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REVIEW ARTICLE

Synergistic UAV Motion: A Comprehensive Review on Advancing Multi-Agent Coordination

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Abstract

Collective motion has been a pivotal area of research, especially due to its substantial importance in Unmanned Aerial Vehicle (UAV) systems for several purposes, including path planning, formation control, and trajectory tracking. UAVs significantly enhance coordination, flexibility, and operational efficiency in practical applications such as search-and-rescue operations, environmental monitoring, and smart city construction. Notwithstanding the progress in UAV technology, significant problems persist, especially in attaining dependable and effective coordination in intricate, dynamic, and unexpected settings. This study offers a comprehensive examination of the fundamental principles, models, and tactics employed to comprehend and regulate collective motion in UAV systems. This paper methodically analyses recent breakthroughs, exposes deficiencies in existing approaches, and emphasises case studies demonstrating the practical application of collective motion. The survey examines the substantial practical effects of collective motion on improving UAV operations, emphasizing scalability, resilience, and adaptability. This review is significant for its potential to inform future research and practical applications. It seeks to provide a systematic framework for the advancement of more resilient and scalable UAV collaboration models, aiming to tackle the ongoing challenges in the domain. The insights offered are essential for academics and practitioners aiming to enhance UAV collaboration in dynamic environments, facilitating the development of more sophisticated, flexible, and mission-resilient multi-UAV systems. This study is set to significantly advance UAV technology, having extensive ramifications for several industries.

Keywords: collective motion, dynamic agent systems, formation control, path planning and swarm intelligence.

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1 Introduction

Collective behaviour is common in natural and artificial systems. Collective motion in robotics, especially multi-wheeled robot systems and UAVs, is popular. Understanding individual agent interactions

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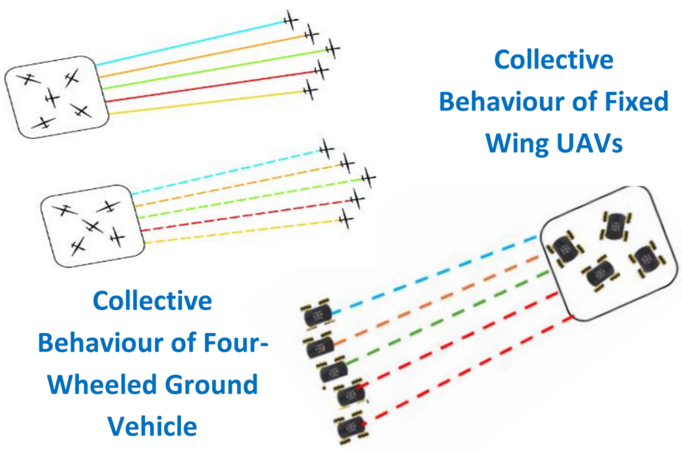

Figure 1. Effective Coordination Multi-UAVs and Multi-UGVs.

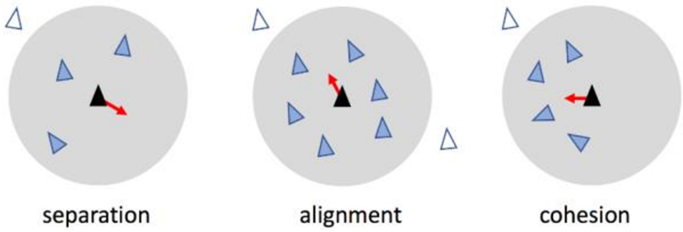

Figure 2. Illustration of the control rules employed by Boids.

that yield coordinated collective activity is important in robotics, swarm intelligence, and social dynamics [1, 2]. Multi-robot systems improve search and rescue, environmental surveillance, and logistics by clustering robots to achieve common goals. Collective motion allows multi-robot systems to synchronize robot motions for faster work completion. Multi-robot collective motion requires path planning and trajectory formulation to navigate complex terrain without collisions. Unmanned Aerial Vehicles (UAVs), or drones, are used in surveillance, transport, and mapping [3, 4]. Many UAV activities require multiple drones to work together, and collective mobility is crucial for optimal coordination and collaboration, as shown in Figure 1.

Path planning and trajectory development are crucial in UAV systems, as they allow drones to navigate intricate surroundings while ensuring safe separation from one another [5]. The investigation of collective behaviour dynamics in multi-robot systems and UAVs continues to be a prominent research domain, due to its capacity to substantially improve the performance, dependability, and scalability of these systems. Researchers have increasingly utilized bio-inspired algorithms, based on natural phenomena like insect swarms and bird flocks, to describe and optimize collective motion in these systems.

Collective motion denotes the synchronized movement of a collection of agents, such as birds, fish, or humans, that seem to function as a unified organism. This phenomenon has garnered considerable interest across multiple disciplines, including physics, biology, engineering, and computer science, owing to its prospective applications in swarm robotics, unmanned aerial vehicles, and social dynamics. The examination of collective motion entails comprehending how individual agents engage with one another and their surroundings to generate emergent behaviors at the group level. Dynamic agents can alter their state over time, presenting distinct problems and opportunities for research in collective motion [6, 7]. Dynamic agents may display intricate and erratic behaviors, resulting in innovative and unforeseen collective dynamics.

The development of multi-UAV systems has been influenced by the 1986 introduction of Reynolds' Boids model, which played a key role in modelling flocking behaviour. The model is based on three fundamental principles: separation (preventing collisions), alignment (synchronizing movement with peers), and cohesiveness (maintaining proximity to the group), all of which are essential for coordinating autonomous agents without centralized oversight as illustrated in Figure 2.

These straightforward, nature-derived principles have demonstrated efficacy in regulating UAV formations and wheeled robots, facilitating harmonious collective movement through local interactions among agents. The development of multi-UAV and wheeled robot systems commenced with an emphasis on individual autonomy. Advancements in sensors, control algorithms, and communication technologies facilitated the shift to collaborative systems, allowing numerous UAVs or robots to jointly execute more intricate tasks, including surveillance, search and rescue, and mapping. Initial studies focused on fundamental navigation and control; but, as research advanced, collaborative activities evolved to be more intricate and effective.

