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Research Advance in Swarm Robotics

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Abstract

The research progress of swarm robotics is reviewed in details. The swarm robotics inspired from nature is a combination of swarm intelligence and robotics, which shows a great potential in several aspects. First of all, the cooperation of nature swarm and swarm intelligence are briefly introduced, and the special features of the swarm robotics are summarized compared to a single robot and other multi-individual systems. Then the modeling methods for swarm robotics are described, followed by a list of several widely used swarm robotics entity projects and simulation platforms. Finally, as a main part of this paper, the current research on the swarm robotic algorithms are presented in detail, including cooperative control mechanisms in swarm robotics for flocking, navigating and searching applications.

Keywords: Swarm robotics; Cooperative control; Modeling; Simulation; Swarm intelligence

1. From nature swarm to swarm intelligence

1.1. Cooperation of nature swarms

Most swarm intelligence researches are inspired from how the nature swarms, such as social insects, fishes or mammals, interact with each other in the swarm in real life [1]. These swarms range in size from a few individuals living in the small natural areas to highly organized colonies that may occupy the large territories and consist of more than millions of individuals. The group behaviors emerging in the swarms show great flexibility and robustness [2], such as path planning [3], nest constructing [4], task allocation [5] and many other complex collective behaviors in various nature swarm [6–8].

The individuals in the nature swarm shows very poor abilities, yet the complex group behaviors can emerge in the whole swarm, such as migrating of bird crowds and fish schools, and foraging of ant and bee colonies as shown in Fig. 1. It's tough for an individual to complete the task itself, even a human being without certain experiences finds it difficultly, but a swarm of animals can handle it easily. Researchers have observed the intelligent group behaviors emerging from a group of individuals with poor abilities through local communication and information transmission.

1.1.1. Bacteria colonies

Bacteria often function as multicellular aggregates known as biofilms, exchanging the molecular signals for inter-cell communication [9]. The communal benefits of multicellular cooperation include a cellular division of labor, collectively defending against antagonists, accessing more resources and optimizing the population survival by differentiating the distinct cell types. The resistance to antibacterial agents of the bacteria in the biofilms is 500 times more than that of individual bacteria of same kind [10].

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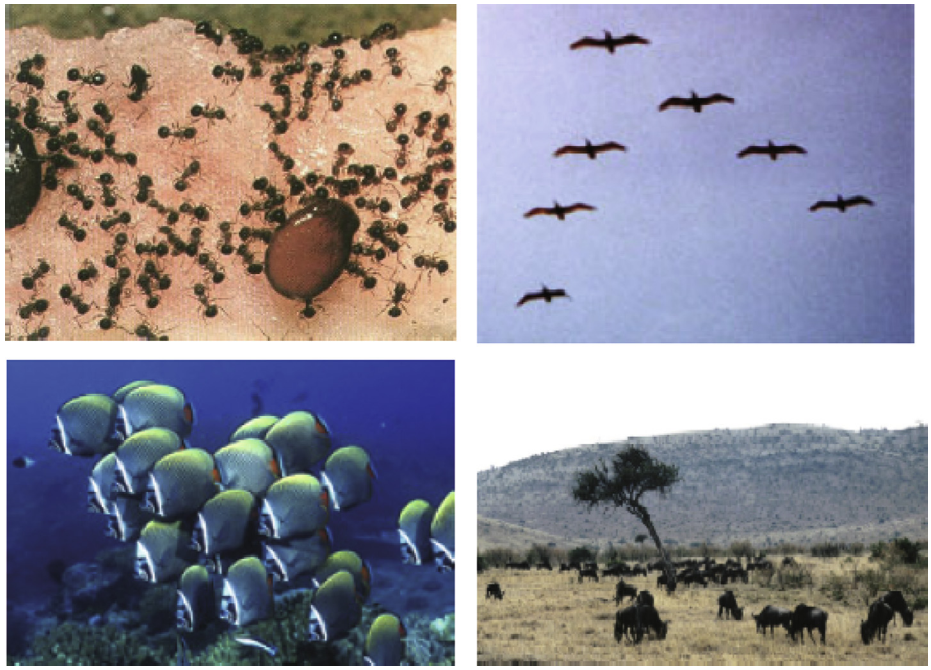

Fig. 1. Biological swarms in the nature.

1.1.2. Fish schools

Fish schools swim in the disciplined phalanxes and are able to stream up and down at impressive speeds and make a startling change in the shape of the school without collision as if their motions were choreographed. The fishes pay close attention to their neighbors when schooling with the help of eyes on the sides of heads and “schooling marks” on their shoulders [11]. The fishes can benefit from fish schools in foraging [12] and predator avoidance [13].

1.1.3. Ant and Bee colonies

Ants communicate with each other using pheromone, sound, and touch [14]. An ant with a successful attempt leaves a trail marking the shortest route on its return. Successful trails are followed by more ants, reinforcing the better routes and gradually identifying the best path [15]. Experiments in Ref. [16] suggest that the arts can choose the roles based on previous performance. The ants with higher successful rate intensify their foraging attempts while the others venture on fewer times or even change to other roles.

1.1.4. Locusts

Buhl et al. [17] confirmed the prediction from theoretical physics that, as the density of animals in the group increases, the group rapidly transits from disordered movement of individuals to highly aligned collective movement. They also demonstrated a dynamic instability in motion of that the groups can switch a direction without external perturbation, potentially facilitating the rapid transfer of directional information.

1.1.5. Bird crowds

A long time ago, the human being has made use of birds’ ability to precisely location home from more than 5000 km away. The birds gather into special formations during migration and locate the destinations with the aid of a variety of senses including sun compass, time calculation, magnetic fields, visual landmarks as well as olfactory cues [18].

1.1.6. Primates

The cooperation of primates can be complex, they can make the tools and use them to acquire food or interact socially, deception [19], recognize their kin and conspecifics [20] and learn to use the symbols and understand the aspects of human language. The primates also use vocalization, gestures, and facial expression to convey their psychological state.

1.1.7. Human beings

Dyer et al. [21] has shown leadership and consensus decision making can occur without verbal communication or obvious signaling in a group of humans. They found that a small informed minority could guide a group of naive individuals to a target with improved time and accuracy efficiency. Even when conflicting directional information was given to different members, a consensus decision can be made efficiently.

From the introduction above, it can be easily seen that, as the cooperation of the swarm increases, the group behaviors become more complex while the population size goes down and each individual plays a more important role in the behavior.

It’s difficult to imagine how such sophisticated abilities can emerge from the swarm consisting of such simple individuals with limited cognitive and communicating abilities.

Nevertheless, in the most cases, a whole swarm of individuals do have the ability to solve many complex problems easily while a single individual of the same species cannot. Of course, in such organism without organizer, there still exist some mechanisms yet undiscovered which promise to divide the whole task into the small pieces for individuals to handle the outputs of agents and aggregates them into the collective behaviors [2]. The purpose of our research on swarm intelligence and swarm robotics is to explore such mechanisms for real-life applications [22].

1.2. Swarm intelligence

As an emerging research area, the swarm intelligence has attracted many researchers' attention since the concept was proposed in 1980s. It has now become an interdisciplinary frontier and focus of many disciplines including artificial intelligence, economics, sociology, biology, etc. It has been observed a long time ago that some species survive in the cruel nature taking the advantage of the power of swarms, rather than the wisdom of individuals. The individuals in such swarm are not highly intelligent, yet they complete the complex tasks through cooperation and division of labor and show high intelligence as a whole swarm which is highly self-organized and self-adaptive.

Swarm intelligence is a soft bionic of the nature swarms, i.e. it simulates the social structures and interactions of the swarm rather than the structure of an individual in traditional artificial intelligence. The individuals can be regarded as agents with simple and single abilities. Some of them have the ability to evolve themselves when dealing with certain problems to make better compatibility [23]. A swarm intelligence system usually consists of a group of simple individuals autonomously controlled by a plain set of rules and local interactions. These individuals are not necessarily unwise, but are relatively simple compared to the global intelligence achieved through the system. Some intelligent behaviors never observed in a single individual will soon emerge when several individuals begin cooperate or compete. The swarm can complete the tasks that a complex individual can do while having high robustness and flexibility and low cost. Swarm intelligence takes the full advantage of the swarm without the need of centralized control and global model, and provides a great solution for large-scale sophisticated problems.

2. Definition and features

2.1. Definition of swarm robotics

Swarm robotics is a new approach to the coordination of multi-robot systems which consist of large numbers of mostly simple physical robots. It is supposed that a desired collective behavior emerges from the interaction between the robots and the interaction of robots with the environment. This approach emerged in the field of artificial swarm intelligence as well as the biological study of insects, ants and other fields in the nature, where a swarm behavior occurs.

The research on the swarm robotics is to study the design of large amount of relatively simple robots, their physical body and their controlling behaviors. The individuals in the swarm are normally simple, small and low cost so as to take the advantage of a large population. A key component of the system is the communication between the agents in the group which is normally local, and guarantees the system to be scalable and robust.

A plain set of rules at individual level can produce a large set of complex behaviors at the swarm level. The rules of controlling the individuals are abstracted from the cooperative behavior in the nature swarm. The swarm is distributed and de-centralized, and the system shows high efficiency, parallelism, scalability and robustness.

