

5 Swarm Robotics

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5.1 Introduction

Swarm robotics is the study of how independent robots can interact as a group, giving rise to collective behaviors that a single such robot could not achieve on its own (Dorigo et al. 2014; see figure 5.1). The field can be considered an application of swarm intelligence, as defined by Bonabeau et al. (1999), and its approaches to robot control are typically based on principles of self-organization (Hamann 2018b). Swarm robotics is studied in pursuit of the oft-cited benefits that distributed or self-organized control can provide, in particular: robustness, flexibility, and scalability.

5.1.1 What Is a Swarm?

A swarm is a system of agents, whether natural or artificial, in which the characterizing behaviors occur at the group level rather than the individual level. An agent (e.g., a particle, insect, person, or robot), as defined by Russell and Norvig (2016), is “just something that acts,” and typically, it acts autonomously. Though systems of agents may show swarm behaviors that vary considerably, these behaviors are unified by their characteristic level of organization.

Swarm behaviors are not organized by a central entity that dictates instructions to individuals and likewise are not directly organized by the individuals themselves. Rather, swarm behaviors arise from the complex nonlinear dynamics of local interactions occurring in a distributed and decentralized system. Such dynamics are studied in many fields (cf. Bar-Yam 1997), being both observed in natural systems and developed in artificial ones. In nonliving systems studied in physics, self-organization can, for instance, be observed in Rayleigh-Bénard convection—wherein heating a fluid layer from below induces the formation of regular cellular patterns—or in self-organized criticality, which is seen, for example, in the power-law probability distribution of avalanche sizes. Swarm behaviors are notably widespread in biology—for instance, in social organisms. They include mobility behaviors such as flocking birds or marching locusts and spatial manipulation behaviors such as foraging in ants and honeybees or construction in termites and wasps. Artificial swarm behaviors have been studied for a broad range of tasks, including foraging (Pinciroli et al. 2012; see also the link in the additional resources section), object retrieval (Dorigo et al.



Figure 5.1

Example of a robot swarm consisting of the Kilobot. *Source:* From Rubenstein et al. 2012.

2013), and construction (Werfel et al. 2014), and recently have even been investigated for hybridization with natural systems (Hamann et al. 2017). Although real-world artificial swarms have rarely been deployed according to publicly available information, recent exceptions—in particular the NASA (2015) swarms of nanosatellites—suggest their application may become more common.

Because the behaviors that characterize a swarm occur at the group level, they can only be observed with a minimum of three agents, and many swarm behaviors will require far more. A precise definition of swarm size, as provided by Beni (2004), would be a system that is best represented as a multi-body problem, as it is respectively too large and too small for its dynamics to be well described as a few-body problem or by mean-field approximation.

5.1.2 Self-Organization and the Micro-Macro Link

Self-organization is the mechanism by which macroscale (i.e., global or systemwide) spatial and temporal structures can generate from microscale (i.e., local or peer-to-peer) interactions. In physical and biological systems, it can be observed in Rayleigh-Bénard convection, cell differentiation and embryogenesis, or pigmentation patterns in animals. In self-organizing systems, the macrostructures may generate from a combination of short-range and long-range interactions, as seen in reaction-diffusion models of biological activation-inhibition mechanisms (Meinhardt and Gierer 2000).

In swarm robotics, the link between micro- and macroscale occurs not directly but via self-organization. Actions of individual robots (i.e., microscale, or local) are typically primitive and involve a high degree of uncertainty, as they are informed only by limited knowledge and by short-range sensing and communication (see section 5.2). By contrast, collective actions of the robot swarm (i.e., macroscale, or global) are more sophisticated

and are capable of solving complex tasks. The macroscale is where development, testing, and analysis of swarm behaviors take place, while the implementation of robot controllers (i.e., executable code) occurs at the microscale. Therefore, in developing robot swarms, the desired global behaviors must be translated to local controllers, but due to the nonlinear dynamics of self-organization, this task is challenging. No generalized method has currently been developed to compile macro specifications into micro implementations, and the management of the “micro-macro link” is a key challenge in developing self-organized control (see section 5.3).

Self-organization, as defined by Bonabeau et al. (1999), functions via certain features that must be present in the system. These features are positive and negative feedback, fluctuations (i.e., random events), and multiple microscale interactions. Multiple interactions are an evident requirement, as self-organized behaviors arise from them. Positive and negative feedback are necessary to modulate deviations in the system and work in tandem to steer a robot swarm toward equilibrium or consensus. Positive feedback on its own will continuously reinforce a trend that may be based on a minor random deviation and, in all cases, will eventually surpass the desired target, creating what we might call a snowball effect or bubble. The incorporation of negative feedback is crucial to damp overshoots and tempers the impact of random deviations. Fluctuations are manageable in a swarm because of positive and negative feedback, but they are also a necessary feature, as they enable a balance between exploration and exploitation. Exploration allows a swarm to search for desired targets, while exploitation allows it to remain at those targets once they are found; a balance of these two tendencies stops a swarm from getting “stuck.” For instance, if positive feedback in a robot swarm steers it to exploit a reasonably good solution, fluctuations will be crucial for the swarm to escape that local optimum and find a better one. Likewise, if a swarm has found the best solution for a current environment, fluctuations allow it to adapt to future environmental changes by discovering that a different solution has since become superior.

5.1.3 Cognitive and Bioinspired Machine Behavior

Artificial swarms were originally heavily inspired by processes observed in biology. For instance, the dynamics governing flocks of birds, herds of mammals, and schools of fish were the inspiration behind the Reynolds (1987) model for multiagent computer graphics. Another key biological inspiration has been *stigmergy*, as seen, for instance, in ant colonies (Bonabeau et al. 1999). Stigmergy is a class of mechanisms whereby social insects do not communicate directly but rather communicate by modifying their environment in response to its current configuration, inducing nonlinear cascades of behaviors and environmental changes. In cognitive science, key perspectives such as that of Couzin (2009) consider natural stigmergy to be a cognitive mechanism. It is often considered a model of group cognition not only for insects but also for other domains such as social systems, and it can operate with many types of environmental features. In ant colonies foraging for food, for instance, the environmental cues involved in stigmergy are pheromone trails left collectively by the ants. Stigmergy has inspired the artificial swarm metaheuristic of “ant colony optimization” (Dorigo and Di Caro 1999), along with many swarm robotics approaches such as termite-inspired construction in response to the observed shape of a climbable structure (Werfel et al. 2014).