Both multi-UAV and wheeled robot systems fundamentally depend on decentralized control techniques, wherein each agent makes decisions based on its immediate environment, akin to natural flocks or swarms. This distributed methodology guarantees system resilience and scalability, as the failure of individual components does not compromise overall performance. Furthermore, progress in

AI and machine learning persistently improves the decision-making capacities of these systems, rendering them more resilient and adaptable for diverse dynamic applications [8–10]. In the past decade, substantial advancements in sensor technology have greatly enhanced study on the orientation tactics of free-flying birds, especially the hierarchical techniques seen in pigeon flocks. Research indicates that the collective trajectory of pigeon flocks is a balance between an individual's preferred route and the leader's expertise, highlighting the intricate decision-making mechanisms inside animal groupings [11]. Prominent research issues in this domain encompass the examination of leader-follower dynamics within avian flocks, the impact of environmental signals on navigation, and the significance of communication in sustaining flock cohesion [12]. Furthermore, studies have investigated how hierarchical decision-making in animal groups, such as pigeons, might improve environmental awareness and offer protection from predators, with these tactics being applied to robotic swarms for practical use [13]. Researchers have employed bio-inspired algorithms to replicate avian behaviour in UAVs, tackling challenges related to collision avoidance, optimal path planning, and energy-efficient navigation.

Nonetheless, creating effective robot controllers to emulate these natural behaviors presents a considerable difficulty owing to the intricacies of mimicking decentralized coordination, real-time decision-making, and adaptability to changing surroundings [14]. This work is novel due to its thorough integration of hierarchical strategies from pigeon flocks into robotic swarm systems, emphasizing the connection between bio-inspired collective motion theories and their practical application in multi-robot and UAV systems. This study seeks to augment the efficiency and resilience of swarm robots in applications including environmental monitoring, search and rescue, and autonomous exploration by refining control algorithms and sensor integration, thereby advancing the frontiers of existing research.

This study article seeks to comprehensively examine and analyze the collective motion of dynamic agents, encompassing animals, people, and robots, in many settings. It examines the principal elements that affect collective behaviour, including communication range, velocity, and sensory ability. The research utilizes mathematical models and simulation methods to enhance comprehension of the fundamental principles regulating collective motion in dynamic agents. Furthermore, it provides empirical validation via real-world tests to confirm the feasibility and precision of the provided models and simulations. This review primarily contributes a thorough analysis of collective behaviour, emphasizing the concepts of self-organization and emergence among dynamic agents. It presents mathematical models and various simulation approaches that encapsulate the dynamic interactions of agents across multiple settings. Moreover, the study corroborates these models through established experimental methods, offering efficient means to evaluate their viability. The study examines the practical applications of collective behaviour algorithms, specifically in swarm robots, traffic management, and social dynamics, highlighting their tangible ramifications. This work advances comprehension of collective motion by addressing both theoretical and practical aspects, considerably contributing to advancements in knowledge and technology in this subject.

This review manuscript comprises multiple sections, with Section 1 addressing the introduction to collective motion of multi-UAVs, including background, scope, contributions, and organization of the work. Section 2 delineates the cutting-edge parameters for examining the collection motion of dynamic agents on autonomous vehicles. Section 3 examines the problem description and recommended solutions for several facets of formation control, path planning, and path tracking in multi-UAV systems. Section 4 examines the latest progress and innovations in LoRa networks. Section 5 delineates the conclusions and prospective methodologies for assessing diverse IoT applications and optimization-related challenges. This organization has been illustrated in Figure 3.

2 State of the Art Approaches

2.1 Discussion related cutting-edge parameters

The increasingly widespread use of autonomous vehicles, both aerial and ground-based, makes collective motion of dynamic agents an essential aspect for incorporating these systems into an endless number of applications. Besides, in recent years, the use of Multi-Robot Systems (MRS) has spread, consisting of both Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs), gaining versatility and robustness in their operation.

Unmanned Aerial Vehicle (UAV) swarm formation has applications in many areas of research, such as infrastructure inspection, surveillance, target tracking,

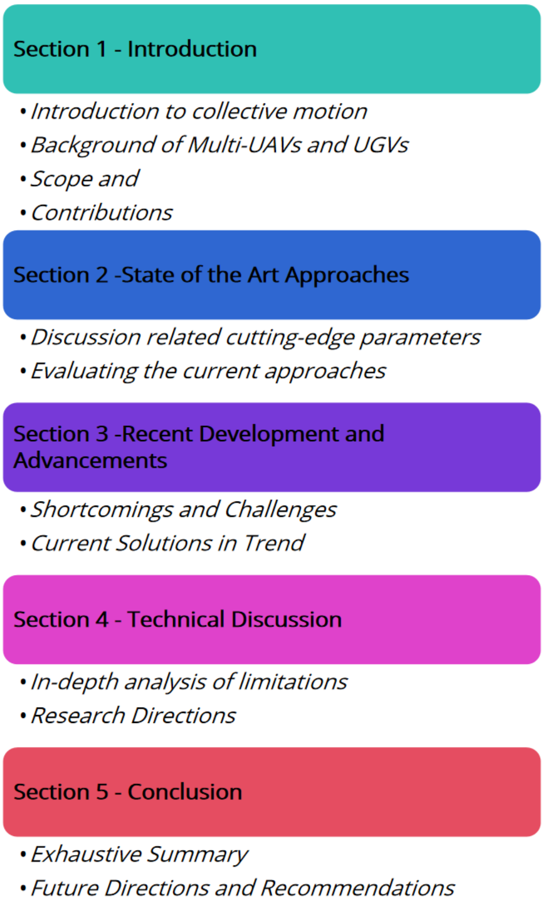

Figure 3. Organization of this review manuscript.

and precision agriculture. In some of the contributions such as in [15], it proposes decentralized control method for UAVs in the context of formation control. In this paper, a decision-theoretic formulation called decentralized Markov decision process (Dec-MDP) were developed near real-time decentralized control methods to drive a UAV swarm from an initial formation to a desired formation in the shortest possible time. In [16], it presents distributed algorithm DMTF that can develop multiple teams simultaneously in the first attempt. In this algorithm, a type of multiple team formation problem was considered in a dynamic multi-agent setting where agents have limited information about an environment, so they coordinate among themselves by exchanging messages to accomplish a given mission composed of multi-robot tasks. Researcher proposes an algorithm using genetic algorithm (GA) to achieve distance based formation, with the implementation of two different types of chromosomes, one for the distance solution, and the other for collision avoidance [17]. In this approach, the use of combined processing power of all robots in a PGA that migrates possible solutions in order to reduce processing time and achieve consensus between the robots to a solution.

