Area Exploration Strategies for UAV Swarms A Structured Overview

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***Abstract*—Unmanned Aerial Vehicle (UAV) swarms are promising for wide-area exploration. Due to their relatively low cost and efficient environment coverage they are of great interest for many applications. This paper presents a structured overview of different state-of-the-art studies and methods that present a number of architectures for a multitude of applications, but in this work especially Search and Rescue (SAR). Also presented are remaining open challenges, compromises that need to be made and recommendations for future research. This paper may be seen as a representative but incomplete overview of the research field as well as its domains and aspects.**

***Index Terms*—UAV swarm, UAV swarm exploration, UAV coordination, Multi-UAV systems**

I. Introduction

UAVS have a wide range of use cases in civil, industrial, military, and emergency service domains. Therefore, their research has been of interest for more than two decades as pioneered by Burgard et al. [1]. This includes among other things fast area exploration and coverage, goal-directed architectures, data harvesting from Internet of Things (IoT) devices and SAR missions.

The classical pipeline for UAV exploration starts at the lowest level with mapping, usually done via Simultaneous Localization and Mapping (SLAM), Light Detection and Ranging (LiDAR) or similar sensor-based techniques. Then frontiers, the edges between the known and unknown, are detected, viewpoints selected and the trajectory computed. The different presented architectures apply this pattern in a variety of ways. In recent years the research field has grown and matured, especially in the context of single UAV exploration where a hierarchical framework named "Fast UAV Exploration using incremental frontier structure and hierarchical planning (FUEL)" [2] presented a hierarchical planner 3–8 times faster than other state-of-the-art architectures. The planner computes a global coverage path utilizing local viewpoint refinement and computes minimum time trajectories.

With multiple UAVs new challenges arise. These include among others task allocation, communication bandwidth, formation control, fault tolerance, scalable coordination and overlap avoidance for optimal, complete, robust and fast exploration. This also leads to different kinds of the control architecture; centralized (with a main controller), decentralized (with distributed computation) and hybrid alternatives. The focus has therefore shifted from drone-to-drone path planning for localized optimal trajectories to scalable and efficient path planning. Different research domains have evolved from this and can be grouped as follows: frontier-based with hierarchical planning, bio-inspired and self-organizing as well as learning-based and neural-network methods. Multi-UAV exploration remains challenging due to additional tensions and missing real-world testing. Tensions are formulated as current taxonomy axes:

- Coordination vs. communication, the question of how much single UAVs really need to communicate for efficient coordination.
- Coverage efficiency vs. safety and resilience, the trade-off of known-field exploitation and cautious exploration.
- Scalability vs. optimality where centralized approaches approximate optimality but become fragile, computationally expensive and decentralized approaches become suboptimal due to inconsistencies and duplications.

A systematic overview was done in 2024 reflecting on a decade of advances in UAV swarm control by Cetinsaya et al. [3]. This represents the shift from single-UAV control towards swarm control.

One especially fitting use case is SAR demanding additional features from UAV swarms such as detection-time as the primary metric, multi-modal imaging, more complex communication constraints, the need for fast area coverage and detection of potentially occluded targets (e.g. hidden under rubble). Also a priori knowledge, like areas of greater interest due to increased success probability, might be introduced. Since this area is of great interest, research papers have been published before, in 2020 by Queralta et al. [4] investigating heterogeneous SAR robotic teams and in 2025 specifically for drones and drone swarms in SAR by Quero and Martinez-Carranza [5].

This paper reviews recent advances in UAV swarm exploration and then focuses on SAR-specific adaptations. The reviewed papers were selected based on time of release, estimated impact, novelty, contribution to the proposed taxonomy axes and in parts SAR relevance. Also included Section II covers general exploration architectures. In section III SAR-specific sensing, coordination and benchmarking are covered. Section IV discusses open challenges and future directions followed by the authors conclusions.

II. General UAV swarm exploration

UAV swarm exploration has different tasks to tackle. For example position estimation, localization, efficient path planning for fast environment exploration, inter-drone communication and collision avoidance. The difference between the architecture style-groups hierarchical planner, bio-inspired and learning-based differ in the approach taken on planning, communication, coordination and other things. At the lowest level a drone needs to know where it and potentially neighboring drones are. This is usually done with sensors such as LiDAR, stereo or RGB. Different improvements to robustness against sensor noise, accuracy and communication bandwidth have been proposed. Tian et al. [6] presented a fully distributed architecture with only peer-to-peer communication to inherently improve robustness and minimize communication overhead. Zhu et al. [7] have managed to make their system more scalable by reducing computation time with scaling swarms to sub-linear which is a significant progress in terms of large swarms.

