

7 Evolutionary Swarm Robotics: A Theoretical and Methodological Itinerary from Individual Neurocontrollers to Collective Behaviors

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7.1 Introduction

In the last decade, swarm robotics gathered much attention in the research community. By drawing inspiration from social insects and other self-organizing systems, it focuses on large robot groups featuring distributed control, adaptation, high robustness, and flexibility. Various reasons lay behind this interest in similar multi-robot systems. Above all, inspiration comes from the observation of social activities, which are based on concepts like division of labor, cooperation, and communication. If societies are organized in such a way in order to be more efficient, then robotic groups also could benefit from similar paradigms.

As Kube and Zhang (1993) have pointed out, “Constructing tools from a collection of individuals is not a novel endeavor for humankind. A chain is a collection of links, a rake a collection of tines, and a broom a collection of bristles. Sweeping the sidewalk would certainly be difficult with a single or even a few bristles. Thus there must exist tasks that are easier to accomplish using a collection of robots, rather than just one.”

A multi-robot approach can have many advantages over a single-robot system. First, a monolithic robot able to accomplish various tasks in varying environmental conditions is difficult to design. Moreover, the single-robot approach suffers from the problem that even small failures of the robotic unit may prevent the accomplishment of the whole task. On the contrary, a multi-robot approach can benefit from the parallelism of operation to be more efficient, from the versatility of its multiple, possibly heterogeneous units, and from the inherent redundancy in using multiple agents (Jones and Mataric 2006).

Swarm robotics pushes the cooperative approach to its extreme. It represents a theoretical and methodological approach to the design of “intelligent” multi-robot systems inspired by the efficiency and robustness observed in social insects in performing collective tasks (Bonabeau, Dorigo, and Theraulaz 1999). Collective motion in fish, birds, and mammals, as well as collective decisions, synchronization, and social differentiation are examples of collective responses observed in natural swarms (for some recent

reviews, see Camazine et al. 2001; Franks et al. 2002; Couzin and Krause 2003; Sumpter 2006; Couzin 2007).

In all these examples, the individual behavior is relatively simple, but the global system behavior presents complex features that result from the multiple interactions of the system components. Similarly, in a swarm robotics system, the complexity of the group behavior should not reside in the individual controller, but in the interactions among the individuals. Thus, the main challenge in designing a swarm robotics system is represented by the need to identify suitable interaction rules among the individual robots. In other words, the challenge is designing the individual control rules that can lead to the desired global behavior.

In the preceding perspective, self-organization is the mechanism that can explain how complex collective behaviors can be obtained in a swarm robotics system from simple individual rules. In this context, a complex collective behavior should be intended as some spatiotemporal organization in a system that is brought forth through the interactions among the system components. Not every collective behavior is self-organized, though (Camazine et al. 2001). The presence of a leader in the group, the presence of blueprints or recipes to be followed by the individual system components clashes with the concept of self-organization, at least at the level of description in which leader or blueprints are involved. Another condition in which a collective behavior cannot be considered self-organizing is when environmental cues or heterogeneities are exploited to support the group organization. For instance, animals that aggregate in a warm part of the environment following a temperature gradient do not self-organize. But animals that aggregate to stay warm, and therefore create and support a temperature gradient in the environment, do self-organize. In both cases, the observer may recognize the presence of some structure (the aggregate) that correlates with the presence of an environmental heterogeneity (the temperature gradient). However, the two examples are radically different from the organizational point of view. Similar natural examples can be easily given also for the presence of leader or blueprints, to show that not every collective behavior is self-organizing (Camazine et al. 2001). Both the leader and the blueprint can be recognized as the place where the behavioral complexity of the group is centralized. In other words, the complexity of the group behavior does not result from the multiple interactions among the individual behaviors. Rather, the group behavior results from a fixed pattern of interactions among the system components that is either decided beforehand (in the case of a blueprint) or is centrally or continuously re-planned, or both (in the case of a leader). In both cases, there is limited room for adaptiveness to unknown, unpredictable situations resulting from a highly dynamical environment, both physical and social.

The unpredictable nature of the (social) environment makes it difficult to predict in advance, and therefore design, the behavioral sequence and the pattern of

interactions that would lead to a certain group behavior. Moreover, “the adaptiveness of an autonomous multi-robot system is reduced if the circumstances an agent should take into account to make a decision concerning individual or collective behaviour are defined by a set of a priori assumptions” (Tuci et al. 2006b). This design problem can be bypassed by relying on evolutionary robotics (ER) techniques as an automatic methodology to synthesize the swarm behavior (Trianni, Nolfi, and Dorigo 2008). In past researches conducted within the SWARM-BOTS project, we experimented with different tasks and defined a methodology that proved viable for the synthesis of self-organizing systems.

We focused on two particular kinds of self-organizing systems: (1) systems that are able to achieve and maintain a certain organization, and (2) systems close to a bifurcation point, where robot-robot interactions and randomness lead to one or the other solution. In both cases, the problem is solved without placing any assumption on the kind of interaction pattern that would have been exploited to achieve a certain goal. Even more important, we have shown that determining a priori a certain form of interaction may result in worse performance with respect to an assumption-free setup.

We present the SWARM-BOTS project’s experience in section 7.2, and in section 7.3 we discuss in detail some examples of problems studied exploiting the ER approach. Then, in section 7.4 we speculate on the current limitations of the ER approach, and the future role of ER in the development of more complex behaviors and cognitive abilities for robotic swarms.

7.2 Swarm Robotics and the Swarm-bots

Even though research in swarm robotics is relatively novel, it is quickly developing thanks to the contribution of various pioneer studies (Kube and Zhang 1993; Beckers, Holland, and Deneubourg 1994; Holland and Melhuish 1999; Martinoli, Ijspeert, and Mondada 1999; Krieger, Billeter, and Keller 2000). The SWARM-BOTS project made a significant contribution to the field in the design and development of an innovative swarm robotics platform: the swarm-bot (Mondada, Floreano, and Gambardella 2004; Dorigo et al. 2004). A swarm-bot is defined as a self-assembling, self-organizing artifact formed by a number of independent robotic units, called s-bots. In the swarm-bot form, the s-bots become a single robotic system that can move and reconfigure. Physical connections between s-bots are essential for solving many collective tasks, such as the retrieval of a heavy object. Also, during navigation on rough terrain, physical links can serve as support when the swarm-bot has to pass over a hole wider than a single s-bot, or when it has to pass through a steep concave region.

However, for tasks such as searching for a goal location or tracing an optimal path to a goal, a swarm of s-bots can be more efficient. An s-bot is a small mobile autonomous robot with self-assembling capabilities, shown in figure 7.1. It weighs 700 g and