The term "Path Planning" determines the route planned for an object for any specified mission, which includes various obstacles along the path. The planned path restricts the UAV from possible crashes from obstacles or neighboring UAVs. Path planning is more feasible when operating with large quantities of robots. Path planning of aerial systems is categorized into motion-based and tracking-based approaches. Researchers compared two hybrid optimization algorithms for path planning and determined which one is more efficient. In this proposed approach, both algorithms use a modified ACO, called Max-Min Ant Colony optimization algorithm (MMACO) to enhance their effectiveness further [18]. The proposed MMACO algorithm has tremendous problem-solving skills, especially in complex environments. Researchers proposed modified symbiotic organisms search (MSOS) algorithm to generate the smooth and planned path flyable for UAVs. In this approach, the collaboration of HIPSO-MSOS were introduced where the experimental results show that the proposed algorithm can successfully generate feasible and effective paths for each UAV, and its performance is superior to the other five algorithms, namely PSO, Firefly, DE, MSOS and HSGWO-MSOS algorithms in terms of accuracy, convergence speed, stability and robustness [19]. In [20], it presents an improved ant colony optimization (ACO) algorithm based on particle swarm optimization (PSO) to find the optimal path for AUVs to reach specified destination in complex environment. This combined algorithm can overcome disadvantages of the traditional ACO algorithm such as falling into local extremum, poor quality, and low accuracy. The experimental results show that the proposed improved ACO algorithm is more efficient and feasible in path planning for autonomous vehicle than the traditional ant colony optimization algorithm.

Accurate and precise trajectory tracking is also a crucial aspect for unmanned aerial vehicles (UAVs) to operate in disturbed and complex environments. In one of the contributions [21], one may see two nonlinear adaptive control methods to design position and attitude control system for a quadrotor. The proposed design adaptation mechanisms compensate parameter uncertainties and disturbances during the flights. There is also a method to tune neuro-fuzzy controllers using metaheuristic optimization to achieve global performance requirements [22]. This study proposed a robust and intelligent control method based on neuro-fuzzy inference system (ANFIS) and pigeon-inspired optimization (PIO) algorithm to govern the behavior of a 3-DOF quadrotor unmanned aerial vehicle. Researcher addresses the designing of a robust controller for an automatic landing, trajectory tracking, and take-off missions of quadrotor unmanned aerial vehicle (QUAV) [23]. The proposed control system can guide the QUAV to track the previously defined reference trajectories. For obstacle avoidance, a vector field histogram algorithm is used to avoid collision of the QUAV with obstructing obstacles that block the QUAV's path.

2.2 Evaluating the current approaches

The growing integration of autonomous vehicles, including UAVs and UGVs, has underscored the need of collective motion and path planning for dynamic agents in many applications. Numerous research has tackled these difficulties with various methodologies, from decentralized control to sophisticated optimization algorithms. For example, [15] introduced a decentralized Markov decision process (Dec-MDP) for UAV formation control, facilitating near real-time coordination and minimizing transition durations between forms. Likewise, [16] presented the DMTF method, enabling multi-team creation in dynamic settings via communication among agents possessing restricted environmental knowledge. The genetic algorithm (GA) technique in [17] utilized two chromosomal types for formation control, enhancing processing efficiency by allocating computing duties among all agents. Regarding path planning, [18] improved the efficacy of the Ant Colony optimization (ACO) algorithm by implementing the Max-Min Ant Colony optimization (MMACO), exhibiting greater problem-solving abilities in intricate situations. The MSOS technique presented in [19] enhanced UAV path planning by increasing accuracy, convergence speed, and robustness. Furthermore, [20] integrated Particle Swarm optimization (PSO) with Ant Colony Optimizations (ACO) to mitigate ACO's deficiencies, including inadequate accuracy and local extremum challenges, thus improving the efficacy of path planning for autonomous underwater vehicles (AUVs). Nonlinear adaptive control approaches and intelligent controllers, as outlined in [21] and [22], have demonstrated efficacy in adjusting for disturbances and parameter uncertainties in the field of trajectory tracking, while also ensuring robust performance in intricate situations. [23] devised a control system for automated landing and trajectory tracking in QUAVs, employing the vector field histogram technique for obstacle evasion. These varied methodologies underscore the range of ways for tackling control, path planning, and trajectory tracking issues in UAV and multi-agent systems, illustrating the advantages and disadvantages of each approach.

The rapid advancements in Unmanned Aerial Vehicle (UAV) technology have underscored several critical challenges in the domain of multi-UAV formation and path planning. A primary concern is formation control, which necessitates the design of control inputs to achieve specific configurations tailored to mission requirements. For instance, resilience optimization in multi-UAV systems relies heavily on initial parameters and reconfiguration strategies, as proposed by [24]. Moreover, as artificial intelligence continues to evolve, mobile robots are becoming increasingly autonomous, capable of undertaking complex tasks that would otherwise require human intervention. In this context, challenges such as local minima and target unreachability in cooperative formations have been addressed through innovative methods like the dynamic virtual target point [25].

The significance of evolutionary algorithm-based methods in UAV path planning cannot be overstated. Research, such as that by [26], introduces novel algorithms that leverage biogeography-based learning to enhance path optimization. However, unexpected obstacles during collective flights can complicate path planning, necessitating robust solutions. Comparative studies of hybrid optimization algorithms, including modified Ant Colony Optimization (ACO) combined with Differential Evolution and Cauchy Mutant approaches, highlight the ongoing search for efficiency in this domain [27].

3 Recent Developments and Advancements

3.1 Shortcomings and Challenges

Over the past decade, substantial advancements have transpired in the domain of collective vehicle motion, especially with dynamic agents for UAVs. The collective motion of UAVs is particularly challenging due to several complexities overlooked by previous planning strategies: the heightened significance of differential constraints, atmospheric turbulence that hinders precise adherence to pre-computed plans, uncertainty regarding the vehicle's state, and restricted environmental knowledge stemming from

Table 1. Evaluation of Control, Path Planning, and Trajectory Tracking Approaches.

Methods	Key Contributions	Limitations
Dec-MDP [15]	Real-time decentralized control for UAV formation (efficient formation transition)	Limited to small-scale formations
DMTF Algorithm [16]	Distributed team formation for multi-robot systems (real-time coordination with limited info)	Complexity increases with number of agents
Genetic Algorithm (GA) [17]	Distance-based formation control using chromosomes for formation and collision avoidance (faster processing via PGA)	Requires higher computational resources
Max-Min Ant Colony Optimization (MMACO) [18]	Enhanced UAV path planning in complex environments (improved problem-solving capabilities)	Susceptible to dynamic obstacle changes
MSOS Algorithm [19]	Smooth path generation for UAVs (high accuracy, convergence speed, robustness)	Performance dependent on algorithm tuning
PSO and ACO Combination [20]	Optimal AUV path planning (overcomes ACO's local extremum issues)	Mainly applicable in AUV contexts
Nonlinear Adaptive Control [21]	Quadrotor UAV control (adaptive compensation for disturbances, robust position and attitude control)	Limited scalability for large systems
ANFIS-PIO Control [22]	Quadrotor UAV control using neuro-fuzzy controller (global performance tuning through metaheuristic optimization)	Complex controller design
Vector Field Histogram Algorithm [23]	QUAV trajectory tracking with obstacle avoidance.	Requires precise sensor input

limited sensor capabilities [28]. The year-wise examination of collective motion, encompassing formation, path planning, and path trajectory, is presented in Tables 1, 2, 3, 4. Initially, a thorough analysis of formation control is presented, followed by discussions on path planning and trajectory.

