A Survey on Intelligent Control for Multiagent Systems

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***Abstract*—In practice, the dual constraints of limited interaction capabilities and system uncertainties make it difficult for large-scale multiagent systems (MASs) to achieve intelligent collaboration with incomplete local relative information. In this article, a review is conducted on the recent development of MASs intended for intelligent control, including consensus problem, formation control, and flocking control. Based on the limitations of the interaction level and the constraints of the individual system level, the published results on intelligent control are categorized into limited sensing-based control, event-based control, pinning-based control, resilient control, and collaborative control under system constraints. Also, the applications of intelligent control for MASs are presented, especially for robotics, complex networks, and transportation. Finally, a discussion is given about the challenges and future directions of research in this field.**

***Index Terms*—Consensus problem, flocking control, formation control, intelligent control, multiagent systems (MASs), multilevel constraints.**

I. Introduction

MULTIAGENT collaborative intelligence technology has led to revolutionary changes for the practical applications of robotics, complex networks, and transportation in recent years [1]–[3]. In the meantime, however, it also presents challenges as distributed and reliable intelligence technology is required to perform cooperation tasks for large-scale multiagent systems (MASs) in the context of incomplete local relative information. Inspired by the collaborative behaviors observed in nature, such as bird migration in groups and flocking behaviors of fish schools, collaborative awareness, task assignment, and intelligent control of MASs have attracted much attention from various fields over the past decades [4]–[6]. As the fundamental way to ensure the successful collaborative missions for MASs, advanced intelligent control strategies are the focus in this survey article.

From the perspective of computer science, an agent refers to a computing system operating in an environment with certain levels of autonomy and capability of sensing, decision making, and acting [1]. As shown in Fig. 1, there are four features commonly used to describe an agent, including autonomy, reactivity, sociality, and proactiveness. Autonomy means that an agent is capable to operate without the direct intervention of other entities and exercising control over its own actions. Reactivity is defined as the capability of an agent to make a response to the changes in the environment and convert its sensory inputs to actions. Sociality means that an agent has the capability to make communications with others, while proactiveness stands that an agent can do more than acting in response to the environment. However, the capability of a single agent is limited, especially in dealing with complex tasks.

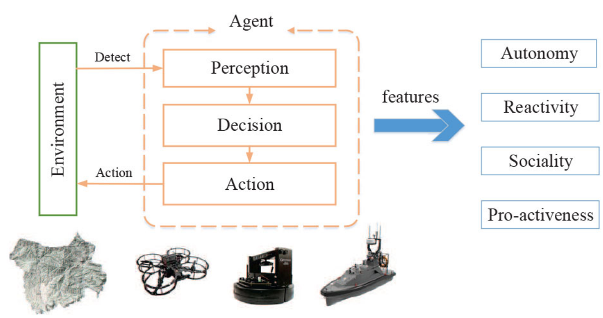

Fig. 1. Agent and its features.

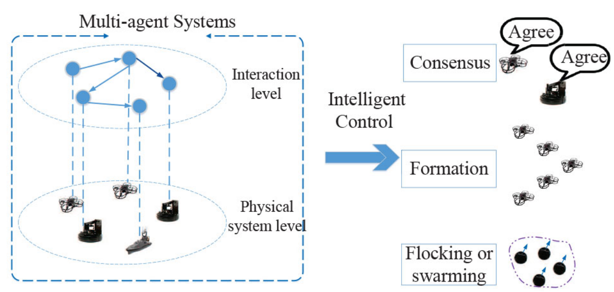

Fig. 2. Intelligent control for MASs.

A MAS refers to a group of agents. It is capable to interact, coordinate their behavior, and cooperate to achieve some common goals [1]. In comparison with single-agent systems, MASs provide a more effective and robust way to solve various complex problems by means of collaborative intelligence. As shown in Fig. 2, a MAS consists of an information interaction level and a physical system level. At the interaction level, information is exchanged not only between individual agents but also between agents and their ambient environment through either communication networks or sensor perception.

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In practice, the range of communication capabilities and perception is limited for a single agent. At the physical system level, constraints, such as uncertainties and complex heterogeneous dynamics, can have a severe impact on the performance of MASs.

As for the work on intelligent control of MASs, it focuses on three major problems, including consensus problem, formation control problem, and flocking/swarming problem. As the foundation of research on collaborative intelligence, the consensus problem of MASs has now been extensively investigated for all agents to achieve a common goal [3], [7]–[11]. As an extension to consensus problems, formation control aims at driving intractable agents to maintain and move as desired geometric shapes to perform predefined tasks, such as effective search, patrol, and exploration [6], [12], [13]. As a self-organizing behavior, flocking or swarming is derived from small-size animals with lower intelligence [14]–[16], for example, bees, fish school, and bird swarms, in the process of migrating, cruising, or avoiding enemies. Swarming is also extended to describe the behavior of lifeless agents, such as robots. Swarm intelligence not only expands individual capability but also improves the overall level of survivability.

Depending on different control structures, the approaches taken for the intelligent control for MASs can be classified into centralized control [17] and distributed control [18]. In respect of centralized control, there is a control center or host in place to coordinate the information transmission and the final process of task completion. However, the failure of the control center will hinder the entire system from functioning as normal. To improve the robustness of the whole MASs, distributed control approaches have been widely studied, where all agents determine their behavior separately based on local information. The design of distributed intelligent control that only relies on incomplete local information has been a study focus in recent years [2], [7], [18].

Information interaction and system dynamics play a vital role in the intelligent control for the entire MASs. At the interaction level, the information interaction between agents relies on the capabilities of each agent to carry out sensing and communication. In general, the information level of practical MASs is subject to a limited range of perception without communication, limited bandwidth with communication, limited network resources, and other network-induced issues. According to the different limitations on the interaction level, the recently proposed methods to solve MAS collaborative control can be categorized into limited sensing-based control [19], event-driven control [20], pinning control [21], and resilient control [22].

At the system level, an overview of theoretic advancements in consensus, formation control, and flocking control has been presented for MASs with single-integrator and double-integrator dynamics under fixed and switching topologies in [11] and [23]–[25]. In addition to linear MASs, a large number of works on reliable intelligent control have been intensively investigated for homogeneous nonlinear MASs under systems uncertainties and disturbances [7], [26]–[28]. Compared with homogeneous agents, heterogeneous agents show greater flexibility in task allocation depending on different capabilities in cooperative operations. As one of the basic heterogeneous systems, hybrid-order MASs consist of different order integrator systems were described in [29]–[32]. However, the less restrictive heterogeneous systems with different orders and different dynamics are more commonly applied in practice. In recent years, the robust output regulation control exercised by general heterogeneous MASs has attracted a great number of attention [33]–[36]. Subsequently, it was extended to solve the formation control problem and the flocking problem encountered by heterogeneous systems. The challenge still arises from the systems due to the limitations of uncertainties and heterogeneous dynamics.

