency. Lightweight UAVs equipped with wireless transceivers offload computationally intensive sensing tasks to cloud servers over high-bandwidth, low-latency links, offering a low-cost solution for real-time indoor sensing missions. Collectively, the remaining challenges in edge-enabled sensing include high energy consumption, limited bandwidth, and latency issues during data offloading, as well as security vulnerabilities and the need for lightweight, optimized AI models for real-world indoor deployments.

Key Takeaways and Benchmarking Discussion: An overview of the reviewed articles, contributions, and benchmarking is presented in Table 10 for edge utilization in indoor UAVs. The key takeaways are as follows:

1) Most studies utilize edge offloading to reduce onboard computation and improve latency in indoor UAV applications.
2) High-performance setups (e.g., 5G-enabled testbeds, Raspberry Pi + NCS accelerators) achieve low delay and high frame rates. Flexible offloading schemes offer adaptability to local, edge, and cloud nodes.
3) Joint optimization methods (e.g., trajectory, navigation, resource allocation) can reduce system delay by up to 30%, but depend on ideal assumptions.
4) Edge computing research contribution is in the initial stages of practical implementation. Real-world deployment or mobility-aware performance modeling has been conducted by a few researchers.
5) Hybrid edge-offloading strategies with real-time, QoS-aware adaptability and integration with ML show the most potential for indoor UAV networks.

V. RESEARCH CHALLENGES FOR INDOOR AUTONOMOUS DRONES

This section highlights the key technical challenges in autonomous multi-UAV systems and presents the corresponding opportunities for future research.

A. OBSTACLE AVOIDANCE

1) REAL-TIME DETECTION

Real-time detection and prediction of dynamic obstacles in cluttered, GPS-denied indoor spaces remains difficult. Reactive avoidance alone is insufficient, particularly at high speeds or in confined areas.

2) FAULT-TOLERANT HANDLING

Developing fault-tolerant formation control for multi-UAVs in obstacle-rich indoor spaces is difficult because actuators, sensors, communication, and mechanical faults can disrupt coordination. Most existing approaches address isolated fault types and overlook dynamic indoor conditions, thereby making reliable mission execution and collision avoidance challenging.

3) DISTINGUISHED CAPABILITY

Most indoor multi-UAV systems detect obstacles without distinguishing their types, leading to unsafe uniform avoidance in environments with humans, machines, or transparent surfaces.

4) FUTURE WORK DIRECTION

Future work should focus on lightweight trajectory forecasting under noisy or partial sensing, along with fault-tolerant and resilient control, supported by integrated failure simulations. Additional directions include onboard segmentation and obstacle classification for adaptive avoidance and the development of learning or optimization algorithms that operate efficiently on resource-constrained embedded hardware. Realistic modeling of dynamic indoor environments (e.g., moving humans or equipment) must be incorporated into ROS 2 simulation frameworks to evaluate the algorithms under challenging conditions. Finally, establishing real-world indoor testbeds is critical for validating the robustness, scalability, and safety of these systems prior to industrial deployment.

B. MULTI-UAV CONTROL SYSTEMS

1) DISTRIBUTED STABILITY

Maintaining globally stable coordination under real indoor communication impairments, such as latency, dropouts, jitter, and bandwidth asymmetry, remains unresolved, as most controllers assume synchronous or idealized networking conditions.

2) SCALABLE MULTI-AGENT CONTROL

Current RL-, MPC-, and optimization-based controllers do not scale efficiently to large UAV teams; the joint state and action spaces grow rapidly, degrading the real-time responsiveness and swarm cohesion.

3) FUTURE WORK DIRECTION

Future work should focus on communication-aware distributed control laws that guarantee stability under uncertain wireless conditions, alongside hierarchical or factorized multi-agent learning architectures that enable real-time coordination for large UAV teams without prohibitive computational costs.

C. COMMUNICATION AND NETWORKING

1) NETWORK CONGESTION

Multiple UAVs transmitting video and telemetry over shared Wi-Fi can quickly overload limited spectrum, especially in confined spaces. Existing static allocation schemes degrade with the scale. The challenge is to design scalable, lightweight congestion control algorithms that adapt to fluctuating conditions and QoS demands and are validated in realistic testbeds.

