REVIEW

Speical Topic: Tri-Co Robots

From animal collective behaviors to swarm robotic cooperation

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ABSTRACT

The collective behaviors of animals, from schooling fish to packing wolves and flocking birds, display plenty of fascinating phenomena that result from simple interaction rules among individuals. The emergent intelligent properties of the animal collective behaviors, such as self-organization, robustness, adaptability, and expansibility, have inspired the design of autonomous unmanned swarm systems. This article reviews several typical natural collective behaviors, introduces the origin and connotation of swarm intelligence, gives the application case of animal collective behaviors. On this basis, the article focuses on the forefront of progress and bionic achievements of aerial, ground and marine robotics swarms, illustrating the mapping relationship from biological cooperative mechanisms to cooperative unmanned cluster systems. Finally, considering the significance of Coexisting-Cooperative-Cognitive (Tri-Co) human-machine system, the key technologies to be solved are given as the reference directions for the subsequent exploration.

Keywords: collective behaviors, swarm intelligence, cooperative robotics swarm, human-machine system

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INTRODUCTION

With the rapid technological development of the smart robot, varieties of robots are widely used in modern production and life. Many types of robots have emerged in the swarm, ranging in overall size from macro- to micro-, even nanometers [1–3]. The intelligent robots with high autonomy could be capable to conduct the sophisticated tasks in complex, unknown environments. A swarm is composed of three or more robots that cooperate to accomplish the tasks with limited or little control from human operators [4]. Like social insects living together in colonies to transcend individual limitations, the swarm-robot system allows for parsimonious solutions to robotic tasks with quite fewer resources than the comparable single-robot system [5]. This mainly benefits from the simple local interaction rules, which lead to emergent collective behaviors. Inspired by the study of natural systems, engineering principles can be extracted for the application of swarm-robot systems with comparable abilities containing parallel and distributed processing and control, locality of the interaction, scalability of the group, adaptation to the external variation, resilience to the losses and failures of the individual component [6–8]. A swarm-robot system has the following essential attributes [9]: – Robots are autonomous. – Robots can interact with the surroundings and give feedback to modify the environment. – Robots possess local perceiving and communicating capabilities. – Robots do not exploit centralized swarm control or global knowledge. – Robots cooperate with each other to complish the given task. On the basis of these, properties of a swarm-robot system shall mainly include distribution of the organization, simplicity of the individual, flexibility of the action mode, and intelligence on the swarm level explained as follows [10,11].

Distribution of the organization

There is no central node in the swarm and each individual follows simple behavioral rules with local perception, planning, and communication abilities. Through local information interaction with the environment and neighbors, individuals adjust their behavior modes to adapt to the dynamic environment. Swarm can gain the stigmergy globally. Meanwhile, distributed framework promotes the self-healing capability and scalability of the system [12]. The introduction or removal of individuals does not require a change in the program or subsequent reprogramming either results in the huge enhancement or reduction of the whole swarm performance. Robust swarm operation in spite of individual failure or environmental changes can be attributed to the decentralized control, shared perception information, inherent redundancy from a large-scale swarm, and the simplicity of individuals.

Simplicity of the individual

The abilities or behavior rules adopted by individuals in a group are quite simple. Each individual performs only one or a limited number of actions and makes a few simple responses to external situations. This seemingly clumsy individual behavior makes the group extremely efficient, reflecting the emergence of intelligence. Thus, the swarm system is not a simple sum of individuals, but through the self-organization, coordination, and cooperation between individuals to realize the multiplication and even exponential growth of the capacity.

Flexibility of the action mode

Flexibility mainly describes the swarm's adaptability to the environment. The swarm individuals adapt to the environment changes by adjusting their behaviors. In social animals, flexibility is promoted by the redundancy of the swarm size, simplicity of behaviors, and other cooperated mechanisms. The flexibility is usually inconsistent with the stability of swarm systems, while the communities in nature tend to be both stable and flexible. From a physical point of view, the swarm could possibly maintain the balance between stability and flexibility during the system phase transition while moving near the critical point [13].

Intelligence on the swarm level

Individuals exchange and share information through perceiving the environment situation, respond to external stimuli based on certain behavioral rules, and enhance the swarm adaptability via adjusting the state, which is a process of learning and evolution. Individuals adaptively change their own behaviors according to the feedback information from the environment to achieve strategies and experiences learning thereby obtaining the best adaptability to the external environment. The learning and evolution processes take place both in time and space manifested in the interactive learning of self-historical and external experiences, respectively.

NATURAL COLLECTIVE BEHAVIOR

The natural collective behaviors of animals, from schooling fish to packing wolves and flocking birds, have long intrigued observers of nature and scientists. The emergent properties have risen in collective motion via simple interactions among individuals, like self-organization, distribution, robustness, adaptivity, etc. Thus, much attention has been placed on revealing delicate local interaction rules, which lead to emergent collective behaviors.

Bird flocks

Birds often fly in aggregations to display a variety of fascinating phenomena that reflect an obvious degree of the swarm coordination and collective response. As a typical example of a small group, pigeon flocks possess a group size from several to dozens of individuals. A well-defined hierarchical structure has been found among pigeon flocks and the birds in the higher rank are more influential in the decision-making process of the flock [14]. From the perspective of evolution, the hierarchical organization of a pigeon flock might be more efficient and stable than an egalitarian one. In contrast, starling flocking is a paradigmatic example of a huge-scale group containing thousands of individuals. The local interactions are ruled by topological (fixed number of neighbors) but not metric distance (neighbors within a certain distance). Furthermore, the fixed number of interaction neighbors is independent of flock density. This interaction mechanism ensures fast information transfer and structural robustness that confer benefits to the collective efficiency [15,16]. Different from the pigeon and starling, larger birds like the ibis show an affinity for V-formation flight bringing aerodynamic advantages in their annual migration. The following bird in the V-formation could benefit from the aerodynamic up-wash generated by the leading individual [17,18]. Meanwhile, a social dilemma comes out around the issue of the volunteers flying in front. A human-guided autumn migrational flight suggested that ibis cooperates by directly pairwise switches in leading a formation. That is the time that they spend in the wake of one another is matched with the time in the leading position. The direct reciprocation mechanism has a substantial influence on the scale and cohesion of the flight formations.

