PHOENIX: A Multi-Agent UAV System for Geospatially Prioritized SAR

Alexander Pascual, Soo Young Shin*
* Kumoh National Institute of Technology
apascual@kumoh.ac.kr, * wdragon@kumoh.ac.kr

Abstract

This paper introduces **PHOENIX**, a multi-UAV search and rescue (SAR) framework that integrates: **P**enguin Swarm Optimization for global path allocation; a **H**ybrid control architecture combining global coordination with decentralized autonomy; **O**ptimized energy usage through battery-aware mission planning; **E**ntropy-based reinforcement learning using Soft Actor-Critic (SAC) for adaptive local navigation; **N**avigational intelligence informed by terrain and flight dynamics; **I**nformation-driven search prioritizing geospatial and clue-based victim likelihood; and **X**-agent formation control to maintain coordinated swarm behavior. PHOENIX achieves superior coverage, adaptability, and efficiency in uncertain environments, offering a bio-inspired, AI-driven solution for real-world SAR operations.

Ⅰ. Introduction

Search and Rescue (SAR) missions in complex environments demand systems capable of rapid, intelligent, and adaptive response across vast and often unknown terrains. Unmanned Aerial Vehicles (UAVs) have emerged as transformative assets in these domains due to their mobility, deployability, and scalability. However, traditional UAV-based SAR approaches often lack dynamic adaptability, fail to prioritize regions effectively based on victim likelihood, or are limited by energy inefficiencies and centralized bottlenecks.

In the broader context of SAR UAV research, works such as [1] coverage optimization employment, while [2] and [3] explore deep reinforcement learning for terrain navigation. Bio-inspired swarm models (e.g., Particle Swarm Optimization [4], Ant Colony Optimization [5]) offer promising scalability, yet lack terrain-awareness or adaptive energy efficiency. PHOENIX seeks to address these gaps by tightly integrating multiple specialized modules in a unified, multi-agent architecture.

We introduce **PHOENIX**, a conceptual multi-UAV SAR framework designed to overcome these limitations by integrating bio-inspired swarm intelligence, decentralized control, adaptive navigation, and geospatially-informed search logic. PHOENIX aims to optimize coverage, maintain swarm coordination, and dynamically adapt to terrain, energy constraints, and probabilistic victim presence.

The motivation stems from the need for a scalable, intelligent aerial SAR system that can operate effectively in uncertain, high-stakes environments such as natural disasters or remote terrain incidents. Contributions include:

1. A novel integration of Penguin Swarm Optimization with entropy-based reinforcement learning for hybrid global-local planning.
2. Battery-aware, terrain-informed mission architecture that balances coverage with UAV endurance.
3. A geospatial prioritization strategy and formation-aware control mechanism to drive information-efficient search and robust swarm behavior.

Ⅱ. Method

A. System Overview

PHOENIX is composed of autonomous UAV agents operating under a hybrid control architecture, blending centralized planning for global optimization with decentralized autonomy for local adaptation. Each UAV is equipped with onboard sensors, communication modules, and AI-based navigation and decision units. The system follows a five-stage operational model: (1) Global Path Allocation, (2) Formation Initialization, (3) Mission Execution with Adaptive Navigation, (4) Energy-Aware Routing, and (5) Dynamic Reprioritization.

B. Core Modules

1. Penguin Swarm Optimization (PeSO):

   PHOENIX leverages PeSO, a variant of swarm intelligence inspired by the coordinated hunting of penguins, to perform global path allocation. This enables diverse UAVs to optimize search trajectories based on thermal conditions, elevation maps, and historical victim location probabilities. The algorithm promotes distributed workload while avoiding redundant overlap.

2. Hybrid Control Architecture:

   A layered control system allows centralized task assignment at mission onset, transitioning into localized autonomy through decentralized decision-making modules. UAVs share partial state updates, enhancing robustness to communication losses and facilitating scalability.

3. Optimized Energy Planning:

   Each UAV continually updates a cost function based on remaining battery, distance from charging stations, and priority of assigned regions. This results in energy-optimized routing that dynamically alters course to prevent mission abortion due to low battery.

4. Entropy-based Reinforcement Learning:

   UAVs are trained via entropy-regularized reinforcement learning (Soft Actor-Critic) to navigate unpredictable terrain. The SAC framework enables agents to balance exploration and exploitation in real-time while avoiding obstacles and maximizing terrain coverage.

5. Navigational Intelligence:

   Flight planning integrates Digital Elevation Models (DEMs) and aerodynamic constraints, ensuring feasible paths respecting ascent rates, no-fly zones, and wind-resistance profiles.

6. Information-driven Geospatially Prioritized Search:

   Each UAV continually updates a cost function based on remaining battery, distance from charging stations, and priority of assigned regions. This results in energy-optimized routing that dynamically alters course to prevent mission abortion due to low battery.

7. X-Agent Formation Control:

   To maintain swarm cohesion and facilitate coordinated behaviors (e.g., area partitioning, collaborative scanning), PHOENIX employs an X-agent formation strategy, where central leader UAVs regulate sub-swarms via inter-UAV communication and geometric alignment.

C. Contributions and Expected Results

By applying the aforementioned modules, the integrated framework combines swarm intelligence, reinforcement learning, and geospatial modeling for an end-to-end SAR UAV solution. Hybrid control ensures scalability and resilience of the swarm for a robust decentralized control architecture. Energy-aware routing and adaptive learning enhances mission longevity and terrain traversal which makes the system efficient and provides wider coverage. Moreover, geospatial modeling allows resource allocation to regions with higher likelihood of victim presence. Expected outcomes in simulations for synthetic disaster environments (e.g., urban collapse, forest terrain) will improve its coverage efficiency, mission continuity, and successful victim localization rate.

Ⅲ. Conclusion

PHOENIX proposes a novel, multi-faceted UAV-based SAR system tailored for high-impact, real-world applications in dynamic and uncertain environments. By merging bio-inspired swarm behavior, reinforcement learning, geospatial reasoning, and decentralized autonomy, the framework offers a significant leap in the design of intelligent aerial SAR agents. Future work includes real-world deployment in controlled disaster simulation zones and integration with ground-based robotic agents for hybrid rescue strategies.

ACKNOWLEDGMENT

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program (IITP-2025-RS-2024-00437190) supervised by the IITP(Institute for Information & Communications Technology Planning & Evaluation, 50%) This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(2018R1A6A1A03024003, 50%).

REFERENCES

[1] L. Merino, F. Caballero, J. R. Martinez-de Dios, and A. Ollero, "Cooperative Fire Detection using Unmanned Aerial Vehicles," Proceedings of the 2005 IEEE International Conference on Robotics and Automation, Barcelona, Spain, 2005, pp. 1884-1889.

[2] Z. Cao, G. Chen, "Enhanced Deep Reinforcement Learning for Integrated Navigation in Multi-UAV Systems," Chinese Journal of Aeronautics, 2025, https://doi.org/10.1016/j.cja.2025.103497.

[3] A. Goldhoorn, A Garrell, R. Alquezar, and A. Sanfeliu, "Searching and Tracking People in Urban Environments with Static and Dynamic Obstacles," Robotics and Autonomous Systems, vol. 98, 2017, pp. 147-157.

[4] J. Kennedy and R. Eberhart, "Particle swarm optimization," Proceedings of ICNN'95 - International Conference on Neural Networks, Perth, WA, Australia, 1995, pp. 1942-1948 vol.4.

[5] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," in IEEE Transactions on Evolutionary Computation, vol. 1, no. 1, pp. 53-66, April 1997.