Cognitive sources of bioinspiration are common in swarm robotics and self-organized control. Slime mold, a type of amoeboid organism that spatially navigates via the self-organization of thousands of cells, does not have internal memory. It instead uses a form of spatial, external memory to steer its exploration. Slime molds have been used as models for optimization and self-organization generally. What may be considered minimal cognition in plants has in part inspired self-organized grammars such as Lindenmayer systems. The distributed steering of plant morphology in response to stimuli has inspired a “vascular morphogenesis controller” used for adaptation in robot swarm aggregation (Divband Soorati et al. 2019). In social insects, collective behaviors other than stigmergy have also been studied, such as thermoregulatory behaviors in honeybees, which have inspired “Beeclust” (Schmickl and Hamann 2011) control for robot swarm aggregation. Further inspiration may come from human social and economic systems, which are increasingly considered a form of swarm intelligence and often involve social cognition. Models used for social systems are also implemented in robots—for example, the voter model, used on online social networks, is often used for decision-making in a robot swarm (e.g., Valentini et al. 2014). Further cognitive sources of bioinspiration are discussed in sections 1.5 and 1.6.3, as emerging perspectives consider swarms a “liquid brain” class of cognition (Piñero and Solé 2019) or, alternatively, renew their consideration as a “superorganism” to which psychology models and theories can be applied (Reina et al. 2018).

5.1.4 Scalability

Changing a system’s size can cause problems. A system that is too large may have low performance due to bottlenecks, while a system that is too small may have low performance due to limited opportunities for collaboration between entities. Parallel computing defines speedup as $S = T_1/T_N$, where T_1 is the time one has to wait for the result of computation using one CPU, and T_N is the time for the same computation using N CPUs. In a presumably ideal case, one achieves linear speedups of $S = N$; a doubled system size results in doubled performance. A multirobot system is scalable if the same control algorithm can be used for both large and small numbers of robots while obtaining reasonable speedups (Hamann 2018b). Although any nontrivial multirobot scenario requires some coordination among the robots (see section 5.2), coordination can be avoided by preassigning areas of operation to each robot. This way, a multirobot scenario is effectively broken down into multiple single-robot scenarios in the form of trivial parallelization. However, if we want to make the system robust against robot failures (see section 5.1.5), then each robot should check the operation areas of other robots to see whether they accomplish their respective tasks. This requires online coordination to administrate task allocation. Disallowing collaboration between robots would also exclude the possibility of generating superlinear speedups (cf. Hamann 2018a).

Swarm robotics research targets maximal scalability—that is, the possibility of scaling to virtually any system size. The necessary requirements to achieve this are a strictly decentralized approach and limited communication. All robots exclusively use local communication and local information. Instead of point-to-point communication across the whole swarm, robots are restricted to only communicate with neighbors (“narrowcast”). If the robot density $\rho = N/A$ (number of robots N per area A) is constant, then the neighborhood size is constant,

and scaling the system is a change in the number of robots N and the provided area A . Even if these requirements are satisfied, a robot swarm may still fail to scale perfectly due to limited shared resources (e.g., the entrance to a base station) or because the required information cannot be propagated through the swarm quickly enough (e.g., by diffusion). Conversely, an advantage is that speedups of $S > N$ can potentially be achieved when robots collaborate (Hamann 2018a), for example, to cross a gap or to manipulate objects.

5.1.5 Fault Tolerance

For any engineered system, but especially in robotics, it is challenging to prepare for failures and unanticipated changes in the environment. As a simple definition, fault tolerance is a system's ability to continue functioning despite the occurrence of faults and failures. Multi-robot systems have a supposedly higher degree of fault tolerance than a single robot due merely to the system's inherent redundancy; this applies even more to robot swarms. In swarm robotics, losing one or more robots is supposed to have a limited impact on performance. Because the system is decentralized, each robot relies on local information only, and all or many robots can take over the task of another robot. The high potential for fault tolerance in robot swarms is illustrated by comparing the vulnerability of single space probe missions to the concept of swarms of nanosatellites (NASA 2015). Winfield and Nembrini (2006) have shown that the potential for fault tolerance in robot swarms has possibly been overestimated and is not necessarily an inherent feature. Partial failures of robots may be harmful, and systemwide vulnerability to faults can occur, even in robot swarms.

In a study on fault tolerance and fault detection, Christensen et al. (2009) leverage multiple equivalent units, letting them monitor each other and detect anomalies. Features that have been defined to describe robot behaviors are first determined by each robot for its neighbors and used to detect faulty behavior. In a second step, the robots collectively determine whether a robot should be considered faulty and consequentially ignored. Faulty robots decrease swarm size, such that fault tolerance requires the swarm to adapt online to changes in size. Recently, Wahby et al. (2019) have proposed a mechanism that allows robots to continuously monitor the swarm density. If a considerable change is detected, each robot adapts the parameters of its control algorithm to compensate for the changed density. In summary, there is high potential for fault tolerance in swarm robotics, but it is not inherent in all cases. Each robot is required to monitor its neighbors and relevant environmental features to detect faults or crucial changes and to adapt accordingly.

5.2 Robot-Robot Interaction

Based on the added value of automating a task with a single robot, it can seem advantageous to add another robot, and then many more. The subsequent question is whether and how the robots should interact. Allowing the robots to interact and collaborate can introduce considerable complexity to the system. One option to avoid increased complexity is the simple parallelization of tasks, with negligible communication. In a cleaning task, for example, each robot might be assigned a separate area, so that there cannot be interference between robots. One might then argue that zero interaction between robots is ideal, as this keeps the system simple. However, robot-robot interaction brings many advantageous

possibilities, such as true collaboration between robots or a performance increase that goes beyond parallelization.