Fish schools

Fish schools also exhibit complex and coordinated collective behaviors which link the individual behavior to the properties in the dynamic swarm [19]. Fish schools are investigated to move collectively with the high alignment through a selfish mechanism [20]. There exist three pivotal rules for the social interactions of fish different from other collective animals. (1) Attraction: Fish have the ability to copy another individual's heading to some extent [21]. (2) Repulsion: Speed regulation is a major component of repulsion, and speed changing is transmitted to the surrounding individuals. (3) Interactions: The single nearest neighbor dominates social interactions to a large extent [22]. Three rules described above help account for the group cohesion and social information amplification responding to speedy variations in speed and direction.

Wolf packs

Wolf packs regularly engage in cooperative hunting through coordinative actions, which is an important aspect of cooperation [23]. There exists an obvious linear and completely transitive hierarchy based on the direction of submissive behaviors in the wolf packs [24]. The rank order is positively correlated to the age but not the body weight. The dominance relationships remain constant across competitive and not competitive contexts [25]. Moreover, as the more gregarious carnivoran species, wolves have highly developed reconciliation behaviors, which help to reduce aggression between group members, restore social cohesiveness and preserve valuable cooperative relationships [26]. The above relationships help wolf packs to improve the efficiency of cooperative hunting.

Mapping theory

There are many similarities between the biological swarm and the unmanned system swarm as listed in Table 1 [10]. Efforts have been made to model abstract biological collective behaviors mathematically. There are three typical models of collective motion playing foundational roles. Reynolds proposed a distributed behavioral model by imitating the aggregate motion of a flock of birds, namely the boid flock model [27]. Three basic rules in the collective group have been summarized as collision avoidance, velocity matching and flock centering. In order to investigate clustering, transport, and phase transition in nonequilibrium systems, a novel pattern is described to explore the appearance of the self-ordered particle motion in the biologically encouraged interaction [28]. In the Viseck model, the position and the angle of the particle are defined as

$$\mathbf{x}_i\left(t+1\right)=\mathbf{x}_i\left(t\right)+\mathbf{v}_i\left(t\right)\cdot\Delta t \tag{1}$$

$$\theta\left(t+1\right)=\left\langle\theta\left(t\right)\right\rangle_r+\Delta\theta \tag{2}$$

Couzin *et al* presented a more biologically realistic model to simulate the swarm collective behaviors arising from the local repulsion, alignment and attractive trending on the basis of the location and direction of the individuals relative to its neighbors [29]. Couzin model defined three nonoverlapping behavioral zones consisting of "zone of repulsion" (zor), "zone of orientation" (zoo), and "zone of attraction" (zoa). Through the adjustment of parameters in simulation, the collective behaviors could possess the characteristics of natural groups. The desired state of each individual is updated by

$$\begin{cases}\mathbf{d}_r\left(t+\tau\right)=-\sum_{j\neq i}^{n_r}\dfrac{\mathbf{r}_{ij}\left(t\right)}{\left|\mathbf{r}_{ij}\left(t\right)\right|}, j\in\text{zor}\\ \mathbf{d}_o\left(t+\tau\right)=\sum_{j=1}^{n_o}\dfrac{\mathbf{v}_{j}\left(t\right)}{\left|\mathbf{v}_{j}\left(t\right)\right|}, j\in\text{zoo}\\ \mathbf{d}_a\left(t+\tau\right)=\sum_{j\neq i}^{n_a}\dfrac{\mathbf{r}_{ij}\left(t\right)}{\left|\mathbf{r}_{ij}\left(t\right)\right|}, j\in\text{zoa}\end{cases} \tag{3}$$

Numerous variants of the above models have come into sight considering various realistic situations. On this basis, the swarm models have been tested on the real hardware of swarm robotics [30].

SWARM INTELLIGENCE

Swarm Intelligence (SI) is defined as the emergence of consistent global collective motion from the swarm cooperative behaviors through the local interaction with the environment in [31]. The swarm consists of a large number of homogenous, unsophisticated entities without any central control or management. Each entity in the swarm executes quite simple and most often repetitive tasks. They interact with the environment and the other ones as an approach to conquer individual cognitive restrictions and yield a global behavior to emerge [32,33].

Table 1. Mapping mechanisms from biological swarm to unmanned system swarm.

Characteristics	Biological swarm	Unmanned system swarm
Distribution of the organization	No central nodes Each individual interacts with neighbors;	No command control center; Each unmanned system makes decisions autonomously;
Simplicity of the individual	Simper perception and motion abilities; Simple behavior rules;	Small size, low cost, partial sensors or loads equipped;
Flexibility of the action mode	Adaptive to the environmental changes able to avoid predators;	Adaptive to the environment with incomplete information, uncertainties and dynamics;
Intelligence on the swarm level	The swarm possesses high efficiency and emergent intelligence;	Multiplied operational capabilities and improved survivability are obtained under amplification effects.

fig1.pdf

Figure 1. From animal collective behaviors to cooperative unmanned swarm systems.

The establishment of SI models is based on the observation of natural mechanisms to attain the comprehension of the patterns and rules resulting in the flock behaviors. It has already been observed in the animal systems like birds, fish, or insects that though the aim of the swarm is sometimes rather complicated, each individual utilizes relatively simple rules, and interacts with their surrounding environment and individuals. Typically, one single flock individual has insufficient ability to find one superior solution while the swarm is capable under the appropriate conditions [34]. More specifically, inspiration for SI is not constrained by nature swarms, but rather to any complicated artificial system consisting of the interaction entities which possess excellent characteristics, including regulation, homeostasis, collective decision-making, and periodic patterns. The aim of SI is to understand conditions, rules, and interaction patterns which is able to promote the emergence of collective swarm behaviors.

Wang and Beni firstly introduced the term ”swarm intelligence” in 1989 to give the dynamics of swarm robots which can be framed as a form of intelligent collective behavior [35]. This signifies that the swarm collective behaviors have begun to be studied not only in the fields of the nature sciences. Conversely, this comprehension is able to be adopted to cast a light on how collective behaviors emerge in natural swarms and to introduce new artificial systems with swarm intelligence. There are five principles for the SI algorithms to adhere in the aspect of proximity, quality, diverse response, steadiness, and adaptability [36]. Firstly, the population is able to implement basic time and space computations. Secondly, the population is able to react to the quality elements in the surroundings. Thirdly, the population does not need to commit its activities along the exceedingly narrow channels. Fourthly, the population does not need to change the swarm behavior mode along with the variation in the environment. Lastly, the population is capable to change the behavior mode under the appropriate computational price. Swarm intelligence i.e. Collective Intelligence (CI), has two basic properties, including the amplification effect on individual intelligence and the scalability to the number of participating individuals [37]. A large swarm can significantly amplify individual intelligence. From the perspective of interaction, the essence of swarm intelligence can also contain the following three key points: (1) Exploration: swarm individuals independently explore the space for the current problem and obtain a series of information. (2) Integration: all information explored by individuals is merged in some way. (3) Feedback: the individual is stimulated to continue exploring by the feedback of merged group information.