A. Decentralized Hierarchical Planning

Frontier-, Next-best-View- and sampling-based path planning algorithms have been pioneered back in 1997 by Yamauchi [8] where a frontier is defined as "the boundary between open space and uncharted territory". In general this kind of algorithm identifies dense clusters of frontiers and tries to explore them efficiently organized by estimation of information gain. Tran et al. [9] propose a new strategy that maintains a close-knit flight formation for a faster exploration time and to maintain reliability against uncertain communication, single robotic failure, sensor- and positional-uncertainty and to be self-organizing in a completely unknown environment. The first time a fully decentralized collaborative exploration for multiple UAVs that is field tested was introduced in 2023 by RACER [10]. It uses an online hgrid decomposition of the area, pairwise drone interaction and a Capacitated Vehicle Routing Problem (CVRP)-based workload balancing for fully autonomous real-world exploration. Another key contribution is the reduced communication overhead and improved exploration time in comparison to other simulation-only validated architectures. Next-best-View (NBV) planning has certain similarities to the frontier-based approach but chooses the next sensor viewpoint that promises the greatest information gain and is often used for a 3D-reconstruction of the explored terrain. Gui et al. [11] propose a new dynamic centroid-based method that partitions the 3D working area in which each UAV generates new targets in its own partition using onboard computation. This approach has been verified both in simulations and real-world experiments. Among reviewed categories, decentralized hierarchical planning appears closest to field deployment because several systems include real-world validation. Recent approaches demonstrate improved scalability in reported experiments, real-world validation and interpretable behavior. At a very large swarm-scale the characteristic pairwise interaction and communication of drones may become a limiting factor due to global inconsistencies.

B. Bio-Inspired and Self-Organizing Approaches

Bio-inspired approaches try to utilize existing, observable algorithms in living animal flocks. Phung et al. [12] use a motion-encoded Particle Swarm Optimization (PSO) to solve the problem of optimal search for a moving target. Their approach is an improved version of PSO that performs 24% better and nearly 5 times faster exploration times. For large-scale swarms the authors state that parallel computation is needed to further improve execution time. While this approach is especially tailored for moving targets Kareem et al. [13] propose a framework that integrates thermal sensing and optimization-based coordination but explicitly states that it is not intended for moving targets. Different bio-inspired algorithms are tested under the same conditions. A different direction is taken by Wang et al. [14] where the authors introduce an adaptive goal-directed strategy that also performs well in confined spaces (e.g. canyons). This approach separates informed and uninformed agents which improves computation efficiency but also introduces the need for maintaining the formation. It only uses local perception and was validated in indoor experiments with six drones. The goal-directed strategy differs from the general exploration problem. Bio-inspired approaches characteristically have very low communication needs, maintain inherent robustness and present simple local rules. These strengths get partially mitigated by weaker global optimality guarantees, in general no formal coverage bounds. They seem to be best suited for early-stage search or as a fallback layer when communication bandwidth degrades.

C. Learning-Based and Graph-Based Methods

Due to recent advancements in Generative AI and understanding of the accompanying technologies learning-based, graph-based and neural-network methods have gained traction. Gao et al. [15] propose a novel Deep Reinforcement Learning (DRL) approach utilizing a Convolutional Neural Network (CNN) for environmental data extraction and a reward system with unified modeling of coverage efficiency and safe landing embedded directly in the reward system. The recent GoalSwarm [16] by James et al. introduces a novel Open-Vocabulary target detection system. Although many restrictions apply the use of Bayesian spatial reasoning for frontier scoring and Open-Vocabulary make it a new approach to further expand the already wide application range.

Learning-based methods are promising with regard to their capabilities and wide application possibilities when it comes to large UAV swarms due to the great possibility to incorporate existing other approaches and greater approximation of an optimal strategy. These methods often remain difficult to validate because learned policies may depend on simulation assumptions, training data quality, onboard compute limits, and environmental conditions that differ from real deployments.

III. Search and Rescue (SAR) - Focus

"SAR refers to organized efforts to locate and assist people in peril, often during crises such as natural disasters, maritime incidents, or urban emergencies" [17]. This includes different types such as: ground, mountain, urban, combat and maritime SAR. In all of these use cases UAV swarms promise significant aid with a large variety of possible uses.

A. What Makes SAR Different

SAR lays the focus on the different environments including difficult terrains, possible elevation gains or losses, likely obstacles and dense environments that need to be traversed. Also

SAR has higher standards regarding robust communication and exploration. But most important and noticeably is the shifted focus: from whole area coverage to rapid Object of Interest (OOI)-detection.

In addition to the more representative view of Quero and Martinez-Carranza [5] the analysis of Manaseswaran et al. [18] provides insight to the more pressing opportunities by comparing, mainly, two approaches utilizing generative AI and Machine Learning. Together these papers explore recent advancements in UAV use for SAR missions.