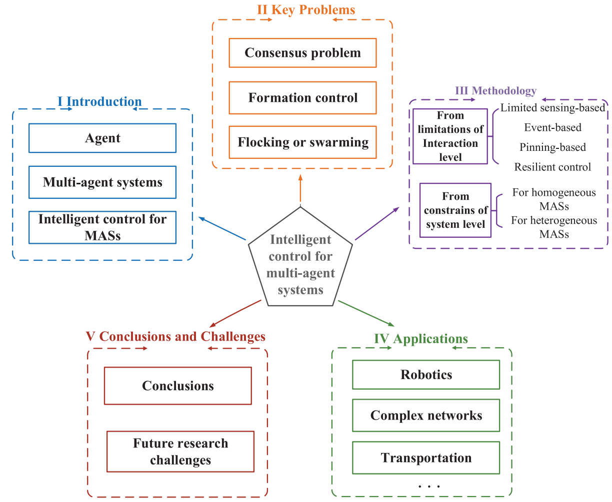

Fig. 3. Structure of the article.

In this article, a survey is conducted on the recent study of MASs in intelligent control considering the constraints of information interaction level and system level. We try our best to summarize the relevant research work in recent years, and apologize for missing some contributions on the topic, if any.

The overall structure of the article is shown in Fig. 3. The background and basic concepts are introduced in Section I. Preliminaries and three major problems with intelligent control for MASs are described in Section II, including consensus, formation, and flocking problems. In Section III, the recent advancement of the methodologists to tackle the underlying problems is described with the constraints of the interaction level and system level. Then, a review is presented on the main applications of robotics, complex networks, and transportation in Section IV. The conclusion and challenges ahead are discussed in Section V.

II. Preliminaries and Key Problems of Intelligent Control for MASs

In this section, preliminaries about graph theory and three key issues of intelligent control are recalled, including consensus problem, formation control, and flocking or swarming.

In general, the information exchange among agents is modeled by a directed or undirected graph [37]. In a graph $G = (V, E)$, V represents a finite nonempty set of nodes and E is an edge set, which contains ordered pairs of nodes in

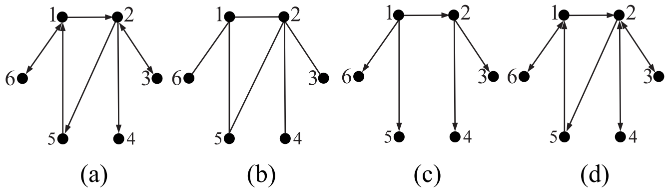

Fig. 4. Graphs with different features. (a) Directed graph. (b) Undirected graph. (c) Spanning tree. (d) Connected graph.

a directed graph and unordered pairs of nodes in an undirected graph. For example, $(i_1, i_2) \in E$ indicates that i_2 obtains the information from i_1 in a directed graph [Fig. 4(a)], and i_1 and i_2 can obtain the information from each other in an undirected graph [Fig. 4(b)]. The neighbor set of agent i is $N_i = \{j \in V | (j, i) \in E\}$. A graph contains a spanning tree if there is a path between one node and all other nodes [Fig. 4(c)]; a graph is connected if there is a path between every pair of distinct nodes [Fig. 4(d)]. For a graph G, an adjacency matrix $A = [a_{ij}]$ specifies the interconnection topology of MASs, where

$$a_{ij} = \begin{cases} 0 & i = j, \text{ or } (j, i) \notin E \\ 1 & (j, i) \in E. \end{cases} \tag{1}$$

The Laplacian matrix L of graph G is $L = D - A$ where $D = \text{diag}(d_1, d_2, \ldots, d_n)$ is the degree matrix with diagonal elements $d_i = \sum_j a_{ij}$.

A. Consensus Problem

As one of the research foundations for intelligent control for MASs, consensus refers to all systems reaching an agreement on certain interests regarding to their states and the concept comes from distributed computing systems and management science. A typical consensus theoretical framework was presented in [11], and the framework established some communication rules among the agent and their neighbor agents in the networks in order to achieve a common goal. The study also emphasized that graph theory and Laplace matrix were the core means to solve the consensus problem. Another work linked the minimum spanning tree theory in the graph with the information consensus framework [23] and proposed the minimum necessary and sufficient condition of information consensus for MASs under changing topologies, which laid the foundation for the research of dynamic topologies.

According to the theoretical frameworks, consensus problems can be divided into leaderless consensus problem and leader–follower consensus problem.

Problem 1: A general leaderless consensus problem is to design a controller for a MAS to meet

$$\lim_{t\to\infty} \left\| z_i(t) - z_j(t) \right\| = \mathbf{0}, \quad j \in N_i \tag{2}$$

where $z_i(t) \in \mathbb{R}^m$ and $z_j(t) \in \mathbb{R}^m$ represent the state or output of ith agent and jth agent, respectively. N_i is the neighbor set of agent i.

Problem 2: A general leader–follower consensus problem is to design a controller for a MAS to meet

$$\lim_{t\to\infty} \| z_i(t) - z_0(t) \| = \mathbf{0}, \quad i = 1, 2, \ldots, n \tag{3}$$

TABLE I
RECENT WORKS ON CONSENSUS PROBLEMS

Features	Classification	References
From consensus structure	Leaderless consensus	[38]–[40]
	Leader-follower consensus	[40]–[46]
From interaction level	Event-based	[9], [47]–[57]
	Pinning-based	[53], [58]–[60]
	Resilient control	[61], [62]
From system level	Homogeneous linear	[38], [39], [63]
	Homogeneous nonlinear	[7], [27], [40], [45], [64]
	Heterogeneous linear	[42], [65], [66]
	Heterogeneous nonlinear	[30], [67]–[69]

where $z_i(t) \in \mathbb{R}^m$ represents the state or output of agent i. $z_0(t) \in \mathbb{R}^m$ is a common desired trajectory for all agents to track asymptotically.

Remark 1: It is worth noting that the leader can be a real physical system, or a virtual reference system designed according to the tasks. The final consensus of all agents without reference to their initial conditions in the leader–follower consensus problem. In terms of the leaderless consensus problem, all agents finally reach a consensus, which is related to the initial state of the system and the information interaction topology.

A summary of recent works on Problems 1 and 2 is outlined in Table I, corresponding to different features and constraints from system level and interaction level.

B. Formation Control Problem

Formation control is designed to drive the moving interacting agents to achieve or maintain a specified geometry for a coordinated goal. The formation control problem can be uniformly summarized into a consensus-based structure [70], after considering the reference formation dynamics and the motion characteristics of the agent.

Most results on formation control have focused on two main problems: 1) leaderless formation control problem and 2) formation tracking problem.

Problem 3: A general leaderless formation control problem is to design a controller for a MAS to meet

$$\lim_{t\to\infty} \left\| \left(z_i(t) - z_j(t)\right) - \left(f_i - f_j\right) \right\| = \mathbf{0}, \quad j \in N_i \tag{4}$$

where $(f_i - f_j)$ represents the reference formation deviation between agent i and agent j.

Problem 4: A general formation tracking problem is to design a controller for a MAS to meet

$$\lim_{t\to\infty} \| z_i(t) - f_{i0} - z_0(t) \| = \mathbf{0}, \quad i = 1, 2, \ldots, n \tag{5}$$

where $f_{i0} \in \mathbb{R}^m$ is a referent formation deviation regards to a desired trajectory $z_0(t) \in \mathbb{R}^m$. If f_{i0} is a dynamic formation variable, the problem is extended to a time-varying formation problem.