After extensive exploration by researchers, swarm intelligence progressively evolved into two main branches: Swarm Intelligence Algorithm and Distributed Swarm System. As Dorigo defined, Swarm Intelligence includes the trial design of the algorithms and devices for solving distributed problems under the inspiration of collective behaviors in social animal colonies [38]. Swarm Intelligence Algorithms refer to a form of nature-based optimization algorithms designed at the core of the cooperative behavior of animals within specific communities for optimization problems. The most popular SI frameworks, such as Particle Swarm Optimization (PSO) algorithm [39] and Ant Colony Optimization (ACO) algorithm [40], consist of a swarm of minimalist agents which are designed under the references of individual properties in nature societies. The spread of the concept to artificial systems was begun with the research of swarm robotics, which is well defined by Şahin and Spears [41]: "Swarm robotics is the study of how a swarm of relatively simple physically embodied agents can be constructed to collectively accomplish tasks that are beyond the capabilities of a single one" and "Swarm robotics emphasizes self-organization and emergence while keeping in mind the issues of scalability and robustness". Distributed Swarm System refers to the employment of swarm intelligence technologies for the analysis of swarm behaviors where the entities are physical robots including aerial robots, ground robots, marine robots, and other platforms. By taking inspiration from social animals, distributed swarm systems aim to develop robotics systems with similar swarm intelligence features which also characterize social animals [42]. Thus, a large number of robots with quite simple behaviors could achieve the desired collective behavior through the local interactions with the neighbor robots and the environment.

The design of a swarm-robot system with SI has been facing many challenges with respect to the employment of the biological inspiration tool. From the perspective of engineering application, it is indispensable to design the self-organization structure, local communication mechanism, and feedback control method.

Self-organization structure

The significance of self-organization design needs to be emphasized since the system could achieve the complex task via the simple rules of the individual. It is therefore highly desirable to seek self-organization behaviors in a swarm robotic system, as they can be obtained with minimal cost. Therefore, self-organization behaviors are supposed to be obtained in the swarm robotic system. Nevertheless, the definition of simple local rules for each individual is particularly challenging since it has an indirect relationship with complex global properties. To design the control system of the self-organized robotic swarm, the definitions of the individual rules need to be given to promote the system's desired pattern. The robotic swarms possess the superiorities in redundancy and the ability to handle multiple tasks simultaneously than a single robot. The definition of individual self-organized behavior should adapt to the dynamic situation to promote the robustness of the swarm system. Through the self-organized rule, if a robot stops functioning, one in the swarm can replace it with no significant influence upon the system.

Local communication mechanism

In fact, global behaviors emerge from the local interactions which have not been coded directly in the individual's behavior rules. Thus, it is necessary to discover the interaction relationship among individuals and the environment resulting in self-organization. Then, the desired global behavior should be decomposed into simple individual behaviors and their interactions with the neighbors. The stigmergy mentioned above is a core concept of the biological community in nature inspired by the nesting behavior of termites, defining the information coordination mechanism of the self-organized individual [43]. Stigmergy can be regarded as an indirect or implicit communication mechanism to provide an efficient cooperation mechanism for simple individuals lacking memory and communication capabilities. Designing an implicit communication mechanism and combining it with traditional explicit communication can effectively solve the circumstances of communication conflicts and deadlocks. From the perspective of information flow, designing the local interaction mechanism can not only enhance the coordination ability and robustness of the swarm system but also improve communication efficiency to break through the bottleneck effect of communication.

Feedback control method

From the perspective of control theory, feedback is one of the basic intrinsic elements of autonomous swarm behaviors, including both positive and negative feedback. The positive feedback strengthens the weak response of the swarm at the initial time and urges this swarm to cope with the change in the external environment. Negative feedback acts as damping to suppress the disturbance input. Positive and negative feedback promote rapidity and stability, respectively. The balance between the two elements enables the group to respond quickly to the dynamic environment and remain stable in the face of uncertain disturbances.

The structure of the self-organized swarm system is illustrated in Fig. 2, displaying a global behavior via the interaction with the environment. Aiming at the process of programming, the method is employed to decompose the process into two steps [44]. Firstly, the global behavior is composed of individual behaviors and local interactions between their neighbors and environment. Next, the explicit and implicit communication modes among the individuals are defined and the mechanism of information perceiving and pheromone releasing is set between the individual and the environment. Further, the positive and negative feedback mechanisms are designed under the stimulus in the environment. Last, these phases are coded into the control program embedded into each individual. This process is complex because the definition of individual behavior rules should be corresponding to the desired swarm model. Thus, it is an expected method to take inspiration from the biological community to simplify decomposition from the global cooperative behaviors to individual interaction rules. In the case of UAV close formation inspired by the ibis V-formation migration, four steps are consistent with the above structure. Firstly, the UAV motion of the close formation is decomposed into the leading-following relationship of the pairwise individuals. Secondly, the direct reciprocation model is constructed for individual interactions. Thirdly, the fuel cost or the flight length conditions are defined to trigger the pairwise position switches in the UAV swarm. Lastly, the above three steps are programmed in the same way for each individual.

UNMANNED SWARM SYSTEMS

Aerial robotics swarm

A swarm of Unmanned Aerial Vehicles (UAVs) is a group of aerial robots working cooperatively to accomplish the given aim [45]. Each UAV can be controlled by ground stations and remoting control units in hand, or processors loaded on the aircraft autonomously. On this basis, the UAV swarm can be classified into fully and partly (semi) autonomous swarms. From another perspective, the classification can be divided into centralized, distributed, and hybrid control swarms. In the centralized control swarm, the drones are positioned in the hierarchy of multiple layers. Each drone receives commands from its leader individual at the upper layer without its decision-making. The ground station plays the role of the top layer in the hierarchy. This structure is easy to implement the task algorithms but possesses the problems like poor real-time and anti-disturbance performance. In the distributed control swarm, all drones are positioned in a single layer and regarded as their own leader with independent decision-making capability. This structure could overcome the boundedness of the centralized structure, which is robust and adaptive to the dynamic complex environment. While the hybrid swarms possess both centralized and distributed characteristics. Drone nodes are grouped and assigned by function, type, authority, etc. The nodes located separately in the higher and lower layers form the centralized control swarms and the nodes in the same layers form a distributed control swarm. Hybrid control swarms are established to be clear in the labor division, highly stable under disturbance, easy of maintenance, but complicated to design the structure.