The potential applications of swarm robotics include the tasks that demand the miniaturization, like distributed sensing tasks in micro machinery or the human body. On the other hand, the swarm robotics can be suited to the tasks that demand the cheap designs, such as mining task or agricultural foraging task. The swarm robotics can be also involved in the tasks that require large space and time cost, and are dangerous to the human being or the robots themselves, such as post-disaster relief, target searching, military applications, etc.

2.2. Characteristics of nature swarms

Since the swarm robotics is mostly inspired from the nature swarms, it's a good reference for analyzing the characteristics of nature swarms. The research of swarm robotics started a century ago.

The first hypothesis is quite personified [24] and assumes that each individual has a unique ID for cooperation and communication. The information exchange in the swarm is regarded as a centralized network. The queens in ant and bee colonies are supposed to be responsible for transmitting and assigning the information to each agent [25]. However, Jha, et al. [26] proved that the network in the swarm is decentralized. Thanks to the research in recent half century, the biologists can now assert that there are no unique IDs or other globally storage information in the network. No single agent can access to all the information in the network and a pacemaker is therefore inexistent.

The biologists now believe that the social swarms are organized as a decentralized system distributed in the whole environment which can be described through a probabilistic model [27]. The agents in the swarm follow their own rules according to local information. The group behaviors emerge from these local rules which affect information exchange and topology structure in the swarm. The rules are also the key component to keep the whole structure to be flexible and robust even when the sophisticated behaviors are emerged.

2.3. Advantages of swarm robotics

The advantages and characteristics of the swarm robotics system are presented by comparing a single robot and other similar systems with multiple individuals. These characteristics are quite similar to that of nature swarm.

2.3.1. Comparing with a single robot

To complete a sophisticated task, a single robot must be designed with complicated structure and control modules resulting in high cost of design, construction and maintenance. Single robot is vulnerable especially when a small broken part of the robot may affect the whole system and it's difficult to predict what will happen. The swarm robotics can achieve the same ability through inter-group cooperation and takes the advantage of reusability of the simple agents and the low cost of construction and maintenance. The swarm robotics also takes the advantage of high parallelism and is especially suitable for large scale tasks.

A single robot is inspired from human behaviors by comparing the corresponding nature species of these researching areas, while the swarm robotics is inspired from the social animals. Due to the restriction of current technology, it's hard to simulate the human interactions using machines or computers while the mechanisms in animal groups are easier to apply. This gives the swarm robotics a bright future in dealing with complex and large scale problems. The advantages of swarm robotics are described below.

2.3.1.1. Parallel. The population size of swarm robotics is usually quite large, and it can deal with multiple targets in one task. This indicates that the swarm can perform the tasks involving multiple targets distributed in a vast range in the environment, and the search of the swarm would save time significantly.

2.3.1.2. Scalable. The interaction in the swarm is local, allowing the individuals to join or quit the task at any time without interrupting the whole swarm. The swarm can adapt to the change in population through implicit task re-allocating schemes without the need of any external operation. This also indicates that the system is adaptable for different sizes of population without any modification of the software or hardware which is very useful for real-life application.

2.3.1.3. Stable. Similar to scalability, the swarm robotics systems are not affected greatly even when part of the swarm quits due to the majeure factors. The swarm can still work towards the objective of the task although their performances may degrade inevitably with fewer robots. This feature is especially useful for the tasks in a dangerous environment.

2.3.1.4. Economical. As mentioned above, the cost of swarm robotics is significantly low in designing, manufacturing and daily maintaining. The whole system is cheaper than a complex single robot even, if hundreds or thousands of robots exist in a swarm. Since the individuals in the swarm can be massively produced while a single robot requires precision machining.

2.3.1.5. Energy efficient. Since the individuals in the swarm are much smaller and simpler than a giant robot, the energy cost is far beyond the cost of a single robot compared with the battery size. This means that the life time of the swarm is enlarged. In an environment without fueling facilities or where wired electricity is forbidden, the swarm robotics can be much useful than traditional single robot.

In conclusion, the swarm robotics can be applied to sophisticated problems involving large amount of time, space or targets, and a certain danger may exist in the environment. The typical applications are as follows: UAV controlling, post-disaster relief, mining, geological survey, military applications and cooperative transportation. The swarm robotics can complete these tasks through cooperative behavior emerged from the individuals while a single robot can barely adapt to such situation. This is the reason why the swarm robotics has become an important research field in last decade.

2.3.2. Different from other multi-agent systems

There exist several research areas inspired from the nature swarm, which are often confused with swarm robotics, such as multi-agent system and sensor network. These research areas also utilize the cooperative behavior emerged from the multiple agents in the group for specialized tasks. However, there are several differences between these systems, which can distinguish these systems fundamentally, as shown in Table 1.

From Table 1, it can be easily deduced that the main differences among swarm robotics and other systems are population, control, homogeneity and functional extension. Multi-agent and sensor network systems mainly focus on the

Table 1
Comparison of swarm robotics and other systems.

	Swarm robotics	Multi-robot system	Sensor network	Multi-agent system
Population Size	Variation in great range	Small	Fixed	In a small range
Control	Decentralized and autonomous	Centralized or remote	Centralized or remote	Centralized or hierarchical or network
Homogeneity	Homogeneous	Usually heterogeneous	Homogeneous	Homogeneous or heterogeneous
Flexibility	High	Low	Low	Medium
Scalability	High	Low	Medium	Medium
Environment	Unknown	Known or unknown	Known	Known
Motion	Yes	Yes	No	Rare
Typical applications	Post-disaster relief Military application Dangerous application	Transportation Sensing Robot football	Surveillance Medical care Environmental protection	Net resources management Distributed control

behaviors of multiple static agents in the known environments while the robots in the multi-robot systems are quite small, usually heterogeneous and are externally controlled.

Since homogeneity and scalability are considered at the beginning of the system design, the swarm robotics shows great flexibility and adaptability compared with other systems. The multi-robot systems usually involve the heterogeneous robots, and may achieve better performance on specialized tasks at the cost of flexibility, reusability and scalability. Besides scalability which is introduced in previous section, the characteristics of swarm robotics among other three cooperative systems are listed in Table 1.

2.3.2.1. Autonomous. The individuals in swarm robotics systems must be autonomous, i.e. capable of interacting and motioning in the environment. With these key functions, the cooperative mechanisms inspired from the nature swarms can be introduced into the swarm robotics. Although the systems, like sensor networks, are far different from the swarm robotics from such point of view, but the research on the area can indeed throw some lights on swarm robotics research.

2.3.2.2. Decentralization. With a good set of cooperative rules, the individuals can complete the task without centralized controls which promises the scalability and flexibility of the swarm. At the same time, the swarm can benefit more in the environments when communication is interrupted or lagged and improves the reaction speed and precision of the swarm.

2.3.2.3. Local sensing and communications. Due to the restriction of hardware and cost, the robots in the swarm usually have a limited range of sensing and communicating and thus the whole swarm is distributed in the environment. Actually, the use of global communications will lead to a significant decline in scalability and flexibility, as the communication cost is explode exponentially as the population grows. Nevertheless, certain controlling global communications are acceptable, for instance, updating the controlling strategies or sending the terminal signals, so long as it's not used in the interaction between individuals.

2.3.2.4. Homogenous. In a swarm robotics system, the robots should be divided into the roles as few as possible and the number of robots acting as each role should be as large as possible. The role here indicates the physical structure of the robot or other states that cannot be changed into one another dynamically during the task. A state in a finite state machine does not count in our definition. This definition indicates a swarm, no matter how large it is, is not considered as swarm robotics if the roles of robots are divided meticulously. For instance, the robots football usually is not considered as swarm robotics, since each individual in the team is assigned a special role during the game.

2.3.2.5. Flexibility. A swarm with high flexibility can deal with different tasks with the same hardware and minor changes in the software, as the nature swarms can finish various tasks in the same swarm. The individuals in the swarm show different abilities and cooperation strategy when they deal with different tasks. The swarm robotics should provide such flexibility, especially in similar tasks, such as foraging, flocking or searching. The swarm can switch to different strategies according to the environment. The robots can adapt to the environment through machine learning from the past moves and can change to a better strategy.

2.4. Application scopes of swarm robotics

The study of robotics application in target search has grown substantially in the recent years. It is more preferable for the dangerous or inaccessible working area. The problems involved in swarm robotics research can be classified into two classes. One class of the problems is mainly based on the patterns, such as aggregation, cartography, migration, self-organizing grids, deployment of distributed agents and area coverage. Another class of problems focuses on the entities in the environment, e.g. searching for the targets [28], detecting the odor sources [29], locating the ore veins in wild field [30], foraging, rescuing the victims in disaster areas [31] and etc. Besides these problems, the swarm robotics can also be involved into more sophisticated problems, mostly hybrid of these two classes, including cooperative transportation, demining [32], exploring a planet [33] and navigating in large area.

Several potential application scopes [34] of swarm robotics which are very suitable are described below.

2.4.1. Tasks cover large area

Swarm robotics system is distributed and specialized for the tasks requiring a large area of space, e.g. large coverage. The robots in the swarm are distributed in the environment and can detect the dynamic change of the entire area, such as chemical leaks or pollution. The swarm robotics can complete such tasks in a better way than sensor network since each robot can patrol in an area rather than stay still. This means that the swarm can monitor the area with fewer agents. Besides monitoring, the robots in the swarm can locate the source, move towards the area and take quick actions. In an urgent case, the robots can aggregate into a patch to block the source as a temporary solution.

