Chapter

Motion Planning of UAV Swarm: Recent Challenges and Approaches

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Abstract

The unmanned aerial vehicle (UAV) swarm is gaining massive interest for researchers as it has huge significance over a single UAV. Many studies focus only on a few challenges of this complex multidisciplinary group. Most of them have certain limitations. This paper aims to recognize and arrange relevant research for evaluating motion planning techniques and models for a swarm from the viewpoint of control, path planning, architecture, communication, monitoring and tracking, and safety issues. Then, a state-of-the-art understanding of the UAV swarm and an overview of swarm intelligence (SI) are provided in this research. Multiple challenges are considered, and some approaches are presented. Findings show that swarm intelligence is leading in this era and is the most significant approach for UAV swarm that offers distinct contributions in different environments. This integration of studies will serve as a basis for knowledge concerning swarm, create guidelines for motion planning issues, and strengthens support for existing methods. Moreover, this paper possesses the capacity to engender new strategies that can serve as the grounds for future work.

Keywords: UAV, swarm intelligence, motion planning, swarm challenges, flight, aerial mission

1. Introduction

UAV has significance in our lives due to their potential applications. Single UAVs are restricted to limited power, capabilities, sensing, and flight time. This has raised a requisite for employing swarms of UAV systems. UAV swarm conquers the exploitations and restrictions of an unaccompanied UAV and assists larger teams to cooperate for successful aerial missions. Swarm has benefits and brings versatile possibilities as the strength lies in numbers. Many of them are task completion in less time, redundancy, and collaborative task execution.

1.1 Background

Swarming is not a contemporary conception. It existed in nature and was motivated by the cooperation and mutual communication of biological populations [1]. Studying the flocking of birds, movement of the ant colony, cooperation of bees, schools of fish, and predation of wolves the concept of the swarm of UAVs came into existence. The unity of the animal kingdom makes it possible to achieve a common challenging and complex goal.

Nevertheless, swarming is not restricted to a natural phenomenon. It is also inspired by a military tactic in which many units from multiple axes coverage attack a common target in a coordinated and deliberately structured form [2]. Since the fourth century, swarming has been observed throughout military history. However, today swarming has changed the traditional concepts of command and control into innovative ones. Moreover, a single person is capable to command and control several UAVs at a time.

1.2 Related work

Swarm of UAVs is evolving because of its significant capabilities of long-range operations, enhanced robustness, and flexibility [3]. Swarm intelligence has a high impact on many fields such as technology, science, society, and various systems like inspection, tracking, transporting, and many others [4]. For the motion planning of UAV swarms, many improvements in terms of control designs, path planning algorithms, communication structure, monitoring and tracking architectures, and safe flight protocols are considered in different studies [5].

The researchers combined computational techniques with mathematical models in [6] to examine the communication effects. The modeling process was simplified through this approach, but the process of modeling was slow and run out of memory. In [7] a controller based on a decentralized, leader-follower strategy, and a geometry of the tree-based network were suggested. This study achieved the arrival of multi-UAVs at a common spot with maintained synchronization. Moreover, the suggested design showed flexibility and robust performance. However, this study was bounded to a limited number of UAVs. In [8] researchers developed a framework for novel path planning of UAV swarm. This proposed algorithm resulted in efficient path planning with a reduction in energy and inspection time. Additionally, it provided the guidelines for determining various parameters.

In [9] the study presented an algorithm for computing the control of swarm and modeling their distributed behavior. The examination and simulations have shown the communication latency effects on different scenarios. In [10] an improved algorithm with resilience metric is proposed while considering the limited communication range effects. This strategy is implemented in a surveillance mission, which showed its significance as a more realistic method that can face efficiently the external disturbance and threats. In a recent study [11], the concepts of PIO algorithm, proportional-integral controller, and proportional integral differential controller are employed for the formation control of UAV clusters. This strategy has outperformed the traditional methods and provided a safe flight protocol. Further extensive reflection on how this technology has evolved is in the section of the related survey.

1.3 Motivation and contribution

The motivation for this paper is to gather multiple challenges, which can hinder the performance of a UAV swarm, on a single platform. Moreover, to provide appropriate approaches as the solutions to achieve optimal motion planning. This study can assist researchers in exploring multiple motion planning strategies with their contributions and limitations. The appropriate selection of the motion planning techniques and models can complete the complex tasks quickly and targets the applications dotage as well. Following are the significant contributions of this paper:

- To provide an explanation of swarm intelligence and the challenges it faces.
- To present a detailed analysis of the motion planning techniques with their contributions and limitations from several research articles from more than the last decade.
- To recommend future directions to guide the researchers.

1.4 Organization of the Paper

The paper is organized into many sections. Section 2 provides the state-of-the-art of UAV swarms. Section 3 evaluates the concept of swarm intelligence. Section 4 presents challenges faced by the UAV swarm. Section 5 reflects on an extensive survey of the techniques and models used to address many challenges concerning the UAV swarm. Section 6 discusses the key findings and limitations. Section 7 gives the conclusion, and Section 8 recommends some future work for further research and development.

2. State-of-the-art

The swarm makes decisions collectively and completes its aerial mission using relatively simple instructions due to the Artificial Intelligence (AI) technology and edge computing [12]. Features like following the leader and missions, path planning, sensing, and avoiding are already developed in the Veronte Autopilot. This advancement in the features makes teamwork possible and ensures task success. Surveillance and attack induction is a milestone event in the swarm globally. This game-changing capability of the swarm of UAVs is benefitting both larger as well as smaller nations. Other significant aspects of swarming include combined decision-making, self-healing, and adaptive formation flying. The swarm of UAVs is still in the progressing phase as further research is being conducted to further enhance the systems. Further focus includes the expansion of capability of artificial swarm intelligence, increase in the autonomy state among the swarm agents, and commodification to reduce the cost impacts.

The most amazing aspect of the UAV swarm is its application for both civilian and military purposes using swarm intelligence [13]. The civilian agencies are using the swarm technology for bigger plans. The National Aeronautics and Space Administration (NASA) is also employing this AI-based swarm technology for climate change analysis [14]. This results in the accomplishment of the required things, which were not possible while using one. Moreover, many developed nations have passed regulations to widespread the commercial application of UAV swarms. The swarm shows tremendous performance in power line and structure inspections, precision agriculture, surveying, search and rescue operations, and others.

However, the swarm of UAVs gained the spotlight for its potential and efficiency in military usage. If in combat, some of the UAVs of the swarm get shot down then still the remaining ones complete the mission with similar tactics, power, and flexibility. Raytheon demonstrated this by employing swarm operation during a field exercise of the US Defense Advanced Research Projects Agency (DARPA) program [15]. The

Raytheon swarm had the communication and coordination ability. Moreover, all the individuals had sensors, cameras, and Tactical Assault Kit (TAK) integration capability for environmental explorations.

The swarm technology is enhancing the capabilities of the military in complex environmental tasks. Many militaries, like the US and China militaries, are in a lead in testing and observing the simulations for swarm operations on the highest levels [16]. Some militaries, like the British military, are using this technology for real-time operations. The UK has also experimented with Leonardo's Brite Cloud for swarming that contained electronic warfare jammers. Similarly, soon Russia aims large UAV swarm induction, "Flock 93," in its army. Moreover, it is trying to fill the gap by 2025. Iran, Turkey, and India are also attempting efforts to mature and proliferate this technology using distributed intelligence and edge computing. Swarms of UAVs are the future of aerial wars, and the future is now [17].

3. Preliminaries of swarm intelligence (SI)

In this world, we observe that all individuals wish to amplify their intelligence. For this goal, they think and prefer working together, like a bee swarm, fish scull, and birds flock together. This is because they believe that they are smarter in a group rather than being alone. A new intelligence that is formed due to the deep interconnection of the real system having feedback loops is known as swarm intelligence [18]. In simple words, a swarm is a brain of all the brains that are smarter than individual ones. Swarm intelligence is an evolving area of bio-inspired artificial intelligence [19].

Moreover, using swarm intelligence, many heads follow a single mind. All the individuals follow clear rules and interact not with each other but with the environment as well. This adaptive strategy requires a large mass of individuals. It is capable of scheduling, clustering, optimizing, and routing a cluster of similar individuals. Swarm intelligence emphasizes the task's relative position in the schedule. It follows the summation evaluation rule for scheduling. A collaboration of all the similar individuals in a swarm is known as clustering. For example, UAVs of a swarm are different from other clusters' UAVs. It is capable to provide the best and low-cost solution from all the feasible outcomes through optimization. Moreover, it has potential capabilities of routing. It imitates the principle of ants in which forward ants gather the information while the backward ants utilize that information [20].

