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Review

State-of-the-Art Flocking Strategies for the Collective Motion of Multi-Robots

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Abstract: The technological revolution has transformed the area of labor with reference to automation and robotization in various domains. The employment of robots automates these disciplines, rendering beneficial impacts as robots are cost-effective, reliable, accurate, productive, flexible, and safe. Usually, single robots are deployed to accomplish specific tasks. The purpose of this study is to focus on the next step in robot research, collaborative multi-robot systems, through flocking control in particular, improving their self-adaptive and self-learning abilities. This review is conducted to gain extensive knowledge related to swarming, or cluster flocking. The evolution of flocking laws from inception is delineated, swarming/cluster flocking is conceptualized, and the flocking phenomenon in multi-robots is evaluated. The taxonomy of flocking control based on different schemes, structures, and strategies is presented. Flocking control based on traditional and trending approaches, as well as hybrid control paradigms, is observed to elevate the robustness and performance of multi-robot systems for collective motion. Opportunities for deploying robots with flocking control in various domains are also discussed. Some challenges are also explored, requiring future considerations. Finally, the flocking problem is defined and an abstraction of flocking control-based multiple UAVs is presented by leveraging the potentials of various methods. The significance of this review is to inspire academics and practitioners to adopt multi-robot systems with flocking control for swiftly performing tasks and saving energy.

Keywords: multi-robot systems; flocking control; cluster; swarm; collective motion; UAVs; leader–follower; behavior-based approach; hybrid control; path planning; obstacle avoidance

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1. Introduction

From the beginning of human civilization, robotic technology has progressed towards precision and intelligence [1]. The requirements for labor-saving devices by various industries became key enablers for robotic automation. Robots were deployed to perform various repetitive tasks to reduce labor, ensure uniformity, and produce various affirmative outcomes. However, performing complex tasks on an individual basis is infeasible for robots; therefore, the concept of multi-robot systems was introduced. Multi-robot systems are designed to integrate different principles, enabling a large number of robots to accomplish complex tasks by interacting with each other, as well as with their environment. A survey identified that swarm robotics play a significant role in transcending the restrictions of a single robot by allowing cooperation between multiple robots [2]. This survey also demonstrated the popularity of small drones or micro air vehicles (MAVs), pushing researchers to execute elements of smaller and larger teams, multi-robot systems, clusters, flocks, and swarms, enhancing their robustness, flexibility, and scalability.

Multi-robot systems are classified into two major groups: heterogeneous and homogeneous groups [3]. In a heterogeneous group, different kinds of robots are assigned different duties and responsibilities, whereas in a homogeneous group, the same robots perform a similar task following the same strategy. For instance, four non-holonomic wheeled Khepera III robots are considered in [4]. These complex systems are required to integrate various aspects of decision-making, behavior control, path planning, trajectory tracking, and environmental perception. Additionally, controlling multiple robots in a system is significant for coordinating robots to exhibit collective behaviors, maintaining their structure, and ensuring safety. All these are achieved by flocking control. The term flocking indicates the behavior of various interacting agents (the terms robot and agent are used interchangeably) with shared goals, such as schools of fish, groups of birds, and swarms of insects. Flocking is referred to as a coordinated task executed by dynamic agents using self-organized natural networks. Moreover, researchers categorize flocking control strategies into line flocking and swarming, or cluster flocking [5]. Figure 1 shows that line flocking pursues the motion of geese, whereas cluster flocking observes the motion of schools of fish. Cluster flocking in swarming control is the focus of this research, and this trend will be discussed from a specific perspective.

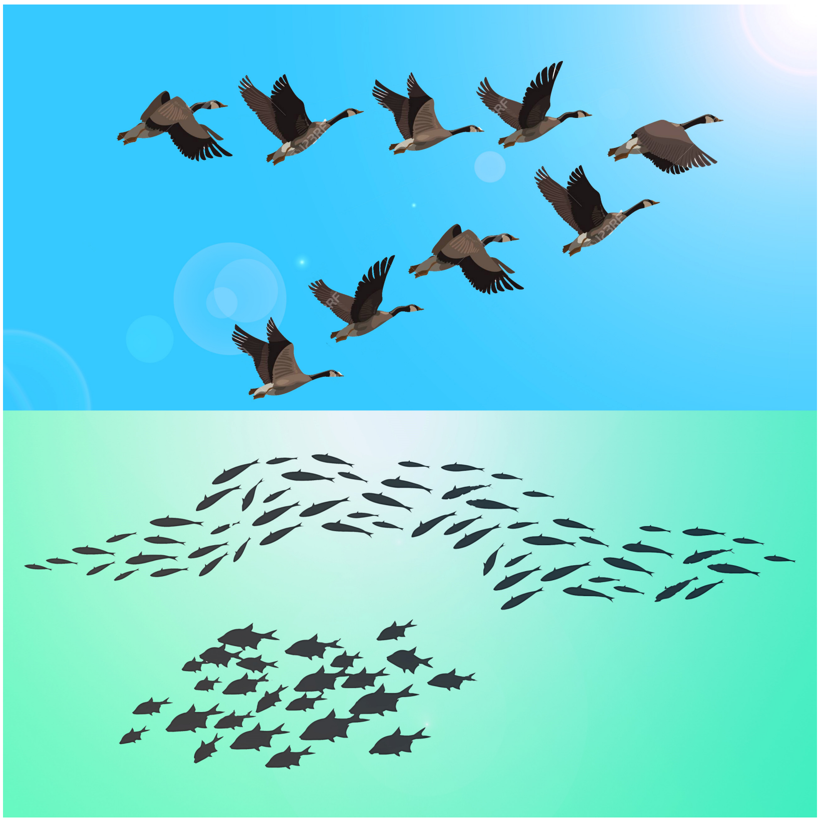

Figure 1. Migration of geese and schools of fish based on the data in Ref. [6].

Flocking control for multiple robots is founded on various schemes. Reference [7] evaluates two schemes, centralized and decentralized, for multi-agent systems of unmanned aerial vehicles (UAVs). In addition, another study defines flocking control based on centralized, decentralized, and hybrid schemes for UAV flocks [8]. According to this study, centralization enables UAVs to achieve a common goal via the decision-making of a single agent or ground station. Decentralization is conveyed among flock members through messages. On the other hand, hybrid schemes integrate central management with distributed decisions. Flocking formations are grouped into leader–follower, behavior-based, and virtual structures [9]. The leader–follower structure assigns a leader which is followed by the remaining robots, which are referred to as followers. Only the leader is responsible for planning trajectories, while the followers are restricted to following the coordinates of their leader. Next is the behavior-based structure in which every single robot shows multiple behaviors according to sensory inputs such as goal seeking, obstacle avoidance, and formation keeping. Contrarily, the virtual structure drives a virtual rigid structure for a group of robots, maintaining a rigid geometric relationship based on a virtual leader or point.

Several approaches to constructing flocking formations are potential field, swarm intelligence (SI), neural networks (NNs), and hybrid approaches [10]. The selection of approach depends on the specific need of the desired behavior of the robotic swarm and its application. Furthermore, multi-robot systems must follow the principles of path planning, trajectory tracking, and obstacle avoidance. In path planning, the objective is to plan the shortest collision-free path from the initial point to the final point, whereas in trajectory tracking, each part of the path is to be attained in a specified time. In certain application tasks, the robots must change the shape of their formation, which may require obstacle avoidance protocols. These protocols assist every individual robot to reach its destination securely while bypassing various obstacles [11]. Moreover, with technical advancements and the incorporation of evolving technologies, such as artificial intelligence (AI), Internet of Things (IoT), big data, cloud computing, etc., the usage of multiple robots is increasing. Multi-robot systems are extensively deployed in the monitoring and management of manufacturing, construction, agriculture, logistics and warehouses, healthcare, and various other domains [12].

1.1. Related Surveys

With the evolution of multi-agent robots, flocking control has been adopted more explicitly. A significant number of studies have considered different aspects of multiple robots with flocking control. An analysis of the recent literature indicates that fewer considerations are given to line flocking. Most of the published review papers are focused on swarm or cluster flocking, analyzing flocking convergence, energy savings, and the minimal requirements of communication and computation. Most of the analyzed research is focused on specific flocking strategies and particular multi-robot systems. Much attention is given to signify their applications in various domains and identify challenges for improvements.

An overview of flocking behavior approaches is offered in [5]. Flocking approaches are classified into cluster and line flocking. The discussed approaches are aimed at energy saving and establishing minimal communication and computational requirements through event-driven planning and neighbor filtering. Another study also carries out a general review of flocking strategies, specifically the optimized schemes that ensure safety for swarm robots [13]. This study maintains aspects of certain systems, for instance, event-driven planning, reduced communication needs, energy, and computational requirements. Researchers evaluate various extensively applied distributed flocking control strategies and present potential prospects for their applications in diverse fields [14]. They further elaborate on the development status at home and abroad, and predict development avenues in the aviation domain. Communication, speed estimation, and collision avoidance are the most discussed challenges in this work.

A comprehensive analysis of cooperative control based on flocking, consensus, and guidance law is proposed for UAVs [15]. The challenges of velocity matching, collision avoidance, cohesion, and complex nonlinear dynamics are highlighted. The discussed applications of cooperative systems are military, mapping, surveillance, border patrol, and search and rescue. In the next survey, UAVs are proposed to be grouped into clusters and flocks [8]. The aggravated challenges in their management and control are identified, and machine learning (ML) methods as solutions are reviewed. Flocks are widely used in the agriculture domain, for security purposes, and in wireless communication applications. On the other hand, this paper presents extensive knowledge of flocking strategies, the application of flocking control-based robots in agriculture, manufacturing, transportation, logistics, healthcare, and medicine, and challenges that hinder performance and the flocking of robots.

Recently, various techniques have been surveyed to promote the cooperative motion planning of multiple robots [16]. This survey evaluates techniques of path planning, task-based motion planning, and obstacle avoidance. This review also explores the significant role of AI. Implementations of clusters or swarms of multi-agent systems are explored in relation to the military, logistics, industry, agriculture, and other domains. In another study, reinforcement learning (RL) approaches are proposed as promising solutions for autonomous multi-UAVs [17]. An overview of RL approaches and their applications in the context of sensing and collection, trajectory planning, localization, network security, etc., are presented. The challenges of multi-objective optimization, resource allocation, cooperation, distributed deep reinforcement learning (DRL) frameworks, joint trajectories, and model training and implementation are also identified. To further advance the deployment of multi-agent grouping or flocking in swarms, researchers propose DRL frameworks and show their tremendous significance [18]. This survey provides insights into versatile applications of DRL-based multi-robot systems of swarm behavior, convergence and exploration, information collection, path planning, task allocation, object transportation, pursuit–evasion, and construction. Certain identified challenges that hinder their wider adaptation are scalability, the data-hungry nature of DRL approaches, lack of resources, the transfer of learned models to real applications, and others. In contrast, this review presents comprehensive knowledge of flocking control, delineating various schemes, structures, and approaches. Moreover, this paper does not focus on any specific flocking or swarming model of multi-agent systems. Instead, this review examines the roles of these cooperative robots in various domains and identifies some challenges.

1.2. Motivation

Multi-agent systems possess the unique advantages of flexibility, scalability, robustness, and significant application prospects. Learning from interesting natural phenomena and examining the group behavior of biological colonies, for instance fish gathering and bird migration, in which all agents coordinate without any organizer, facilitates multi-agent systems with the characteristics of self-organization. This enables systems to become insensitive to local individual faults and failures. Thus, flocking control strategies based on collective behavior inspired by these natural phenomena are increasingly important. This motivates us to provide valuable insights for practitioners and researchers by analyzing the recent studies concerning flocking strategies and compiling them on one platform. This comprehensive review paper aims to promote these strategies for the collective motion of multi-agent systems.