2.4.2. Tasks dangerous to robot

Thanks to the scalability and stability, the swarm provides redundancy for dealing with dangerous tasks. The swarm can suffer loss of robots to a great extent before the job has to be terminated. The robots are very cheap and are preferred for the areas which probably damage the workers. In some tasks, the robots may be irretrievable after the task, and the use of complex and expensive robots are thus economically unacceptable while the swarm robotics with cheap individuals can provide the reasonable solutions. For example, Murphy et al. [35] summarized the usage of robotics in mine rescue and recovery. They pointed out that although several applications already in use, the robots are beyond the requirement to show a desired performance in the tough environment under the ground. They proposed 33 requirements for the robots so as to achieve an acceptable behavior.

2.4.3. Tasks require scaling population

Workload of some tasks may change over time, and the swarm size should be scaled based upon the current workload for high efficiency in both time and economics. For example, in the task of clearing oil leakage after tank accidents, the swarm should maintain a high population when the oil leaks fast at the beginning of the task and gradually reduce the robots when the leak source is plugged and the leaking area is almost cleared. The swarm also scales among different regions if the progress of these regions becomes unbalanced.

Stormont [28] described the potential for using the swarms of autonomous robots to react a disaster site in the first 24 h. He summarized the swarm that can search for the victims with the highest probability of finding survivors, and made some suggestions for future research in this area.

2.4.4. Tasks require redundancy

Robustness in the swarm robotics systems mainly benefits from the redundancy of the swarm, i.e. removing some robots does not have a significant impact on the performance. Some tasks focus on the result rather than the process, i.e. the system should make sure that the task will be completed successfully, mostly in the way of increasing redundancy.

2.4.5. Swarm robotics system in real life

In the recent years, the researchers have already utilized the swarm robotics in several real-life applications including most of the tasks mentioned above.

William et al. proposed a framework, called Physicomimetics, for the distributed control of swarms [36]. They focused on the robotic behaviors that are similar to those shown by solids, liquids, and gases. The different formations are adopted for the different tasks, including distributed sensing, obstacle avoidance, surveillance and sweeping.

Correll [37] proposed a swarm-intelligent inspection system to inspect of blades in a jet turbine. The system is based on a swarm of autonomous, miniature robots, using only onboard, local sensors.

MIT's Senseable City Lab developed a fleet of low-cost oil absorbing robots called Seaswarm [38] for ocean-skimming and oil removal. A nanomaterial robot can absorb oil up to 20 times of its weight. The system provides an autonomous and low cost solution for ocean environment protection.

Roombots [39] is a novel self-reconfiguring modular robotic system. The autonomous modular robots can alter its shape to adapt to a given task and working environment, such as self-assembly and reconfiguration of static objects like furniture in the day-to-day environment.

Formica [40] is a scalable, biologically-inspired swarm robotics platform. Its novel mechanical design permits production on standard circuit board assembly lines. The system takes the advantage of small cheap, long-life robots, supports the peripherals, and can be scaled to a population with several hundred individuals. Scientists believe such swarms are suitable solutions for the tasks like Mars reconnaissance, earthquake recovery, etc.

Swarm robotics can be useful for military application as well. Pettinaro et al. [41] proposed a self-reconfigurable robot system for foraging, searching and rescuing, which has the ability to cope with occasional failure. Military experts believe that the bionic aero vehicles inspired from swarm intelligence technology will become applicable in a few years. It can be foreseen that machine bees or cockroaches with reconnaissance equipment and bombs will possibly show up in future war.

3. Modeling swarm robotics

3.1. General model of swarm robotics

Swarm robotics model is a key component of cooperative algorithm that controls the behaviors and interactions of all individuals. In the model, the robots in the swarm should have some basic functions, such as sensing, communicating, motioning, etc.

The model is divided into three modules based on the functions which the module utilizes to accomplish certain behaviors: information exchange, basic and advanced behavior. The information exchange among three modules plays the most important role in the model. The Robots in the swarm exchange the information with each other and propagate the information to the whole swarm through autonomous behaviors resulting in the swarm-level cooperation.

General model of swarm robotics is shown in Fig. 2. The robots communicate with each other. In some cases, the global positioning or central commands are introduced, but the swarm should still be able to complete the task if global communication is blocked.

3.1.1. Information exchange module

Information exchange is inevitable when the robots cooperate with one another, and is the core part for controlling swarm behaviors. The main functions of individuals involved in this module are limited sensing and local communication. Information exchange of a robot falls into two categories: interaction with robot or environment. The strategies can be either same or different for the swarm due to different applications.

In the nature swarms, the individuals can have the direct interaction, such as tentacle, gesture or voice. However, the indirect interactions are far more subtle. The individuals sense the information in the environment, react and leave the messages back to the environment. Environment act as the sticky notes, and the pheromones are the most common pencils in wild [42]. Such mechanism with positive feedback can optimize the robot-level behaviors, and the swarm-level behaviors can finally emerge [43].

There are three ways of information sharing in the swarm [44]: direct communication, communication through environment and sensing. More than one type of interaction can be

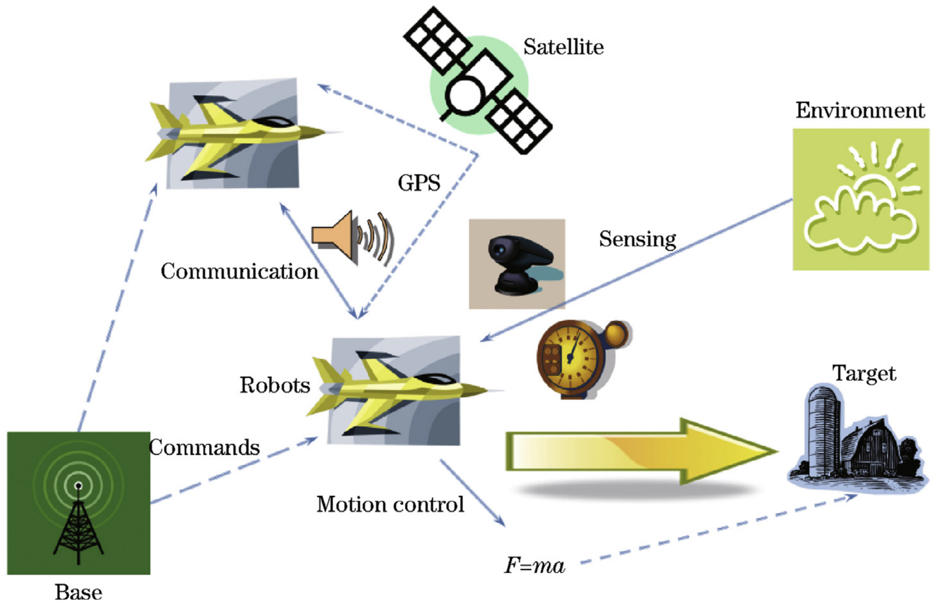

Fig. 2. General model of swarm robotics.

used in one swarm, for instance, each robot senses the environment and communicates with their neighbor. Balch [45] discussed the influences of three types of communications on the swarm performance. He designed three tasks and compared the performance in simulation. Some researchers also discussed the possibility of swarm cooperating without communications; however, communication and sensing can indeed improve the efficiency of swarm for most applications.

3.1.1.1. Direct communication. Direct communication is similar to wireless network and also consists of two types: peer-to-peer and broadcast. Thanks to the development in mobile devices, several existing technologies can be adopted immediately. Hawick et al. [46] proposed a physical architecture for a swarm of tri-wheel robots using both IEEE802.11b wireless Ethernet and Bluetooth. However, the wireless sensors cost almost half of a total robot. Another disadvantage of such scheme is that the bandwidth required will go into an exponential explosion as the population grows. In this way, the direct communication in the swarm should be limited.

Although several existing wireless technologies are available, the protocols and topologies that are specialized for swarm robotics remain undiscovered. The existing computer networks are designed for data processing and information sharing between the nodes. Communications in swarm robotics should take the full advantage of local sensing and motioning abilities while pay special attention to boost the cooperative behaviors of individuals and dynamic topologies of the swarm [47].

3.1.1.2. Communication through environment. Environment can act as an intermediary for robots' interaction. The robots leave their traces in the environment after one action to stimulate other robots which can sense the trace, without direct communication among individuals. In this way, the subsequent actions tend to reinforce and build on each other, leading to the spontaneous emergence of swarm-level activities. The swarm is imitated as ants or bees and interacts with the help of virtual pheromones. Such interactive scheme is exempted from the exponential explosion of the population but has some limitation on the environment to support the pheromones.

Ranjbar-Sahraei et al. [48] implemented a coverage approach using the markers in the environment without direct communication. Payton et al. [49] proposed a swarm robotics using the biologically inspired notion of 'virtual pheromone' for distributed computing mesh embedded in the environment. The virtual pheromones are propagated in the swarm other than the environment. Grushin and Reggia [50] solved a problem of self-assembly of pre-specified 3D structures from the blocks of different sizes with a swarm of robotics using stigmergy.

3.1.1.3. Sensing. The individuals can sense the robots and environment nearby using on-board sensors if they can distinguish the robots and other objects from the environment. The robots sense the objects or targets in the environment and accomplish the tasks like obstacle avoidance, target search, flocking, etc. The main issue of this scheme is how to integrate all the sensors in the swarm efficiently for cooperation. Cortes et al. [51] explored how to control and coordinate a group of autonomous vehicles, regarded as the agents with sensors, in an adaptive, distributed and asynchronous way.

