An Overview of Swarm Coordinated Control

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***Abstract*—In recent years, with the rapid development of swarm control technology, the swarm system has shown broad application prospects in military, civil, and other fields, which has gradually become a research hotspot in the area of automatic control. To further promote the development of swarm technology, this paper reviews the detail research on swarm control especially the results after 2018. In order to cover all the important and hot topics in the field of swarm control research, we conducted a literature search based on the *Google Scholar* and *Web of Science* databases and collected hundreds of articles on swarm control for review. The topics include swarm, formation, consistency, topology switching, delay control, convergence time control, obstacle avoidance, path planning, etc. Besides, the evaluation methods and application like vicinagearth security are introduced. Then, based on the latest existing research methods and results, the future research directions is proposed, including survival intelligence-based, learning-based, and heterogeneous control-based. In conclusion, the main purpose of this paper is to sort out the latest achievements in the development of swarm control technology, providing important research references for scholars.**

***Impact Statement*– Swarm coordinated control is an important research content and frontier development direction in the field of artificial intelligence and control at present. Swarm system have been widely used in civilian and military fields. Research on swarm coordinated control is helpful to improve the efficiency of multi-robot collaborative operation and make the swarm system further unmanned, intelligent, and autonomous. This survey reviews the latest research on swarm coordinated control from 2018 to 2023, which is committed to presenting the latest research results on swarm control technologies, methods, and applications for scholars. This paper expounds on the science and importance of swarm control, and provides new insights and ideas for the in-depth study of swarm control. At the same time, our paper is conducive to expanding the scope of influence of swarm system research and also contributes to the further development of artificial intelligence technology.**

***Index Terms*—Swarm control, Formation, Topology, Swarm Evaluation, Vicinagearth Security, Swarm Application.**

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I. Introduction

THE concept of swarm originated from biological research [1]. The swarm have the abilities of self-organization, cooperation, and high environmental adaptability via individual decision-making and information interaction between agents. Inspired by this, a large number of scholars have studied intelligent swarm systems by simulating the behavior of biological groups in nature, which realized the sensory interaction, information transmission and cooperative work between multi-robot system. Compared with a single agent system, the swarm have stronger survivability and cost advantages, which the complex works can be completed based on the scale advantage of the swarm. The current research on swarm system has been widely used in military and civilian fields [2]. For example, currently, the attention of many scholars has been attracted by vicinagearth security [3], a technology that consists of defense, protection, safety, and rescue. While swarm intelligence provides an intelligent solution for vicinagearth security, satisfied its requirements of cross-domain, three-dimensional, and collaborative. The methodology and main subjects involved in this survey are shown in Fig. 1.

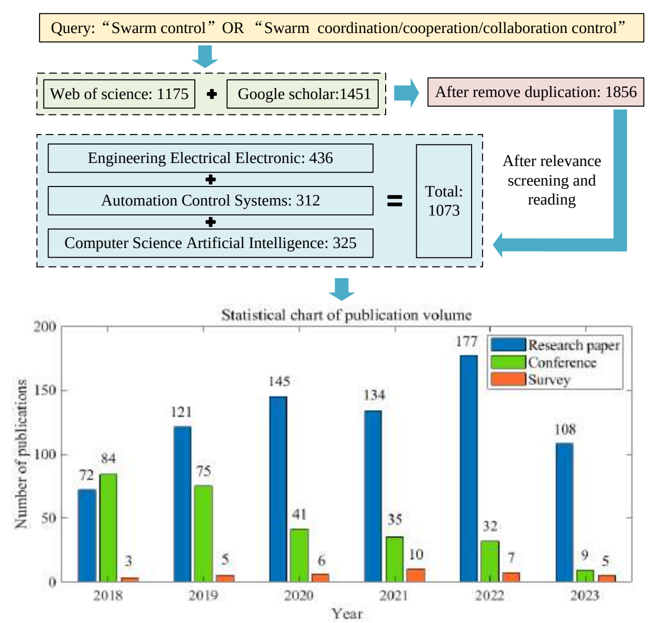

Fig. 1. Methodology and main topics in this survey article[1].

Four key words mainly 'swarm control' were selected, 1856 effective and highly relevant references were obtained

[1]The statistical data on the publication volume in 2023 is as of July 1, 2023, that is, only the number of papers published in half a year has been counted.

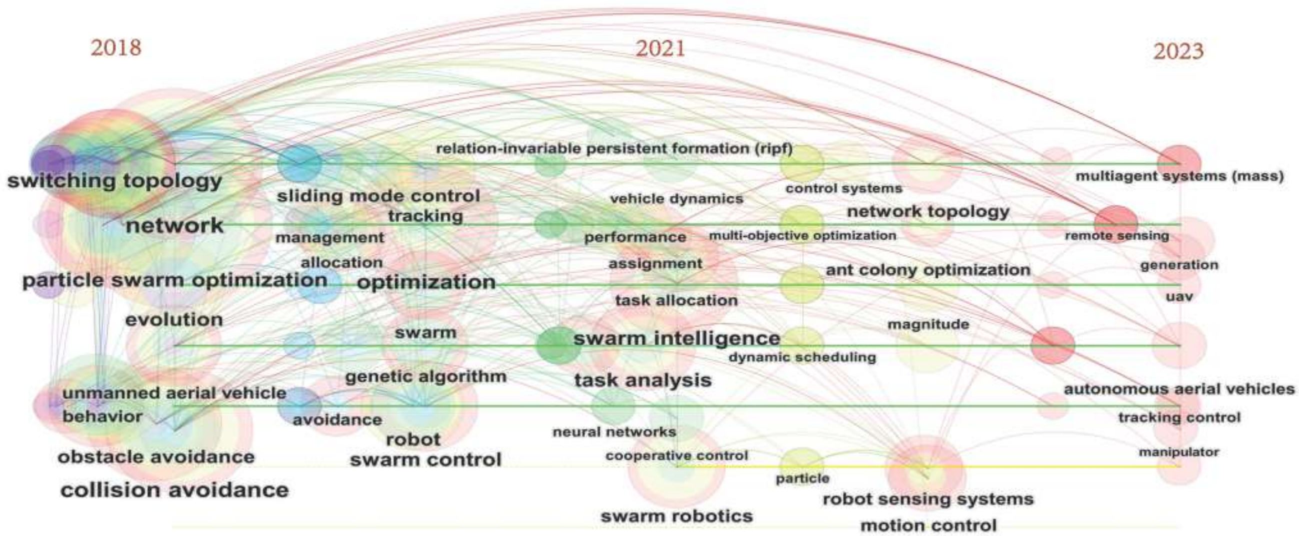

Fig. 2. Highlighting swarm control research keywords based on Citespace in recent 6 years.

through searched on *Google Scholar* and *Web of Science*. On this basis, screening and intensive reading were carried out, and finally 1073 references were effectively reviewed, mainly involving the disciplines of *Engineering Electrical Electronic*, *Automation Control Systems*, and *Computer Science Artificial Intelligence*. It can be seen from the statistical chart of publication volume in Fig. 1 that the number of published papers about swarm control generally shows an increasing trend, especially research papers. That is to say, swarm control has gradually attracted the attention of more and more scholars, becoming a research hotspot from now on.

The most critical problem in the swarm system is the coordinated control problem. The key words of swarm control research based on Citespace in recent six years (2018-2023) are highlighted in Fig. 2. Since the 21st century, swarm coordination control has made rapid breakthroughs in the application style and technology level, which has achieved very significant results [4]. Compared with traditional manual formation control, the current swarm control is more autonomous and intelligent [5], which can complete efficient work at a lower cost. At present, the accuracy, comprehensiveness, and reliability of swarm control are gradually improving [6], [7].

Regarding the latest research on swarm control, Ref. [8] introduced digital twin technology to swarm system, which proposed a metaverse for scalable control of robot swarms, while an adaptive framework for different levels of autonomy is used. Ref. [9] used optimization mean-shift algorithm in machine learning to realized robot swarm control. Ref. [10] researched the 3D hybrid formation control for underwater robot swarm, refers to the contents about switching topologies, unmeasurable velocities, and system constraints. Aiming at the heterogeneous swarm control, a two-layer topology method to solve the problem of high communication difficulty and complex computation in large-scale system was proposed in Ref. [11]. Ref. [12] designed a robust adaptive region tracking control method for swarm system, which used the time-varying formation to realized the decentralized control. Besides, a morphological computation and decentralized learning in a sterically interacting robots swarm was researched in Ref. [13].

As a research hotspot, the research results of swarm control are constantly being updated. Therefore, it is necessary to sort out and summarize the latest research content, which can help researchers quickly understand and grasp the latest developments, clarifying the future research direction. At first, several typical survey papers were selected to compare the content of their reviews in Table. I. It can be seen that the existing reviews on swarms either fail to track the latest academic developments or pay more attention to multi-agent systems and formation systems. There are also surveys oriented to practical objects, such as a survey of unmanned aerial vehicle (UAV) swarm research [14], [15], while the review on swarm control is still scarce. Therefore, the more novel and detailed swarm control survey should be presented.

Currently, The analysis of swarm system should be carried out from the aspects of swarm model, performance control, coordination control, and application [16]. Swarm control needs to involve many key technologies to deal with complex control objects with time delay or interference, and to meet specific requirements for control. On the other hand, swarm control is inseparable from the coordination and maneuver between agents. Therefore, key issues such as formation, obstacle avoidance, path planning, and task allocation must be considered to ensure the safety, autonomy, and intelligence of the swarm system [17]. In addition, evaluation is also an important part of swarm control, needing the evaluation conclusions in terms of swarm performance, applicability, and fault tolerance. The evaluation of the swarm is an important bridge from the theoretical research to the actual application, which has great significance for testing the development level of the swarm. On the other hand, with the continuous development of communication, intelligent manufacturing, control and other disciplines, the swarm will surely show a broader application prospect and bring more convenience to human production and life, which is also a part that needs to be

TABLE I
COMPARISON OF REPRESENTATIVE REVIEWS.

Research content \ Reference	[14]	[15]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	Our review
Models	✓	✓				✓			✓	✓		✓
Communication/network		✓	✓	✓			✓	✓	✓		✓	✓
Time-delay control		✓									✓	✓
Disturbance control					✓				✓		✓	✓
Convergence time control		✓										✓
Accuracy control											✓	✓
Consumption Control		✓					✓					✓
Formation	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓
Obstacle avoidance	✓	✓		✓		✓			✓		✓	✓
Path planning	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Task assignment	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Evaluation		✓		✓			✓			✓		✓
Hardware/sensors	✓	✓	✓					✓		✓		✓
Application	✓	✓	✓	✓	✓			✓		✓	✓	✓

Remarks: (1) The comparative content covered in Table. I refers to the classification in Appendix X, which can quickly sort out the existing review content for readers, showing the comprehensiveness of this paper. (2) The reference selected in this table comprehensively covers the theoretical research and application of swarm control. Among them, Ref. [14], Ref. [21], Ref. [22], Ref. [23] and Ref. [29] focuses on UAV swarms; Ref. [15] focuses on multi-agents; Ref. [27] focuses on unmanned ships; Ref. [24], Ref. [26], and Ref. [28] focuses on robotics; Ref. [25] focuses on swarm fault-tolerant control. (3) Ref. [25] is a survey of fault diagnosis for swarm systems. It is also an important research content in swarm control, which is in line with the survival intelligence-based swarm control proposed in Section VII. Due to the detailed review in Ref. [25], our paper does not elaborate too much on this aspect.

focused on [18], [19].

Compared with other swarm control overview papers [14], [15], [20], in this paper, we reviewed the latest swarm control research results, especially the research after 2018. The research in the past 6 years has covered all key and hot research contents of swarm control. The Appendix X is the control architecture of swarm system. The contributions of this paper can be summarized as follows.

