On some new Applications of Swarm Robotics

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ABSTRACT: The research progress of swarm robotics is reviewed in details. The swarm robotics is a new approach to the coordination of multi-robotic systems which is inspired from nature and is a combination of swarm intelligence and robotics, which shows cooperation of nature swarm and swarm intelligence and describes the modelling methods of swarm robotics, followed by a list of several widely used swarm robotics entity projects and simulation platforms. In this paper, classification of existing researches, problems and algorithms aroused in the study of swarm robotics are presented including cooperative control mechanisms in swarm robotics for flocking, navigating and searching applications.

Keywords: Cooperative control, Modelling, Simulation, Swarm robotics applications.

1. Introduction

Swarm robotics is the study of how to coordinate large groups of relatively simple robots through the use of local rules. It takes inspiration from societies of insects that can perform tasks that are beyond the capabilities of the individuals. 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]. SR is closely related to the idea of SI and it shares its interest in self-organized decentralized systems. Hence, it offers several advantages for robotic applications such as scalability, and robustness due to redundancy [2] such as path planning [3], nest constructing [4], task allocation [5] and many other complex collective behaviours in various nature swarm [6-8].

2. Cooperation of Nature Swarms

The individuals in the nature swarm shows very poor abilities, yet the complex group behaviours 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.

3. Swarm Intelligence

A swarm intelligence system consists typically of a population of relatively simple agents (relatively homogenous or there are a few types of them [9]) interacting only locally with themselves and with their environment, without having a global knowledge about their own state and of the state of the world. Moreover, the overall observed behaviour is emerged in response to the local environment and to local interactions between the agents that follow often very simple rules [10].

Natural swarm based theories have been applied to solve analogous engineering problems in several domains engineering from combinatorial optimization to rooting communication network as well as robotics applications, etc. (for a recent comprehensive review, readers can refer to [11]). The most well-known swarm based algorithms are: Ant Colony Optimization Algorithms (ACO), Particle Swarm Optimization Algorithms (PSO), Artificial Fish Swarm Algorithm (AFSA) and Bee based Algorithms. The ACO algorithm is inspired from the foraging behaviour of ant colonies in finding shortest paths from their nests to food sources. The source of inspiration of PSO based algorithms comes especially from the behaviour observed in bird flocking or fish schooling when they are moving together for long distances to search for food sources, whereas The AFSO algorithm is inspired from the collective movement observed in the different behaviours exhibited by fishes such as searching for food, following other fishes, protecting the group against dangers and stochastic search [12]. Bee based algorithms can be classified into three different main groups: (1) the honeybee' foraging behaviour based algorithms, (2) the ones based on mating behaviour in honeybee, and (3) the queen bee evolution process based algorithms (more details can be find in [13].)

4. Multi-Robot System

Multi-robot systems (MRS) are born to overcome the lack in information processing capability and many other aspects of single robots that are not capable to dial with special tasks; which, in order to be efficiently completed, need cooperation and collaboration between groups of robots [14]. Since its introduction in the late 1980s, various works (such as: cellular robotics, collective robotics, and distributed robotics) have been issued to describe group of simple physical robots collaborating together to perform specific tasks. MRS have also achieve a great success and made a great progress in many areas such as cooperative transportation and aggregation, environmental monitoring, search-and-rescue missions, foraging, and space exploration [15].