2) ADAPTIVE NETWORK PREDICTION

Indoor links suffer from latency spikes, jitters, NLoS, and multipath fading, causing disconnections in mission-critical tasks. Current ML models are too static. The challenge is to build real-time, AI-driven predictive models that proactively adapt UAV communication to the degrading network conditions.

3) ENHANCED SECURITY NETWORK

UAV-to-UAV communication indoors is vulnerable to spoofing and jamming, risking coordinated operations. The challenge is to design lightweight, decentralized, and adaptive security frameworks that ensure low-latency, resilient, and safe communication for multi-UAV missions.

4) FUTURE RESEARCH DIRECTION

Future studies should focus on developing adaptive and energy-efficient networking protocols to ensure reliable multi-UAV communication in constrained indoor environments. The combination of 5G, Wi-Fi, and Li-Fi technologies can significantly enhance localization accuracy and provide high-throughput, low-latency connectivity for indoor missions. Federated and reinforcement learning approaches offer scalable and autonomous coordination capabilities, motivating further research for real-time deployment. Practical indoor testbeds, secure communication layers, and unified communication–computation frameworks are essential for validating algorithms under realistic conditions and for supporting time-critical tasks such as collaborative sensing and control.

D. COMPUTATION AND MISSION PLANNING

1) HETEROGENEOUS RESOURCES

Multi-UAV systems have diverse processors and limited energy. Assigning identical tasks (e.g., mapping, sensing, and detection) causes delays and failures. The challenge is to design computation-aware task allocation frameworks that adapt workloads to UAV capabilities and energy levels in real time.

2) REAL-TIME ADAPTIVE RE-PLANNING

Current mission planners often rely on static 2D maps, overlooking the complexity of 3D indoor spaces (warehouses, shelves, stairwells). Static plans fail when the environment changes. The challenge is to create real-time 3D mission re-planning algorithms that adapt paths, tasks, and altitudes while ensuring collision avoidance and coordination in the evolving spaces.

3) ENERGY CONSTRAINT

Indoor multi-UAV systems remain constrained by limited flight endurance. Current state-of-the-art indoor nano- and micro-UAVs typically achieve 5–12 min of sustained operation, whereas larger indoor-capable platforms rarely exceed 15–20 min in cluttered environments. Many real indoor missions (inventory scanning, persistent surveillance, cooperative mapping) require 30–60 min of continuous operation, indicating a $2\times$–$4\times$ gap between current battery capabilities and mission needs. Recent advances, such as wireless inductive charging pads, in-flight wireless power transfer, and hybrid energy systems (battery–supercapacitor combinations), offer potential pathways; however, scaling them to multi-UAV indoor environments remains an open research frontier.

4) FUTURE RESEARCH DIRECTION

Real-time 3D mission re-planning, including vertical optimization and online adaptation from live sensor data, is essential for responsive indoor UAV operations. Future systems must enable large-scale cooperative control without performance degradation, supported by ML-driven decision-making and edge computing, to offload intensive tasks and improve adaptability. The development of advanced simulation frameworks, real-world testbeds, and approaches that integrate semantic cognition, decentralized planning, and real-time onboard optimization will accelerate reliable, fully autonomous multi-UAV missions.

E. LOCALIZATION, NAVIGATION, AND SENSING

1) COMPLEX OBSTACLES

Indoor UAVs encounter irregular shapes, glossy/transparent surfaces, and poor lighting, causing faulty sensor readings and unsafe avoidance. The challenge is to develop real-time segmentation algorithms that classify obstacles by type and are robust to noise, reflections, and transparency.

2) LOCALIZATION DRIFT

Sensor drift, SLAM errors, and mid-flight failures degrade accuracy in GPS-denied indoor spaces. Crosstalk among UAVs, metallic interference, and vibrations reduce reliability. The challenge is to design fault-tolerant localization with real-time failure detection, redundancy, and learning-based compensation capabilities.