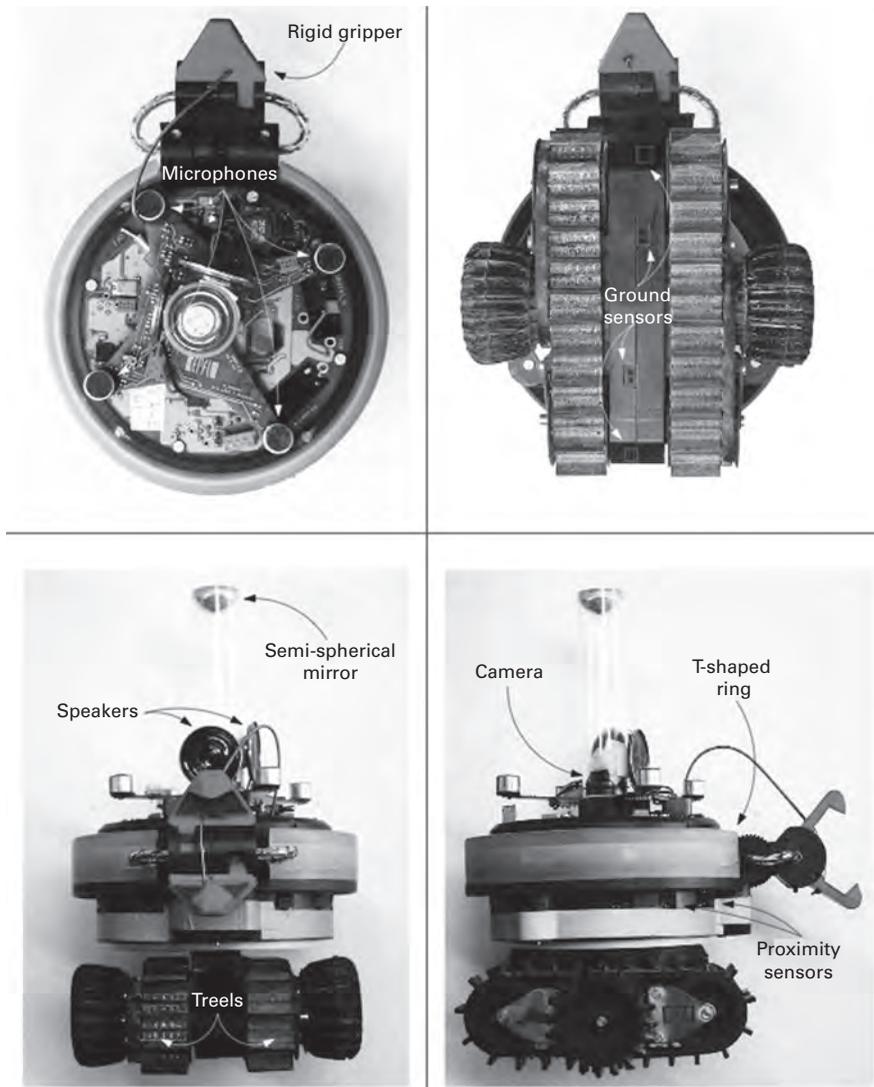


Figure 7.1

View of the s-bot from different sides. The main components are indicated (see text for more details).

its main body has a diameter of about 12 cm. Its design is innovative concerning both sensors and actuators. The traction system is composed of both tracks and wheels—referred to as “treels”—that provide the s-bot with a differential drive motion. The wheels are connected to the chassis, which contains the batteries, some sensors, and the corresponding electronics. The main body is a cylindrical turret mounted on the chassis by means of a motorized joint that allows the relative rotation of the two parts. The gripper is mounted on the turret and can be used for connecting rigidly to other s-bots or to some objects. The shape of the gripper closely matches the T-shaped ring placed around the s-bot’s turret, so that a firm connection can be established. The gripper not only opens and closes, but also has a degree of freedom for lifting the grasped objects. The corresponding motor is powerful enough to lift another s-bot.

An s-bot is provided with many sensory systems, useful for the perception of the surrounding environment or for proprioception. Infrared proximity sensors are distributed around the rotating turret. Four proximity sensors placed under the chassis—referred to as “ground sensors”—can be used for perceiving holes or the terrain’s roughness (see figure 7.1). Additionally, an s-bot is provided with eight light sensors uniformly distributed around the turret, two temperature/humidity sensors, a three-axis accelerometer and incremental encoders on each degree of freedom. Each robot is also equipped with sensors and devices to detect and communicate with other s-bots, such as an omni-directional camera, colored LEDs around the s-bots’ turret, microphones, and loudspeakers (see figure 7.1). Eight groups of three colored LEDs each—red, green, and blue—are mounted around the turret. They can be used to emit a color that can represent a particular internal state of the robot.

The color emitted by a robot can be detected by other s-bots using the omni-directional camera, which allows the robot to grab panoramic views of the scene surrounding an s-bot. The loudspeaker can be used to emit a sound signal, which can be perceived by the microphones and processed by the on-board CPU. In addition to a large number of sensors for perceiving the environment, several sensors provide each s-bot with information about physical contacts, efforts, and reactions at the interconnection joints with other s-bots. These include torque sensors on most joints as well as a traction sensor, which detects the direction and the intensity of the pulling force that the turret exerts on the chassis resulting from the forces applied by other connected s-bots.

7.3 Experiments

By exploiting the swarm-bot robotic platform, we performed a series of experiments, all characterized by a coherent methodological approach. First of all, evolution was always performed in a simulated environment, which was designed to model the relevant features of the s-bot. When required by the experimental setup, the simulation

exploited a full 3D physics simulation. This is the case for the experiments presented in section 7.3.1, in which pulling/pushing forces have a fundamental role in the swarm-bot behavior. Otherwise, we employed minimal simulations. In any case, the evolved controllers have been ported to reality to test the viability of the obtained controllers.

All evolutionary experiments share the same methodological approach. The algorithm is run for a fixed number of generations and works on a single population of genotypes. Each genotype encodes the parameters of a single neural network controller. During evolution, a genotype is mapped into a control structure that is cloned and downloaded in all the s-bots taking part in the experiment (i.e., we make use of a homogeneous group of s-bots). Each genotype is evaluated over multiple trials. The fitness of a genotype is the average performance computed over the trials in which the corresponding neural controller is tested. The homogeneous group resulting from a single genotype allows us to simplify the fitness assignment problem. In fact, a single controller is evaluated and selected for the group performance. This group selection also facilitates the evolution of cooperative strategies, given that there is no competition between different individuals in the group.

In the following sections 7.3.1–7.3.4, we present four different experiments performed within the SWARM-BOTS project exploiting the ER approach: coordinated motion and hole avoidance, synchronization, categorization, and self-assembly. In all four sections, we first introduce the scenario in which these experiments have been performed, we discuss the experimental setup, and finally we draw some conclusions about the lesson learned from the study.

7.3.1 Coordinated Motion and Hole Avoidance

The Scenario

For a swarm-bot to move coherently, s-bots need to negotiate a common direction of motion and maintain the group coordination against external disturbances. The coordinated motion of the assembled structure must take into account the variable number of assembled units, as well as a varying topology. Moreover, the swarm-bot's navigation must be efficient with respect to any obstacle and other hazards such as holes and rough terrain, which may be perceived only by a limited subset of the connected s-bots.

Coordinated motion has been widely studied in the literature (Balch and Arkin 1998; Fredslund and Mataric 2002; Quinn et al. 2003; Spector et al. 2005). However, in the swarm-bot case, it takes a different flavor, due to the physical connections among the s-bots, which open the way to study novel interaction modalities that can be exploited for coordination. The experimental scenario can be summarized as follows: at the beginning of a trial, the s-bots start with their chassis oriented in a random direction. Their goal is to choose a common direction of motion on the basis of only

the information provided by their traction sensor, and then to move as far as possible from the starting position (Baldassarre et al. 2007). In a different set of experiments, the experimental arena presents holes and open borders, in which a swarm-bot risks remaining trapped. In this case, s-bots must coordinate with the rest of the group to avoid falling (Trianni and Dorigo 2006). Notice that this task is more difficult than it might appear at first sight. First, the group is not driven by a centralized controller (i.e., the control is distributed). Moreover, s-bots cannot use any type of landmark in the environment, such as light sources, or exploit predefined hierarchies between them to coordinate (i.e., there is no “leader robot” that decides and communicates to the other robots the direction of motion of the whole group). Finally, the s-bots do not have a predefined trajectory to follow, nor they are aware of their relative positions or about the structure of the swarm-bot in which they are assembled. As a consequence, the common direction of motion of the group should result from a self-organizing process based on local interactions, which are shaped as traction forces. The problem of designing a controller capable of producing such a self-organized coordination is tackled using feed-forward neural networks synthesized by artificial evolution.

