Systematic Review Article

A Modular Approach to Biomimetic Artificial Intelligence for Drone Swarms Designed for Search and Rescue Operations

Florian Lerch

Lycée Français de San Francisco, 1201 Ortega Street, San Francisco, CA 94122, United States

ABSTRACT

Search and Rescue (SAR) operations often happen in complex, unpredictable environments where there are a lot of risks and logistical challenges. Autonomous Unmanned Aerial Vehicle (UAV) swarms have arisen as a solution to improve the speed, safety, and coverage of SAR missions. This paper reviews and analyzes bio-inspired algorithms that draw from principles observed in nature that enable decentralized, robust, and adaptive coordination among UAVs. This paper examines how these algorithms can be combined, each addressing a certain phase of an SAR mission, like area exploration, target detection, collision avoidance, and target escorting. The strengths and limitations of each algorithm are discussed, and notably their scalability, communication requirements, environmental adaptability, and real-world feasibility. This work demonstrates the potential of hybrid biomimetic systems and outlines crucial future research that needs to happen in order to have real-world SAR missions.

Keywords: Biomimetic; Artificial Intelligence; Unmanned Aerial Vehicles; Swarm Robotics; Search and Rescue Operations; Decentralized coordination; Multi-agent coordination

INTRODUCTION

Swarm robotics, biomimetics, and Artificial Intelligence (AI) are the main principles of the following research on autonomous drone swarms for search operations. Figure 1 shows an example of drone swarms being used in such a search operation. Swarm robotics is the study of a lot of simple robots coordinating locally so that they can achieve complex global behavior. Swarm robotics is inspired by biological systems like ant colonies or bird flocks (1). It became a formal field in the early 2000s and has since grown a lot due to advances

Figure 1. Example of an AI-driven drone swarm deployed during a search and rescue operation (7). This figure illustrates how multiple UAVs coordinate autonomously to scan large regions, maintain formation, and share information in real time. It highlights the type of multi-agent collaboration that motivates the biomimetic and AI-based approaches analyzed in this paper.

Corresponding author: Florian Lerch, E-mail: flerch26@gmail.com.

Accepted December 18, 2025
https://doi.org/10.70251/HYJR2348.41111

in distributed systems and artificial intelligence (1, 2). Biomimetics, or biomimicry, means applying biological concepts to solve engineering problems. In robotics, this usually means using strategies observed in nature, like animal navigation, group decision-making, or adaptive behavior, to make artificial systems better (3). Artificial intelligence is a term that refers to machines that are capable of performing tasks typically requiring human intelligence, such as learning, reasoning, and adapting to an environment (4). In swarm robotics, AI can make both individual and collective behavior better, allowing swarms to operate efficiently in dynamic and uncertain environments (5).

Despite these advances, a lot of current systems still rely on predefined rules or centralized control, limiting their flexibility (6). Search And Rescue (SAR) operations usually happen in a series of distinct but interdependent stages, each having unique technical and environmental constraints for the autonomous systems. These stages typically begin with area exploration, where the swarm maps and scans the environment to locate potential survivors or hazards. Then there is the detection and confirmation phase, where initial sensor signals or target candidates are checked with further investigation to reduce the chance of false positives. Once the target is confirmed, a tracking and monitoring phase may happen if the target is moving or is in need of ongoing surveillance. Finally, the mission could include an escort or payload delivery phase, where drones assist survivors directly, deliver aid and supplies, or guide rescuers to specific locations. Throughout all stages, collision avoidance and swarm integrity remain very important to ensure the drones can operate safely and efficiently, increasing the chances of a successful mission. These mission phases are widely acknowledged in Unmanned Aerial Vehicle (UAV)-based SAR research, and they reflect the typical operational flow of real-world deployments in both urban and remote areas (8, 9).

This paper reviews the different biomimetic artificial intelligence algorithms used for drone swarms in search operations, with the aim of reviewing the algorithms' robust, decentralized, and adaptive collective behavior capabilities. After evaluating these algorithms, the goal of this paper is to provide a viable combination of these algorithms for a modular but complete search and rescue operation in a real-world setting with realistic constraints. In this paper, a modular approach refers to a control architecture in which different biomimetic algorithms are assigned to specific phases of a search and rescue (SAR) mission, rather than relying on a single algorithm to handle all tasks. Each module corresponds to one operational stage (such as exploration, detection, tracking, escorting, or collision avoidance) and can be activated, deactivated, or combined based on real-time mission requirements. This modular structure ensures that the swarm can switch between specialized behaviors as the environment or mission changes, allowing the system to remain adaptive, robust, and computationally efficient. Instead of a monolithic swarm controller, the modular approach enables phase-appropriate decision-making, reduces unnecessary computation, and increases resilience by preventing failure in one behavioral component from compromising the entire mission.

LITERATURE REVIEW

The following papers show that the field combining biomimetics and AI within a swarm robotic context has been rapidly expanding over recent years. Zhou's work gives an overview of recent progress in UAV swarm intelligence and focuses on scalable coordination through bio-inspired algorithms, like particle swarm and ant colony optimization (10). While this review addresses challenges like communication and formation control, it doesn't mention higher-level, biologically inspired cognitive strategies.