3) LOW-LIGHT ENVIRONMENTS

SLAM and vision degrade in dark or dimly lit spaces (e.g., tunnels, warehouses), leading to drift and poor tracking. Multi-UAV interference amplifies the errors. The challenge is to develop low-light-resilient SLAM, sensor fusion, and adaptive navigation using alternative sensing methods (e.g., thermal or event-based cameras).

4) COMPLEX ENVIRONMENT ADAPTABILITY

The adaptability of UAVs to dense and dynamic indoor spaces is strongly influenced by the computational complexities of perception and mapping algorithms. High-fidelity 3D SLAM pipelines (e.g., VIO–LiDAR fusion) often require 20–40 GFLOPS of processing capacity and introduce perception latencies of 80–150 ms. In contrast, safe navigation in fast-changing indoor environments typically requires reaction times below 30–50 ms to avoid collisions with moving obstacles. This mismatch reveals a significant performance

TABLE 11. Unified summary of research challenges and future directions for indoor autonomous multi-UAV systems.

Domain	Key Challenges (Summary)	Future Research Directions (Summary)
Obstacle Avoidance	★ Dynamic obstacle prediction ★ Fault-tolerant coordination ★ Obstacle classification (humans, machines, transparent surfaces)	★ Lightweight trajectory prediction ★ Resilient and redundant control ★ Onboard segmentation ★ Realistic indoor simulation and testbeds
Multi-UAV Control Systems	★ Stability degradation under latency, jitter, and packet drops ★ Scalability limits of RL/MPC/optimization controllers ★ Coordination loss due to bandwidth asymmetry and communication impairments	★ Communication-aware distributed control laws ★ Hierarchical and factorized multi-agent learning ★ Event-triggered and asynchronous control for reduced network load ★ Network–control co-design for robust coordination
Communication and Networking	★ Spectrum overload in dense UAV traffic ★ Latency, jitter, NLoS, multipath ★ Spoofing and jamming vulnerabilities ★ Wireless Charging and battery status communication	★ Adaptive, energy-efficient networking ★ Hybrid 5G / Wi-Fi / Li-Fi ★ Federated learning and RL for coordination ★ Secure communication layers ★ Integrated communication–computation frameworks
Computation & Mission Planning	★ Heterogeneous compute/energy resources ★ Static 2D planning in dynamic 3D environments ★ Optimized planning for low power consumption	★ Real-time 3D replanning ★ Online sensor-driven updates ★ Scalable cooperative control ★ Edge-assisted computation offloading ★ Semantic cognition and decentralized onboard optimization
Localization, Navigation & Sensing	★ Complex/reflective obstacles ★ SLAM drift and sensor failures ★ Low-light degradation	★ Noise-robust segmentation ★ Fault-tolerant localization ★ Low-light SLAM with thermal/event sensors ★ RL and graph-based navigation ★ Edge–UAV cooperative processing
Machine Learning	★ ML-SLAM sensitivity to lighting/noise ★ Limited compute for cooperative ML ★ Low-latency ML for Wi-Fi 7	★ Lightweight real-time ML-SLAM ★ Synthetic data + domain adaptation ★ Multi-agent RL + decentralized policies ★ Energy-efficient ML for channel selection ★ XAI-based safety validation
Edge Computing	★ Dynamic offloading constraints ★ QoS degradation under congestion/mobility	★ Priority-aware offloading ★ Bandwidth-aware edge association ★ Mobility prediction for seamless handoff ★ Secure and privacy-preserving offloading

gap, as the current mapping accuracy often comes at the cost of insufficient real-time responsiveness. Achieving both high-fidelity mapping and sub-50-ms reaction windows remains a core challenge for deploying autonomous UAVs in cluttered indoor domains.

5) FUTURE RESEARCH DIRECTION

Future work should advance robust real-time perception, including noise-resilient segmentation, fault-tolerant localization with redundancy and learning-based correction, and low-light SLAM through thermal or event-based fusion. Reinforcement learning, deep Q-networks, and graph-driven models must be further developed to support adaptive localization, SLAM, and quality-of-service-aware navigation for precise, context-aware path planning.

F. MACHINE LEARNING

1) ACCURATE NAVIGATION AND LOCALIZATION

ML-based SLAM struggles with lighting changes, dynamic obstacles, and sensor noise. The limited indoor datasets restrict generalization. The challenge is to design an adaptive, real-time ML-SLAM that learns on-the-fly with minimal data for robust GPS-denied localization.