Results Obtained

As mentioned earlier, in order to move in a coordinated way s-bots can rely only on the traction sensor information, which provides a coarse indication of the average direction of motion of the group. By physically integrating the pulling/pushing forces that the connected s-bots produce, the traction sensor provides compact information that can be exploited for coordination. The problem is therefore designing a controller that would let the group self-organize by interacting through physical forces. The results obtained evolving coordinated motion are extremely interesting (Baldassarre et al. 2007). The evolved neural network encodes simple control rules that allow the robots to consistently achieve a common direction of motion in a very short time, and compensate possible misalignments during motion. In general terms, the evolved strategy is based on two feedback loops. Positive feedback makes robots match the average direction of motion of the group, as it is perceived through the traction sensor. Negative feedback makes robots persist in their own direction of motion, but when the traction and motion directions are opposite. Thus the positive feedback allows for a fast convergence toward a common direction of motion, which is stabilized by the negative feedback loop that avoids deadlock conditions.

All this is synthesized in a simple neural network evolved in simulation and tested on real robots (see figure 7.2). The performance of the evolved controllers in terms of robustness, adaptation to varying environmental conditions, and scalability to different number of robots and different topologies is striking, demonstrating how evolution

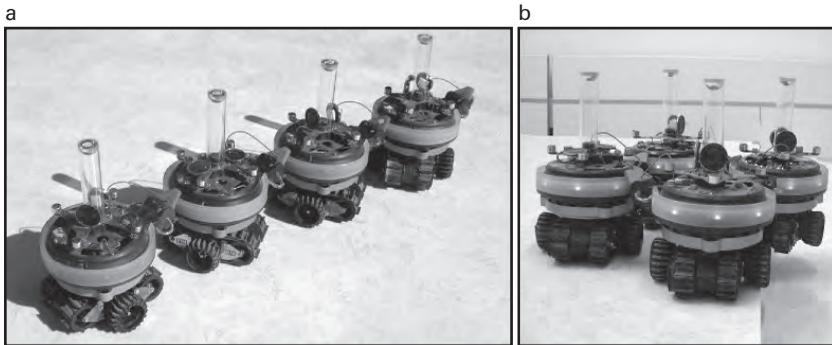


Figure 7.2

(a) Four real s-bots forming a linear swarm-bot during coordinated motion. (b) A physical swarm-bot while performing hole avoidance. Notice how physical connections among the s-bots can serve as support when a robot is suspended out of the arena, still allowing the whole system to work.

synthesized a very efficient self-organizing behavior for coordinated motion (Baldassarre et al. 2007).

Exploiting a similar setup, we also studied how a swarm-bot can navigate in an arena presenting holes or open borders in which the robots risk remaining trapped (Trianni and Dorigo 2006). In this case, we investigated how the swarm-bot can maintain coordination despite the presence of hazardous situations that are perceived only by a subset of the robots involved. To this purpose, some form of communication may be necessary to the group for a quick reaction. We tested three different communication modalities: (1) direct interactions (DI) through pulling/pushing forces, (2) direct communication (DC), handcrafted as a single-tone signal emitted as a reflex to the perception of the hazard, and (3) direct communication in which signaling was controlled by the evolved neural network (evolved communication, EC). In all cases, the s-bots' motion was controlled by a simple perceptron network similar to the one used for coordinated motion. Additionally, s-bots could use their sensors for perceiving the presence of holes in the ground. In the DC and EC setups, s-bots could also communicate with each other through sound signaling (Trianni and Dorigo 2006).

The results obtained show that it is possible to evolve efficient navigation strategies with each communication paradigm we devised. In the DI setup, when only direct interactions are present, the pulling/pushing forces are sufficient to trigger collective hole avoidance. However, in some cases the swarm-bot is not able to avoid falling because the signal encoded in the traction force produced by the s-bots that perceive the hazard may not be strong enough to trigger the reaction of the whole group. A different situation can be observed in the DC and EC setup, in which direct

communication allows a faster reaction of the whole group, as the emitted signal immediately reaches all the s-bots. Therefore, the use of direct communication among the s-bots is particularly beneficial in the case of hole avoidance. It is worth noting that direct communication acts here as a reinforcement of the direct interactions among the s-bots. In fact, s-bots react faster to the detection of the hole when they receive a sound signal, without waiting to perceive a traction strong enough to trigger the hole avoidance behavior. However, traction is still necessary for avoiding the hole and coordinating the motion of the swarm-bot as a whole.

We performed a statistical analysis to compare the three different setups we studied, and the results obtained showed that the completely evolved setup outperforms the setup in which direct communication is handcrafted. This result is in our eyes particularly significant, because it shows how artificial evolution can synthesize solutions that would be very hard to design with conventional approaches. In fact, the most effective solutions discovered by evolution exploit some interesting mechanisms for the inhibition of communication that would have been difficult to devise without any a priori knowledge of the system's dynamics (Trianni and Dorigo 2006).

The Lesson Learned

The experiments performed with coordinated motion and hole avoidance revealed how direct interactions through pulling/pushing forces can be exploited to obtain robust coordination strategies in a swarm-bot. The connections among s-bots in fact represent an important means of transferring information through physical forces. However, exploiting such information is not an easy endeavor if a precise model of the traction sensor is not available. In particular, with respect to the synthesis of self-organizing behaviors, the top-down approach runs into troubles due to the complex dynamical interactions among the system components that can hardly be predicted or modeled. The evolutionary approach, instead, does not need any precise model of the system. It is sufficient to test potential solutions and to compare their performance on the basis of a user-defined metric. With respect to handcrafted solutions, the evolutionary approach can achieve a better performance as it can better exploit all system features, without being constrained by a priori assumptions. This is clear in the hole avoidance experiments, which show how the handcrafted reflex signaling, which seemed perfectly reasonable at first sight, is outperformed by the evolved signaling strategy, which could exploit self-inhibitory mechanisms that are counterintuitive for a "naive" designer.

7.3.2 Synchronization

The Scenario

An important feature of a swarm robotics system is the coordination of the activities through time. Normally, robots can be involved in different tasks, and higher

efficiency may be achieved through the synchronization of the activities within the swarm. Synchrony is a pervasive phenomenon: examples of synchronous behaviors can be found in the inanimate world as well as among living organisms (Strogatz 2003). The synchronization behaviors observed in nature can be a powerful source of inspiration for the design of swarm robotic systems, where emphasis is given to the emergence of coherent group behaviors from simple individual rules. Much work takes inspiration from the self-organized behavior of fireflies or similar chorusing behaviors (Holland and Melhuish 1997; Wischmann et al. 2006; Christensen, O'Grady, and Dorigo 2009). Here, we present a study of self-organizing synchronization in a group of robots based on minimal behavioral and communication strategies (Trianni and Nolfi 2009). We follow the basic idea that if an individual displays a periodic behavior, it can synchronize with other (nearly) identical individuals by temporarily modifying its behavior in order to reduce the phase difference with the rest of the group. In this work, the period and the phase of the individual behavior are defined by the sensorimotor coordination of the robot, that is, by the dynamical interactions with the environment that result from the robot embodiment. The studied task requires that each robot in the group display a simple periodic behavior, which should be entrained with the periodic behavior of the other robots present in the arena. The individual periodic behavior consists in oscillations along the y-direction of a rectangular arena (see figure 7.3). Oscillations are possible through the exploitation of a symmetric gradient in shades of gray painted on the ground.