In multirobot systems, different forms of robot-robot interaction can result in the emergence of collective behaviors for given tasks. These forms of interaction can be the following: direct, using explicit signaling; indirect, based on observed change in behavior or cues left in the environment; or simple physical contact. Robots interacting by physically connecting and docking to one another have been studied in reconfigurable modular robotics and in a robot swarm inspired by self-assembly in ants (Groß and Dorigo 2009). The remainder of this section describes methods of direct and indirect communication (i.e., not exclusively physical contact).

5.2.1 Direct Communication (Signals)

Robots might need to communicate their strategic decisions, progress, environmental perspective, or presence. In multirobot systems with centralized control, the robots use global communication to negotiate a strategy and assign roles. In robot swarms, by contrast, communication is constrained to be local. Therefore, infrared communication is a popular method for signaling, as it allows reliable short-range obstacle detection, distance calculation, and data communication. For example, in the Beeclust (Schmickl and Hamann 2011) control algorithm, inspired by the hive navigation behavior of young honeybees, infrared short-range obstacle detection is used for aggregation according to luminance. In the Beeclust algorithm, robots perform a random walk while turning away from obstacles and pausing when encountering another robot. A paused robot uses its luminance sensor reading e to determine the waiting period w , according to $w(e) = w_{\max} e^2 / e^2 + k$. Using infrared communication for kin recognition and communication of environmental perceptions, Wahby et al. (2019) extended the Beeclust algorithm to achieve adaptive aggregation in dynamic conditions (see figure 5.2). Other common signaling methods include short-range radio communication and visual communication via LED color. For instance, Groß et al. (2006) used blue-and-red light signals

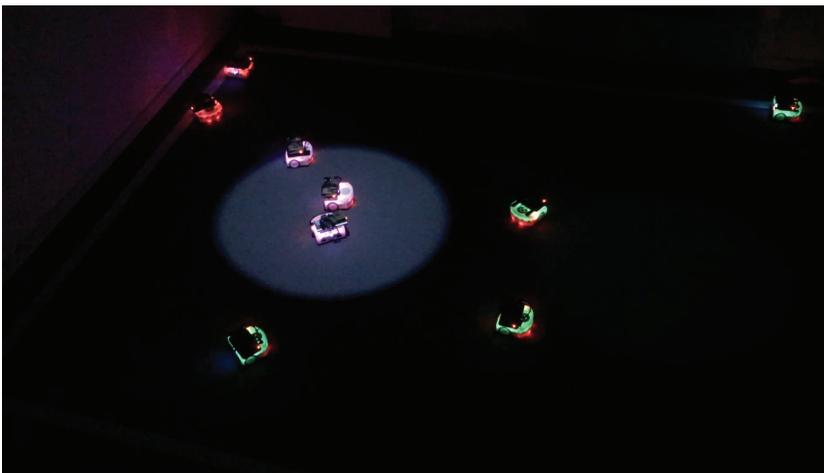


Figure 5.2

A swarm of nine robots adapting their behavior according to detected conditions in an aggregation task. *Source:* From Wahby et al. 2019.

to influence the formation of self-assembled connection patterns for a robot swarm. Other methods such as odor and sound have also been studied. For instance, inspired by necrophoric pheromone communication that triggers corpse-removal behavior in bees, Purnama-djaja and Russell (2005) have built two mobile robots that perform a rescue task, equipped with tin oxide gas sensors. By using an odor localization algorithm, the robots can find and rescue a plastic foam artificial robot (i.e., a malfunctioning robot replica) that is releasing a chemical vapor.

5.2.2 Indirect Communication (Cues)

In indirect communication approaches, a robot in a swarm does not explicitly signal other robots or directly exchange data. Instead, the robots adjust their behavior based only on their observations of the local environment. These observations can relate to changes in the behavior of other robots or changes made to the environment (i.e., stigmergy; see section 5.1.3). Several indirect approaches have also been used to implement flocking behaviors without estimating neighbors' relative headings. For instance, Ferrante et al. (2012) defined attraction/repulsion dynamics for linear and angular velocities based only on range and bearing proximity values. Similarly, Yasuda et al. (2014) defined a topological interaction model that relies only on the proximity of local neighbors. In these approaches, the interaction is based only on the observed changes in the movement behavior of peer robots, and the robots adapt their motion accordingly.

5.2.3 Challenges of Communicating Robots

Communication is essential to allow robots to collaborate but can also be a potential bottleneck when dozens, or even hundreds, of robots need to communicate. Radio and sound communication both suffer from interference if prohibitively many senders operate in bounded areas simultaneously. Many protocols for radio communication also have further limitations and do not scale easily (e.g., Bluetooth, carrier-sense multiple access with collision avoidance [CSMA/CA]). Therefore, many swarm robotics implementations rely on other forms of communication, such as infrared with limited range (typically less than 15 cm) narrowcasting to direct neighbors.

Various hardware platforms also come with their own respective challenges. For example, aerial drone-based search and rescue missions operate in detrimental environments while requiring high bandwidth and an extensive communication range to transfer real-time footage. Many typical communication techniques are highly limited in such cases. For instance, Wi-Fi supports up to 250 m for outdoor communication, which can be a limitation in search and rescue missions that can extend to several kilometers between neighboring drones. Worldwide interoperability for microwave access network (WiMAX) technology supports a communication range of up to 30 km and is therefore a good candidate for tasks in which drones require long-range communication. The capabilities of current 4G+ mobile networks can also support the coverage and transfer rates of drones deployed at low altitudes. As a further improvement, upcoming 5G networks may provide more robust and effective connectivity for long-range communication in swarms of drones.

Underwater communication is more challenging than aerial communication because water absorbs most electromagnetic radiation except for a portion of the visible spectrum.