Remark 2: Note that formation control Problems 3 and 4 can be viewed as extensions of consensus Problems 1 and 2, respectively, with respect to a reference formation deviation. For example, as shown in Fig. 5, the agent i needs to maintain a diamond formation deviation $(f_i - f_j)$ with its neighbor agent j, in leaderless formation control Problem 3. Therefore, the main

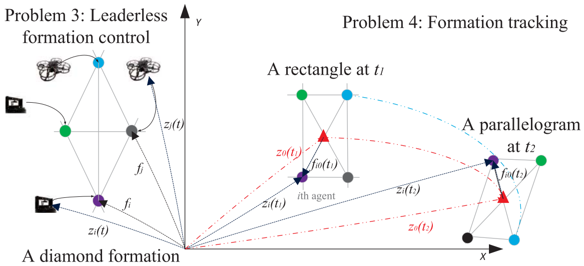

Fig. 5. Leaderless formation problem and formation tracking problem.

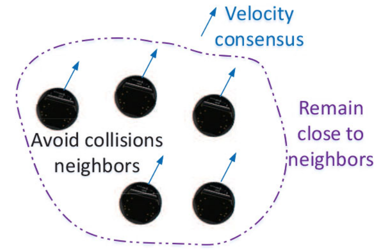

Fig. 6. Flocking or swarming control problem.

TABLE II
RECENT WORKS ON FORMATION CONTROL

Features	Classification	References
Formation problems	Leaderless formation	[19], [74]–[77]
	Formation tracking	[78]–[83]
From interaction level	Limited sensing-based	[19], [75], [84]–[86]
	Event-based	[13], [22], [74], [83], [87]
	Pinning-based	[87], [88]
	Resilient control	[74], [89], [90]
From system level	Homogeneous linear	[91], [92]
	Homogeneous nonlinear	[22], [74], [81], [88], [93]
	Heterogeneous linear	[32], [77], [82]
	Heterogeneous nonlinear	[79], [80], [94]–[96]

focus of Problem 3 is to form a formation. As for formation tracking Problem 4, there are a moving target $z_0(t)$ to track and a formation deviation f_{i0} to keep for agent i. In Fig. 5, a MAS aims to track a desired trajectory $z_0(t)$ from a rectangle to a parallelogram.

The approaches for formation control reported in the literature include the leader–follower control [12], [71], the behavior-based control [72], and the virtual structure approach [73]. In the leader–follower approach, the controller relies heavily on a single leader state. For the behavior-based formation method, several basic control behaviors of the agent are defined and weighted to obtain the final formation control inputs for the group. However, group behaviors are difficult to define. In the virtual structure approach, the formation of agents is regarded as a single object in the virtual structure, which limits the application domain as it only controls the motion of one object. The existing results can also be divided into position-based, displacement-based, and distance-based control, according to the sensing capability and the interaction topology of MASs [6]. Focusing on the constraints and features from the system level and the interaction level of agents, we list some related works on formation control in Table II.

C. Flocking or Swarming Control Problem

The flocking or swarming control problem of MASs is to perform a macroscopic overall synchronization, such as aggregate together and maintain the same direction, by using local interaction and behavioral rules between agents. The Boid model was first proposed based on computer simulation technology to describe bird swarms, which follows three rules: 1) cohesion: remain close to neighbors; 2) separation: avoid collision with neighbors; and 3) alignment: match velocity with neighbors [97]. The work in [98] simplified the Boid model and described the behavior of birds as a discrete model, the Vicsek model. Its advantage is to quantitatively analyze the flocking behavior by changing the population density and noise intensity, from the point of view of statistical mechanics. These models provide a solid foundation for the research of the flocking problem.

According to the model and rules, the flocking control problem can be described as follows.

Problem 5: A general flocking/swarming control problem is to design a controller for a MAS to meet the three following rules.

1) *Cohesion:* Remain close to neighbors

$$\lim_{t\to\infty} \sum_{i=1}^{n} \sum_{j=1}^{n} \left\| p_i(t) - p_j(t) \right\| < R, \quad j \in N_i \tag{6}$$

where $p_i(t) \in \mathbb{R}^m$ and $p_j(t) \in \mathbb{R}^m$ represent the positions of ith agent and jth agent, respectively. R is the maximum value of the sum of relative distances between agents.

2) *Separation:* Avoid collision with neighbors

$$\lim_{t\to\infty} \left\| p_i(t) - p_j(t) \right\| \geq d_{ij}, \quad j \in N_i \tag{7}$$

where d_{ij} is the minimum safety distance between agent i and agent j.

3) *Alignment:* Match velocity with neighbors

$$\lim_{t\to\infty} \left\| v_i(t) - v_j(t) \right\| = \mathbf{0}, \quad j \in N_i \tag{8}$$

where $v_i(t) \in \mathbb{R}^m$ and $v_j(t) \in \mathbb{R}^m$ denote the velocities of agent i and agent j, respectively.

To solve the problem according to the three rules shown in Fig. 6, a theoretical framework was proposed for the design of distributed flocking algorithms of second-order MASs [25]. The work in [99] analyzed the stability properties of flocking algorithms for second-order MASs under switching networks. We summarize some recent works on flocking and swarming problems in Table III, corresponding to different features and constraints from the system level and the interaction level.

III. METHODOLOGIES OF INTELLIGENT CONTROL FOR MASs

In this section, we review the results reported for the collaborative intelligence of MASs and outline advanced methodologies based on the limitations of information interaction level and the constraints of system level, respectively.

Passive sensing and active communication are the two important means of information interactions. For example, if

TABLE III
RECENT WORKS ON FLOCKING OR SWARMING CONTROL

Features	Classification	References
From interaction level	Limited sensing-based	[15], [16], [100]
	Event-based	[101]–[106]
	Pinning-based	[107], [108]
	Resilient control	[109]
From system level	Homogeneous linear	[110], [111]
	Homogeneous nonlinear	[101], [102], [112]–[117]
	Heterogeneous linear	[118]
	Heterogeneous nonlinear	[119], [120]

each agent is equipped with advanced sensors, which make them able to detect the location of neighbors, then communication is not required in formation control. However, the detection range of a single agent is usually limited. It becomes relatively easy for collaboration if agents can directly interact with key information through the network, such as locations and velocities. While communication networks are restricted by limited bandwidth, limited resources, and other network-induced issues. From the limitations of information interaction, we focus on reviewing the following popular and important topics: limited sensing-based control, event-based control, pinning-based control, and resilient control.

A. Limited Sensing-Based Control

Under certain situations such as an electrostatic shielding environment, the communication between agents is unavailable or very limited. Sensor-based perception is another alternative to achieve multiagent collaboration. In fact, it is beneficial to realize distributed control if agents can completely perceive neighbors and the environment independently. Moreover, the system can be immune to any network problems due to the independence of the communication network. However, for a single agent, the detection range of sensors, such as cameras and infrared sensors, is locally limited. Note that range-only sensing agents usually refer to robotics rather than network agents. Therefore, most of the existing results on limited sensing-based control have focused on solving formation control problems and flocking control problems [25], [75]. As shown in Fig. 7, formation reference denotes static or dynamic predefined displacement references regard to different formation shapes, while flocking reference refers to a moving rendezvous point as the group objective [25]. There are two key issues: 1) how does the agent determine the most suitable position relative to its neighbors? and 2) how to achieve collaboration actions without collisions?