3.1 Aspects of SI

Major aspects of swarm intelligence include distribution, stigmergy, cooperation, self-organization, emergence, and imitating natural behavior [21]. Distribution is the prime characteristic of swarm intelligence as all the individuals are capable to select their actions and perform them. The phenomenon with which the agents interact through environmental alteration indirectly is called stigmergy. This phenomenon provides them with awareness of their surroundings and disconnects the interactions of the individuals. Another significant behavior is the cooperation of all the UAVs in a swarm [22]. UAVs cooperate for solving complex tasks and show their collective behavior using swarm intelligence. Another aspect of swarm intelligence is self-organization. This behavior is based on positive feedback, negative feedback, fluctuations amplification, and different social interactions. Positive feedback is the amplification that gives better outcomes by allocating more UAVs to them. Negative feedback is to stabilize so that not all the UAVs converge to a similar state. The self-organization phenomena usually observe a tension between both the feedbacks, such as complex networks, markets, cellular automata, and many others. Another characteristic is emergence, which can be weak or strong. The emergence is said to be weak if the individual behavior is traceable from the emergent properties. The emergence is said to be strong if the individual behavior cannot be traced from the properties of emergence. Moreover, a swarm of UAVs is modeled by taking inspiration from natural swarm behavior. Generally, swarm behavior includes foraging, constructing a nest, and moving together in the environment. Hence, imitating these natural swarm behaviors is another key aspect of swarm intelligence [23].

3.2 Levels of SI

There are two levels of swarm intelligence. The first level employs a positive feedback pheromone for marking shorter paths and an entry signal for others. Whereas the second level of swarm intelligence employs a negative pheromone for marking unpleasant routes and no entry signal for others.

3.3 Principles to follow in SI

A swarm follows five principles generally. The proximity principle, the quality principle, diverse response principle, stability principle, and adaptability principle [24]. Following the proximity principle, the basic swarm individuals can easily respond to the environmental variance that is caused by interactions among them. The quality principle allows a swarm to respond to quality factors like location safety only. The diverse response principle enables to design of the distribution in such a way that all the individuals are protected from environmental fluctuations to a maximum level. The stability principle restricts the swarm to show a stable behavior with the changes in the environment. The adaptability principle shows the sensitivity of a swarm as the behavior of the swarm changes with the change in environment. The most widely used principles are attraction between all individuals, collision avoidance, and self-organization. While following attraction they come closer and focus on a similar direction. While following the collision avoidance principle, they keep a particular distance between them to avoid collisions. Whereas, in self-organization rule, they interact with the neighbors but do not trust all.

3.4 Mechanism of SI

The mechanisms of swarm intelligence are regarding the environment, interactions, and activities of the individuals in a swarm. No direct communication takes among the individuals in a swarm [25]. They interact with each other through environmental alterations. Thus, environmental alterations serve as external memory. This simulation of work is done by applying the stigmergy behavior of all the swarm members. Moreover, the individuals choose their actions with an equilibrium between a perception-reaction model and any random model. Then, they react and move according to this perception-reaction model while perceiving and affecting the local environmental properties.

3.5 Languages used for SI

Proto-swarm, swarm, Star-Logo, and growing point are some programming languages for swarm intelligence. The proto-swarm language uses amorphous medium abstraction to program the swarm [26]. This amorphous medium abstraction is obtained by utilizing a language that is from the continuous space-time model of Proto and a runtime library that estimates the model on the provided hardware. Another language for swarm intelligence is a distributed programming language called a swarm. The basic concept for it is to move the computation rather than the data. Swarm is analogous to the Java bytecode interpreter with a primitive version. Now it is applied as a Scala library. Star-Logo is not only a programming language but also a programmable modeling environment of a decentralized system. By utilizing this programming language, different real-life scenarios can be modeled like market economies, bird flocks, traffic jams, etc. Whereas, to program amorphous computing medium growing point language is essential. This programming language has the capacity of generating pre-specified and complex patterns like the interconnection form of an arbitrary electrical circuit.

3.6 Significance of SI

There is much significance of swarm intelligence; some of them are discussed here. It enables the swarm to be flexible while responding to external challenges and internal disturbances. It completes the tasks with robust performance even with the failure of some agents [27]. It allows the scalability to range from a few to a million individuals in a swarm. No central authority or control lies in the flocking of individuals. It is completely adaptable and provides self-organized solutions only. The propagation of changes is very rapid in the networks. All these are beneficial for clusters of individuals.

4. Swarm challenges

4.1 Swarm control

The basis of a UAV swarm is to control all the individual UAVs during the planned path. To solve the reconstruction, anti-collision, search, and tracking issues in the swarm formations the development of proper control system frameworks and controllers is required [28]. Centralized and distributed are the two major control platforms for the automation-equipped clusters. The main advantage of the centralized platform is achieving higher quality in outputs but with the limitation of limited scalability. Whereas the main contribution of the decentralized platform is its enhanced scalability, which is less complex. The network of the UAV swarm guarantees the nodes' connectivity and simplifies the application designs. Sensor inputs with the environmental and target's prior knowledge are the essentials for the traditional models.

Various research overcome these issues using multi-layer distributed control frameworks. The designing of the controller is crucial in the process design of the UAVs. Many studies suggest using the ANFIS controller for the learning error reduction and quality improvement of the controller. During the movement of UAVs following a specific path, the target tracking performance is directly affected by the control of the airborne gimbal system. Some studies propose the nonlinear Hammerstein block structure for modeling gimbal systems to enhance the efficiency of the model predictive controller (MPC). This also improves the performance of the target tracking under external interference in real-time. Other approaches for formation control are leader-follower strategy, consensus theory, virtual structure method,

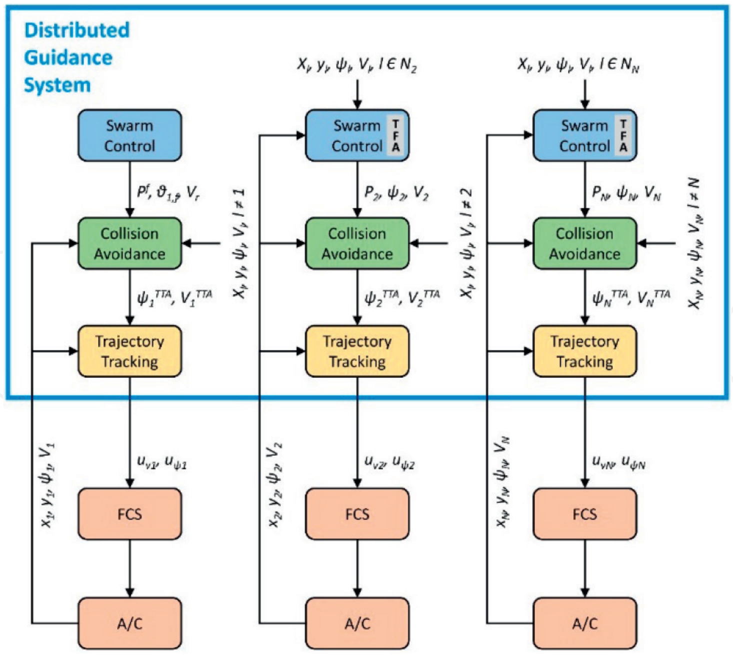

Figure 1.
Distributed guidance model using leader-follower controller.

behavior method, etc. **Figure 1** represents the concept of distributed guidance model using a leader-follower controller as given in [29]. The leader guidance algorithm is given in the first column of this figure, whereas the other two columns represent the followers. The preassigned topology in this model cannot be altered.