In such task; even the simplicity in design and the low-

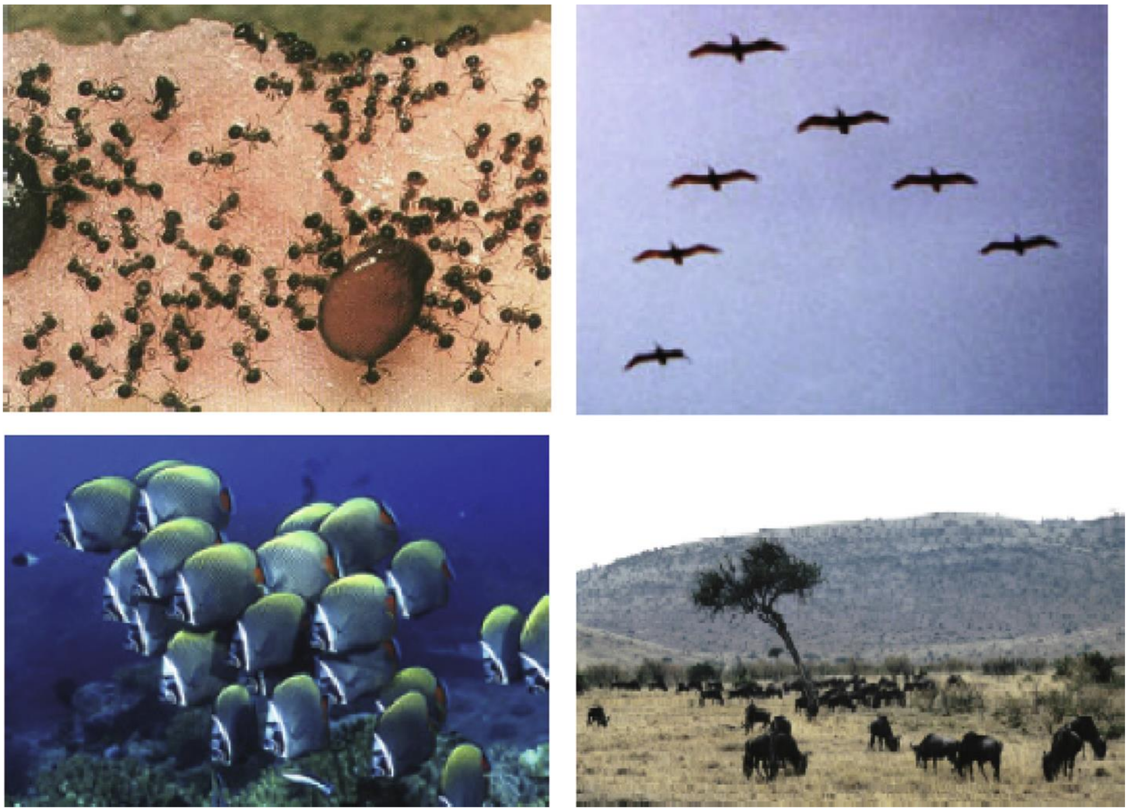


Fig. 1. Biological swarms in the nature

cost in productivity, as well as the increase in capabilities, flexibility, and fault tolerance advantages gained when using multi-robots instead of a single one; however with the new arising challenges such as decentralization in control and self-organization, researchers in multi robotic field begun to make attention to the increase progress known in swarm intelligence systems giving birth to the new sub-domain research *"swarm robotics"*.

5. Swarm Robotics

Swarm robotics is the study of how large number of relatively simple physically embodied agents can be designed such that a desired collective behaviour emerges from the local interactions among agents and between the agents and the environment.

Characteristics of Swarm Robotics:

i) Robots of the swarm must be autonomous robots, able to sense and actuate in a real environment.

ii) The number of robots in the swarm must be large or at least the control rules allow it.

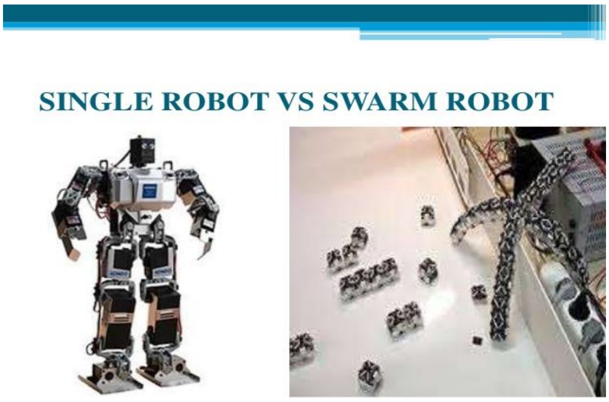
iii) Robots must be homogeneous. There can exist different types of robots in the swarm, but these group must not be too many.

iv) The robots must be incapable or inefficient respect to the main task they have to solve, this is, they need to collaborate in order to succeed or to improve the performance.

v) Robots have only local communication and sensing capabilities. It ensures the coordination is distributed, so scalability becomes one of the properties of the system

6. Comparison of Swarm Robotic (SR) and MRS

	Swarm robotics	**MRS**
Population Size	Variation in great range	Small
Control	Decentralized	Centralized/remote
Homogeneity	Homogenous	Heterogeneous
Flexibility	High	Low
Scalability	High	Low
Environment	Unknown	Known/unknown
	Yes	Yes



7. Swarm Robot vs. Single Robot

vi) Swarm robots can perform a large number of task domain.
vii) Swarm robots have greater efficiency.
viii) Swarm robots have improved performance.
ix) Swarm robots have fault tolerance.
x) They are robust in nature.
xi) Swarm robots are having low economic costs.

8. Applications of Swarm Robotics

Several potential application scopes [16] of swarm robotics which are very suitable are described below.

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. 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. [17] 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 behaviour.

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 [18] 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.