1) In this paper, a novel swarm research architecture is proposed. Firstly, starting from the swarm control model, complexity, requirements, these key technologies of the swarm are reviewed. At the same time, the key swarm coordination issue like formation, obstacle avoidance, etc. in swarm control are reviewed. Unlike other survey, the evaluation of the swarm system is also reviewed. Finally, swarm application objects and scenarios are summarized. This division method shows the important research content of swarm control more intuitively and clearly, with clear logic and high readability.
2) A clear definition of the swarm system is proposed, which is from the perspective of self-organization behavior and quantity. In the meanwhile, the relationship between the swarm control, the multi-agent consensus control, and the formation maintenance is illustrated clearly, which is conducive to further research on swarm control.
3) Based on the supported on the database from *Google Scholar* and *Web of Science*, the research results of swarm control in the past six years are highlighted in this paper. The main purpose of doing so is to track the most cutting-edge swarm control research trends, sort out the development context and structure of swarm control, providing significant reference value for further research in the future.
4) Considering on the existing limitations and practical application difficulties faced by swarm system, three main future research directions are proposed, including swarm survival intelligence, intelligent control, and heterogeneous control. These directions are the result of tracking the latest intelligence technology, which has high guiding significance in further research.

This paper is organized as follows: we devote Section II to a introduction of several basic theory and model of swarm system. The key technologies of swarm performance control are reviewed in Section III, from the perspective of controlling complexity and requirements. Section IV reviews the key swarm coordination issues, which mentioned formation, obstacle avoidance, path planning and task assignment. Section V is the evaluation of swarm. Besides, multiple application scenarios and platforms of swarm are summarized in Section VI. The future research of swarm system is prospected in Section VII. Section VIII concludes the review of this paper.

II. PROBLEM DESCRIPTION AND SWARM MODELING

In this section, the problem of swarm control is illustrated, and the model of swarm communication, swarm intelligent units are given.

A. Problem description

Different from traditional multi-agent consensus control, swarm systems are mainly distinguished in communication topology and self-organizing performance. For the communication topology, swarm system can construct communication topologies by artificial generative method or self-organized method, while multi-agents cannot. RIPF (Relation-invariable persistent formation) is a common self-organizing topology construction method in swarm system, which mentioned the the normalization adjacency matrix and normalization degree matrix. As for self-organizing performance, swarm can realize aggregation or dispersion when swarm works [30]. Besides, the number of intelligent units in the swarm system is basically more than 10. When it is less than 10, the system is also called the formation system [14].

In this section, we introduced an swarm aggregation–dispersion function. which can be defined as f_{ij}. The τth derivative of f_{ij} can be denoted as $f_{ij,\tau}$. In this way, the traditional consensus control and formation maintenance problem can be treated as the special cases of swarm control. The swarm system can be defined as

Definition 1: If a swarm system is composed of more than ten intelligent units , when it satisfies

(1) *The intelligent units can automatically construct a communication topology, which can also be switched when swarm moves;*

(2) *The swarm model contains a time-varying function term: aggregation–dispersion function f_{ij}. When f_{ij} is 0, the swarm control problem is transformed into the consensus problem; When f_{ij} represents the expected relative error between each intelligent units Δ_i, the swarm control problem is transformed into a formation maintenance problem.*

the system can be called a swarm system, which corresponding control methods are called swarm control.

B. Swarm communication model

1) Directed/undirected topology: Graph theory is an important part of studying swarm communication [31]–[34]. In graph theory, the communication topology between agents can be expressed as $\boldsymbol{G} = (\boldsymbol{v}, \boldsymbol{\varepsilon})$, where $\boldsymbol{v} = \{v_1, v_2, ..., v_n\}$ is the set of nodes and $\boldsymbol{\varepsilon} \subseteq v \times v$ is the set of edges; n is the number of nodes. If there is the information interaction between node i and node j, then there are edges that connect the two nodes. When $(i, j) \in \boldsymbol{\varepsilon} \Longleftrightarrow (j, i) \in \boldsymbol{\varepsilon}$, the graph $\boldsymbol{G}$ is called undirected. If there is a path between any two nodes, the undirected graph $\boldsymbol{G}$ is called connected. Based on the definition of undirected graph, it can be known that any two connected nodes in the graph are bidirectional. To describe the relationship between nodes and edges, for an undirected graph $\boldsymbol{G}$ with n nodes. The degree matrix can be defined as $\boldsymbol{D} = diagd_i$, where $d_i = \sum_{j=1}^{n} a_{ij}$. Then, we define the normalization adjacency matrix $\bar{\boldsymbol{A}} = [\bar{a}_{ij}]_{n\times n}(i, j = 1, \cdots, n)$ as

$$\bar{a}_{ij} = \begin{cases} \bar{a}_{ij} d_i & , d_i \neq 0 \\ \bar{a}_{ij} & , d_i = 0 \end{cases} \tag{1}$$

And the normalization degree matrix can be described as $\bar{\boldsymbol{D}} = diag(\bar{d}_i)$, where

$$\begin{cases} \bar{d}_i = 1 & , d_i \neq 0 \\ \bar{d}_i = 0 & , d_i = 0 \end{cases} \tag{2}$$

Besides, to describe the communication between nodes, the Laplace matrix $\boldsymbol{L}$ of graph $\boldsymbol{G}$ can be defined as

$$\boldsymbol{L} = \bar{\boldsymbol{D}} - \bar{\boldsymbol{A}} \tag{3}$$

2) Fixed/ switch topology: The topological relationship between nodes in a fixed topology does not change with time, while the topological relationship between nodes in a switched topology is time-varying. Swarm collaboration based on switching topology has always been a research hotspot in the field of control. In the swarm, the communication topology may change due to the change of agent position or the connection and disconnection of communication between agents [35]. In addition, the convergence of the swarm system is closely related to the connectivity of the network topology. Therefore, swarm control under switching topology is still a critical research direction.

In the current study, a smooth transition method in communication was proposed in Ref. [36], which was designed by the sliding mode control, ensuring the communication security of swarm when the communication topology changing. Ref. [37] porposed a distributed robust control method for the formation, which could make the system change formation with static and switching topologies under high robustness. A self-organized system with fixed and switching topology was designed in Ref. [30], which can construct the communication topology automatically and realize system stability asymptotically under the fixed and switching topology.

3) Two-way topology: In Two-way topology, there exists a directed graph $\hat{\boldsymbol{G}} = (\hat{\boldsymbol{V}}_G, \hat{\boldsymbol{E}}_G, \hat{\boldsymbol{A}}_G)$ with structural balance, where $\hat{\boldsymbol{V}}_G = \{v_1, v_2, ..., v_N\}$ is the set for nodes. Then, the intelligent units in the system are divided into two teams ($\boldsymbol{V}_1$ and $\boldsymbol{V}_2$), which satisfy $\boldsymbol{V}_1 \cup \boldsymbol{V}_2 = \{v_1, v_2, ..., v_N\}$ and $\boldsymbol{V}_1 \cap \boldsymbol{V}_2 = \phi$, where ϕ represents the empty set. At this time, the elements of the adjacency matrix $\hat{\boldsymbol{A}}_G$ can be expressed as

$$a_{ij} = \begin{cases} 1 & , j \Rightarrow i \, and \, i, j \in \boldsymbol{V}_1 \, or \, \boldsymbol{V}_2 \\ -1 & , j \Rightarrow i \, and \, i \in \boldsymbol{V}_1, j \in \boldsymbol{V}_2 \, or \, i \in \boldsymbol{V}_2, j \in \boldsymbol{V}_1 \\ 0 & , j \models i \end{cases} \tag{4}$$

where $j \Rightarrow i$ represents that intelligent unit i can receive information from j, otherwise it is indicated by $j \models i$.

The swarm structure under the two-way topology not only has a cooperative relationship, but also has a competitive relationship, which is in line with the nature of group animals with collaboration and competition. Therefore, the two-way topology is a reasonable research and development trend. In Ref. [38], considering that information cannot be completely transmitted between intelligent units due to external interference, a two-way topology was used to solve the problem of distributed swarm consistency control

C. Swarm agent model

Consistency can be defined as one or some states of all agents in a swarm tend to be consistent over time [39]–[41]. A consensus protocol is a process by which individuals interact in a swarm system. The basic idea of consistency algorithm is to assign similar dynamic properties to the information state of each agent in the swarm [42], [43].

1) Integrator model: (1) First-order integrator systems: The swarm state equation consisting of the first-order integral dynamical system can be defined as

$$\dot{\boldsymbol{x}}_i = \boldsymbol{u}_i, \quad i = 1, 2, ..., n \tag{5}$$

where, $\boldsymbol{x}_i \in \mathbb{R}^m$ is the system status of the ith agent in the swarm; $\boldsymbol{u}_i \in \mathbb{R}^m$ is the control input of the ith agent; n is the number of swarm agents; $\mathbb{R}$ refers to the set of real numbers.

The general consistency control algorithm of first-order integrator model is

$$\boldsymbol{u}_i = -\sum_{j=1}^{n} \bar{a}_{ij}(t)(\boldsymbol{x}_i - \boldsymbol{x}_j + \Delta_i), \quad i = 1, 2, ..., n \tag{6}$$

where $\bar{a}_{ij}$ is the element (i, j)th of the normalization adjacency matrix $\boldsymbol{A}(t) \in \mathbb{R}^{n \times n}$ at time t.

Then, Eq. (5) and Eq. (6) can be written in matrix form as

$$\dot{\boldsymbol{x}}_i = -\left[\boldsymbol{L}(t) \otimes \boldsymbol{I}_m\right] \boldsymbol{x} \tag{7}$$

where, $\boldsymbol{x} = \left[\boldsymbol{x}_1^T \quad \boldsymbol{x}_2^T \quad ... \quad \boldsymbol{x}_n^T\right]^T$; $\boldsymbol{L}(t) \in \mathbb{R}^{n \times n}$ is the asymmetric Laplace matrix at time t; $\otimes$ representing the Kronecker product. Therefore, when $t \to \infty$, if we have

$$\left\| \boldsymbol{x}_i(t) - \boldsymbol{x}_j(t) + \Delta_i \right\| \to 0 \tag{8}$$

the swarm can be considered to consistent, where $\|\cdot\|$ represents the Euclidean norm in $\mathbb{R}^n$.

As for the practical study for the first-order integrator model. The consensus problem for multi-agent in a swarm with finite-time was addressed in Ref. [44], which nonlinear control protocols were based on the first- and second-order agents. In Ref. [45], the consensus problem for first-order agent in swarm system was investigated, which was under the environment with unknown communication delay.

(2) Second-order integrator systems: The swarm state equation consisting of the second-order integral dynamical system can be defined as

$$\begin{cases} \dot{\boldsymbol{x}}_i = \boldsymbol{v}_i \\ \dot{\boldsymbol{v}}_i = \boldsymbol{u}_i \end{cases} \qquad i = 1, 2, ..., n \tag{9}$$

where, the $\boldsymbol{x}_i \in \mathbb{R}^m$ is the system status of the ith agent in the swarm; $\boldsymbol{v}_i \in \mathbb{R}^m$ is the state derivative of $\boldsymbol{x}_i$; $\boldsymbol{u}_i \in \mathbb{R}^m$ is the control input of the ith agent.

The general consistency control algorithm can be designed as

$$\boldsymbol{u}_i = -\sum_{j=1}^{n} \bar{a}_{ij}(t) \left[(\boldsymbol{x}_i - \boldsymbol{x}_j + \Delta_i) - \gamma(t)(\boldsymbol{v}_i - \boldsymbol{v}_j)\right], \quad i = 1, 2, ..., n \tag{10}$$

where, $\bar{a}_{ij}$ is the element (i, j)th of the normalization adjacency matrix $\boldsymbol{A}(t) \in \mathbb{R}^{n \times n}$ at time t; $\gamma(t)$ is a positive number for any time t. Therefore, when $t \to \infty$, if we have

$$\left\| \boldsymbol{x}_i(t) - \boldsymbol{x}_j(t) + \Delta_i \right\| \to 0, \quad \left\| \boldsymbol{v}_i(t) - \boldsymbol{v}_j(t) \right\| \to 0 \tag{11}$$

the swarm can be considered to consistent.

