1. UAV swarms: research, challenges, and future directions

Advancements in Swarm Robotics (SR) leverage aerial mobility, high-speed maneuverability, and expansive coverage capabilities. SR aims to develop scalable, robust systems in which groups of robots collaborate with each other and their environment to execute complex tasks efficiently. Inspired by natural social behaviors, such systems outperform single-robot counterparts in multitasking, scalability, cost-efficiency, robustness, and adaptability.

Swarm Intelligence (SI) algorithms facilitate collaborative decision-making and coordination for UAV swarms, enabling effective exploration and navigation in dynamic environments. A critical focus area is swarm formation control, which aims to maintain stable flight formations and minimize inter-robot distance variations. Recent advances in Artificial Intelligence (AI), Deep Learning (DL), and Machine Learning (ML) play pivotal roles in overcoming challenges and enhancing overall SR performance.

SI is widely applied in UAV swarms for path planning, collision avoidance, formation control, and collective decision-making, enabling efficient and adaptive operations in complex scenarios.

The contributions of this paper include:

- ❖ Exploration of coordinated path planning, task assignment, formation control, and communication.
- ❖ An analysis of security and privacy considerations.
- ❖ An overview of the integration of AI and ML in enhancing UAV swarm capabilities.
- ❖ An assessment of the diverse applications in civilian and military sectors.

Features and characteristics of UAV swarms

Feature	Description
Cost-effectiveness	Utilizing a group of specialized robots for various tasks is more cost-effective than building a single versatile robot.
Scalability	Maintaining effectiveness and performance even as the number of robots increases.
Robustness & Survivability	Maintaining functionality in adverse conditions, reconfiguring to mitigate impacts of robot failures.

Feature	Description
Adaptability & Flexibility	Adjusting collective behavior to respond to environmental changes or new mission objectives.
Parallelism	Performing tasks concurrently and independently, enhancing system performance and efficiency.
Redundancy & Fault-tolerance	Overcoming single points of failure by reconfiguring remaining robots to compensate for failures.
Multi-tasking	Dividing tasks into sub-tasks for simultaneous completion, leading to faster mission completion.
Distributability	Coordinating and distributing tasks based on individual robot capabilities, increasing efficiency and adaptability.

2. UAV Swarm Rounding Strategy Based on Deep Reinforcement Learning Goal Consistency with Multi-Head Soft Attention Algorithm

Multi-Agent Reinforcement Learning (MARL) has been widely used in many fields, such as games, robots, communication and so on. Based on the Centralized Training with Decentralized Execution (CTDE) learning framework, this paper proposed a multi-agent reinforcement learning model with goal consistency by multi-head soft attention (GCMSA). Multi-head soft attention mechanism is used to determine the importance of information, promote the consistency of target cognition, and improve the decision-making efficiency. At the same time, in order to increase the authenticity of the roundup scene, the escape strategy of the target is imported and the task boundary of the agents is set.

The major contributions and innovations of this paper include the following:

1. Increases the escape strategy of the target and, considering the boundary of the task scenario, the reward functions when the target is in different positions are set, respectively, which makes the task scenario closer to reality.
2. The observation vectors of a UAV are parameterized into low-level cognitive vectors. Then, an MSA module based on the multi-head attention mechanism is designed to determine the importance level of the input information, which realizes the efficient selection of the target information by the intelligent body and promotes decision-making efficiency.

Method

They proposed a novel algorithm, goal consistency with multi-head soft attention (GCMSA), to facilitate efficient target rounding up by UAV swarms. Based on the actor–critic framework, they adopted the training mode of Centralized Training Distributed Execution (CTDE). In the local perspective, the multi-head soft attention (MSA) module is used to complete the cognitive process between each UAV and the target, and then the important target information is determined. In the global perspective, the critic will use the information of all UAVs, complete the information cognitive process between UAVs, and output the observation–action value function.