This visible light can furthermore travel only a few hundred meters in clear water and much shorter distances in cloudy water. Reliable acoustic modems have therefore been developed for long-range underwater communication and have been used in a swarm of autonomous underwater vehicles for communication and navigation (Behrje et al. 2018). Recently, Farr et al. (2010) have developed an optical communication method based on exchanging packets of modulated blue-green light. This method is faster and cheaper than acoustic modems but supports a shorter communication range.

5.3 Methods of Designing Robot Swarms

Designing controllers for robot swarms can be approached in the following two key ways: either with the human designer in the loop or automatically based on methods of optimization or machine learning. Both options can be challenging because of the micro-macro problem. Collective effects of many robot-robot interactions are difficult to anticipate analytically, and similarly, macroscale rewards used in automatic design cannot easily be traced back to behaviors of individual robots (see section 1.1.2).

5.3.1 Design with the Human in the Loop

The traditional approach of designing and implementing robot control algorithms is, of course, based on keeping the human in the loop; in other words, a human engineer programs the robot. In swarm robotics, often but not necessarily, control of the individual robot is kept simple because system complexity on the macroscale is supposed to emerge from robot-robot interactions. Therefore, focus has been placed primarily on simple reactive control without memory and the frameworks of behavior-based robotics. Often robot swarms have a controller based on a finite state machine. Designing a simple state-machine controller for a robot swarm is usually challenging because of the micro-macro problem (see section 5.1.2).

Even experienced robot swarm programmers need to follow an iterative trial-and-error process until the parameters of the algorithm are fine-tuned and the desired swarm behavior is achieved.

Some approaches introduce mechanisms to allow the robots to automatically adapt the parameters of a manually designed algorithm, at runtime, according to the surrounding conditions (e.g., Wahby et al. 2019). However, these approaches offer adaptive solutions tailored for task-specific scenarios and could fail in scenarios with unanticipated features. An intermediate next step before applying an automated approach is to support the human designer with models. While a trial-and-error approach uses robot simulations to estimate the result of the current algorithm design, another approach is to instead increase the level of abstraction and use a model of swarm dynamics. The objective of the modeling approach is to get generic predictions of swarm behavior for a given algorithm, rather than episodic samples from simulations. Probabilistic macroscale models are often used. The challenge is to find models that are abstract but still allow for a clear connection to the underlying control algorithm. For example, Hamann and Wörn (2008) modeled space and allowed for a mathematical connection between micro- and macroscale.

5.3.2 Evolutionary Swarm Robotics

Among automatic approaches to swarm design, artificial evolution—originally inspired by evolutionary biology—can be considered the most widespread. Evolutionary robotics (Nolfi and Floreano 2000) is a commonly followed approach outside of swarms (see chapter 4) and has been considered a framework to study generalized models of cognition (Harvey et al. 2005). The typical evolutionary swarm robotics approach is to evolve an artificial neural network controller (i.e., neuroevolution) in simulation (see link to the MultiNEAT software library in the additional resources section) in a homogeneous swarm (e.g., Baldassarre et al. 2003). Finite-state machines have also sometimes been evolved, instead of the typical neural network. A main challenge in evolutionary robotics in general, but especially in swarms, is the transfer to reality, as the evolutionary process can exploit any errors in the modeling of the experimental setup, thereby overfitting to the simulation. This “reality gap” can be addressed using the Koos et al. (2012) “transferability approach” (i.e., evaluating the evolved controllers both in simulation and in the real setup), seen, for instance, in the swarm scenario explicated in section 1.4. Online evolution (i.e., embodied evolution) is attractive for its accuracy but unattractive for its slowness, which is exacerbated in swarms. A solution to this conflict has been proposed by O’Dowd et al. (2011) via coevolution of the controller with the respective simulator. Automatic design approaches besides evolution exist, such as the modular control architecture “AutoMoDe,” where a probabilistic finite-state machine comprises a priori parametric modules wired by an optimization process (Francesca et al. 2014).

5.3.3 Neuro- and Bioinspired Automatic Design

Some inspiration sources for robot swarms have also inspired heuristics. For instance, particle swarm optimization inspired by flocking has been used in distributed versions for multirobot learning (Di Mario et al. 2015).

Artificial neural networks (ANNs)—roughly neuroinspired—have proven highly effective in many fields and have also been explored in swarm robotics (for the related topics of machine learning for robotics and neurorobotics, see chapters 3 and 9.) In a common approach, each robot in a swarm receives the same full ANN controller, evolved off-line. The “odNEAT” approach by Silva et al. (2015) extends to neuroevolution that is online and decentralized. Distributed neural networks have also been proposed. In the approach of Otte (2018), each robot holds a slice of neurons in a swarm-wide ANN, enabled by parallel neural network training. In an alternative neuroinspired approach, Mathews et al. (2017) have developed “mergeable nervous systems,” where attached robots can flexibly fuse their distributed control systems into a shared adaptive network.

5.4 Indoor and Outdoor Applications of Robot Swarms

Swarm robotics research often focuses on fundamental models and design approaches, supported by experiments in laboratory environments. Although basic characteristics of robot swarms, such as scalability, would evidently have an impact on applications, specific applied scenarios have rarely been studied directly. Some approaches have indirectly studied a specific industrial or field task despite conducting only laboratory experiments.

For an industrial task, a laboratory approach can use a stand-in robot to replicate the key sensing and actuation capabilities of a patented industrial robot and then use the laboratory stand-in to study self-organized control (e.g., reconfigurable fiber deployment in manufacturing; Eschke et al. 2019). Swarm robotics approaches in laboratory environments have also proposed solutions to field tasks—such as the problem of impassable step height in disaster relief—for example, by distributed construction of amorphous ramps (Napp and Nagpal 2014). In another approach, elements from the field can be brought into laboratory environments for experiments, as seen in biohybrid robotics research with plants (Wahby et al. 2018).