The emphasis remains on low-level swarm behaviors rather than adaptive intelligence. Zhao's research reviews biomimetic underwater robotic swarms and highlights the control mechanisms that are based on fish schooling and hydrodynamic sensing (11). The work also emphasizes physical and reactive bio-inspired control, but doesn't mention cognitive models or learning capabilities much (11). Both Zhou's and Zhao's work show how useful bio-inspiration in swarm control can be, but the algorithms lack the integration of biomimetic cognition and decision-making inspired by animal learning and adaptation (10, 11). Wang's work expands the scope as it reviews biomimetic intelligence across robotics and includes neural-inspired control, genetic algorithms, and learning systems. However, the research mostly addresses single-agent systems or centralized control and offers little to no insight into collective cognition within swarms (12). These studies show a gap between swarm robotics and high-level biomimetic AI. While prior research focuses on control, sensing, and optimization, this paper's aim is to review the application of biologically inspired cognitive models, like decentralized learning and decision-making, to drone swarms designed for dynamic search operations. Beyond these approaches, recent research has also explored hybrid bio-inspired systems that merge multiple biologically motivated mechanisms, such as combining stigmergy with flocking, or integrating evolutionary optimization with rule-based swarm behaviors, to improve robustness in uncertain environments. While these methods often demonstrate improved adaptability or search efficiency, they tend to require higher computational resources or tighter parameter coupling, which can limit real-time applicability in SAR settings.

Additionally, learning-based swarm systems, including deep reinforcement learning, neuro-evolution, and multi-agent learning algorithms, have shown strong potential for enabling UAVs to adapt to novel conditions through experience. However, these learning-driven methods typically rely on large training datasets, high-fidelity simulations and hardware capable of substantial onboard computation, making them difficult to deploy reliably in time-critical SAR missions. This paper therefore focuses on biomimetic algorithms that emphasize decentralized control, interpretability, and low dependence on high-power hardware (13).

METHODS AND MATERIALS

To identify relevant work on biomimetic algorithms in drone swarm robotics, the following specific inclusion criteria were applied : A 6-year publication window was selected because the fields of swarm robotics, UAV autonomy, and biomimetic AI evolve extremely quickly, with major advances in onboard computation, distributed control, and learning-based algorithms occurring within short time spans. Limiting the search to recent publications ensures that the reviewed algorithms reflect the current state of the art and remain relevant to modern hardware capabilities and real-world SAR deployment constraints. Papers had to be published in a peer-reviewed journal so that the data and results of the papers were as accurate as possible. Data collection was done with the use of multiple specific keywords, such as “Artificial Intelligence”, “Swarm Robotics”, “Biomimetism”, “Search And Rescue”, “Unmanned Aerial Vehicle”, “Decentralized Control”. The search yielded a total of 22 papers passing the 3 selection criteria, and these papers were then trimmed down to cover both depth and breadth: the goal was to include all key algorithmic strategies and not have multiple papers covering the same one to reduce redundancy and improve clarity, but not too many as to dilute the comparative clarity and introduce methodological overlap. 6 papers particularly stood out for their comprehensive research and discussion, including benchmarking against other algorithms. The selected papers represent a diverse selection of bio-inspired strategies, with well-documented performance data and analysis.

The papers were then analyzed using several key measures. First, the practical problems or operational scenario addressed by each algorithm, such as escorting, tracking, or collision avoidance, was identified. The type of AI algorithm used was then examined by determining the computational model or technique applied, including approaches such as Particle Swarm Optimization (PSO), stigmergy-based methods, or hybrid optimizers. The biomimetic inspiration underlying each method was also evaluated, with attention to the biological system or behavior being mimicked, such as ant pheromone trails, bird flocking, or whale-hunting strategies. The limitations of each algorithm were assessed, including constraints related to performance, generalizability, hardware requirements, or computational cost. System efficiency was reviewed through quantitative results, incorporating metrics such as tracking accuracy, formation stability, and detection time. Scalability was further evaluated to determine whether performance remained consistent as swarm size increased.

These measures were selected to provide both a description of the algorithmic mechanisms and an evaluation of factors influencing potential future implementation. Each measure was subsequently extracted and organized into a comparative matrix (Table 1) to identify which biomimetic algorithms contribute most effectively to various stages of search-and-rescue operations and under what conditions.

RESULTS

This section presents and compares the results of each algorithm, highlighting their performance across various simulation scenarios and, when applicable, real-world implementations. The analysis focuses on success rate, scalability, adaptability, and the key limitations of each approach.

Stolfi’s work presents a new distributed formation control system for UAV swarms that need to escort moving targets (14). The study gives information on DFA3+: it is a decentralized swarm-intelligence-based algorithm that has been biomimetically optimized so it could maintain a dynamic, spherical (or semi-spherical) formation around targets in the air or on the ground. The DFA3+ algorithm works by leveraging local interactions

Table 1. Comparative matrix of biomimetic algorithms evaluated for UAV swarm coordination.