In Unmanned Aircraft Systems Roadmap 2005-2030 issued by Office of the Secretary of Defense (OSD), an onion-like layered series of capabilities has been adopted to define ten levels of autonomy. The definitions handle the span from the remote operation and preprogrammed flight by a single aircraft to the autonomous swarm flight [46]. Small Unmanned Aircraft Systems (SUAS) Flight Plan 2016-2036 issued by United States Air Force emphasized the broad prospects and high value of small unmanned aerial systems from the strategic level. And new concepts of using SUAS to realize tactical to strategic level mission goals are augmented or redefined including swarming, teaming, and loyal wingman, corresponding to machine-to-machine, man-to-man, man-to-machine means. China Electronics Standardization Institute successively promulgated the white paper on the development of intelligent unmanned swarm systems in 2021 and group standard of information technology unmanned swarm terminology in 2022, which put forward the urgent need to establish a unified intelligent unmanned swarm technology system and standard system for the guidance of industry development in the product lift cycle of the design, development, operation and maintenance [47,48]. These all send a signal that the development trend of UAVs is from a single drone to multiple drones and UAV swarms, and the

Fig.2.jpg

Figure 2. The structure of a self-organized swarm system.

control architectures of UAV swarms step from centralization forward distribution. Through efficient cooperation, autonomous UAV swarm systems can embody more excellent coordination, intelligence, and autonomy than manual systems. The cooperation of a UAV swarm has the following characteristics leading to discernible advantages in situation awareness, task efficiency, etc. 1) solve the conflicts between multiple UAVs in the same space effectively; 2) possess efficient information sharing, fault resistance, and self-healing capabilities via the decentralized communication network; 3) obtain the high decision accuracy with distributed swarm intelligence; 4) improve the detection accuracy of active and passive detection through adopting the distributed detection method. For the advancement of the cooperation technology, there are mainly four aspects supposed to be executed.

- Aerial launch and recovery

To satisfy the needs of long-range, low-cost, multi-wavelength, hierarchical mission execution capabilities of large-scale UAV swarms, aerial launch and recovery technology develop rapidly. The "launch-work-recovery-relaunch" mission execution mode can significantly improve the efficiency ratio and sortie efficiency of autonomous UAV swarms. Aerial launch usually considers two methods, i.e. ejection and distribution. The current aerial launch projects are mostly conducted with a large transport plane or bomber which flies to the pre-defined location carrying a large number of small UAVs, drops them to perform reconnaissance, attack, or interference tasks, and recover after the tasks are completed or the battery is low. In the tests carried out on Oct 25th 2016, three U.S. Navy F/A-18 Hornet two-seat variants successfully released a "swarm" of 103 Perdix semi-autonomous drones during flight. On Mar 19th 2019, NASA tested a swarm of 100 US Navy Cicada drones released by four large drones (called Hives). The Cicadas are mounted on the underside of a Hive drone and then released on demand with a mechanical switch [49]. As announced in Sep 2020 by China Academic of Electronics and Information Technology, the land launch and air launch of fixed-wing UAV swarm have been verified, reflecting the capabilities of formation reconfiguration, ground observation and attack, precision strike, and others. U.S. Defense Advanced Research Projects Agency (DARPA) Gremlins program has been exploring the concept of employing large aircraft as the launch platforms for recoverable UAV swarms since 2016. On Oct 29th 2021, a Lockheed C-130A Hercules aircraft launched and recovered an X-61A Gremlins Air Vehicle (GAV) in flight for the first time in Utah. C-130 could employ two recovery approaches to catch an X-61 Gremlins drone in flight using the mechanical arm or metal cable, respectively [50].

- Communication network

Facing the challenges of complex battlefield environments such as land, sea, air, space, electromagnetic, and network, establishing reliable communication networks among the UAV swarm is the key to carrying out cooperative tasks. Generally, the reliability of the communication network has many challenging parameters such as time delay [51], switching topologies [52], node-link interruption [53], presence of jammers [54], and unpredictable noisy channels [55]. In the aspect of theoretical exploration, the communication network of a UAV swarm is usually considered via the graph theory method, which introduces the network, node, and link to be graph, vertex, and edge, respectively. At the same time, the flight tests in the real environment have also made phased progress. As demonstrated on August 27 2015 at Camp Roberts, Timothy Chung Group of Naval Postgraduate School achieved an autonomous swarm of 50 UAVs among which each individual is equipped with three communications systems to establish the network system [56]. The swarm of CH-4 UAVs successfully completed a number of flight missions in 2016 through sensing and cooperating, such as over-the-horizon flight, line-of-sight relay of satellite communication, and simultaneous transmission of multi-channel satellite communication. In 2017, 119 small fixed-wing UAVs completed the autonomous formation tasks released by China Academic of Electronics and Information Technology with the hierarchical clustering approach to build a self-organized network.

- Decision-making and control

Based on the interaction topology network, the UAV swarm could carry out the information aggregation and fusion, make decisions on the next mission, and move on to complete the current action [57]. First, the UAV individual could acquire the situation elements at the current time and space environment, fuse and analyze the information, and obtain the predictive inference of the states at the next moment to establish the situation awareness. However, the actual battlefield environment is faced with challenges, such as incomplete information, the existence of interference, deception, and attack signals [58]. Second, the decision-making process based on the environment cognition arranges the UAV swarm to execute the mission at a specific pattern depending on the dynamic task allocation and coordinated control mechanism [59]. Correspondingly, the task assignment algorithm and interaction mode are supposed to be well designed to support the swarm cooperative decision-making process, which is recently inspired by biological swarm behaviors in various applications [60]. Third, UAV swarms take action to perform the assigned tasks via different configurations of formation control. There are several key technologies necessary for autonomous flight, including formation maintenance [61,62], formation reconfiguration [63,64], obstacle avoidance [65], energy conservation [66].

