Reflections on the future of swarm robotics

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INTRODUCTION

Swarm robotics deals with the design, construction and deployment of large groups of robots that coordinate and cooperatively solve a problem or perform a task. It takes inspiration from natural self-organising systems such as social insects, fish schools or bird flocks, characterised by emergent collective behaviour based on simple local interaction rules (Camazine et al., 2001; Sumpter, 2010). Typically, swarm robotics extracts engineering principles from the study of those natural systems, in order to provide multi-robot systems with similar abilities. This way, it aims to build systems that are more robust, fault-tolerant and flexible than single robots, and that can better adapt their behaviour to changes in the environment.

Swarm robotics started out as an application of swarm intelligence (Bonabeau et al., 1999), that is, the computational modelling of collective, self-organising behaviour that has resulted in several successful optimization algorithms now being used in fields ranging from telecommunications to simulation and prediction of crowd behaviour. However, it has quickly become evident that achieving swarm behaviour in robots demands much more than simply applying swarm intelligence algorithms to existing robotic platforms. In fact, it often requires to completely rethink traditional robotic activities such as perception, control, localisation, and the very design of the robotic platforms themselves.

Over the last two decades, researchers working in swarm robotics have made significant progress, providing proofs-of-concept of robot swarms that paved the way to new and promising robotic applications, as well as to a better understanding of how complex behaviours emerge in nature. However, as of today, no real-world application of swarm robotics exists, and only few published experiments have been able to control behaviour in a number of robots that can effectively be compared to the size of biological swarms or flocks. More research is needed to bring robot swarms out of the lab and into the real world.

In order to significantly push forward the state of the art, make robot swarms robust, scalable and controllable, and move towards real-world applications, research in swarm robotics must focus on a number of open challenges such as: how to extract design principles from the study of biological systems; how to move from low-level behavioural rules to the desired high-level behaviour; how to manage the gap between simulations and real experiments, and between lab experiments and real-world domains; and how to develop hybrid design methodologies based on the right mix of centralised and decentralised approaches that can produce emergent behaviour in a computationally economic way, while keeping the system controllable. The way these challenges will be addressed will decide the future of swarm robotics and whether it can live up to its potential.

In the following, after a brief history of the field, we summarise the main lessons learned during the pioneering phase of swarm robotics, we analyse the main open challenges and provide examples of innovative and promising approaches to tackle them. Finally, we suggest the most likely fields of application for swarm robotics and assess its potential impact in selected industries, by showing application scenarios that cannot be achieved by a single robot, or by a few robots controlled in a traditional, centralised way.

A BRIEF HISTORY OF SWARM ROBOTICS

In the last two decades, swarm robotics has grown from a small domain initiated by a few studies with a clear biological inspiration (Kube and Zhang, 1993; Beckers et al., 1994; Holland and Melhuish, 1999) to a mature research field involving several labs and researchers worldwide. A search with Google Scholar shows that the phrase "swarm robotics" made its first appearance in 1991, but its usage remained very limited until 2003 when it started to grow considerably. Similarly, a search with SCOPUS returns a comparable increasing trend (see Figure 1). These data show that, even though the swarm robotics research field finds its roots in a few seminal works published in the 1990s, it is only with the year 2000 that it started to significantly grow.

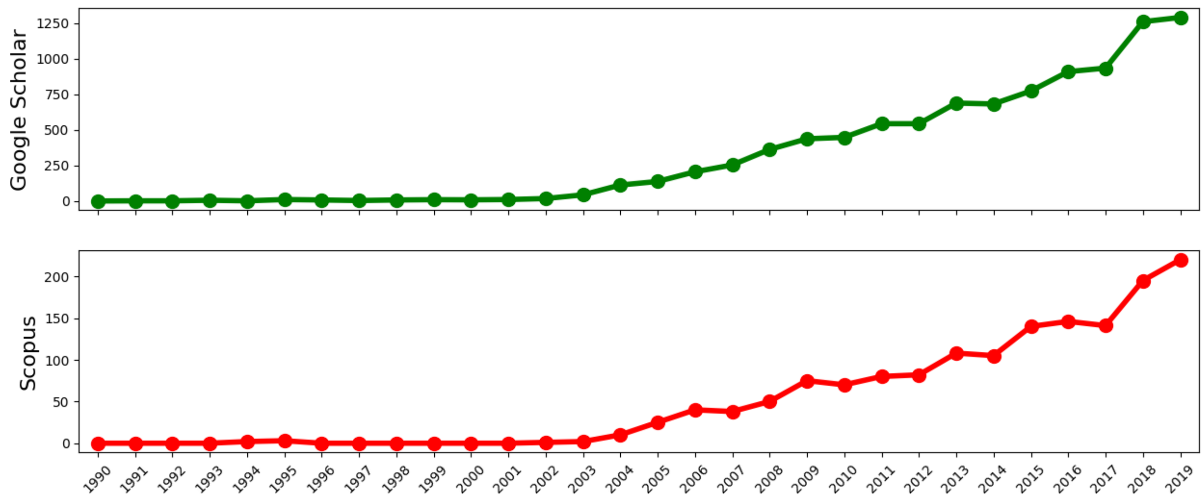

Figure 1: Citation count for the search "swarm robotics" in Google Scholar and in Scopus. Both show the same tendency, with an exponential growth from year 2000 on.