1.3. Methodology and Paper Contributions

A variety of research has been conducted on flocking control techniques for different robots, ranging from mobile robots to unmanned vehicles, covering UAVs, MAVs, unmanned underwater vehicles (UUVs), unmanned surface vehicles (USVs), and unmanned ground vehicles (UGVs). This diverse variety of multi-robot systems is considered and recent advances in flocking control strategies are reviewed in this paper. The search was conducted by developing a search protocol. Research articles were explored via the scientific repositories of the ScienceDirect, IEEE Xplorer, Springer, MDPI, and Google Scholar databases. A combination of keywords from two groups was used to develop strings, and the Boolean operator "and" was applied. The first group contained motion-related keywords: "collective motion, coordinated motion, cluster, swarm, and flock". The other group comprised appellations of different agents (robots or any unmanned vehicles), such as "robots, UAVs, MAVs, drones, unmanned marine vehicles (UMVs), and UGVs". For inclusion, preference was given to the most recent studies ranging from 2024 to 2019. However, some seminal studies were also searched to collect information and insight on how the flocking concept was introduced into control systems. White papers or unpublished papers are not included in this review. After sorting out the first set of references, this paper also examined other related articles. In the final phase, title-based and abstract-based filtering was carried out. Irrelevant papers were excluded. Information was aggregated and analyzed from the selected articles and finally consolidated in this manuscript.

The novelty of this review is significant compared to related surveys in the existing literature, as this review shows all-inclusive aspects. The main contributions of this research are as follows:

- Laws of flocking and swarm or cluster flocking are evaluated.
- Flocking control methods founded on schemes, structures, and classic and state-of-the-art strategies are aggregated and reviewed.
- Applications of multi-robot systems with flocking control and their significance in various domains are explored.
- The challenges of implementing flocking control and multi-robot systems are identified.
- The problem statement of flocking is defined and a solution to the flocking problem is presented in terms of formation control, obstacle avoidance, and approaching targets.

1.4. Paper Organization

The remaining paper is organized into eight sections, as illustrated in Figure 2. Section 2 elaborates on the preliminaries of the flocking phenomenon while evaluating flocking laws and swarming or cluster flocking, and reveals the flocking phenomenon in multi-robot systems. Section 3 classifies flocking control based on schemes, structures, and strategies. Section 4 deliberates on the applications of flocking robots in different scopes. Section 5 details some identified challenges which require future consideration. Section 6 presents the flocking problem statement and flocking control-based multi-robot systems. Section 7 presents the discussion section, whereas Section 8 concludes the paper and evaluates future research directions.

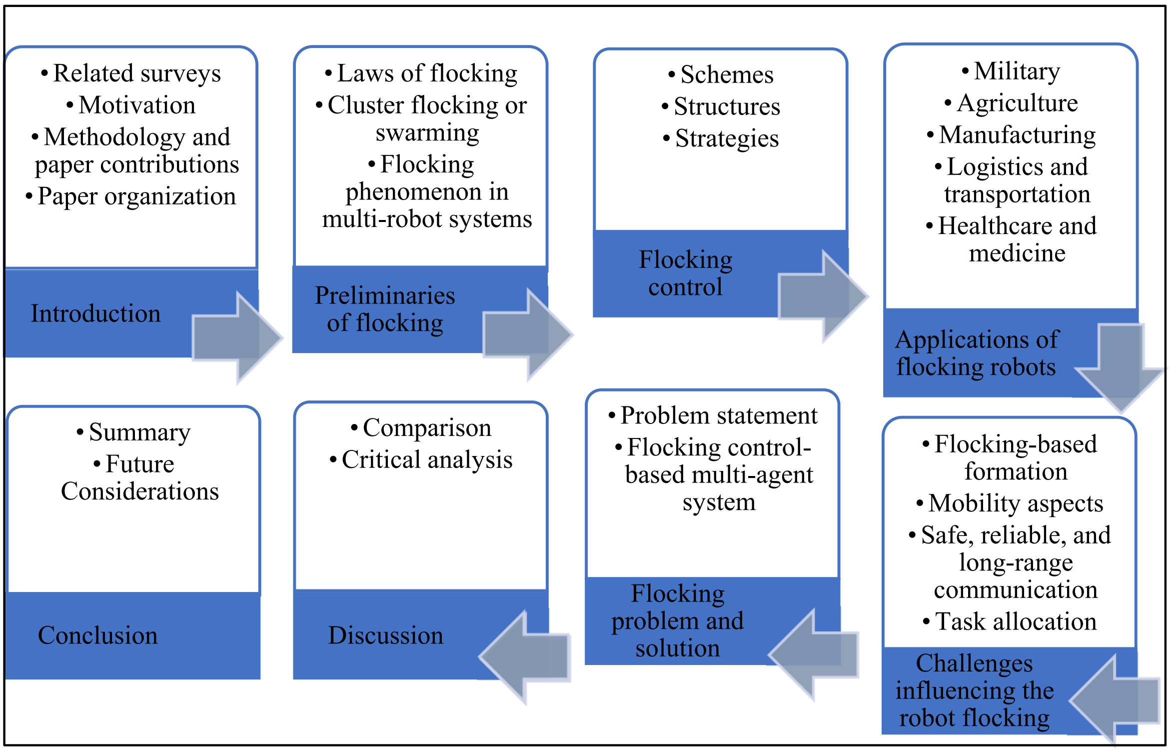

Figure 2. Paper organization.

2. Preliminaries of Flocking Control

Flocking refers to self-propelled agents, their organizations, and spontaneous movements with less environmental information. Flocking follows state-updating rules to form orderly movements, such as those of flying birds, bacterial flora, etc. Flocking control is gaining more attention in robot applications. Robot flocking is inspired by the fact that, in bird flocking, closer neighbors are more influential than farther ones [19]. This section conceptualizes flocking models, cluster flocking or swarming, and the flocking phenomenon in multi-robot systems.

2.1. Laws of Flocking

Flocking control was first simulated by Reynolds in 1987 [20]. Reynolds introduced three basic rules to establish flocking motion models. These rules are based on separation behavior, alignment behavior, and cohesion behavior, as shown in Figure 3. Figure 3a presents the alignment behavior involves matching velocity with neighbors according to the designated combination of speed and heading. Figure 3b illustrates the cohesion behavior is related to flock centering, which keeps robots nearer to the center of flocks. Figure 3c shows the separation behavior that is related to collision avoidance, which means avoiding overcrowding or collisions with neighbors. In Equation (1), a cost function is imposed, where the first term captures the separation and cohesion behaviors and the second term captures the alignment behavior:

$$J_i = \mathrm{V}\left(\left\|p_j(t) - p_i(t)\right\|\right) + \sum_{j \in N_i(t)} \left\|\dot{p}_j(t) - \dot{p}_i(t)\right\|^2 \quad (1)$$

Here, i is an agent with v_i (t) velocity and p_i (t) position belonging to a swarm of N, the number of agents. j is its neighboring agent at any specific instant time, such as $j \in N_i(t)$. $\left\|p_j(t) - p_i(t)\right\|$ is the distance between these agents, $\left\|\dot{p}_j(t) - \dot{p}_i(t)\right\|$ is its transformed second-order linear system, and V denotes the attractive and repulsive potential function.

Later, in 2004, Tanner expounded the flocking conception in an interconnected vehicle group and framed decentralized control with gradient-based and velocity consensus terms [21]. Another pioneering model was given by Viscek, in 2005, where every member aligns its motion with its neighbor's average movement direction until the movements of all members are aligned [22]. Viscek's model restricted members to follow the trajectory tightly, so that the entire system moved along the desired path. Later, in 2006, another flocking framework was proposed by Olfati-Saber [23]. In Olfati-Saber's architecture, three types of agents—α-agents, β-agents, and ɣ-agents—are used to model the swarm agents, obstacles, and shared group objectives. Shaped potential functions describe these agent interactions and allow for the individual tuning of inter-agent forces (attractive and repulsive). To validate that the particles exhibit collective behavior, Cucker–Smale also proposed models for the appearance of flocking behavior for both discrete and continuous time in 2007 [24]. In the same year, Lee-Sponge considered multiple agents flocking, incorporated their inertial effects, and evolved a stable flocking control law based on game theory [25]. The proposed control law exponentially stabilized their internal group shape to a desired one and ensured the convergence of every agent's velocity to the centroid velocity. With advances in the flocking model, various attempts have been made to verify flocking phenomena through experiments.

All these rules laid the foundations for flocking controllers. Researchers follow these rules to design flocking behaviors for robots of a system, such as in [26,27]. The authors adopt five behavioral rules of alignment, separation, cohesion, avoidance, and migration for a swarm of drones and implement an adaptive weighting mechanism for their control [26]. The results validate the effectiveness of the applied control scheme. Another study achieves a flocking behavior based on a simulated annealing (SA) algorithm for AmigoBots (mobile robots) in an environment with unknown obstacles [27]. SA reduces the potential functions by searching the quasi-optimal position of robots. The system acts out separation and alignment behaviors efficiently.

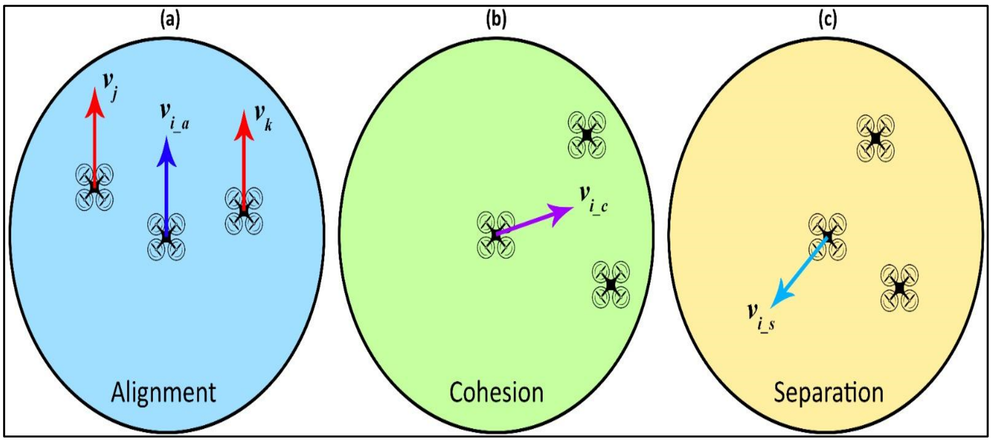

Figure 3. Reynolds rules: alignment rule, cohesion rule, and separation rule based on the data in Ref. [28].

Optimal Reynolds flocking controllers are designed by integrating two approaches [5]. One is a reactive approach, possessing no prior environmental information, whereas, other is a planning approach, requiring some prior environmental knowledge. In the reactive group, the agents establish a movement strategy according to the basic flocking rules and consider local information, such as the behavior of their neighbors. This local information is generated by the neighbors' state, which keeps on updating. However, predator information is included in other strategies that work as additional populations for forcing movement and avoiding sub-groups of agents in a system. Researchers propose model reactive control using iterative learning for a UAV fleet [29]. This controller is expressed as

$$u^*_{t+1} = argmin_{u \in U}\{\|y_o - F(y_{t-1}, u_{t-1}, y_t, u_t)\|\} \tag{2}$$

Here, u_t is the input command and y_t is the output response at time t. U is the action space (backward, forward, no move, up, down, right, left). u^*_t is the uniformly selected action of the leaders and F is the learned model that supports the controller. The UAV employs its earliest state y_o, and according to the forward model F, the UAV finds the best action for launching the target state. The applied strategy efficiently sustains the flocking structure while following the leaders, who are controlled independently and remotely.