In the researches of second-order model, Ref. [46] provided a state-feedback controllers and impulsive protocols for swarm agent, achieving the adaptive control for the swarm system, which was composed of the second-order agents with unknown nonlinear terms. A finite-time consensus control method was proposed in Ref. [47], which was based on an event-triggered control algorithm to make the swarm system with intrinsic nonlinear dynamics and external bounded disturbances stay steady. In other words, low-order integral models are widely used in control research on swarm-critical problems.

(3) High-order integrator swarm systems: The basic high-order multi-agent model can be represented by the following n-order integrator

$$\begin{cases} \dot{\boldsymbol{x}}_i^{(0)} = \boldsymbol{x}_i^{(1)} \\ \quad \vdots \\ \dot{\boldsymbol{x}}_i^{(l-2)} = \boldsymbol{x}_i^{(l-1)} \\ \dot{\boldsymbol{x}}_i^{(l-1)} = \boldsymbol{u}_i \end{cases} \tag{12}$$

where, $\boldsymbol{x}_i^{(k)} \in \mathbb{R}^m, k = 0, 1, ..., l-1 (l \geqslant 3)$; l represents the model order of each agent; $\boldsymbol{x}_i^{(k)}$ is the kth derivative of x_i and have $\boldsymbol{x}_i^{(0)} = \boldsymbol{x}_i$.

The general consistency control algorithm of high-order integrator model is

$$\boldsymbol{u}_i = -\sum_{j=1}^{n} g_{ij} k_{ij} \left[\sum_{k=0}^{l-1} \gamma_k (\boldsymbol{x}_i^k - \boldsymbol{x}_j^k)\right], \quad i \in 1, 2, ..., n \tag{13}$$

where, $k_{ij} > 0$; $\gamma_k > 0$; $g_{ii} := 0$; if agent j can transfer information to agent i, then $g_{ij} = 1$; otherwise, $g_{ij} = 0$.

Then, Eq. (11) and Eq. (12) can be written in matrix form as

$$\begin{bmatrix} \dot{\boldsymbol{x}}_i^{(0)} \\ \dot{\boldsymbol{x}}_i^{(1)} \\ \vdots \\ \dot{\boldsymbol{x}}_i^{(l-1)} \end{bmatrix} = (\boldsymbol{\Gamma} \otimes \boldsymbol{I_m}) \begin{bmatrix} \boldsymbol{x}_i^{(0)} \\ \boldsymbol{x}_i^{(1)} \\ \vdots \\ \boldsymbol{x}_i^{(l-1)} \end{bmatrix} \tag{14}$$

$\forall i \neq j$, when $k = 0, 1, ..., l-1$, if we have $\boldsymbol{x}_i^{(k)} \to \boldsymbol{x}_j^{(k)}$, the swarm can be considered to consistent.

As for the research on swarm system composed of higher-order model, Ref. [48] proposed two families of consensus algorithms based on sliding-mode control and variable-gain finite-time observer respectively, solving the finite time consensus problem for heterogeneous swarm system with high-order nonlinear model. Ref. [49] transformed the consensus control problem to a stability problem and proposed a robust control method for swarm system.

(4) Euler-Lagrangian integrator swarm systems: Consider an n-dimensional multi-agent system consisting of m Euler Lagrangian particles, which can be expressed as:

$$\boldsymbol{M}_i(\boldsymbol{q}_i)\ddot{\boldsymbol{q}}_i + \boldsymbol{C}_i(\boldsymbol{q}_i, \dot{\boldsymbol{q}}_i)\dot{\boldsymbol{q}}_i + \boldsymbol{F}_i(\dot{\boldsymbol{q}}_i) + \boldsymbol{G}_i(\boldsymbol{q}_i) + \boldsymbol{d}_i(t) = \boldsymbol{u}_i(t) \tag{15}$$

where, $i \in [1, n]$, $\boldsymbol{q}_i, \dot{\boldsymbol{q}}_i \in \mathbb{R}^n$ refer to the position and velocity of agent i respectively; $\boldsymbol{M}_i(\boldsymbol{q}_i) \in \mathbb{R}^{n \times n}$ is the inertia matrix; $\boldsymbol{C}_i(\boldsymbol{q}_i, \dot{\boldsymbol{q}}_i) \in \mathbb{R}^{n \times n}$ is the Coriolis-centripetal matrix; $\boldsymbol{F}_i(\dot{\boldsymbol{q}}_i) \in \mathbb{R}^n$ refers to the friction force; $\boldsymbol{G}_i(\boldsymbol{q}_i) \in \mathbb{R}^n$ is the gravity; $\boldsymbol{d}_i \in \mathbb{R}^n$ is the bounded disturbance; $\boldsymbol{u}_i \in \mathbb{R}^n$ is the control input. When $t \to \infty$, if we have $\boldsymbol{q}_i \to \boldsymbol{q}_0$ and $\dot{\boldsymbol{q}}_i \to \dot{\boldsymbol{q}}_0$, the swarm can be considered to consistent.

There also has much research based on the Euler-Lagrangian integrator model. Ref. [50] proposed a finite-time leaderless consensus control method, which can make the Euler-Lagrangian system reach consensus within finite time. The distributed cooperative optimization problem for swarm control was investigated in Ref. [51], which optimized function can use for the Euler-Lagrangian agents with global equality and inequality constraints.

2) Single and multiple I/O model: For the control object of the swarm system, it can be divided from the perspective of number of the input and output. Specifically, it can be expressed as SISO (Single-Input Single-Output), SIMO (Single-Input Multiple-Output), SIMO, and MIMO.

Ref. [52] proposed a fixed-time adaptive output feedback control method based on the MIMO nonlinear systems, where the system states can be measured via the designed observer. Based on the MIMO discrete time-varying linear systems, a model predictive control method used swarm intelligence was proposed in Ref. [53]. The method overcame the difficulty in solving the algebraic Riccati equation of finite-horizon optimal state control.

3) Linear and nonlinear model: Similarly, it can be divided from whether the swarm system is a linear model, in which the stability of the swarm linear control system is only related to the structure and parameters of the system, but not to the system input. The stability of the swarm nonlinear control system depends not only on the structure and parameters of the system, but also on the amplitude and initial conditions of the input signal.

At present, swarm systems are widely used in the fields of robotics and aerospace, while the system models involved in these fields are highly nonlinear, which corresponding nonlinear control algorithms often need to be designed. Ref. [54] proposed an adaptive swarm control method within saturated input based on the nonlinear coupling degree, considering the connection strength between agents. To overcome the influence of heterogeneous nonlinear dynamics and unmeasured states in practical systems, an adaptive swarm controller was proposed in Ref. [55].

4) Continuous and discrete model: In control theory, the more common division is to judge whether the swarm system model is a continuous or discontinuous (discrete) system. The structures of these two control systems are different, and the analysis methods adopted are completely different. Among them, the continuous system can be expressed by differential equations, transfer functions and state equations; while the discrete system field can be expressed by means of difference equations and discrete state equations.

Ref. [56] provided a dynamic discrete pigeon-inspired optimization method to improve the cooperative search-attack mission planning for multiple unmanned aerial vehicles, under this control method, the UAVs can autonomously coordinate the movements and finish the search and attack missions to realize an optimal configuration. The complete controllability and structural controllability of discrete-time system is researched in Ref. [57], considering the time-delays under leader-follower strategy.

III. Swarm performance control

In this section, the key control technology of the swarm system are elaborated, which from the perspective of system control complexity and control requirements.

A. Swarm control complexity

1) Time delay system: Due to the complex composition of the swarm system, it is easy to generate time delay in the process of system sensing, control execution, and mutual communication. However, stable control in delay environment has a critical impact on system performance [58]. Besides, considering that the swarm is easily interfered by the communication distance and the uncertain environment during the process, time delay in the system is also non-uniform. In this section, a continuous-time high-order linear swarm system is taken as an example, which state equation can be expressed as

$$\dot{\boldsymbol{x}}_i(t) = \boldsymbol{A}\boldsymbol{x}_i(t) + \boldsymbol{B}\boldsymbol{u}_i(t), \quad i \in 1, 2, ..., n \tag{16}$$

where, i is the agent's number in the swarm; $\boldsymbol{x}_i$ is the system state variables; $\boldsymbol{u}_i$ refers to the control input of ith agent; $\boldsymbol{A}$, $\boldsymbol{B}$ are the parameter matrix respectively.

Then, we can define

$$\boldsymbol{\xi}_i(t) = \sum_{j=0}^{n} a_{ij}(\boldsymbol{x}_i(t) - \boldsymbol{x}_j(t)), \quad i = 1, 2, ..., n \tag{17}$$

Write Eq. (16) and Eq. (17) as a global matrix form as

$$\dot{\boldsymbol{X}}(t) = (\boldsymbol{I}_n \otimes \boldsymbol{A})\boldsymbol{X}(t) + (\boldsymbol{I}_n \otimes \boldsymbol{B})\boldsymbol{U}(t) \tag{18}$$

where, $\boldsymbol{X}(t) = \left[\boldsymbol{X}_1^T, \boldsymbol{X}_2^T, ..\boldsymbol{X}_n^T\right]$; $\boldsymbol{U}(t) = \left[\boldsymbol{u}_1^T, \boldsymbol{u}_2^T, ..\boldsymbol{u}_n^T\right]$.

$$\boldsymbol{\xi}(t) = (\boldsymbol{L} \otimes \boldsymbol{I}_p)(\boldsymbol{X}(t) - \boldsymbol{1}_n \otimes \boldsymbol{x}_0(t)) \tag{19}$$

where, $\boldsymbol{\xi}(t) = \left[\boldsymbol{\xi}_1^T, \boldsymbol{\xi}_2^T, ..\boldsymbol{\xi}_n^T\right]$; $\boldsymbol{L}$ is Laplace matrix; $\boldsymbol{x}_0$ is the status for the swarm virtual leader.

Then, the derivative with respect to time t on both sides of Eq. (19) is calculated as

$$\dot{\boldsymbol{\xi}}(t) = (\boldsymbol{I}_n \otimes \boldsymbol{A})\boldsymbol{\xi}(t) + (\boldsymbol{L} \otimes \boldsymbol{B})(\boldsymbol{U}(t) + \boldsymbol{w}(t)) \tag{20}$$

The following swarm delay coordination controller can be designed

$$\boldsymbol{u}_i(t) = \boldsymbol{K}\boldsymbol{\xi}_i(t - \tau_i(t)) \tag{21}$$

where $\boldsymbol{K}$ is the gain matrix to be solved; τ_i is non-uniform delay parameter.

Substituting Eq. (21) into Eq. (20) , the following closed-loop system can be obtained

$$\dot{\boldsymbol{\xi}}(t) = (\boldsymbol{I}_N \otimes \boldsymbol{A})\boldsymbol{\xi}(t) + (\boldsymbol{L} \otimes \boldsymbol{B}\boldsymbol{K})\boldsymbol{\xi}_\tau(t) \tag{22}$$

where $\boldsymbol{\xi}_\tau(t) = \left[\boldsymbol{\xi}_1^T(t - \tau_1(t)), ..., \boldsymbol{\xi}_n^T(t - \tau_n(t))\right]^T$.

Therefore, in order to ensure the stable control of the swarm system under the influence of time delay, it is necessary to ensure that Eq. (22) is asymptotically stable.

As for the research of time delay control, to solve the control problem in multi-agent system with communication delays, a proportional integral (PI) predictive control was designed in Ref. [59], which can compensate the delays via multistep output predictions. Based on the linear matrix inequality (LMI) criteria, a dynamic output consensus protocols with time delays was proposed in Ref. [60], which can be used in high-order linear singular swarm systems. The containment control issue was studied in Ref. [61], which proposed the necessary and sufficient condition for containment control without time-delay. Via using the z-transformation and Routh Criterion, the effects on different step-sizes on stability of the swarm systems were verified.

TABLE II
COMPARISON OF DIFFERENT CONVERGENCE TIME CONTROL METHODS.