Synchronization of robots movements can be achieved by exploiting a binary, global communication: each robot can produce a continuous tone with fixed frequency and intensity. When a tone is emitted, it is perceived by every robot in the arena, including the signaling one. The tone is perceived in a binary way, that is, either there is someone signaling in the arena, or there is no one. This is a very minimal

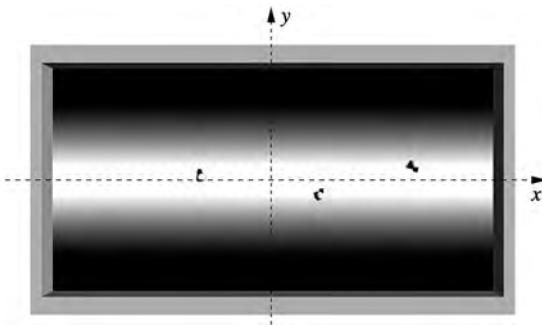


Figure 7.3

Snapshot of a simulation showing three robots in the experimental arena. The dashed lines indicate the reference frame used in the experiments.

communication system for a swarm of robots, which carries no information about the number of signalers, or about their position in the environment. No assumption is made on the way the robots should move on the arena, and on the way they should communicate. All the behavioral rules are designed by the evolution of feedforward neural controllers.

Results Obtained

We performed twenty evolutionary replications, each resulting in the evolution of efficient synchronization behaviors. The individual ability to perform oscillatory movements is based on the perception of the gradient painted on the arena floor, which gives information about the direction parallel to the y-axis and about the point where to perform a U-turn and move back toward the x-axis. The main role of the evolved communication strategy is to provide a coupling between the oscillating s-bots, in order to achieve synchronization: we observed that s-bots change their behavior in response to a perceived communication signal coming from other robots. Recall that the communication signal, being binary and global, does not carry information about either the sender or about its oscillation phase. The reaction to a perceived signal is therefore adapted by evolution to allow the robots to reduce the phase difference between their oscillations, eventually achieving synchronous movements. In summary, the evolved synchronization behaviors are the results of the dynamical relationship between the robot and the environment, modulated through the communicative interactions among robots. No further complexity is required at the level of the neural controller: simple and reactive behavioral and communication strategies are sufficient to implement effective synchronization mechanisms. To better understand the dynamical relationship between individual sensorimotor coordination and communication, we introduced a dynamical system model of the robots interacting with the environment and among each other (Trianni and Nolfi 2009).

This model offers us the possibility to deeply understand the evolved behaviors, both at the individual and collective level, by uncovering the mechanisms that artificial evolution synthesized to maximize the user-defined utility function. We assumed an idealized, noise-free and collision-free environment, and we modeled the s-bot individual behavior as it is produced by the evolved neural network. By coupling the individual behaviors through the communication channel, we could study the effects of perturbations through sound signals over the robot oscillations. We analyzed the different evolutionary runs performed, and we discovered two alternative mechanisms for synchronization. With the modulation mechanism, s-bots synchronize by tuning their oscillatory frequency in response to the perceived communication signal coming from other robots, in order to match the other robots' oscillations. They do so basically by anticipating or delaying the U-turn. With the reset mechanism, s-bots "reset" their oscillation phase by moving to a particular position over the painted

gradient, waiting for the other robots to reach a similar position. Qualitatively, similar mechanisms are also observed in biological oscillators. For instance, different species of fireflies present different synchronization mechanisms, based on delayed or advanced phase responses.

Besides studying the synchronization mechanisms, we performed a scalability analysis to test all evolved behaviors with varying group sizes. While scalability is ensured for small groups, we found that physical interactions may prevent the system from scaling to very large number of robots due to the higher probability of performing collision-avoidance maneuvers. Still, the evolved synchronization mechanism scales well if there are no physical interactions. We found that many controllers present perfect scalability, with only a slight decrease in performance due to the longer time required by larger groups to perfectly synchronize. Some controllers, however, present a communicative interference that prevents large groups from synchronizing: the signals emitted by different s-bots overlap in time and are perceived as a fixed signaling pattern. If the perceived signal does not vary in time, it does not bring information to be exploited for synchronization. This problem is mainly due to the global and binary communication form, in which the signal emitted by an s-bot is perceived by any other s-bot anywhere in the arena. Moreover, from the perception point of view, there is no difference between a single s-bot and a thousand signaling at the same time. In order to understand the conditions under which this communicative interference takes place, we again exploited the mathematical model. We found that scalability can be predicted just by looking at the features of the individual behavior: the synchronization behavior scales to any number of robots provided that an s-bot that perceives a communication signal never emits a signal itself. This is a very interesting result, as it directly relates the collective behavior to the individual one, and indicates which are the building blocks for obtaining scalability in the system under study (Trianni and Nolfi 2009).

The Lesson Learned

The synchronization experiments show how temporal coordination can be achieved exploiting simple self-organizing rules. To this purpose, it is not necessary to provide robots with complex behaviors and time-dependent structures. Instead, we show that a minimal complexity of the behavioral and communicative repertoire is sufficient to observe the onset of synchronization. Robots can be described as embodied oscillators, their behavior being characterized by a period and a phase. In this perspective, the movements of an s-bot correspond to advancements of its oscillation phase. Robots can modulate their oscillations simply by moving in the environment and by modifying their dynamical relationship with it. Such modulations are brought forth in response to the perceived communication signals, which also depend on the dynamical relationship between the s-bot and the environment.

In this perspective, the dynamical system analysis proved very useful: we introduced a dynamical system model of the robots interacting with the environment and each other. This model offered us the possibility to deeply understand the evolved behaviors, both at the individual and collective level, by uncovering the mechanisms that artificial evolution synthesized to maximize the user-defined utility function. Moreover, the developed model can be used to predict the ability of the evolved behavior to efficiently scale with the group size. We believe that such predictions are of fundamental importance to quickly select or discard obtained solutions without performing a time-demanding scalability analysis, as well as to engineer swarm robotic systems that present the desired properties. For instance, the knowledge acquired through the performed analysis could be exploited to improve the experimental setup. We have found that the communicative interferences that prevent the group from synchronizing are caused by a communication channel that is neither additive nor local. The locality of communication certainly is an important issue to take into account when studying a realistic experimental setup. Additivity, that is, the capability of perceiving the influence of multiple signals at the same time, is also crucial for self-organizing behaviors. We tested the latter issue, and we discovered that it is sufficient to provide the robots with the average signaling activity of the group to systematically evolve scalable behaviors (Trianni and Nolfi 2011).

7.3.3 Categorization, Integration over Time, and Collective Decisions

The Scenario

A general problem common to biology and robotics concerns the understanding of the mechanisms necessary to decide whether to pursue a particular activity or to give up and perform alternative behaviors. This problem is common to many activities that natural or artificial agents are required to carry out. Autonomous agents may be asked to change their behavior in response to the information gained through repeated interactions with their environment. For example, after various unsuccessful attempts to retrieve a heavy prey, an ant may decide to give up and change its behavior by either cutting the prey or recruiting some nest-mates for collective transport (Detrain and Deneubourg 1997). This example suggests that autonomous agents require adaptive mechanisms to decide whether it is better to pursue solitary actions or to initiate cooperative strategies.