The other alternative is the planning approach. The information related to the environment and neighbors is already provided to the agents; therefore, each agent plans an optimal trajectory. These approaches depict a better behavior in terms of performance. The only restriction is the high computational cost that poses much higher demands for the design of every single agent. As these strategies do not have a central control system conceptually, communication links are established between nearby agents that limit planning to only some agents that share information. A dynamic and cooperative strategy named the particle swarm optimization pathfinding (PSOP) algorithm is developed for the dynamic control and navigation of UAV groups in dynamic, unknown environments [30]. This research also develops a drone flock control for reducing collisions. PSOP updates every UAV agent's velocity with Equation (3), as follows:

$$V(t) = wv(t-1) + c_1 r_1\,(p_{best} - p) + c_2 r_2\,(g_{best} - p) \tag{3}$$

Here, w is the inertia, c_1 and c_2 are constants, and $v(t)$ represents velocity at time t. r_1, r_2 belongs to [0,1], whereas p denotes the current position, p_{best} denotes the personal best position, and g_{best} denotes the group best position. Each agent personally determines the highest-quality position (*pBest*). Whereas, the highest-quality position found by any agent is called gBest. Both values are recorded. The developed controller generates accurate, high-quality, computationally efficient, and more usable paths.

2.2. Cluster Flocking and Swarming

The notion of cluster flocking and swarming refers to the aggregate motion of small birds, such as pigeons, sparrows, etc. Its significance in natural systems is not entirely explored. In addition, various assumptions are proposed in the literature. For instance, predator invasion, sensor fusion, and flock size estimation are the main benefits of cluster flocking. Two-level control using flocking control and a decentralized function approximating RL (FA-MARL) is proposed in multi-robot systems [31]. Results show that the applied strategies give a powerful performance in unexplored states, converge, reduce variable numbers, ensure formation maintenance, and avoid predators.

Some studies suggest that leadership-based cluster flocking is optimal. A self-organized flocking strategy is suggested for a heterogeneous robotic swarm system [32]. This self-organized flocking model is a collaboration of collective motion, obstacle avoidance functions, and an optimal controller that enables the lead to steer the swarm through a collision-free trajectory. Findings reveal that applying the proposed mechanisms to swarms requires less storage and power. Others discover that a leader is not always necessary for generating organized motions of clusters. A constraint-driven optimal controller is proposed for multi-robot systems, where agents reduce energy consumption depending on tasks and safety constraints [33]. This study presents velocity consensus as an optimal solution and suggests the introduction of slack variables when each agent can partially observe the global state. In particular cases, specific robots act as gate-way nodes and receive control information before other agents. The mission is disrupted if these robots are identified by an adversary who observes all the agents' trajectories and self-organized flocking strategies to recognize the leader. Thus, another crucial facet, privacy, is introduced in the flocking of mobile robots [34]. Private flocking controllers are proposed using the co-optimization mechanism of the genetic algorithm (GA) and a data-driven adversarial discriminator. The flocking parameters are optimized to hinder the leader inference, improving the flocking performance, and an adversarial discriminator is trained. Results yield high flocking performance and ensure the hindrance of leader.

2.3. Flocking Phenomenon in Multi-Robot Systems

Multi-robot systems, composed of mobile robots or unmanned vehicles, are capable of performing tasks even in areas that threaten human life. Every robot in these systems is simple and has limited design capabilities within its local environment to enhance system scalability. Although applying simple flocking rules involves the treatment of robots as a single entity, emerging collective behavior can be used to attain a common objective [35]. This strength has inspired various researchers to impose flocking phenomena on multi-robot systems to design desirable capabilities that can solve robust and scalable problems.

Some desirable characteristics of multi-robot systems are adaptability, fault tolerance, efficient communication, safety related to obstacle and collision avoidance, etc. Adaptability is an essential characteristic for robots working collectively in a varying constrained environment. Flocking cooperative control based on a distance graph attention (DGAT) mechanism and the RL algorithm is developed for a multi-agent cooperative system under a communication constraint environment in [36]. Using the DGAT mechanism, the number of observed agents does not constrain the policy network input, showing good environmental adaptability to the communication delay and distance and improving the network adaptability to a dynamic scale. Researchers present an optimized flocking, O-flocking, by integrating a GA with a flocking framework for a robotic swarm [37]. This research enhances the adaptivity, scalability, and reliability of the swarm in autonomous navigation.

Faults, either temporary or permanent, in any single member of a multi-robot system can affect the complete mission. Identifying and isolating the fault and mitigating its effects is essential. One study implements a hybrid GA with particle swarm optimization (PSO) to design a fault-tolerant control that can detect and isolate severe actuator faults and reconfigure the formation of healthy mobile robots to complete missions [38]. Another study proposes a self-organized flocking algorithm employing a leader–follower approach and fault-tolerant features [39]. While navigating towards a destination, the weary leader of the multi-robot system is automatically replaced by its next follower, imitating the self-healing function in this study. Next, the fundamental feature in multi-agent systems is efficient communication, ensuring the cooperative coordination and information security of unmanned vehicle groups. An improved Olfati-Saber flocking algorithm with a virtual leader and virtual communication circle is suggested for UAV swarms in [40]. This applied method controls the communication power of every agent and improves the moving function, ensuring secure and stable communication and the collision-free movement of the UAV swarm. The problems of communication distance and delays are also addressed in [36].

Obstacle avoidance and collision avoidance are other major necessities to ensure safety, and are studied in [41–43]. A parallel-triggered scheme is introduced in the virtual leader–follower flocking control of multi-UAV platforms [41]. This strategy improves the quality of flight systems by solving the flight stability issue in terms of obstacle conditions and performing collision avoidance maneuvers. A multi-agent deep reinforcement learning (MADRL) approach with a collision-avoidance policy is developed for multi-UAVs in obstacle-cluttered environments in [42]. The collision-avoiding flocking task is split into various subtasks. MADRL performs well even when the subtasks (obstacles) are progressively increased, and solves them in a staged manner. Another study deploys a bio-inspired compact UAV swarm in an outdoor environment and an ultraviolet direction and ranging (UVDAR) technique for perceiving the local neighborhood, ensuring self-organization and safe navigation among obstacles [43].

3. Flocking Control

This section presents the taxonomy of flocking control into schemes, flocking structures, and approaches, as portrayed in Figure 4. Flocking schemes are categorized into four schemes: distributed, decentralized, centralized, and hybrid schemes based on computational and communication frameworks. Flocking control structures are classified into leader–follower-based, behavior-based, virtual structure-based, pinning-based, and dynamic adaptive flocking structures corresponding to composed topologies. Furthermore, flocking control strategies are classified into artificial potential field (APF), model predictive control (MPC), SI with little bio-inspired, AI, and hybrid control paradigms.

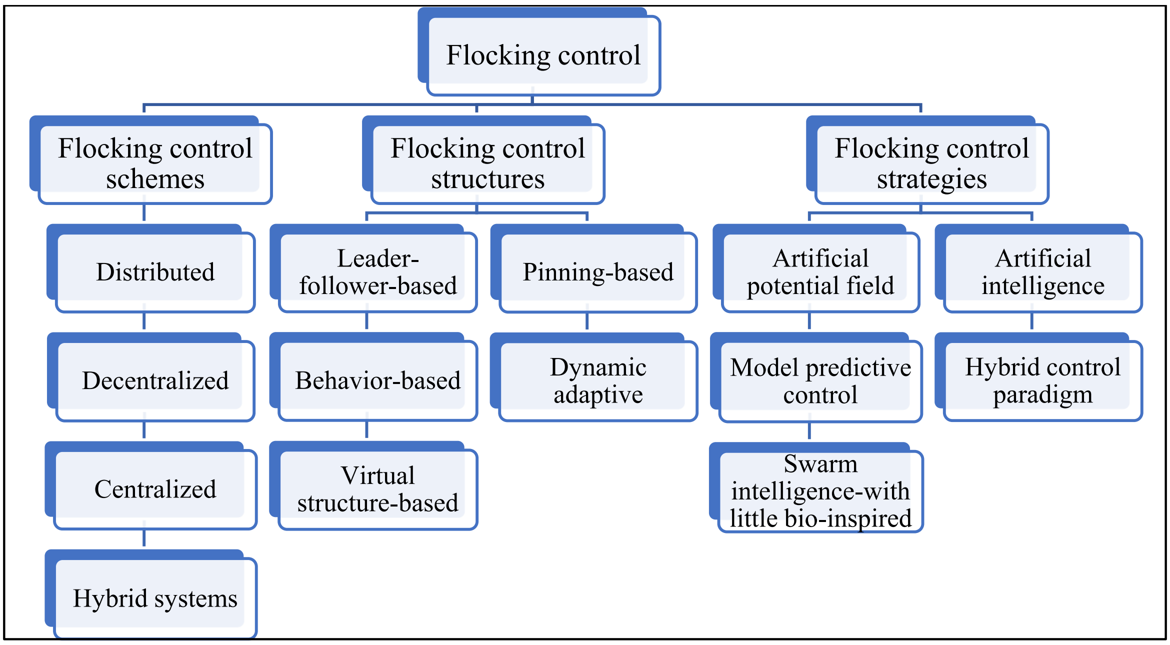

Figure 4. Classification of flocking control into schemes, structures, and strategies.

3.1. Flocking Control Schemes

Local and global knowledge distribution among all members of a multi-robot system has a driving role in controlling flocking phenomena. In case of non-uniform environmental knowledge, or if the agents are required to be controlled externally, flocking control schemes are grouped into distributed, decentralized, centralized, and hybrid schemes. The distributed schemes [12,17,20] allow agents to communicate and share information with other agents. Every robot act as a processing unit and is capable of analyzing the environment and making decisions independently. Comparably, distributed schemes have more scalable system structures and robust communications [40,41,44]. Conversely, decentralized schemes are independent control techniques that do not allow communication between agents. The agents explore the environment independently, with no leader or supervisor, through randomized motion control. For instance, a decentralized control implementing a rendezvous algorithm has been proposed that allows a mobile agent's group (with restricted communication capabilities) to reach its destination while avoiding collisions [45]. In this research, fixed towers with localization sensors direct mobile agent groups with noisy positional data, and improved flocking rules ensure collision-free movements.

Centralized schemes require additional communication and computational capabilities. Centralized schemes have a core unit, such as a ground receiving station, a motion capture external system, a global positioning system (GPS), or an agent with efficient computing power. All the team members are connected to this core unit, which collects their data and monitors and coordinates their group behavior with responsibility. A platform with a drone swarm, a motion capture system named OptiTrack, a ground control system (GCS), and a router are designed under a complex environment [28]. OptiTrack acquires the ground truth of velocity and position for every swarm member while the GCS transfers these parameters to some specified drones. Flocking swarms accomplish missions with greater flexibility. In addition, centralized frameworks are commonly adopted to ensure flocking stability and enhance the communication efficiency of autonomous underwater vehicles (AUVs) in deep-sea exploration and maritime transportation systems. For instance, a software-defined networking (SDN) controller acts as a leader or director for improving flexibility and managing AUV flock-founded underwater wireless networks (UWNs) with the objective of empowering smart oceans [46]. In a similar way, a centralized management feature of SDN-enabled AUV flocks efficiently accomplishes underwater path planning operations better than distributed ones. In another work [47], a co-design solution for flocking and channel estimation is developed for AUV flocks in maritime transportation systems. The results reveal the superior performance of the co-design controller while taking into account the issues of shadow, path loss, and multipath fading channels. Reference [7] defines a centralized protocol, as outlined in Equation (4), and a decentralized protocol, as outlined in Equation (5):

$$a_i^c(w) = c\sum_{j\in N} u_{ij}\left(x_j^w - x_i^w\right) \tag{4}$$

$$a_i^d(w) = -c\sum_{j\epsilon N} f_{ij}\left(x_j^w - x_i^w\right) \tag{5}$$

Here, a_i^c is the centralized control and a_i^d denotes the decentralized control applied to agent i. N is the number of agents, with agent i and neighboring agent j in a graph. Agent i is at position x_i and has velocity v_i, acceleration a_i, and centralization strength or coupling factor c. Agent j is at position x_j. The symbol w is a step-in time T (iteration number), u_{ij} is the connection strength, and f_{ij} is the weakening centering effect.