Method	Ref	Function	Definite Convergence Time	Related to Initial Conditions	Related to System Parameters
Finite time	[69] [70]	$T_f \leq \frac{1}{\alpha(1-\gamma)} ln \frac{\alpha V^{(1-\gamma)}(x_0)+\beta}{\beta}$	×	✓	✓
Fixed time	[71] [72]	$T_x \leq \frac{1}{\varpi_1(1-\chi)} + \frac{1}{\varpi_2(\theta-1)}$	×	×	✓
Predetermined time	[73] [74]	$T_p(T_p > 0)$	✓	×	×

2) Disturbance system: Due to the large number and variety of swarm which needs to perform complex tasks, the swarm is susceptible to interference from the inside or outside [62]. Therefore, many scholars have researched the stability control of swarm system under disturbance and uncertain environments [63]. Similar to the previous section, a continuous-time high-order linear swarm system can be expressed as

$$\dot{\boldsymbol{x}}_i(t) = \boldsymbol{A}\boldsymbol{x}_i(t) + \boldsymbol{B}\boldsymbol{u}_i(t) + \boldsymbol{B}\boldsymbol{w}_i(t), \quad i \in 1, 2, ..., n \tag{23}$$

where $\boldsymbol{w}_i$ indicates the external disturbance input of the system.

Write Eq. (23) as a global matrix form as

$$\dot{\boldsymbol{X}}(t) = (\boldsymbol{I}_n \otimes \boldsymbol{A})\boldsymbol{X}(t) + (\boldsymbol{I}_n \otimes \boldsymbol{B})(\boldsymbol{U}(t) + \boldsymbol{w}(t)) \tag{24}$$

where $\boldsymbol{w}(t) = \left[\boldsymbol{w}_1^T, \boldsymbol{w}_2^T, ..\boldsymbol{w}_n^T\right]$.

At this time, we can calculate the derivative with respect to time t on both sides of Eq. (19) again based on the system expression in Eq. (23) as

$$\dot{\boldsymbol{\xi}}(t) = (\boldsymbol{I}_n \otimes \boldsymbol{A})\boldsymbol{\xi}(t) + (\boldsymbol{L} \otimes \boldsymbol{B})(\boldsymbol{U}(t) + \boldsymbol{w}(t)) \tag{25}$$

When Eq. (25) can asymptotically stable, the swarm stability control under the disturbance environment is realized.

For the swarm system with disturbance and uncertainty, the common methods are sliding mode control, robust control, and etc. A fully distributed control protocol based on an adaptive σ-modification method was proposed in Ref. [64], which has a better control effect under time delays and external disturbances. In Ref. [65], an adaptive leader–follower consensus control method was proposed, which was under the unknown control directions.

B. Swarm control requirements

1) Convergence time control: The stability theory is an important basis for judging whether a controller can make the system stable, while the convergence rate of the system consistency is an important index for evaluating the stability of the system [66]. To further improve the control effect of the swarm system, many scholars turn to the research on the system convergence time control [67], [68], which main based on the finite time control, fixed time control, predetermined time control. Table II is the comparison of different convergence time control methods.

(1) Finite time control

The convergence time of the finite time T_f completely depends on the initial conditions and parameters of the system. This problem can be described by a continuous nonlinear system as shown in Eq. (26).

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}(t, \boldsymbol{x}) + \boldsymbol{u} \tag{26}$$

where $\boldsymbol{f}(\cdot)$ is a nonlinear function used to describe the dynamic characteristics of the system, and have $\boldsymbol{f}(t, 0) = 0$. If there is a positive definite Lyapunov function V, which first derivative satisfies

$$\dot{V}_t \leq -\alpha V(t) - \beta V^{\gamma}(t) \tag{27}$$

where, α, β are the positive real number; $0 < \gamma < 1$. The system can be converged in time T_f, which can be calculated as

$$T_f \leq \frac{1}{\alpha(1-\gamma)} ln \frac{\alpha V^{(1-\gamma)}(x_0) + \beta}{\beta} \tag{28}$$

The consensus protocol of the system Eq. (26) can be designed as

$$\boldsymbol{u}_i = sign\left(\sum_{j=1}^{n} a_{ij}(\boldsymbol{x}_j - \boldsymbol{x}_i)\right)\left|\sum_{j=1}^{n} a_{ij}(\boldsymbol{x}_j - \boldsymbol{x}_i)\right|^{\alpha_i} \tag{29}$$

where $0 < \alpha_i < 1$.

At present, finite-time control is widely used, such as in the fields of multi-agents and aerospace [75]. Besides, a finite-time track control method was proposed in Ref. [76], which can make the agents reach an aggregation in finite-time. The essential part of this method was choosing the interaction matrix. Ref. [69] reviewed the research in finite/fixed-time control, which sorted out some fundamental concepts and categorized the research results on the finite/fixed-time stabilization and tracking control. In the meanwhile, several engineering applications and future directions were also be enumerated.

(2) Fixed time control

Fixed time control means the convergence time T_x does not depend on the initial conditions, but is affected by the system parameters, which the convergence time cannot be set arbitrarily. Consider a system of the form as

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}(t, \boldsymbol{x}), \boldsymbol{x}(0) = \boldsymbol{x}_0 \tag{30}$$

where $\boldsymbol{f}(t, \boldsymbol{x})$ is the continuous function defined in the real domain. Suppose the origin is the equilibrium point of system in Eq. (30). If there is a positive definite function $V(x)$, which derivative satisfies the following inequality

$$\dot{V}(x) \leq -\varpi_1 V^{\chi}(x) - \varpi_2 V^{\theta}(x) \tag{31}$$

where, χ and θ satisfy $\chi \in (0, 1)$ and $\theta \in (1, \infty)$ respectively; ϖ_1 and ϖ_2 are the positive number. At this time, the system in Eq. (30) is fixed time stable, where the convergence time T_x can be calculated as

$$T_x \leq \frac{1}{\varpi_1(1-\chi)} + \frac{1}{\varpi_2(\theta-1)} \tag{32}$$

As for fixed time control, Ref. [77] proposed a fixed-time consensus algorithm based on event-triggered control, which can deal with the system with delay input and uncertain disturbances. Based on the fixed time control, Ref. [71] did the research on fixed-time stabilization (FXTSB) for an uncertain impulsive distributed delay static neural networks (UIDSNNs), which new criteria were proposed to handle the impulsive effect.

(3) Predetermined time control

Predetermined time control refers to the convergence time T_p can be pre-set explicitly, which independent of the system initial values and system parameters. Based on the system expression of Eq. (26), the control problem is transformed into designing an appropriate control input $\boldsymbol{u}$, which can make the system state $\boldsymbol{x}(t)$converges to 0 at an arbitrarily set time parameter T_p.

Then, a positive definite and continuous Lyapunov candidate function can be defined as $V(\boldsymbol{x}(t), t)$, and have $V(0, t) = 0$. If the parameter $b \geq 0$ and $k > 0$ exist, in the time interval $t \in [t_0, T_p)$, the Lyapunov's first-order time derivative satisfy

$$\dot{V}(x(t), t) \leq -bV - k\varphi(t_0, T_p)V \tag{33}$$

then we have

$$\begin{cases} V(x(t), t) \leq -\mu^{-k}(t_0, T_p)e^{-b(t-t_0)}V(t_0), & t \in [t_0, T_p) \\ V(x(t), t) = 0, & t \in [T_p, \infty) \end{cases} \tag{34}$$

where $\mu(t_0, T_p)$ is a time-varying scaling function, which can define as follows

$$\mu(t_0, T_p)\begin{cases} 1, & t \in [0, t_0) \\ \left(\frac{T_p}{T_p+t_0-t}\right)^p, & t \in [t_0, T_p) \\ 1, & t \in [T_p, \infty) \end{cases} \tag{35}$$

where, $p > 1; t_0 \geq 0; T_p > 0$. The first derivative of $\mu(t_0, T_p)$ with respect to time t is:

$$\dot{\mu}(t_0, T_p)\begin{cases} 1, & t \in [0, t_0) \\ \frac{p}{T_p-t_0}\mu(t_0, T_p)^{1+\frac{1}{p}}, & t \in [t_0, T_p) \\ 1, & t \in [T_p, \infty) \end{cases} \tag{36}$$

In terms of predetermined time control, a three-dimensional prescribed-time cooperative control method was designed in Ref. [78], which can be used in different attacking scenarios for multimissiles, overcoming the drawbacks of finite/fixed-time cooperative guidance law. A distributed practical predefined-time observer was introduced to estimate the trajectory of the whole system in Ref. [79]. To further reduce the converge time of homogeneous and heterogeneous linear multi-agent systems, a predefined-time cooperative control method was designed [80], which achieved the distributed optimization for the swarm under undirected and connected communication topologies.

2) Convergence accuracy control: To make the control system work at the desired state performance, guaranteed cost control is introduced to the swarm system. Guaranteed cost control refers to making the performance indicators of the swarm system meet certain requirements while the system is robust and stable [81].

Taking the time-varying formation performance of the swarm system in Eq. (16) as an example, the cost function is constructed as

$$J = J_1 + J_1 \tag{37}$$

where

$$J_1 = \sum_{i=1}^{n}\int_0^\infty (\boldsymbol{x}_i(t) - \boldsymbol{h}_i(t))^T\boldsymbol{Q}(\boldsymbol{x}_i(t) - \boldsymbol{h}_i(t))dt \tag{38}$$

$$\begin{aligned} J_2 = \frac{1}{2}\sum_{i=1}^{n}\int_0^\infty \sum_{j\in N_i}\bar{a}_{ij}(\boldsymbol{x}_j(t) - \boldsymbol{h}_j(t) - (\boldsymbol{x}_i(t) \\ - \boldsymbol{h}_i(t)))^T\boldsymbol{Q}(\boldsymbol{x}_j(t) - \boldsymbol{h}_j(t) - (\boldsymbol{x}_i(t) - \boldsymbol{h}_i(t)))dt \end{aligned} \tag{39}$$

where, $\boldsymbol{h}(t)$ is used to describe the desired configuration of the swarm and can be expressed as $\boldsymbol{h}(t) = \left[\boldsymbol{h}_1^T(t), \boldsymbol{h}_2^T(t), ..., \boldsymbol{h}_N^T(t)\right]^T$; $\boldsymbol{Q}$ is a symmetric positive definite matrix; N_i represents the neighbor set of the ith node in the topological graph $\boldsymbol{G}$, J_1 represents the cost function of the agent itself, and J_2 represents the cost function between each agent.

In this way, under the swarm guaranteed cost control, all agents in the swarm satisfied

$$\lim_{t\to\infty}(\boldsymbol{x}_i(t) - \boldsymbol{h}_i(t)) = 0 \quad (i = 1, 2, ..., n) \tag{40}$$

and $J < J^*$, where J^* is the upper bound of guaranteed cost.

Considering the advantages of guaranteed cost control, this method have already been used in swarm control. Ref. [82] proposed a guaranteed cost consensus control laws for multi-agent system with switching topologies, balanced the problem between the consensus coordination performances and the energy consumptions of control system. Based on the event triggering mechanism, a guaranteed cost consensus for distributed system was proposed in Ref. [83], using the BMI (bilinear matrix inequality) method to reduce the conservativeness of controller design.

3) Consumption control: With the expansion of the swarm scale and the improvement of the task complexity, the magnitude of the data transmitted by the swarm communication continues to increase [84]. However, if the control system of the swarm is in the working state for a long time, it will inevitably cause unnecessary resource consumption. Therefore, some scholars put forward the requirement of starting the control system from the perspective of event triggering [85]. Compared to control schemes with continuous or periodic communication, event-triggered control enables controller updates based on event content to achieve and maintain system performance.

Based on the system model in Eq. 5 and the control law in Eq. 6, the event-triggered mechanism is introduced into the swarm consistency control, the event-triggered consistency protocol can be expressed as

$$\boldsymbol{u}_i = -\sum_{j=1}^{n} a_{ij}(t)(\boldsymbol{x}(S_{k,i})_i - \boldsymbol{x}_j(S_{k,i})), \quad t \in [S_{k,i}, S_{k+1,i}) \tag{41}$$

where $S_{k,i}$ indicates the time at which the agent i controller performs sampling updates, and $0 = S_{0,i} < S_{1,i} < ... < S_{k,i} <$ ....