The main difference between communication and sensing is whether the individuals send out the messages actively or receive the messages passively. Although more precise and abundant communication requires more complex hardware and synchronization, the cost of bandwidth, energy and time will grow extremely fast as population grows. The cooperative model of swarm robotics should try to simplify the communication and use as much sensing as possible. Colors, luminance and relative positions can be used for sensing and can provide rich information without communication. In some tasks, the swarm can exchange all the information only with the sensors.

3.1.2. Basic behavior module

Basic behaviors of individuals include functions such as motioning and local planning which is one of most significant differences of swarm robotics than the multi-agent and sensor network systems. The robots and their behavior controls are homogeneous and form the fundaments of group behaviors. Based on the input from communication or sensing, the robots compute their desired movements. With an excellent control module, the swarm can rely less on the communication with the help of prediction and more direct interactions, rather than broadcast. The swarm can improve the performance with less information exchange and high scalability.

3.1.3. Advanced behavior module

Robots in complex swarm robotic systems may have the extra functions including but not limited to task decomposition, task allocation, adaptive learning, and etc [52]. The robots with these functions in hardware can simplify the design of the algorithm yet lead to a more complex physical design of real robot. The robots can also achieve the similar functions with carefully designed cooperative algorithms. The implement of such functions in hardware or software depends on the physical designs of the robots, controllers and sensors so as to make better use of the components [53]. Details of how robots cooperating with each other are presented in Section 3.3.

Task allocation and learning are emphasized here as they are normally quite important to a swarm of robots. Task decomposition and allocation can greatly improve efficiency for especially complex tasks. Kalra and Martinoli [54] compared the costs and benefits of different types of task allocation approaches in noisy world. Learning is also useful since the parameters of the control mechanism are hard to be tuned. With the help of self-adaptive learning and optimizing methods, the swarm shows better adaptability in the different environments. Pugh and Martinoli [55] discussed the problem of using different learning methods in the swarm robotics and compared their performance in simulation. Zhang et al. [56] applied an evolutionary neural network to evolve the swarm robotics controllers and used their method in the structure inspection problem.

3.2. Modeling methods for swarm robotics

Modeling is a method used in many research fields to better understand the internals of the system that is investigated. Modeling helps to the swarm robotics since a swarm robotic algorithm is supposed to be scalable to hundreds of thousands of robots in population. The time and money are limited for such scale of experiments, the experiments can be done in an easier way.

Considering the characteristics of swarm robotics, the modeling methods are divided into four types according to Ref. [57]: sensor-based, microscopic, macroscopic and swarm intelligence-based. The four methods are described in detail in this section.

3.2.1. Sensor-based modeling

In the sensor-based modeling method, the sensors and actuators of the robots are modeled as the main components of the system along with the objects in the environment. Then the interactions of the robots are modeled as realistically and simply as possible. This modeling method is mostly used, and the oldest method is used for robotic experiment.

The earlier research using sensor-based modeling methods [58,59] did not consider the real physical limitations, now the researchers introduce the physical principle into the model [60,61].

3.2.2. Microscopic modeling

In the microscopic modeling, the robots and interactions are modeled as a finite state machine. The behaviors of each robot are defined as several states, and the transfer conditions are based on the input from communication and sensing. Since the model is based on the behaviors of each robot, the simulation should be run for several times to obtain the averaged behaviors of the swarm.

In the most swarm robotics research, the probabilistic microscopic model is used, since noise can be modeled as probability in the model. In a probabilistic microscopic model [62], the probabilities are valued from the experiments of real robots, and the model is iterated with these probabilities for state transfer in the simulation to predict the behavior of the swarm.

3.2.3. Macroscopic modeling

Macroscopic modeling is a modeling method opposite to the microscopic modeling. In the macroscopic modeling, the system behavior is defined as difference equation, and a system state represents the average number of robots in this state at the time step.

The main difference between microscopic and macroscopic models is the granularity of the models. The microscopic model for the behavior at individual level is used to simulate the group behaviors while the macroscopic model simulates the behaviors at the swarm level. The microscopic model iterates the swarm behavior, and the macroscopic model can give out the final state of the swarm. In this way, the macroscopic model can have a global glance at the swarm while the microscopic model can show the details of the swarm behaviors [63].

Probabilistic macroscopic models are also widely used by the researchers. Martinoli et al. [64] applied the macroscopic modeling to stick the pulling problem from a basic model which contains only two states up to the model with all states. They also compared the microscopic, macroscopic and sensor-based models and described the shortages of macroscopic model.

3.2.4. Modeling from swarm intelligence algorithms

Cooperative schemes from swarm intelligence algorithms have been introduced into the swarm robotics in many researches. Since the robots use the same or similar schemes with these algorithms, the models and other methods used to analyze these algorithms, which are quite mature than that in swarm robotics, can be used directly for robot research.

The most commonly used algorithm from swarm intelligence is the particle swarm optimization (PSO) which mimics the flocking process of the birds. The particles fly in the field and search for the best. It can be found obviously that many commons remain between PSO and swarm robotics. A mapping between particle and robot can be presented easily [65].

Besides PSO, the researchers also introduce other swarm intelligence algorithms into swarm robotics. Many successful swarm models were inspired from the ant colonies. These inspired approaches provide an effective heuristics for searching in dynamic environment [66] and routing [67]. Many other algorithms are summarized in Sections 5.3 and 5.4.

However, there are still many problems when a cooperative scheme from swarm intelligence is introduced. The schemes in these algorithms consider the most global interactions and introduce large amount of random moves for high diversity. Some schemes also contain the operations to reset the positions of searching agents. However, these operations are unavailable for swarm robotics. How can the schemes in swarm robotics avoid such operations while taking full advantage of the scalability and flexibility is a future research direction.

3.3. Cooperation schemes between robots

Cooperation belongs to the advanced behavior in the swarm robotics model. In swarm robotics, cooperation occurs at two levels: individual level and swarm level. The former is must for robot's activities and coordinates the inputs from environment with the response, learning and adapting behaviors. The latter is an aggregation of former cooperation, resulting in the typical collective tasks such as gather, disperse or formation. Several sub-problems have been proposed for cooperation between robots which are described in detail in this section.

The schemes introduced in this section are focused on the physical layer of the robot. The cooperation schemes at algorithm level are summarized in Section 5 which introduces the swarm robotic algorithms.

3.3.1. Architecture of swarm

The architecture of the swarm is a framework for robotic activities and interactions and determines the topology for information exchange among robots. The swarm performance in cooperation depends largely on the architecture. The architecture of the swarm should be selected carefully according to the scale, relations and cooperation of the robots [52].

3.3.2. Locating

Global coordinating systems do not exist in the swarm. Therefore, each robot in the swarm has to maintain a local coordinating system and should be able to distinguish, identify and locate the nearby robots. Thus, a method for rapidly locating other robots using on-board sensors is very important for swarm robotics [68].

The absolute positioning technologies from single robots have been applied in some researches [69], and the combination of sensors with special filters has been adopted [70,71]. The sensors can sense different waves, including ultrasonic, visible light, infrared ray or sound [72].

However, the relative positioning of swarm robotics are more realistic since the abilities of the robots are limited and no global controls exist. Therefore a light weighted relative positioning algorithm need to be found. Pugh and Martinoli [73] characterized and improved an existing infrared relative localization module used to find the range and bearing between the robots in small scale swarm robotics system. Kelly and Martinoli [74] developed an on-board localization system using infrared sensors for indoor applications. A three dimensional relative positioning sensor for indoor flying robots was proposed by Roberts et al. [75], designed to enable the spatial coordination and goal-directed flight of inter-robot.

3.3.3. Physical connections

Physical connections are used in the situations that single robot can overcome, such as overpassing large gaps or cooperative transportation. In these tasks, the robots should communicate and dock before they continue to execute their tasks. Mondada et al. [76] introduced several types of physical connections, sensors and actuators for overcoming the gaps and stairs. Wang and Liu [77] developed a localizing and docking method using infrared ray. Zhang et al. [78] proposed a reconfigurable robot with limited structures and fixed number of modules for urban search and rescue. Nouyan and Dorigo [79] solved the exploration and navigation tasks in an unknown environment using chained robots. The dynamics and qualities of the chain formation process are evaluated in simulation.

3.3.4. Self-organization and self-assembly

Self-organization is a dynamic scheme for building a global structure through only local interactions of the basic units. The basic units or robots do not share a global control or have an external commander. The swarm level structure emerges from the individual level. A robot interacts with the others through the structures already built, i.e. behaviors of robots are guided by process of the building. Such schemes can be easily found in the nature, as ant or bee colonies building the nests. Self-organization can be conducted by the biological study on these animal behaviors.

During the process of nest building, the ants can interact with the environment in two ways: discrete or continuous. The discrete interaction reacts to the type of stimulation while the continuous interaction reacts to the amount of stimulation. A model utilizing the discrete interaction has been proposed: the position a unit to be arranged is decided by the structure nearby. Simulation shows the model can result in a structure very similar to bee cave [80].

Self-assembly system can be inspired from the bee cave construction model. The behaviors in the swarm are conducted by the existing structures and prior knowledge. Payton et al. [81] used the pheromones to enhance such schemes. The swarm starts with random behaviors and converges to a pattern. As an example, the swarm-bots Project [47] introduced in Section 4.1.3 is a self-organization and self-assembly system. Each robot has multiple connector port, so that the swarm can aggregate into a large structure.