Previously, researchers have relied on centralized schemes. However, due to the weak reliability and fault tolerance of centralized strategies, distributed strategy-based systems are considered more competitive. Research designs have distributed flocking control and suggest that centralized flocking control for UAVs under obstacle environments is a multi-objective optimization problem [48]. Some studies develop flocking control systems in new hybrid frameworks and integrate the distributed control of flock members with centralized management. Combining the essence of both schemes incorporates the benefits of information availability and efficiency with less complexity in time and space. Reference [49] presents centralized control for mission planning at swarm level, with a distributed control for state estimation, navigation, and mission execution at robot level. The designed hybrid control overcomes the limitations of a single MAV and facilitates the deployment of MAV or UAV swarms. In addition, another study develops a hierarchical-interaction-based framework for a second-order multi-agent system composed of an MAV and two UAV swarms [50]. The proposed controller design has a trajectory-tracking controller and a distributed controller for MAV and UAV swarms, respectively, which efficiently address the cooperative control problem.

3.2. Flocking Control Structures

Controlling is essential to achieve better cooperation among multi-robot systems or large-scale swarms. Various flocking structures based on different configurations are proposed in the literature to organize multi-agent systems. These include leader–follower, virtual, pinning-based, and dynamic adaptive flocking control structures. A brief description of the mentioned flocking structures is given below.

3.2.1. Leader–Follower-Based Flocking Structure

In leader–follower flocking structures, one agent is manually or dynamically assigned as a leader according to some criteria, while others are entitled as followers. Figure 5 shows a swarm with one leader (UAV 0) and five follower agents (UAV 1 to UAV 5). The swarm leader has more capabilities and global knowledge of a path, acts independently, and potentially holds the movement direction of the entire flocking structure by navigating along a predetermined path. Later, the followers identify and follow their leader while maintaining the formation. One study models leader–follower flight for MAV swarms and utilizes an ultra-wideband (UWB) localization sensor for communication and a higher-accuracy estimation of range and motion [51]. The onboard sensors efficiently enable the followers to track their leader's trajectory during an entire flight in an indoor environment. The implementation of the leader–follower control structure is simple and extensively adopted for flocking agents by researchers.

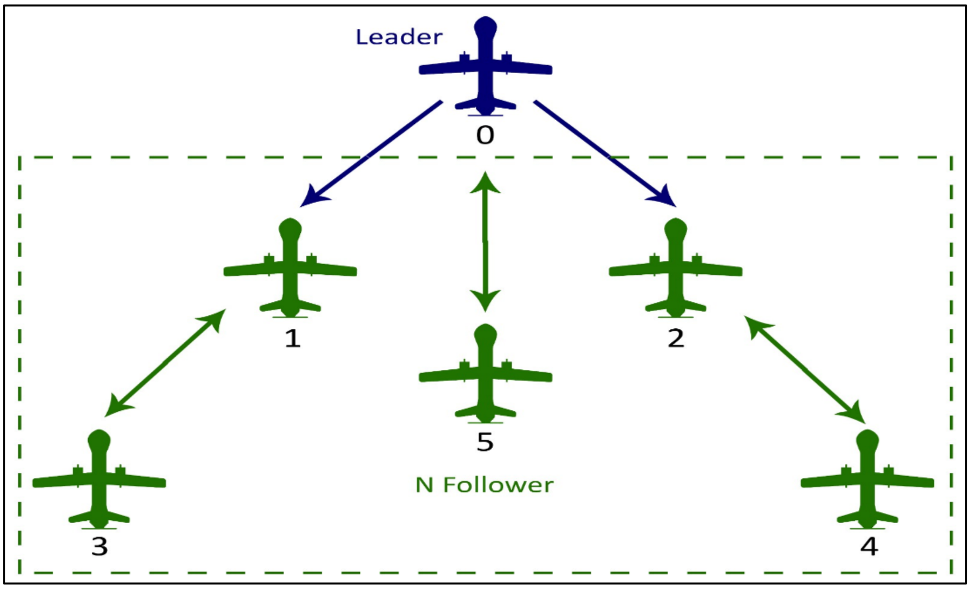

Figure 5. Leader–follower-based flocking structure based on the data in Ref. [52].

In leader–follower flocking structures, two communication issues exist. A broad body of literature focuses on the agent–leader communication problem, which arises as the leader information is only supplied to the informed agents. However, the subsequent communication issue, emerging because agents face failures in obtaining or transmitting information, is ignored. In this regard, study [53] presents an improved Olfati-Saber framework with a local feedback mechanism, addressing the effects of agent–leader communication and agent self-communication issues on flocking cohesion and integrity. The proposed potential function promotes more agent interaction and allows the informed agents to transmit information exhaustively, improving flocking cohesion and integrity while reducing time.

3.2.2. Behavior-Based Flocking Structure

Agents of a multi-robot system are specified with various expected behaviors of cohesion, obstacle avoidance, collision avoidance, etc. Behavior-based flocking structures are constructed when these expected and desired behaviors are required for multiple tasks. A behavior-based approach is developed to investigate collision problems between UAV flocks [54]. This approach ensures safety when flocks meet. A more intuitive behavior-based decentralized method is proposed for robot swarms [55]. Artificial force, reliant on neighbor interactions, is elucidated in this work in terms of maintaining shape integrity and encountering obstacles. The aforementioned paper concludes that some shapes are more convenient to form and maintain than others.

Coordinating robot swarms in a circular structure requires robots to orbit with constant speed rather than controlling the spatial relations between them. The authors of [56] propose behavioral-based circular structures for robot swarms. They model and coordinate swarming robots based on tornado schooling fish behavior with distributed decision-making ability. This dense robot swarm maintains speed for orbiting a circular path, ensuring no collisions, adding resiliency, and facilitating practical applications.

3.2.3. Virtual Structure-Based Flocking Design

Flocking robots maintain virtual links or connections with other neighbors and form a coveted geometric pattern in virtual structures. First, the kinematics and dynamical features of the required structures are determined, and then the corresponding features of the virtual destination are deduced. Finally, an appropriate control law is designed to track the corresponding characteristics of the virtual destination. Some studies propose a virtual leader to handle the formation problem of multi-agent flocks, employing a rigid virtual structure in which the agents have to track the movement of a fixed point. For example, a virtual leader is constructed to generate and maintain a desired formation [41]. Then, the aforesaid study treats the formation transformation by shifting the relative positional relationship between the virtual leader and each UAV in a distributed manner. In another study [57], the fundamental Reynolds flocking principles are aligned with APF-based virtual leader-based formation to execute intricate maneuvers within a swarm while maintaining desired configurations. APF-based virtual leaders seamlessly integrate local and global control, ensuring appropriate force range with real agents and effectively generating smooth navigation in an obstacle-laden environment.

Flexible formations that may be modified according to the environment and rigid formations such as circles can be formed using virtual reference points, but require a clear target position of every single agent from initial to aimed formations. From this perspective, a virtual structure approach is employed for UAV swarms to express and track formation reference points uniformly [58]. Figure 6 displays a 10-node network with a leader UAV following a virtual guidance point to track a reference trajectory. All the coordinator and follower UAVs in this figure configure themselves according to the leader.

3.2.4. Pinning-Based Flocking Structure

The dynamic control of every robot is not essential to achieve flock behavior stability, especially in dynamic networks. Therefore, leader-related knowledge is not necessary for all group members. Only a few agents are pinned agents, commonly referred to as informed agents, which are supplemented with the leader information. Figure 6 shows that Agent 4 and Agent 5 are the pinned agents. The navigational feedback term is owned by these agents only, which allows a satisfactory occurrence of the flocking phenomenon. However, selecting pinning nodes is an NP-hard problem. From this context, researchers employ the matrix eigenvalue theory for the optimal nomination of pinning agents [59]. The results illustrate that pinning control attains multi-agent synchronization and accelerates the convergence rate for flocking.

Pinning control handles the motion of large-scale multi-agent groups. From a network perspective, a self-organized flocking model of a drone swarm with pinning control is developed [60]. Driver drones (pinning agents) are selected using multiple selection strategies. Controlling these well-selected drones commands the massive motion of a drone swarm. Further, these well-selected drones are capable of carrying out tasks robustly and efficiently. While controlling large-scale groups, pinning control reduces energy consumption and ensures that there is no collision. A pinning control is implemented for the modified virtual leader–follower Cucker–Smale model with external perturbation with regard to [61]. The introduction of a virtual leader model with pinning control allows adaptability and flexibility in acquiring specific speed and restricting external perturbations, enabling the system to attain asymptotic flocking. Moreover, the pinning control addresses the collision avoidance issue of the Cucker–Smale flocking model.

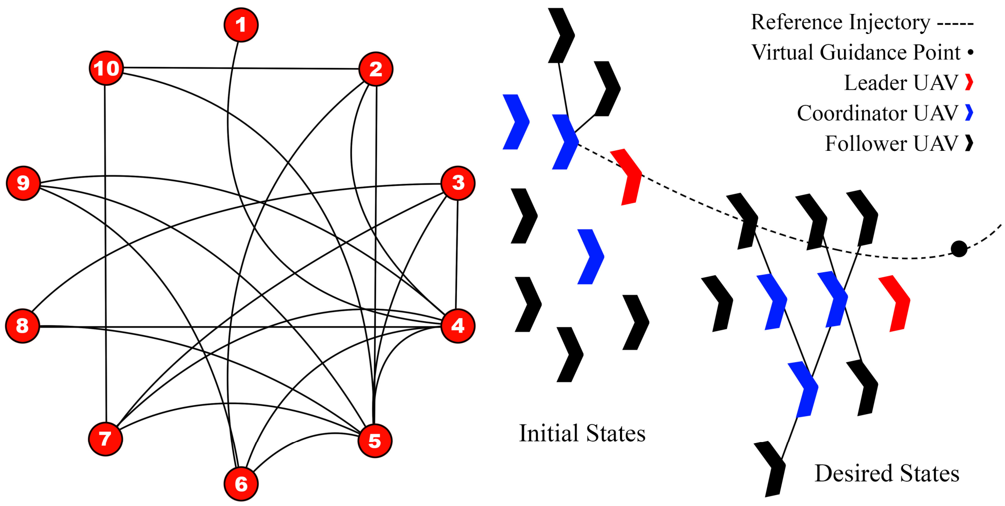

Figure 6. Pinning-based and virtual-based flocking structures based on the data in Refs. [62,63].

3.2.5. Dynamic Adaptive Flocking Structure

Dynamic adaptive flocking structures are used to design specific frameworks to express other leader–follower structures, virtual structures, etc., in special cases. In dynamic adaptive flocking structures, flocks or swarms reconfigure their formations according to environmental changes, wind interferences, obstacles, the addition or loss of agents, and diversified task requirements. Flocking based on such structures facilitates the real-time deployment of swarms, maintains cohesion, ensures the avoidance of obstacles, and reforms configurations, as depicted in Figure 7. Researchers have designed pigeon behavior approaches, multiple virtual point formation shapes, and decision functions allowing UAV swarms to switch or adjust their structure in real and complex environments [64]. Some authors developed an adaptive decentralized control founded on vector fields and backstepping for UAV swarms and discarded the assumption of strictly following circular positioning under atmospheric disturbances [65]. This new decentralized flocking control enables the swarm to coordinate its flocking to a particular circular path, destabilize the formation if needed, and apply adaptive self-tuning to neutralize effects.