'Goal consistency' comes from deep reinforcement learning (DRL) ensures the swarm's behavior remains coordinated and aligned with the shared objective. Let the swarm's goal is to surround a target, each drone must move so the *group* keeps that shape.

'Multi-Head Soft Attention' comes from transformer neural networks (used in AI models like GPT). It allows the model to focus on multiple types of information at once. **Multi-head** is a model uses *several "attention heads"* to look at different parts of the input (for example, other drones' positions, velocities, goals, etc.). **Soft attention** is a model gives different weights to different inputs, not just picking one.

Goal consistency with multi-head soft attention is a swarm coordination method where each drone uses an attention-based neural network to focus on the most relevant teammates and environment features, ensuring all agents act in a way that is consistent with the overall group goal.

Centralized Training, Distributed Execution = Learn together, act alone.

Centralized Training: during the training, all drones (agents) share all information (states, actions, rewards, and sometimes other drones' data) and central (trainer) that learns from the entire swarm's experience.

Distributed Execution: drones are deployed each drone acts independently, using only its local sensors and communication data, no central controller.

Conclusion: this paper introduced AI-based swarm coordination method GCMSA that allows multiple drones to learn together and act independently to surround a moving target more effectively using attention and goal consistency mechanisms.

3. Computational offloading into UAV swarm networks: a systematic literature review

Computational offloading in UAV swarm networks means transferring heavy computing tasks from one drone to **other drones, edge servers,** or the **cloud** to save energy, reduce delay, and increase the swarm's overall intelligence and performance, because like **Object detection, Target tracking, Path planning, and AI decision-making** are **computationally expensive**.

Types of offloading:

1. Vertical Offloading: Drone sends data to a ground station, edge, or cloud
2. Horizontal Offloading: Drone offloads computation to another drone in the swarm.
3. Hybrid Offloading

Mobile Edge Computing (MEC) servers are deployed in various locations, such as cellular base stations, aggregation points, customer premises, wireless access points (APs), or even UAVs. These servers play a crucial role in processing, analyzing, and storing latency-sensitive or location-aware data. By being located close to the data source, MEC servers offer several benefits, including lower latency, availability even during cloud or internet outages, and an improved user experience.

UAV swarm network architectures:

Mesh: Fully decentralized; each UAV is a node in an ad hoc network, sharing information via multi-hop routing.

Star: Centralized control; UAVs connect to a central node, but this creates a single point of failure.

Cluster-based: UAVs form local clusters led by a cluster head, combining intra-cluster coordination with inter-cluster mesh communication.

Hybrid: Combines features of multiple architectures (e.g., central server + mesh), offering flexibility for different missions.**_x0007_Task characteristics**

In UAV swarm systems, each task's offloading decision depends on its **priority, size, latency, and data requirements**. Tasks nearing their deadline get higher priority, defined by the formula (Priority = 1 / (T_{Deadline} - T_{Current})). Large or computation-heavy tasks, such as high-resolution video analysis, are offloaded to MEC servers because of UAVs' limited onboard resources. Real-time, latency-sensitive tasks are processed locally or by nearby UAVs to meet strict timing needs.

_x0007_UAV Characteristics

This section explains the main factors that influence task offloading and coordination in UAV swarm networks. UAVs with limited computing power or low battery tend to offload tasks to nearby MEC servers to save energy and processing load. Communication capability also affects offloading if bandwidth is low or links are unstable, tasks are sent to MEC servers with stronger connections. Mobility, as fast-moving UAVs experience frequent handovers that increase latency, so offloading must adapt to UAV trajectories using mobility models like Gauss–Markov or Random Waypoint. To ensure safety, UAVs maintain a minimum separation distance to avoid collisions. Efficient collaboration and coordination are essential so UAVs can share resources, exchange task information, and make distributed decisions without a central controller. Because UAV swarms are heterogeneous (different power, processors, links) and their network topology changes dynamically as they move, adaptive algorithms are required for offloading and consensus.