4.2 Swarm path planning

The path planning of a UAV swarm is quite challenging [30]. To solve this NP-hard problem many studies suggest path-planning algorithms. These algorithms are categorized into classic algorithms and meta-heuristic algorithms as shown in **Figure 2**. Classic algorithms require environmental information while meta-heuristic algorithms require information on the real-time position and measured environmental elements. Road map algorithm (RMA), A* algorithm, and artificial potential field (APF) method

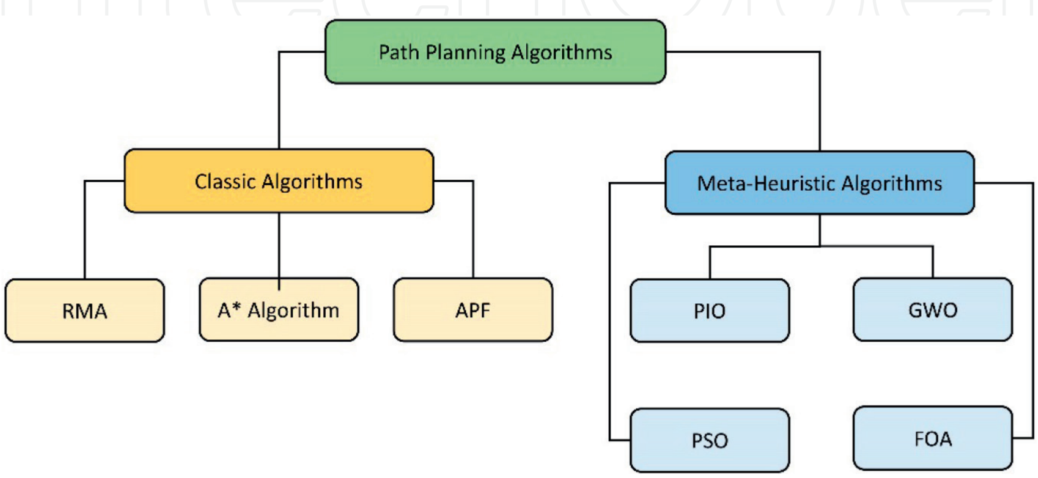

Figure 2.
Path planning algorithms for UAV swarm.

are some examples of classic algorithms as presented in **Figure 2**. Particle swarm optimization (PSO), pigeon-inspired optimization algorithm (PIO), fruit fly optimization algorithm (FOA), and gray wolf optimization algorithm (GWO) are some examples of meta-heuristic algorithms as given in **Figure 2**.

The swarm path planning can be categorized into dynamic path planning, 3D path planning, area coverage path planning, and optimal path planning [31]. Dynamic path planning is essential for the task performance of a UAV swarm in a complex environment. To ensure dynamic path planning many researchers suggest using collision probability with Kalman Filter, the artificial potential field (APF) with the wall-follow method (WFM) method, trail detection, scene-understanding frameworks, and so on. All these methods provide better direction estimation, better performance, and avoid path conflicts. 3D path planning is complicated, but many studies apply meta-heuristic algorithms for dealing with it. Like the GWO algorithm realizes the feasible flight trajectory, the FOA algorithm performs local optimization and PIO optimizes the initial path.

All these algorithms work efficiently for 3D path planning of UAV swarms under threats and emergencies. Path planning in which UAVs can move at all the areas of interest points is area coverage path planning. Many studies suggest a five-state Markov chain model, improved potential game theory, and a cyber-physical system for it. For optimal path planning battery capacity of UAVs, matching performance, and energy consumption are serious considerations. Studies suggest a coupled and distributed planning strategy, mobile crowd perception system (MCS), and energy-efficient data collection frameworks for optimal path planning.

4.3 Swarm architecture

For swarm implementations, the architecture of UAVs is of much importance [32]. Architecture is a combination of design, management, and optimization techniques. Swarm architecture can be based on communication, mission doctrine, control, etc. Communication-based swarm architecture has two forms. Ad-hoc network-based architecture and infrastructure-based swarm architecture. Both are promising architectures and perform well under complex environments.

Considering the operational mission for designing a swarm architecture is also important. Studies consider it imprudent if the mission doctrine is not considered. Current approaches include bottom-up modeling approaches and top-down design approaches for designing swarm systems. Similarly, control-based architectures are also beneficial for the swarm. **Figure 3** gives a mission-based architecture for swarm composability (MASC) as presented in [33]. This framework focuses on the phases, tactics, plays, and algorithms. According to this figure, mission explains the entire task, phases evaluate specific periods, tactics are the individuals' usage in a particular order for task performance, the play describes the swarm behavior and algorithms are the procedures. Moreover, linking distributed behavior control methods with centralized coordination can efficiently work for swarm aerial missions. The aerospace architecture can perform the thinking task, execution task, reaction task, and socialization task efficiently. Moreover, the Internet of Things (IoT) supports swarm architectures and facilitates interactions as well.

4.4 Swarm monitoring and tracking

Another prime challenge for a swarm is monitoring and tracking. All the UAVs' positions, status, and the external environment change concerning time during

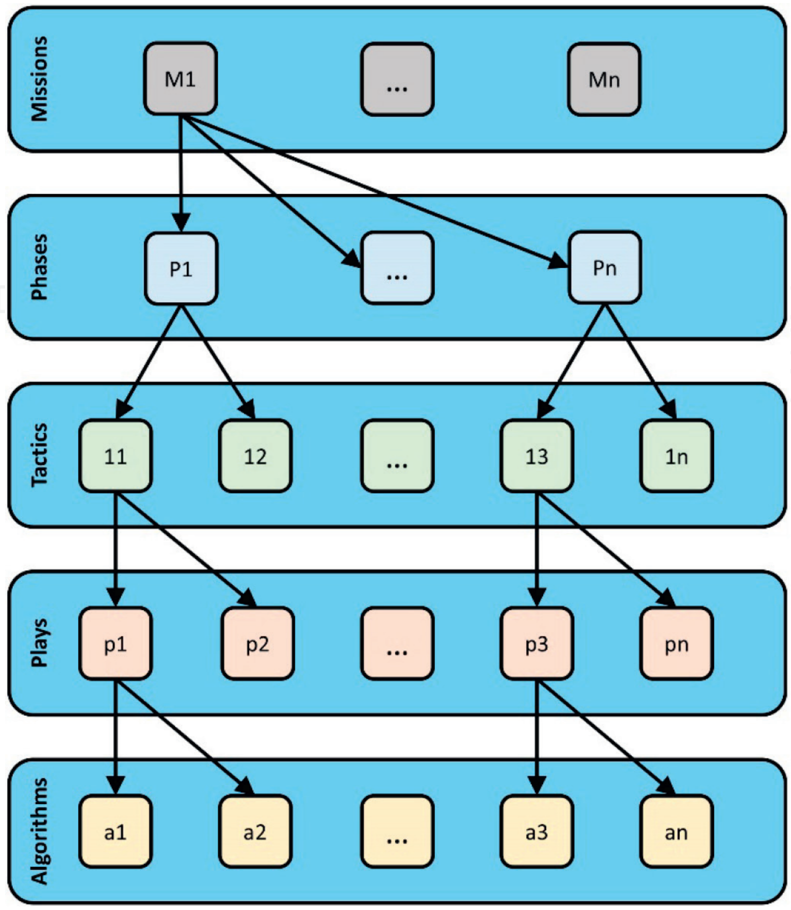

Figure 3.
MASC framework.

a swarm's operation. Moreover, the swarm adapts to these changes and adjusts its behavior accordingly. For this, continuous monitoring and tracking are essential. Many researchers propose different control models, simulation models, and simulation tools for solving monitoring and tracking challenge. Dynamic Data-Driven Application System (DDDAS) is a solution, which assists in the environment and the mission's adaptation [34].

Target searching requires consideration of effective methods and control strategies. If the target knows about the mobility and position of the searcher, then the searching complexity will be enhanced. The distributed strategy also provides solutions to the Automatic Target Recognition (ATR) issue. Many researchers suggest layered detection solutions, learning-edge software, and optimal technology for tracking UAVs in a swarm. **Figure 4** represents spatial distribution using an improved bean optimization algorithm (BOA) that is based on the population evolution model as developed in [35]. In this figure, the swarm space is distributed into three layers, a temporary dispatch layer, an individual layer, and a parent layer. BOA shows effective target search capabilities, emerging group intelligence, and distributed collaborative interaction. The individuals' distribution using BOA can be given as,