3.1.1 Formation control

Zhihao et al. [22] devised a framework for a distributed Model Predictive Control (MPC) approach for Unmanned Aerial Vehicle (UAV) formation. In this approach, each UAV exclusively exchanges information with neighboring units, and the resultant local FHOCPs are resolved using a straightforward PSO algorithm. The VTG methodology is formulated and included into the distributed MPC framework for trajectory tracking and obstacle evasion. Wu et al. [23] examined the issues of formation control and obstacle avoidance, which are regarded as two critical challenges for UAVs. This study employs the standard model and the autopilot model for obstacle avoidance and formation control. Huang et al. [24] investigated obstacle avoidance and swift rebuilding of UAV formations to enhance their adaptability to complicated dynamic environments. This technique establishes a model for obstacles and formation constraints in complex environments and proposes a Bi-directional Rapidly Exploring Random Tree (Bi-RRT*) algorithm based on a greedy strategy to achieve obstacle avoidance. Shao et al. [25] introduced a chaos-based Logistic map to enhance the initial distribution of particles. This study replaces the conventional constant acceleration coefficients and maximum velocity with adaptive linear-varying counterparts, which alter during the optimization process and enhance solution optimality. Liu et al. [26] introduced a distributed optimum control approach to address the trajectory tracking issue in heterogeneous UAV formation systems with a constrained-input leader, as seen in Figure 4.

This method initially formulates the optimal trajectory

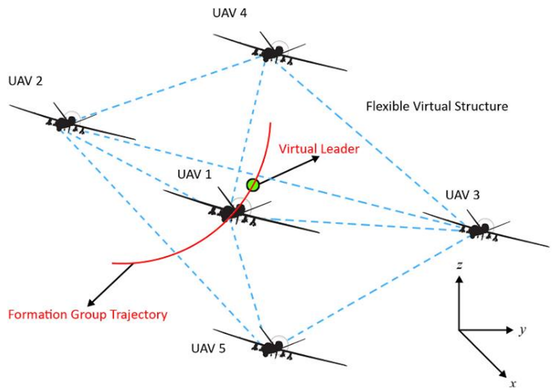

Figure 4. Heterogeneous UAV formation systems.

tracking issue for heterogeneous systems. A model-free off-policy reinforcement learning approach is developed to derive the numerical solution for the distributed optimal controller, requiring solely the information of the formation leader. Hasan et al. [27] proposed the establishment of a multi-vehicle network system that considers several graph topologies, including circular and hexagonal configurations. This technique employs a Consensus algorithm for vector dependency. This paper's primary contribution is the application of Particle Swarm optimization (PSO) to determine the optimal feedback gain. Najm et al. [28] suggested a consensus control law for a multi-agent system characterized by a leader–follower communication topology using three quadrotor agents. This research use the genetic algorithm (GA) as the optimization technique to adjust the consensus control settings. The comprehensive nonlinear model is employed in the simulations without additional simplifications, but a simplified model is utilized for the theoretical design of the controller. López et al. [29] introduced an alternate approach for attaining distance-based formation. This method uses a Genetic Algorithm to identify an optimal solution based on angle, distance, and a suitable constant velocity to prevent collisions. Nath et al. [30] introduced a distributed method, DMTF, capable of simultaneously forming many teams, marking, to our knowledge, the first effort in this domain. This study involves the development of a prototype model of the proposed algorithm within ARGoS, a multi-robot simulation environment, which was subjected to rigorous testing through extensive simulations. Nath et al. [31] presented a distributed methodology for task execution across many scenarios. In these methodologies, the capabilities of robots and the skills necessary for job execution are denoted as p-dimensional binary skill vectors. In practical applications, it is preferable to examine real-valued talents. This research presents a distributed architecture that conducted extensive trials in a RoboCup rescue simulation environment. The experimental findings demonstrate the effectiveness of the method. Huo et al. [32] examined the issue of cooperative circular formation with constrained target knowledge for numerous Unmanned Aerial Vehicle (UAV) systems. This work proposes a pigeon-inspired strategy for circular formation control to achieve the desired circular distribution in a plane, drawing on intelligent pigeon behaviour while hovering. Azam et al. [33] devised a decentralized control approach for unmanned aerial vehicles (UAVs) pertaining to formation control. The objective of this study is to navigate the UAV swarm from an initial geographic area to a different geographic area, where the swarm is required to assume a three-dimensional configuration. Qiang et al. [34] devised an innovative resilience optimisation method for multi-UAV formation reconfiguration, employing a universal resilience metric that serves as a reference framework to assess resilience alterations following a random attack across various mission types. To improve the convergence rate and accuracy of Ant Colony Optimisation (ACO) in global optimisation, researchers recommend refining state transfer functions to better direct ant movement, utilising artificial potential field heuristics to affect path selection, and optimising the pheromone update mechanism to enhance decision-making and exploration equilibrium. The enhancements seek to attain expedited convergence and superior answers in intricate optimisation challenges [35].

3.1.2 *Path planning*

Shin et al. [36] delineates a methodology for addressing the path planning challenges faced by unmanned aerial vehicles (UAVs) in hostile situations, encompassing radar-guided surface-to-air missiles (SAMs) and unidentified threats. The proposed algorithm consists of pre-processing phases, a multi-swarm PSO algorithm, and post-processing processes. Wang et al. [37] introduced the CM-PIO cooperative path planning approach to enhance UAV performance in confined spaces. In comparison to the conventional PIO approach, the results indicate that the solution of the suggested method has superior robustness. Qu et al. [38] introduced an innovative reinforcement learning-based grey wolf optimizer algorithm termed RLGWO. The suggested technique incorporates reinforcement learning, enabling the individual to adaptively switch operations based on

Table 2. Summary of Techniques, Key Findings, and Limitations in Multi-UAV Formation Control and Path Planning.