In order to solve the two problems, a novel scalable formation control strategy was proposed to solve Problem 3, when the communication network is completely unreachable [75]. Consider a first-order MASs under a control input $u_i(t)$

$$\begin{aligned}\dot{p}_i(t) &= u_i(t), \quad i = 1, 2, \ldots, n\\ u_i(t) &= f(N_i, g(N_i, F))\end{aligned} \tag{9}$$

where $p_i \in \mathbb{R}^m$ and $u_i \in \mathbb{R}^m$ present the position and control input of the ith agent, respectively. Suppose the sensing range is limited, the neighbor set is defined as

$$N_i = \left\{(j, i) \in E \middle| \left\|p_i(t) - p_j(t)\right\| < r_i\right\}$$

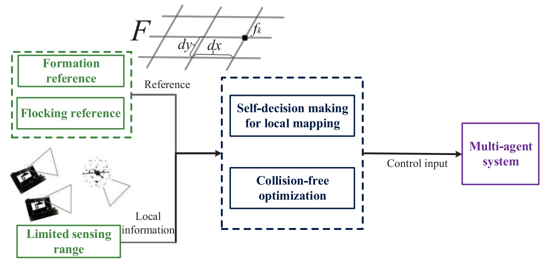

Fig. 7. Limited sensing-based intelligent control.

where r_i is the sensing range of the ith agent, which can be different for heterogeneous agents. The control force f aims to form a reference formation F, which is a set of scalable displacement vectors $F = \{\ldots, f_{-1}, f_0, f_1, \ldots\}$. The element $f_k \in \mathbb{R}^m$ is based on m linearly independent basis vectors, where $m = 2$ or $m = 3$ indicates the reference formation is in two dimensions or three dimensions. For instance, a 2-dimensional (2-D) scalable formation F is shown in Fig. 7, where d_x and d_y are two linearly independent vectors. For any $f_k \in F$, $f_k = ad_x + bd_y$, $a, b \in Z$ always holds. Note that the basis vectors of F are known for all agents. The local mapping function g is conducted on each agent to choose which vectors in F are the suitable displacement according to the neighbor set N_i. Based on local optimization methods, multiobject mapping protocols without conflict and range control strategies have been investigated in [19], [75], and [84]. In addition to collision-free matching, obstacle avoidance algorithms have also been extended to the formation control in Problems 3 and 4 without communication [121] and with limited communication only on identities and mapping decisions [76]. In order to reduce the computation burden and avoid the infinite trajectory loop, the probability was introduced in mapping and distributed control strategies [85], [86].

As for the flocking control in Problem 5, most of the works have focused on the implementation of three rules for agents subject to a limited range-based perception or interaction. A theoretical flocking framework was proposed of a second-order MASs [25]

$$\dot{p}_i(t) = v_i(t), \quad \dot{v}_i(t) = u_i(t) \quad i = 1, 2, \ldots, n \tag{10}$$

under the control force

$$\begin{aligned}u_i(t) &= f_i^g + f_i^d + f_i^r\\ &= \sum_{j\in N_i} \psi\left(\left\|p_j - p_i\right\|_\sigma\right)(\mathbf{n_{ij}}) + \sum_{j\in N_i}(v_j - v_i)\\ &\quad + c_1((p_0(t) - p_i(t))) + c_2((v_0(t) - v_i(t)))\end{aligned} \tag{11}$$

where the system state $x_i(t) = [p_i(t),\ v_i(t)]^T$ consists of position $p_i \in \mathbb{R}^m$ and velocity $v_i \in \mathbb{R}^m$ of the ith agent. To implement the three rules, control input consists of three items: 1) gradient-based term f_i^g; 2) velocity consensus item f_i^d; and 3) navigational feedback term f_i^r, where ψ is a potential function based on σ-norm of the relative distance for collision avoidance. $(\mathbf{n_{ij}})$ represents a vector connecting agent i and agent j. Parameters c_1 and c_2 denote the position control law

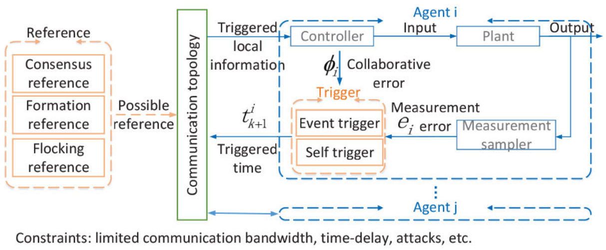

Fig. 8. Event-based intelligent control.

and velocity control law of the navigational feedback, respectively. They are designed to meet $c_1, c_2 > 0$. The flocking reference position $p_0 \in \mathbb{R}^m$ and velocity $v_0 \in \mathbb{R}^m$ indicate a rendezvous point, which can be viewed as a group objective. The connectivity preservation of formation control was also been discussed in [25].

Based on the basic flocking framework, flocking control solutions to Problem 5 were provided based on potential field [14] and learning-based approach [15], [16]. Without a communication channel, learning vision-based flocking algorithms was proposed for multidrone swarms [15]. Flocking control was developed for a first-order MAS subject to limited heterogeneous interaction range [100]. However, connectivity preservation is still a challenge for high-order nonlinear MASs, when the sensing capability of the agent is insufficient.

B. Event-Based Intelligent Control

The communication-based MASs make up for the lack of perception of some agents and effectively realize collaboration by directly interacting with the information of interest through the network. However, limited network resources and communication bandwidth have largely restricted information transmission between agents. Event-based distributed interaction mechanisms were proposed to alleviate this limitation [9], [47]–[57]. Without collecting the state information of all agents at every moment, the distributed event-triggered strategy can better save communication resources and effectively reduce the frequency of information transmission between agents and update of agent control protocols.

The structure of event-based distributed intelligent control is shown in Fig. 8, where each agent independently determines its own behaviors. The trigger determines the interaction time interval of each agent according to the measurement error from the sampler and the collaboration error from the controller. The controller updates the local information and possible reference information at each trigger moment. Note that the possible reference information here refers to the consensus reference, or the formation reference, or the flocking reference information. For the leaderless consensus problem in Problem 1, there is no external reference information. The event-based distributed trigger strategy mainly involves three key issues: 1) how to determine the trigger time; 2) how to design the distributed control laws; and 3) how to exclude the unlimited trigger phenomenon, Zeno phenomenon [122]. We take the event-based control for second-order MASs (10) as an example.

1) Trigger Mechanism: It is designed to determine the trigger time in next step t_{k+1}^i. The recent works mainly focus on two common mechanisms, event-triggered mechanism, and self-triggered mechanism, as follows:

$$\begin{aligned} &(1)\quad t_{k+1}^i = \inf\left\{t > t_k^i | f(e_i) > g(e_i, \phi_i)\right\} \\ &(2)\quad t_{k+1}^i = t_k^i + \sigma_i \end{aligned} \tag{12}$$

where $f(e_i)$ and $g(e_i, \phi_i))$ are the trigger functions based on measurement error e_i and collaboration error ϕ_i. The next time is triggered if the condition is met. Note that the trigger functions are only based on local information without the prior information of the topology matrix by adding adaptive laws in $f(e_i)$ or $g(e_i, \phi_i)$ [47]–[50]. The second mechanism is the self-triggered strategy, where the time interval of next broadcast σ_i can be calculated based on the information of the current trigger time without the need to continuously monitor the changes of events [104]. Although event monitoring costs are reduced, additional computational costs are added.