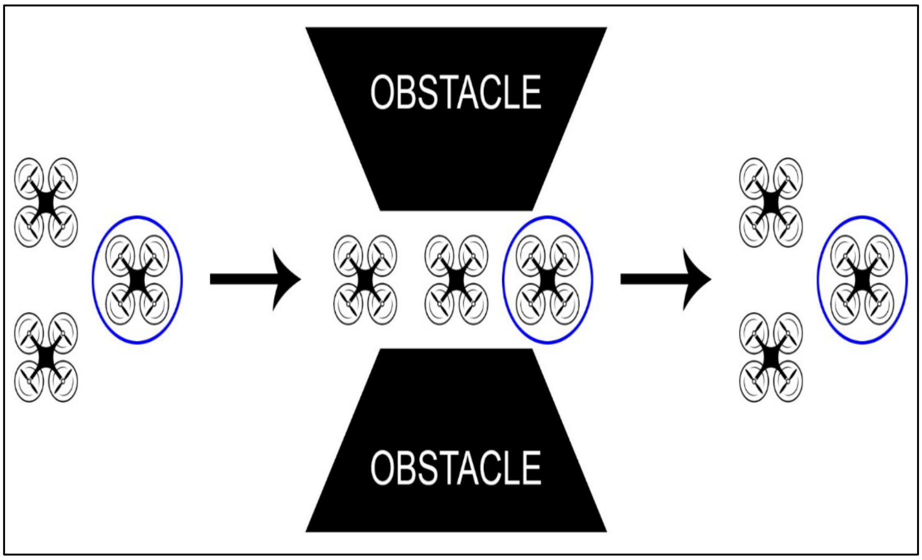

Figure 7. Dynamic adaptive flocking structure based on the data in Ref. [66].

In some cases, Reynolds rule-based strategies are incapable of acquiring intricate adaptive learning mechanisms similar to birds navigating dynamic environments. Reference [67] incorporates the MARL approach into Boid modeling for drone swarms. The results reveal that the applied methodology trains individual drones and optimizes individual and collective behavior, allowing autonomous decision-making and drones to excel in adaptability and proficiency in navigating mutable, complex environments. In the case of flying a swarm through narrow corridors restricted by obstacles, reactive behaviors usually lead to congestion, ultimately slowing down speed and reducing the distance between swarming agents, enhancing collision risks. Considering these issues, a decentralized behavioral model from extended Reynolds rules and graph search algorithm A^*-based path planning is employed to operate a drone swarm and adapt to an environment with obstacles [68]. This study proposes mean field game (MFG) theory for learning and predicting the behavior of large-scale interacting agents and considers Cucker–Smale kinematics for agents. A reference trajectory is updated and optimized through the A* algorithm, which divides the considered swarm into sub-swarms, anticipates congestion, avoids slowing down, and forces the swarm to revolve around obstacles.

3.3. Flocking Control Strategies

Methods based on Reynolds rules, the Cucker–Smale model, APF, and MPC are widely employed as traditional strategies. Contrarily, swarm intelligence with little bio-inspired strategies and AI-based techniques are newer, modern methods for developing flocking control as a result of advancements in research and technology. Moreover, hybrid approaches are also considered by researchers. Some of these approaches are delineated below.

3.3.1. Artificial Potential Field Method

APF is a traditional technique to formulate flocking control, employing attractive and repulsive forces. In multi-agent systems, agents navigate through APF, where attractive forces bring them closer to neighboring agents and ensure formation convergence. Repulsive forces propel them away from neighbors and obstacles and guarantee the absence of collisions. APF is used to address the obstacle avoidance issue for multiple USVs in [69] and UAV swarms in [58]. Reynolds rules form the basis of this. Moreover, APF theory is integrated into the SDN controller of AUV flock-based UWNs for avoiding extensive obstacles and no-go areas in [46] and for early warning obstacle avoidance in [70]. Besides handling obstacle and collision avoidance problems, APF is extensively adopted for stabilizing flocking formations in complex, unknown environments.

Certain studies have improved the performance of APF, complementing flocking control. Rather than applying the APF method directly, a mapping procedure is added, and APF topology is controlled for a swarm of unmanned vehicles [71]. Mission efficiency is significantly boosted by controlling APF topology. Moreover, the applied strategy leads to maintaining network connectivity, avoiding collisions, and executing missions in versatile environments. In another work, the conventional APF function is improved using a light transmission model for a UAV swarm to boost the APF performance [72]. Improved APF function realizes swarms with attraction in remote range, repulsion in short range, and position and speed cooperation in mid-range in large-scale swarming systems.

3.3.2. Model Predictive Control

MPC is also considered a classic method instead of a modern one for controllers and has existed for several decades. In MPC, control sequences are optimized over a defined time using a predictive framework of system dynamics. The constraints on inputs and the state of the system are also considered. The optimization problem is addressed to regulate optimal control action, usually with feedback-incorporating ability at every time interval. However, MPC has not gained as much popularity in the flocking domain as modern techniques have. Nevertheless, MPC offers opportunities for handling complex dynamics, incorporating constraints, and ensuring stability for flocking systems [73]. In [74], researchers determine that Reynolds rules-based reactive behaviors of flocking UAVs in swarm robotic systems can be derived with potential fields, but that this may cause inefficient motion and collisions. Therefore, they implement MPC with an emphasis on other agents' predicted states in a computationally efficient manner, and generate faster, safer, optimum, and smoother flocking in static and dynamic obstacle environments in simulation and indoor experiments.

MPC, capable of adjusting interaction forces (attractive and repulsive), is suggested for flocking agents [75]. This distributive framework addresses obstacle avoidance, input constraints, and group objective pursuits. Another study designs distributed MPC (DMPC) to refine the coordinated performance of UAV swarms [63]. Every UAV agent is equipped with independent MPC to employ predictive information to respond to and induce collective motion. Thus, DMPC proves to be effective, maintains the desired structure under typical situations, and improves the collaboration among leaders, coordinators, and followers, enhancing coordination efficiency. Similarly, MPC-based distributed control is developed to maintain connectivity and ensure dynamic formation and the absence of collisions among UAV swarming agents and between static obstacles and swarming agents [76].

3.3.3. Swarm Intelligence with Little Bio-Inspired Approaches

Swarm intelligence (SI) with little bio-inspired approaches considers a group of agents as a whole and takes opportunities from appropriate decisions, actions, or experiences of these entities. SI is the soft bionics of natural groups. All SI strategies with little bio-inspired algorithms mimic the collective behavior of decentralized and self-organized systems. SI-based bio-inspired flocking with a leader–follower-based structure is designed for large-sized flapping-wing flying robots (LFWFRs) [77]. The designed control increases the flight efficiency and search range of LFWFRs, maintains relative distance, handles trajectory divergence problems, and realizes multiple formation and flight modes.

Insect-inspired SI techniques include bee colony optimization (BCO), butterfly optimization (BO), the dragonfly algorithm (DA), the firefly algorithm (FA), mosquito flying optimization (MFO), and ant colony optimization (ACO). Taking inspiration from the two mate-locating behaviors—perching and patrolling—of butterflies (male), researchers [78] introduced the BO algorithm for solving multi-modal and multi-dimensional optimization problems. BO employs patrolling behavior for search space exploration and perching behavior for search space exploitation. The findings revealed that BO outperformed PSO, artificial bee colony (ABC), and differential evolution (DE) in terms of accuracy, efficiency, and capability. Study [79] proposed DA, another novel SI algorithm, based on static and dynamic dragonfly swarming behavior. DA controls five behavioral rules—cohesion, separation, alignment, attraction (food searching), and distraction (enemy avoiding)—of swarm individuals. Further, binary DA (BDA) and multi-objective DA (MODA) were also considered. DA and BDA improved the initial random population and converged towards the global optimum, whereas MODA determined accurate approximations with high uniform distribution. To address nonlinear global optimization problems, the authors of [80] integrated Lévy walk and FA to combine random search methods as an eagle strategy. The results illustrated that this strategy is effective for stochastic optimization with a high success rate. Other researchers [81] modeled and incorporated mosquitoes' sliding and flying motion behavior in MFO, which proved to be accurate, convergent, and efficient for global minima.

Motivated by the lifestyle and characteristics of birds, various SI algorithms have been introduced, such as the cuckoo optimization algorithm (COA), pigeon-inspired optimization (PIO), PSO, the starling-behavior-inspired approach, and the bat algorithm (BA). For instance, in [82], researchers developed a cuckoo optimization algorithm (COA) while admiring the influence of cuckoo lifestyle, egg-laying, and breeding characteristics. COA proved to be a fast, convergent, and global optima achiever appropriate for continuous nonlinear optimization problems. Taking inspiration from starlings, other authors developed a distributed framework for UAV swarms [83]. The flocking control founded on starling behavior allows the UAV swarm to aggregate, improve speed and order, and ensure collision-free motion planning under an environment with static and dynamic obstacles. On the other hand, BA is suggested for a multi-robot system under an occluded environment [84]. BA proves to be exceptionally useful for maintaining strong cohesiveness among agents and switch formations whenever obstructions appear.

3.3.4. Artificial Intelligence

The potentials of AI-based flocking strategies have displayed remarkable results in diverse applications. Extensively adopted AI techniques include ML [8], RL [85], multi-agent reinforcement learning (MARL) [86], DRL [87], NNs [88], and fuzzy logic [89,90]. Among these, ML algorithms assist robots in understanding their surroundings, identifying and recognizing patterns [91], and interpreting data. Various aspects of ML methods are provided and surveyed for managing UAV flocks [8]. ML methods successfully address formation, maintenance, and other computational challenges of managing UAV flocks. Another AI technique, the RL algorithm, applies a reward function for iteratively guiding agents' actions and gains success in flocking control. Researchers analyze the performance of multi-objective RL for planning the decentralized control of UAV flocks [85]. The results illustrate that RL planning acquires way-point-based flocking while accounting for wind gusts. Alternatively, MARL frameworks enable multiple robots to learn collectively via inter-robot and environmental interactions [86]. Correspondingly, DRL techniques use trial and error to instruct agents to learn optimal flocking behaviors employing no explicit rules. A DRL-based architecture for UAV flocks is developed that trains an end-to-end flocking control and solves the leader–follower structure issue in continuous spaces [87].

NNs, specifically graph recurrent neural networks (GRNNs) and graph convolutional neural networks (GCNNs), are applied to agents for learning and imitating flocking behavior by incorporating historical data. The potentials of GRNNs and GCNNs are explored for learning optimal flocking-based decentralized controllers to tackle communication delays [88]. The naturally distributed architectures of NNs prove to be stable and equivariant, resulting in good scalability with transferability properties. The other AI technique, fuzzy logic, enables more flexible flocking control by defining rules as fuzzy sets and linguistic variables. Furthermore, fuzzy schemes are considered to solve multiple optimization problems of guidance, navigation, and obstacle avoidance in a similar manner. As noted in the literature [89], fuzzy logic is used for obstacle avoidance and the navigation of multi-robot systems. Correspondingly, fuzzy logic is applied to empower the navigation of robot swarms in an arbitrary-shaped environment [90]. Rather than avoiding massive obstacles, the employed distributed behavioral control based on fuzzy logic first transforms the swarming structure to a linear configuration and then follows the obstacle boundary. Moreover, groups have unusual effects on collective dynamics due to their reduced tendency to form stable patterns. In this regard, one study [91] proposes a cluster analysis algorithm, QuickBundles (QB), for the spatial–temporal and tractography analysis of the movement of pedestrians. QB clusters their trajectories and manages large trajectory quantities both from efficiency and effectiveness perspectives.