4. Entity projects and simulations

4.1. Swarm robotics entity projects

In recent years, the swarm robotics has become a research topic in which the Chinese researchers have an interest, yet most of these are quite simple and only are simulated in the computer [82]. The Project SI [83] is a relatively complete project of real robots.

In the early 1980s, the researchers from Europe and USA have begun to research on developing a group of mobile robots. Some earlier projects include CEBOT [84], SWARMS [85], ACTRESS [86], etc. However, these projects are quite preliminary. As the research on swarm robotics has gone deeper in computer simulation, the entity projects have also been boosted. Nowadays, there are several projects that provide the designs of a swarm of robots which will be briefly summarized in this Section.

4.1.1. Project SI

Project SI [87] was developed by the Embedded Lab of Shanghai Jiaotong University. The project consists of a swarm of mobile robots, named eMouse, controlled by the swarm inspired algorithms. The robots are designed to be reconfigurable in sensors and communication protocols, cheap in cost and strong in motion control. The eMouse does not contain the sensors when the interfaces are designed but left for connecting the different sensors for various applications.

The project team has completed the design of the fifth generation of robot and implemented several cooperative algorithms on the system. They implemented several primitives [88], including clump, disperse, generalized disperse, attract, swarm, scan and message transmission. Based on a set of testing tools, for instance, monitoring through trace extraction and live update over wireless network, they solved the real life applications inspired from swarm intelligence.

4.1.2. Sambots

Sambots is a project for a swarm of self-assembly robots [89]. Multiple Sambots can form new structures through self-assembly and self-reconfiguration. The team realized the robots by the innovative design of docking mechanism and the reasonable distribution of the perception system [90]. The docking mechanism is installed on an active docking interface, which can rotate around the main body of the robot. With such scheme, the robots can connect with others robots freely to form a chained structure. Sambots can compose several structures through different configurations, including snake, caterpillar, ring, triangle, six-limbed insects, etc.

4.1.3. Swarm-bots project

Swarm-bots [47], sponsored by the Future and Emerging Technologies program of the European Commission, is a project for exploring the design, implementation and simulation of self-organizing and self-assembling artifacts. The project, lasting 42 months, was successfully completed on March 31, 2005.

The main scientific objective of the Swarm-bots project is to explore a new approach to the design and implementation of self-organizing and self-assembling artifacts. The aim of the team is to construct a large swarm-bot using a number of simpler, insect-like, robots(s-bots) with relatively cheap components and capable of self-assembling and self-organizing to adapt to its environment. The project developed both simulation and entity robots and presented their results on the two platforms.

4.1.4. Swarmanoid project

Since October 1, 2006, the Swarmanoid project has extended the work done in the Swarm-bots project to three dimensional environment. The team introduced three types of small insect robots: eye-bot, hand-bot, and foot-bot, which differ from s-bots in previous project. Swarmanoid consists of a total number of 60 robots from the three types. The team has won the AAAI 2011 video competition.

The eye-bots capable to fly or attach to the ceiling are designed to sense and analyze the environment from a high position to provide an overview. The foot-bots, previously named as s-bots, are able to move on rough terrain and transport either objects or other robots. The hand-bots climb the vertical surfaces of walls or objects and work in a space zone between those covered by the foot-bots (the ground) and eye-bots (the ceiling). With the combination of three types of robots, the swarm can handle those tasks that require operations in all dimensions. The team also developed the distributed control algorithms and communications as well as a simulation platform [91] for the project.

4.1.5. Pheromone robotics project

The Pheromone Robotics Project [92], started in 2000, is coordinated by Professor David. The project aims to provide a robust, scalable approach for achieving the swarm level behaviors using a large number of small-scale robots in surveillance, reconnaissance, hazard detection, path finding, payload conveyance and small-scale actuation [81]. The team exploited the notion of a virtual pheromone, and implemented the simple beacons and directional sensors mounted on each robot. The virtual pheromones only facilitate simple communication and coordination with little on-board processing.

4.1.6. I-swarm project

The I-swarm project [93], hosted by Professor Heinz from 2004, combines micro-robotics, distributed and adaptive systems as well as self-organizing biological swarm systems. The project facilitates the mass-production of micro-robots, which can then be used as a real swarm consisting of more than 100 micro-robot clients. These clients are all equipped with limited sensors and intelligence, each with a size of less than $3 \times 3 \times 2$ mm and velocity of 1.5 mm/s. With such tiny size, the swarm can work cooperatively in a small world (such as inside creatures) at very cheap cost.

4.1.7. iRobot swarm project

iRobot Swarm Project [94] is projected by MIT for cooperating over 100 robots. The goal of the project is to develop the distributed algorithms for robotic swarms composed of hundreds of individual robots robust to complex real-world environment and tolerant to the addition or failure of any number of individuals. The project team has developed a global monitoring device and an automatic charging station. The most of work of the project was done by Mclurkin and his colleagues [95].

4.1.8. E-puck education robot

The main goal of this project is to develop a miniature mobile robot for education use. The robots have several features specialized for such purpose. The robots have a clean mechanical structure simple to understand, operate and maintain. The robots are cheap and flexible, and can cover a large spectrum of educational activities thanks to a large potential in sensors, processing power and extensions [96].

Researches based on e-puck project have already exceeded 60 by the end of 2010. The potential educational fields include mobile robotics, real-time programming, embedded system, signal processing, image or sound feature extraction, human–machine interaction or collective system.

4.1.9. Kobot project

Kobot [97], conducted by Middle East Technical University, is a new mobile robot platform which is a specially designed a swarm robotics. The robots are equipped with an infrared-based short range sensing system for measuring the distance from obstacles to a novel sensing the relative headings of neighboring robots.

4.1.10. Kilobot project

Kilobot project [98] aims to design a robot system for testing the collective algorithms with a population of hundreds or thousands of robots. Each robot is made of low-cost parts and takes 5 min to be fully assembled. The system also provides several overall operations for a large swarm, such as updating programs, powering on, charging all robots and returning home.

4.2. Simulation platforms

The research on swarm robotic system requires a plenty of physical robots, making it hard to afford for many research institutions [99]. The computer simulation is developed to visually test the structures and algorithms on computer. Although the final aim of the research is real robots, it is often very useful to perform simulation prior to the investigation of real robots. Simulations are easier to setup, less expensive, normally faster and more convenient to use than physical swarms [100]. In this section, several widely used simulation platforms are summarized.

4.2.1. Player/stage

The widely-used Player Project [101] is one of the most famous simulators and aims to produce free software for robot and sensor research. Player project is a robot server that provides full access and control of robotic platform, sensors and actuators for researchers. Stage [102] is a scalable simulator that is interfaced to Player and can simulate a population of 1000 mobile robots in a 2D bitmapped environment in parallel. Physics is simulated in a purely kinematic fashion, and noise is ignored in Stage.

4.2.2. Gazebo

Gazebo [103] is a simulator that extends Stage for 3D outdoor environments. It generates the realistic sensor feedback and applies the ODE physic engine instead of the naive one in Stage. Gazebo presents a standard Player interface in addition to its own native interface. In this way, the controllers written for Stage can be used in Gazebo and vice-versa.

4.2.3. ÜberSim

The ÜberSim [104] is a simulator developed at Carnegie Mellon for a rapid validation before uploading the program to real robot soccer scenarios. ÜberSim uses ODE physics engine for realistic motions and interactions. Although originally designed for Soccer robots, the custom robots and sensors can be written in C in the simulator and the program can be uploaded to the robots using TCP/IP.

4.2.4. USARSim

USARSim [105], shorted for Urban Search and Rescue Simulation, is a high fidelity multi-robot simulator originally developed for search and rescue (SAR) research activities of the Robocup contest. It has now become one of the most complete general purpose tools for robotics research and education. It is built upon a widely used commercial game engine, Unreal Engine 2.0. The simulator takes full advantage of high accuracy physics, noise simulation and numerous geometrics and models from the engine. Evaluations have shown that USARSim can simulate the real time robots well enough for researchers due to the high fidelity physics engine.

4.2.5. Enki

Enki [106] is an open source, fast 2D physics based robot simulator written in C++. It is able to simulate the cinematics, collision, sensors and cameras of robots working on a flat surface. Enki is able to simulate the robot swarms hundred times faster on the desktop computer than real-time robots. Enki is built to support several existing real robot systems, including swarm-bots and E-puck, while user can customize their own robots into the platform.

4.2.6. Webots

Webots [100] is a development environment used to model, program and simulate the mobile robots available for more than 10 years. With Webots, the user can design the complex robotic setups, with one or several, similar or different robots with a large choice of pre-defined sensors and actuators. The objects in the environment can be customized by the user. Webots also provides a remote controller for testing the real robots. Until now, Webots robot simulator has been used in more than 1018 universities and research centers in the worldwide.

4.2.7. Breve

Breve [107] is a simulation package designed for simulating large distributed artificial life systems in a continuous 3D world. Behaviors and interactions of agents are defined using Python. Breve uses ODE physics engine and OpenGL library that allows the observers to view the simulation in the 3D world from any position and direction. Users can interact at run time with the simulation using a web interface. Multiple simulations can interact and exchange individuals over the network.