$$X_{ij}(t+1) = X_i(t),\ if\ X_{ij}(t+1)\ is\ a\ parent \tag{1}$$

$$G(X_i(t)),\ if\ X_{ij}(t+1)\ is\ not\ a\ parent \tag{2}$$

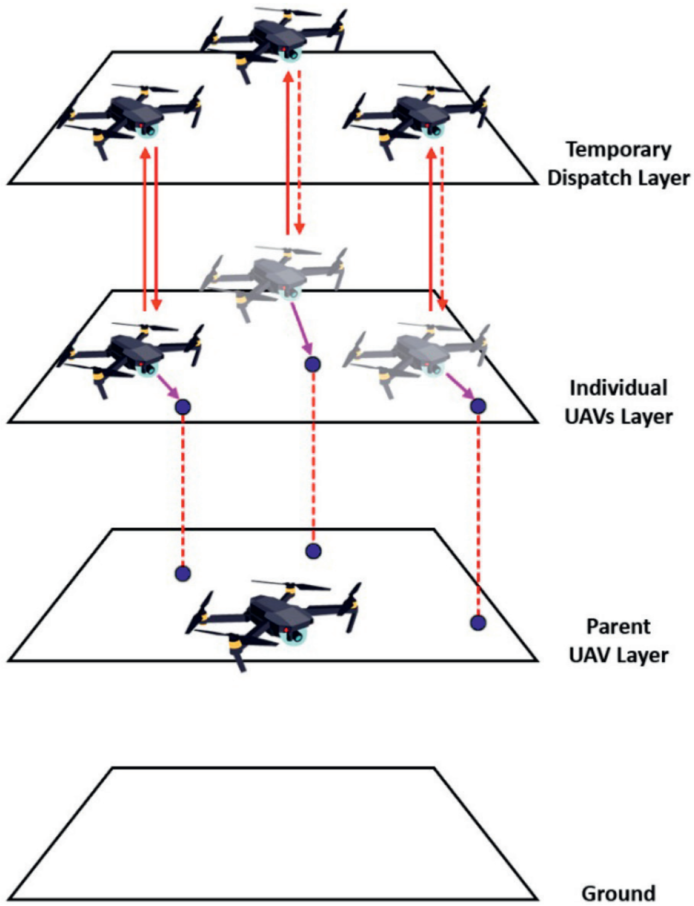

Figure 4.
Spatial distribution of individual UAVs.

Here, the parent *i* generates the position of individual *j* and is denoted by $X_{ij}(t+1)$, the $X_i(t)$ denotes the parent *i*, and $G(X_i(t))$ gives the distributed function.

4.5 Swarm communication

Communication is one of the prime challenges for UAV swarms [36]. Under a noisy and complex environment, a swarm requires accurate and efficient data communication for the task executions. Data communication depends upon an appropriate structured network. **Figure 5** shows that wireless ad-hoc networks are capable to provide efficient communications as presented in [37]. A base station is connected with two UAVs in this figure. Both of these UAVs are further connected to a different group of UAVs. The intraconnection of UAVs is independent but the interconnection is dependent on the base station. Three forms of networks include Flying Ad-hoc Network (FANET), Mobile Adhoc Network (MANET), and Vehicle Adhoc Networks (VANET). FANET network provides a network for communication between a few UAVs with GCS, while the rest of the UAVs communicate with each other. FANET enhances the range of communication as well as the connectivity in areas with limited cellular infrastructure and obstacles. Whereas MANET and VANET are interlinked with FANET. Therefore, FANET possesses similar features to both the other forms except a few ones like mobility, better connectivity, energy constraints,

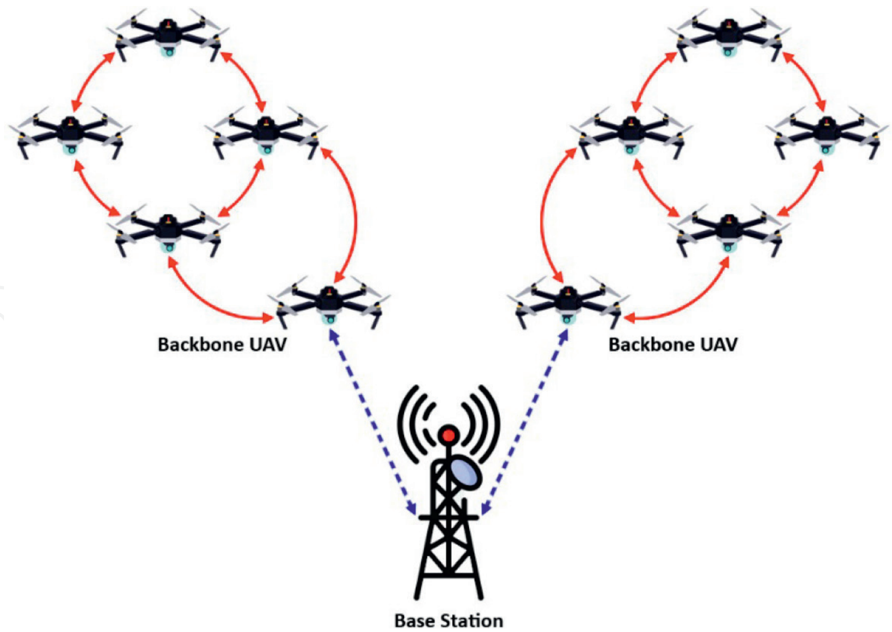

Figure 5.
Ad-hoc network for multi-group UAV.

etc. MANET does not require any support from the infrastructure of the internet and is formed with a required number of mobile devices. Whereas the VANET consists of terrestrial vehicles.

For quick deployment UAVs act as aerial base stations in a swarm to support the infrastructure of the communication. This wireless networking is implemented successfully between UAV and Internet of Things (UAV-IoT), UAV and cellular unloading (UAV-CO), UAV and emergency communications (UAV-EC), and others. These improve transmission efficiency and reduce response delays. Moreover, efficient communication can also solve other challenges like cooperation, control, and path planning. Hence, the foundation of a UAV swarm is effective communication.

4.6 Swarm safe distance protocol

In UAV swarm collaboration, the self-organization behavior becomes essential for each UAV. Transfer of data and communication take place among all the UAVs for appropriate decision-making during self-organizing swarm flights. But there is a risk of collision among UAVs in complex flight conditions. Hence, one of the key challenges is to provide a collision avoidance protocol for safe flights [38]. These protocols are necessary because of the continuous mobility of UAVs, limited resources, and air links instability. All the UAV members of a swarm must know each other's positions using a multi-hop connection. Most of these require a global positioning system (GPS) and in the absence of GPS, the location of a UAV can be estimated using the Euclidean distance formula with three nodes of known positions. Several kinds of research provide safe flight protocols using goose swarm algorithms, Reynolds rule, and pigeon flock algorithm. Other than this, many optimization algorithms can promote the UAV swarm consensus. Reynolds protocol uses three flocking behavioral rules. First is the separation rule in which a UAV attempts to move away from neighboring UAVs in a swarm. Second is the alignment rule in which UAV attempts to align the velocity with the neighboring UAV to avoid collisions. The third is the cohesion rule-following which the UAV tries to share the same position by coming closer to the neighboring UAVs to form clusters. A self-organized flight model using Reynolds Rules is given using the idea of [39]. All these rules are summarized in the following equation,

$$J_i = V\left(\| s_{ij}(t) \|\right) + \sum_{j\in Ni(t)} \| \dot{s}i(t) \|^2 \tag{3}$$

Here N shows the number of UAVs in a swarm, s_{ij} is the position of two UAVs i, and j in time t and $j \in \mathrm{N}i\ (t)$ with V represents an attractive–repulsive potential function with a local minimum. These rules provide a proper safe flight protocol among the UAV swarm but still have limitations, which should be improved to achieve safer trajectory planning.

5. Related survey

Successful motion planning of UAV swarms requires significant optimization algorithms with relevant infrastructures or models. **Table 1** provides a comprehensive exploration of techniques and models applied for the motion planning of a swarm of UAVs. This review will provide a detailed and better understanding of appropriate techniques for challenges faced by UAV flocks used in previous and current studies.

Kim et al. [40] considered the Kalman filter with Covariance Intersection (CI) algorithm and smoothing, and string-matching methodologies to observe the airborne monitoring using a swarm of UAVs. The researchers employed the hidden Markov model (HMM) for path planning and achieved an increment in the tracking accuracy and a reduction in the tracking error. Oh et al. [41] suggested a vector field guidance approach to track the moving objects. The study further introduced a two-phase approach; K-means clustering with Fisher information matrix (FIM) and cooperative standoff tracking method for this purpose. The results showed standoff group tracking successfully, allowed local replanning, and kept all the targets of interest within the sensor's field-of-view (FOV). Sampedro et al. [42] presented Global Mission Planner (GMP) and Agent Mission Planner (AMP) for a UAV swarm. Their proposal gave a complete operative, robust, scalable, and flexible framework that automatically performed many high-level missions.