- Technical application and verification

The maturity of cooperative algorithms and technologies requires multiple iterations of technical application and validation experiments. The research group in Hungary proposed a flocking model ensuring seamlessly navigating in confined spaces which is verified by 30 real drones in 2018 [67]. Researchers in China have developed miniature but fully autonomous drones and palm-sized swarm platforms with on-board perception, localization, and control capabilities via imitating the birds for trajectory planning approaches in 2022 [68]. The China Academy of Electronics and Information Technology (CAEIT) reportedly carried out the experiment with 200 fixed-wing drones simultaneously launched to switch between various configurations and carry out reconnaissance and attacking missions on ground targets in 2018 [69]. The US Army conducted 2022 Experimental Demonstration Gateway Exercise (EDGE 2022) from late April to early May to test interoperability, the network, electronic warfare, multi-intelligence sensors, interactive drone swarming and enhanced sustainment on the largest interactive drone swarm to date, redefined as "Wolfpack" [70].

Ground robotics swarm

Ground robots in a swarm have always intrigued researchers and engineers due to their wide application in military operations, social activities, intelligent manufacturing, etc. Besides the advantages shared by aerial robots, ground robots play a key role in restricted space and environments with portability, concealment, and flexibility. There are three frontier research topics in three different operation spaces.

- Micro-nano robot swarm

Micro- and nanorobotics is an emerging field of the research arising from the cross-fusion of micro/nano technologies and robotics [3]. Compared with the macroscopic robots, nano and micro-robots could conduct tasks on an exceedingly small scale because of the characteristics of low weight, small size, large thrust-to-weight rate, high sensitivity and high flexibility. Thus, micro- and nanorobots have intrigued researchers and opened up numerous application frontiers, including drug delivery, disease diagnosis, and minimally invasive surgery. As a single micro-nano robot is limited in size and functions, micro-nano robot swarm has gradually become the research focus, promoting the trend of cooperation. Swimming microrobots that gain the energy supply from external magnetic fields show various intelligent collective behaviors, varying from self-organized to cooperative movement. A strategy for reconfigurable magnetic microrobot swarm is presented to emulate the cooperative mechanisms and self-organization phenomena of natural swarms. The strategy utilizes the alternating magnetic domains to program the hematite colloidal particles intoribbonlike, chain, liquid and vortex microrobotic systems and enables speedy and reversible changes between them [71]. Moreover, present microrobot swarms are short of the intelligent behaviors to autonomously regulate the distribution and move to adapt to environmental change. An autonomous environment accommodative micro-robot swarm is designed by the deep learning-based real-time distribution planning method [72]. Each robot possesses the real-time appropriate decision-making capability for unknown and unstructured environments. For environment-adaptive microrobot swarm navigation, four different autonomy levels are defined and the corresponding system components are designed.

• Manipulator swarm

The cooperation among multiple industrial robots will bring cooperative motion planning and synchronous motion control problems of multiple manipulators under constraints [73]. In multi-manipulator cooperative motion planning, it is essential to customize the cooperative manner, in order to safely and efficiently achieve the desired manipulation task. The manipulator in the space station is one of the key pieces of equipment for the construction, operation, maintenance and expansion of the space station. With the growing complexity of the space tasks and the development of related technologies, space manipulator technology presents a trend of configuration from single-arm operation to multi-arm operation. Japanese Experiment Model Remote Manipulator System (JEMRMS) consists of two arms, Main Arm (MA) and Small Fine Arm (SFA) [74]. The end effector of MA can grapple the common grapple fixtures in the space station and the SFA can perform more dexterous tasks than the MA. The China Space Station manipulator consists of one in the core module and another in the laboratory module [75]. The two arms can work independently or cooperatively or can be combined as one arm to expand the operating range. The synchronous motion control problem is another research focus. The problem of distributed control of multiple redundant mobile manipulators is tackled by a distributed proximal gradient algorithm [76]. The formation control tasks are introduced as equality constraints with the variables being the velocities. Then the manipulator swarm could collectively transport an object tracking a desired trajectory with energy and manipulability optimized. The cooperative problem of the multi-manipulator could be considered as multi-agent system. The key problem to solving the consistency and coordination control is to design appropriate protocols or algorithms to ensure the consistency of each manipulator and the stability of the system [77]. In the future, space manipulators with multi-manipulator configurations will be developed to complete more complex operations through multi-manipulator cooperative movement.

• Unmanned ground vehicle (UGV) swarm

The cooperation of UGVs in swarm puts forward requirements of precise positioning and navigation technology in both indoor and outdoor environments. The outdoor environment supports positioning and navigation device like GPS, IMU, electronic compass and other sensors. On the contrary, the lack of prior information and GPS signal greatly increases the difficulty of navigation and positioning technology in indoor or GPS-denied environments. Thus, it is suitable to utilize vision-based systems as an alternative for indoor environments [78]. Therein, visual SLAM technologies [79] have the characteristics of small size, light weight, high precision, better real-time performance, low cost, etc. Each UGV in the swarm interacts with other individuals to share the environment information and optimize the task assignment, so as to improve the overall operational effectiveness via the cooperative mechanism. Therefore, it is necessary to conduct a deep study about autonomous path planning, obstacle avoidance, cooperative consensus control, and other technologies [80]. The exploration and verification of the swarm cooperative algorithm are developed more in-depth with the UGV system. Swarm intelligence is also widely regarded as the key technology to improve the capacity of swarm systems. E-puck robots which are unveiled by the École Polytechnique Fédérale de Lausanne have been employed to test the controllers for the collective foraging to handle the noise in global positioning data and the robustness of the swarm with the form of broadcast messages [81]. Kilobot robots designed by Harvard University realized programmable self-assembly of complicated two-dimensional shapes in a thousand-scale swarm through local interactions and cooperative algorithms [82]. Particle robotics are controlled to achieve autonomous locomotion, phototaxis, and object transport via the simple distributed algorithm inspired by collective cell migration phenomena in biology [83]. With the appearance of intelligent UGV like BigDog [84], various of swarm robotics competitions like DARPA Subterranean Challenge and Swarmathon have risen to greatly propel the development of multiple UGVs systems [85,86]. The swarm of cooperative UGVs, as the extension of human's hands, eyes and ears, could assist them to conduct the more complicated tasks, particularly for hazardous tasks like bomb disposal. DARPA's OFFensive Swarm-Enabled

Tactics (OFFSET) program deployed swarms of autonomous air and ground vehicles to demonstrate a raid in an urban area during the agency's third field experiment in 2022 [87]. Shenyang Institute of Automation, Chinese Academy of Sciences demonstrated a new mode for onsite security of large-scale mass events based on the cooperation of unmanned aerial and ground systems in 2021.