4.2.8. V-REP

V-REP [108] is an open resource 3D robot simulator that allows creating entire robotic systems, simulating and interacting with dedicated hardware. V-REP is based on a distributed control architecture: control programs (or scripts) can be directly attached to the objects in the scene and run simultaneously in both threaded and non-threaded fashions. This makes it very versatile and ideal for multi-robot application, and allows the users to model the robotic systems in a similar fashion as in reality where control is most of the time also distributed. V-REP possesses several calculation modules, such as sensor simulation (proximity or camera), inverse and forward kinematics, two physics engines (Bullet and ODE), path planning, minimum distance calculation, graphing, etc.

4.2.9. ARGoS

ARGoS [109] is a new pluggable, multi-physics engine for simulating the massive heterogeneous swarm robotics in real time. Contrary to other simulators, every entity in ARGoS is described as a plug-in one and easy to implement and use. In this way, the multiple physics engines can be used in one experiment, and the robots can migrate from one to another in a transparent way. Results have shown that ARGoS can simulate about 10,000 wheeled robots with full dynamics in real-time. ARGoS is also able to be implemented in parallel in the simulation.

4.2.10. TeamBots

TeamBots [110] is a collection of Java simulation for mobile robotics research. Some execution on mobile robots sometimes requires low-level libraries in C. TeamBots supports the prototyping, simulation and execution of multirobot control systems and is compatible with the Nomad 150 robot by Nomadic Technologies and Cye robot by Personal Robotics.

5. Cooperative algorithms

Research on swarm robotics so far is still quite simple. Most of the algorithms are designed for every encountering application, but an algorithm with high usability has been undiscovered. A main reason for such situation is that there is still not a common and standard definition for swarm robotics system and application problems. The problems abstracted in swarm robotics research are in a wide variety with different problem definition and setups, and it's hard to provide a uniform description for all the problems. No benchmark test has yet been proposed. Therefore, different researching works can provide little experience to each other and these different algorithms cannot compare to each other easily. Thus the whole progress of swarm robotics research is still quite slow.

5.1. Earlier progress of swarm robotics algorithms

In the earlier years of swarm intelligence research, the scientists simulated the cooperative mechanisms in the nature and explored the possibility of reproducing these swam behaviors in the artificial agents.

Self-organizing clustering observed in bacteria was one of the first swarm behaviors reproduced by the scientists [111]. The individuals in the swarm are controlled by a simple rule: the possibility of joining or leaving a colony is conducted by the density nearby. In the experiment, 1500 individuals in the swarm gradually clustered into three colonies without any prior information or external control.

A similar approach simulating ants' behavior of clearing up the graves was also proposed [112]. The task of the swarm is to collect all the items in the area together. There are no predefined storage spots available. Individual in the swarm follows a simple and local rule to transport an item from a spot of low density to high density only. Experiment shows that the swarm completes the task for collecting 80 items without communication. They also explored the how these rules can impact on the result.

Another famous attempt for simulating the cooperating abilities in the early years is the stick pulling experiment [62]. In this experiment, the stick is too long for one robot to pull it out, i.e. two robots have to pull out the stick together. The aim of this test is to verify the swarm can emerge simple intelligence with simple rules even if no communication is available. The swarm can finish the task by the rule of that a robot waits for other robots for a random time before leaving for another stick.

Dispersing uniformly in an indoor environment is one of the early algorithms that focus on the distributed structure of swarm robotics. McLurkin and Smith [96] proposed an algorithm for a swarm of iRobot. The algorithm is divided into two steps executed alternately: one disperses the robots and the other detects the border. In this way, the swarm can gradually expand in the environment.

5.2. Features of swarm robotics algorithm

A swarm robotics algorithm must fit and make full use of the features of swarm robotics. The algorithm should explore the cooperation between robots and share some features with swarm robotics system. For example, Stirling et al. [113] studied a swarm of flying robots searching in an indoor environment containing rooms and corridors. They introduced a strategy that saves energy significantly, i.e. the robots move one by one while all other robots pin to the roof to save energy. However, the swarm is required to transit the whole environment with very poor time efficiency. Since only one robot is moving at a time, the cooperative advantage of the swarm can hardly bring into play. It is hard to be classified as swarm robots algorithm in this case.

Five features of swarm robotics algorithm are specially emphasized in this section: simple, scalable, decentralized, local and parallel.

5.2.1. Simple

Since the capability of each robot is limited, the algorithm should therefore be as easy as possible. A simple algorithm can help to reduce the cost of a single robot. Even complex and efficient swarm behaviors can emerge form a well-designed simple cooperative algorithm. In most cases, the robots are considered to be a finite state machine with only a few states.

5.2.2. Scalable

The algorithm designed for swarm robotics must be scalable for any population size so that the system is a scalable one. In an algorithm, the designer should consider allowing the robots to join and especially quit the swarm dynamically. All the operations of the robots that interact with the whole swarm should be designed carefully so as not to affect the performance when a population is very large.

5.2.3. Decentralization

The robots in a swarm are autonomous and so would the algorithm be. An algorithm should always avoid any external and centralized controls. Although an individual may be affected by others, it should make the decision on its own. A decentralized algorithm is quite possible to be scalable.

5.2.4. Local

Local communication and local interaction are the special features of swarm robotics. The algorithm should also follow this rule as it is the key for scalability. Since the robots can simulate global communication and interaction system using local systems with specially designed scheme and some delay for the information to propagate in the swarm, direct use of global operations should be avoided.

5.2.5. Parallel

The swarm usually consists of many robots. Therefore, the algorithms should be as parallel as possible so that the robots can deal with multiple targets in the same time, which is one of the advantages of the swarm robotics.

According to these features, the scientists have proposed many swarm robotics algorithms. However, the research of swarm robotics is still at the start, and the main interests of the researchers are some basic tasks, such as formation control, obstacle avoidance and etc. A unified framework has yet not been proposed. As the research progress in future, several benchmark applications should be proposed and the algorithms will unleash various characteristics of the swarm robotics, such as scalable, robustness and flexibility. By that time, the researchers can focus more on the complicated problems consisting in these benchmark applications, resulting in more applicable algorithms for real life problems.

5.3. Fundamental tasks of swarm robotics

In the past decades, the swarm robotics has been deployed in various scopes of applications [95], including odor localization, mobile sensor networking, medical operations, surveillance and search-and-rescue. The tasks of these applications are very sophisticated and hard to propose a direct solution. To solve these tasks, several basic tasks have been proposed by the swarm robotics researchers, such as flocking, navigating, obstacle avoidance, etc. Among these tasks, flocking is the most important and fundamental one. Apparently, coordinating a large number of robots at the swarm level with individual rules is not an easy task. Therefore, the emerging group behavior from interactions of robots with environment and other robots has been the main interest of the research since the area has been introduced.

Flocking is widely observed in many nature swarms or even human beings. The creatures in the social groups show a great diversity in their population due to the differences in age, morphology, nutritional state, personality and leadership status of the individuals, thus it is surprised that they can achieve flocking with limited rules and interactions in such a blended group. The inspiring schemes from these groups can aid in developing the basic tasks of flocking, directed navigating, searching and obstacle avoidance.

5.3.1. Flocking strategy and formation

The “Boids” model, proposed by Reynolds [114] in 1987, is a typical individual model for flocking behavior using distance metrics. The model has been widely adopted in various applications including spacecraft, UAV, robot, and etc. In these applications, the group behaviors cannot be explicitly defined at group level and the individual rules are adopted [115].

The most common use of the “Boids” model in swarm robotics flocking is in the form of virtual forces. Hettiarachchi and Spears [116] introduced a “Physicomimetics” framework which controls the robots’ behavior using physical forces virtually generated by the interactions. They employed two types of forces from the physic laws: Newtonian Force Law and Lennard-Jones Force Law, and the swarms showed quite similar results with the real material following these laws in their simulation.

Moeslinger et al. [117] proposed a flocking behavior for robots which interprets all the interactions as attraction and repulsion forces only. The forces are decided by whether the distance falls in attraction and repulsion zones. With different setup of two zones, they achieved flocking for a small group in a constrained environment.

Hashimoto et al. [118] proposed a control algorithm for a swarm of robots based on the gravity center of the local swarms which are overlapped partially to increase the stability of the whole swarm. Local forces such as attraction and repulsion are also applied to each robot to increase the stability of the local swarm and thus the entire swarm.

Lawton et al. [119] presented a behavior-based approach to formation maneuvers. They decomposed complex formation maneuvers into a sequence of maneuvers between formation patterns. They presented three formation control strategies to deal with different topologies and purposes.

Although most models in swarm robotics assume that the individuals interact with all their neighbors within certain distance, some biological researches provide a new idea. By reconstructing the three dimensional positions of a few thousands of birds during flocking, Ballerini et al. [120] showed that the interaction does not depend on the metric distance, but rather on the topological distance with six to seven neighbors on average. Various computer simulations in computer also show that a topological interaction grants significantly higher cohesion of the aggregation compared with a standard metric one.

Based on such observation, some researchers also proposed selecting strategies before interacting with nearby robots so that only a fixed number of neighbors are used. Lee and Chong [121] proposed a flocking control inspired from the fish schools. They selected two neighbors for team maintenance and local interactions. Ercan et al. [122] introduced a regular tetrahedron formation strategy for selecting three neighbors that forms the best tetrahedron to ensure formation.

Miyagawa [123] has shown that the swarms can flock without distance information. He utilized a strategy inspired from tau-margin, assuming the animals especially birds perceive time to contact rather than distance. The robots in the swarm are equipped with light bulbs of 10W so as to perceive tau-margin by utilizing optical inverse square law.