At present, the research on event triggering is mainly as follows: An event-triggered adaptive sliding mode control was proposed in Ref. [86], which added the event-triggered mechanism to observer channel, having remarkable control effect on nonlinear system with actuator fault and deception attack. To avoid the Zeno behavior in event-triggered, Ref. [87] researched the nonlinear systems Lyapunov stability and event-triggered delayed impulsive control based on the neural networks, which control method has the effectiveness in time delay system control. To further improve the control effect, an event-triggered control method with preset convergence time was proposed in Ref [88], where the computational complexity can be reduced via a predefined time filter. Similar to the event-triggered control, Ref. [89] proposed a self-triggered-organized formation, which can make the multi robots form the leader–follower consensus smoothly.

IV. Swarm coordination control

In this section, the key coordination issue of the swarm system are illustrated, including the topic about formation control, obstacle avoidance, path planning, and task assignment.

A. Formation control

For swarm with physical constraints, the efficient and feasible formation design is a critical part in control. For many years, researchers have modeled swarm formations based on biological swarm behavior, which simulated the behavior of swarm separation, cohesion, and alignment [36]. The mainstream formation control methods in the existing literature are: leader-follower method, behavior-based method, and virtual structure method.

1) Leader-follower scheme: The leader-follower is a global formation control method consisting of one or several leaders and followers [90]. The swarm formation can be realized via the followers tracking the leader's angle, position, speed, and other state information. Based on the fixed-wing UAVs swarm control, Ref. [91] proposed a 3D leader-follower formation where considered the UAVs' motion constraints and disturbances. A leader-follower-based particle swarm optimization (LFPSO) algorithm was proposed in Ref. [92], which was inspired by multi-agent system.

The advantage of this formation is that when the leader's motion state is determined, the rest of the followers can track the leader to achieve formation control. However, when the leader fails, the formation may not be formed, affecting the overall swarm control.

2) Behavioral scheme: The idea of behavior-based formation control is to design the local control actions of each agent, such as obstacle avoidance and formation transformation. When the external environment changes, the agent changes the movement direction and movement speed accordingly, so as to realize the formation change suitable for the environment change. Ref. [93] proposed a behavior-based cooperative intelligence method of autonomous flying robots swarm, which can cooperatively gather situational awareness data quickly after a major natural disaster. Meanwhile, a behavior-based method were proposed in Ref. [94], which was useful to guide the unmanned agent system in an unknown or dynamically changing environment.

The advantages of the behavior-based method are mainly manifested in that the formation of agents can well realize distributed control, which can complete various actions with good timeliness. However, it is difficult to precisely define the swarm behavior mathematically. Especially when the number of agents is too large, the system can not be stable based solely on the behavior method.

3) Virtual structure scheme: The control idea of the virtual structure method is based on the characteristics of rigid structures, which makes the decentralized agents move according to a specific control law to form a rigid fixed formation. Based on the distribute control, a swarm formation control and maintenance method was realized in Ref. [95], which realized the position and speed consistency control between each UAV and their virtual leader. Ref. [96] proposed a formation generation algorithm and obstacle avoidance method for UAV formation, providing a high efficient of formation shape maintain and change.

Compared with the leader-follower strategy, the virtual structure method does not require a real leader, and the formation design is simpler, which the swarm can quickly reach the desired formation. However, when the formation changes, the corresponding control algorithm needs to be redesigned, which the algorithm has poor adaptability.

B. Coordinated obstacle avoidance

Obstacle avoidance is an important factor for the safety of swarm execution tasks [97]. The commonly used obstacle avoidance control methods can be divided into potential field method, geometric method, intelligent algorithm, control theory, and machine learning method. Fig. 3 is a schematic diagram of the summary for these methods.

The calculation based on the potential field method is simple and has high real-time performance, but it is easy to fall into the local minimum problem [98]; the method based on the geometric model is simple to calculate while needs to consider many physical constraints; the intelligent algorithm requires a long time iteration optimization. whiach may not suitable for systems with high real-time requirements; control theory method has better predictive control effects, but higher requirements for system models; machine learning-based algorithms can achieve collision avoidance effects, but requires a lot of data training. Therefore, to meet the obstacle avoidance requirements of complex swarm, existing methods may need to be improved or combined [99]. The specific research status is as follows

1) Potential field method: A novel collision avoidance method based path following guidance was proposed in Ref. [100], which consider the complex unknowns including uncertain dynamics and time-varying disturbances for multiple under-actuated surface vehicles (USVs). Based on self-organizing migrating algorithm, Ref. [101] proposed an obstacle avoidance algorithm for swarm robot under unknown environment, which fitness function was based on the function of attraction from the target and the repulsion of the obstacles.

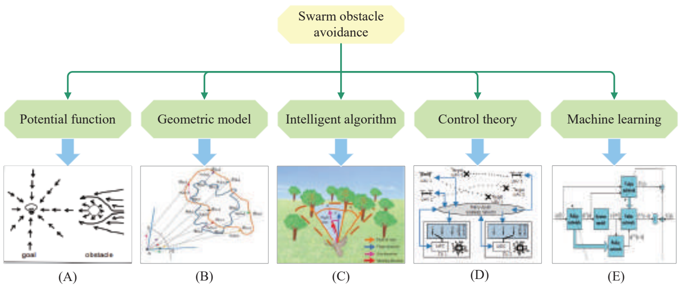

Fig. 3. Control method of obstacle avoidance in swarm[2].

2) Geometric method: Ref. [102] proposed a geometrical region-based shape control methodology, which employed a two-level hierarchical control strategy to achieve it. To achieve coordinated curved path following and handle collision avoidance for the fixed-wing UAVs simultaneously, a novel curved path following scheme based on a virtual structure and a kinematic model was proposed in Ref. [103].

3) Intelligent algorithm method: The constraints on the maneuverability of UAV were proposed in Ref. [104], which used the particle swarm optimization (PSO) algorithm. To control the swarm robots moving through obstacle fields towards a goal, generalized Lennard-Jones(LJ) force law was introduced in Ref. [105], which combined with offline evolutionary learning.

4) Control theory method: Based on the leader-follower configurations, a novel distributed model predictive control method was proposed in Ref. [106], which make the multi-vehicle formations moving under uncertain environments. A swarm model that generates self-organized, safe, and cohesive trajectories was proposed in Ref. [107] based on the distributed predictive, which can solve an optimization problem in real-time.

5) Machine learning method: A secure and safe distributed cooperative control law was proposed in Ref. [108],which was used for the situation of multiple platoons of automated vehicles under unknown data falsification attacks on driving commands. To solve the formation control with collision avoidance problem based on the leader–follower structure, Ref. [109] provided a novel control method based on deep reinforcement learning (RL).

C. Path planning

Swarm path planning is to plan a path from the starting point to the target point under certain constraints, which the specified performance index is optimal. Compared with the control of a single agent, swarm path planning needs to consider both spatial and temporal coordination constraints. The swarm path planning algorithm is essentially a multi-constraint combinatorial optimization algorithm [115], which current main methods include traditional planning methods, intelligent optimization algorithms and path planning under machine learning.

1) Traditional method: Traditional path planning algorithms are relatively mature, which have been widely used in single-machine planning. Traditional algorithms are mainly divided into graph-based search method, sampling method and dubins algorithm. Ref. [116] proposed a multi-agent time-based A* path-planning method, which method enabled each agent to physically complete the translation path synchronously. To solve the dynamic path planning and motion control problem for micro robotic swarms, an enhanced bidirectional rapidly-exploring random tree star (EB-RRT*) method was provided in Ref. [117], which dynamically plan the optimal path for obstacle avoidance according to the physical size of the swarm.

2) Intelligent optimization algorithm: Most of the intelligent optimization algorithms search for the optimal solution in space by imitating the foraging and hunting behavior of group organisms. These algorithms can solve high-dimensional complex and multi-constrained optimization problems. Common algorithms include genetic algorithm (GA), ant colony algorithm (ACO), particle swarm algorithm (PSO). In view of a new genetic algorithm, a path planning method based on probability maps was provided in Ref. [120], which used a new genetic operator to select chromosome for crossover operation. Based on improved particle swarm optimization, Ref. [121] provided a three dimensional path planning algorithm for UAVs, which speeded up the convergence and increased the solution optimality in the same time.

3) Machine learning: To overcome the shortcomings of most algorithms with poor path adaptability, long search time, low convergence accuracy, and easy to fall into local optimum, researchers have been experimenting with different techniques. The machine learning methods have received the most attention, including reinforcement learning, neural network and other methods. Ref. [123] provided a path planning method based on the reinforcement learning, which combined with the convolution neural network, showing the flexible and efficient movement of the robots under various environments. Ref. [125] provided a deep learning-based real-time distribution planning method for microrobot swarm navigation, which make the microrobot swarms with distribution reconfigurability adapt to environments during navigation.

Due to the complex application scenarios of swarm, it may be difficult for a single control algorithm to achieve optimal planning. Therefore, a hybrid algorithm combining various algorithms should be considered. Table III is the comparison of swarm path planning algorithms.

D. Task assignment

Task assignment is an important guarantee for the swarm to complete the specified task, which is an important part of the swarm system [126]. According to the relevance of swarm

[2]In Fig. 3, Sub-figure A refers to the force diagram of the agent under the traditional artificial potential field (APF) method, including the attraction from the target and the repulsive force of the obstacle [110]; B is the geometric interpretation of the collision cone in Ref. [111]; C is the pigeon-inspired obstacle-avoidance model in Ref. [112], which can make agents fly through a complex environment with multiple obstacles; An event-triggered distributed model predictive control structure was shown in D [113]; E is the structural sketch of the control policy in Ref. [114], which proposed a cooperative control with reinforcement learning for swarm system under unknown dynamic environment.

TABLE III
COMPARISON OF SWARM PATH PLANNING ALGORITHMS.

Method	Reference	Algorithm	Advantage	Disadvantage
TM	[116]	A*	Quickly	Not smooth, Low safety
	[117]	RRT	No modeling, Law calculation	Affected by the number of sampling points
	[118] [119]	Dubins	Consider constraints	Complex
IOA	[120]	GA	Simple, Easy to implement	Unstable
	[121]	PSO		Slow to converge
	[122]	ACO		Easy to local optimum
ML	[123]	RL	High robustness, Learning association ability	Training time
	[124]	NN		Training data
	[125]	DL		Training blindness

Abbreviations in the table: TM-Traditional method; IOA-Intelligent optimization algorithm; ML-Machine learning; A*-A star algorithm; RRT-Rapidly-exploring random trees; GA-Genetic algorithm; PSO-Particle swarm optimization; ACO-Ant clony optimization; RL-Reinforcement learning; NN-Neural network; DL-Deep learning.

tasks, it can be divided into collaborative task assignment and independent task assignment [127]; based on the nature of the swarm environment, it can be divided into static task assignment and dynamic task assignment; it can also be divided into centralized, distributed and hierarchical task assignment according to the control structure.

In the current study, consider the communications cost and running time, Ref. [128] provided a compromise based on the Extreme-Comm and Card-Dealer's algorithm. which can provide a solution for dynamic task assignment in robot swarms. Combining with the particle swarm optimization and genetic algorithm, a wolf pack algorithm was proposed in Ref. [129] for swarm to task assignment.

V. EVALUATION

To qualitatively and quantitatively the swarm control system, it is necessary to analyze the system in combination with the effectiveness evaluation method, which can further improve the main advantages of the unmanned swarm such as robustness, flexibility, and scalability.

A. Evaluation Index System

The determination of evaluation indexes is the primary and basic link in the swarm evaluation, which determines the rationality and effectiveness of the final evaluation conclusion. Therefore, it is a key issue to design a reasonable index to quantify the autonomy and coordination of the swarm system. Considering that the current swarm evaluation content is relatively scattered, quantitative evaluation can be carried out for actual task requirements in the actual evaluation. Fig. 4 shows the framework of swarm comprehensive evaluation index, which can be evaluated from four aspects: perception, analysis, decision-making and action. During the evaluation process, some key capabilities of swarm need to be considered, specifically including task assignment, path plannings, collaborative formation, communication networking, and coordination, etc.