Marine robotics swarm

Unmanned Marine Vehicles (UMVs) refer to marine robots moving above and below the water with no operation from the human on board. UMVs are usually equipped with the necessary sensors and payloads to accomplish neither civilian or military missions, such as environmental monitoring, target surveillance, region reconnoissance.

UMV consists of Unmanned Surface Vehicles (USVs) and Unmanned Underwater Vehicles (UUVs). Therein, USVs are a type of unmanned surface vessel that can be fully autonomous, semi-autonomous, or switched to manual control. They are able to navigate autonomously and avoid obstacles intelligently via following the current parameters and waypoints obtained from programs. This makes them ideal for data collection, autonomous hydrographic surveys and military applications. UUVs are supposed to carry out tasks without the real-time supervision and intervention from the operator. They are capable of crusing on a predetermined couse, publishing and receiving the information and making decisions according to the posture change driven by the embedded program. UUVs mainly incorporate Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs). The development of ROVs could overcome the limitations of the operators and manned marine vehicles. Therefore, they are remotely operated by the crew on the nearby vehicles and connected to their operating bases through the umbilical cord link. This link can provide both lines and power supply, communication and data links. ROVs are usually placed in four categories according to sizes as work-class ROVs, observation- or inspection-class ROVs, mini- or micro-ROVs. They could be employed in the military and civilian scenarios such as pipeline and offshore platform inspection tasks. AUVs can perform the task lasting for several months without direct real-time control.They could execute the pre-programmed predefined waypoints normally and make decisions on the emergent circumstances via intelligent algorithms. Most AUVs are powered by the battery and propelled by thrusters. Therein, the underwater gliders use buoyancy changes to ajust the depth and work for sampling or monitoring tasks. AUVs with no link to the ground could possess high operability and travel to the remoting positions, narrow complicated pathways [88]. Other AUV applications include oil and gas exploration, seabed surveying, and anti-submarine warfare.

Compared with land and air environments, the ocean water environment has more disturbances, such as ocean currents, faults and complex submarine topography. Underwater acoustic communication is an effective way of underwater communication, but the propagation speed of the acoustic wave is 5 orders of magnitude lower than that of electromagnetic waves, leading to problems such as low information transmission speed, serious delay, packet loss and fast attenuation. Meanwhile, it is difficult for one single UMV to conduct complicated tasks. However, the AUV swarm could implement tasks cooperatively to achieve greater efficiency in the complex marine environment [89]. Thus, multi-UUV cooperation will improve the intelligence and efficiency of multiple individuals performing tasks independently, enabling them to better accomplish tasks that can not be conducted by one individual. There are two key technologies in the cooperation of a UUV swarm.

- Communication technology

Connected communication is the basis of reasonable and efficient cooperation between UMVs. Because the underwater environment has a strong attenuation effect on electromagnetic waves and light waves, long-distance communication relies heavily on underwater acoustic communication at present. Underwater acoustic communication is realized by the underwater acoustic communication machine carried by UMVs, and the communication content can be request, response, task, target, state information, control instruction and so on. However, the acoustic wave will generate a large transmission delay so real-time communication between UMVs is difficult to achieve. Moreover, the transmission distance of acoustic waves is limited by carrier frequency and transmitting power. The scattering, transmission loss and echo interference of acoustic waves in water have effects on the distance and quality of underwater acoustic communication. Thus, experts in related fields have done a lot of research to explore the communication methods, such as IR sensors [90], blue light [91] and computer vision [92].

- Navigation and location technology

Navigation and location technology is the prerequisite and key technology of cooperation in the multi-UMV swarm. However, due to the complex underwater environment and the limitations of UMV itself in size, the methods to achieve multi-UMV locations are limited. It mainly includes 1) Acoustic navigation location: Although this method has high accuracy, the cost of baseline layout is high and the location accuracy is limited by the coverage of baseline. 2) UMV navigation presumption: This method is characterized by simple operation and low cost, but the location error is accumulated with time. 3) Inertial navigation: This method possesses high precision with the expensive cost of high precision inertial equipment, especially in a large-scale group. 4) Geophysical guidance (gravity matching, geomagnetic matching, etc.): This method needs to provide a corresponding matching database, which is not suitable for unknown regions. 5) Multiple-UMV cooperative location: A small number of UMVs are equipped with high-precision navigation equipment to provide accurate relative positioning information for other UMVs. Other UMVs utilize relative positioning information to correct their location errors. Multiple-UMV cooperative navigation has the characteristics of moderate cost and simple implementation, which can meet the needs of the rapid location. However, cooperative navigation usually relies on underwater acoustic communication for location information transmission resulting in a large transmission delay.

Many scholars have reaped significant development among the theory research and hardware implementation of multi-UMV cooperation. In the respect of cooperation control, multiple UMVs are supposed to meet task requirements and environmental constraints. Due to the environment disturbance, discussions on this topic have been conducted aiming at weak communication topology [93], communication delays [94], ocean current disturbances [95], navigation and localization [96], etc. Under the physical limitation of UMVs, circumstances, such as uncertain dynamics, parametric uncertainties and actuator saturation, are not evitable to be considered [97–99]. As for the complex coordination of centralized explicit communication, the implicit or hybrid centralized coordination approaches have risen inspired by the collective behaviors of fish schooling [100,101]. At the practical level, there are several significant efforts to deploy underwater swarm cooperation. Nekton Research Institute in UK is going on with the advancement of the micro-UUVs and the Underwater Multi-Agent Platform (UMAP). The platform is comprised of N-UUVs and the supporting infrastructure that have been employed in the research of distributed search, formation control, oceanographic survey and other related research [102]. DARPA's Collaborative Networked Autonomous Vehicles (CNAV) program has been deployed from 2009 which utilizes a shared acoustic network to distribute data for underwater target detection, location and tracking missions. The system, coupled with a stationary passive sonar node, is used in the Distributed Agile Submarine Hunting System (DASH) to detect submarine targets over a wide area [103]. Exercise Unmanned Warrior organized by Royal Navy and its partners in academia and industry is a display of autonomous robotic systems that carry out a dazzling array of air, surface and sub-surface tasking, from underwater surveying to mine countermeasures. China Ship Scientific Research Center has conducted three sea trials for formation networking tasks of “Haixiang” underwater gliders. The tests obtained temperature, salinity, oxygen concentration, chlorophyll and other marine environment measurement data in relevant waters, covering an area of 112 square kilometers.