Technique used	Key Findings	Limitation	Year
Suggested (PSO) with Cauchy mutant (CM) operators	Proposed method found optimum obstacle-avoiding path with highest fitness value.	boosting fitness but lowering terrain, radar, and collision costs	2021
Design Adaptive Learning-based Pigeon-Inspired Optimization (ALPIO) algorithm	Resilience optimisation is studied.	Each UAV will face hostile attacks and tactics throughout reconfiguration.	2022
VTG based MPC- Finite-Horizon Optimal Control Problem (FHOCP)	Collaboration between VTG and MPC for trajectory tracking and obstacle avoidance	3D formation control design. Conduct a UAV formation control flight test to prove the distributed MPC technique works.	2020
APF & Improved ACO	The proposed optimisation method speeds up ACO's global convergence and fixes the algorithm's easy local optimum transition.	In-depth optimisation of the above path planning methods for higher-dimensionality and more complex environments	2022
Hybrid ICA-PSO and MPC-PSO	The ICA-PSO and MPC-PSO algorithms work better together to prevent static and dynamic obstacles.	Several UAV communication topologies may accelerate consensus convergence.	2020
BI-RRT Algorithm Based on GREEDY strategy	Proposed technique proved effective and secure in 3D.	Rolling detection and obstacle avoidance settings may make UAVs more alert.	2020
Improved PSO with Mutation strategy	The proposed CIPSO method optimizes formation system solutions better.	Combining 3-DOF UAV models for formation route planning. Planning a different route when unexpected threats or obstacles arise.	2020
Reinforcement learning (RL)	Distributed optimal control for heterogeneous UAV f ormation system trajectory tracking.	The full quadrotor nonlinear model will be examined while solving the optimal formation control problem for nonlinear systems.	2020
Particle Swarm Optimization (PSO)	The proposed PSO method improves iteration efficiency for faster vehicles.	Formation tracking is a hot topic that could become a UAV issue.	2020
Local Search-based Ant Colony Optimization (LF-ACO)	The proposed approach improved the distance factor heuristic function by making the target point more appealing to ants.	To improve planning, use neural networks to identify target characteristics and weights.	2022
Suggested Pigeon inspired circular formation	Proposed approach solved intelligent pigeon behaviour circular formation problem.	A multi-UAV testbed will evaluate the control law.	2021
GA genetic Algorithm	Nonlinear quadrotor model shows closed-loop stability of proposed control strategy.	To control the single agent UA using the proposed consensus control approach and its nonlinear model.	2020
Parallel Genetic Algorithm	Genetic Algorithm is used to construct distance-based structures based on angle, distance, and constant velocity to avoid collisions.	study of Multi-objective evolutionary algorithm optimisation	2020
DMTF distributed algorithm for multi team formation	Proposed distributed method In a dynamic multi-agent system with little environment knowledge, DMTF helped several teams.	Test the system with actual robots using the prototype.	2020
decentralized Markov decision process	Using decentralized UAV swarm formation control, proposed method drives starting geographical region to another to build 3D shape. Swarm	Adapts to 3D forms and can be used to perceive a scene's surroundings for 3D reconstruction.	2021

cumulative performance. The proposed algorithm for UAV path planning incorporates four operations for everyone: exploration, exploitation, geometric adjustment, and optimal adjustment. Ge et al. [39] introduced a three-dimensional environmental model for oilfields, encompassing static oil-well equipment and dynamic impediments. This paper presents an enhanced pigeon-inspired optimisation algorithm, termed PIOFOA, designed to address path planning challenges in a three-dimensional dynamic oilfield environment. Das et al. [40] proposed a novel method to calculate an optimal collision-free trajectory for each robot in each intricate environment. The suggested approach calculates the deadlock-free upcoming coordinates of an individual robot from its current coordinates while minimizing the path length for each robot by effectively balancing intensification and diversity. Che et al. [41] introduced an enhanced Ant Colony Optimisation (ACO) algorithm derived from Particle Swarm Optimisation (PSO) to address the limitations of the conventional ACO approach, including susceptibility to local extrema, suboptimal

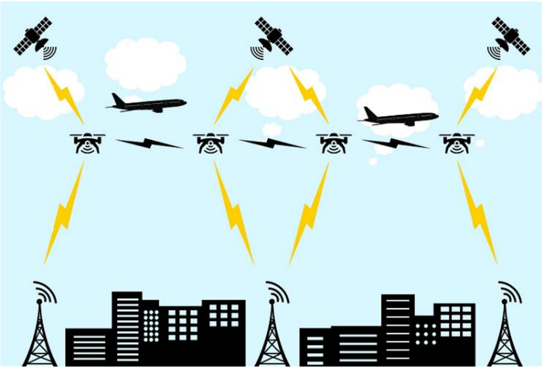

Figure 5. Intelligent Path Tracking for Mobile Robot.

quality, and reduced accuracy. The experimental results indicate that the enhanced ACO algorithm is more efficient and practical for path planning in autonomous underwater vehicles compared to the conventional ant colony method. Ajeil et al. [42] presented a study focused on the design of intelligent path planning algorithms for mobile robots in both static and dynamic contexts, utilising swarm intelligence optimisation, as illustrated in Figure 5. Simulations demonstrated that the suggested path planning algorithms achieve enhanced performance by identifying the shortest and most collision-free path across diverse static and dynamic settings.

Shafiq et al. [43] examines the path planning and control of several colonies or clusters of unmanned aerial vehicles (UAVs) operating within a hazardous environment. The proposed architectural design constrains, lemmatizes the pheromone, and identifies the optimal ants that subsequently create the most efficient path. Chen et al. [44] introduced an adaptive particle swarm optimisation technique that dynamically modifies the inertial weight and two learning variables during the iterative search phase. The simulation results indicate that the proposed adaptive particle swarm optimisation algorithm exhibits superior global search capability and search accuracy compared to the traditional particle swarm optimisation technique. Li et al. [45] proposed a strategy for minimizing mission duration to cover a designated set of target sites within a monitoring area using numerous UAVs. This methodology discusses an enhanced ant colony optimisation (ACO) that integrates ACO with a greedy strategy. He et al. [46] introduced the time stamp segmentation (TSS) model to streamline the management of coordination costs for UAVs, subsequently proposing a novel hybrid algorithm termed HIPSO-MSOS, which integrates improved particle swarm optimisation (IPSO) with modified symbiotic organisms search (MSOS). Ji et al. [47] presented six types of terrain functions for UAV path planning to replicate real-world applications. The double-dynamic biogeography-based learning approach substitutes the conventional learning mechanism of personal and global best particles for the selection of learning particles. In this technique, each particle will acquire knowledge from the superior of two chosen particles that are not inferior to itself. Jiang et al. [48] introduced hybrid algorithms utilising bio-inspired calculations to enhance the stability and speed of path planning solutions. This article compares two hybrid models of Ant Colony Optimisation regarding convergence time, specifically the Max-Min Ant Colony Optimisation method combined with Differential Evolution and Cauchy mutation operators. Ali et al. [49] examines the path planning for several colonies utilising several unmanned aerial vehicles in a dynamic setting. This technique addresses the shortcomings of existing classical ant colony optimisation and maximum-minimum ant colony optimisation, while resolving the conflict between excessive information and global optimization. Such kinds of approaches are summarized in the Table 3.