Yang et al. [43] analyzed eleven swarm intelligence (SI) algorithms for UAV swarm. This research explained the features and principles of these algorithms and analyzed different algorithm combinations and task assignments for multiple UAVs. Hocraffer and Nam [44] performed a meta-examination of the human-system interface concerning human factors. The analysis provided a basis to start research, enhanced situation awareness (SA), and yielded efficient results. Lee and Kim [45] studied multirotor dynamic models with linear and nonlinear controllers for trajectory tracking control of multi-UAVs. The study showed that linear controllers were easily applicable, robust, and provide optimality and some nonlinear controllers were also easily applicable, intuitive, and gave global stability. Yang et al. [46] linked an orthogonal multi-swarm cooperative particle swarm optimization algorithm with a knowledge base model (MCPSO-K). This technique converged faster, avoided premature convergence, lessened the computational costs, and ensured the uniform distribution of particles.

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[40]	Kim et al. (2010)	Kalman filter with CI and smoothing Boyer-Moore algorithm HMM	Monitoring and tracking	• Enhances the tracking accuracy • Reduces the tracking error by 50%	• Shows weaving behavior • Requires decision-making integrations
[41]	Oh et al. (2015)	Vector field guidance approach Two-phase approach. K-means clustering with FIM and Cooperative standoff tracking method	Target tracking	• Gives standoff group tracking successfully • Allows local replanning and keeps all the targets of interest within the sensor's FOV	• Has many implementation issues • Shows imperfect communication effects and measurement data association effects
[42]	Sampedro et al. (2016)	GMP AMP	Architecture, target detection, and exploration	• Gives a complete operative, robust, scalable, and flexible framework • Performs automatically many high-level missions	• Does not focus on various behavior functionalities • Does not include time-based or autonomy-based optimization approaches
[43]	Yang et al. (2017)	SI	Management and task assignments	• Explains features and principles of many SI algorithms • Analyzes SI combinations and task assignments for multiple UAVs	• Does not consider parameter optimization and swarm robot application • Does not focus on algorithms for computational cost and convergence speed
[44]	Hocraffer and Nam (2017)	Human-system interface	Human-system interfaces	• Focuses on the human-system interface and human factors concerns • Provides a basis to start research and gives efficient results • Enhances SA	• More effective interfaces are required • Requires more research
[45]	Lee and Kim (2017)	Multirotor dynamic models Linear and non-linear controllers	Trajectory tracking control	• Linear controllers are easily applicable, robust, and provide optimality • Some non-linear controllers are easily applicable, intuitive, and give global stability	• Linear controllers require more modification, and some have limited applications • Some non-linear controllers do not work if noise or model error exists and lack robustness

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[46]	Yang et al. (2017)	MCPSO-K	Cooperation, searching, and path planning	• Converges faster and avoids premature convergence • Lessens the computational costs • Ensures the uniform distribution of particles	• Requires adjustment of information interaction at the swarm level
[47]	Guastella et al. (2018)	Modified A* algorithm	Path planning	• Reduces the computational time • Improves path trajectories • Improves targets' automatic redistribution	• No visible path for the two UAVs
[48]	Duan et al. (2018)	MA with VND	Path planning	• Optimizes the path routing • Gives highly effective results • Solves CVRP even NP-hard problems efficiently	• Does not consider delivery and pickup issues simultaneously
[49]	Koohifar et al. (2018)	EKF Recursive Bayesian estimator CRLB	Localization and path planning	• Plans the future tracking trajectory • Enhances the performance • CRLB and the Bayesian estimator outperform	• Shows higher computational costs • Non-convex optimization can be more significant
[50]	Shao et al. (2018)	RISE-ESO controller Residual estimation error	Trajectory tracking control	• Tackles the lumped disturbance issues • Achieves tracking accuracy, effectiveness, and superiority	• Does not include real-time flight experiment
[51]	Campion et al. (2018)	Cellular mobile infrastructure Machine learning Distributed control algorithms M2M and 5G networks	Communication and control architecture	• Alleviates limiting factors for previous studies • Enhances efficiency of the swarm and commercial usage	• Does not apply practically on a commercial level
[52]	Shao et al. (2018)	ESO-based robust controllers DSC design DOB control techniques	Trajectory tracking control	• Shows effective and superior results in tracking • Shows increased anti-disturbance capability	• Requires further modifications for output feedback–based controllers

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[53]	Mammarella et al. (2018)	SMPC Guidance algorithm	Trajectory tracking control	• Deals efficiently with noise and parametric uncertainty • Guarantees real-time tracking • Ensures performance with good stability	• May require an onboard fellow computer
[54]	Huang and Fie (2018)	GBPSO	Path planning	• Improves the ability to search and avoids the local minimum • Provides the feasible optimal path with superior quality and speed	• Requires further improvements in terms of accuracy and searching efficiency
[55]	Ghazzai et al. (2018)	Bandwidth hungry and delay-tolerant applications mm-Wave and μ-Wave communication modules Hierarchical iterative approach	Path planning and communication	• Increases the stopping locations • Minimizes the service time	• Does not consider non-orthogonal transmission while applying μ-wave • Requires limiting the interference effect during extra coordination
[56]	Liu et al. (2018)	Distributed formation control algorithm MPC Disturbance estimation method	Control	• Convenient for the formations of arbitrary, time-varying prescribed shapes • Achieves a balanced configuration on a prescribed 2D or 3D shape	• Requires algorithm extension for 3D situations having different obstacles • Needs human operator directions
[57]	Xuan-Mung et al. (2019)	RAS-BSC Lyapunov theory	Trajectory tracking control	• Provides the stability of the closed-loop system • Bounds the tracking errors and ESO errors • Rapid and robust in the uncertainties • Gives superior performance	• Designing of for landing quadrotor in moving platform • Not applicable in multi-agent systems • Slow response time
[58]	Fabra et al. (2019)	MUSCOP	Coordination and synchronization	• Achieves swarm cohesion with a high degree under multiple conditions • Allows least synchronization delays with low position offset errors	• Does not validate the proposed protocol with different formations

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[59]	Causa et al. (2019)	Multi-GNSS constellation approach Edge cost estimation	Path planning	• Decreases the computation time and entire mission time • Provides a rapid solution to the task assignment issue and planning for offline and in near real-time scenarios	• Has high computational cost
[60]	Brown and Anderson (2019)	Quintic polynomials trajectory generation method OMOPSO Area search radar model	Trajectory optimization and surveillance	• Gives maximum number of better trajectories • Reduces the time to revisit and fuel consumption and enhances the detection probability	• Requires excessive fuel to fly at higher altitudes
[61]	Mehiar et al. (2019)	QRDPSO	Searching and obstacle avoidance	• Provides a more stable, efficient, and quick optimal solution • Avoids obstacles and overcomes the communication constraints • Reaches the global best for search and rescue operations	• Requires more energy conservation and enhanced lifetime
[62]	Wang et al. (2020)	Leader-following model Routh–Hurwitz criterion Consensus protocol MPC	Control and stability	• Predicts the changes in the leader's state • Lessens the consensus achievement time • Keeps the formation shape	• Not extended to nonlinear systems • Does not consider disturbance issue
[63]	Altan (2020)	PSO HHO	Control and path following	• Performs the best for multiple geometric paths • Quickly determines the controller parameters • HHO outperforms and overcomes the stabilization issues • HHO gives the least settling and peak time and overshoot	• Does not focus on model-based controller design

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[64]	Wang et al. (2020)	NRI model Mapping Table	Trajectory prediction	• Improves the position detection performance • Projects the motion in 3D space into a 2D plane • The designed algorithm predicts the trajectory and gives high accuracy	• Does not consider the height information • Does not include trajectory prediction in 3D space
[65]	Rubí et al. (2020)	BS and FL algorithms NLGL CC algorithms	Path following control	• BS outperforms for yaw error and path distance • CC needs fewer data and proves to be easily applicable for any path type	• Does not consider experimental platform features
[66]	Selma et al. (2020)	ANFIS-PSO	Trajectory tracking control	• Adjusts automatically the ANFIS parameters • Minimizes tracking error by improving the controller quality • Gives high performance	• limitations of classical control laws are solved in the absence of model parameters not found
[67]	Liu et al. (2020)	Kinetic controller The BAT-based topology control algorithm FANET	Control and communication	• Can perform a neighbor selection • Reduces the communication overhead significantly	• Does not consider delay, interference, and other communication constraints
[68]	Madridano et al. (2020)	3D PRM algorithm ROS architecture MavLink protocol Pixhawk autopilot Hungarian method	Control and communication	• Generates optimal solutions using minimum time • Lessens the computational time • Reduces the total traveling distance	• Requires producing a node and developing an MRTA algorithm for allocation efficiently • Does not mount onboard sensors for dynamics obstacles detection
[69]	Zhou et al. (2020)	Hierarchical control framework SI	Decision-making, path planning, control, communication, and application	• Categorizes the major technologies with trends, future research, and limitations	• Requires expensive loads for high performance • Needs to improve safety relation