HUMAN-MACHINE SYSTEM

In biology, the experiments of bird flocks under human intervention provide an innovative way to further study the mechanisms of flock movement and communication interaction. The free flight experiments for long distances have accomplished the human control upon the robo-pigeon by neural stimulation [104]. Then, the contrast experiments have been conducted on the basis of the brain microstimulation technology to design the controlled variables. The robo-pigeon with the higher hierarchical level may effectively balance their preferred directional choice in the flock [105]. Nowadays, biological experiments where a robotic falcon dashes into the pigeon flock help researchers to analyze the species-specific pattern of the collective escape behavior [106]. Due to the possibility of introducing human factors into a natural bird flock, it is more hopeful for us to further understand the collective behavior and mechanism from the animal behavior paradigms.

Due to the capability limitation of the unmanned system in the aspects of situational awareness and real-time decision-making, the cooperation of human wisdom and unmanned systems qualifies as a force-multiplier and improves the level of autonomy and intelligence to meet the growing challenges in complex environments. Specifically, combining the advantages of manned and unmanned systems could strength the task efficiency and effectiveness while offer security and lower risk to operators and assets simultaneously. Fig. 3 shows the Coexisting-Cooperative-Cognitive (Tri-Co) framework incorporating the manned operating platform and unmanned systems into one team. The mission aim of the system is defined by a command-and-control-entity (C2) regarded as information input [107]. The Environment perceived by platform sensors is considered as input of the command and control center and unmanned systems to provide situational information. There exist different roles in the team. The human operator has the highest authority and accomplishes decision-making tasks with the suggestions of Assisted Decision-making System (ADS), i.e. an automated planning aid [108]. Unmanned Systems are delegated to accomplish the tasks by the commands directly from human operators or ADS. This Tri-Co framework helps operators to supervise and control unmanned systems with a maintainable workload.

U.S. Army Unmanned Aircraft Systems Roadmap 2010-2035 issued in 2010, covered a 25-year period divided into three distinct periods: Near-term, Mid-term, and Far-term. Far-term emphasized drastic commonality and capability improvements of both manned and unmanned systems to lay the foundation for man-machine cooperation. Small Unmanned Aircraft Systems (SUAS) Flight Plan 2016-2036 proposed the concept of loyal wingman highlighting the man-to-machine means. Unmanned Systems Integrated Roadmap 2017-2042 addressed the critical need of interoperability to promote the capability synergy of manned and unmanned systems in 2018. The artificial intelligence (AI) strategic development plan announced by Chinese State Council in 2017 covered man-machine cooperation eight times and considered it one of the key technologies for establishing the key generic technology system in the area of artificial intelligence. Professor Tianran Wang pointed out that the next generation of robots will cooperate with the human in the Opening Ceremony of 2018 National Robot Development Forum and RoboCup China competition. In the 2018 IEEE/CSAA Guidance, Navigation and Control Conference, professor Bangkui Fan pointed out that the high degree of cooperation between manned and unmanned systems is the key to realizing the practical application of UAV swarm. Besides, the National Natural Science Foundation of China launched the first major research program in the field of robotics in China on the advice of experts, including Han Ding, Xuejun Yang and Nanning Zheng, to promote basic research on Coexisting-Cooperative-Cognitive Robots (Tri-Co Robots). Thus, it has become an important development trend to adopt the cooperation of manned and unmanned systems to realize the multiplication and even exponential increase of the task capability in the cross-domain platform systems.

Aiming at achieving the autonomous cooperation of manned-unmanned system, professor Jie Chen proposed the research challenges containing four aspects [109]: (1) System level: organizational structure and collaboration mode; (2) Decision-making level: task allocation and behavior planning; (3) Control level: cooperative motion control; (4) Security level: security of command control. Zheng et al. proposed a vision of human-centric networked unmanned systems: Unmanned Intelligent Cluster (UnIC). The cooperation can be achieved by knowledge sharing and social awareness between distributed unmanned systems and humans [110]. Generally, the presence of a human operator could contribute to the next points: (1) recognize and mitigate the boundedness of autonomous unmanned systems; (2) obtain the critical information unavailable to unmanned systems to improve the mission effectiveness; (3) convey the changes of task goals timely [111]. The control methods that an operator exerts on the swarm can be summarized into four categories: (1) the operator could control the unmanned system via algorithm and behavior selection while the unmanned swarm has a high degree of autonomy [112]; (2) parameter setting method appears in most cases with indirect effects on the swarm [113]; (3) the operators influence the swarm via the direct or virtual environmental factors [114]; (4) the operators select to control a subset of leading individuals to reduce control complex [115].

The level of swarm autonomy (LOA) can be divided into three ranks roughly: manual, mixed-initiative (MI), and fully autonomous LOA [116]. Three basic modes of unmanned-fig3.pdf

Figure 3. Tri-Co Framework of Human-Machine-Environment system.

manned cooperation under the confrontational situation are given in [117]. A fully centralized mode represents the unmanned systems cooperating with the man operator. The finitely centralized distribution mode represents that the unmanned systems are assisted by the man operator. Acentric distribution mode represents that the unmanned systems and man operator complement their skills. Five different levels of Interoperability (LOI) are defined more explicitly by NATO Standardization Agreement 4586 (STANAG 4586) to describe how operators control both the UAVs and the payload. Level 1 - Indirect transmission/receipt of UAV-related metadata and data; Level 2 - Direct transmission/receipt of UAV-related metadata and data; Level 3 - Control and monitoring of UAV payload, rather than the unit; Level 4 - Control and monitoring of the UAV, with no launch and recovery; Level 5 - Control and monitoring of the UAV, containing launch and recovery. It can be seen that Level 5 requires the installation of a fully Remote Pilot Station (RPS) in the manned aircraft and offers the crew maximum control.