It is recently becoming more common for swarm robotics research to conduct field experiments. The “subCULTron” EU project (Thenius et al. 2016) is testing its swarm of underwater robots for marine monitoring in a lagoon environment in Venice, Italy (see in-process field photos printed in Hamann [2018b]). Another project, “SAGA,” develops a swarm of quadrotor UAVs for field monitoring and mapping of agricultural conditions—for instance, with weed detection (Albani et al. 2017).

5.4.1 Example Outdoor Scenario

In order to provide a didactic example of an indoor or outdoor application, we give a detailed walk-through of an approach by Duarte et al. (2016) because it is the first published instance of real field experiments with a robot swarm. Duarte et al. (2016) use ten autonomous aquatic surface vehicles and test them in a shallow open-water environment in Lisbon, Portugal. The robots are differential drive boat vehicles that use inexpensive and accessible off-the-shelf components. They are 60 cm at their longest dimension, are capable of up to 1.7 m/s linear speed and 90°/s rotational speed, and comprise components costing roughly three hundred euros per robot. Each boat robot is equipped for decentralized communication with other robots via a wireless ad hoc network for UDP (User Datagram Protocol) broadcasting and is equipped with GPS and a compass. The controllers output linear and rotational speeds, which are used to calculate motor speeds based on the real robot dynamics (affected by friction and inertia in water). The controller inputs are three values representing locations in the environment, calculated from GPS and compass readings of the robot and its neighbors, as communicated over the wireless network.

Using these robots and controllers, Duarte et al. (2016) have conducted simulated and real field experiments for four different tasks that require coordination between robots. The robot controllers are evolved in simulation,¹ then transferred to real field experiments in open water using the transferability approach of evolutionary robotics (see section 5.3.2). In the first task, homing, the swarm collectively moves to a target in the environment while avoiding collisions. During evolution, controllers are rewarded for minimizing distance d to the target; specifically, the average value of $\Delta d/d_{t=0}$ for each robot at each time step, multiplied by coefficient S to penalize controllers when robots get less than 3 m apart. The second and third tasks are dispersion and aggregation, in which the robots should either spread out over a large area without losing contact with neighbors or should move toward each other to form clusters after starting from a spread-out configuration. The fourth task is area monitoring, in which the robots should move around to collectively give continual coverage to a defined and limited area. The four behaviors are combined into a single “multicontroller” mission in the field, which was not previously evolved for

or tested in simulation. The researchers equip the robots with temperature sensors for this mission and select the highest-performing controllers from each respective task. The four controllers are triggered sequentially in the swarm, successfully completing an application-oriented mission of sampling water temperature. Within this mission, the robot swarm moves in a close group from the starting point to the target area, disperses and monitors the full area, then aggregates back into a close group and returns to the initial starting point.

5.5 Swarm Cognition and Psychology

As introduced in section 5.1.3, collective cognition is found in many natural swarms and is a target in engineering artificial ones. An established perspective on natural swarms is that their collective behaviors bear commonalities with neural mechanisms and therefore should be studied in the same framework of cognitive science (Couzin 2009; Trianni et al. 2011). Another perspective holds that swarms should be studied as an independent class of cognition, forming what can be considered “liquid brains” (Piñero and Solé 2019).

Processes of collective cognition that are investigated in swarms include collective perception (Schmickl et al. 2006), collective memory (Couzin et al. 2002), collective learning (Montes de Oca and Stützle 2008), and collective decision-making (see section 5.6). Cognitive processes observed in simple organisms that rely on decentralization, such as ants, have commonly inspired swarm robotics. Examples inspired by more complex organisms, or by coordination that is not strictly decentralized, are far more rare. However, there are a few examples. Regarding more complex organisms with higher-order cognition and centralized nervous systems, there has been inspiration from neuroscience (e.g., in automatic design methods for swarms) and human psychology (e.g., in natural swarms that can be considered superorganisms). Regarding coordination that is not strictly decentralized, species with hierarchical social structures (e.g., baboons) display coordination strategies that may, speculatively, be relevant to multirobot control. It has also been proposed that simpler social animals such as schooling fish, often considered to exclusively use peer-to-peer communication for movement, may sometimes use hierarchical social structures with temporary leaders for fast predator response (Ioannou 2017). We therefore look to neuroscience and human psychology—in addition to models of complex social structures such as those seen in online social networks or hierarchical animal groups—for key theories that may have potential for useful application in a robot swarm.

Key theories from psychology and neuroscience have thus far been implemented in models of swarm behavior in a few seminal works on collective decision-making, described in detail in section 5.6.3. Implementations of such theories have not occurred in models of swarm perception, memory, or learning. We therefore describe existing swarm robotics examples related to these aspects of cognition and review some of the key psychology and neuroscience theories that are potentially relevant to distributed and decentralized robot cognition. As our aim is to follow a natural inspiration source only insofar as is useful for the engineering task at hand, we present theories based on their potential relevance to robot control, without taking a stance on the positions of those theories within their originating disciplines.

5.5.1 Collective Perception and Attention

In existing strategies for collective perception in a robot swarm, peers trade information capturing their individual perceptions with their local neighbors, progressively building consensus about the perceived environment. For instance, they signal votes or hypotheses about perceived features (Valentini et al. 2014) or share “trophallaxis-inspired” cues about implicit elapsed time since they last reached a target (Schmickl et al. 2006). It is typically held that natural swarms similarly use distributed strategies for perception. However, it is sometimes conversely held that in some social animals, such as fish, the improved predator perception of larger groups may result simply from a pooled visual field and the temporary leadership of a faster-moving individual (Ioannou 2017), without any peer-to-peer communication about perception.

Established human psychology laws for stimuli-response mechanisms have been shown to be relevant to collective decision-making—for instance, in terms of the speed-accuracy trade-off in swarms—and may also relate to collective perception. In disciplines such as human-computer interaction, motor speed-accuracy trade-offs have been well described by the psychology principle of Fitts’s law, proposed by Paul Fitts in 1954, wherein the size and distance of a target predict movement patterns toward it. Though established as a motor law, it has been shown to hold for agents’ perception of action (Grosjean et al. 2007), an important aspect of robot-robot collaboration in swarms. As another example, psychology has established a relationship between attention levels and the exploration-exploitation trade-off in foraging (Van den Driessche et al. 2019), a task often studied in swarm robotics.