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[70]	Wubben et al. (2020)	MUSCOP protocol Ardu-Sim	Resilience and synchronization	• Handles the loss of a leader and backup leaders efficiently • Introduces an ignorable flight times delay	• Does not address swarm split-up situation
[71]	Selma et al. (2020)	Hybrid ANFIS-IACO controller	Trajectory tracking control	• Proves the superior performance • Reduces the errors, MSE and RSE significantly • Allows the UAVs to reach the desired trajectory in a minimum period	• Applicable to only a 2D vertical plane.
[72]	Altan and Hacıoğlu (2020)	Newton–Euler method-based 3-axis gimbal system Hammerstein model MPC	Control and target tracking	• Tracks the target with stability • Shows robustness even under external disturbances	• Does not track an aerial target
[73]	Sanalitro et al. (2020)	Fly-Crane system Optimization-based tuning method Inner or outer loop approach	Control	• Deals with parametric uncertainties • Performs rotating and translating of particular trajectories • Guarantees stability and enhances the performance of $H\infty$	• Needs to keep the motion low • Requires relaxation in the structure
[74]	Chen and Rho (2020)	SI SOMs	Tactical deployment and communication	• Enables self-organization for UAV arrays • Allows reconfiguration of the UAVs into hubs or terminals • Shares information efficiently	• Requires big-data cloud centers to handle huge data
[75]	Qing et al. (2021)	IACO Minimum-snap algorithm ZCBF	Collision avoidance	• Gives optimal results for decision-making in real-time • Evaluates collision-free effectiveness	• Does not perform in the real flight
[76]	Miao et al. (2021)	A multi-hop mobile relay system MSEE maximization transmission scheme BCD SCA Dinkelbach method	Secrecy and energy efficiency, and communication	• Guarantees the convergence • Provides major improvements in energy efficiency and secrecy rate	• Does not include channel models, real-time communications, and unknown nodes' locations

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[77]	Shao et al. (2021)	Multi-segment strategy IPSO-GPM	Trajectory planning and obstacle avoidance	• Increases obtained solution optimality • Generates high-quality trajectories • Takes minimum running time	• Does not select collocation points • Does not generate trajectory with dynamic obstacles
[78]	Gu et al. (2021)	NIT	Identification	• Gives a quick response, accuracy • Proves to be effective, fault-tolerant, and stable in complex environments	• Sensitive to nuance • Only suitable for high-dimensional trajectories
[79]	Ling et al. (2021)	Out-of-the-box trajectory plotting Multi-round Monte Carlo simulation	Communication, estimation, perception fusion, and path planning	• Works in noise and unstable communication • Proves to be useful for cooperative swarm application	• Does not consider additional mode functionalities and reinforcement learning-based cooperative planning algorithm
[80]	Yao et al. (2021)	Swarm intelligence-based automatic inspection optimization algorithm	Inspection and communication	• Controls the UAVs effectively • Improves the autonomy and inspection efficiency • Minimizes the cost of inspection	• Does not avoid path repetition
[81]	Xia et al. (2021)	MARL-MUSAC	Monitoring and target tracking	• Allows making intelligent flight decisions • Reduces the power consumption • Enhances the tracking success rates • Gives high performances for detection coverage	• Not valid for different formations
[82]	Nnamani et al. (2021)	Grid-structured approach	Communication	• Improves the secrecy rate of ground communications • Improves physical layer security • Evaluates the optimal radius of the eavesdropper's unknown location	• No real-time communications
[83]	Xu et al. (2021)	Communication-aware centralized and decentralized controllers	Trajectory tracking control and communication	• Achieves high waypoint tracking accuracy • Decentralized controller outperforms • Maintains the stability	• Does not suppress Cochannel noise • Does not ignore multipath effects

Ref.	Author (Year)	Applied Technique/Model	Challenges Addressed	Contributions	Limitation
[84]	Sharma et al. (2021)	SI	Environmental knowledge, communication, obstacle avoidance, and target tracking	• PSO has a low computational complexity • ACO possesses good scalability • Firefly utilizes a single operator for solution searching	• Needs to explore an improved, hybrid optimization algorithm with no limitations
[85]	Han et al. (2021)	backscatter communication system MIMO CLT-based approach	Communication	• Performs well to detect parasite devices and separate parasite signals • Reduces the energy consumption • Optimizes the trajectory planning	• Requires a large number of antennas to reduce the channel distribution error
[86]	Zhou et al. (2021)	MTT system Cooperative tracking algorithm Multi-objective Lyapunov optimization model	Target tracking and collision avoidance	• Reduces the execution complexity and energy consumption • Improves the prediction accuracy of trajectory	• Reduces the consumption of energy of the system only if the episodes increase
[87]	Brown and Raj (2021)	Reactive tracking Reactive tracking with predictive pre-positioning	Formation, tracking, and communication	• Shows superior tracking performance	• Requires offsetting the angular orientation of surveillance's adjacent rings for the voids' size-reduction
[88]	Sastre et al. (2022)	Improved CSTH CED_CSTH ArduSim simulator VTOL with KMA	Take-off and collision avoidance	• Allows the computation time optimization • Ensures safe distancing • Improves the time required for take-off • KMA proves to be the most reasonable choice for realistic conditions	• Requires more reduction in take-off time and the number of resulting UAV batches
[89]	Bansal et al. (2022)	SHOTS PUFs Mao Boyd's logic approach Christofides algorithm	Communication, physical security, and scalability	• Achieves scalability • Guarantees physical security • Resists against various attacks • Outperforms and reduces computational costs	• Requires further reduction in the attestation and computation time

Table 1.
A comprehensive review of the motion planning of the swarm of UAVs applying various techniques and models.

Guastella et al. [47] considered operating space as a 3-directional (3D) grid and applied the modified A* algorithm for path planning of multi-UAVs. The researchers found a reduction in computational time, improvement in planned trajectories, and automatic redistribution of targets. Duan et al. [48] gave a novel hybrid metaheuristic approach by linking memetic algorithm (MA) with variable neighborhood descend (VND) algorithm for path planning of multiple UAVs. The results yielded an optimization in routes, gave highly effective results, and solved capacity vehicle routing problems (CVRP) and even Non-deterministic Polynomial-time hard (NP-hard) problems efficiently. Koohifar et al. [49] applied the extended Kalman filter (EKF) with recursive Bayesian estimator, and Cramer-Rao lower bound (CRLB) path planning for UAV swarms. The analysis showed that the proposed method planned the future tracking trajectory successfully. Moreover, CRLB outperformed and enhanced the performance as well.

Shao et al. [50] combined a robust integral of the sign of the error (RISE) feedback controller with an extended state observer (ESO) and used residual estimation error. This strategy tackled the lumped disturbance issues and achieved tracking accuracy, effectiveness, and superiority. Campion et al. [51] studied cellular mobile infrastructure, machine learning and distributed control algorithms, machine-to-machine (M2M) communication, and 5th generation (5G) networks for UAV swarm. This study showed that the applied techniques alleviated limiting factors for previous studies and enhanced the efficiency of the swarm and commercial usage. Shao et al. [52] proposed extended state observer (ESO)-based robust controllers with dynamic surface control (DSC) design and disturbance observer-based (DOB) control techniques. This proposal showed effective and superior results in tracking with increased anti-disturbance capability. Mammarella et al. [53] applied sample-based stochastic model predictive control (SMPC) and guidance algorithm for tracking control of UAV swarm. The applied algorithms dealt efficiently with noise and parametric uncertainty and guaranteed real-time tracking and performance with good stability.

Huang and Fie [54] introduced the global best path with a competitive approach to particle swarm optimization (GBPSO). This developed strategy improved the ability to search, avoided the local minimum, and provided the feasible optimal path with superior quality and speed. Ghazzai et al. [55] suggested applications of bandwidth-hungry and delay-tolerant and exploited typical microwave (μ-Wave) and the high-rate millimeter wave bands (mm-Wave) for trajectory optimization. Further, the research also implemented a hierarchical iterative approach. The dual-band increased the stopping locations and minimized the service time of multi-UAVs. Liu et al. [56] implemented distributed formation control algorithm with a fast model predictive control method and disturbance estimation method. This strategy was convenient for the formations of arbitrary, time-varying prescribed shapes and achieved a balanced configuration on a prescribed 2-directional (2D) or 3D shape.