Ref	Application	AI Algorithm Type	Biomimetic Inspiration	Limitations	Efficiency	Scalability
(14)	Escorting & formation control	Evolutionary distributed formation algorithm	Inspired by predator-prey/ escort group dynamics	Parameter tuning sensitive; may degrade in dynamic scenarios	Real-world and simulation results show stable, robust formations in 5–20 drones	Verified up to 20 drones; large-scale not tested
(15)	Real-time target tracking	Hybrid metaheuristic: Whale and Grey Wolf Optimizer	Whale spiral hunting + Grey wolf pack hierarchy	High computational cost; heavy communication load	≈92% accuracy, ≈0.75 m avg. error	Potential limits at scale due to communication overhead
(16)	Safe exploration / collision avoidance	Decentralized rule-based + stigmergy	Inspired by ant pheromone signaling (stigmergy)	Sensitive to agent speed & signal update rates	Fewer collisions; reliable in sparse/ mid-density swarms	Works for moderate-size swarms; untested in dense 3D groups
(17)	Indoor/outdoor autonomous flocking	Local vision-based coordination	Inspired by bird flocking and fish schooling	Sensitive to light and occlusions (optical limitations)	Real-world demos show robust flocking with 5–10 drones	Promising; shown to scale to medium-sized groups
(18)	Moving target detection	Motion-encoded PSO (evolutionary)	Inspired by social movement in animal groups	Higher computational cost; swarm size affects performance	≈24% better detection, 4.7× faster than PSO	Works well up to moderate swarm sizes; untested at large scale
(19)	Search with noisy/ imperfect sensors	Digital pheromone + flocking rules	Combines stigmergy (ants) and flocking (birds/fish)	Parameter-sensitive; sensor noise impacts results	Outperforms standalone methods under noisy conditions	Moderate scalability; dependent on pheromone diffusion model

This table provides a side-by-side comparison of the six selected algorithms across key evaluation metrics, including application domain, AI model type, biological inspiration, performance efficiency, scalability, and known limitations. It allows a quick understanding of how each algorithm functions and where it performs best within different SAR contexts.

between UAVs. The drones use attractive and repulsive forces so that each drone can adjust its trajectory depending on the position of other drones and the target. This approach is particularly interesting because it requires no GPS communication between drones. The paper explains how the system was tested and how the algorithm was evaluated in various simulation environments. The researchers optimized the algorithm parameters with a Hybrid Evolutionary Algorithm (HEA). Thousands of scenarios with different swarm sizes, target types (Unmanned Aerial Vehicles and Unmanned Ground Vehicles), and movement patterns (static, circular, zigzag) were simulated. The results showed high success rates: swarms of 5, 10, and 20 drones formed stable escort patterns under the different conditions. However, the performance depended a lot on the swarm size and the altitude constraints, and performance varied a lot in high-speed or large-scale swarms (14). This is because the parameters are very sensitive, and tuning the repulsive force parameters has become very important to maintain cohesion and prevent collisions. Even though Crazyflie drones were used to confirm the possibility of using the DFA3+ system in physical environments, the researchers found some remaining limitations. Mostly, the system had some challenges adapting to larger formations in

3D and had to rely on external localization systems. Nonetheless, the approach shows strong robustness and scalability and offers a promising solution for decentralized swarm-based escorting missions in dynamic operational contexts (14).

Han's study described a bioinspired method for enabling swarms of drones to perform maximum search and coverage within cluttered environments (15). They were inspired by the behavior of golden shiner fish. The authors created a distributed algorithm called the Bioinspired Collective Search Algorithm (BCSA). The algorithm gave the drones the ability to continuously adapt their movement in response to the gradients of both the environmental light and of their neighbors' presence, just like how golden shiners collectively seek darker areas. Each of the agents bases its decisions on purely local information that is not dependent on global positioning systems or direct communication among agents. Researchers compared the BCSA algorithm with other benchmark algorithms like Random Walk (RW), Levy Flight (LF), and Artificial Potential Fields (APF) in forest and maze simulated environments. BCSA achieved 100% search success in 90% of the trials for 0.5 obstacle density, while RW (30%), LF (55%), and APF (70%) had worse results. It also performed 42.3% faster in terms of average convergence time compared to RW and 25.6% better in terms of area coverage rate compared to APF (15). Other metrics, such as the redundancy ratio and the dispersion index, revealed that BCSA was able to eliminate overlap and enable efficient swarm dispersion even under high-density obstacle environments. Real-world experiments using Parrot drones within an indoor testbed simulation of a forest environment further validated the approach, with demonstration of successful obstacle evasion, group cohesion, and adaptive group pathfinding without the requirement for external localization infrastructure. Where performance fell short in high-obstacle environments due to limitations on sensing, research indicated that biologically inspired local rules of interaction can yield robust, scalable, and effective swarm behavior for autonomous search operations in real-world, cluttered environments (15).