3.1.3 Path trajectory

Teng et al. [50] construct a trajectory planner based on particle swarm optimisation and a proposed surveillance area importance update mechanism targeted at generating three-dimensional (3D) optimal surveillance trajectories for numerous monitoring drones depicted in the Figure 6. A multi-objective fitness function that takes into account energy consumption, flight risk, and the priority of surveillance areas is proposed in this method for the purpose of evaluating the trajectories that are generated by the trajectory planner.

Selma et al. [51] introduces an innovative tracking hybrid controller for a quadrotor UAV, integrating a robust adaptive neuro-fuzzy inference system (ANFIS) with a particle swarm optimisation (PSO) algorithm. The ANFIS-PSO controller is employed to regulate the dynamics of a quadrotor UAV with three degrees of freedom. The controller enables the manipulation of UAV movement to follow a specified trajectory in a two-dimensional vertical plane. Rubi et al. [52] introduced a trajectory tracking problem involving the monitoring of a timed reference position. This method eliminates the issue of time dependency, yielding numerous benefits for control performance and design. Selma et al. [53] introduces an innovative tracking hybrid controller for a quadrotor UAV that

Table 3. Summary of Techniques, Key Contributions, and Limitations in Multi-UAV Path Planning and Trajectory control.

Technique used	Key Findings	Limitation	Year
DDBLPSO (Double Dynamic Biogeography-based Learning Particle Swarm Optimization)	Efficient global optimization and UAV path planning for six types of terrain with collaboration, showing superior performance compared to PSO and BBO variants.	Gap for improvement in standard deviation (Std).	2022
Improved PSO Approach	Solves UAV path planning in adversarial environments with radar-guided SAMs and unknown threats. Efficient in performance and number of iterations.	Data availability is a challenge for practical applications.	2020
CM-PIO Algorithm	Identifies optimum path for each UAV, surpassing traditional Pigeon Inspired Optimization.	Needs further analysis of diverse environments.	2020
Hybrid Metaheuristic MMACO and Differential Evolution (DE)	Provides optimal 3D path planning for multiple UAVs with collaboration between MMACO and DE strategies.	Limited to 3D environments; future potential for other dimensional routes.	2023
MMACO and Vicsek-based Multi-Agent System (MAS)	Enhances convergence rate and colony performance for multi-UAV path planning, surpassing NSGA-II.	Requires further scalability in terms of UAV colonies and numbers.	2021
Adaptive PSO (Adjusting Inertia Weight and Learning Factor)	Efficient 3D path planning for fixed-wing UAVs in complex environments with dynamic threats.	Needs enhanced avoidance strategies for dynamic threats.	2021
Improved ACO with Greedy Strategy	Optimizes mission time for multi-UAVs, effectively covering targets.	Future comparisons with other optimization techniques are needed for performance validation.	2021
RLGWO (Reinforced Grey Wolf Optimizer)	Provides optimal 3D flight paths in complex environments with better efficiency than IGWO, GWO, and EEGWO.	NFL theorem limitations: no single optimal solution fits all applications.	2020
PIOFOA (Pigeon Inspired Optimization with Fruit Fly Optimization Algorithm)	Optimizes UAV path planning for total length, height, time, and electricity use, suitable for dynamic 3D environments like oil fields.	Requires better path planning for aerial robot collaboration in dynamic environments.	2020
HIPSO-MSOS	Efficient and accurate path planning for UAVs, ensuring real-time obstacle avoidance with superior convergence speed.	Needs further testing for real-time formation control in obstacle-laden environments.	2021
MMACO-CM (Max-Min Ant Colony Optimization with Cauchy Mutant)	Solves path planning with faster convergence times, surpassing MMACO-DE.	Requires hardware implementation and comparison with simulation results.	2022
IPSO-EOPs (Improved PSO with Enhanced Operators)	Outperforms DE and IPSO in multi-robot path planning with energy optimization and minimal path deviation.	Visual perception-based path planning for dynamic environments remains a challenge.	2020
Improved ACO with PSO	Identifies optimal paths for Autonomous Underwater Vehicles (AUVs) in complex 3D environments, avoiding collisions with dynamic obstacles.	Requires improvements for collision-free navigation in complex undersea terrains.	2020
ABCO Algorithm (Artificial Bee Colony Optimization)	Optimizes mobile robot path planning in dynamic and static environments.	Needs grid resolution improvements for smoother and more efficient paths.	2020

integrates a strong adaptive neuro-fuzzy inference system (ANFIS) controller with an Improved Particle Swarm Optimisation algorithm (IPSO) model utilising functional inertia weight. The controller is designed

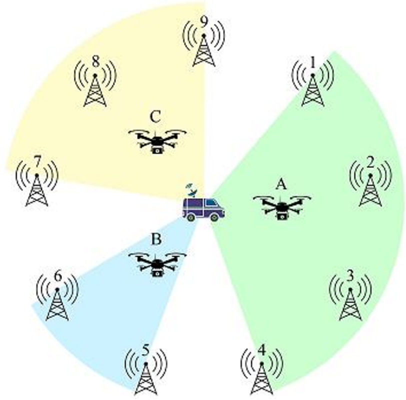

Figure 6. Surveillance Trajectories for Monitoring Drones.

for a quadrotor with three degrees of freedom (3 DOF), represented by its non-linear dynamical mathematical model. Abdul Samed et al. [54] discusses the development of a resilient controller for the autonomous landing, trajectory tracking, and take-off operations of a quadrotor unmanned aerial vehicle (QUAV). This technique examines the QUAV's dynamic model, which encompasses nonlinearity, uncertainty, and coupling, resulting in a highly complicated system. The proposed controller may regulate both position and orientation, as well as manage the driving motors. Madridano et al. [55] provides a comprehensive overview of trajectory planning to facilitate a comparison of the methodologies and algorithms documented in the literature for addressing trajectory issues within MRS. This method effectively demonstrates the applicability of these techniques across several domains, highlighting their significance for attaining autonomous and secure navigation of diverse vehicle kinds. Selma et al. [56] proposed a sophisticated control methodology utilising an adaptive neuro-fuzzy inference system (ANFIS) and a pigeon-inspired optimisation algorithm (PIO) to regulate the dynamics of a three-degree of freedom (3-DOF) quadrotor UAV.

The ANFIS controller is designed to regulate the UAV's movement to follow a specified reference trajectory in a two-dimensional vertical plane.