There are two common designs of measurement error

$$\begin{aligned} &(1)\quad e_i(t) = \hat{x}_i(t) - x_i(t) = x_i\left(t_k^i\right) - x_i(t) \\ &(2)\quad e_i(t) = \hat{x}_i(t) - x_i(t) = e^{A\left(t - t_k^i\right)} x_i\left(t_k^i\right) - x_i(t) \end{aligned} \tag{13}$$

where t_k^i is the kth trigger time of agent i, and $\hat{x}_i(t)$ represents the estimation of x_i in the time period $t \in [t_k^i, t_{k+1}^i)$. The state value at the time of the last trigger is used in the first strategy [48], [51]–[54]. The second approximation scheme of $x_i(t)$ is based on the system state matrix A. System model-based estimation more accurately approximates the state of the system during the time period [49], [50].

The design of the collaboration error is based on different intelligent control problems. For leader–follower consensus Problem 2, formation control in Problem 4, and flocking tracking control in Problem 5, the collaborative errors are generally formed as

$$(1)\quad \phi_i(t) = \sum_{j \in N_i} a_{ij}\left(\hat{x}_j(t) - \hat{x}_i(t)\right) + a_{i0}\left(\hat{x}_0(t) - \hat{x}_i(t)\right) \tag{14}$$

$$\begin{aligned} (2)\quad \phi_i(t) = &\sum_{j \in N_i} a_{ij}\left(\left(\hat{x}_j(t) - \hat{x}_i(t)\right) - \left(\hat{f}_j(t) - \hat{f}_i(t)\right)\right) \\ &+ a_{i0}\left(\left(\hat{x}_0(t) - \hat{x}_i(t) - \left(\hat{f}_{i0}(t) - \hat{x}_i(t)\right)\right)\right) \end{aligned} \tag{15}$$

$$\begin{aligned} (3)\quad \phi_i(t) = &\sum_{j \in N_i} a_{ij}\left(\hat{v}_j(t) - \hat{v}_i(t)\right) \\ &+ c_1\left(\left(\hat{p}_0(t) - \hat{p}_i(t)\right)\right) + c_2\left(\left(\hat{v}_0(t) - \hat{v}_i(t)\right)\right) \end{aligned} \tag{16}$$

where $\hat{x}_0(t)$ is the state estimation of a real leader or a virtual leader indexed by number zero, which can be regarded as consensus reference. If the agent i is informed by the leader, $a_{i0} = 1$, otherwise, $a_{i0} = 0$. $\hat{f}_i(t)$ is the estimation of formation reference at time $t \in [t_k^i, t_{k+1}^i)$ [83]. As for leaderless consensus Problem 1 and formation control without a reference leader in Problem 3, the terms related to a_{i0} are zero [51], [52]. For flocking control in (16), the collaborative error composes of the velocity consensus error and flocking tracking error, where $\hat{x}_0(t) = [\hat{p}_0(t),\ \hat{v}_0(t)]$ is the estimation of a flocking reference trajectory with position and velocity [103].

2) Control Strategies: are also designed in terms of intelligent control Problems 1–5. For consensus and formation control problems, the controller aims to eliminate collaborative errors by

$$u_i(t) = K_i\phi_i(t) \tag{17}$$

where K_i is the control law matrix based on ARE (algebraic Riccati equation) [9], [47], [49] and LMI (linear matrix inequality) [13], [48], [83]. Quantized event-triggered control is another improvement direction to save more network resources under limited bandwidth by the quantized control law

$$u_i(t) = K_i q_u(\phi_i(t)) \tag{18}$$

where q_u is a quantized function to convert the collaborative error into a discrete form [48], [53].

For flocking control in Problem 5, one form of control protocol is

$$u_i(t) = \sum_{j\in N_i} \psi\left(\left\|\hat{p}_j - \hat{p}_i\right\|_\sigma\right)(\mathbf{n_{ij}}) + \phi_i(t) \tag{19}$$

where ψ is a potential function [101]–[103] to remain close to neighbors without collisions. Another control strategy is based on the distributed model predictive control by solving optimization problems to satisfy the flocking rules [104], [106].

3) Proof That the Zeno Phenomenon Is Excluded: If an event is triggered infinitely within a finite time, the phenomenon is called Zeno phenomenon [122]. In the study of an event-based mechanism, one of the key tasks is to exclude Zeno phenomenon. One widely used method is to prove that there must be a positive lower bound on the interval length between any two trigger moments [57], [105], [106]

$$t^i_{k+1} - t^i_k \geq \tau > 0 \tag{20}$$

where τ is a positive constant that ensures the Zeno phenomenon is excluded.

The work in [123] also looked at the issue, and proposed another method. That is, if Zeno's behavior is assumed to exist, then there is at least a gathering point for the time-triggered sequence. By verifying that this assumption contradicts the existing attributes of the system, it is proved that Zeno's behavior can be excluded.

In addition to deal with the limited bandwidth of communication networks, event-based strategies are used to solve other problems subject to time delay [55], [56], [123], network attacks [22], [57], [74], switching topologies [9], and multiplicative faults [47]. However, to the best of our knowledge, there is a lack of fully distributed trigger strategies and methods to effectively exclude Zeno behavior, which does not involve any global information (such as the number of agents, Laplace matrix, etc.), especially for generalized linear and complex nonlinear MASs.

C. Pinning-Based Intelligent Control

The realization of information collaboration for MASs usually requires the assumption of the original connectivity of the communication topology [23]. However, this assumption is difficult to be satisfied especially for MASs under time-varying topologies. Moreover, for real-world large-scale MASs, such as complex power grids and multidrone light show systems, there are generally a large number of nodes or control points in their communication networks. It is usually difficult and expensive to put controllers to all nodes to control the whole system. Pinning-based control is one of the effective solutions for the issues. The basic idea of pinning control is by adding a pinner to control a small fraction of agents so that the whole MASs can achieve collaborative performance. As shown in Fig. 9, a pinner (or virtual leader) is added to the system and defines its desired trajectory, according to different intelligent control Problems 1–5. The pinner only controls some pinned agents (agent 2, agent 3, and agent 7) from different groups (G_1, G_2, and G_3) to ensure global collaboration, and the choice of pinned agent to inform the reference information is via the pinning strategies. Therefore, the realization of global collaboration and the design of pinning strategies are two key issues of the pinning-based intelligent control.

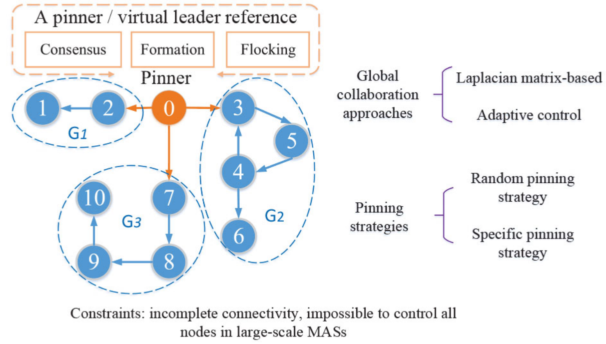

Fig. 9. Pinning-based intelligent control.