1. 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.

9. General model of Swarm Robotics

Swarm robotics model is a key component of cooperative algorithm that controls the behaviours 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 behaviours: information exchange, basic and advanced behaviour.

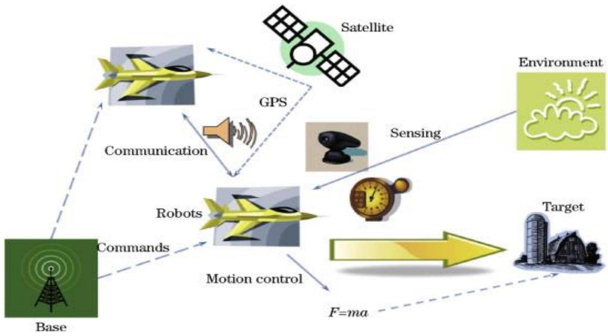


Fig.2. General model of swarm robotics

10. Techniques

The goal of this section is to classify the articles published in the swarm robotics literature according to the methods used to design or to analyze swarm robotics.

Design methods

Design is the phase in which a system is planned and developed starting from the initial specifications and requirements. Unfortunately, in swarm robotics there are still no formal or precise ways to design individual level behaviours that produce the desired collective behaviour. The intuition of the human designer is still the
main ingredient in the development of swarm robotics systems. We divide the design methods into two categories: behaviour-based design and automatic design.

Behaviour-based design methods

In swarm robotics, the most commonly used design method involve developing, by hand, the individual behaviours of the robots which results in the collective behaviour of the swarm. Designing a behaviour for a swarm robotics system is a trial and error process: individual behaviours are iteratively adjusted and tuned until the resulting collective behaviour is obtained. For this reason, behaviour-based design is inherently a bottom-up process.

1. Probabilistic finite state machine design

Generally, in swarm robotics, an individual robot does not plan its future actions, but it takes decisions only on the basis of its sensory inputs and/or its internal memory (Brooks, 1986). One of the most adopted design method to obtain such behaviours is the use of a finite state machine, henceforth FSM.
In swarm robotics, probabilistic FSMs (henceforth PFSMs) are more commonly used. Behaviours obtained through the use of PFSMs are asynchronous, thus allowing the robots to show different individual behaviours at the same time. Asynchronicity can also be used to reduce interference.
In PFSMs, the transition probability between states can be fixed or can change over time. The transition probability is fixed when a single probability value is defined and used throughout the execution of the collective behaviour. An example can be found in the work of Soysal and S¸ahin (2005). The transition probability is not fixed when it is defined through a mathematical function of one or more parameters of the system. One of the most widely used function is the response threshold function developed by Granovetter (1978). In the response threshold function, the probability to switch to a new state is usually related to the current state of the robot. The transition probability p depends on: s, a stimulus that represents a measure of the transition urgency; θ, a threshold on the stimulus; and β, a sensitivity parameter. The function is non-linear: When s << θ, the transition probability is very low, whereas when s >> θ it is very high. In the example in the figure, s ranges in [0, 100], θ = 50 and β = 8.