3.2 Current Solutions in Trend

Recent breakthroughs have introduced various interesting methods for optimising neuro-fuzzy controllers through metaheuristic techniques, which are increasingly relevant in the domain of collective motion for multi-agent systems, including swarms of unmanned aerial vehicles (UAVs). Selma et al. [57] developed an approach utilising metaheuristic algorithms to enhance neuro-fuzzy controllers, allowing them to satisfy worldwide performance standards. This method combines an adaptive neuro-fuzzy inference system (ANFIS) with the pigeon-inspired optimisation (PIO) algorithm to effectively regulate the behaviour of a 3-DOF quadrotor UAV, providing improved stability and manoeuvrability in collective motion situations. Khan et al. [58] examined vehicle routing algorithms, including the Capacitated Vehicle Routing Problem (CVRP), Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), and Genetic Algorithm (GA), assessing their efficacy in several real-time situations. These methods can be modified for swarm UAVs in applications such as medical aid delivery within dynamic situations, highlighting the necessity for resilient path planning in swarms with varying vehicle capacities and task distributions.

Qadir et al. [59] further advanced the discipline by providing innovative metaheuristic algorithms for collision-free path planning in UAVs, particularly pertinent in disaster situations such as forest fires. This technique targets the root cause of ecological harm and facilitates swift rescue operations by optimising collective UAV behaviour, rendering it an essential solution for pre-disaster and emergency response initiatives. Shao et al. [60] proposed a hierarchical trajectory optimisation method that integrates enhanced PSO with the Gauss pseudo-spectral method (GPM), demonstrating efficacy in optimising collective trajectories for UAV swarms. This stratified approach enables swarms to create accurate trajectories and facilitate seamless transitions, markedly enhancing the dynamic capabilities of cooperative UAV operations. Navabi et al. [61] improved trajectory tracking by creating an adaptive sliding mode controller (ASMC) optimized by particle swarm optimisation (PSO) to address the nonlinear dynamics of quadcopters. This approach, when applied to collective UAV systems, enhances tracking and stability in the face of uncertainty, rendering it optimal for swarm coordination where reliable performance is essential.

Wang et al. [62] utilized a multiple-population genetic algorithm (MPGA) to enhance the improved Stanley controller (IMP-ST) for autonomous tractor models. This optimisation method can be applied to swarming systems to enhance tracking and coordination in collective motion, especially in agricultural or industrial contexts necessitating synchronized robotic movement. Ultimately, Mir et al. [63] provided a comprehensive summary of

Table 4. Summary of Techniques, Key Contributions, and Limitations in Multi-UAV Path Planning and Trajectory control.

Technique used	Key Findings	Limitation	Year
PSO-based optimal adaptive sliding mode controller (ASMC)	Applied on a quadcopter to address trajectory tracking control with mass and inertia uncertainties. Strength: Effective control under uncertain model parameters.	Potential errors in parameter estimation and rotor inertia uncertainty.	2022
PSO-based trajectory planner	Developed for multiple drones (UAVs) to plan 3D optimal surveillance trajectories. Strength: Enhanced trajectory planning efficiency for multi-drone systems.	Future work involves applying PSO to more than two drones for broader applications.	2020
Improved Stanley Controller (IMP-ST) with MPGA	Applied to two-wheel tractors for improved path tracking. Strength: Significant reduction in lateral errors during navigation.	Practical tests with real tractors are needed for verification.	2022
Communication techniques for space exploration	Focused on UAVs and vehicles for ground, aerial, and underwater exploration. Strength: Enhances autonomous system communication in space exploration.	Future work could use multi-robot coverage techniques for improved robustness.	2022
Trajectory planning algorithms for MRS	Applied to UAVs and UGVs for solving multi-robot system (MRS) path planning problems. Strength: Comprehensive review of trajectory planning techniques.	Future studies should address the difficulties faced in real-world applications.	2021
Hybrid ANFIS and PSO algorithm	Applied to quadcopters for UAV trajectory control in 2D plane. Strength: Reduces tracking error and improves control quality with PSO optimization.	Future work should focus on automatic optimization of parameters to enhance system performance.	2020
Backstepping and feedback linearization with NLGL and Carrot-Chasing algorithms	Applied to quadrotor simulation for trajectory tracking along helix paths. Strength: Eliminates time-dependence in control design, improving control performance.	Real flight experiments are needed to validate these algorithms.	2020
ANFIS with Improved PSO (IPSO)	Applied to quadrotors for optimizing ANFIS membership functions. Strength: Improves performance through PSO in trajectory tracking.	Intelligence-based control techniques may help address parameter measurement difficulties.	2020
ANFIS and pigeon-inspired optimization (PIO)	Applied to UAVs for trajectory following in a 2D vertical plane. Strength: Directs UAV movement with ANFIS and enhances trajectory quality using PIO.	The EAS algorithm could further improve convergence in optimization.	2020
Adaptive fuzzy, PID and PSO	Applied to quadrotor UAVs for trajectory tracking. Strength: Capable of guiding UAVs to follow predefined trajectories.	Future work may explore adaptive model predictive control in unknown environments and evaluate performance with dynamic obstacles.	2023
ANFIS and PIO	Applied to UAVs for controlling trajectory in 2D planes. Strength: Improves tracking error and trajectory quality through PIO.	EAS algorithm could be considered for global optimization challenges.	2022
Swarm UAV interception	Focused on intercepting multiple UAVs with a swarm using SI algorithms. Strength: Provides a comprehensive review of SI algorithms for 3D path planning.	Hybrid optimization algorithms could enhance interception strategies.	2022
UAV navigation for medical emergencies	PSO, ACO, and GA applied for UAV navigation in medical emergencies. Strength: Achieves smooth, effective navigation for real-time medical aid.	Future work may involve applying CVRP algorithms without computational resource limitations.	2021
Pre-disaster assessment path planning	Applied DGBCO algorithm for UAV path planning in disaster situations. Strength: Reduces transportation costs and computational time.	GWO algorithm could be used for enhanced robotics pathfinding in future work.	2021
Incorporating flight time into UAV dynamics	Applied GPM and PSO for trajectory planning. Strength: Improves convergence speed and enhances solution optimality.	Future research may address dynamic obstacle avoidance in rapidly generated trajectories.	2021

communication methodologies essential for space exploration, encompassing the enhancement of terrestrial, aerial, and subaqueous vehicles. Efficient communication protocols are crucial for coordinated activities in swarms, facilitating seamless interaction among UAVs during collective missions. Sharma et al. [64] concentrated on swarm UAVs engaging multiple aerial targets in three-dimensional space, tackling the complexities of dynamic restrictions in multi-target interception. This understanding establishes the basis for advanced collective motion techniques, enabling swarm UAVs to perform intricate tasks, such as coordinated interceptions, with exceptional precision. These methodologies highlight the increasing trend of amalgamating optimisation algorithms with sophisticated control systems to address the intricate issues of collective motion in multi-agent systems, especially UAV swarms. These trending solutions are summarized in Table 4.