Initially the study of swarm robotics was aimed at testing the concept of stigmergy (see Box 1 for the definition of this and other concepts used in the article) as a means of indirect communication and coordination among robots. Following a few initial attempts (Beckers et al., 1994; Kube and Zhang, 1993; Holland and Melhuish, 1999), several studies appeared after 2000 focussed on tasks such as object retrieval (foraging, Krieger et al., 2000; stick pulling, Ijspeert et al., 2001), clustering (Agassunoun et al., 2004) and sorting of objects (Wilson et al., 2004). These studies started from known behaviours observed in social insects, and deployed robot swarms demonstrating similar behaviour. In a few cases, the robot swarm was exploited to closely replicate the dynamics observed in biological systems (e.g., aggregation in cockroaches, Garnier et al., 2008), leading to the first example of a mixed biological-robotic society (Halloy et al., 2007). Additionally, swarms of robots have been used as a tool to address biological questions (e.g., the trail network geometry to find the shortest path between a food source and a nest, see Garnier et al., 2013).

One of the first international projects to investigate cooperation in a swarm of robots was the *Swarm-bots* project, funded by the European Union between 2001 and 2005. In this project a swarm of up to 20 robots capable of self-assembly—i.e., physically connecting to each other to form a cooperating structure—were used to study a number of swarm behaviours such as collective transport, area coverage, and object search (Dorigo et al., 2004; Mondada et al., 2005). The main result of the project was to demonstrate what—at the present day—remains the only example of self-organised teams of robots that cooperate to solve a complex task, with the robots in the swarm taking different roles over time (Nouyan et al., 2009). The *Swarmanoid* project (2006-2010) extended the ideas and algorithms developed in *Swarm-bots* to heterogeneous robot swarms composed of three types of robots—flying, climbing and ground-based—that collaborated to carry out a search and retrieval task (Dorigo et al., 2011, 2013).

In the 2000s, in parallel with the successful demonstration of the swarm robotics paradigm, research on hardware miniaturisation promised the deployment of hundreds, possibly thousands of cooperating robots. Robots became smaller and ever-more minimalist, up to attempts of designs at the millimetre scale (see Figure 2). Several challenges related to hardware miniaturization and to the integration of a sufficient sensor suite, however, hindered progress in this direction. It was only a few years later that a hardware concept appeared supporting experimentation with a thousand robots: the Kilobot (Rubenstein et al., 2014a). The Kilobot was conceived to support the first demonstration of a large robot swarm designed for shape formation (Rubenstein et al., 2014b), and has been later used for several successful studies, allowing swarm robotics to be demonstrated in physical settings with hundreds of robots (Valentini et al., 2016; Slavkov et al., 2018; Talamali et al., 2020).

Swarm robotics is not limited to ground platforms: recent work has considered aquatic surface (Duarte et al., 2016) and underwater robots (Zahadat and Schmickl, 2016), as well as swarms of flying drones (Vásárhelyi et al., 2018; McGuire et al., 2019). While aquatic and underwater technologies still need substantial development efforts to become mature, drones are instead already commercialised and represent a very promising platform for remote sensing applications in different domains, being currently hindered only by the lack of a legal framework authorising autonomous and group flight.

Beyond hardware platforms, controlling robot swarms has represented the main focus of research. An extensive report of the different approaches so far available in the literature is beyond the scope of this perspective (but see Brambilla et al., 2013; Trianni and Campo, 2015; Francesca and Birattari, 2016; Garattoni and Birattari, 2016; Valentini et al., 2017). The main directions taken so far include: the development of analytical models of swarm systems to guide the robotics implementation (Prorok et al., 2011, Massink et al., 2013; Elamvazhuthi and Berman, 2019); the adoption of (evolutionary) optimisation approaches where robots are guided by minimalistic controllers (neural networks, Trianni, 2008; controllers without computation, Gauci et al., 2014; finite-state machines, Francesca et al., 2015; grammar-based controllers, Ferrante et al., 2015) and the development of design and verification methodologies (Reina et al., 2015; Brambilla et al., 2015). The definition of a reliable and efficient engineering methodology for robot swarms is still on the fringes of current research, and will likely require substantial effort in the years to come.