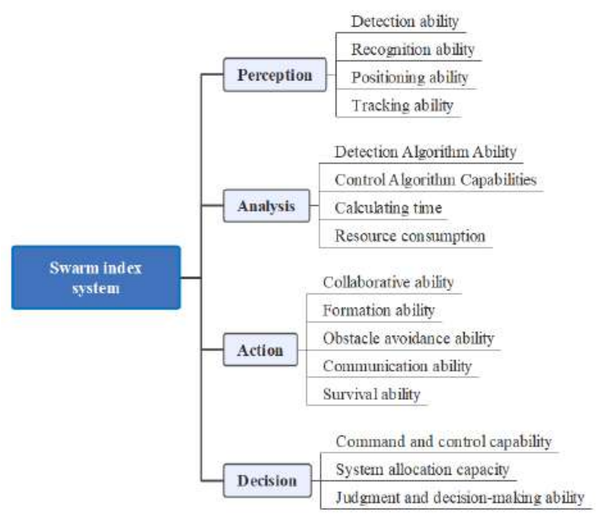

Fig. 4. Swarm evaluation index system.

B. Evaluation Methods and Researches

Selecting an appropriate evaluation method is another important issue in swarm evaluation [130]. At present, the common evaluation methods are divided into four main categories, which have been specifically divided in Fig. 5. The mathematical statistics method is the most basic and commonly used method. Its basic principle is to express the indexes to be evaluated as random variables, use the mathematical statistics method to estimate and test the data obtained through multiple experiments. Finally, the evaluation results can be obtained. Experience driven methods include the expert experience method, analytic hierarchy process (AHP), and fuzzy comprehensive evaluation method. Among them, the expert experience method is the most subjective. The AHP method is to decompose complex problems layer by layer, and then quantitatively analyze them with the help of human subjective experience. The fuzzy comprehensive evaluation method depends on fuzzy mathematics. However, these methods are highly subjective. The data driven method needs to establish a nonlinear model between the input indicators and the output through a large amount of data generated during the swarm test. Similarly, the model driven method is to establish a functional relationship through the relationship between indexes for quantification. The common methods of this category are the ADC (Availability, Dependability, Capacity) method and the data envelopment analysis method. The advantages and disadvantages of these methods are compared in Table IV .

Research on swarm evaluation, Ref. [131] proposed an

TABLE IV
COMPARISON OF DIFFERENT SWARM EVALUATION METHODS.

Method	Advantages	Disadvantages
Mathematical statistics	Strict, commonly used	Need multiple experiments, heavy workload
Experience driven	Practical, logical	Subjectivity, difficult to quantify non-linear relationships
Data driven	Strong advantage in qualitative and non-deterministic	Need a lot of data and training time
Model driven	Objectivity, comprehensive	Rigorous modeling is required

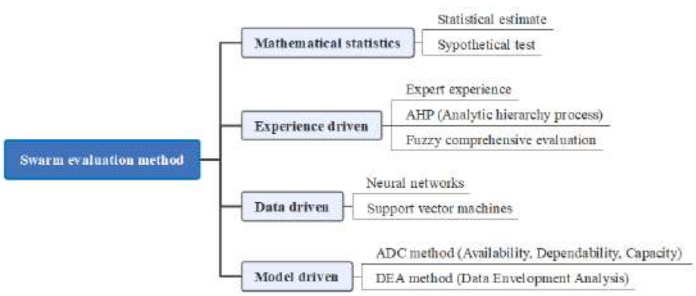

Fig. 5. Swarm evaluation methods.

operational effectiveness evaluation method of UAV swarm, using the rate-variable in-trees modeling method. Different form the traditional qualitative analysis, the proposed method took the survival rate and mission completion degree of UAVs as evaluation indicators, which has a high reference value. Ref. [132] proposed a new manned/unmanned aerial vehicle (MAV/UAV) collaborative combat network model construction method, combining the index system with complex network. Based on discrete artificial potential field, a boundary performance evaluation probablity method of UAV swarm was proposed in Ref. [133].

VI. SWARM PLATFORM AND APPLICATION

A. Module

A swarm physical verification platform is built by multiple modules, Through the sensor detection, positioning and navigation, communication connection, information sharing, and coordinated control between each modules, the swarm coordinated control can be finally realized. Different platforms may have different module configurations, which need to be designed and customized according to actual needs [26].

1) Control module: The control module is responsible for monitoring and controlling the entire swarm system in real time. Taking UAVs swarm as example, the control module can issue and control the UAVs, including takeoff, landing, navigation, attitude adjustment, etc [19].

2) Communication module: The communication module is used to realize the communication between agents in the swarm, which wireless communication technology (such as Wi-Fi or Bluetooth) or other dedicated communication equipment can be used to ensure real-time data transmission and collaboration between agents.

3) Positioning and Navigation Module: The positioning and navigation module is used to provide positioning, navigation and path planning functions for the agent in the swarm. The positioning devices such as Global Positioning System (GPS), inertial navigation system (INS), Global Navigation Satellite System (GNSS) and visual sensors are integrated to achieve autonomous movement of the agent.

4) Perception and perception decision-making module: To sensor the surrounding environment, perception and perception decision-making module is used. The commonly used sensors are distance sensors, image sensors, and laser radar. Besides, the perception decision-making algorithms is researched. By processing the perception data, the agent can judge information such as obstacles and target positions, which corresponding motion decisions can be made.

5) Data processing and analysis module: The data processing and analysis module is responsible for collecting, storing and processing swarm data, including data acquisition equipment, database management system and analysis algorithm.

6) Virtual simulation module: To simulate swarm movement, collaborative operation and scene testing, a simulation environment for the physical verification platform can be provided via the virtual simulation module. Through this module, the effectiveness of system performance and algorithms can be tested in advance, reducing the risk and cost of physical verification.

7) User Interface Module: The user interface module is used to provide an interactive interface between the user and the swarm physical platform, so that the user can monitor and control the swarm system. The user interface include graphical interface, instruction input interface, etc.

B. Platform and typical experiment

With the continuous development of swarm system, various swarm platforms have been developed and processed by many scholars and companies [26], such as *Kobot*, *E-puck*, *Jasmine*, *I-Swarm*, *AMiR*, and *mROBerTO*. The platform contains virtual system simulation platform and physical system platform. Based on the existing platform three main swarm experiments are selected to introduce. Aiming at the formation and obstacle avoidance control of large-scale fixed-wing UAV swarm, a multi-layer group structure is adopted to realize the actual flight experiment of 21 UAVs in Ref. [19]. Ref. [9] proposed a the mean-shift algorithm empowers the robot swarm to assemble highly complex shapes with strong adaptability, which research was verified by experiments with swarms of 50 ground robots. Ref. [134] validated their model on real hardware, which carried out field experiments with a self-organized swarm included 30 UAVs. This experiment is the largest of such aerial outdoor systems without central control reported to date showing swarm with collective collision and object avoidance.

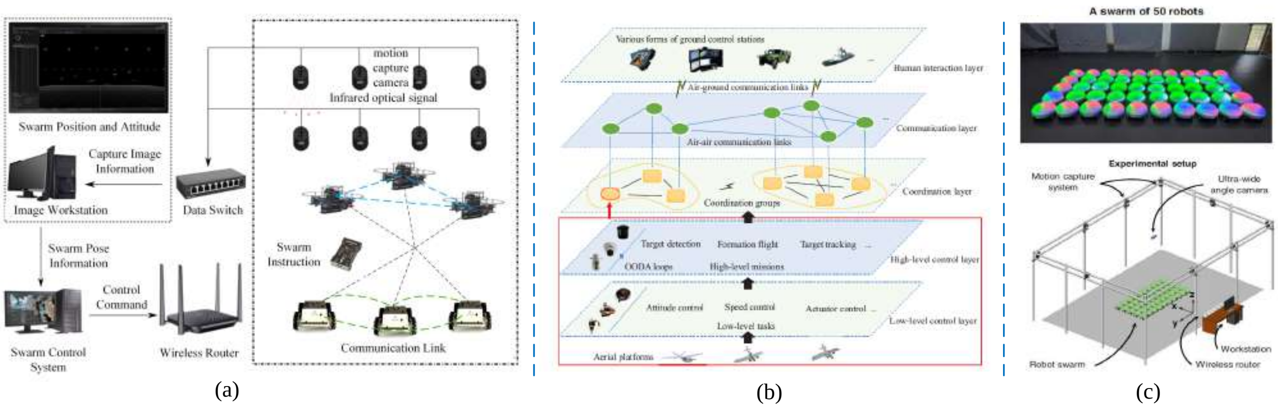

Fig. 6. Typical swarm experiment platform[3].

C. Application

1) Application objects: In this section, for further clarity of review, we sort the application out from the perspective of different kinds of individual agents.

Unmanned aerial vehicle: UAV is the most common application carrier of swarm system. Based on the complex network theory-based, Ref. [135] proposed a robustness evaluation method for a UAV swarming system, which consider the dynamic evolution of UAV swarms, including dynamic reconfiguration and information correlation. Ref. [136] provided a distributed swarm control method for Large-scale fixed-wing UAV, which provided the collision avoidance and formation maneuver strategy correspondingly. Ref. [137] proposed a fixed wing UAV swarm cooperate methods and experiments, which used the multi-layered group-based architecture to demonstrate actual flight of 21 UAVs. *Unmanned ground vehicle*: As for the swarm research based on unmanned ground vehicle, a new set of switched velocity controllers of UGVs swarm based on the multiple Lyapunov functions was proposed in Ref. [138], which make the UGVs to navigate autonomously by hierarchal landmarks in a complex work surroundings to their equilibrium state. In Ref. [139], a heuristic method that combined the Floyd's algorithm and PSO algorithm was proposed, which was based on an idea of autonomous last-mile delivery, using multiple unmanned ground vehicles to minimize the maximum make span to complete all tasks. Consider the physical and geographical constraints for a mobile stations swarm, Ref. [140] proposed a mission aware motion planning (MAP) framework, which can provided efficient resources supply for UAVs performing mission.

Unmanned ship: In term of unmanned ship study, based on a three-degree-of-freedom model of surface vehicle, a model predictive control (MPC) for a way-point tracking was proposed in Ref. [141], which improved the performance for underactuated marine surface vessels of path following. Ref. [142] is a review of multiple autonomous surface vehicles cooperate control in recently years, including the recent results on trajectory-guided, path-guided, and target-guided coordinated control. The marine surface vehicles maneuver control was researched in Ref. [143], which used two path update laws based on error feedback and filtering scheme.

Multi-robot system: To maximize the effectiveness of swarm systems in different occasions, self-reconfigurable robot systems have gradually emerged. Ref. [144] proposed a reconfigurable swarm of identical low-cost quadruped robots to collectively complete the challenging terradynamic tasks. When a single agent or several groups of agents cannot complete the task, the swarm system will be decentralized and reconfigured to complete complex tasks together. Besides, the study of swarm systems can also be applied to microsystems, such as micro/nanomachines [145]. The process of such swarm self-assembly could be achieved via fuel induced control methods, which has broad application prospects in bio-medicine. Then, there are also scholars who are inspired by biological fish swarms to develop a bionic fish swarm control system [146]. Ref. [147] proposed a fish swarm system, which could make the underwater robots synchrony, dispersion/aggregation, dynamic circle formation, and search-capture, having the wide prospect in environmental monitoring.

2) Application scenarios: In the current study, swarm has been applied in many fields, which specifically includes the following aspects.

Precision agriculture: The swarm system provides more sufficient productivity and more efficient work force for large-scale [148], modern and precise agricultural production [149].

Cargo delivery: Different individual agents in the swarm system can undertake the tasks of transportation, loading and unloading, packaging, processing and distribution, respectively. The efficiency of logistics delivery is accelerated via the division and cooperation of swarm [150], [151].

Commercial performance: The swarm system can also be used in various commercial activities, such as drone performances, which has broad market prospects [152].

Rescue and disaster relief: The spread and changes of the disaster situation can be detected and perceived via the swarm in time, which can improve the efficiency of disaster relief work and reduce the casualties of rescue workers by changing the formation and dividing the work independently [153].