We confronted with the decision-making problem by designing the experimental scenario depicted in figure 7.4. Robots are positioned within a boundless arena containing a light source. Their goal is to reach a target area around the light sources. The color of the arena floor is white except for a circular band around the lamp, within which the floor is in shades of gray. The robots can freely move within the band, but they are not allowed to cross the black edge. The latter can be imagined as an obstacle or a trough that prevents the robot from further approaching the light. The goal of

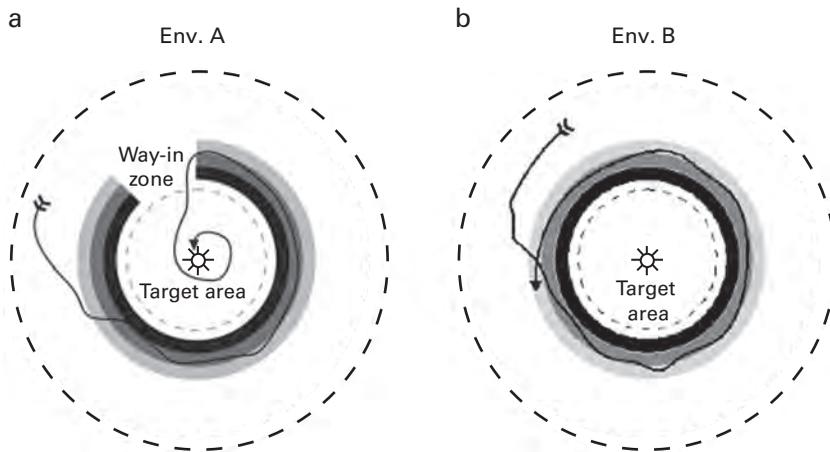


Figure 7.4

Depiction of the task. (a) Env. A is characterized by the way in zone. The target area, centered on the light, is indicated by the dashed circle. (b) In Env. B there is no way in zone and the target area cannot be reached. The continuous lines are an example of a good navigation strategy for one robot.

the experiments is to show that the robots can learn to discriminate between two types of environments. In the first type—referred to as Env. A—the band presents a discontinuity (see figure 7.4a). This discontinuity, referred to as the “way in zone,” is a sector of the band in which the floor is white. In the second type—referred to as Env. B—the band completely surrounds the light (see figure 7.4b). The way in zone represents the path along which the robots are allowed to safely reach the light in Env. A. Successful robots should prove capable of performing phototaxis and of moving over the circular band in search for the way in zone, without crossing the black edge. When placed in Env. A, the robots should always reach the target area. When placed in Env. B, on the contrary, the robot should initiate an alternative action, such as signaling or moving away in order to search for other light sources.

Initial experimentation was performed using a single robot controlled by an evolved continuous-time recurrent neural network (CTRNN) (Beer 1995). The results revealed that decision making could be performed by exploiting a temporal cue: the Env. B can be “recognized” by the persistence of a particular perceptual state for the amount of time necessary to discover that there is no way in zone. The flow of time, in turns, can be recognized through the integration of the perceptual information available to the robot. This means that the movements of the robot should bring forth the persistence of a certain perceptual condition, and the discrimination can be made only if the latter is maintained long enough.

We repeated the experiments using two robots having the same sensorimotor capabilities (Ampatzis et al. 2008). Additionally, robots are provided with a communication system similar to the one used in the synchronization experiments: they can emit a single frequency tone that is perceived everywhere in the arena in a binary way. The experiments have been performed by varying the initial position of the two robots, and by rewarding them when they perform antiphototaxis when placed in Env. B. However, no explicit reward was given for communication among the robots. In this way, we aimed at observing whether cooperative communicative behavior could emerge or not.

Results Obtained

Twenty evolutionary simulation runs, each using a different random initialization, were performed for 12,000 generations. Thirteen evolutionary runs produced successful groups of robots: both robots approach the band and subsequently (1) reach the target area through the way in zone in Env. A; (2) leave the band performing antiphototaxis in Env. B. The discrimination between the two environments is possible by exploiting the integration over time and the ability of the leaky integrators that form the robot's neural controller. While moving over the circular band, the s-bot accumulates evidence about the absence of the way in zone. If the latter is found, the integration over time is stopped and the robot continues performing phototaxis. If, instead, the way in zone is not present, after approximately one loop, the robot leaves the band. This evolved behavior closely resembles the one obtained with a single robot. However, a closer look reveals that among the thirteen successful groups, nine make use of sound signaling. In particular, signaling strongly characterizes the behavioral strategies of the groups when they are located in Env. B. In Env. A signaling is, for all these groups, negligible.

Note that the emission of sound is not demanded in order to navigate toward the target and discriminate Env. A from Env. B. Indeed, the task and the fitness function do not require the robots to display signaling behavior. Mechanisms for phototaxis, antiphototaxis, and memory are sufficient for a robot to accomplish the task. In order to reveal the adaptive significance of sound signaling, further tests have been performed.

We looked at the behavior of the robots that emit sound during a successful trial in each type of environment. We recorded the behavior of the robots in both a normal condition and a condition in which the robots cannot hear each other's sounds.

In the normal condition we notice that as soon as one of the robots starts signaling, both robots initiate an antiphototactic movement. But when communication signals are blocked, we notice that each robot initiates antiphototaxis only at the time when it starts emitting its own sound. Sound signaling has therefore the function of stimulating antiphototaxis also for those robots that have not yet gathered enough evidence about the absence of the way in zone.

These results show that most successful strategies employ signaling behavior and communication among the members of the groups. However, communication was not explicitly rewarded: communicating and noncommunicating groups could in principle obtain equal fitness. This means that communication may have other functions that influence its adaptive significance. By looking at the behavior of all successful groups, we discovered that whenever signaling is functionally relevant, robots employ it in Env. B as a self-produced perceptual cue. This cue induces the emitter as well as the other robot of the group to change its behavior from light seeking to light avoiding.

This evidence constrains our investigation on the adaptive significance of sound signaling to two functions: on the one hand, sound is the means by which a robot emitter switches from phototaxis to antiphototaxis. We refer to this as the “solitary” function. On the other hand, sound is the means by which the robot emitter influences the behavior of the other robot. We refer to this as the “social” function. From the data we gathered, it appears that signaling is beneficial mainly because of its “social” function.

The selective advantage of signaling groups is given by the beneficial effects of communication with respect to a robust disambiguation of Env. A from Env. B. The task in fact requires one to find an optimal trade-off between speed and accuracy of the decision.

The beneficial effect of communication corresponds to robust individual decision making and faster group reaction, since signaler and hearer react at the same time. In fact, a robust individual decision requires longer time spent over the circular band to accumulate evidence of the absence of the way in zone, due to the environmental noise that influences the sensors and to the uncertainty of the action outcomes. In total, in those groups in which antiphototaxis is triggered by the perception of sound, a robot that by itself is not ready to make a decision concerning the nature of the environment can rely on the decision taken by the other robot of the group. In average, communication allows the group to accomplish the task earlier, and more reliably. In this way, signaling groups are better adapted to the “danger” of discrimination mistakes in Env. A than are nonsignaling groups, and thus “early” signaling seems to be an issue that has been taken care of by evolution. In fact, once signaling groups evolve, their signaling behavior is refined by categorizing the world later than in the case of nonsignaling groups. This happens in order to ensure that the chances of a potential disadvantage resulting from social behavior are minimized. In other words, the use of communication in a system can also affect aspects of the behavior not directly related to communication (i.e., the process of integration of inputs over time).

The Lesson Learned

The experiments presented in this section show how individual decision making and group behavior can be coevolved to obtain a robust and efficient system. The need to

perform a decision on the basis of information accumulated over time creates a natural trade-off between speed and accuracy. Each s-bot has to resolve a dilemma: to continue searching for the way in zone, or to leave for good? The solution, under normal evolutionary pressures, would be to tune the individual behavior to limit the time spent searching to the minimum. However, the introduction of other robots contemporaneously solving the same task, and the possibility of communication, changes the evolutionary dynamics. By exploiting the information gathered by other robots, it is possible to improve the accuracy of the group decision without reducing the decision speed. This is a relevant fact, which justifies the usage of a collective robotics setup even for those conditions in which it is not explicitly required. Additionally, the exploitation of communicative strategies allows each robot to spread acquired information to the group, and to share information retrieval duties among group members: in fact, as soon as communication is in place, the individual behavior can be refined to exploit the redundancy of the system to the maximum.