In biology, sensorimotor processes are key to perception, especially in coordination between individuals. Santana and Correia (2010) propose that, by considering attention in isolation from subsequent motor system processes, biological neural mechanisms might inspire approaches to swarm perception. For example, mechanisms governing selective attention could be transferred to robot swarms to establish a relationship between attention behaviors and predictions or motivations.

5.5.2 External and Collective Memory

Behavioral science has proposed a variety of group memory concepts in natural swarms, such as the “joint memory” proposition of Thierry et al. (1995), including, first, a collective type in which memories of individuals are coupled and, second, an external type in which memory refers to the environment. External memory might be saved in modifications to the environment, as in stigmergy, or may simply comprise references to landmarks in the environment (e.g., to facilitate novel actions rather than the repetition of remembered actions). In artificial swarms, a simple approach is to equip agents with local memory of their own history to enhance performance when interacting with the environment. Another approach, which can be applied to foraging in robot swarms, is the use of a maplike representation of terrain features, which may be predetermined or built adaptively (Kumar and Sahin 2003). The most common approach in robot swarms is evidently the external memory approach of stigmergy, which can also be combined with other types of memory, such as short-term memory of individual history. Short-term memory in a swarm is discussed further below, in relation to a natural swarm being considered a superorganism.

Theoretical biology notably provides simulation-based evidence of collective memory in swarms, demonstrating that the history of swarm structure has an impact on the different collective behaviors that might arise from identical individual behaviors (Couzin et al. 2002). In honeybees, Beekman (2005) has experimentally demonstrated individual memories of past stimuli that may affect subsequent interactions and collective behavior, as agents triggered by others to revisit a site that is still remembered will be more efficient (e.g., by avoiding unsuccessful route attempts).

In the coupled-memory type proposed by Thierry et al. (1995), individuals manage their own memory of an opinion or piece of information and communicate that individual memory to others—for instance, in honeybees, each knows only a portion of information about an environment. In existing robot swarms, there are typically no subgroups of spatial memory distribution across a swarm (i.e., the opinions held by individuals vary, but the topic on which they have opinions is homogeneous). However, the role that an individual plays in information processing in a swarm may be influenced by its spatial position. It is notable that distributed memory in the brain is heavily differentiated according to spatial distribution, but the physical connections present in biological neural circuits may limit them as a direct inspiration source for robot swarms. In social insects, differentiated memory subgroups have been shown to arise, specifically, when a small group of individuals becomes short-term specialists for a repeated, temporary task (Diez et al. 2011).

5.5.3 Social and Collective Learning

Social learning, or collective learning, refers to the process of behavior development via observation and imitation of neighbors (Rendell et al. 2010). A common mechanism in swarms that may be considered a simple form of social learning is the disproportionately large influence that a few informed individuals have on the behavior of a group. The proportion of informed agents needed to maintain accuracy has even been shown to decrease with increasing group size (cf. Couzin 2009). Procedures to reach consensus in collective decision-making (addressed as its own aspect of cognition in section 5.6) have also been considered a type of social learning in animal groups, in cases in which agents are selective about the neighbors they imitate (Rendell et al. 2010). This selectivity has roughly inspired a social-learning approach in artificial swarms, where a large group reaches consensus more quickly by incrementally adding agents to an initially small decision-making subgroup (Montes de Oca and Stützle 2008). In another approach, artificial agents follow instructions from a leader and use these downstream instructions to indirectly learn the respective task so they can collectively reconstruct it if the leader is lost (Karydis et al. 2016).

In social animals, associative learning in an individual has been frequently studied, establishing a direct link between individual preferences and actions. However, Kao et al. (2014) contend that the majority of the animals studied in lab conditions will naturally exist in social groups, where collective learning will break the established relationship between preference and action in associative learning. The influence of collective learning on associative learning in animals has yet to be studied directly (Kao et al. 2014), although related established studies on honeybees have examined both associative learning by cues and social learning by the well-known mechanism of dance communication. The effect of

agent individuality (i.e., behavioral heterogeneity) on natural swarm dynamics has been studied, possibly bringing implications for robot swarms (Saffre et al. 2018).

Burini et al. (2016) have proposed a unified formulation of collective-learning dynamics using kinetic theory, including learning of abilities and of social messages. Their formulation presumes heterogeneity in the group (i.e., the “population-thinking” approach)—in a robot swarm, such heterogeneity could potentially be characterized as deviations in behaviors or opinions during progression toward consensus. Approaches to opinion consensus in robot swarms have been studied in collective decision-making.

5.6 Collective Decision-Making in Robots

Collective decision-making is the key mechanism of swarm cognition. A robot swarm can only act as a whole by ensuring consensus or vast majorities for certain coordinated actions. Achieving such consensus and coordination in a swarm, particularly in unknown or dynamic environments, requires swarm-wide sensing, information processing, and action selection.

5.6.1 Swarm Autonomy and Swarm Awareness

Following the agent models of Russell and Norvig (2016), the autonomy of an agent originates from its ability to make informed decisions. Similarly, a robot swarm can only be autonomous and self-governing on a macroscale if the swarm as a whole is capable of making informed decisions. This requires a form of collective decision-making that ensures the collection of relevant information, collective processing of that information, and a subsequent swarm-wide decision of what to do next. In addition, the swarm needs to reach awareness that a decision is necessary and that a consensus or large majority has been achieved such that the decision-making process concludes (Hamann 2018b). As pointed out, for example, by Khaluf et al. (2019), this corresponds to common subdivisions of human decision-making, such as identifying the problem, obtaining information (identification of options and their quality), and evaluating it.