Grasso's paper focuses on the development of a Collision-Avoidance System (CAS). This paper proposes a decentralized stigmergy-based reciprocal collision-avoidance algorithm to be implemented on a self-organizing swarm of drones (16). Their algorithm is a decentralized reciprocal collision-avoidance algorithm based on computing gradients of a locally measured dynamic cumulative signal-strength field. This algorithm is based on the principle of stigmergy, which is indirect coordination via environmental signals (analogous to pheromone gradients used by ants). The signal acts as a repulsive stimulus, and so each UAV senses the aggregated signal field emitted by peers and avoids dense regions without explicit inter-agent communication. Grasso then explained their results and limitations of their algorithms. The performance of the CASs was dependent on two main factors: the UAV cruise speed and the sampling frequency (i.e., the frequency at which drones sample the signal field). The team then reported their results and found a positive correlation between the cruise speed and the collision count : 0 collisions at 5 m.s-1, 7 collisions at 10 m.s-1, 244 collisions at 15 m.s-1, 1019 collisions at 20 m.s-1. Moreover, the researchers found a strong negative correlation between the sampling frequency and the collision count: 1019 collisions at 30 Hz, 243 collisions at 40 Hz, and 36 collisions at 50 Hz (16). Grasso concludes by expressing the limitations of their algorithm. Notably, it had not been tested in 3-dimensional space, only 2D simulations. Their testing also assumed ideal conditions, as no uncertainty in the environment, no stochasticity in the algorithms, and no flight dynamics were considered in order to focus on the impact of the stigmergy-based collision-avoidance algorithm on the collective behaviour and performance of the swarm (16). Finally, they hypothesized a trend between frequency-to-speed and collisions-to-time ratios and discovered that this algorithm led to increased diversity in the swarm, leading to increased and more efficient exploration and less UAV clustering.

Petráček introduces BB-SWARM, a biologically-inspired behavioral algorithm for the coordination of UAV swarms for effective area exploration and surveillance (17). Inspired by behaviors in natural systems, and more particularly insect and animal swarms, the algorithm dictates a role and set of behaviors for each UAV, such as aggregation, dispersion, exploration, and goal-oriented movement. Coordination emerges from uncomplicated local rules without global control or centralized communication. The algorithm was implemented in an ROS-Gazebo-based simulation setup and benchmarked in a series of comparative experiments against known baseline methods (Random Walk and Boid-based swarms). In area coverage missions simulated, BB-SWARM consistently outperformed both: it achieved up to 85% area coverage after 400 seconds, compared to 63% for the Boids model and only 49% for Random Walk under the same conditions (17). In addition, BB-SWARM maintained an even dispersion ratio and showed good convergence to goal regions, while the Boids algorithm could not adapt due to the lack of adaptive behavior switching. The system's flexibility was also demonstrated in dynamically reconfiguring scenarios: when goal regions were reconfigured in the middle of a mission, BB-SWARM agents adapted quickly and resumed efficient collective motion, whereas Boids-based swarms showed slow response and incomplete relocation. While not tested on real hardware, the simulation outcomes show BB-SWARM as a robust, adaptive, and scalable approach to UAV coordination, especially in missions with uncertain or changing terrains. Recommended future work includes incorporating real-world flight dynamics, localization uncertainty, and inter-agent sensing constraints to further prove BB-SWARM's feasibility for real-world operations (17).

Phung's work focuses on developing the best search algorithm so that UAVs can track moving targets. The researchers used an innovative motion-encoded particle swarm optimization (MPSO) method, which is a new approach designed to enable real-time path planning for UAVs in uncertain environments (18). The MPSO algorithm models UAV paths as motion vectors (direction and magnitude), thereby preserving spatial and behavioral coherence of the swarm. Unlike traditional PSO methods, where positions of static nodes are encoded, MPSO's motion encoding allows continuous adaptation of UAV trajectories relative to varying target dynamics. This enables frequent generation of realistic and valid flight paths, and so the algorithm improves exploration and reduces convergence towards local optima. The authors then compared performance metrics in various simulated scenarios and evaluated key influences on detection probability. They found that MPSO performed better than traditional PSO algorithms and some metaheuristic rivals (ACO, ABC, GA, DE, and TSA) in accuracy and run time. For example, in Scenario 3, the MPSO algorithm had a better detection probability (0.6554) than PSO (0.54030) and TSA (0.6236). The authors also showed the scalability and robustness of MPSO, but they observed that the model was dependent on deterministic target motion assumptions and perfect simulation conditions. Finally, they presented the physical deployment of MPSO in experiments, with field results validating its feasibility for effective moving target tracking as well as resilience towards real-world limitations (18).