Barnes et al. [115] presented a method for organizing a swarm of unmanned vehicles into a user-defined formation by utilizing artificial potential fields generated from normal and sigmoid functions. The potential functions along with nonlinear limiting functions are used to control the shape of swarm to user desired geometry.

5.3.2. Directed flocking

Besides the flocking strategy, the direction control in flocking is the most concern in flocking research and has been widely adopted in navigation, migration and searching applications. Until now, a large number of researches have been made on directing the swarm with target positions and propagating information in the swarm.

5.3.2.1. Informed individual. A common and naive strategy of direct flocking is the "informed individual". It was first observed in nature swarms by Couzin and his colleagues [124], who conducted a study on effective leadership and decision-making in animal groups and published their work in *Nature*. In their experiment, only a few of the individuals in the group are aware of the target direction. The results demonstrate that these informed individual can lead the whole group towards the destination. Later, Correll, et al. [125] utilized such scheme in cow herd to guild the swarm.

From then on, the similar schemes have been also introduced to swarm robotics. McLurkin [126] developed a strategy in his mater thesis for the task of following the leader with a linear formation. The robots line up in the topology, follow the predecessors and guide the successors. The leader is guided by other controls for the final destination of the group. The group forms the line without any external orders and can handle the obstacles in the environment and the communication failures that may encounter.

Nasseri and Asadpour [127] investigated the controlling effects of a swarm with only a small fraction of robots having the knowledge of final goal. The informed robots cannot transmit information directly, yet the swarm can flock towards the desired target in simulation. They also investigated how the parameters can influence on the performance.

A self-organized flocking behavior for a swarm of robots was presented by Turgut et al. [128] without using the emulated sensors or the priori knowledge of the destination. The simulation shows that, with only local interactions, the robots can share a common flocking direction in a self-organized process until the sensing noise exceeds to a certain extent. In their follow-up work [129], they studied how the swarm can be steered toward a desired direction by guiding some of individuals externally. The results are qualitative in accordance with the ones that were predicted using modal in Ref. [124] model. The two works were evaluated in both physical systems and simulations in an environment with obstacles.

Stranieri [130] studied the self-organized flocking behaviors of two types of robots: aligning and non-aligning. An aligning robot has the ability to agree on a common heading direction with its neighbors. A heterogeneous swarm of these two kinds of robots can achieve good flocking performance in simulation if the motion control strategy and interact mechanisms are carefully designed.

5.3.2.2. Potential field functions. Another commonly used swarm formation control strategy is the potential field function. Ge and Fua [131] presented a scalable and flexible approach to effectively control the formation of a group of robots. They introduced the artificial potential trenches and represented the formation structures in terms of queues and vertices, rather than with nodes. The robots are attracted to and move along the bottom of the potential trench and distribute with respect to the density nearby automatically. In their follow up work, Fua et al. [132] investigated the operation of the queue-formation structure with limited communication. Information interaction is classified as two scales: the fast-time and slow-time scale. The former scale involves only local real time communication, and in the latter scale, information is less demanding and can be collected over a longer time from the swarm. In this way, the swarm is incrementally guided into the specific formation in a more efficient manner.

The aggregation, foraging, and formation control of robots were investigated by Gazi et al. [133], which are controlled by using artificial potential and sliding mode. They considered a significantly more realistic and more difficult setting with non-holonomic unicycle agent dynamics models compared with other studies.

Blach and Hybinette [134] presented a new class of potential functions for navigating the swarm towards a goal location in obstacle environment. The approach is inspired by the same way that molecules “snap” into place as they form crystals and the swarm can arrange themselves in a geometric formation.

5.3.3. Positioning and navigation

In flocking and migration, the positioning of goal, nearby robots and various obstacles in the fields is also an important task. In the application taking place in the large outdoor environment, the global positioning is expensive and requires more hardware, which is unaffordable for swarm robotics. Thus, the local positioning in flocking should be specially focused.

5.3.3.1. Navigation. Rothermich et al. [135] developed a distributed localizing and mapping method based on a swarm of iRobots. Since the swarm does not share a global coordinating system, the swarm should gather and move together to maintain a virtual system. In the swarm, some robots serve as the beacons if they run into a newly searched area, and they turn back to the role of mapping and searching if there are already enough beacons nearby. With such scheme, the swarm can maintain the coordinating system to draw the map with high accuracy in a distributed way.

Correll and Martinoli [136] developed an intelligent inspection system with on-board local sensors. In their proposed strategy, part of the robots in the swarm act as the beacons, and the strategy is compared to other beaconless approaches. They also analyzed the system with probabilistic microscopic and macroscopic models.

Spears et al. [137] developed a relative localization module for determining the positions of nearby robots based on trilateration for searching problems. The robots identify the nearby robots with three marking points equipped physically on robots to match the distance and direction of their neighbors. This strategy is fully distributed, scalable, inexpensive and robust. The system provides a framework for both localization and information exchange.

Stirling et al. [138] presented a new autonomous flight methodology for autonomous navigation and goal directed flight in unknown indoor environments using a swarm of flying robots. The approach is entirely decentralized and relies only on local sensing without global positioning, communication, or prior information about the environment.

Marjovi et al. [139] proposed a navigation method by guiding the swarm using wireless connections when the odor sources are searched. At least three individuals in the swarm act as the beacons which broadcast the coordinates to the whole swarm to maintain a global coordinate system while the others search for the odor. The shortcoming of this research is that the beacons are broadcasting the coordination in a large area while other robots should detect the distance with the beacons from a long distance, which requires expensive hardware.

5.3.3.2. Simulating ant colonies. Ant colonies in the nature are famous for the navigation and migration behaviors with the help of pheromones. The researchers of the swarm robotics society employed such scheme into swarm robotics by simulating the pheromones using part of the robots in the swarm which serve as the beacons.

An interesting study was proposed by Sperati et al. [140]. In their experiment, a robotic swarm manages to collectively explore the environment, forming a path to navigate between two target areas, which are too distant to be perceived by an agent at the same time. The robots continuously move back and forth between the two locations while they interact with their neighbors. The behaviors of the robots are controlled by a neural network and the swarm evolves to optimize the path. They observed that the swarm finally converges to the shortest path. In their follow-up work, one of the schemes simulating ant colonies was proposed [141]. They searched for an efficient exploration and navigation strategy for the same problem. They evaluated one run of a robot through the time and distance spent to find the path and optimize the searching using the evolutionary methods. The final results show that the swarm has great flexibility and robustness.

Ducatelle et al. [142] investigated how the simple local interactions between the robots of the different swarms can cooperate to solve the complex tasks by using eye-bots and foot-bots from the swarmanoid project. The foot-bots move back and forth between source and target and avoid the obstacles without any interaction with other foot-bots; the eye-bots simulate the pheromones in the environment and guide passing by foot-bot with local direction. The eye-bots update the weights of the directions and move towards the optimized path to accelerate the searching process. Simulation results show that the system is capable of finding a shortest path and spreading in an automatic traffic.

5.3.4. Obstacle avoidance

Obstacle avoidance is also considered an important basic task in the swarm robotics society. In most researches, some sort of potential functions has been applied to the robots. The swarm steers around the encountered obstacles according to the potential fields. Khatib [143] first introduced this concept in real-time obstacle avoidance in 1986. He used a time-varying artificial potential field for moving obstacles. This solution successfully converted the traditionally high level planning problem into distributed real-time operations even in complex environment.

Some recent examples also used such scheme. Das et al. [144] proposed an approach that switches between several controllers, depending on the state of the robot for obstacle avoidance. Shao et al. [145] proposed a similar kinematic controller and modified the desired bearing to steer the robots around the obstacles. Do [146] used a potential function for avoiding collisions within the swarm. The function alters the robots' trajectory if they are not at their heading direction. In Ref. [122], the obstacles generate a virtual repulsive force similar to the mechanism in atomic nucleus, and the robots play the roles of electrons to fly around the nucleus.

Kurabayashi and Osagawa [147] proposed formation transition and obstacle avoidance adapting to the geometrical features appearing in Delaunay diagram. The robots select their neighbors in the diagram by the proposed strategy and form a topology connecting all the individuals lead by a certain robot. The algorithm shows some flexibility but is vulnerable in robustness.

Min et al. [148] proposed a new method for avoiding the obstacles in dynamic environment based on the second order motion model for robotics. A mathematical model based on the destination of robot, velocity and direction of obstacles was proposed and optimized using PSO. Simulation experiment shows that the method is better than the tradition artificial potential field methods, though it requires a large amount of computation since each robot maintains a PSO model separately.

5.4. Swarm robotics searching algorithms

Currently, swarm robotic searching algorithm is one of the most concerns of the researchers besides those basic tasks mentioned in previous section. In this section, the searching strategies are classified in two types: one inspired from the swarm intelligence algorithms and the other inspired form other methods. These two types of algorithms are different in many aspects, such as searching scheme, target detection method and information exchange inside the swarm.

5.4.1. Inspired from swarm intelligence algorithms

From the general point of view, swarm optimization algorithms share several similarities with swarm robotics searching, e.g. searching for the best points using a swarm of individuals. Particle swarm optimization (PSO) is the swarm intelligence approach that is adopted mostly in the swarm robotics due to the great similarity with flocking and searching schemes. Besides PSO, other methods have also inspired many successful approaches, such as ant colony optimization (ACO) and glowworm swarm optimization (GSO). The scope of these approaches includes path finding, navigation, odor localization, etc.