In swarm robotics, and also in opinion dynamics and related fields, some aspects of swarm awareness are often ignored (Khaluf et al. 2019). Experiments often isolate one aspect, for instance, by starting immediately with the collective decision-making process before being stopped by an external observer once a sufficient majority is reached. The challenge of extending beyond experiments of isolated aspects will be crucial to achieving full swarm awareness. For full swarm awareness, each robot needs to be sensitive to changes in the environment or in the (signaled) states of its neighbors. If the swarm in a critical situation does not collectively detect that a collective decision is required, then the swarm may split, crash, or otherwise fail at its task. Similarly, to ensure the decision-making process ends, each robot needs to estimate when to stop switching opinions. As each robot relies on local information only, this estimation is necessarily probabilistic. This can be implemented as each robot voting for ending the collective decision-making process, which consequently means that we are embedding another decision-making process into the system. This can be even more challenging when the swarm has to adapt to environmental conditions and adaptively balance the speed versus accuracy of its decision-making process. So collective decisions make a swarm autonomous on a macroscale but

also require sophisticated forms of information diffusion, gossiping, and sharing of internal states to create swarm awareness of globally required swarm actions.

5.6.2 Methods of Collective Decision-Making

Methods of implementing a complete collective decision-making system include all of the following: starting and ending the process, exploring options, disseminating knowledge about options, processing that information in an individual robot, and ensuring the swarm decides accurately and quickly (Hamann 2018b). These parts are all complex and cannot be discussed in full detail here. Even more complexity would be added when considering modeling techniques that deal with underlying dynamic networks and, for instance, try to predict expected convergence times. Instead, this section focuses on the decision-making mechanism of an individual robot and the impact of different algorithm choices by looking at two simple techniques. Assuming that a robot operates iteratively on three phases (explore, disseminate, and switch opinion), here we focus only on the opinion-switch phase. Take, for instance, a robot that collects messages from its neighbors that include merely whether they are in favor of option red or option blue. Then it is reasonable to count red and blue messages, to determine the majority, and to switch to the majority opinion (or keep it if the robot already has that opinion).

This straightforward approach is called *majority rule* (e.g., Valentini et al. 2015)—that is, in a decision between two opinions, the opinion of robot r_i switches if it does not match the majority opinion in $[r_i, r_{i+n}]$, where n is the number of robots in the neighborhood. Example code for majority rule can be found in the PyCX repository (Sayama 2013). If each robot follows this simple rule, then the expectation may be that the swarm will converge on a consensus, given enough time. In general, this is true, but it can be complicated by noise or by inhomogeneously distributed robots in space (Valentini et al. 2015). A second straightforward approach is the *voter model* (e.g., Valentini et al. 2014)—that is, the opinion of robot r_i switches to a uniformly randomly selected opinion from the robots in the neighborhood, $[r_{i+1}, r_{i+n}]$. Example code for a voter model can also be found in the PyCX repository (Sayama 2013). Although it may seem counterintuitive, the voter model is a useful option for a decision-making mechanism. In decision-making, and also in collective decision-making, there exists a speed-accuracy trade-off (also mentioned at the end of section 5.6.3). This trade-off means that a decision-making process can be either fast or accurate but not both at the same time. Whether a given decision mechanism is better than another will always depend on the requirements of a given application scenario. In general, the majority rule is fast but relatively inaccurate, while the voter model is accurate but slow. There is no simple description that can provide an intuitive understanding of that finding except that the voter model tends to be more forgiving to local temporary deviations, while majority rule tends to exploit the current local system state. A better understanding requires deeper study of the different modeling techniques of collective decision-making.

5.6.3 Psychology of the Robot-Swarm Superorganism

One demonstrated approach to modeling collective decision-making in a swarm is to take inspiration from established mechanisms in human psychology and apply them to the whole swarm as if it were one organism. The group cognition and organization seen in

natural swarms has sometimes prompted their biological characterization as *superorganisms* (cf. Wilson and Sober 1989). In a superorganism, such as a honeybee colony, natural selection might operate according to the survival of the colony as a unit, evolving a tightly interdependent group and establishing a higher class of biological organization. This tighter interdependence can be seen in social apoptosis in honeybees, where colony immunity is supported by the increased infection susceptibility of individual sacrificial bees (Page et al. 2016). The superorganism concept can look similar to the established *group selection* mechanism in evolution of cooperation but has also been proposed as distinct. Without commenting on evolutionary biology, here we refer to the superorganism as a useful analogy concerning natural swarms, and potentially robot swarms. Natural swarms have been shown to perform typical organism-level functions at the level of the group, for instance, by a “common stomach” to regulate foraging (Schmickl and Karsai 2016) or neurologically by governing speed-accuracy trade-offs similarly to the brains of individual animals (Sasaki and Pratt 2018). Collective decision-making in colonies responding to stimuli has notably been shown to follow certain established laws of human psychology (Pais et al. 2013; Reina et al. 2018), a generality that may extend to robot swarms.

The signals and cues of robot swarm communication described in section 5.2 are also seen in natural swarms, as stimuli that might be shaped differently by selection—in evolutionary biology, signals are stimuli formed for the express purpose of communication, while cues are stimuli that may trigger responses but have not necessarily developed for that function. As shown by Reina et al. (2018), although stronger signals are known to lead to faster decisions and avoidance of deadlocks, they may also lead to negative performance effects. In simulated honeybee colonies, Reina et al. (2018) demonstrated that when measuring signaling by signal-to-noise ratio, increased signaling worsens the group ability to differentiate between similar stimuli. This is reminiscent of the well-known exploration-exploitation trade-off in swarm robotics. As described in section 1.1.2, exploration and exploitation are necessary mechanisms in self-organization. Achieving the optimal balance between exploiting already known solutions and exploring to find new (possibly better) solutions cannot be solved generically as it depends on the respective task and environment. For example, in a bistable regime where a robot swarm should select the best site but finds two equally good sites, the main challenge for the exploration-exploitation trade-off is to break symmetry effectively (Hamann et al. 2012).