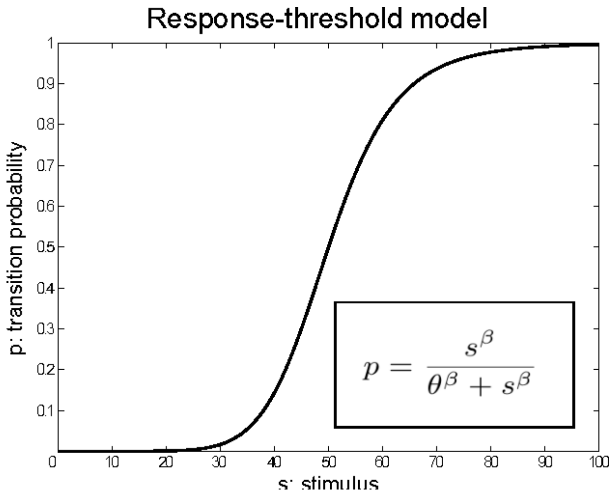


Fig. 3 The response threshold function

2. Virtual physics-based design

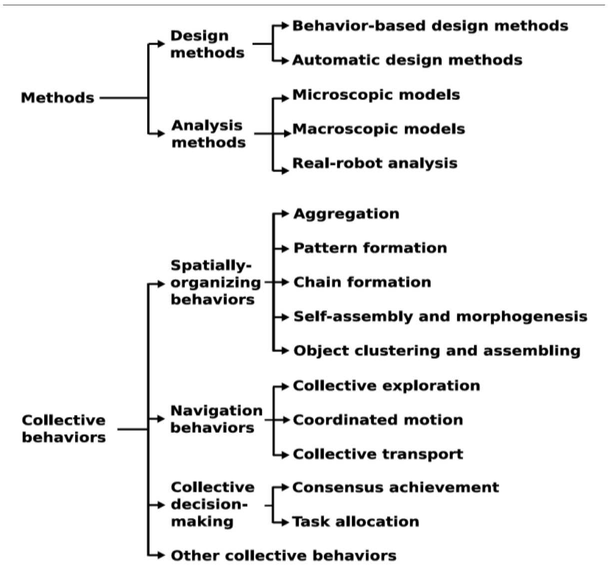
The virtual physics-based design method draws inspiration from physics. Each robot is considered as a virtual particle that exerts virtual forces on other robots. One of the first works using virtual physics-based design was by Khatib (1986), who used the concept of artificial potential field. In this and in some following works, the robots are subject to repulsive virtual forces originating from the environment: the goal is associated with an attractive force and the obstacles to repulsive forces.
The main advantages of virtual physics-based design methods are: i) a single mathematical rule smoothly translates the entire sensory inputs space into the actuators output space without the need for multiple rules or behaviours; ii) the obtained behaviours can be combined using vectorial operations; iii) some properties (such as robustness, stability, etc.) can be proved using theoretical tools from physics, control theory or graph theory.

3. Automatic design methods

Automatic design methods are methods with which a behaviour can be learned by a robot without the explicit intervention of the developer. Automatic design methods are typically studied within machine learning, a very broad research domain that spans across artificial intelligence and statistics. The application of machine learning methods to multi-robot systems is called cooperative multi-agent learning.
The section is organized as follows. We first introduce reinforcement learning (Kaelbling et al., 1996; Sutton and Barto, 1998) and we identify the key challenges of the application of the methods developed for reinforcement learning to swarm robotics. We then present evolutionary robotics (Nolfi and Floreano, 2000), the application of evolutionary computation techniques to single and multi-robot systems.

4. Reinforcement Learning

RL traditionally refers to a class of learning problems: an agent learns a behaviour through trial-and-error interactions with an environment and by receiving positive and negative feedback for its actions. In RL,



the robot receives a reward for its actions. The goal of the robot is to learn automatically an optimal policy, that is, the optimal behaviour mapping robot states to robot actions. The behaviour is optimal in the sense that it maximizes the rewards received from the environment.

5. Evolutionary robotics - Evolutionary robotics (Nolfi and Floreano, 2000) (henceforth ER) is an automatic design method that applies evolutionary computation techniques (Goldberg, 1989; Holland, 1975) to single and multi-robot systems. Evolutionary computation is inspired by the Darwinian principle of natural selection and evolution. In ER, the individual behaviour can be represented in many ways, such as finite state machines or virtual force functions (Hettiarachchi, 2007). Typically, the evolutionary method is used to find the parameters of an artificial neural network (henceforth NN). Although several types of NN exist in the literature, they can be roughly categorized in two main classes: feed forward NN (Fine, 1999) and recurrent NN (Beer and Gallagher, 1992; Elman, 1990). Feed-forward NNs are used for individual behaviours that require no memory of previous observations and actions. Conversely, recurrent NNs are used for individual behaviours that require a memory of previously seen input patterns. ER with recurrent neural networks has been extensively studied in swarm robotics by Ampatzis (2008).

11. Analysis and Results

Analysis is an essential phase in an engineering process. In the analysis phase, the swarm engineer is interested in seeing whether a general property of the designed collective behaviour holds or not. The ultimate goal to obtain is that a swarm of real robots exhibits the desired collective behaviour with the desired properties. Properties of the collective behaviours are usually analyzed by means of models.

Swarm robotics systems can be modelled at two different levels: the individual level, or microscopic level, that models the characteristics of the single individuals and the interactions among them; the collective level, or macroscopic level, that models the characteristics of the entire swarm. The development of models for analyzing swarm robotics systems at both levels of abstraction is still a subject of study and research.

Microscopic models

Microscopic models take into account each robot individually, analyzing both robot-to-robot and robot-to-environment interactions. In the swarm robotics field, many models have been developed with different levels of abstraction: the simplest models consider the robots as point-masses; intermediate complexity models consider 2D worlds with kinematic physics; more complex models consider 3D worlds with dynamic physics where the details of each sensor and actuator are modelled.

Microscopic models in which the elements composing a system are simulated with the use of a computer are traditionally called simulations. Simulations are among the most used tools to analyze and validate swarm robotics systems. The vast majority of the works presented have been analyzed using simulators.