3.3.5. Hybrid Control Paradigms

Multiple approaches are combined to enhance performance and robustness by leveraging the potential of various strategies. Numerous research bodies have acknowledged the strengths in the context of cluster flocking and swarming. APF is proposed with Lévy flight (LF), a bio-inspired random movement technique, for a swarm of mobile robots [92]. LF-APF acquires the flocking effect, enabling the swarm to adapt to the environment and reform the flocking structure. Researchers recommend LF-APF for flapping drones. A dynamic PSO is integrated with fractional-order velocity-incorporated history-guided estimation (PSO-FOHE) for dynamically optimized flocking [93]. PSO-FOHE improves the synchronization, efficiency, and safety of the swarm with no prior environmental information.

Pre-tuned fuzzy interference is not robust under uncertain dynamic environments. A fuzzy technique is infused into an RL approach (Fuzzy-RL), formulating an adaptive distributed technique for flock systems to tackle the limitations of pre-tuned fuzzy interference [94]. Fuzzy-RL schemes handle various objectives of collision avoidance, leader–follower flocking structure, and velocity consensus when dynamic disturbances are faced. Reference [95] suggests an RL-based leader–follower flocking and designs a homogeneous graph neural network (HGNN). The HGNN is founded on a multi-agent deep deterministic policy gradient (MADDPG) method. The findings reveal a faster cluster consensus with more stable control in contrast to traditional RL-based strategies. In a similar way, RL is also integrated with SI algorithms to overcome the fission–fusion behavior of UAV swarms in environments with unknown dynamic obstacles [96]. This study initially proposes starling-inspired interaction in UAVs for faster local convergence with reduced overhead communication and subsequently develops a self-organized fission–fusion controller for autonomous reconfiguration. Eventually, an RL-based sub-swarm confrontation algorithm is designed to optimize path planning, handle adversarial motion while encountering dynamic obstacles, and reduce energy expenditure.

Table 1 provides a comparative analysis of the flocking control schemes, structures, and strategies discussed in these sections.

Table 1. Comparative analysis of flocking control schemes, structures, and strategies.

Reference	Multi-Agent System	Focus	Flocking Scheme	Flocking Structure and Strategy	Advantages	Limitations
De Sá and Neto [7]	UAVs	Collision avoidance	Centralized and decentralized	Virtual structure with leader	➢ Shows satisfactory results.	➢ An increase in agent numbers enhances collision avoidance matrix complexity, affecting method efficiency.
Konda et al. [31]	Multi-robot flocks	Predator avoidance	Distributed	FA-MARL	➢ Gives a powerful performance in unexplored states. ➢ Converges. ➢ Reduces variable numbers. ➢ Ensures formation maintenance. ➢ Avoids predators.	➢ The action space requires discretization. ➢ Applicable for less sophisticated predators only.

Table 1. *Cont.*

Reference	Multi-Agent System	Focus	Flocking Scheme	Flocking Structure and Strategy	Advantages	Limitations
Ban et al. [32]	Robot swarm	Collision and obstacle avoidance	Distributed	Self-organized flocking with a leader–follower approach	➢ Enables the leader to steer the swarm through a collision-free trajectory.	➢ Does not focus on optimization of parameters.
Beaver and Malikopoulos [33]	Multi-robot cluster	Energy-reducing cluster flocking	Decentralized	Behavior-based and constraint-driven paradigm	➢ Enables agents to reduce energy consumption.	➢ Does not cover dynamic topology or environmental obstacles.
Zheng et al. [34]	Mobile robot flocks	Flocking with privacy	Decentralized	GA-data-driven adversarial discriminator and leader–follower structure	➢ Gives high performance. ➢ Hinders the leader's inference.	➢ A slower process. ➢ Hiding a leader along reference linear trajectories increases the difficulty.
Fu et al. [44]	UAV swarm	Formation maintenance and reconstruction	Distributed	Virtual leader and APF	➢ Generates and maintains a desired structure. ➢ Flexible transforms formation. ➢ Effectively avoids obstacles.	➢ Does not incorporate time delay into communication.
Lin et al. [46]	AUV flock-based UWNs	Path planning	Centralized	APF	➢ Generates exact path planning. ➢ Efficiently manages AUVs, improves flexibility and scalability. ➢ Avoids obstacles and no-go areas.	➢ AUVs designated for underwater exploration plan their cruising path without considering overall control states.
Van Der Helm et al. [51]	MAV swarms	Indoor leader–follower flight	Distributed	Leader–follower control	➢ Followers efficiently track leader. ➢ Shows harmony between MAV behavior and localization sensor.	➢ Can initially falsely converge to spurious states. ➢ Less memory-efficient.
Li et al. [53]	Multi-agent flocks	Communication barriers affecting cohesion	Distributed	Leader–follower structure and local feedback mechanism	➢ Enhances cohesion and integrity, as well as reduces the time for flock formation. ➢ Promotes interaction and broad information transmission by informed agents.	➢ Does not account for energy consumption, environmental perturbations, or damping forces.
Wang et al. [54]	UAV flock	Obstacle avoidance	Distributed	Boid model behavior-based approach, improved APF, and detect velocity obstacles approach	➢ Forms more space to avoid collisions. ➢ Generates shorter trajectories.	➢ Detect velocity obstacles approach gives more complicated calculations.
Soma et al. [55]	Robot swarm	Shape formation and maintenance	Decentralized	Wall-following behavior-based and leader–follower approach	➢ Maintains shape integrity. ➢ Reduces the sensory overhead and shape distortion.	➢ Involves some amount of shape deformation in the final state.
Bautista and de Marina [56]	Robot swarm	Circular formation	Distributed	Tornado schooling fish behavior-based approach	➢ Robots maintain speed. ➢ Facilitates smooth, safe, and scalable overtakes.	➢ Assumes unicycles with constant speeds.
Kang et al. [57]	UAV swarm	Optimal configuration with intricate maneuver execution	Distributed	Reynold principle and virtual APF-based leader control	➢ Coordinates local and global trajectory optimization. ➢ Avoids obstacles and preserves formation.	➢ Requires an adjustable environment. ➢ Not reliant on practical applications.
Liu et al. [59]	Multi-agent flocks	Optimal selection of pinning nodes	Distributed	Pinning control with virtual leader	➢ Attains synchronization. ➢ Accelerates convergence rate. ➢ Handles motion of a large-scale group.	➢ -.

Table 1. *Cont.*

Reference	Multi-Agent System	Focus	Flocking Scheme	Flocking Structure and Strategy	Advantages	Limitations
Ren et al. [61]	Multi-agent system	Collision avoidance	-	Virtual leader–follower Cucker–Smale model with pinning control	➢ Attains asymptotic flocking. ➢ Improves flocking speed.	➢ Flocking behavior is attainable only if the specified perturbations meet, reducing model robustness.
Qu et al. [94]	Multi-agent flocks	Flock-guidance	Distributed	Fuzzy-RL and leader–follower structure	➢ Formulates an adaptive control. ➢ Ensures collision avoidance.	➢ Does not consider time-varying graph topologies.

4. Applications of Flocking Robots

Flocking control strategies enhance the capabilities of robots in terms of response, connectivity with other robots, stability, adaptability to the environment, and robustness. Flocking control-based robots are extensively deployed within the military, agriculture, manufacturing, logistics and transportation, healthcare, and medicine fields, as displayed in Figure 8. These robots portray significant application prospects, such as surveillance, rescues or reconnaissance, spraying and harvesting, transporting objects in fixed formations, and others.

Figure 8. Flocking robots employed in different domains based on the data in Refs. [97–99].

4.1. Military Discipline

Robot swarms driven by flocking algorithms can perform military missions, for example, surveillance zone forming, capturing evader targets, the rescue of unknown environments, or reconnaissance. Researchers portray military environments by considering complex environments with virtual dynamic and static obstacles [100]. A modified version of semi-flocking and α-lattice flocking algorithms is designed with multiple virtual leaders for mobile agents. LaSalle's invariance principle and Lyapunov stability theorem prove the stability ability, and simulations display the effectiveness of the applied flocking algorithm for UAV-based military applications. Another study validates flocking control as a solution for deploying multi-agent systems in satellite or motion-capture-denied environments [101]. This study implements flocking control based on the Lennard-Jones potential function for a UAV swarm that allows efficient and independent cooperative motion in global navigation satellite systems (GNSSs) or other external positioning system-denied environments. A survey is conducted to identify the potential of cooperated and intelligent multi-UMV systems for carrying out maritime missions, including military and civilian applications [102]. This review concludes that UMV swarms or clusters, in heterogeneous and homogeneous combinations, enhance military power and economic strength, and minimize human intervention risk.

4.2. Agricultural Field

Advanced and cooperative robots are deployed for performing complex tasks in precision agriculture. Distributed cooperative control also tackles three-dimensional (3D) flocking problems, including the barrier and sweep coverage issues of precision agriculture. A multi-region strategy founded on Voronoi partitions is proposed for a multi-UAV system [103]. This developed control mechanism addresses dynamic and static coverage problems and shows robustness against vehicles' failure. Moreover, swarm robots play a significant role in agricultural mechanization. To reduce the socio-economic costs of agricultural machinery, small robot tractors operate as multi-robots in a swarm configuration. A swarm of ten small tractor robots is deployed, showing their feasibility for deep plowing and efficiency in field capacity and costs over a large tractor [104]. Other researchers apply the particle swarm optimization-enhanced fuzzy Stanley model (PSO-FSM) to boost unmanned operations in farmland [105]. These algorithms modify the control gain adaptively subject to different actuator saturation conditions and velocities. The simulation verifies the full-coverage path tracking of a mobile robot, while the experiment validates its usage in an unmanned combined harvester under slippery soil conditions.

4.3. Manufacturing Sector

Multi-robots are extensively used to monitor and inspect production lines and assemble products with exceptional speed and precision in industries. In unstructured environments of manufacturing plants, researchers suggest bio-inspired techniques to coordinate and control the motion of autonomous X vehicles (AXVs), where X denotes vehicles driving on the ground, guided vehicles, vehicles driving underwater, and aerial or space vehicles [106]. Bio-inspired techniques advance the future applications of coordinated multiple entities in manufacturing, last-mile delivery, large warehouses, logistics, and other areas. Furthermore, their intelligence and learning capabilities enable them to perform dangerous tasks such as welding and monitoring hazardous environments. Moreover, they are also programmed to follow and observe safety protocols and notify workers if something goes wrong.

4.4. Logistics and Transportation Area

Autonomous robots work in warehouses to perform packaging, picking, dropping, tightening, aligning, and delivery tasks. The logistics environment may comprise multiple obstacles. Therefore, these robots must realize their formation to reach their destination while working together. A consensus-based flocking formation control and obstacle avoidance strategy are suggested for non-holonomic multiple-wheeled mobile robots of the logistics sector [107]. The applied strategies ensure the formation when the robots navigate around obstacles. Another study also improves the overall performance of the warehouse for handling storage pods [108]. This research offers a collision-free optimal path for a coordinated multi-robot system using a smart distance metric-based approach.

For intelligent material transportation in warehouses and industries, an autonomous multi-robot system is deployed using an extended Dijkstra algorithm integrated with the Delaunay triangulation method for path planning [109]. In this research, very-large-scale-integration (VLSI) architectures are also equipped with behavioral control and leadership-swapping methods for accomplishing tasks in dynamic situations. Moreover, the robots ought to be capable of self-learning, self-adapting, and self-adjusting. In this context, optimized flocking control with wall-following behavior control is designed for an orderly motion of multi-robots in logistics [11]. RL is also applied to enhance robots' predictive and analytic abilities to memorize their working environment and quickly plan their next moves.