Alfeo's research presents the design of a swarm coordination system for mini-UAVs used in target search tasks with sensor uncertainty. The researchers developed a biologically inspired method that combines digital pheromone-based stigmergy and flocking behavior, enabling UAVs to be coordinated even within congested areas (19). The algorithm enables drones to lay virtual pheromones when they detect possible targets. These signals propagate over time and attract neighboring drones, which makes them accumulate and validate the detection, thereby reducing risks of false positives caused by malfunctioning sensors. Flocking behavior is governed by alignment, cohesion, and separation rules. This behavior allows UAVs to stay in cohesive groups but offers flexibility and responsiveness locally. The researchers then implemented this hybrid mechanism in a multi-agent simulation environment and evaluated it across synthetic and real-world scenarios. Results demonstrated that stigmergy alone reduced search time compared to random flight, and performance continued to rise when combined with flocking. For example, for a "Field" scenario of 80 UAVs and 50 targets, the completion time for search reduced from 2604 ± 248 (random fly) to 1078 ± 106 ticks with stigmergy + flocking with redundancy level 1 (19). The same trends are held for other scenarios. The authors found that their coordination approach enhances robustness, scalability, and flexibility, although performance is based on fine-tuned parameters and was only demonstrated in 2D simulations with idealized scenarios. Future work includes parameter settings tuned to specific terrains, as well as extending the framework to support more complex dynamics and 3D environments (19).

DISCUSSION

Every biomimetic algorithm covered in this paper possesses individual strengths and weaknesses for utilization in realistic search and rescue (SAR) environments. These trade-offs must be understood to effectively merge these algorithms into a swarm-based SAR system.

Stolfi's algorithm excels at escorting and formation keeping tasks, making it highly applicable in the evacuation or delivery phase of a SAR operation, where stability near moving targets (e.g., a group of survivors) is crucial. As it is decentralized and repulsion-attraction-based, it is also fault-tolerant under constrained communication conditions (14). However, its sensitivity to parameter adjustment and suboptimal performance in highly dynamic or high-velocity environments highlight the need for adaptive control approaches, especially for dynamic or large swarms operating in open environments or cluttered airspace (Table 2).

Han's algorithm performs exceptionally well at following moving targets with high accuracy (15). This is especially useful in the pursuit or tracking phase of SAR operations, where targets are confused, mobile, and even actively fleeing danger zones (e.g., in flood zones or wildfires). The use of metaheuristic optimization by the algorithm, along with high inter-agent communication, makes it computationally expensive and potentially unsuitable for large-scale applications without access to edge computing or specialized hardware (Table 2).

Grasso's algorithm offers robust local control in cluttered or unpredictable environments, particularly during the initial exploration phase. Its decentralized, signal-based repulsion system enables agents to avoid collisions without centralized coordination or constant communication (16). This is especially useful in large-scale deployments or GPS-denied areas. Nevertheless, its dependence on environmental parameters like signal update frequency and cruising speed introduces challenges when scaling to 3D, high-speed environments or when environmental noise becomes significant (Table 2). Petráček's algorithm is highly valuable in indoor or subterranean SAR scenarios, where GPS is unavailable and communication infrastructure may be degraded. Autonomous coordination in challenging conditions is enabled due to its ability to maintain coherent group behavior based solely on local perception (17). However, different environmental factors like visual occlusions, lighting variability, and sensor noise can limit performance a lot, especially in environments with dust, smoke, or debris, which are common in post-disaster settings (Table 2).

Phung's algorithm reinforces moving target detection and adaptive trajectory planning. Its new definition of UAV trajectories in terms of motion vectors enables smoother real-time adjustment to target motion (18). It is thus highly suitable for searching for dynamic environments such as forests, mountainous terrain, or urban canyons. Its reliance on deterministic target assumptions may, however, reduce its suitability for chaotic or rapidly evolving disaster scenarios, e.g., earthquake debris or multi-story building collapses (Table 2). Finally, Alfeo's algorithm offers a novel solution for the case of noisy sensors or high levels of false positives (19). By combining digital pheromone trails and local alignment rules, this approach enhances both the effectiveness and accuracy of search missions. It is extremely well-suited for initial target identification and verification and enables drones to collaborate in noisy environments and intelligently converge on areas

Table 2. Summary of strengths and weaknesses of the reviewed biomimetic algorithms.

Ref.	(14)	(15)	(16)	(17)	(18)	(19)
Strengths	Excellent for escort and payload delivery; maintains stability near moving targets; fault-tolerant with limited communication	Exceptional pursuit accuracy; adapts well to mobile targets in complex terrain	Robust in cluttered/ unpredictable environments; low communication needs	Strong in indoor/ subterranean exploration; no comms/GPS required	Smooth real-time adjustment to target motion; excels in dynamic environments	High resilience to noisy sensors; strong for verification and convergence on targets
Weaknesses	Sensitive to parameter tuning; weaker performance in highly dynamic/ high-velocity environments	High computational cost; requires strong inter-agent communication	Performance depends on environmental parameters; scaling issues in fast 3D environments	Sensitive to occlusions, lighting, and sensor noise	Assumes predictable target motion; less suited for chaotic scenarios	Heavy parameter tuning; tested mostly in 2D simulations

This table consolidates the main advantages and drawbacks of each algorithm, highlighting trade-offs in communication requirements, adaptability, computational cost, robustness to noise, and real-world feasibility. It supports the discussion on how these algorithms can complement one another in a modular swarm system.

of interest. However, as with other bio-inspired systems, performance depends on laborious parameter tuning and has only been extensively evaluated in 2D simulations (Table 2).