4 Technical Analysis

4.1 In-depth analysis of limitations

Selma et al. [57] proposed a methodology for optimising neuro-fuzzy controllers through metaheuristic techniques, specifically targeting the attainment of global performance criteria in control systems. Nonetheless, although the adaptive neuro-fuzzy inference system (ANFIS) and pigeon-inspired optimisation (PIO) algorithm proved effective in controlling the behaviour of a 3-DOF quadrotor UAV, the system's performance may be constrained by the intricacy of real-time fuzzy controller tuning, particularly in dynamic environments. Khan et al. [58] similarly emphasized vehicle routing techniques including CVRP, PSO, ACO, and GA; nonetheless, their scalability continues to be a constraint. The comparison indicates that while these algorithms can provide real-time medical assistance, their effectiveness may decline with more vehicle capacity and quantity, implying a possible limitation in heavily congested situations. Qadir et al. [59] introduced advanced metaheuristic algorithms for collision-free path planning in disaster scenarios, specifically in regions susceptible to bushfires. Notwithstanding the efficacy in predisaster evaluation, the intricacy and real-time flexibility of the algorithms in swiftly evolving contexts such as forest fires pose a significant difficulty. Shao et al. [60] proposed a hierarchical trajectory optimisation framework that combines enhanced PSO with GPM; nonetheless, the dependence on initial values obtained from PSO may result in inferior outcomes in intricate and uncertain situations. Navabi et al. [61] noted that although the PSO-optimized adaptive sliding mode controller (ASMC) enhanced trajectory tracking control for quadcopters, it could not adequately resolve concerns related to parameter uncertainty and real-world disturbances, particularly under harsh operational situations. Ultimately, Wang et al. [62] and Mir et al. [63] highlighted path tracking and communication methodologies, respectively; however, the practical implementation of Wang's enhanced Stanley controller on tractors and Mir's communication strategies for space exploration vehicles is limited by environmental variability and the necessity for additional validation in real-world scenarios. Sharma et al.'s [64] methodology for swarm UAV target interception encounters difficulties in achieving real-time, collision-free three-dimensional path planning amongst intricate kinematic limitations.

4.2 Research Directions

Future research should concentrate on improving the adaptability and robustness of the proposed algorithms to address these limitations. Selma et al.'s [57] methodology could be enhanced by integrating real-time optimisation approaches that dynamically modify ANFIS parameters in response to fluctuating ambient variables, hence facilitating more robust UAV control. Khan et al. [58] posits that additional investigation into hybrid algorithms, which integrate the advantages of CVRP, PSO, ACO, and GA, may enhance scalability in vehicle routing, especially in extensive fleets in crowded metropolitan settings. Qadir et al.'s [59] study on disaster response path planning could be enhanced by using machine learning models that forecast environmental changes, enabling the algorithms to adapt more efficiently to dynamic settings such as bushfires. Shao et al. [60] could investigate more adaptable initial value estimation methods for the PSO-GPM model to more effectively address unforeseen impediments in trajectory optimisation, enhancing both convergence rate and solution optimality. Navabi et al. [61] may mitigate the constraints of parameter uncertainty in quadcopter control by integrating advanced estimate techniques, such as robust adaptive algorithms, capable of dynamically adjusting for model uncertainties. Furthermore, Wang et al.'s [62] enhanced Stanley controller might undergo testing in real-world scenarios, with additional investigation into its applicability to more sophisticated tractor models or other autonomous vehicles. Mir et al. [63]

advocates for the investigation of multi-robot coverage methodologies to enhance communication resilience in space exploration. Javed et al. [64] emphasises the necessity for hybrid optimisation techniques to address dynamic restrictions in UAV swarm target interception, potentially enhancing performance in real-time operations. Subsequent efforts should concentrate on overcoming these problems to enhance the applicability of the offered methodologies in real-world contexts. The proliferation of UAVs has generated increasing interest in applications involving the collaborative operation of many drones to execute intricate tasks. The examination of collective behaviour in UAVs, especially regarding dynamic agents, provides critical insights into the coordination of several drones for activities including surveillance, delivery, and mapping. This study investigated the principles of self-organization and emergence, which are essential to the collective movement of dynamic agents. A comprehensive mathematical model was created to elucidate the interactions among agents and simulate many scenarios, establishing a robust theoretical framework for the behaviour of UAV swarms.

The presented models were experimentally validated using established methodologies, facilitating a comparison between simulated outcomes and actual performance. The investigation verified that self-organizing concepts may be effectively applied to UAVs, improving their collective behaviour in tasks necessitating high degrees of cooperation. Nevertheless, the experiments underscored specific limits in the existing models, especially in managing intricate, dynamic situations where elements like external disturbances and communication delays can considerably affect swarm effectiveness.

5 Conclusion

Despite the progress that has been made in understanding and simulating the behaviour of collective Unmanned Aerial Vehicles (UAVs), there are still significant problems that need to be addressed in order to fully realize the potential of swarm intelligence in UAV systems. Robust communication continues to be a critical challenge, particularly in real-time operations, as unmanned aerial vehicles (UAVs) routinely come into contact with surroundings that have communication links that are either unreliable or degraded. However, real-world environmental elements such as wind, terrain variations, and barriers contribute complications that are sometimes imperfectly captured in simulations. Although the current understanding of UAV swarm dynamics has made significant progress, this does not mean that everything is perfect. It is essential to address these gaps in order to successfully transfer theoretical models into practical applications that are applicable in the real world. In addition, scalability continues to be a source of urgent concern. When applied to small UAV groups, the models and algorithms that are now in use are effective; however, as the size of the swarm increases, they become computationally expensive and inefficient. The existence of this problem highlights the necessity of developing solutions that are scalable, decentralized, and capable of maintaining coordination and flexibility in bigger swarms. Despite the fact that significant progress has been made, the field of unmanned aerial vehicle (UAV) collective behaviour continues to face the issue of ensuring robust and efficient coordination in complicated contexts.

Future research should concentrate on creating decentralized algorithms that ensure UAV coordination despite disrupted or delayed communication. This is crucial for swarms functioning in situations characterized by significant communication lag or interruption. A key aim is scalability, focusing on the development of algorithms that effectively control bigger UAV swarms without compromising performance. Enhancing simulation realism is essential, as existing models frequently neglect to account for real-world complications such as fluctuating wind conditions and barriers. Additional field tests are required to corroborate theoretical models. Furthermore, the integration of AI with swarm robotics may augment real-time adaptability, decision-making, and operational efficiency, allowing UAVs to foresee environmental alterations and enhance performance under volatile settings.

Conflicts of Interest

The authors declare no conflicts of interest.

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