4.5. Healthcare and Medicine Domain

Robots are employed to work collaboratively to monitor patients, disinfect rooms, and automate diagnostics and treatments to assist and perform minimally invasive surgeries. This improves efficiency and cost savings. Swarming robots were assigned to manage hospital systems during the COVID-19 pandemic [110]. These robots are designated to aggregate biomedical waste, clean floors, and perform disinfection operations, reducing risk to medical staff and doctors. In emergent conditions, multi-robot systems may deliver medical supplies, manage biological waste, and act as a portable health clinic platform. Two cases of drug delivery using UAVs in swarms, fleets, and flocks as a dependable service in emergency and normal modes are explored [111]. The models of the UAV fleet are based on queuing theory and result in effective delivery. One study deploys a swarm of self-organizing UAVs as a portable health clinic platform and applies a leader–follower strategy [112]. These UAVs are embedded with essential COVID-19 medications and sensors to test and treat people at home and report to a base station. This advancement reduces human interventions and means that patients can be treated at the doorstep during curfew conditions.

Table 2 presents some analyzed multi-agent systems with flocking control strategies in the above-mentioned domains. This table illustrates the significant advantages of incorporating flocking control for UAV swarms, AXVs, a swarm of small robot tractors, a mobile vehicle with a combined harvester, multi-wheeled mobile robots, and multi-robot systems in all the considered domains. Flocking control can be seen to leverage multi-agent systems' abilities to operate adaptively, autonomously, and coordinately. For instance, in military discipline, flocking control enables mobile robots and UAV swarms to spread out while maintaining cohesiveness and aligned flocking. The cooperative behavior among UAVs permits continuous communication without any satellite constellation or navigation system. Using flocking control-based multi-agents in agricultural fields offers the opportunity for precision agriculture and automated harvesting. UAV systems efficiently address coverage problems with greater accuracy. On the other hand, a swarm of ground-based robots operate in a coordinated framework to improve plowing, field capacity, automated harvesting, and agricultural productivity.

Table 2. Summary of multi-agent systems and applied strategies in different application areas.

Reference	Multi-Agent System	Applied Strategies	Application Area	Simulation/Experiment	Remarks
Wei and Chen [100]	Mobile agents	Semi-flocking and α-lattice flocking-based algorithms with multiple virtual leaders	Military	Simulation	➢ Simple and reduces computational complexities. ➢ Shows effectiveness for UAV-based missions of reconnaissance, surveillance, and rescue.
Amorim et al. [101]	UAV swarm	Proximal control-based self-organized flocking	Military	Experiment	➢ Maintains cohesiveness and aligned flocking. ➢ Does not require motion capture or GNSS.
Elmokadem and Savkin [103]	Multi-UAV system	Voronoi partitions-based multi-region strategy	Agriculture	Simulation	➢ Addresses 3D dynamic and static coverage problems. ➢ Proves to be computationally efficient, scalable, and robust against failures.
Albiero et al. [104]	A swarm of small robot tractors	Swarm flocking	Agriculture	Simulation	➢ Feasible for deep plowing. ➢ Efficient in field capacity over a large tractor.

Table 2. *Cont.*

Reference	Multi-Agent System	Applied Strategies	Application Area	Simulation/Experiment	Remarks
Sun et al. [105]	Mobile vehicle and a combine harvester	PSO-FSM	Agriculture	Both	➢ Modifies the control gain. ➢ Allows full coverage path tracking. ➢ Boosts unmanned operation of combine harvester in slippery soil conditions.
Caruntu et al. [106]	AXVs	Bio-inspired approaches	Manufacturing	Both	➢ Avoids collisions and congestion. ➢ Provides optimal solutions with constant speed.
Koung et al. [107]	Multi-wheeled mobile robots	Consensus-based flocking with obstacle avoidance	Logistics and transportation	Both	➢ Ensures formation and avoids obstacles.
Sharma and Doriya [108]	Multi-robot system	Smart distance metric-based approach	Logistics and transportation	Experiment	➢ Determines a collision-free optimal path. ➢ Improves the overall performance.
Divya Vani et al. [109]	Multi-robot system	Extended Dijkstra algorithm–Delaunay triangulation method and behavioral control with leadership-swapping methods	Logistics and transportation	Simulation	➢ Efficiently plans path. ➢ Intelligently transports materials in a dynamic environment.
Kharchenko et al. [111]	UAV's fleet	Queuing theory	Healthcare and medicine	Experiment	➢ Delivers medicines in emergent and normal modes.
Qassab and Ibrahim [112]	UAV swam	Self-organizing with a leader–follower strategy	Healthcare and medicine	Simulation	➢ Facilitates patients. ➢ Reduces human interventions.

Coordinated unmanned vehicles can perform complex tasks in manufacturing industries while avoiding collisions and congestion. In logistics and transportation, multi-wheeled robots and multi-robot systems operating under flocking control ensure coordination and efficient routine, as well as the avoidance of obstacles and the distribution of tasks. This improves overall performance and enables intelligent inventory management and warehouse automation in a dynamic environment. In the healthcare and medicine domain, UAV fleets and swarms are observed to perform disinfection, sterilization, and medicine delivery. Coordinated UAVs determine the fastest routes to optimize medical supplies distribution, seeing to patients while lessening staff burden, especially in high-risk environments, such as pandemics. These applications signify that flocking or swarming allows scalability, autonomy, and efficiency to multi-agent systems to improve operations across various domains.

5. Challenges Influencing Robot Flocking

This section presents some identified challenges that can influence robot flocking. These challenges are related to flocking formation, mobility, communication problems between robots, task allocation, localization, and unreliability for real-world applications. The recognized challenges must be addressed to promote the application of flocking multi-agent systems.

5.1. Challenges of Flocking-Based Formation

Modeling a flock is problematic for physically distributed robots. Moreover, unknown and complex environments may comprise dynamic obstacles. Therefore, designing the initial configuration for a desired formation and its maintenance under low-density conditions is challenging. All agents are required to collaborate in constructing and preserving flocking-based formations in complex scenarios, especially where they have to turn at sharp corners [113]. Multi-disciplinary approaches are needed to efficiently design and maintain formations.

Various studies regard topology, connection structure, and interaction networks between agents as integral aspects of flocking formation and maintenance. The methods become robust to multi-agent systems if they account for time-varying graph topologies and dynamic topologies. Reference [94] does not consider time-varying graph topologies. However, incorporating such graphs through distributed optimization or switching control allows the connections to evolve and overcome shifts between different topologies. Study [59] assumed a Laplacian matrix for eigenvalue analysis and did not depend on changing topologies or time-varying networks, limiting its effectiveness in real-life applications.

5.2. Dilemmas of Mobility Aspects

Coordinated motion is essential for organizing robots as a flock or a swarm [114]. Local interactions with environmental cues may influence their mobility patterns. External environmental signals, such as terrain variation and obstacles, impact the speed of flocking robots. The authors of [57] highlight that the implemented forces on agents increase when moving through narrow passages with obstacles. The APF-based virtual leaders considered for this study are integral to moving with reduced velocity. Therefore, more autonomous or ML-based adaptive control laws are needed to anticipate and adjust for obstacles. Similarly, study [56] assumed unicycles with constant speeds, restricting this method's application for scenarios where agents must alter their speed because of external factors. Incorporating speed control methods, such as feedback control loops or proportional speed controllers, may adjust every agent's velocity dynamically.

Besides avoiding obstacles, keeping a similar distance between agents in swarms is also necessary and requires velocity consensus. For instance, study [33] does not cover dynamic topology or environments for achieving velocity consensus with inter-agent distance stabilization. This work delineates the Tanner model's usage [21] in dynamic topology for addressing consensus issues in future research. In addition, expanding the number of agents enhances the complexity of parameter adjustment and the collision avoidance matrix dimension in the study [7]. Reference [32] also does not optimize parameters. Machine learning-based optimization techniques, such as the gravitational search algorithm, can influence the parametric value according to dimensions, local factors, and agent numbers, improving performance as the number of agents increases. Thus, understanding the aggregation and dispersion dynamics of robots and adopting systems with self-organizing capabilities is crucial.

5.3. Lack of Safe, Reliable, and Long-Range Communication

Another legitimate concern related to robots is the fast information transmission required to plan their trajectories, allocate tasks, and coordinate their movement and formation [115]. This transmission assists the robots in achieving their overall objectives efficiently. Therefore, information must be communicated while taking privacy, safety and security, resource allocation, mobility, reliability, and adaptability into consideration. Moreover, the literature emphasizes the requirement of robust communication protocols in dynamic environments. Reliable communication strategies are essential to address the issues of potential signal loss and limited communication range.

The use of high-frequency communication and ranging hardware is apparent from study [51]. However, this study accentuates that further optimizing the consistency and frequency of exchanging messages will be valuable.

5.4. Issues of Task Allocation and Localization

Multi-agent systems are deployed with collective objectives. Decentralized mechanisms are essential for acquiring collective objectives that enable robots to analyze tasks. Moreover, roles among robots are dynamically reassigned according to the requirements of the system [12]. Flexible flocking strategies must be adopted that allow dynamic task reconfiguration for robots to address evolving scenarios where changes occur in the environment. During tasks, damping forces (friction forces) act on the robots, causing agents to dissipate energy. Reference [53] does not concentrate on any damping forces that may affect the multi-agent system's stability.

Study [51] uses an extended Kalman Filter (EKF) for range-based localization. The applied methodology initially falsely converges to spurious states. However, running multiple or more thorough estimation filters, such as particle filters, may lead to numerous ambiguous states in identifying the correct estimate. Another identified weakness of the applied controller is its lower memory efficiency. Less memory-efficient polynomial trajectories are alternative solutions that may result in fewer data and smoother trajectories.

5.5. Unreliability for Real-World Applications

Focusing on specific conditions lessens the effectiveness and applicability of methods in practical scenarios. Mild assumptions are not idealized conditions, as considered in study [56]. Mild assumptions may compromise safety and scalability and demand robust control mechanisms to ensure scalability and safety under less ideal conditions. In reference [31], the proposed method corresponds to the state space and deploys less sophisticated predators, restricting performance in continuous action space scenarios. However, actor–critic RL models can modify the applied method for practical applications. In work [61], the supposed conditions also constrain the system's performance in real-world applications. Adaptive control based on ML approaches may adjust the flocking behavior, reflecting changing perturbations. In reference [59], relying on synchronization indices for pinning point selection may limit the approach's scalability to large-scale systems. Incorporating robustness to multiple pinning nodes, external disturbances, and additional indices (fault tolerance or energy efficiency) considerations may address these restrictions.

Other crucial considerations for practical applications are time and energy consumption and environmental perturbations. The applied leader–follower control in reference [34] is observed to be a slower process. Similarly, the proposed approach in [57] takes more time and has higher computational costs due to its complexity and calculation. Reference [53] does not account for energy consumption or external perturbations (wind, weather, speed). These deliberations can bridge the gap between real-world manifestation and theoretical concepts.