7.3.4 Self-assembly and Autonomous Role Allocation

The Scenario

Self-assembly is a ubiquitous process in nature. According to Whitesides and Grzybowski (2002), it is defined as “the autonomous organisation of components into patterns or structures without human intervention.” At the nano- or microscopic scale, the interaction among components is essentially stochastic and depends on their shape, structure, or chemical nature. Nature also provides many examples of self-assembly at the macroscopic scale, the most striking being animals forming collective structures by connecting to one another. Individuals of various ant, bee, and wasp species self-assemble and manage to build complex structures such as bivouacs and ladders (Anderson, Theraulaz, and Deneubourg 2002; Hölldobler and Wilson 1978).

As mentioned in section 7.1, the robotics community has been largely inspired from cooperative behavior in animal societies when designing controllers for groups of robots that have to accomplish a given task. In particular, self-assembly provides a novel form of cooperation in groups of robots. However, it is important to notice that some characteristics of the hardware may impose important constraints on the control of the modules of a self-assembling system. As argued by Tuci et al. (2006a), some hardware platforms consist of morphologically heterogeneous modules that can only play a predefined role in the assembly process. In others, the hardware design does not allow, for example, the assembly of more than two modules, or requires extremely precise alignment during the connection phase—that is, it requires a great accuracy. The swarm-bot platform, thanks to its sensors and actuators and its connection apparatus, does not severely constrain the design of control mechanisms for self-assembly. The lack of hardware constraints and the homogeneity of the robots require that self-assembly be achieved through a differentiation of roles, resulting in the definition of

an s-bot gripper (i.e., the robot that makes the action of gripping) and an s-bot gripee (i.e., the robot that is gripped). In work carried out within the SWARM-BOTS project by using control design techniques other than ER, the s-bot gripper/s-bot gripee differentiation was either predefined (Groß et al. 2006) or based on stochastic events and a complex communication protocol (O’Grady et al. 2005). Thanks to the use of ER we designed control strategies for real assembling robots that are not constrained by either morphological or behavioral heterogeneities introduced by the hardware and control method, respectively (see Ampatzis et al. 2009, for details). Instead of a priori defining the mechanisms leading to role allocation and self-assembly, ER allowed us to let behavioral heterogeneity emerge from the interaction among the system’s homogeneous components. Moreover, coordination and cooperation in self-assembly between physical robots is achieved without requiring explicit signaling of internal states, as assumed, for example, in Groß et al. 2006.

Self-assembly is studied in a scenario in which two s-bots are positioned in a boundless arena at a distance randomly generated in the interval [25 cm,30 cm], and with predefined initial orientations. The robots are required to approach each other and to physically assemble through the gripper. The agents perceive each other through their omni-directional camera mounted on the turret, which returns rough information about robot distance and orientation. We also make use of the optical barrier mounted on the gripper, which informs a robot about the presence of an object between the gripper claws. The agent controller is composed of a CTRNN, whose control parameters are evolved through a rank-based evolutionary algorithm.

Results Obtained

The results of this work prove that dynamical neural networks shaped by evolutionary computation techniques directly controlling the robots’ actuators can provide physical robots with all the required mechanisms to autonomously perform self-assembly. Owing to the ER approach, the assembly is initiated and regulated by perceptual cues that are brought forth by the homogeneous robots through their dynamical interactions. Moreover, in spite of the system being homogeneous, role allocation—in other words, who is the s-bot gripper and who is the s-bot gripee—is successfully accomplished by the robots through an autonomous negotiation phase between the two s-bots, as confirmed by our behavioral analyses (see figure 7.5). We observed that role allocation unfolds in time during the entire duration of a trial.

Whenever the two robots have different initial perceptions, the role that each s-bot assumes can be predicted knowing the combination of the initial relative orientations of the robots. In other words, the combination of relative orientations leads to a pattern of interactions among the robots with a predictable outcome, from the observer point of view. However, a robot has no such information. Perceiving the other robot at a specific distance and orientation does not inform a robot about the role it will

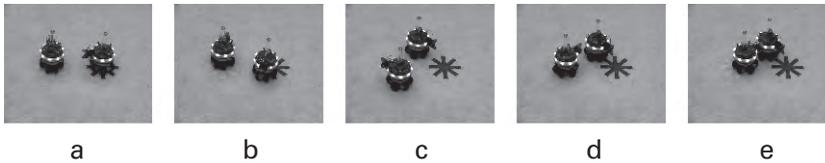


Figure 7.5

Snapshots from a successful trial: (a) initial configuration, (b) starting phase, (c) role allocation phase, (d) gripping phase, (e) success (grip).

assume at the end of the trial. In summary, whenever the initial orientations are asymmetrical, robots engage in a role negotiation phase, and the dynamical system composed of the two interacting robots almost always converges at the same final condition, which depends only on the initial conditions.

In those cases in which the robots start with an identical perception, symmetry does not hinder the robots from autonomously allocating different roles to successfully accomplish their goal. The robots engage in a dynamical interaction, which eventually leads to a role assignment. However, in this case it is not possible to predict the outcome of the role allocation process: both robots have 50 percent probability of assuming the s-bot gripper or the s-bot gripee role. Post-evaluation tests have shown that the random noise inherent in the system is the causal factor that drives the system through sequences of actions that turn out to be successful. In other words, the dynamical system composed by the two interacting robots starts from an unstable equilibrium point, from which it can converge at either stable condition, that is, at one of the two alternative role allocations. It is important to notice that the symmetry breaking is performed by exploiting randomness present in the system, which is amplified by the neural controllers as a result of the evolutionary optimization.

Finally, tests with real robots revealed that the evolved mechanisms proved to be robust with respect to changes in the color of the light displayed by the LEDs. Furthermore, the self-assembling robotic system designed by using ER techniques exhibits recovery capabilities that could not be observed during the artificial evolution and that were not coded or foreseen by the experimenter (Ampatzis et al. 2009). Such a feature in our case comes for free, while in the case of Groß et al.'s experiments (2006) a recovery mechanism had to be designed as a specific behavioral module to be activated every time the robots failed to achieve assembly.

The Lesson Learned

The main contribution of this work lies in the design of control strategies for real assembling robots that are not constrained by morphological or behavioral heterogeneities introduced by the hardware and control method, respectively. Contrary to the

modular or hand-coded controllers described by Groß et al. (2006) and O'Grady et al. (2005), the evolutionary robotics approach did not require the experimenter to make any a priori assumption concerning the roles of the robots during self-assembly (i.e., either s-bot gripper or s-bot gripee) or about their status (e.g., either capable of moving or required not to move). We showed with physical robots that coordination and cooperation in self-assembly do not require explicit signaling of internal states, as assumed, for example, by Groß et al. (2006). In other words, we present a setup that requires minimal cognitive and communicative capacities on behalf of the robots. The absence of a priori assumptions allows evolution to exploit the dynamical interaction among the robots to produce an autonomous role allocation mechanism. This can be considered an example of a self-organizing system close to a bifurcation point, in which the random fluctuations of the system are amplified to let the system overcome the impasse given by symmetric starting conditions and converge toward a desired solution.