Xuan-Mung et al. [57] used a robust saturated tracking backstepping controller (RAS-BSC) and Lyapunov theory. The researchers found that the proposed mechanisms provided the stability of the closed-loop system and bounded the tracking errors and extended state observer (ESO) errors. Moreover, it was rapid and robust in the uncertainties and gave a superior performance. Fabra et al. [58] suggested a Mission-based UAV Swarm Coordination Protocol (MUSCOP) for a swarm of UAVs. This study achieved swarm cohesion with a high degree under multiple conditions and allowed the least synchronization delays with low position offset errors. Causa et al. [59] employed a multi-global navigation satellite system (multi-GNSS) constellation approach and edge cost estimation method for path planning of multiple UAVs.

These approaches decreased the computation time and entire mission time providing a rapid solution to the task assignment issue and planning for offline and in near real-time scenarios.

Brown and Anderson [60] applied the Quintic polynomials trajectory generation method, multi-objective particle swarm optimization (OMOPSO) and area search radar model to optimize the trajectories for the UAV swarm. This combination gave a maximum number of better trajectories, reduced the time to revisit and fuel consumption, and enhanced the detection probability. Mehiar et al. [61] developed Quantum Robot Darwinian particle swarm optimization (QRDPSO) for UAV flocks. This optimization algorithm provided a more stable, efficient, and quick optimal solution, avoided obstacles, and overcome communication constraints. Moreover, it reached the global best for search and rescue operations. Wang et al. [62] suggested a Leader-following model, Routh–Hurwitz criterion, a consensus protocol, and a model predictive controller for multiple UAVs. The applied approaches predicted the changes in the leader's state, reduced the consensus achievement time, and kept the formation shape.

Altan [63] proposed metaheuristic optimization algorithms, Harris Hawks Optimization (HHO), and Particle Swarm Optimization (PSO) for UAV swarm. His suggested methods performed the best for multiple geometric paths and quickly determined the controller parameters. HHO outperformed, overcome the stabilization issues, and gave the least settling, peak time, and overshoot. Wang et al. [64] developed Neural Relational Inference (NRI) model along with a Mapping Table between the UAV swarm and the spring particles. The results of the developed method were able to improve the position detection performance. Moreover, it projected the motion in 3D space into a 2D plane and the designed algorithm predicted the trajectory and gave high accuracy. Rubí et al. [65] employed four PF algorithms namely, backstepping (BS) and feedback linearization (FL) algorithms, Non-Linear Guidance Law (NLGL) algorithm, and Carrot-Chasing (CC) geometric algorithms for UAV swarms. In comparing, the results of path following BS outperformed for yaw error and path distance and the CC algorithm needed fewer data and proved to be easily applicable for any path type. Selma et al. [66] used a hybrid controller, adaptive neuro-fuzzy inference system (ANFIS), and PSO algorithms for trajectory tracking of multiple UAVs. The results evaluated that the PSO algorithm adjusted automatically the ANFIS parameters, minimized tracking error by improving the controller quality, and gave a high performance.

Liu et al. [67] suggested a kinetic controller, distributed β-angle test (BAT)-based topology control algorithm, and Flying ad-hoc network (FANET) for UAV flocking. This mechanism could perform neighbor selection and reduce the communication overhead significantly. Madridano et al. [68] applied the 3D probabilistic roadmaps (PRM) algorithm, Robot Operating System (ROS) architecture, Mav-Link protocol, Pixhawk autopilot, and Hungarian method for trajectory planning in 3D. This combination generated optimal solutions using minimum time and lessened the computational time and the total traveling distance. Zhou et al. [69] analyzed the Hierarchical control framework with different SI algorithms. This analysis categorized the major technologies with trends, future research, and limitations. Wubben et al. [70] employed MUSCOP protocol and an emulation tool, Ardu-Sim, to provide resilience to multiple UAVs. This protocol handled the loss of leaders and backup leaders efficiently and introduced an ignorable flight time delay.

Selma et al. [71] applied an adaptive-network-based fuzzy inference system (ANFIS) and improved ant colony optimization (IACO) for controlling trajectory tracking tasks. This strategy proved its superior performance, reduced the mean squared error (MSE) along with root mean squared error (RMSE) significantly, and allowed the UAVs to reach the desired trajectory in a minimum period. Altan and Hacıoğlu [72] used Newton–Euler method-based 3-axis gimbal system, the Hammerstein model, and the model predictive control (MPC) algorithm for target tracking. This mechanism tracked the target with stability and showed robustness even under external disturbances. Sanalitro et al. [73] suggested a Fly-Crane system with an optimization-based tuning method and an inner or outer loop approach. This system dealt with parametric uncertainties performed by rotating and translating trajectories, guaranteed stability, and enhanced the performance of $H\infty$. Chen and Rho [74] introduced the SI technique with self-organizing maps (SOMs) based on requests from end-users (EUs). This technique allowed self-organization for UAV arrays and reconfiguration of the UAVs into hubs or terminals. Moreover, it shared information efficiently.

Qing et al. [75] applied improved ant colony optimization (ACO), minimum-snap algorithm, and zeroing control barrier function (ZCBF) for multiple swarms. The results evaluated that the proposed algorithms gave optimal results for decision-making in real-time. Moreover, it efficiently provided collision and avoidance-free trajectories. Miao et al. [76] proposed a multi-hop mobile relay system, the minimum secrecy energy efficiency (MSEE) maximization transmission scheme, and generated an algorithm using the block coordinate descent method (BCD), successive convex approximation (SCA) techniques, and Dinkelbach method for multiple UAVs. The results guaranteed the convergence and provided major improvements in energy efficiency and secrecy rate. Shao et al. [77] linked multi-segment strategy with improved particle swarm optimization-Gauss pseudo-spectral method (IPSO-GPM) for UAV swarms. The outcomes evaluated that the applied mechanisms increased obtained solution optimality, generated high-quality trajectories, and took minimum running time.

Gu et al. [78] suggested Network Integrated trajectory clustering (NIT) for determining subgroups of a flock of UAVs. This clustering showed a quick response and accuracy and proved to be effective, fault-tolerant, and stable in complex environments. Ling et al. [79] presented a planning algorithm; out-of-the-box trajectory plotting with multi-round Monte Carlo simulation for UAV swarms. This developed algorithm worked in noise and unstable communication and proved to be useful for cooperative swarm applications. Yao et al. [80] employed swarm intelligence and optimization algorithms for UAV swarms. The results showed that the proposed algorithm controlled the UAVs effectively improved the autonomy and inspection efficiency and minimized the cost of the inspection. Xia et al. [81] suggested multi-agent reinforcement learning (MARL) with multi-UAV soft actor-critic (MUSAC) for the UAV swarm. The suggested mechanism allowed to make intelligent flight decisions, reduced the power consumption, enhanced the tracking success rates, and gave high performances for detection coverage.

Nnamani et al. [82] applied a grid-structured approach to the UAV swarm. The outcomes showed improvement in the secrecy rate of communications and physical layer security and evaluated the optimal radius of the eavesdropper's unknown location. Xu et al. [83] designed communication-aware centralized and decentralized controllers for UAV swarm. Their proposed controllers achieved high waypoint tracking accuracy. Between both controllers, the decentralized controller outperformed and maintained stability. Sharma et al. [84] studied multiple SI algorithms for path planning of UAV swarm. This analysis showed that PSO had low computational complexity, ACO possessed good scalability, and Firefly utilized a single operator for solution searching. Han et al. [85] employed a backscatter communication system with the massive multiple-input multiple-output (MIMO) and Central limit theorem (CLT)-based approach to analyze the performance and optimize the trajectory. This combination performed well to detect parasite devices and separate parasite signals. Moreover, it reduced energy consumption and optimized trajectory planning.

Zhou et al. [86] used Multi-Target Tracking (MTT) system, an intelligent UAV swarm-based cooperative tracking algorithm, and a multi-objective Lyapunov optimization model. The results showed a reduction in the execution in the complexity and energy consumption with an improvement in the prediction accuracy of trajectory. Brown and Raj [87] applied reactive tracking and reactive tracking with predictive pre-positioning to study the effects of initial swarm formation. The tracking gave a superior performance.

Sastre et al. [88] applied collision-less swarm take-off heuristic (CSTH) with two improvements and Euclidean distance-based CSTH (ED-CSTH) algorithms to analyze the trajectory and batch generations. This study also used the ArduSim simulator and vertical take-off and landing (VTOL) techniques with Kuhn-Munkres Algorithm (KMA) for UAV swarms. The proposed method showed the computation time optimization, ensured safe distancing, and improved the time required for take-off. Whereas KMA proved to be the most reasonable choice for realistic conditions. Bansal et al. [89] proposed a scalable authentication-attestation protocol, SHOTS, with Physical Unclonable Functions (PUFs), Mao Boyd logic approach, and Christofides algorithm for UAV swarms. The authors suggested a lightweight authentication and attestation mechanism for UAV swarms that makes use of Physical Unclonable Functions (PUFs) to ensure physical security as well as the necessary trust in a lightweight manner.