6. Flocking Problems and Solutions

The behavior of robots working in a multi-agent system appears as a consequence of simple commands executed by every robot corresponding to the detected events in an environment. Consider a multi-agent system of UAVs in which each agent has assigned properties of position and velocity. The environment is two-dimensional and has some narrow passages and its boundary is limited to restrict the agents' motion. All the agents are modeled with specified kinematics. The coordination system is accredited to the properties of agents that satisfy the trajectory. In any region, agents are assumed to move on a trajectory that follows the behavior of their belonging neighborhood. The neighborhood can be formed in different ways as a consequence of its coordination strategy, including information given by the agents, the distance between the agents, and the specific landmarks or geometric partitions of the environment. The obstacles are convex with a known number of inaccessible regions that are closed and possess properties similar to the boundary so that the agents' movement is restricted. Restricting their motion to the convergence problem also reduces their energy consumption. The distributed control of the agent is formed during the system evolution, whereas information feedback is carried out using filters that correspond to the designed task. The system is also postulated to be served with estimated population size and the coordination of collaborated actions.

A solution to this problem is flocking control. The group of continuously moving agents forms a flocking cluster; then, as the distance between the pair of agents becomes finite, they form swarms. For optimal flocking, swarming is constructed on behavior-based and leader–follower structures. The behavior-based controller comprises collision avoidance behavior with flock-centering and obstacle avoidance behavior. The collision avoidance behavior coordinates the agents to enter and maintain a formation while preventing inter-agent collisions. Additionally, the obstacle avoidance behavior employs the acquired information and searches for the nearest free space. The center of mass, or virtual leader of the swarm, is defined by following a planned trajectory in such a manner as to not intersect with any obstacle. All the agents in the formation know the relative position of their neighboring agents. These agents follow their leader by measuring this relative position. A navigation function is employed, forcing agents to reach their target and attain the desired flocking structure while following their leader and ensuring collision and obstacle avoidance. The control law forces the agents to move with a velocity similar to their leader, allowing them to move in the desired relative position according to their neighbors. If an agent is in the influence region of its neighboring agent or nearby obstacle, then the repulsive functions push that agent's trajectory away from both the neighboring agent and the obstacle. These repulsive functions ensure that the agent neither collides with its neighbor nor meets any obstacle.

If the swarming agents are required to move through a narrow passage that is impossible with the existing size of the flocking structure, then the inter-agent distances are reduced, contracting the flocking structure size. However, each agent must be familiar with the smallest possible diameter to encircle the formation. Here, the leader is responsible for sharing the information or estimating the diameter value. Then, the leader shares these parameters with its neighbors and finalizes it. If two unequal scaling factors are broadcasted from neighboring agents, then the higher value is retained. This behavior conserves the trajectory more in terms of collision avoidance. Changing the size of a flocking formation ensures safe passage through a narrow corridor and collision avoidance with non-convex obstacles in many situations. After passing through a narrow space, the flocking structure returns to its original size. The motion strategy of the agents is displayed in Figure 9.

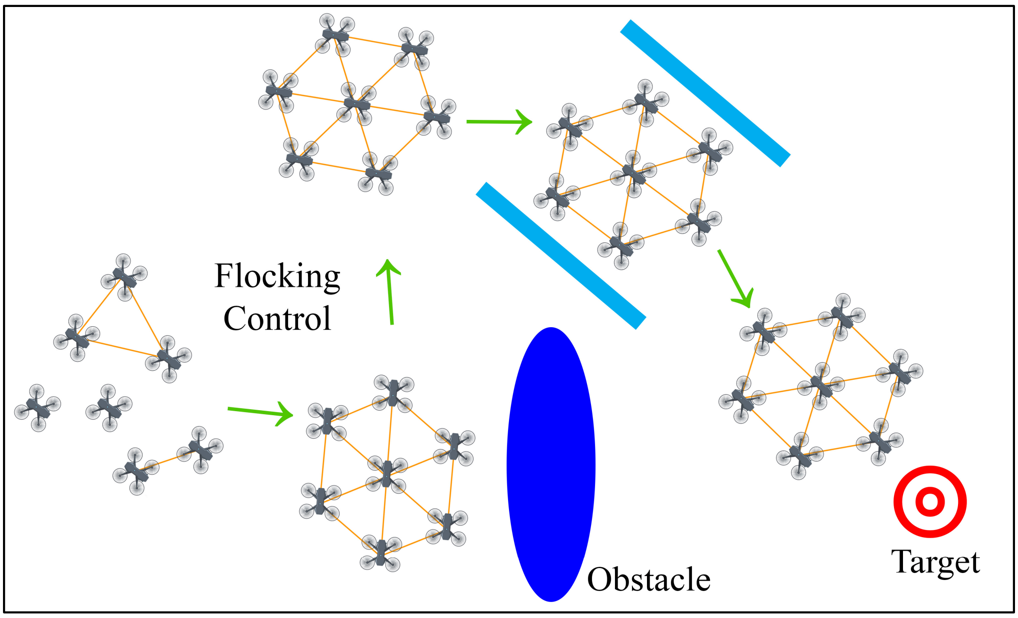

Figure 9. Flocking motion control of multi-UAVs based on data in Ref. [11].

7. Discussion

This manuscript deliberates on flocking control for collective motions of multi-robot systems. Examining existing review papers, this paper evaluates the necessity of a more comprehensive survey. Reynolds is acknowledged for devising the flocking control concept. The Reynolds flocking model is observed to serve as a guideline for flocking controllers and is widely adopted for designing the behaviors of robots and unmanned vehicles for multi-agent systems. An analysis of the recent literature shows that tremendous advancement has introduced various flocking laws such as avoidance, migration, etc., enhancing the collective performance of team members. Researchers rely extensively on cluster flocking and swarming, as these ensure formation, fast convergence, reduced energy consumption, and powerful performance in unexplored states. The flocking phenomenon based on these rules is observed to manage robots as a single system, enabling them to develop collective behavior and the desirable capabilities of fault tolerance, scalability, adaptability, safe navigation, and efficient communication. All these factors lead multi-agent systems to accomplish a common task.

Flocking control is designed in centralized, decentralized, distributed, and hybrid manners. Among these, decentralized and hybrid control schemes are more desirable for larger flocks or swarms, as these schemes supplement scalability and address the susceptibility of centralized agents. The analysis of flocking structures and approaches reveals that every structure and technique have different opportunities and limitations. Table 3 delivers a brief comparison of the identified strengths and weaknesses of flocking control schemes, structures, and approaches. The tabular results suggest the best method for flocking control is dependent on multiple factors of mission requirements, robots' features, complexity levels, etc. Moreover, new directions for flocking controls are identified as SI with little bio-inspired and AI-based strategies that allow more stable control, faster cluster consensus, and predictive and analytic capabilities.

Table 3. Comparative analysis of different flocking control aspects.

Flocking Control	Categories	Opportunities	Weaknesses
Schemes	Distributed	➢ Allows information sharing and robust communication. ➢ Designs more scalable systems. ➢ Ensures collision-free motion.	
	Decentralized	➢ Independent technique. ➢ Does not require a leader.	➢ No inter-agent communication. ➢ Requires localization sensors.
	Centralized	➢ Ensures flocking stability. ➢ Enhances communication efficiency of the grouped agents. ➢ Suitable for underwater missions.	➢ Requires additional communication and computational capabilities. ➢ Necessities global information. ➢ Has weak reliability and fault tolerance.
	Hybrid system	➢ Provides information availability and efficiency with less complexity. ➢ Addresses issues at robot-level and swarm-level.	➢ Requires global information. ➢ May suffer if centralized controller fails.
Structures	Leader–follower	➢ Simple to form. ➢ Allows efficient trajectory tracking.	➢ Depends on leader. ➢ Capabilities and global knowledge are supplied only to the leader. ➢ Less robust.
	Behavior-based	➢ Ensures safety. ➢ Maintains shape integrity. ➢ Accomplishes different objective missions.	➢ Only some shapes are convenient to model and maintain. ➢ Less stable.
	Virtual structure	➢ Models rigid and flexible structures. ➢ High stability.	➢ Requires a clear target position for every single agent. ➢ Poor flexibility and adaptability in the presence of obstacles.
	Pinning-based	➢ Acquires synchronization. ➢ Accelerates convergence rate. ➢ Handles motion of large-scale groups. ➢ Accomplishes tasks robustly and efficiently.	➢ Selection of pinning nodes is difficult. ➢ Navigational feedback term is owned by pinning agents only.
	Dynamic adaptive structure	➢ Generates, maintains, and reconfigures formations. ➢ Facilitates real-time deployment. ➢ Ensures safety.	

Table 3. *Cont.*

Flocking Control	Categories	Opportunities	Weaknesses
Strategies	APF	➢ Guarantees formation convergence.	➢ Requires improvements to realize larger swarms. ➢ May lead to local minima and lacks global optimization.
	MPC	➢ Handles complex dynamics. ➢ Ensures flocking stability and safety. ➢ Handles input constraints and group objective pursuits. ➢ Improves collaboration.	➢ Has not gained much popularity.
	SI with little bio-inspired	➢ Increases flight efficiency and search range. ➢ Ensures collision-free motion. ➢ Handles trajectory divergence problems. ➢ Realizes multiple formations.	➢ Parameter tuning is difficult. ➢ Requires improved shepherd movement laws.
	AI techniques	➢ Solve multiple optimization problems. ➢ Generate, maintain, and transform structures. ➢ Efficiently manage flocks. ➢ Account for wind gusts. ➢ Train end-to-end flocking control and solve the leader–follower structure issue in continuous spaces. ➢ Tackle communication delays. ➢ Good scalability.	➢ Require higher training. ➢ Need significant computations.
	Hybrid control paradigms	➢ Enhance performance and robustness. ➢ Stronger adaptability and ability to reform structures. ➢ Faster cluster consensus with more stable control.	

The section outlining the applications of flocking robots highlights that most research is conducted using mobile robots and UAVs. Different reliable flocking-based strategies are implemented with leader–follower and behavioral formation controls. The opportunities of these integrations include reductions in computational complexities, optimal path planning, obstacle avoidance, robustness against failures, and improvements in overall performance. Summing up, flocking robots are powerful tools to reduce human intervention risk and enhance economic benefits. Open challenges that require further consideration include formation, communication, mobility, and task allocation issues. Maintaining formation while passing through narrow passages or turning at sharp corners is quite challenging. Furthermore, mobility patterns are usually influenced by local interactions and environment cues. Therefore, robots must be furnished with self-organizing capabilities for organizing flocks or swarms. These reliable communication and dynamic task allocation issues must be addressed for flexible flocking.

8. Conclusions

Extensive literature has been devised on flocking control strategies for multi-robot systems. An analysis of the existing literature is carried out, reflecting that most studies are focused on flocking convergence, reducing communication and computation requirements, and energy savings. This research evaluates flocking laws based on alignment, separation, cohesion, migration, and avoidance. Swarm or cluster flocking and the flocking phenomenon in multi-robots are discussed, revealing that their incorporation revolutionizes aspects of robots and allows them to work in flocks and swarms with or without humans. The integration of these robots and automation modifies our ways of living and working. Centralized, distributed, decentralized, and hybrid frameworks are explained as flocking schemes. Leader–follower, behavior-based, virtual structure-based, pinning-based, and dynamic adaptive flocking structures are discussed. Classic and state-of-the-art flocking control strategies, including APF, MPC, SI with little bio-inspired, AI techniques, and hybrid control paradigms, are delineated. Robots are widely deployed with flocking control in the military, agriculture, manufacturing, transportation and logistics, and healthcare and medicine. Some challenges that require future consideration are formation control, mobility aspects, and communication. Further integration with computer science, engineering, biology, and physics may result in the design of more evolved systems and flocking strategies, fostering improvement in the collective motion of multi-robot systems. In the end, coordination among agents and system design is defined as an integral flocking problem. A solution to this flocking problem is provided as cluster flocking or swarming based on behavior-based and leader–follower structures. This research may assist developers in selecting an appropriate flocking structure and approach in a decentralized, hybrid, centralized, or distributed manner for flocking agents, according to their requirements.

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