7.4 Discussion

The experiments presented in section 7.3 are representative of a coherent theoretical and methodological approach to the synthesis of self-organizing behaviors for a swarm robotics system. What are the limits of this approach? The main problem to deal with is the evolvability of the system related to the scaling in complexity of the collective behavior. By practicing with evolutionary swarm robotics, it appears rather easy to evolve self-organizing behaviors in which the system achieves and maintains a certain spatiotemporal pattern. For instance, coordinated motion of the swarm-bot and synchronization are not particularly difficult to evolve (e.g., they require few generations, and successful controllers are almost always obtained), once a suitable experimental setup has been defined (see sections 7.3.1 and 7.3.2).

On the one hand, this is justified by the simplicity of the neural controller and the rather limited number of free parameters that need to be optimized by the evolutionary machinery. On the other hand, the quality of the interactions among the robots contains in itself part of the solution to the self-organization problem.

In the whole, simple controllers and well-defined interactions represent a perfect starting point for the evolution of self-organizing behavior. As a matter of fact, in similar conditions successful behaviors are systematically obtained in all evolutionary runs.

However, the situation is slightly different when evolution must produce self-organizing systems close to a bifurcation point, in which multiple solutions are possible as a result of the interactions, feedback loops, and randomness of the system. This is the case of the categorization experiment, in which robots had to take a collective decision (section 7.3.3), and of the self-assembly experiment, in which

complementary roles needed to emerge from the robot-robot interactions and the amplification of random fluctuations of the system (section 7.3.4). In similar conditions, evolvability is limited by the need to contemporaneously evolve different behavioral traits, and by the presence of multiple stable conditions, which create local optima in which evolution may remain trapped. In the experiments we performed, many generations were necessary to find a suitable solution. Also, the success rate was never close to 100 percent, and some evolutionary runs resulted in partial solutions of the problem. The evolution of communication raises a similar problem, requiring evolution of both the signal and the response to the signal, which individually may be counteradaptive or neutral with respect to the devised fitness function (see section 7.3.3).

The experiments presented in section 7.3.3 are interesting also from a different point of view, that is, the influence that the individual behavior has on the evolution of the group behavior. Here, we can distinguish between two organizational levels: (1) the individual level, in which sensorimotor coordination and integration over time support the decision making, and (2) the collective level, in which information spreading through communication leads to increased group efficiency. We believe that future directions in evolutionary swarm robotics should focus on systems characterized by multiple levels of organization. More complex self-organizing behaviors can be obtained through a layered evolution that proceeds through individual sensorimotor coordination, individual categorization abilities, and communication and exploitation of the social environment, aiming at some collective intelligence. As experienced in our experiments, each different level of organization is supported by the lower levels, and in turns influences their dynamics. In a swarm robotics scenario, the influences of the higher organizational level on the lower ones could be exploited to simplify the individual behavior in favor of more robust, collective solutions. Brought to the limit, each robot in the swarm could behave as a neuron-like device that can move in the environment and interact, physically or through communication, with neighboring robots, while the swarm brings forth complex processes as a whole. In this respect, we believe that the cognitive abilities of swarms should be studied and compared with those observed in the vertebrate brain, in the attempt to find the common mechanisms that underlie cognition. In this respect, robotics models of swarm behavior may represent extremely powerful tools for the study of swarm cognition (Trianni et al. 2011).

Another possible direction in the study of evolutionary swarm robotics concerns the exploitation of heterogeneous swarms, in which different types of robots are organized in swarms, which cooperate for a collective goal. We investigated swarms of heterogeneous robots within the project Swarmanoid,¹ in which three types of robots have been studied: eye-bots, foot-bots, and hand-bots. Eye-bots are robots specialized

in sensing and analyzing the environment from a high position to provide an overview that foot-bots or hand-bots cannot have. Eye-bots fly or are attached to the ceiling. Hand-bots are specialized in moving and acting in a space zone between the one covered by the foot-bots (the ground) and the one covered by the eye-bots (the ceiling). Hand-bots can climb vertical surfaces. Foot-bots are specialized in moving on rough terrain and transporting either objects or other robots. They are based on the s-bot platform, and extend it with novel functionalities. The combination of these three types of autonomous agents forms a heterogeneous swarm robotic system that is capable of operating in a 3D space.

Generally speaking, dealing with heterogeneity in a collective robotics setup often leads to specialization and teamwork: the task is broken down on the basis of the different robots available, and roles are assigned correspondingly. With heterogeneous swarms, the redundancy of the system opens the way to various scenarios. On one extreme, the classical scenario accounts for different swarms that specialize in particular subtasks, and are loosely coupled. For instance, a swarm of eye-bots is responsible of locating areas of particular interest, such as areas that contain objects to be retrieved. The eye-bots direct the action of a swarm of foot-bots, which collectively retrieve such objects. On the other extreme, robots can form a swarm of homogeneous entities, where each entity is a small, heterogeneous, tightly cooperating team. For instance, two or three foot-bots can self-assemble to transport a single hand-bot, thereby creating a small team, which can coordinate its activities within a swarm of similar foot-bot/hand-bot teams. Between these two extreme scenarios, there can be an infinite blend of possibilities for cooperating heterogeneous swarms. In this respect, ER can give a strong contribution to define the individual behaviors, and shape the self-organization of the heterogeneous swarm. In particular, ER can be exploited to define the behavior of the heterogeneous robots by evolving one controller for each robot type. An alternative, interesting scenario consists of synthesizing homogeneous controllers for heterogeneous robots, in which the controller adapts to the dynamics of the robot on which it is downloaded without a priori knowledge of its type. We performed preliminary studies by evolving controllers for a heterogeneous group of three simulated robots (Tuci et al. 2008). The agents are required to cooperate in order to avoid collisions when approaching a light source. The robots are morphologically different: two of them are equipped with infrared sensors, one with light sensors. Thus, the two morphologically identical robots should take care of obstacle avoidance, while the other one should take care of phototaxis. Since all the agents can emit and perceive sound, the group's coordination of actions is based on acoustic communication. The results of this study are a "proof-of-concept": they show that dynamic artificial neural networks can be successfully synthesized by artificial evolution to design the neural mechanisms required to underpin the behavioral strategies and adaptive communication capabilities demanded by this task. Thus, ER

represents a promising method that should be considered in future research works dealing with the design of homogeneous controllers for groups of heterogeneous cooperating and communicating robots.

In conclusion, based on the results obtained in past research and on the prospect of future achievements, we believe that the bidirectional influence arrow connecting ER and swarm robotics can be enforced in both directions. ER can offer swarm robotics a bias-free method to automatically obtain robust and sophisticated control structures that exploit aspects of the experimental setup not always evident a priori to the experimenter. Equally, swarm robotics can broaden the horizons of ER beyond the current limits. In our opinion, the swarm cognition approach and studies with heterogeneous swarms are two of the most promising directions.

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References

- Ampatzis, C., E. Tuci, V. Trianni, A. L. Christensen, and M. Dorigo. 2009. Evolving autonomous self-assembly in homogeneous robots. *Artificial Life* 15 (4): 465–484.
- Ampatzis, C., E. Tuci, V. Trianni, and M. Dorigo. 2008. Evolution of signaling in a multi-robot system: Categorization and communication. *Adaptive Behavior* 16 (1): 5–26.
- Anderson, C., G. Theraulaz, and J.-L. Deneubourg. 2002. Self-assemblages in insect societies. *Insectes Sociaux* 49 (2): 99–110.
- Balch, T., and R. C. Arkin. 1998. Behavior-based formation control for multirobot teams. *IEEE Transactions on Robotics and Automation* 14 (6):926–939.
- Baldassarre, G., V. Trianni, M. Bonani, F. Mondada, M. Dorigo, and S. Nolfi. 2007. Self-organised coordinated motion in groups of physically connected robots. *IEEE Transactions on Systems, Man, and Cybernetics. Part B, Cybernetics* 37 (1): 224–239.
- Beckers, R., O. E. Holland, and J.-L. Deneubourg. 1994. From local actions to global tasks: Stigmergy and collective robotics. In *Proceedings of the 4th International Workshop on the Synthesis and Simulation of Living Systems (Artificial Life IV)*, ed. R. A. Brooks and P. Maes, 181–189. Cambridge, MA: MIT Press.
- Beer, R. D. 1995. A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence* 72:173–215.
- Bonabeau, E., M. Dorigo, and G. Theraulaz. 1999. *Swarm Intelligence: From Natural to Artificial Systems*. New York: Oxford University Press.