The swarm intelligence shows great ability in scalable, flexibility and robustness and is suitable for real life applications with the aid of various existing strategies. However, the shortcomings of these algorithms are also introduced in the same time, e.g. large quantity of random moves, global interactions and especially tending to get trapped in the local minimal. Couceiro et al. [149] proposed a RDPSO for solving the last issue. They divide the swarms into sub-swarms with dynamic topology updated in several iterations based on a reward and punishment mechanism. However, the sub-swarms are divided ignoring the distance metrics and escape the local minimum at the cost of global communication and coordinating system.

There exist three types of methods in using the swarm intelligence algorithms so far:

5.4.1.1. Optimizing the parameters. The first type of searching algorithms inspires the strategies from other methods with several parameters which are hard to be optimized, such as neural network or heuristic schemes. The swarm intelligence algorithms are employed to optimize these parameters.

Meng [150] proposed a collective construction task for searching the randomly distributed building blocks and transporting these blocks to the predefined locations. The method employs the virtual pheromone trail for information exchange and the task allocation for cooperative transportation. A modified PSO was proposed to balance the exploration and exploitation in their work.

Pugh [151] explored the use of PSO for the noisy problems of unsupervised robotic learning. He adapted a technique of overcoming noise from genetic algorithm (GA) and evaluated it on unsupervised learning of obstacle avoidance using a swarm of robots. In his follow-up work with Martinoli [152], they presented an adaptive strategy for localization of multiple targets. The search algorithm is inspired from chemotaxis behavior in bacteria, and the algorithmic parameters are updated using PSO.

To overcome the weakness and difficulty of the logical design of behavioral rules, Oh and Suk [153] proposed an artificial neural network controller that is applied to the mission of searching the obstructive areas using a swarm of UAVs. Genetic algorithm is applied to evolve the weights in the neural network which shows superior results to other controllers.

Yang and Li [154] proposed a path planning algorithm based on improved PSO. The center of the path is described as cubic splines, and the path planning is equivalent to parameter optimization of these cubic splines. Results show that the obstacle avoiding paths can be optimized using such scheme.

5.4.1.2. Modeling the individual behaviors. In this type of algorithms, each robot is regarded as a particle or agent correspondingly in the swarm intelligence algorithm. The searching environment is normally interpreted as fitness values. The swarm uses the fitness to search for the targets.

Pugh and Martinoli [155] explored the possibility of adopting PSO strategies in swarm robotics searching directly.

Each robot is regarded as a particle and various neighborhood topologies, and PSO update strategies are verified. In their follow-up work [156], they designed an effective algorithm that allows a swarm of robots to work together to find the targets. They proposed the techniques inspired from PSO modified to mimic the swarm robotics search process. Analysis of parameters and setups in the model are also presented at an abstracted level.

Marques et al. [29] presented a PSO inspired algorithm for searching the odor sources in a large search space. The robots try to repulse each other when no chemical cue exists nearby to improve the swarm performance. Hereford [157] applied PSO on a swarm of robots searching for the light spots in a room containing the obstacles. Each robot is regarded as a particle and broadcasts its information to the whole swarm. The shortcoming of the experiment is that it only considers three robots with a large amount of global communication to maintain the global best of the swarm.

Derr and Manic [158] considered problem of exploring an unknown environment to find the targets at the unknown locations. They used PSO with a novel adaptive RSS weighting factor to locate targets. Zhu et al. [159] presented a PSO-inspired search algorithm that coordinates the robots to find the targets without precise global information. They also introduced a Cartesian geometry based method for unifying the relative coordinate systems to improve robustness and efficiency.

Zhang et al. [160] proposed a strategy based on modified glowworm swarm optimization for multiple odor source localization. This strategy includes global random search and local GSO based search. A discovered source is marked as forbidden area to ensure that the swarm does not locate this source again.

An interesting resource exploration task on Mars was imagined by Kisdi and Tatnall [161]. They suppose the situation that a lander leads a swarm of workers who cannot interact with each other. The lander is unable to move and serves as a shared memory as well as the coordinator of the swarm. The workers search in the environment in the area ordered by the lander and return their results back to the lander. The scheme of the lander is similar with that of maintaining the archives in multi-objective search in swarm intelligence. Human interaction is also available at the lander to mark the interesting areas.

5.4.1.3. Mixing two methods above. Some algorithms try to use the swarm intelligence model and optimize the parameters using swarm intelligence in the same time. Doctor [162] proposed a method utilizing two layers of PSO for controlling the unmanned mobile robots in target tracing application. The robots are controlled by the schemes in inner layer of the PSO and the parameters of inner layer are optimized by the outer layer. Signal intensity from targets is defined as the fitness to search for the swarm.

The solutions for real-time uniform coverage tasks in military applications under the harsh and bandwidth limited conditions were proposed by Conner et al. [163]. They encode each robot as a genome and exchange speed and direction with neighbors. A force-based genetic algorithm is used at the swarm level to determine the behavior of each robot under the threats of hostile attack, obstacles and intermittent stoppage of communication. The swarm always tries to rearrange the positions to compensate for the missing robots.

5.4.2. Inspired from other methods

Olfaction is a common ability that the animals use in their everyday activities, such as hunting, mating, interacting and evading the predators. Such schemes inspired from the animals have been widely used in the swarm robotics applications, such as localization of odor sources, which have attracted a growing interest in the areas such as anti-terrorist, location of toxic or harmful gas leakage, checking for contraband, exploration of mineral resources in dangerous areas and search-and-rescue in collapsed building [164].

A common olfaction based algorithms can be decomposed into three or four sub procedures first proposed by Hayes [165] and Li [166]. The swarm first searches for a plume and follows the plume to the odor source once a plume is located. The sub-procedures are different from other approaches such as gradient descent method [167], zigzagging method [168], and upwind method [169].

Cui et al. [170] proposed a biasing expansion swarm approach to collaboratively search and locate various number of emission sources in an unknown area using a swarm of simple robots. Jatmiko et al. [171] provided a model of odor-gated rheotaxis combined with chemotaxic and anemotaxic (upstream) methods to solve the odor source localization problems. The combined model can achieve high accuracy in real life scenarios containing dynamic sources, random winds and obstacles.

Russell et al. [172] summarized and compared the implementation and evaluation of four chemotaxis algorithms which provide fast, simple and cost-effective solutions for olfaction based searching applications in obstructive environments. They listed the details of the algorithms together with typical results of these algorithms obtained in both simulated and practical experiments.

Besides olfaction, other searching applications and strategies have been also proposed. Varela et al. [173] developed an algorithm for coordinating a group of UAVs to monitor the environment. The UAV swarm can locate the undesired phenomenon. The UAVs compare the average fitness of last five iterations with their neighbors and select the direction of the best neighbor to search in the next iteration. They validated the algorithm in real UAVs monitoring and industrial area.

Wu and Zhang [174] developed a switching strategy for locating a local minimum in an unknown noisy scalar field. Robots will switch to cooperative exploration only when they are not able to converge to a local minimum at a satisfying rate according to a cooperative filter. The switching strategy can result in faster convergence and is robust to unknown noise and communication delay.

A robust-satisficing approach based on info-gap theory was suggested as a solution for a spatial search-planning problem by Sisso et al. [175]. The swarm is given uncertain prior information data with severe errors. The proposed method shows great superior in robustness to the expected-utility maximizing strategy.

Lee and Ahn [176] proposed a foraging algorithm specially focused on energy efficiency. Through adding several temporal storage stations in the environment the swarm can improve the searching efficiency since the robot will move a shorter distance to the storage before next forage. The swarm is divided into two parts, one part searches for the food and sends the food to the nearest station, while others transfer the food from the station to the nest. In this way, both time and energy efficiency are improved although several prior knowledge about the environment is required.

Besides these common methods, other strategies were also proposed by the researchers. Nouyan and Dorigo [177] proposed a chain based path formation algorithm to generate a chain of robots from nest to a destination unknown to the swarm. In their method, each robot is regarded as a finite state machine with only three states: explore, search and chain. The robot explores in the field for any existing chains, searches for the end and joins. With limited sensing and communication, the swarm can chain up with great robustness and scalability. In their follow-up study [178], they extend the task by transporting the target back to the nest. The robots have to work together and pull the target along the chain back to the nest while the chaining robots will join the transportation after the target passes them. Their work is one of the most complicated tasks that have ever been considered in self-organizing robot swarms in the real life projects.

6. Conclusions

Swarm robotics is a relatively new researching area inspired from swarm intelligence and robotics. Although a number of researches have been proposed, it's still quite far for practical application. The authors hereby proposed several fundamental problems to solve in future before the system can really be adopted in everyday life. How can the cooperative schemes inspired from the nature swarms integrate with the limited sensing and computing abilities for a desired swarm level behavior? How to describe the swarm robotics system in a mathematical model which can predict the system behaviors at both individual and swarm level? How to propose a new and general strategy that can take full advantage of the swarm robotics system? And finally, how to design a swarm of robots with low cost and limited abilities which has the potential to show great swarm level intelligence through carefully designed cooperation?

Besides the cooperative algorithms to provide control for the swarm, the manufacturing is a fundamental need for developing the swarm robotics systems. With the help of advance in Micro Electro Mechanical technology in the aspects of mechanical transmission, sensors, actuators and electronic components, the size and cost of robots have been significantly reduced. The authors believe that the progresses of hardware technology and cooperative schemes in both biology and swarm intelligence in future will boost the development of swarm robotics systems.

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