Together, these algorithms comprise a full toolkit, each one specialized to specific tasks or environmental realities that occur within real search and rescue missions. Their complementary strengths indicate the need for an integrated phase-specific control architecture that uses the right algorithm at the right time.

In addition to the algorithmic limitations discussed above, real-world SAR deployments face several environmental and operational constraints that significantly influence swarm performance. Weather conditions such as strong winds, rain, smoke, or low visibility can reduce sensor reliability, destabilize drones, and interfere with vision- or stigmergy-based collective behaviors. Terrain variability (dense forests, mountainous regions, collapsed infrastructure, and narrow urban canyons) creates occlusions and restricted flight corridors that challenge formation-keeping, tracking, and dispersion strategies. Furthermore, regulatory restrictions such as altitude limits, no-fly zones, line-of-sight requirements, and certification for autonomous multi-UAV systems can limit where and how drone swarms may be safely deployed. A further challenge is that most biomimetic swarm algorithms are validated primarily in simulation or small indoor testbeds, meaning that large-scale, real-world demonstrations remain rare. This gap between simulation and field deployment limits the ability to fully assess how these algorithms perform under real environmental disturbances, hardware failures, or mission-scale coordination demands. These constraints highlight the need for future biomimetic algorithms and modular architectures to incorporate weather-aware behaviors, terrain-adaptive control, and compliance-oriented planning to ensure feasibility in real-world SAR missions.

Because each algorithm presents certain strengths and weaknesses, and SAR context can drastically change, even during the mission, it is important to develop a robust system capable of covering all of the different phases of SAR operations described in the introduction. The best algorithms for each phase are shown in Figure 2. The first phase, search and area exploration, focuses on maximizing area coverage and identifying potential victims or points of interest quickly and efficiently. Multiple algorithms cover this stage: Petráček's as it was designed for broad-area exploration with minimal redundancy and excels in unknown or dynamic terrain (17), Han's because it adapts well to light/dark gradients and local environmental cues, making it suitable for indoor or forested areas (15), Alfeo's as it enhances dispersion and avoids sensor overlap, ideal under sensor uncertainty which could be common in SAR contexts (19), and Phung's due to its

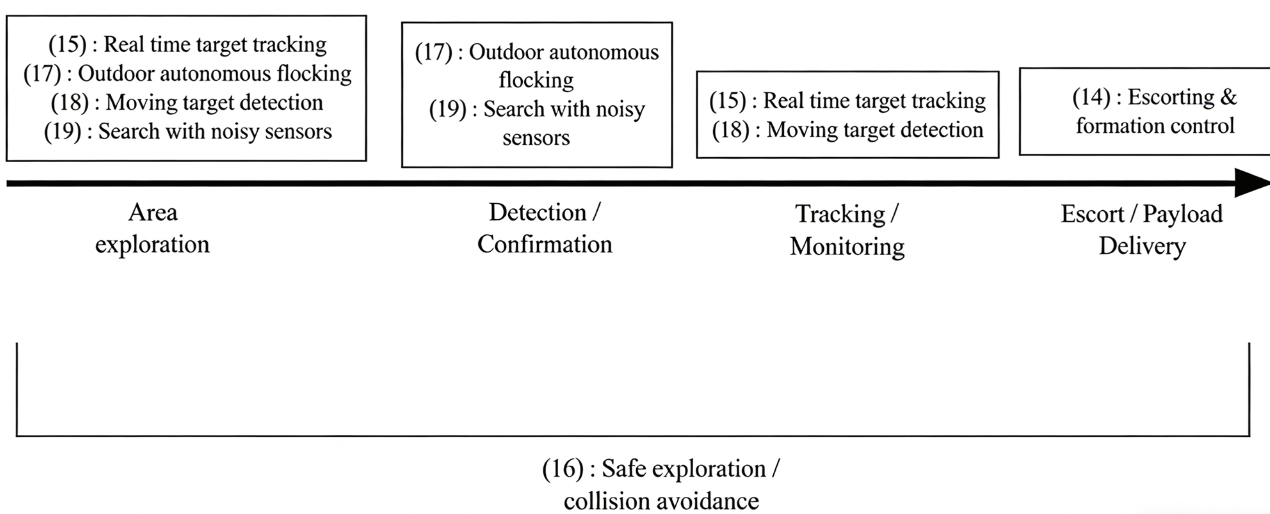

Figure 2. Recommended biomimetic algorithms for each phase of a search and rescue (SAR) mission. This figure maps each SAR phase (exploration, detection, tracking, escorting, and collision avoidance) to the biomimetic algorithms best aligned with that phase's operational requirements. It visually summarizes how a modular swarm-control architecture could combine different bio-inspired methods during a complete mission.

effective in motion-adaptive search, especially when victims or targets are mobile (18).