1) Global Collaboration: Pinning control is widely used to solve the synchronization of complex dynamic networks [58], [59], which is also a special case of leader–follower consensus problems defined in Problem 2 [53], [60]. The general first-order MASs composed of n agents under pinning control are modeled as

$$\begin{aligned}\dot{x}_i(t) = f(x_i(t), t) + c\sum_{j=1}^{n} a_{ij}\Gamma\left(x_j(t) - x_i(t)\right)\\ + cd_i\Gamma(s(t) - x_i(t))\end{aligned} \tag{21}$$

where $x_i(t) \in \mathbb{R}^m$ and $f(x_i(t), t)$ are the state and nonlinear dynamic function of the ith agent, respectively. Coefficients c and d_i are the coupling strength and pinning control gain, respectively. $\Gamma \in \mathbb{R}^{n\times n}$ represents the inner coupling matrix. $s(t) \in \mathbb{R}^m$ denotes the state of a pinner modeled as

$$\dot{s}(t) = f(s(t), t)$$

where $f(s(t), t)$ is a nonlinear continuously differentiable function related to dynamic characteristics of the pinner [21]. One way to ensure consensus for whole MASs is to design suitable coupling strength, pinning control gain, and inner coupling matrix based on the Laplacian matrix, including the extension of the Laplacian matrix and the submatrix of the Laplacian matrix (see [21] for details). However, this approach depends on the properties of the global communication matrix. The global information is difficult to obtain when the Laplacian matrix is time varying or stochastic due to the random selection of pinned agents. In order to overcome this drawback, adaptive pinning consensus strategies have been proposed for the first-order system without relying on any global information. At the same time, by introducing the adaptive rate in the coupling strength and control gain, the conservativeness of the Laplacian-based method has been reduced [21], [59].

In addition to the consensus problem, pinning-based control is also extended to solve formation tracking in Problem 4 [88] and flocking control in Problem 5 [107], [108]. A pinner or a virtual leader is used to provide the reference path for the agents to perform a collaborative task, such as the task of multidrone formation to reach a designated location with the desired trajectory. The relative formation reference respect for the virtual leader is also considered. The work in [88] provided a pinning-based control for nonlinear multidrone formation. Although a pinner describes the desired path of MASs, agents usually do not strictly follow the pinner when they encounter obstacles to avoid in the environment. In terms of the flocking problems defined in Problem 5, the pinner can be regarded as the flocking center with the desired trajectory. Pinning-based strategies for the flocking motion of a MAS have been developed under switching topologies [107] and sampled-data frameworks [108] to minimize the total cost considering pinner tracking, velocity consensus, and obstacle avoidance functions.

2) Pinning Strategies: They are investigated to determine the minimum number of nodes to be controlled and the specific pinned agents. Existing pinning strategies mainly include the random pinning strategy and the specific pinning strategy. The strategy of random selection first searches for strongly connected components [21] to assign groups of agents, and then randomly selects one agent in the group for control. Another method is to first arrange the nodes in descending order according to the difference between the out-degree and the in-degree, and select the first l nodes for control [60]. Both methods need to verify that the pinner is the root node, and there is at least one directed spanning tree in the entire MASs. It is difficult to ensure the connectivity of the original network, especially for arbitrary or changing topologies. Through a reasonable selection of pinned agents, the connectivity under the dynamic topology can be guaranteed at each moment. Many works have pointed out that the specific pinning strategy is more effective than the random pinning strategy in reducing the number of pinned agents [58], [60], [107].

Pinning-based control has been also introduced into some methodologies in control theory, such as the impulsive control [124], robust H_∞ control [125] and finite-time control [126] to improve the system performance under time delay and disturbances.

D. Resilient Control

MASs are likely to suffer from malicious attacks and corruption of sensory data or manipulation of actuators inputs, which can severely and adversely affect system performance. For example, in a denial-of-service attack (DoS), the attacker intends to deny access to the data by making it unavailable to systems. Recently, considerable efforts have been made based on resilient control to detect and defend against attacks for MASs in terms of consensus, formation control, and flocking control defined in Problems 1–5.

A novel event-based resilient control was proposed in [61], which controlled the input signal rather than the state measurement error to solve leaderless consensus in Problem 1 under DoS attacks. For leader–follower consensus in Problem 2 under DoS attacks, the work in [62] provided a distributed fixed-time observer and an improved resilient observer to accurately estimate the leader's information, thus eliminating or weakening the influence of DoS. Reliable formation tracking control for MAS under quantized communication and false data injection (FDI) attacks was investigated in [89] based on a distributed filter with adaptive attack compensator. Both the system reliability in the attacked case and original performance in a no-attack case can be guaranteed with the developed filter. It can also achieve cooperative output regulation of MAS when the communication is not quantized but with potential attacks. For the unbounded malicious attacks, a fully distributed attack-resilient control protocol was proposed in [90] to solve the time-varying formation tracking problem defined in Problem 4. The bounded system stability and uniformly ultimately bounded synchronization performance have been guaranteed. Considering the presence of noncooperative robots, Saulnier *et al.* [109] developed a resilient flocking control approach for Problem 5. The proposed dynamic connectivity management and switching control strategies restricted the communication topology within the resilient threshold and allowed the mobile robots to achieve consensus along with the motion.

To the best of our knowledge, there are still a lack of effective detection and deference theoretical frameworks for MASs under multiple attacks.

E. Intelligent Control for Homogeneous MASs

MASs can be divided into homogeneous and heterogeneous systems, depending on whether the system dynamics are the same or not. In addition to the limitations of the interaction level, the constraints of the system level include nonlinear dynamics, heterogeneous dynamics, system uncertainties, external interference, and actuator and sensor failures.

For linear homogeneous MASs, there are a large number of works on consensus Problems 1 and 2 [38], [39], [63], formation control Problems 3 and 4 [91], [92], and flocking control Problem 5 [110], [111]. However, in practical applications, an agent is always subject to nonlinear dynamics, such as the fight control for multidrone formation [88] and flocking control for robots [102]. Various nonlinear control approaches have been developed for nonlinear MASs under uncertainties and bounded external disturbances, including adaptive control [64], backstepping scheme [88], sliding mode control [7], [93], neural network [27], [93], and fuzzy control [115]. Sliding mode control has been widely used to control nonlinear systems with uncertainties and unknown disturbances, as the controllers can be designed to compensate for the uncertainties and disturbances.

Unforeseen threats may occur in system components, such as sensors, actuators, and controllers. Passive fault-tolerant control is one of the popular methods for managing physical faults or damages, with adaptive strategies. The work in [127] investigated a H_∞ consensus protocol together with an adaptive compensator to tolerate sensor and actuator faults for Problem 1. In [128], a cooperative adaptive fault-tolerant fuzzy control was proposed to solve leader–follower consensus Problem 2 of networked MASs with time-varying actuator faults. Adaptive formation control laws for Problem 4 were designed for unmanned aerial vehicles (UAVs) to tolerate actuator faults [129]. As a typical method of fault-tolerant control, adaptive controllers are used for compensating physical faults and passively tolerate system failures without changing the controller structure. However, the fixed structure has conservative problems and cannot optimize the system performance. To overcome the shortcomings, active fault-tolerant control strategies have been proposed for MASs. The active strategies usually include two functions: 1) fault detection and 2) control reconfiguration [128], [130], [131]. However, most of the existing research results assume that the system will not diverge during the time period of fault detection. This assumption is limited to multiple failures and severe physical damage.