B. Communication-Resilient Decentralized SAR Swarms

The point of unreliable communication between UAVs within a swarm and to the human in-the-loop has been of interest for some time. Horyna et al. [19] propose an approach for decentralized swarm navigation in the direction of a candidate OOI based on real-time detection from the drones' onboard RGB cameras. This includes a self-adaptive communication strategy that utilizes a local visual communication channel that establishes a network connection between neighboring drones without explicit communication. This has been tested and verified in both simulations and real-world field tests. In addition to this Bartolomei et al. [20] propose a new methodology to explore overlooked regions within already explored space. The problem formulation focuses on forest exploration where drones cannot know what lies behind single trees that are recognized as obstacles. The approach utilizes the balance between careful exploration of the unknown and aggressive exploitation of known regions.

Communication-resilient coordination is especially valuable for SAR. The downside is that the range is currently limited by optical line-of-sight and UV-based signaling adds extra hardware that would not be necessary in other use cases.

C. Thermal sensing, Bio-Inspired SAR and Benchmarking

Kareem et al. [13] have proposed the bio-inspired swarm UAV framework discussed in 2.2 but also introduced a novel Exploration Score metric with their modular thermal-based framework. The metric is focused on coverage ratio, redundancy ratio, inter-drone distance and total path length. It is used in [13] to compare 10 different bio-inspired algorithms. The Exploration Score metric makes different architectures more comparable which is an undervalued novelty in the domain. One approach by Sun et al. [21] focuses on UAV swarms in maritime SAR utilizing a YOLOV8 perception model enhanced by a convolutional attention mechanism with an improved diversity-based Ant Colony Optimization (ACO) where the population kind is diversified. Diversifying allows for low-level micromanagement of single agents. This is implemented as different classes of nodes: explorers who find new paths and transporters who optimize these paths, both using digital pheromones. Here the focus lies on collaborative path planning and visual perception. The model achieves better detection performance than other state-of-the-art maritime SAR approaches.

Another important characterization of SAR is the focus on humans. Humans have a heat signature that can be recognized by thermal infrared and other multi-modal sensors. This makes perception quality a central requirement for SAR-oriented UAV systems. Suo et al. released HIT-UAV, a freely available high-altitude infrared thermal dataset for UAV-based object detection [22]. Although HIT-UAV is not a swarm coordination method, it is relevant for SAR because perception quality directly affects Object of Interest (OOI) detection from altitude. RGB-only approaches struggle with camouflage, darkness, and occlusion which makes them suboptimal for SAR. The presented dataset improves architecture comparability and high-value training.

A novel open-source benchmark is proposed by Grøntved et al. [23] that provides 60 wilderness SAR scenarios with probabilistic lost-person models. Together these two works adress the field's long-standing lack of standardized evaluation and enable reproducible perception and planning evaluation for future work, making cumulative progress more probable. This problem is not limited to the SAR field.

IV. Cross-cutting Challenges

Different challenges affect the whole research area. Overcoming these challenges would mean a milestone for the whole research field and therefore for each of its domains. Challenges include among others communication constraints, fault tolerance and the reality gap.

A. Communication vs. Coordination Tension

Communication constraints have piqued the interest of many researchers and how a fault-tolerant, minimal bandwidth, reliable and possibly redundant in independent communication methodology may be proposed. The review in [24] shows that intermittent connectivity, resource constraints, and dynamic environments make offloading decisions a major bottleneck. Incorporating adaptive learning-based approaches might compensate for the issues of an unpredictable context and potentially heterogeneous swarm environments.

B. Resilience and Fault Tolerance

Hamid et al. [25] review resilience in UAV swarms and identify the problem that distributed UAV swarms will inevitably lose agents. The work identifies disruption sources such as hardware failure, jamming, battery and GPS loss as well as the lack of standardized resilience metrics. The work also conducts bibliometric analysis to reveal trends in UAV swarm resilience. Jiang et al. [26] integrate health states into Multi-Agent Reinforcement Learning (MARL) and by making topology adaptations. Failing agents receive special treatment and their architecture as well as behavior differs from healthy agents. Resilience remains under-explored relative to its practical importance in the whole research field but especially in the SAR domain.

C. Reality Gap and Validation Infrastructure

Through extensive research one problem has become very obvious: most architectures and novel approaches lack real-world field tests. Most of which include prerequisites of e.g. perfect and limitless communication or other unrealistic parameters. These factors often make the novelties unfit for real-world testing since they are not extensive enough for this kind of deployment. Especially MARL and bio-inspired methods only validate in simulation. Alqudsi et al. [27] note that scalability claims in simulation rarely hold in physical deployments, which is plausible due to added factors and parameters that come with real-world deployment and have not been thought of or purposefully excluded in the methods creation process making future research more than necessary if the goal is field deployment. Sende et al. [28] have compiled mixed field tests with 5G connectivity to bridge simulated and physical drones. This advances testing to the real world which is vital for further progress. [13] implemented a high-fidelity PX4 and Gazebo, that are autopilot and simulation infrastructures, for reproducible SAR testing both in simulation and field tests. RACER [10] and [19] both present real outdoor experiments and have had great impact thus setting the standard for what a convincing validation looks like. Future, extensive, research should therefore implement real-world testing to further strengthen and validate the taken approach.