The second phase, detection and target confirmation, tries to validate sensor findings, minimize false positives, and confirm the presence of survivors or relevant objects. Two algorithms work well for this stage: Alfeo's encourages drone clustering near suspected targets, verifying hits and reducing noise-based errors (19), while Petráček's allows local convergence in GPS-denied areas, useful in collapsed buildings or underground (17). Once the target is located, the third phase (tracking and monitoring) comes into play. This phase requires algorithms that are capable of following and monitoring the target, potentially over extended periods or while in motion. Han's would work well due to its high-precision tracking of moving targets (15), and Phung's would be excellent for dynamic tracking with real-time path updates, especially in complex or unpredictable terrain (18). Stolfi's DFA3+ algorithm would be ideal for the escort and payload delivery part of the SAR operation, which focuses on safely accompanying victims, guiding them out of danger, or delivering payloads (medical supplies, comms gear, etc.). It would work quite well due to it being designed for formation control and escort missions. It is also designed to maintain protective formations around targets without needing GPS or inter-agent communication, making it perfect for SAR contexts (14).

Finally, collision avoidance and swarm integrity are a crucial part throughout the mission, as they ensure fast and efficient searches, all while minimizing danger to the swarm. A strong algorithm to cover this is important to prevent agent collisions and maintain coverage integrity throughout all mission phases. Grasso's algorithm would work well as it provides lightweight, decentralized avoidance across the swarm (16). This is especially important in confined, dynamic, or GPS-denied environments.

To operate this modular architecture, a swarm must be able to transition between algorithms as the SAR mission evolves. Phase-transition criteria are determined by real-time sensor events and mission objectives: for example, the exploration module runs until a drone registers a confidence-weighted detection, which then triggers a local or swarm-wide switch to the confirmation or tracking module. Detection confidence, motion cues, and cluster agreement serve as thresholds to activate different modules. Because SAR phases often overlap (such as tracking occurring while other drones continue exploring) the system does not rely on strict sequential switching. Instead, different subgroups of the swarm may run different modules simultaneously, with local autonomy enabling drones to adopt roles based on proximity, sensing capability, or mission needs. This allows the swarm to maintain area coverage while dedicating agents to confirmation or escorting tasks.

The modular approach also requires dynamic reconfiguration, meaning that the swarm can adapt behaviors mid-mission without centralized control. This is achieved through decentralized decision-making: each drone evaluates local conditions and selects the appropriate behavioral module, while consensus mechanisms or simple majority rules ensure collective coherence when a global phase shift is needed. If environmental conditions degrade (sudden occlusions, high winds, or sensor noise) drones can revert to more robust modules (e.g., switching from vision-based flocking to stigmergy-based navigation). This flexibility ensures that the swarm can adapt to uncertain and rapidly changing SAR environments while maintaining mission integrity.

CONCLUSION

This paper reviewed and analyzed recent advances in biomimetic artificial intelligence algorithms designed for autonomous UAV swarms in search and rescue (SAR) operations, to identify how specific bio-inspired strategies can be modularly combined to address the various stages of SAR missions under real-world constraints.

A modular approach using biomimetic algorithms is very important due to the rapidly shifting environments and the wide range of contexts of SAR operations. This is why integrating these algorithms is important, as together they can overcome challenges faced by other control algorithms, such as localization challenges due to their heavy reliance on GPS or communication. In order to implement these algorithms properly, certain challenges or limitations have to be addressed in order to deploy these systems. Communication blackouts could happen frequently in remote search areas, which is why it is important to favor vision or stigmergy-based systems that operate with limited or no inter-agent communication, so that a break in communication with a centralized system would not put the whole swarm in jeopardy. Moreover, certain hardware limitations need to be addressed, which could limit the deployment of large swarms for the present. Algorithms like Han's and Phung's may require more processing power, which is only viable on more capable drones or with cloud-edge architecture (15, 18).

Battery and time constraints are also crucial for SAR operations, due to the importance and impact that fast target location and retrieval have. SAR operations require efficiency, and so hybrid algorithms such as (19) reduce redundant search efforts and conserve energy. Sensor uncertainty and noise are also among the biggest challenges in SAR contexts, and so flocking-stigmergy hybrids such as Alfeo's excel under imperfect sensing, making them suitable for post-disaster conditions where noise is high (19). To continue work towards a full UAV swarm capable of fully autonomously completing SAR operations, more work must be done, especially with simulations and testing. Some algorithms need to extend their testing from their current 2D simulations to complex 3D environments to better reflect real-world SAR conditions, such as collapsed buildings, dense forests, or flooded areas. Moreover, a modular control framework that enables real-time switching or blending of different biomimetic algorithms depending on mission stage, terrain, and swarm size would need to be created and extensively tested, first in simulations and eventually with physical testing to validate simulation results, particularly focusing on limitations like processing power, battery life, and sensor accuracy.