F. Intelligent Control for Heterogeneous MASs

During the past decades, research on intelligent control has gradually shifted from homogeneous MASs to heterogeneous MASs. One reason is that it is difficult to equip the same agents with all the necessary sensing and computing equipment. Even for the same agents with the same equipment, it is not truly homogeneous MASs due to asynchronous clocks and uncertainties. Most important of all, heterogeneous MASs have more advantages in terms of formation flexibility and complex task decomposition because of the different functions of individuals.

The primary research on heterogeneous MASs is focused on hybrid-order MASs, such as consensus Problem 1 of first-order and second-order hybrid MASs [66] and formation Problem 3 of first-order and fourth-order hybrid MASs [77]. Graph theory-based matrix methods and Lyapunov theory are used to solve intelligent problems of hybrid-order MASs, but the global communication matrix is required especially for high-order hybrid MASs. Another approach for hybrid-order MASs aims to convert the mixed-order MASs into the same-order MASs and achieve the state consensus of the corresponding order by adding virtual zero states [30]. However, expanding the dimensions of agents may increase the computational load. State consensus is almost impossible for the general heterogeneous systems with different orders and different dynamics. Therefore, the output regulation for a single system is the focus, which can be extended to solve the output consensus problem of heterogeneous MASs [65]. Under the assumption that there exists a solution to the regulation equation [132],

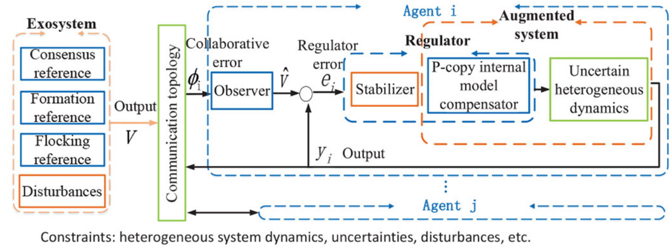

Fig. 10. Output regulation-based intelligent control for heterogeneous MASs.

the output consensus of heterogeneous MASs is solvable. Subsequently, the approach was promoted to solve the problems of formation control Problems 3 and 4 [79], [82], [133] and flocking control Problem 5 [118].

A general intelligent control framework of heterogeneous MASs is shown in Fig. 10, where the output of exosystem v includes reference information that needs to be tracked and disturbances need to be rejected. Since only a part of the agents can be informed by the exosystem, an observer is designed to estimate the output of the exosystem $\hat{v}$ through collaborative error ϕ_i. The intelligent control problem of heterogeneous MASs is transformed into the stabilization problem of distributed augmented systems by a regulator. The regulator is composed of a stabilizer and p-copy internal model to stabilize the system and compensate for uncertainties, receptively. Augmented systems consist of a real agent and an internal model compensator. This method fundamentally uncouples the dynamics of heterogeneous agents and realizes the regulation of exosystem in a distributed manner.

A unified uncertain heterogeneous MAS with n agents of different orders can be modeled as

$$\begin{aligned} \dot{x}_i &= A_{wi}x_i + B_{wi}u_i + E_{wi}v \\ y_i &= C_{wi}x_i + D_{wi}u_i + F_{wi}v, \quad i = 1, 2, \ldots, n \end{aligned} \tag{22}$$

where $x_i \in \mathbb{R}^{n_i}$, $u_i \in \mathbb{R}^{m_i}$, and $y_i \in \mathbb{R}^{p_i}$ represent the state, input, and output variables of the ith agent, respectively. Matrices $\star_{wi} = \star_i + \Delta\star_i$ are the corresponding system matrices with uncertainties $\Delta\star_i$, where $\star = A, B, C, D, E, F$.

The dynamic of an exosystem can be described as follows:

$$\dot{v} = Sv \tag{23}$$

where $v \in \mathbb{R}^{n_0}$ represent the state/output variables of the exosystem, which contains the reference information according to different intelligent Problems 1–5. For example, the dynamic of a time-varying formation [82] is considered as $\dot{f}_i = A_f^i f_i$, and the signal of exosystem v includes the information of virtual leader x_0, time-varying formation dynamics f_i, and disturbance ω.

In order to achieve intelligent collaboration, the general stabilizer and internal model compensator are designed as follows:

$$\begin{aligned} u_i &= K_i^x x_i + K_i^z z_i \\ \dot{z}_i &= \Sigma_1 z_i + \Sigma_2 e_i \end{aligned} \tag{24}$$

where z_i is the state of the dynamic compensator. (Σ_1, Σ_2) is the p-copy internal model pair of S, based on the internal

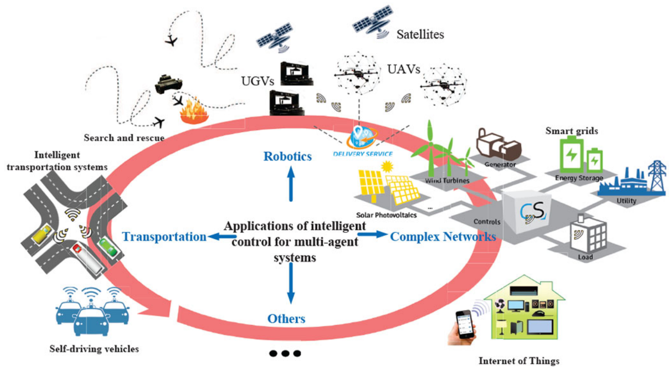

Fig. 11. Applications of intelligent control for MASs.

model principle [132]. The control law $K_i = (K_i^x, \ K_i^z)$ is obtained by the Lyapunov stability theory [82], [132]. The controller aims to eliminate regulation error, which is defined according to different intelligent control Problems 1–5. For example, for the leader–follower consensus in Problem 2, the error is defined as $e_i = y_i - \hat{v}$; for time-varying formation tracking in Problem 4 [79], [82], $e_i = y_i - \hat{v} - f_i$.

It should be noted that the observer converts the collaborative error ϕ_i to regulation error e_i based on the observation $\hat{v}$. Therefore, the design of observers is the core of decoupling heterogeneous dynamics and realizing distributed architecture. In [82], the adaptive distributed observer was proposed under the assumption that the exosystem dynamics S were globally known. Note that the design of the p-copy internal model system also required a known exosystem dynamic matrix. Model-based adaptive controls still involve global information, until an off-policy reinforcement learning strategy was investigated to make up the disadvantages [134].

The intelligent control for linear heterogeneous systems can also be extended to nonlinear systems to deal with consensus problems [30], [67], [68], formation control problems [79], [80], [94]–[96], and flocking control problems [120]. It is worth noting that this method is only applicable to leader-involved Problems 2, 4, and 5. For the leaderless problems as defined in Problems 1 and 3, it will raise a big challenge to discover the common internal model in heterogeneous systems in the absence of the exosystem. Learning-based approaches may be a possible way to address the problems.

IV. Applications of Intelligent Control for MASs

In this section, we present the achievements of intelligent control for MAS applications in the following directions: robotics, computer networks, transportation, and others. A summary of these applications is outlined in Fig. 11 and Table IV.