Macroscopic models

Macroscopic models consider swarm robotics systems as a whole. The individual elements of the systems are not taken into account in favour of a description of the system at a higher level. We classify works in macroscopic modelling into three categories. In the first category, we consider works resorting to rate or differential equations. In the second category, we consider works where classical control and stability theory are used to prove properties of the swarm. In the third category, we consider other approaches.

Rate and differential equations

One of the first works that uses rate equations for modelling swarm robotics systems is by Martinoli et al. (1999). In this and in follow-up works, the term rate equations was used to denote such models. Rate equations describe the time evolution of the proportion of robots in a particular state over the total number of robots.

The procedure is the following: i) First, a set of variables is defined. Usually, one variable is defined for each state of the individual-level PFSM. These variables are used to track the proportion of the robots in the corresponding states. ii) Second, for each variable, an equation is defined (Lerman and Galstyan, 2002). This equation is called rate equation because it is used to describe the time evolution of that variable, that is, the time evolution of the proportion of the robots in the corresponding state.

The rate equations method was used to model many swarm robotics systems. Liu and Winfield (2010) used the rate equations to model another foraging task involving the collection of energy units. The main advantage of the rate equation approach is that it is a systematic method to translate microscopic models into macroscopic models.

Classical control and stability theory

The second set of works uses classical control and stability theory to prove properties of the swarm. Liu et al. (2003) and Gazi and Passino (2005) modelled a swarm of agents in a one-dimensional space using discrete-time discrete-event dynamical systems. Liu and Passino (2004) and Gazi and Passino (2004b) used Lyapunov stability theory to prove that the behavior studied was able to let a swarm achieve coherent social foraging in presence of noise. Similarly, Gazi and Passino (2003, 2004a) proved that, in specific conditions, a swarm of agents aggregates in one point of the environment. Finally, Hsieh et al. (2008) used delay differential equations to model task-allocation (agents allocating and re-allocating to different physical sites), proving the stability of the reached configuration. In the same work, the authors also proposed a method to compute the optimal transition matrix in order to obtain a swarm that reaches the desired configuration.

Other modelling approaches

In the third and final category we consider works in modelling that resort to other mathematical frameworks. Winfield et al. (2005) used linear time temporal logic to define properties of individual robots and of the swarm. The authors defined and proved two properties of the system: safety and liveness. The safety property is verified when the robots do not exhibit undesirable behaviours. The liveness property is verified when the swarm dynamics actually do evolve over time. Kazadi (2009) used a similar approach. The author expressed properties of the swarm with a mathematical language and proved their validity. The author proposed a way to define properties of a swarm robotics problem which he calls "model independent", that is, they do not depend on the actual implementation of the agent/robot. He proposed model-independent properties for two collective behaviours: shape formation and flocking. Soysal and S¸ahin (2007) modelled aggregation using Markov chains and validated the prediction using simulation. The work of Turgut et al. (2008b) represents one of the first modelling attempts to bridge studies of flocking within physics with studies of flocking within robotics.

12. Collective behaviours

In this section, we present a review of the main collective behaviours studied in the literature. We classify these collective behaviours into four main categories: spatially-organizing behaviours, navigation behaviours, collective decision-making and other collective behaviours. In the first category, spatially-organizing behaviours, we consider behaviours that focus on how to organize and distribute robots in space. In the second category, navigation behaviours, we consider behaviours that focus on how to organize and coordinate the movements of a swarm of robots. In the third category, collective decision-making, we consider behaviours that focus on letting a group of robots agree on a common decision or allocate among different parallel tasks. In the last category, other collective behaviours, we consider behaviours that do not fall into any of the categories mentioned above. For each category, we give a brief description of the collective behaviour, its source of inspiration, the most common used approaches and the most significant available results.

Spatially – organizing behaviours

In this section, we describe collective behaviours that focus on how to organize and distribute robots in space. Robots can be organized and distributed in space in several possible ways: aggregates, patterns, chains and structures of physically connected robots.

(A) Aggregation Description –

The goal of aggregation is to cluster all the robots of a swarm in a region of the environment. Despite being a simple collective behaviour, aggregation is a very useful building block, as it allows a swarm of robots to get sufficiently close one another so that they can interact.

Source of inspiration

Aggregation is a very common behaviour in nature. For example, aggregation can be observed in bacteria, cockroaches, bees, fish and penguins (Camazine et al., 2001). Other examples of natural systems performing aggregation have been described by Gr¨unbaum and Okubo (1994); Breder Jr (1954); Jeanson et al. (2005); Am´e et al. (2006).