[3] In Fig. 6, (a) is a platform for air-ground collaborative formation designed by *FEISILAB*; (b) is the multi-layered group-based UAV swarm physical verification platform architecture in Ref. [19]; (c) is the rainbow robot platform in Ref. [9], which swarm scale reached to 50.

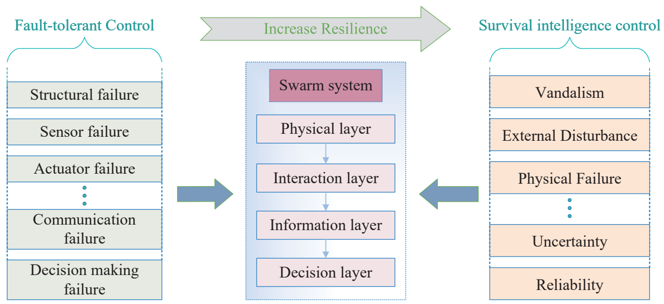

Fig. 7. Survival intelligence control of swarm system.

Military field: Unmanned swarm system are bound to become the mainstream trend of future operations [154], [155]. Swarm systems can be widely used in target search, reconnaissance and surveillance, border patrol search and rescue, and urban anti-terrorism and stability maintenance [156], [157], which is an important manifestation of vicinagearth security.

Aviation field: The swarm system can improve the effect of aerial detection and navigation. Such as satellite formations, each satellite works together, communicates with each other, and jointly realizes tasks such as communication, reconnaissance and navigation [158].

VII. Research trends and future insights

A. Survival intelligence-based swarm control

1) Security control: With the further expansion scale and the complexity structure of the swarm system, the security cooperative control of the swarm become more important [159]. However, the traditional fault-tolerant control can only solve the internal fault problem of the swarm, which lacks a stronger resilience and robustness with the external strong interference and vandalism. Specifically, in conventional swarm fault-tolerant control, the failures can be caused by individual agent failures, communication failures, and formation failures caused by internal interference. The corresponding solutions of swarm fault-tolerant control include methods such as fault detection, controller reconfiguration (By changing controller parameters or updating controller models), adaptive control, and observers designed. However, when the degree of swarm's interference or vandalism further increases, it is necessary to carry out deeper and more global control from the perspective of security control. For example, in terms of communication, the conventional fault-tolerant control can only deal with static and low-level faults, such as communication delay, data packet loss, and so on. In the face of more serious topology failures, it needs to be transformed into a topology reconstruction problem from the perspective of security. Therefore, the system security cooperative control is a further derivative and extended research based on the swarm fault-tolerant control, which is more effective for improving swarm resilience and reliability.

2) Self-healing control: Self-healing control refers to the method that the swarm system can quickly recover its inherent performance and maintain the desired state after being disturbed by the outside world and attacked. That is to say, after the swarm detects and recognizes threats, the swarm makes timely decisions and plans, and controls each intelligent unit for rapid recovery and reconstruction, to improve the fault tolerance and adaptability of the system.

3) Green control: Green control refers to optimizing the swarm control under the premise of fully considering resource consumption. That is to design a swarm control algorithm so that the swarm can complete the task with the optimal strategy under the lowest energy consumption. This control involves multiple topics such as optimal task allocation, time convergence control, trigger control, drive control, etc., which needs comprehensive decision-making and coordinate in a swarm system.

Therefore, to further realize the survival intelligence control, the swarm system can be divided into four layers (physical layer, interaction layer, information layer and decision layer) according to the hierarchical characteristics, where the corresponding survival intelligence control can be carried out to improve the resource utilization and cooperation efficiency. The physical layer control refer to the survival intelligence for the entity components of the single agent, which is also the foundation for the swarm system to smooth operation. The information layer is composed of task information data and information communication components of the system, which is the basis for system interconnection and task coordination. Its survival is directly related to disturbances, data loss, information interruptions, and even cyber attacks in the process of information transmission. The interaction layer refers to the interaction between the swarm and the external environment. The control of this layer will effectively avoid the conflict of system space resources on the basis of fully considering the security constraints. The decision layer is the basis for the swarm system to achieve task diversification, which involves the communication decision-making, control decision-making, and task allocation decision-making. The survival intelligence control of this layer is directly linked to whether the swarm can successfully and optimally complete the task.

In the actual work of the swarm, each layer affects each other, while the threats faced by each layer may evolve to sources that threats other layers at any time, seriously influencing the system survival. Therefore, in future research, it is necessary to study the survival intelligence control of swarm, starting from the different layers of the swarm, and considering strong interference factors as well as the threats brought by human sabotage factors. In addition, it is also necessary to consider the swarm survival intelligence issues in conjunction with the external space environment, which is a macro fault-tolerant research that needs more globalization, intelligence and flexibility.

B. Learning-based swarm control

With the rapid development of artificial intelligence, machine learning such as deep reinforcement learning has gradually begun to be applied to swarm system. Compared with conventional graph theory algorithms, the learning-based artificial intelligence algorithm (LBAI) can be widely used in swarm intelligent control because of its superior computing

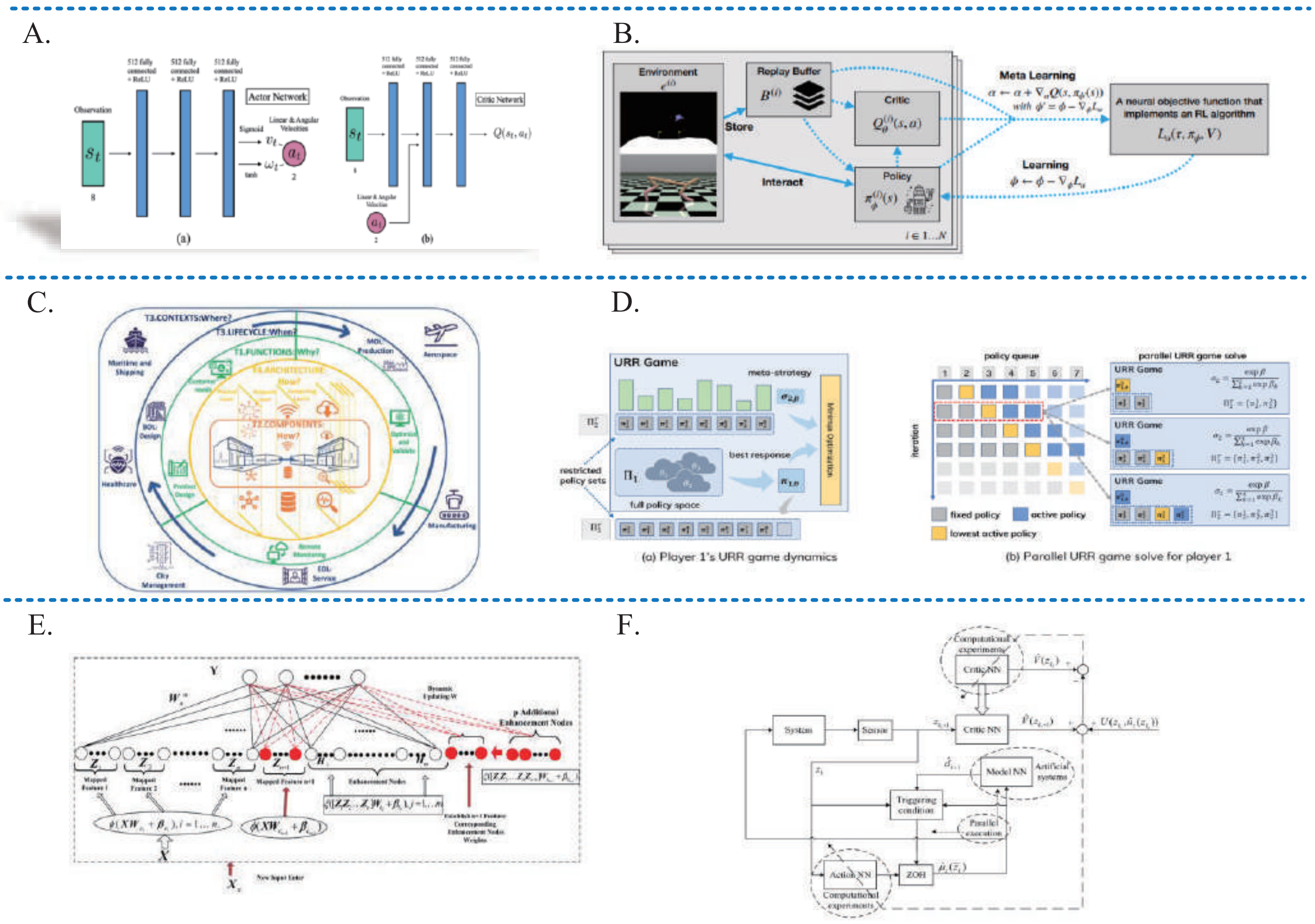

Fig. 8. Intelligent Swarm control based on learning[4].

performance and problem-handling ability. Therefore, LBAI can equipped the swarm system with online learning and autonomous decision-making control capabilities. However, conventional deep reinforcement learning has the drawbacks of high sample complexity, low sample utilization, long training time, and poor generalization ability. Besides, the trained model will be failed when the tasks or environments changed, which is very tedious and complicated. Therefore, future research in this direction can be carried out from the following directions.

1) Iterative learning control: Iterative learning control is an intelligent control method based on input and output controller design, which simulates the learning and self-regulation functions of the human brain. In the iterative learning process, the next control is corrected according to the previous control value and error [166], which is suitable for distributed swarm system with repetitive motion properties. Especially as the scale and complexity of swarm system increase, the advantages of iterative learning, a learning method suitable for complex systems, become more obvious.

2) Meta-reinforcement learning (MRL): The principle of MRL is to learn useful meta-knowledge from a set of related tasks to make the agent acquire the ability of learning, which can improve the learning speed on new tasks and reduce the complexity of samples [167]. MRL plays an important role in solving highly dynamic decision-making tasks and a series of key problems in few-shot learning. Therefore, the learning effect and control efficiency of swarm will be improved by combining MRL with swarm control.

3) Learning based on digital twins: The digital models of real objects, systems, and processes can be created by digital twins, which integrates technologies such as artificial intelligence, Internet of Things, virtual reality, and augmented reality [168]. To further realize the large-scale swarm control in complex environments, learning and control can be carried out from the perspective of digital twins, which can further improve and realize the adaptability and switchability of the swarm system to multi-class task scenarios.

4) Game-based learning: To complement the advantages of the game and learning, these can be combined to use in the swarm syetem. Game theory provides easy-to-handle solution concepts to describe the learning results of multi-agent systems [169]. Reinforcement learning algorithms pro-

[4]In Fig. 8, A is the neural network architecture for the deep reinforcement learning in Ref. [160], which can achieve collision avoidance for the swarm systems; B refers to the schematic of meta reinforcement learning algorithm in Ref. [161]; C illustrates the digital twin paradigm of Ref. [162]; D is overview of efficient Policy Space Response Oracle methods (EPSRO) in Ref. [163], which belongs to the intersection of multi-agent reinforcement learning and game theory; E shows the structure of Broad Learning System in Ref. [164]; F is the novel control structure based on the parallel in Ref. [165].