6. Discussion

The significance of multiple UAVs is expanding their cooperative operations and applications in many fields. Swarms are deployed in many environments such as uncertain, indoor, outdoor, traffic, and many others. Findings show that many challenges such as decision-making, control, path planning, communication, monitoring, tracking, targeting, collision, and obstacle avoidance may hinder the motion planning of a UAV swarm. Survey shows that different approaches are adopted in all the research addressing different challenges. Like mission planning architectures provide a complete operative, robust, scalable, and flexible framework. Many controllers whether linear or nonlinear, proves to be easily applicable, intuitive, robust, and provide optimality and global stability. Improved model predictive controllers ensure real-time monitoring and tracking of swarms. Moreover, they enhance the tracking accuracy, effectiveness, and superiority. Machine learning, 5G networking, and other technologies alleviate limiting factors for previous studies and enhance the efficiency of the swarm and commercial usage. Among all these evolving technologies in this chapter, swarm intelligence is determined as an appropriate solution for the reliable and efficient deployment of swarms. Moreover, it enables self-organization, reconfiguration, control, efficient sharing of information, reduction in inspection costs, and improvement in autonomy.

Besides many mentioned advantages of the swarm and technological development, many important and interesting limitations exist that can hinder the swarm performance. Among these restrictions, the manufacturing cost of the large-scale swarm is still high. Existing loads are huge, expensive, and mostly not appropriate for pursuing high performances. Hence, the lightweight and low-cost loads and platforms are essential for swarm formation. Battery capacity for aerial mission completion is of much significance. Long-lasting batteries are essential for continuous tasks. However, the capacity of the battery can be enhanced by increasing the UAV's weight. And this weight increment will also require an increment in energy consumption. To provide a proper battery solution such systems are essential that can easily and rapidly replace the depleted battery with the supplementary one and are capable to charge other batteries. Another limitation is the privacy protection protocol. This is essential for deploying swarm in sensitive locations safely. Otherwise, it can lead to national security issues.

7. Conclusion

In this chapter, we have presented the state-of-the-art of UAV swarm technology that shows its promising application for different purposes, especially in the military fields. An overview of swarm intelligence, explaining its aspects, levels, mechanisms, followed principles, and significance, is provided in this chapter. Then, the challenges faced by a swarm and approaches given by different researchers are discussed. Moreover, to analyze the motion planning of a swarm, we have studied and compiled multiple kinds of research. All these research papers provide different approaches to counter the challenges faced by a swarm of UAVs. Many of these approaches are based on trending technologies like swarm intelligence and outperform the traditional strategies. All the findings show the significance of using a swarm rather than using a single UAV. Finally, we discuss the key findings of this paper with some limitations and suggest some recommendations for future work.

8. Future work

Although swarm intelligence is in an emerging phase, more progress in this AI-based technology is expected in the upcoming years. Future research can design more intelligent controllers, optimal path planning algorithms, robust architecture, monitoring, target searching strategies, efficient communication structures, and safe flight protocols for swarms. The flight problems and formation maintenance of large-scale swarms still require future explorations. During the modeling process, the size and load of UAVs must be considered to increase the robustness of the swarm control. In the future holistic system, solutions will be provided for integrated task scenarios. Path planning of swarms in a curve requires more efficient algorithms. Moreover, algorithms that can give optimized paths rapidly in any complex environment are future work. The development of low-cost sensors is necessary to address the collective monitoring and target tracking issues but with the capability to provide high accuracy and robustness to noise. More research is required to standardize the communication networking between UAV swarms by upgrading the frequency bands, cooperative countermeasures, and signal distortion monitoring. To enhance the response speed in the threat environments, the focus will be on designing dynamic sensing and powerful safe flight protocols. Considerations are essential for intelligence assisted programs that can meet the next-generation networks. Like 6th generation (6G) network should be used for wireless communication services in swarms. This will extremely enhance the significance of formation, coordination in tasks, machine-human interactions, and many more. Improvements should be made that can understand and adapt to the environment along with this, and it can respond to user feedback rapidly. This can further improve the systems' agility with the reliability and performance of the network.

Conflicts of interest

The authors declare no conflict of interest.

Abbreviations

Acronyms	Definitions
2D	2-Directional
3D	3-Directional
5G	5th Generation
6G	6th Generation
ACO	Ant Colony Optimization
AI	Artificial Intelligence
AMP	Agent Mission Planner
ANFIS	Adaptive Neuro-fuzzy Inference System
APF	Artificial Potential Field
ATR	Automatic Target Recognition
BAT	β-angle Test
BCD	Block Coordinate Descent
BOA	Bean Optimization Algorithm
BS	Backstepping
CC	Carrot-Chasing
CI	Covariance Intersection
CLT	Central Limit Theorem
CRLB	Cramer-Rao Lower Bound
CSTH	Collision-less Swarm Take-off Heuristic
CVRP	Capacity Vehicle Routing Problems
DARPA	Défense Advanced Research Projects Agency
DDDAS	Dynamic Data-Driven Application System
DOB	Disturbance Observer-based
DSC	Dynamic Surface Control
ED-CSTH	Euclidean Distance-based Collision-less Swarm Take-off Heuristic
EKF	Extended Kalman Filter
ESO	Extended State Observer
EUs	End-users
FANET	Flying Ad-hoc Network
FIM	Fisher Information Matrix
FL	Feedback Linearization
FOA	Fruit Fly Optimization Algorithm
FOV	Field-of-View
GBPSO	Global Best Path with Particle Swarm Optimization
GMP	Global Mission Planner
GPS	Global Positioning System

GWO	Gray Wolf Optimization
HHO	Harris Hawks Optimization
HMM	Hidden Markov Model
IACO	Improved Ant Colony Optimization
IoT	Internet of things
IPSO-GPM	Improved Particle Swarm Optimization-Gauss Pseudo-Spectral Method
KMA	Kuhn-Munkres Algorithm
M2M	Machine-to-Machine
MA	Memetic Algorithm
MANET	Mobile Adhoc Network
MARL	Multi-agent Reinforcement Learning
MASC	Mission-based Architecture for Swarm Composability
MCPSO-K	Multi-swarm Cooperative Particle Swarm Optimization Algorithm with Knowledge
MCS	Mobile Crowd Perception System
MIMO	Multiple-input Multiple-output
mm-Wave	MillimeterWave
MPC	Model Predictive Control
MSE	Mean Squared Error
MSEE	Minimum Secrecy Energy Efficiency
MTT	Multitarget Tracking
Multi-GNSS	Multi-Global Navigation Satellite System
MUSAC	Multi-UAV Soft Actor-Critic
MUSCOP	Mission-based UAV Swarm Coordination Protocol
NASA	National Aeronautics and Space Administration
NIT	Network Integrated Trajectory
NLGL	Non-Linear Guidance Law
NP-hard	Non-Deterministic Polynomial-Time hard
NRI	Neural Relational Inference
OMOPSO	Multi-objective Particle Swarm Optimization
PIO	Pigeon-inspired Optimization
PRM	Probabilistic Roadmaps
PSO	Particle Swarm Optimization
PUFs	Physical Unclonable Functions
QRDPSO	Quantum Robot Darwinian Particle Swarm Optimization
RAS-BSC	Robust Saturated Tracking Backstepping Controller
RISE	Robust Integral of the Sign of the Error
RMA	Road Map Algorithm
RMSE	Root Mean Squared Error
ROS	Robot Operating System
SA	Situation Awareness
SCA	Successive Convex Approximation
SI	Swarm Intelligence
SMPC	Stochastic Model Predictive Control
SOMs	Self-organizing Maps
TAK	Tactical Assault Kit
μWave	Microwave
UAV	Unmanned Aerial Vehicle
UAV-CO	Unmanned Aerial Vehicle-Cellular Unloading

UAV-EC	Unmanned Aerial Vehicle-Emergency Communication
UAV-IoT	Unmanned Aerial Vehicle-Internet of Things
VANET	Vehicle Adhoc Network
VND	Variable Neighborhood Descend
VTOL	Vertical Take-off and Landing
WFM	Wall-follow Method
ZCBF	Zeroing Control Barrier Function

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