Approaches

In swarm robotics, aggregation is usually approached in two ways: probabilistic finite state machines (PFSMs) or artificial evolution. The most common approach is based on PFSMs: the robots explore an environment and, when they find other robots, they decide stochastically whether to join or leave the aggregate. In this approach, a stochastic component is often used in order to ensure that eventually only a single aggregate if formed. In the artificial evolution approach, the parameters of a neural network are automatically selected in order to obtain an aggregation behaviour.

Results - Garnier et al. (2005) developed a system in which robots are used to replicate the behaviour observed in cockroaches by Jeanson et al. (2005). The robots are able to collectively aggregate in a circular arena using a PFSM approach. Another example of an aggregation behaviour based on a PFSM was developed by Soysal and S¸ahin (2005). In their work, a robot can be in one of three states: the repel state, in which the robot tends to get away from other robots; the approach state, in which the robot tends to get closer to other robots; and the wait state, in which the robot stand still. Soysal and S¸ahin where able to achieve both moving and static aggregation behaviours by changing the parameters of the system.

follow each other forming a double chain between two designated areas.Differently from other chain formation behaviours, in this work the obtained chain is composed of moving robots.

(B) Pattern formation

Description - Pattern formation aims at deploying robots in a regular and repetitive manner. Robots usually need to keep specific distances between each other in order to create a desired pattern.

Source of inspiration - Pattern formation can be found both in biology and in physics. Some biological examples are the spatial disposition of bacterial colonies and the chromatic patterns on some animal's fur (Meinhardt, 1982). Some physics examples are molecules distribution and crystal formation (Langer, 1980), and B´enard cells (Getling, 1998).

Approaches - The most common way to develop pattern formation behaviors in robot swarms is to use virtual physics-based design. Virtual physics-based design uses virtual forces to coordinate the movements of robots.

Results - Bah¸ceci et al. (2003) presented a review of works on pattern formation in which they analyzed centralized and decentralized behaviors. Another review on the topic has been published in 2009 by Varghese and McKee. Flocchini et al. (2008) focused on a theoretical analysis of pattern formation. The authors were able to formally prove that with a group of fully asynchronous robots it is possible to obtain only a subset of all possible patterns, whereas other patterns are achievable only with some kind of global knowledge such as a common orientation given by a compass.

(C) Chain formation

Description - In the chain formation behaviour, robots have to position themselves in order to connect two points. The chain that they form can then be used as a guide for navigation or for surveillance.

Source of inspiration - The chain formation behaviour takes its inspiration from foraging ants. Deneubourg et al. (1990) studied and modelled the behaviour of Argentine ants which form chains of individuals connecting their nest with foraging areas.

Results - Nouyan et al. (2008) developed a behaviour, based on PFSMs, in which the robots have two different exchangeable roles: explorer and chain member. In the explorer role, the robots are searching for chain members or for the goal area. When they find either a chain member or the goal, they switch to the chain member role and stop. Chain members can become explorer again according to a probability that increases over time if no other robots are perceived. Different configurations and approaches are analyzed and presented. Experiments with real robots and further analysis can be found in Nouyan (2008).

Sperati et al. (2010) used artificial evolution to obtain a chain formation behaviour. In their work, the robots, by using communication through colored LEDs, are able to

(D) Self-assembly and morphogenesis

Description - In robotics, self-assembly is the process by which robots physically connect to each other. Self-assembly is used by a swarm of robots to create structures, sometimes called morphologies, which can be used for different purposes. Examples of such purposes are: to increase stability when navigating in rough terrains and to increase the pulling power of the robots. Morphogenesis focuses on how to obtain structures of physically connected robots.

Source of inspiration - Morphogenesis can be observed in several species of ants. Ants are able to physically connect in order to perform different tasks. Some examples of structures created by ants are bridges, rafts and walls (Anderson et al., 2002).

Approaches - From the swarm robotics perspective, self-assembly and morphogenesis pose two main challenges: how to assemble and generate the desired target structure, and how to control it to tackle specific tasks. Works focusing on the first issue are usually based on probabilistic finite state machines and rely on communication

for coordination. A recent review of the literature on morphogenesis was conducted by Groß and Dorigo (2008b).Work focusing on the second issue, control, makes use either of artificial evolution or of probabilistic finite state machines.