Role of UAV swarm for task offloading

In UAV swarm networks, drones can play three main roles in task offloading: **IoD devices**, **MEC platforms**, or **hybrid systems**. When functioning as **Internet of Drones (IoD)** devices, UAVs mainly act as data collectors, gathering information such as images or sensor readings and offloading it to ground-based or cloud MEC servers for processing. In contrast, when UAVs operate as **Mobile Edge Computing (MEC)** platforms, they collaboratively process data within the swarm itself, sharing computation tasks among multiple UAVs to achieve low-latency, localized decision-making without relying heavily on ground infrastructure. The **hybrid role** combines both approaches which offers flexibility and scalability, enabling the swarm to dynamically balance workloads and adapt to real-time mission demands, making it the most practical and efficient configuration in modern UAV swarm applications.

Differences in UAV swarm offloading from a single UAV or terrestrial MEC

Task offloading in UAV swarms differs significantly from single UAVs or terrestrial MEC systems due to their **distributed, cooperative, and dynamic nature**. Unlike single UAVs, swarms enable **collaborative decision-making and load balancing**, allowing tasks to be shared across multiple UAVs based on their capabilities, energy levels, and proximity to the task, which improves efficiency and reduces latency. UAV swarms also face **unique challenges** such as **heterogeneity of UAV resources, limited communication range, dynamic network topology, and energy constraints**, requiring adaptive and decentralized offloading strategies. Additionally, task offloading must address **security, privacy, quality-of-service (QoS), and cost considerations**, particularly for sensitive or mission-critical applications. Advanced techniques like **Distributed Neural Networks, multi-agent DRL, and clustering algorithms** are often used to optimize task allocation, resource scheduling, and communication while minimizing energy use and operational costs.

Open issues in UAV swarm offloading

Despite significant research on UAV swarm computation offloading, several **open issues remain** that challenge practical deployment. Key gaps include **heterogeneity**, where UAVs from different vendors with varying capabilities and protocols complicate cooperation, revenue sharing, and security. **Fault tolerance** is underexplored, with few strategies for adaptive, self-healing mechanisms in dynamic, distributed swarms. **Scalability** is another challenge, as large swarms require efficient coordination and task allocation under unpredictable mobility and diverse UAV capabilities. **Resource and communication constraints**, such as intermittent links, bandwidth limitations, and inter-UAV interference, further complicate offloading decisions. Additionally, **dynamic network topology** and rapidly changing environmental conditions demand adaptive algorithms for real-time task offloading, load balancing, and resilience. Overall, these issues highlight the need for **robust, scalable, and secure offloading strategies** that account for the complex, heterogeneous, and dynamic nature of UAV swarm operations.

4. AI-Driven Drone Swarms and Their Implications for Future Battlefields

The paper presents a useful overview of military applications of drone swarms, covering offensive, defensive, support, and strategic roles. Examples such as saturation attacks, distributed Intelligence, Surveillance, and Reconnaissance (ISR), logistics support, and counter-UAV defense illustrate potential battlefield uses effectively. Additionally, the sections on strategic and ethical consideration including battlefield transformation, asymmetric warfare, arms race consequences, and accountability in autonomous decision-making are well-explained and highly relevant. Despite these strengths, the paper has several significant weaknesses. Its technical depth is very limited: it does not describe AI algorithms such as reinforcement learning, multi-agent RL (e.g., MADDPG, MAPPO), formation control, decentralized consensus, or communication protocols. There are no formulas, diagrams, models, or simulation results, which reduces its value for technical audiences. The paper also lacks real-world case studies such as US Perdix swarms, China’s FH-97, Israel’s Harpy/Harop systems, or DARPA OFFSET experiments. Important topics in swarm reliability and operations, including fault-tolerant control, jamming resistance, distributed sensing, and energy optimization, are missing. While the discussion of ethics, policy, and future outlook (quantum computing, 6G, and space control) is strong, the absence of technical and operational details limits its usefulness for researchers or engineers.