A. Robotics

The application of MASs on robotics has received extensive attention, especially on UAVs, unmanned ground vehicles (UGVs), and autonomous underwater vehicles (AUVs). The work in [135] proposed a modular architecture of multiUAV collaboration system for search and rescue missions. The framework has been verified and evaluated by outdoor experiments of four prototype UAVs. A multiUAV collaborative approach in disaster management and civil security applications has been validated with real UAVs and wireless sensor networks [136]. Formation protocols and consensus approaches were used to achieve time-varying formations, which were tested and verified by distributed outdoor experiments with five quadrotors [138]. Relative information of neighboring UAVs can be used to construct a time-varying formation control protocol for swarm systems. An outdoor target enclosing experiment was carried out for three follower quadrotor UAVs to enclose a leader quadrotor UAV by time-varying formations [139]. In [140], a life support robot system was developed to perform domestic services that are useful to the well being of the elderly with walking disabilities. A frequent task during life support is the fetching of daily containers, such as serving drinks and food [140].

TABLE IV
Applications of Intelligent Control for MASs

Applications	Feature-specific MAS	Refinance
Robotics	UAVs	[135]–[139]
	UGVs	[140]–[144]
	AUVs	[145], [146]
Complex networks	Smart grid systems	[147]–[149]
	Internet of Things	[150], [151]
Transportation	Traffic light systems	[152]–[154]
	Smart driving systems	[155]

Furthermore, a large number of results on the formation control for hardware multivehicle platforms have been verified under laboratory conditions. A distributed formation control approach for multirotor UAVs was proposed and embedded into the onboard computational units to make them able to keep a balanced formation in 2-D and three dimensional environments [137]. The proposed formation control approach was proved to be feasible for arbitrary formation by both simulations and real-system experiment. In order to lead the UGVs moving into the desired formation quickly, a cooperative coevolutionary algorithm-based distributed model predictive control was proposed in [144], which can greatly improve the performance of formation control as performed by three mobile robots. An adaptive self-organizing map neural network was applied to keep the formation when agents move along the desired path [145]. Both simulations and real AUV systems demonstrated the fault-tolerant characteristic in obstacle avoidance and the benefit of balancing the workload and energy. A modified constrained adaptive controller was proposed to resolve the communication delay and actuator saturation [146]. Simulation and experimental validation showed that the method can effectively compensate for the effects of state delay in 2 and 5 s, respectively. Follower AUVs were able to follow the desired path within the accuracy of 5 cm.

B. Complex Networks

The resource-aware consensus theory of the MASs provides a theoretical reference for smart grid applications. In [147], the MAS-based algorithm has been applied to control voltage and capacitor to optimally set the system. An event-triggered strategy is proved to be an effective method to reduce the communication burden of a network. The two-level reinforcement learning-based controller was proposed in [148], where the parameters were optimized by particle swarm. The results verified the feasibility of the proposed method. Within the decentralized system integrity protection set up, data-driven anomaly detection, and adaptive load rejection were studied in [149]. Anomaly detection has been converted to a multiclassification problem and can be performed by individual agents, but all the interconnected agents devoted to the final decision. Meanwhile, the proposed adaptive load rejection strategy can reduce the DoS attacks.

The application of MASs can be extended to the Internet of Things (IoT) where objects range from sensors to wearable devices. Agent-based resilient control plays a vital role in IoT networks. It is essential to effectively identify the malicious node and prevent further damage. A combined multiagent and multilayered game formulation was proposed in [150], which incorporated a trust model to assess the node/object. The proposed model can significantly improve the accuracy of intrusion detection by experimental test. IoT inevitably introduces a vast amount of real-time data. A multiagent-based real-time scheduling architecture was presented to optimally assign tasks according to the real-time status of machines [151].

C. Transportation

The large-scale intelligent transportation system is one of the typical applications of MASs. Taking the dimension, complicated dynamics, and uncertainties into consideration, Lin *et al.* [152] proposed a centralized multiagent control method with a serial framework. Agents communicate with their neighbors through a model-based predictive control method. Using the traffic data provided by the city of Toronto, an adaptive reinforcement learning-based traffic signal controller was proposed in [153], which can work in two modes: 1) decentralized and 2) centralized. However, the dynamic and complex traffic conditions make it difficult for the model-based and reinforcement learning-based models to make good decisions. In [154], a multiagent recurrent deep deterministic policy gradient algorithm was proposed to control the traffic light in land traffic. Decisions were made independently by each agent, thus avoiding the poor performance caused by an unstable environment. Autonomous driving is another application in intelligent control, among the key complex problems, the formation will be outstanding. Due to the formation changes with the traffic flow and conditions, a dynamic coordination graph was proposed to model the constantly changing topology to coordinate the maneuvers of grouped vehicles in [155], which was proved to be effective than some expert rules.

D. Others

The applications of MASs are not limited to the above-mentioned fields. They have also been widely applied to aerospace, agriculture, industrial production, and medical treatment, to name but a few.

V. Conclusion and Future Research Challenges

In this article, we presented a survey of distributed intelligent control for MASs. Focusing on the constraints from the interaction level and system level, the recent results have been reviewed in terms of consensus problem, formation control problem, and flocking control problem. However, this is far from an exhaustive literature review and some important results might be missed due to the limitation of our knowledge. Furthermore, there still exist several challenges in this area deserving further study.

1) Security is highly challenging for MASs. Most existing works design resilient and robust strategies separately on interaction level and system level. For instance, distributed resilient control under attacks and communication problems tends to use network-level design, where the individual agent with high-fidelity dynamics is usually simplified, and fault-tolerance control mainly focuses on homogeneous system-level robustness. However, the separated security control design on two levels fails to realize quick stability and recover to optimal performance, which poses a threat to the survival of MASs under multiple threats and unknown environments. Therefore, high-reliability intelligent control under both two-level threats is still an open problem to be solved in the future.
2) The design of fully distributed intelligent control and its optimization is still considered as open issues. Although many studies have focused on distributed control approaches, some global information, such as the total number of the agents and the Laplace matrix of the communication topology are still being involved for high-order MASs in intelligent control designs. Verification on global stability, connectivity preservation under dynamic topology, proof of nonZeno phenomenon, and optimization of task assignments are usually not designed with a fully distributed framework. Adaptive control strategies and learning-based techniques are used to resolve this imperfect. However, they inevitably increase the computational load. In real-world applications, agents subject to limited computing capability need to perceive, make decisions, and take actions independently, which raises higher requirements for fully distributed algorithms and optimization techniques.
3) The research on intelligent control for heterogeneous MASs should be enhanced, especially in both theoretic research and applications of heterogeneous multivehicle systems. Although the works on heterogeneous MASs have received extensive attention in the past decades, most of them focused on the fundamental consensus problems and theoretic research. In fact, it is difficult to build truly homogeneous MASs in practical applications. The intelligent control of heterogeneous vehicles, such as UAVs, UGVs, and AUVs, is more promising in practical applications to achieve multidimensional collaboration under complementary capabilities.

4) Verifications for distributed intelligent control strategies in large-scale practical application scenarios are urgently needed. Most existing results are obtained under laboratory conditions with centralized structures. For large-scale MASs, very few studies are carried out in the actual application environment, which leads to the urgent requirements of verifications in the actual application environment.

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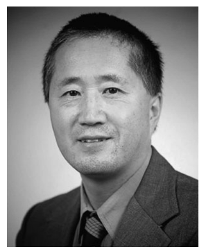

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