2) MULTI-UAV COORDINATION

Limited communication and onboard compute hinder real-time cooperation. Static, rule-based controllers lack adaptability. The challenge is to develop scalable decentralized RL frameworks for formation flying, coverage optimization, and dynamic task sharing in complex indoor missions.

3) ML FOR WIRELESS PROTOCOLS

Applying ML to optimize Wi-Fi 7 (e.g., STR, EMLSR, channel allocation) requires real-time, energy-efficient models. The challenge is to build lightweight ML algorithms that adapt to spectrum dynamics while operating within strict UAV hardware limits for low-latency and reliable communication.

4) FUTURE RESEARCH DIRECTION

Future research should advance real-time adaptive SLAM with online learning from minimal data, supported by lightweight ML models, model compression, and edge–cloud collaborative learning, while also developing high-fidelity simulators and synthetic data pipelines with domain adaptation to bridge the sim-to-real gap. Scalable RL frameworks for formation, coverage, and task sharing should be strengthened, along with research into multi-agent reinforcement learning, federated learning, and decentralized policies that adapt to local observations while enabling global coordination, including energy-efficient ML for mode selection and channel allocation.

G. EDGE COMPUTING

1) TASK OFFLOADING

Efficient offloading is hindered by dynamic factors such as battery level, network quality, compute load, UAV speed, and task urgency. Current models optimize single parameters, which leads to delays. The challenge is to design lightweight real-time algorithms that balance these factors for optimal offloading decisions.

2) RESOURCE MANAGEMENT AND QOS

Multi-UAV systems face degraded QoS from congestion, poor coverage, and uncoordinated resource use. The challenge is to build centralized or SDN-based controllers with ML that predictively manage bandwidth, offloading, coordination, and energy, ensuring reliability under NLoS and dynamic indoor conditions.

3) FUTURE RESEARCH DIRECTION

Future work should design dynamic task offloading and resource allocation algorithms using priority-aware or QoS-driven scheduling, together with adaptive networking protocols and bandwidth-aware offloading schemes that respond to real-time congestion, UAV mobility patterns, and predictive handoff needs for seamless edge association. Integrating secure offloading protocols, strong data encryption, and privacy-preserving computation techniques, such as federated learning or homomorphic encryption, is essential to ensure reliable and privacy-aware edge intelligence for indoor UAV networks.

Table 11 presents a structured challenges and road map that highlights potential future directions to overcome the outlined challenges.

VI. CONCLUSION

Indoor autonomous multi-UAV systems are a rapidly evolving frontier in aerial robotics and intelligent automation, driven by the scalable, safe operations and demand for high efficiency within confined and GPS-denied environments. This work highlights the importance of multi-UAVs in indoor environments, which can be applied to various tasks such as warehouse inventory management using bar codes, monitoring, victim identification, and rescue operations. This survey has provided a holistic synthesis of the state-of-the-art research across the important domains of obstacle avoidance, control systems, resilient communication and networking, mission planning, sensing, localization, and navigation—each of which is requisite for ensuring reliable multi-agent coordination and autonomy. Unlike previous survey papers that focused on specific elements of indoor multi-UAV systems, this study examines multiple interconnected areas for multiple UAVs in indoor operations. The research covered recent methodologies that are being utilized in these elements, presented a comprehensive overview, and benchmarking of published work in each domain. The research answers the research question of how emerging technologies like ML and edge are playing a role in each area. The review highlights how emerging technologies such as deep reinforcement learning, edge computing, federated learning, and multi-RAT networking are reshaping the capabilities of indoor multi-UAVs. Despite advances in progress, significant gaps persist in achieving robust, real-time deployment and ideal indoor autonomy at scale. The majority of existing work remains constrained to simulation environments or limited physical setups, often lacking generalization, hardware integration, or standardized benchmarking.

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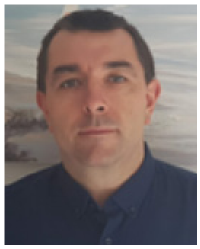

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