Ultimately, this study demonstrates that the combination of biologically inspired AI models, each tailored to specific SAR phases, holds strong potential for enabling fully autonomous, scalable, and resilient drone swarms capable of navigating the unpredictable demands of real-world search and rescue missions.

CONFLICT OF INTEREST

The author declares that there are no conflicts of interest regarding the publication of this article.

REFERENCES

1. Şahin E. Swarm robotics: From sources of inspiration to domains of application. *Lect Notes Comput Sci*. 2005; 3342: 10-20. https://doi.org/10.1007/978-3-540-30552-1_2
2. Brambilla M, Ferrante E, Birattari M, Dorigo M. Swarm robotics: A review from the swarm engineering perspective. *Swarm Intell*. 2013; 7 (1): 1-41. https://doi.org/10.1007/s11721-012-0075-2
3. Bhushan B. Biomimetics: lessons from nature-an overview. *Philos Trans A Math Phys Eng Sci*. 2009; 367 (1893): 1445-86. https://doi.org/10.1098/rsta.2009.0011
4. Russell SJ, Norvig P, Canny JF, Malik JM, Edwards DD. Artificial Intelligence: A Modern Approach. Upper Saddle River (NJ): Prentice Hall; 1995.
5. Shi Z, Tu J, Zhang Q, Liu L, Wei J. A survey of swarm robotics system. *Lect Notes Comput Sci*. 2012; 7517: 127-35. https://doi.org/10.1007/978-3-642-30976-2_68
6. Hu J, Bruno A, Zagieboylo D, Zhao M, *et al*. To centralize or not to centralize: A tale of swarm coordination. arXiv. 2018; arXiv:1812.XXXX.
7. Boyd A. The Pentagon wants AI-driven drone swarms for search and rescue ops (Internet). Nextgov/FCW. 2019. Available from: https://www.nextgov.com/artificial-intelligence/2019/12/pentagon-wants-ai-driven-drone-swarms-search-and-rescue-ops/162113/ (accessed on 2025-08-01)
8. Goodrich MA, Morse BS, Gerhardt D, Cooper JL, *et al*. Supporting wilderness search and rescue using a camera-equipped mini UAV: UAV-enabled WiSAR. *J Field Robot*. 2008; 25 (1-2): 89-110. https://doi.org/10.1002/rob.20226
9. Erdelj M, Król M, Natalizio E. Wireless sensor networks and multi-UAV systems for natural disaster management. *Comput Netw*. 2017; 124: 72-86. https://doi.org/10.1016/j.comnet.2017.05.021
10. Zhou Y, Rao B, Wang W. UAV swarm intelligence: recent advances and future trends. IEEE Access. 2020; 8: 183772-95. https://doi.org/10.1109/ACCESS.2020.3028865
11. Zhao Q, Yang T, Tang G, Yang Y, *et al*. Bio-inspired swarm of underwater robots: a review. *Bioinspir Biomim*. 2025; 20 (1): 015003. https://doi.org/10.1088/1748-3190/ade215
12. Wang J, Chen W, Xiao X, Xu Y, *et al*. A survey of the development of biomimetic intelligence and robotics. Biomim Intell Robot. 2021; 1: 100003. https://doi.org/10.1016/j.birob.2021.100001
13. Song Y, Lim S, Myung H, Lee H, *et al*. Distributed swarm system with hybrid-flocking control for small fixed-wing UAVs: algorithms and flight experiments. *Expert Syst Appl*. 2023; 225: 120137. https://doi.org/10.1016/j.eswa.2023.120457
14. Stolfi DH, Danoy G. Escorting drone swarm formation: a swarm intelligence and evolutionary optimisation approach. *Swarm Intell*. 2025; 19: 55-78. https://doi.org/10.1007/s11721-025-00250-5
15. Han GF. Bio-inspired swarm intelligence for enhanced real-time aerial tracking: integrating whale optimization and grey wolf optimizer algorithms. *Discov Artif Intell*. 2025; 5: 33. https://doi.org/10.1007/s44163-025-00237-5
16. Grasso P, Innocente MS. Stigmergy-based collision-

avoidance algorithm for self-organising swarms. *Adv Intell Syst Comput.* 2022; 1350: 215-26. https://doi.org/10.1007/978-981-16-9573-5_19

17. Petráček P, Walter V, Báča T, Saska M. Bio-inspired compact swarms of unmanned aerial vehicles without communication and external localization. *Bioinspir Biomim.* 2020; 15 (4): 046009. https://doi.org/10.1088/1748-3190/abc6b3
18. Phung MD, Ha QP. Motion-encoded particle swarm optimization for moving target search using UAVs. *Appl Soft Comput.* 2020; 92: 106290. https://doi.org/10.36227/techrxiv.13333298
19. Alfeo AL, Cimino MGCA, De Francesco N, Lazzeri A, Lega M, Vaglini G. Swarm coordination of mini-UAVs for target search using imperfect sensors. *Intell Decis Technol.* 2018; 12 (2): 113-26. https://doi.org/10.3233/IDT-170317