Results - Results on the functional aspect of self-assembly depend strongly on the goal of the system considered. O'Grady et al. (2010) demonstrated that physically connected robots can navigate through difficult terrains better than robots that are not connected. In O'Grady et al.'s work, robots randomly explore an environment

with slopes. Each robot is able to measure the steepness of these slopes and when a slope is steeper than a certain threshold, it can initiate a self-assembling procedure. Once connected into a structure, the robots can navigate in hazardous terrains thanks to the high mechanical stability given by the new morphology. Mondada et al. (2005) showed that physically connected robots are able to cross a ditch that is too large for a single robot to overcome. Finally Groß and Dorigo (2009) showed that physically connected robots are able to obtain better results, in terms of speed and distance, in the transportation of heavy objects when compared to non-connected robots.

(E) Navigation behaviours

- In this section, we describe collective behaviours that cope with the problem of coordinating the movements of a swarm of robots. Collective exploration is a collective behaviour in which robots cooperate to explore an environment and perform navigation. The coordinated motion behaviour is used to make robots move together like a flock of birds or a school of fish.

Description - In this section, we analyze two collective behaviours that, together, can be used to achieve collective exploration of an environment: area coverage and swarm-guided navigation. The goal of area coverage is to deploy robots in an environment in order to create a regular or irregular grid of communicating robots.

Source of inspiration - Area coverage and navigation are common behaviours of social animals. For example, ants use pheromones trails to find the shortest route between two points and bees directly communicate destinations in the environment by means of dances (Camazine et al., 2001). Area coverage has been intensively studied also by the wireless sensor networks (WSN) community. A survey of area coverage behaviours in WSN was conducted by Wang et al. (2009).

Approaches - In swarm robotics, the most common way to tackle area coverage is to use virtual physics-based design to obtain a grid covering the environment. Works on swarm-guided navigation instead focus on communication, thus usually employ probabilistic finite state machines and take inspiration either from network routing protocols or natural systems.

Results - Payton et al. (2001) used robots as "virtual pheromones". Some robots, which are already deployed, are able to create a gradient between the source and the target by exchanging messages. This gradient can then be exploited for navigation by other robots or by a human.

Di Caro et al. (2009) presented a work in which robots are able to navigate from a source to a target location. The proposed behavior is based on communication with other passive robots already available in the environment. These passive robots are assumed busy with other collective behaviours but are able to guide the navigating robots.

Stirling and Floreano (2010) used a swarm of flying robots to achieve area coverage. In their work, the robots are deployed sequentially and each robot determines its position according to the position of the previously deployed robots.

(F) Coordinated motion

Description - In coordinated motion, also known as flocking, robots move in formation similarly to schools of fish or flocks of birds. For a group of autonomous robots, coordinated motion can be very useful as a way to navigate in an environment with limited or no collisions between robots and as a way to improve the sensing abilities of the swarm (Kaminka et al., 2008).

Source of inspiration - Collective motion behaviours are frequent in almost all social animals. In particular, flocking in group of birds or schooling in group of fish are impressive examples of self-organized collective motion (Okubo, 1986). Through coordinated motion, animals gain several advantages, such as a higher survival rate, more precise navigation and reduced energy consumption (Parrish et al.,2002).

Approaches - In swarm robotics, collective motion behaviours are usually based on virtual physics-based design. Robots are supposed to keep a constant distance from one another and an uniform alignment while moving (Reynolds, 1987). Collective motion behaviours have also been obtained via artificial evolution.

Results - C¸ elikkanat and S¸ahin (2010), extending the work of Turgut et al. (2008a), showed that it is possible to insert some "informed" robots in the swarm in order to direct the movement of other "non-informed" robots. The informed robots are the only ones in the group with knowledge of the goal direction. Increasing the number of informed robots or decreasing the individual tendency to follow other robots increase the accuracy of motion of the group with respect to the desired goal direction. These works have been extended by Ferrante et al. (2010b) who developed alternative communication strategies in which some robots explicitly communicate their headings.

(G) Collective transport

Description - Collective transport, also known as group prey retrieval, is a collective behaviour in which a group of robots has to cooperate in order to transport an object. In general, the object is heavy and cannot be moved by a single robot, making cooperation necessary. The robots need to agree on a common direction in order to effectively move the object towards a target.

Source of inspiration - Ants often carry prey cooperatively. Kube and Bonabeau (2000) analyzed how cooperative transport is achieved in ant colonies. When ants find their target, they physically attach to it and then start to pull and push. If they do not perceive any movement after a while, they change the orientation of their body and try again. If even this does not work, they detach, re-attach at a different point and try again.

Approaches - In swarm robotics, collective transport behaviours are obtained by using probabilistic finite state machines or artificial evolution. Cooperation is obtained either through explicit communication of the desired motion direction, or through indirect communication, that is, by measuring the force applied to the carried object by the other robots.