Established psychology laws may govern the dynamics known to be present in natural swarms; for instance, Reina et al. (2018) demonstrated that the exploration-exploitation trade-off in a honeybee colony may be governed by Weber’s law on the perception of external stimuli, proposed by Gustav Fechner in 1858. This law describes differential sensitivity as $dp = dS/S$ —that is, the perceived change in stimulus dS is proportional to the initial stimulus S . In natural swarms, Pais et al. (2013) and Reina et al. (2018) have shown that Weber’s law holds in honeybee colonies choosing between sites in a bistable regime. In swarms that maintain relative spatial distributions, such as flocking birds, Perna et al. (2019) have shown that a simple antidiffusion mechanism based on Weber’s law is alone sufficient to achieve stability, compared to the two or more separate mechanisms needed to balance one another in the classic Reynolds (1987) approach. Similarly, natural flight patterns observed in honeybee colonies have been shown by Reynolds et al. (2013) to be achievable by odometry following Weber’s law.

Another established psychology law—Hick’s law, proposed by William Hick in 1952 and Robert Hyman in 1953—describes a concept termed rate of information gain, holding that reaction time rises linearly with the degree of uncertainty. That is, reaction time $RT = kH$, where H represents the amount of information that must be processed in a given decision. In the case of equally likely alternatives, Hick’s law states that $H = \log_2(n + 1)$, such that H is a logarithmic function of the number n of stimulus-response alternatives. Reina et al. (2018) have found that in a honeybee colony superorganism making a best-of- n decision, reaction time RT rises with the number of alternatives as in Hick’s law but rises exponentially, proposing that this may be due to nonlinearities in the swarm. Another established psychology law that may fit this phenomenon is the Cooney and Troyer (1994) approach that integrates interference susceptibility into a model of reaction time. Alternatively, Reina et al. (2018) have proposed a new model of reaction time RT in a honeybee superorganism: $RT = \alpha \bar{v}^{-\beta} e^{\mu n}$, where \bar{v} is the mean quality or likelihood of the n available options, and α , β , and μ are constants. This new model by Reina et al. (2018) combines Hick’s law with the Pieron law, proposed by Henri Pieron in 1913, wherein reaction time decreases with increasing intensity of stimulus as a power law.

In their implementation of Hick’s law, Reina et al. (2018) have found a trade-off in signal-to-noise ratio in a best-of- n decision, in which increased signaling improves speed but weakens selection quality, fitting with the established speed-accuracy tradeoff seen not only in robot swarm decision-making and in natural decision-making but across many aspects of information processing. A variety of factors demonstrably affect speed and accuracy in decision-making and can potentially have an impact on their trade-off in engineering robot swarms. In animal populations, the speed-accuracy trade-off during selection is proposed to result in a heterogeneous behavioral tendency to be fast or slow, as both strategies may perform similarly due to a related risk-reward trade-off (Sih and Del Giudice 2012). In natural swarms, Pais et al. (2013) have shown that in a honeybee colony where binary alternatives are distinguishable, as defined by Weber’s law, the speed-accuracy trade-off is dependent on cross-inhibition strength (a mechanism observed both in honeybee colonies and in complex brains). In individual human decision-making, when accuracy itself displays a trade-off between true and false positives, a collective approach has been shown to invert that trade-off by both increasing true positives and decreasing false ones (Wolf et al. 2013). Reina et al. (2018) have noted that accuracy in a natural swarm is dependent on the ratio between the time spent exploring versus signaling, reminiscent of the exploration-exploitation trade-off.

5.7 Conclusion

Swarm robotics was initially inspired by behaviors observed in biology, and new advances in artificial swarms continue to be interdependent with those of natural swarms, especially in the study of swarm cognition. Bioinspired and neuroinspired approaches have been used to develop robot swarm models and behaviors—such as the cognitive mechanism of stigmergy—and have influenced popular automatic design methods for swarm controllers, such as neuroevolution. Swarm robotics uses these approaches to address challenges in, for instance, direct and indirect communication, management of the “micro-macro link,”

swarm autonomy, and swarm cognition, and is moving toward applications in the field. Swarm cognition has been studied in terms of collective perception, collective memory, collective learning, and collective decision-making and, in some cases, takes inspiration from human psychology and cognitive sciences. These disciplines may provide swarm robotics with new and useful inspiration sources if measurably novel and not a reformulation of an existing approach, and if effective for the respective engineering task.

Additional Reading and Resources

- The classical introduction to swarm intelligence: Bonabeau, Eric, Marco Dorigo, and Guy Theraulaz. 1999. *Swarm Intelligence: From Natural to Artificial Systems*. Oxford: Oxford University Press.
- A recent, comprehensive overview of swarm robotics, with detailed presentations of methods and example scenarios for the design of large-scale robot swarms: Hamann, Heiko. 2018. *Swarm Robotics: A Formal Approach*. Berlin: Springer.
- A recent perspective of swarm robotics and its future: Dorigo, Marco, Guy Theraulaz, and Vito Trianni. 2021. “Swarm Robotics: Past, Present, and Future.” *Proceedings of the IEEE* 109 (7): 1152–1165.
- A brief summary of swarm robotics’s origins, application domains, and current research issues: Dorigo, M., G. Theraulaz, and V. Trianni. 2021. “Swarm Robotics: Past, Present, and Future.” *Proceedings of the IEEE* 109 (7): 1152–1165. <https://doi.org/10.1109/JPROC.2021.3072740>.
- Software for swarm foraging, in the repository of the ARGoS simulator (Pinciroli et al. 2012): <https://github.com/ilpincy/argos3-examples>.
- MultiNEAT software library for the evolution of neural networks: <http://www.multineat.com>.
- scikit-learn software library for machine learning, including for training neural networks: <https://scikit-learn.org/stable/>.
- Software for majority-rule simulations: <https://github.com/hsayama/PyCX>.

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Note

1. Evolution in Duarte et al. (2016) was conducted in JBotEvolver, available at <https://github.com/BioMachinesLab/jbotevolver>.

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