- Camazine, S., J.-L. Deneubourg, N. Franks, J. Sneyd, G. Theraulaz, and E. Bonabeau. 2001. *Self-Organization in Biological Systems*. Princeton, NJ: Princeton University Press.
- Christensen, A. L., R. O'Grady, and M. Dorigo. 2009. From fireflies to fault-tolerant swarms of robots. *IEEE Transactions on Evolutionary Computation*, Special Issue on Swarm Intelligence 13 (4): 754–766.
- Couzin, I. D. 2007. Collective minds. *Nature* 455 (7129): 715–715.
- Couzin, I. D., and J. Krause. 2003. Self-organization and collective behavior of vertebrates. *Advances in the Study of Behavior* 32:1–75.
- Detrain, C., and J.-L. Deneubourg. 1997. Scavenging by *Pheidole pallidula*: A key for understanding decisionmaking systems in ants. *Animal Behaviour* 53:537–547.
- Dorigo, M., V. Trianni, E. S. Sahin, R. Groß, T. H. Labelle, G. Baldassarre, S. Nolfi, J.-L. Deneubourg, F. Mondada, D. Floreano, and L. M. Gambardella. 2004. Evolving self-organizing behaviors for a swarm-bot. *Autonomous Robots* 17 (2–3): 223–245.
- Franks, N. R., S. C. Pratt, E. B. Mallon, N. F. Britton, and D. J. T. Sumpter. 2002. Information flow, opinion polling and collective intelligence in house-hunting social insects. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 357 (1427): 1567–1583.
- Fredslund, J., and M. J. Matarić. 2002. A general algorithm for robot formations using local sensing and minimal communication. *IEEE Transactions on Robotics and Automation* 18 (5): 837–846.
- Groß, R., M. Bonani, F. Mondada, and M. Dorigo. 2006. Autonomous self-assembly in swarm-bots. *IEEE Transactions on Robotics* 22 (6): 1115–1130.
- Holland, O., and C. Melhuish. 1997. An interactive method for controlling group size in multiple mobile robot systems. In *Proceedings of the 8th International Conference on Advanced Robotics (ICAR '97)*, 201–206. Piscataway, NJ: IEEE Press.
- Holland, O., and C. Melhuish. 1999. Stigmergy, self-organization, and sorting in collective robotics. *Artificial Life* 5 (2): 173–202.
- Hölldobler, B., and E. O. Wilson. 1978. The multiple recruitment systems of the African weaver ant, *Ecophylla longinoda* (latreille) (hymenoptera: formicidae). *Behavioral Ecology and Sociobiology* 3:19–60.
- Jones, C. V., and M. J. Matarić. 2006. Behavior-based coordination in multi-robot systems. In *Autonomous Mobile Robots: Sensing, Control, Decision-Making, and Applications*, ed. S. S. Ge and F. L. Lewis, 549–569. Boca Raton, FL: CRC Press.
- Krieger, M. J. B., J.-B. Billeter, and L. Keller. 2000. Ant-like task allocation and recruitment in cooperative robots. *Nature* 406:992–995.
- Kube, C. R., and H. Zhang. 1993. Collective robotics: From social insects to robots. *Adaptive Behavior* 2 (2): 189–219.

Martinoli, A., A. J. Ijspeert, and F. Mondada. 1999. Understanding collective aggregation mechanisms: From probabilistic modeling to experiments with real robots. *Robotics and Autonomous Systems* 29:51–63.

Mondada, F., G. C. Pettinaro, A. Guignard, I. V. Kwee, D. Floreano, J.-L. Deneubourg, S. Nolfi, L. M. Gambardella, and M. Dorigo. 2004. SWARM-BOT: A new distributed robotic concept. *Autonomous Robots* 17 (2–3): 193–221.

O’Grady, R., R. Grofl, F. Mondada, M. Bonani, and M. Dorigo. 2005. Self-assembly on demand in a group of physical autonomous mobile robots navigating rough terrain. In *Proceedings of the 8th European Conference on Artificial Life (ECAL’05)*, LNCS 3630, 272–281. Berlin: Springer-Verlag.

Quinn, M., L. Smith, G. Mayley, and P. Husbands. 2003. Evolving controllers for a homogeneous system of physical robots: Structured cooperation with minimal sensors. *Philosophical Transactions of the Royal Society of London, Series A: Mathematical, Physical and Engineering Sciences* 361 (1811): 2321–2343.

Spector, L., J. Klein, C. Perry, and M. Feinstein. 2005. Emergence of collective behavior in evolving populations of flying agents. *Genetic Programming and Evolvable Machines* 6 (1): 111–125.

Strogatz, S. H. 2003. *Sync: The Emerging Science of Spontaneous Order*. New York: Hyperion Press.

Sumpter, D. J. T. 2006. The principles of collective animal behaviour. *Philosophical Transactions of the Royal Society of London: Series B* 361:5–22.

Trianni, V., and M. Dorigo. 2006. Self-organisation and communication in groups of simulated and physical robots. *Biological Cybernetics* 95:213–231.

Trianni, V., and S. Nolfi. 2009. Self-organising sync in a robotic swarm: A dynamical system view. *IEEE Transactions on Evolutionary Computation*, Special Issue on Swarm Intelligence 13 (4): 722–741.

Trianni, V., and S. Nolfi. 2011. Engineering the evolution of self-organising behaviours in swarm robotics: A case study. *Artificial Life* 17 (3): 183–202.

Trianni, V., S. Nolfi, and M. Dorigo. 2008. Evolution, self-organisation and swarm robotics. In *Swarm Intelligence. Introduction and Applications, Natural Computing Series*, ed. C. Blum and D. Merkle, 163–192. Berlin, Germany: Springer-Verlag.

Trianni, V., E. Tuci, K. M. Passino, and J. A. R. Marshall. 2011. Swarm cognition: An interdisciplinary approach to the study of self-organising biological collectives. *Swarm Intelligence* 5 (1): 3–18.

Tuci, E., C. Ampatzis, F. Vicentini, and M. Dorigo. 2008. Evolving homogeneous neurocontrollers for a group of heterogeneous robots: Coordinated motion, cooperation, and acoustic communication. *Artificial Life* 14 (2): 157–178.

Tuci, E., R. Grofl, V. Trianni, M. Bonani, F. Mondada, and M. Dorigo. 2006a. Cooperation through self-assembling in multi-robot systems. *ACM Transactions on Autonomous and Adaptive Systems* 1 (2): 115–150.

Tuci, E., R. Grofl, V. Trianni, F. Mondada, M. Bonani, and M. Dorigo. 2006b. Cooperation through self assembling in multi-robot systems. *ACM Transactions on Autonomous and Adaptive Systems* 1 (2): 115–150.

Whitesides, G., and B. Grzybowski. 2002. Self-assembly at all scales. *Science* 295:2418–2421.

Wischmann, S., M. Huelse, J. F. Knabe, and F. Pasemann. 2006. Synchronization of internal neural rhythms in multi-robotic systems. *Adaptive Behavior* 14 (2): 117–127.