In the manned and unmanned air systems, providing pilots or operators the ability to control Unmanned Aerial Systems (UAS) enables them to take full advantage of ISR capabilities to enhance decision-making and improve safety during dull, dirty, and dangerous tasks. As for the manned and unmanned marine systems, divers may cooperate with UMVs to complement each other to accomplish the tasks of underwater salvage, rescue, maintenance, and scientific research together. A variety of devices equipped by the UMVs could reduce divers' loads, and enhance the flexibility and automation level, such as communication modules, multi-beam and side-scan sonar, and ultrashort baseline location system. Meanwhile, UMVs are supposed to assess the physical condition of the divers via the connection with life detection and support systems. Thus, divers have the opportunity to escape dangers or accidents under the alarm and assistance of UMVs. The design of the human-UMVs cooperation system should take the role of operators in complex tasks into account to be flexible, applicable, and more importantly, adopting compliant control methods to guarantee the safety of divers while UMVs approach divers. To solve the complicated and uncertain situations with human-UMVs cooperation system, one of the foremost considerations must be the group role assignment problem (GRAP). Through the role-based collaboration methods, researchers could establish an efficient and flexible system [118]. In the manned and unmanned ground systems, automation is achieved via the heterogenous system of UGV platforms and human decision-making to conduct the work with one excavator operator and one construction planner. The use of UGVs plays a special role in the reduction of human exposure in dangerous zones. The wide application of UGVs raises the requirement for mobile platforms to meet certain quality requirements and also be operated easily by human operators. In the TianGong-2 (TG-2) spacelab mission, a human-robot collaborative on-orbit servicing experiment was conducted as one of the three key tasks. The TG-2 robotic task is designed to complete various prototypical experiments under a micro-environment to validate key technologies of space robots and on-orbit human-robot collaboration, which gain experience and experimental data about robotic on-orbit servicing by assisting or cooperating with human astronauts [119]. Thus, human-machine interfaces (HMI) could be enhanced to allow easier machine operation and interaction. Then, the autonomy level, including the ability of sensing, perceiving, communicating, analyzing, decision-making, and action, could be increased.

FUTURE PROSPECTS

The development directions of the swarm-robot system are preliminarily discussed in this section, as shown in Figure 4.

fig4.pdf

Figure 4. Four development directions of the swarm-robot system.

Deep exploration of swarm intelligent mechanism

The research on the mechanisms of large-scale swarm movement of biological groups, such as birds and fish, has attracted extensive attention from researchers in different fields. Through simple rules and local interactions, biological groups show collective behaviors with strong robustness, high self-adaptiveness, and good scalability, which are the desired characteristics of a swarm-robot system. Although we have a primary understanding of the collective mechanisms in biological swarms through theoretical modeling and empirical analysis, the self-organizing emergence mechanism of swarm intelligence still requires further research. Currently, swarm-robot systems pay more attention to the scale effect, hoping to suppress the enemy with the number advantage through cooperation. However, this line of research is only similar to animal communities in form and intuitionistic. Employing the intelligent mechanisms emerging from the biological swarm behaviors can improve the system efficiency to a greater extent and achieve exponential growth of task effectiveness. In this sense, research on the theory and method of biological swarm intelligence is becoming more and more important related to the heterogeneous group, individual learning, etc. Thus, data analysis from biological swarm experiments will help to reveal the internal mechanism of self-organizing intelligent swarm behaviors. The biological experiments under human intervention could be helpful for the exploration of the intelligent mechanisms in animal swarms. Also, the mapping mechanisms from the animal collective behaviors to swarm robotic cooperation are supposed to be modeled with the task requirements.

Interdisciplinary application of bio-swarm robots

To adapt to the requirements of platform performance, battlefield environment, tactical tasks, the incentive and convergence mechanisms of swarm intelligence in nature are explored to change the bottleneck situation of the intelligent unmanned system with intelligence but no wisdom, sensing but no cognition, specialty but no generality, cooperation but no convergence. On the one hand, the coordinated mechanisms inner biological swarms are supposed to be utilized in the processes of flight management and control, collaborative decision-making, and information sharing. On the other hand, swarm-robot systems are supposed to be endowed with the ability of self-learning and evolution by biological swarm intelligence to gain full autonomy. The autonomous control technology of swarm-robot systems based on bionics is expected to be broken through via the cutting-edge technology research of biology, control, artificial intelligence, robotics, and other interdisciplinary fields. Thus, exploring the phenomenon of swarm intelligence incentive and convergence in the natural community and applying it to the subversive technology of autonomous swarm control of robots are very compatible both in terms of theoretical framework and application requirements.

Smart design of robotic platform

In the complex multi-task environment, the intelligent swarm-robot system is required to comprehensively perceive and understand the environment. At the same time, information sharing and interaction within the swarm for individual decision-making are the basis of a swarm-robot system to achieve high-level autonomous control. The task of environment sensing is required to collect the information data of the robot by the load equipment such as photoelectric and radar, discover the rules and mining the targets from the data, and then identify the targets to improve the global recognition of the complex environment situation and enhance the reliability of the system. Eagle has the sharpest visual acuity among all animals, whose powerful vision perception mechanisms bring abundant inspiration for traditional visual applications. Biological eagle eye vision technology provides a creative way to solve visual perception issues [120].Therein, the theoretical method and application technology of bionic visual perception could promote the development of environment perception and recognition technology.

Vigorously promotion of scenarized competitions

Drawing experiences from the technology development model of military powers, the scenarized competition of the swarm-robot system needs to be promoted vigorously [121]. Firstly, it is important to strengthen the strategic planning of robotic swarm development from the macro level, and integrate it into the equipment system for overall planning. Overseas always pay attention to the cultivation and exploration of civil scientific research strength through large-scale competitions. Therein, the more well-known unmanned aerial vehicle events include International Micro Air Vehicles (IMAV), International Aerial Robotics Competition (IARC), Aviation Competition and Tri-co Robot Challenge in World Robot Contest. It is effective to refer to this model to explore the future intelligent swarm combat concept. Through the promotion of the scenarized competition, the swarm-robot technology has broad prospects not only in penetration reconnaissance, decoy interference, monitoring and fighting, coordinated attack and other national defense fields, but also in intelligent transportation, geological survey, disaster monitoring, agricultural protection, logistics transportation and other national economic development.

CONCLUSION

The coordinated and ordered movements emerging from the aggregation of a large number of individuals in nature provide plenty of examples and abundant inspirations for swarm intelligence research. The kinetic model and behavior mechanism of swarm intelligence promote the development of cooperative control theory and methods of unmanned swarm systems. This article starts with the introduction of natural collective behaviors in schools, packs, and flocks. Then, the connotation and mechanism of swarm intelligence are given on the basis of biological behaviors. Further, SI concept is applied in the cooperative control of three types of unmanned swarms, i.e. aerial robotics swarm, ground robotics swarm, and marine robotics swarm. Moreover, the intervention of human operators has made the mission capability of cross-domain platform systems gain multiple or even exponential growths. The advancement trending of swarm intelligence and swarm system is discussed preliminarily as the reference directions for the subsequent exploration.

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