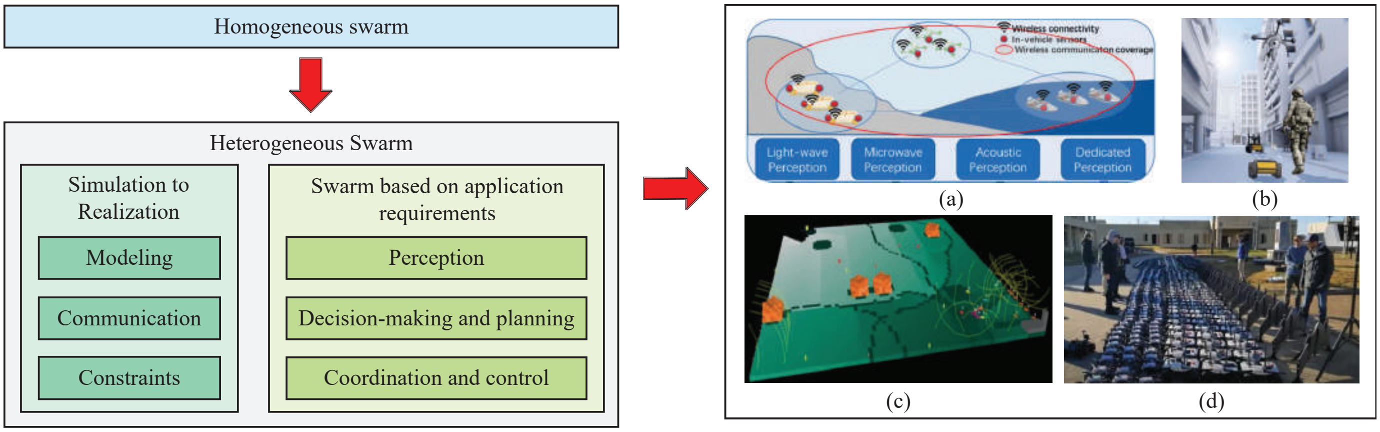

Fig. 9. Heterogeneous swarm system based on application requirements[5].

vide convergent learning algorithms that can be used in In the process of sequential decision-making, where a stable and rational equilibrium can be achieved. In this way, it is helpful for the optimal control of the swarm system for different task scenarios.

5) Broad learning: Further, swarm control can be combined with novel machine learning algorithms [170]. In recent years, C. L. Philip Chen proposed the concept of broad learning, which is a neural network structure that does not rely on deep structures [171]. Compared to the depth structure, the broad structure is very compact and does not need to use gradient descent to update the weights, which computational speed is much better than that of deep learning. When the network accuracy does not meet the requirements, the accuracy can be improved by increasing the broadness of the network. It is suitable for swarm system with few data features but high requirements for real-time prediction.

6) Parallel control: In addition, it is also possible to control the swarm based on some new learning control architectures. Parallel control combines the actual system with the artificial system, which uses the computational experiment of the artificial system to improve the optimal control strategy of the actual system, helping to realize the effective control of a complex system [172]. It has a good application effect for the swarm system control.

In a word, combining novel machine learning algorithms and frameworks with traditional swarm control is an important research direction in the future. In this way, the intelligent and optimal control of large-scale swarm can be solved in complex environments, while the agents in the searm are with high dynamics, strong real-time and asymmetric characteristics.

[5]In Fig. 9, the right part is the research introduction and application scenarios of swarm heterogeneous collaboration, where (a) is the schematic representation of multi-Agent cross domain cooperative perception in Ref. [173]; (b) refers to the imagination image released by Northrop Grumman about Offensive Swarm-Enabled Tactics (OFFSET). (c) is the simulation of swarm cross-domain collaboration Ref. [174]; (d) is the DARPA Offset FX6 Final field experiment, which were tasked with designing, developing, and deploying an open architecture for swarm operations in both physical and virtual environments.

C. Heterogeneous-based swarm control

In the current theoretical and practical research, many scholars focus on the homogeneous swarm model control rather than the heterogeneous swarm system, while most of the heterogeneous swarm research is still at the theoretical level. Therefore, researching heterogeneous swarm system based on application requirements is an essential direction in the future, especially for the large scale. That is, to maximize the value of swarm systems by cooperating with individual components with different characteristics and functions. However, this study faces two following important challenges.

1) Heterogeneous control for practical applications: On the one hand, the current theoretical on heterogeneous swarm study results abundant at present, whereas many problems will inevitably arise in the process of migrating the swarm system from the simulation environment to the real world [175]. Firstly, the entity model in real applications is more complex, where the modeling of heterogeneous individuals also needs to be considered in the modeling process, providing the basic support for swarm coordinated control. Secondly, with the diversified composition of individuals in the swarm, the control constraints are also increased. It is still a big challenge to achieve optimal swarm control with coordinate the physical constraints of different individuals. Besides, the communication strategies in simulated environment may not be enforced on real entity components, which because the differences in information dimension and precision between heterogeneous individuals caused by the environment and hardware. Therefore, the communication difficulty and complexity of heterogeneous swarm are far beyond those of homogeneous research.

2) Heterogeneous control for mission scenarios: On the other hand, it is important for heterogeneous swarm to combine different mission scenarios and collaborative tasks for perception, decision-making and planning, coordination and control. In terms of swarm perception, compared with the homogeneous swarm, the heterogeneous swarm has more perceived dimensions, more perceived scenes, and a wider range of perception [176]. Therefore, the information obtained by heterogeneous swarm is more comprehensive. At this time, it is necessary to design a more efficient swarm perception mechanism to achieve cross-domain (air, sky, and ground) collaborative perception in applications. As for swarm decision-making and planning, it is needed for heterogeneous swarm to combine application requirements to complete system decisions, where should fully consider the functional characteristics of different individuals. In addition, to obtain the optimal executable planning results, the constraints of physical, control, and environmental of individual components should be considered in the decision-making process. Concerning swarm coordination and control, the control algorithms among heterogeneous individuals are not universal, since the heterogeneous individuals cannot directly share experiences and strategies. Therefore, it is more complicated to design an optimal coordinated control heterogeneous algorithm that meets the task requirements. In addition, when there are multi-source interference and multiple threats during the process, it is also a big challenge for the heterogeneous swarm to perform the task with high robustness.

VIII. Conclusion

Swarm control problems have been studied for decades, this paper summarized the related research work on swarm control. On the one hand, this paper sorted out and reviewed the key control technical issues of the swarm system, including not only the swarm control problem, but also formation transformation and maintain, consistency, obstacle avoidance, path planning, and other technologies. On the other hand, this paper gave the evaluation and some application examples of the swarm system in different scenarios. Besides, we proposed the future research directions of swarm control in combination with the latest technological development, which is aimed to promote further research and development of the swarm control theory and application. It is believed that with the advancement of technologies such as UAVs, artificial intelligence (AI), intelligent computing, and networking communications, swarm system will enter a faster and higher stage of development.

This swarm coordinated control review paper is with clear classification and comprehensive content coverage, which reviews all research results before July 2023, having high reference value. However, with the continuous emergence of new technologies, it is difficult for this paper to comprehensively and accurately predict all the future research and development trends of swarm control, which is a relative limitation in this paper. It is needed for readers to combine unknown new technologies in the future with swarm control to create more valuable new swarm intelligence research.

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IX. Biography Section

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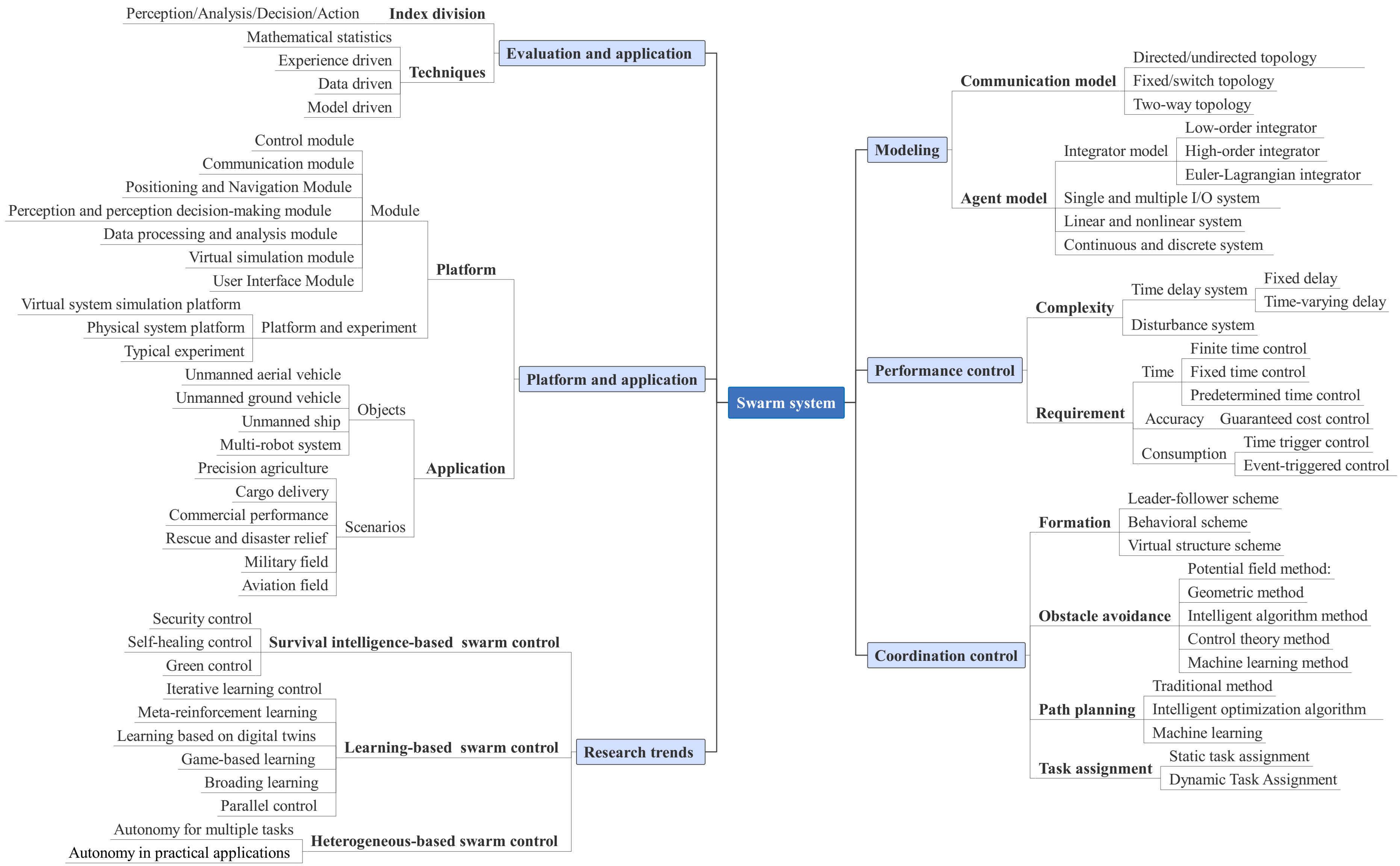
X. Appendix: Architecture of swarm control


Swarm system
Evaluation and application
Index division
Perception/Analysis/Decision/Action
Techniques
Mathematical statistics
Experience driven
Data driven
Model driven
Platform and application
Platform
Module
Control module
Communication module
Positioning and Navigation Module
Perception and perception decision-making module
Data processing and analysis module
Virtual simulation module
User Interface Module
Platform and experiment
Virtual system simulation platform
Physical system platform
Typical experiment
Application
Objects
Unmanned aerial vehicle
Unmanned ground vehicle
Unmanned ship
Multi-robot system
Scenarios
Precision agriculture
Cargo delivery
Commercial performance
Rescue and disaster relief
Military field
Aviation field
Research trends
Survival intelligence-based swarm control
Security control
Self-healing control
Green control
Learning-based swarm control
Iterative learning control
Meta-reinforcement learning
Learning based on digital twins
Game-based learning
Broading learning
Parallel control
Heterogeneous-based swarm control
Autonomy for multiple tasks
Autonomy in practical applications
Modeling
Communication model
Directed/undirected topology
Fixed/switch topology
Two-way topology
Agent model
Integrator model
Low-order integrator
High-order integrator
Euler-Lagrangian integrator
Single and multiple I/O system
Linear and nonlinear system
Continuous and discrete system
Performance control
Complexity
Time delay system
Fixed delay
Time-varying delay
Disturbance system
Requirement
Time
Finite time control
Fixed time control
Predetermined time control
Accuracy
Guaranteed cost control
Consumption
Time trigger control
Event-triggered control
Coordination control
Formation
Leader-follower scheme
Behavioral scheme
Virtual structure scheme
Obstacle avoidance
Potential field method:
Geometric method
Intelligent algorithm method
Control theory method
Machine learning method
Path planning
Traditional method
Intelligent optimization algorithm
Machine learning
Task assignment
Static task assignment
Dynamic Task Assignment