Results - Donald et al. (1997) proposed three behaviours based respectively on: force sensing, position sensing and orientation sensing. This work was one of the first works aimed at studying collective transport without a centralized controller and with limited communication.

Ferrante et al. (2010a) developed a collective transport behavior in which, through communication, a group of robots can agree on a common moving direction towards a goal by averaging the individual desired direction. The proposed solution is able to make robots move towards a common goal while avoiding obstacles. This work was developed for the Swarmanoid project (Dorigo et al., 2012).

(H) Collective decision-making

- Collective decision-making is a collective behaviour in which a swarm of robots collectively makes a decision. Collective decision-making deals with how robots influence each other when making choices. It can be used to answer two opposite needs: agreement and specialization. A typical example of agreement in swarm robotics systems is consensus achievement. The desired outcome of consensus achievement is that all the robots of the swarm eventually converge towards a single decision among the possible alternatives. A typical example of specialization, instead, is task allocation. The desired outcome of task allocation is that the robots of the swarm distribute themselves over the different possible tasks in order to maximize the performance of a system.

(I) Concensus achievement

Description - Consensus achievement is a collective behaviour used to allow a swarm of robots to reach consensus on one choice among different alternatives. The choice is usually the one that maximize the performance of the system. Consensus is generally difficult to achieve in swarm of robots due the fact that very often the best choice may change over time or may not be evident to the robots due to their limited sensing capabilities.

Source of inspiration - Consensus achievement is displayed in many insect species. For example, ants are able to decide between the shortest of two paths using pheromones (Camazine et al., 2001). Bees have mechanisms to collectively decide which is the best foraging area or which is the best nest location among several possibilities (Couzin et al., 2005). These mechanisms work even if not all the individuals in the swarm have an opinion on the best choice. Cockroaches also display consensus achievement behaviors when performing aggregation (Am´e et al.,2006).

Approaches - In swarm robotics, the approaches used for consensus achievement can be divided into two categories according to how communication is used. In the first category, direct communication is used: each robot is able to communicate its preferred choice or some related information. In the second category, instead, indirect communication is used: the decision is performed through some indirect clues, such as the density of the robot population.

Results - Garnier et al. (2005) studied consensus achievement in cockroaches by using a swarm of robots to replicate the experiment by Am´e et al. (2006). In their system, consensus achievement is obtained through indirect communication. The focus of this work is both on consensus achievement and aggregation.

Guti´errez et al. (2010) developed a strategy for consensus achievement through direct communication in a swarm of robots performing foraging. The robots are able to decide between two foraging areas. When two robots get close, they exchange their measured distances between the nest and the latest visited goal. Each robot performs an average of its measured distance with the one received from the other robots. In this way, the robots are able to agree on which area is the closest

to the nest and discard the other one even when the measured distances are noisy.

(J) Task allocation

Description - Task allocation is a collective behaviour in which robots distribute themselves over different tasks. The goal is to maximize the performance of the system by letting the robots dynamically choose which task to perform.

Source of inspiration - Task allocation can be observed in natural systems such as ant and bee colonies – e.g., Theraulaz et al. (1998). For example, in ant or bee colonies, part of the swarm can perform foraging while another part looks after the larvae. Task allocation is not fixed but can change over time.

Approaches - In swarm robotics, task allocation is mainly obtained through the use of probabilistic finite state machines. To promote specialization, the probabilities of selecting one of the available tasks are either different among the robots or they can change in response to task execution or messages from other robots. In swarm robotics, task allocation has been studied almost exclusively on robots performing foraging.

Results - Pini et al. (2011) considered a situation in which robots can choose between carrying a prey directly from the source to the nest and storing it in a dedicated two-sided structure called TAM (Brutschy et al., 2012). Stored prey can be collected by robots waiting on the other side of the structure and carried to the nest. By tuning the maximum waiting time, the authors were able to achieve task allocation, maximizing the throughput of the system.

Conclusion

Swarm robotics is a relatively new research area that takes its inspiration from swarm intelligence and robotics. It is the result of applying swarm intelligence techniques into multi-robotics.

Swarm robotics is an approach to collective robotics that has received a great deal of attention in recent years. Swarm robotics aims at developing systems that are robust, scalable and flexible. 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 behaviour? How to describe the swarm robotics system in a mathematical model which can predict the system behaviours 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?

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I had tried my best to present this information as clearly as possible using basic terms that I hope will be comprehended by the widest spectrum of researchers, analysts and students for further studies.
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