V. Open challenges and recommendations

Although the research has matured in certain domains and the research field has gained traction in recent years open challenges remain that need to be met and overcome to reach the next milestone in UAV swarm exploration. The following presented open challenges have synthesized during the literature review and base the recommendations.

A. *Open challenges*

As shown an often overlooked issue of the field is the incomparability of highly focused methodologies and their highly focused metrics which are the only available comparison for many architectures and thus not extensive enough. This makes the side by side evaluation of algorithms nearly impossible and may result in unrecognized local optima. No cross-method comparison is possible because no fitting framework for general swarm exploration exists.

Efficient computation on cheap hardware is of interest for all domains of swarm UAV exploration. A limiting factor, in addition to already presented ones is battery life. In the past different compromises have been presented such as including relay and meeting functions, including power constraints in path planning in a Deep RL architecture. Alternatively utilizing visual drone tracking algorithms and tackling complex initialization issues has also been done. To this day the battery is still a constraint. MARL-based methods need real-world validation with real onboard computation, limited communication, and sensor noise. These additional parameters would test the methods in real environments. Current regulations (e.g. airspace integration, certification) are not designed for autonomous swarms. SAR deployment with human-in-the-loop supervision is more realistic and given the missing field tests a more desirable short-term solution than fully autonomous solutions. In future work where validation, security, reliability and resiliency of proposed architectures has been extensively tested in field tests with a human-in-the-loop, the legislation might change for at least restricted field tests.

B. *Recommended Research Directions*

A main milestone should be field tests before fully automated deployment is approached, regardless of architecture. Learning-based approaches are promising in different scenarios; maintaining formation with obstacle avoidance, dynamic formation changes, pursuit and ongoing tracking of OOIs in a varying environment. In near future a special focus should lie on generating a unified benchmarking metric and a corresponding framework for researchers to compare their architectures extensively. Standardization would yield real comparability between approaches and methods. It can be seen that although every research domain has its own strengths no single one satisfies all current taxonomy axes: Coverage efficiency vs. safety and resilience, Coordination vs. communication, Scalability vs. Optimality. A combination of the different research domains where the best aspects of different approaches are combined seems plausible. A layered hybrid approach promises great performance utilizing different aspects. At the low level, bio-inspired flocking is suitable due to its fault tolerance, collision avoidance, and partially zero communication bandwidth. At the mid level Graph Neural Network (GNN)-based area assignment is resilient to intermittent communication, being scalable and utilizing pairwise or local drone neighborhood interaction. At the high level a MARL task switching component for adaptive role assignment promises agility regarding task-generation and task allocation because potentially needed new roles can be introduced, e.g. for minimizing blind spots in an explored area or utilizing population diversity. The whole hybrid approach would base on cross-sectoral communication and would need deeper analysis and planning.

Bridging graph-based MARL from simulation to field deployment using the mixed reality pipeline proposed by [28] and their 5G-based connectivity seems promising for further improvements. Another important topic is the need to develop resilience-oriented coordination that can lose a number (proposed: up to 1/4) of agents without mission failure. This, implemented into an architecture in addition to field tests, would further improve the credibility of the contribution. A recent approach taken by [29] integrates synthetic aperture sensing in a signal processing technique that takes measurements from limited size sensors and combines the data to mimic sensor apertures of much greater widths. This would be especially fitting in the SAR use case when it comes to partially hidden or occluded OOIs which then would have a greater detection probability.

VI. Conclusion

Over recent years UAV swarm exploration has evolved from single-UAV baselines to real-world decentralized UAV swarm systems such as RACER [10], bio-inspired flocking methods and learning-based coordination systems. All approaches have their individual strengths and weaknesses but decentralized-hierarchical approaches are closest to real-world implementation while learning-based approaches offer substantial future potential, especially for adaptive coordination, but require stronger validation. SAR-specific work is converging to a focus on communication-resilient coordination and additional sensors including multi-modal sensing as well as the growing attention for standardized benchmarks and datasets. The most productive near-term path combines field-tested decentralized planning with thermal-sensing bio-inspired search, validated through reproducible simulation-to-reality pipelines. A major step will likely come from closing the evaluation and simulation-to-deployment gap instead of an algorithmic breakthrough. In relation to this standardized benchmarking and improved comparability should be highly valued.

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