Box 1: Glossary of key terms used in the article

Adaptivity	The ability to learn/change behaviour to respond to new operating conditions
Automatic design	An approach to the development of control software for robot swarms in which the design problem is cast into an optimization problem. The different design choices define a search space that is explored using an optimization algorithm.
Design pattern	A formal description of a reusable solution to a problem commonly recurring in a certain domain. In swarm robotics, design patterns describe how to define the individual rules to obtain a desired self-organised macroscopic behaviour (e.g., collective decisions, see Reina et al., 2015)

Evolutionary algorithms	Optimization algorithms in which an initial set of candidate solutions is generated and iteratively updated through mechanisms inspired by biological evolution. The population of solutions gradually evolves to maximise an objective function (fitness) through a process that mimics the natural processes of reproduction, mutation, recombination and selection.
Fault tolerance	The capacity of a system to withstand faults of some of it parts with a graceful degradation of performance.
Flexibility	The capacity to solve problems/perform tasks that depart from those chosen at design time.
Model-free & model-based reinforcement learning	Two different approaches to reinforcement learning, a subset of machine learning in which software agents learn to behave efficiently in a given environment by trying to maximise a reward function of their actions. In model-based approaches, the agent is given, or learns, a function that maps its current states and actions to its next states (a model of the environment) so that it knows in advance the outcome of its next move; in model-free approaches the agent finds a good policy through trial-and-error, without explicitly reference the model of the environment.
Phase transition	Phase transition is a physical process whereby a substance changes from one physical state to another such as the freezing of water into ice (liquid to solid) or the heating of water to generate water vapour (liquid to gas). There is a formal analogy between the existence of disordered and ordered states in biological systems and that of similar states or phases in the inert world of physics: disordered liquid, ordered crystal solid. These systems have phase transitions which are changes between the various states or phases. In particular, ordered states are characterised by a notion of order at the scale of the whole system which can be quantified by an order parameter (e.g. the quality of the alignment/polarisation of a school of fish)
Robustness	The capacity to continue to work efficiently in environmental conditions different from those considered at design time.
Scalability	The capacity of a system to continue functioning properly when the number of its components (or in general, the amount of its resources) substantially varies.
Self-organisation	Self-organisation is a process whereby pattern at the global level of a system emerges solely from interactions among the lower-level components of the system, The rules specifying the interactions among the system's components are executed using only local information, without any central authority determining their course of action (Camazine et al., 2001).
Stigmergy	A form of indirect communication between agents where the work performed by an agent leaves a trace in the environment that stimulates the performance of subsequent work by the same or other agents. This mediation via the environment ensures the coordination of actions performed by the agents. It was first described by Grassé (1959) and has played an important role in supporting self-organising mechanisms in swarm robotics (Theraulaz and Bonabeau, 1999; Garnier et al., 2007).

Figure 2: Some of the robots largely used in swarm robotics research: (A) jasmine (Kornienko et al., 2005) (B) alice (Caprari and Siegwart, 2005); (C) kilobots (Rubenstein et al., 2014); (D) e-pucks (Mondada et al., 2009); (E) swarm-bots (Mondada et al., 2004); (F) swarmanoid (Dorigo et al., 2013).

Box 2: Timeline of the swarm robotics research domain - including projections of future developments

1990-2000	A new paradigm is tested in which collaboration is emergent from simple (often bio-inspired) behaviours. First experiments with robots demonstrating self-organisation by means of indirect (stigmergy) and local interactions, with a clear inspiration from swarm intelligence.
2000-2005	The possibility to design robots cooperating in a swarm is extended to several new tasks, entailing manipulation of objects, task allocation and tasks that strictly require collaboration to be solved.
2002-2006	The *Swarm-bots* project demonstrates robot swarms capable of self-assembly, opening to physical forms of collaboration. Robots are capable of building pulling chains and large structures capable of dealing with terrain roughness.
2004-2008	Initial demonstrations of the automatic design of robot swarms by means of evolutionary algorithms, leading to the establishment of the evolutionary swarm robotics approach.
2005-2009	First attempts of developing standard swarm robotics platforms (e-pucks), as well as miniature robots for swarm robotics research (alice, jasmine).
2006-2010	The *Swarmanoid* project demonstrated for the first time heterogeneous robot swarms composed of three groups of robots: flying, climbing and ground-based robots.
2010-2015	Different approaches appear to the design of robot swarms: advanced methods for the automatic design (AutoMoDe, novelty search), design patterns, mean-field models and optimal stochastic approaches.
2014-2019	The “control without computation” approach develops swarm robotics behaviours with direct sensor-actuator mapping and no computation whatsoever.
2016-2020	Swarms of flying drones become available for research, and decentralised solutions are studied and deployed.
2020-2025	*First demonstration of robot swarms capable of autonomously learning the best collective behaviour for any given problem.*
2020-2030	*First civil applications of robot swarms to precision agriculture and infrastructure inspection and maintenance. Military applications largely use non-offensive unmanned drones for mission support.*
2025-2040	*First space exploration mission on the Moon and Mars with miniature rovers, expanding the explored area and demonstrating onsite construction abilities.*
2030-2050	*Miniature robot swarms are demonstrated for target drug delivery inside the rat body, and experimentation with human subjects begins.*

LESSONS LEARNED

The first two decades of research in swarm robotics yielded rich results. The extensive experimental work has taught us a number of important lessons. First, we learned that the types of tasks that can currently be performed by robot swarms is strongly constrained by the still limited capabilities of autonomous robots[1]. To work in a swarm, the individual robots must be capable of interacting and communicating with each other, as well as of recognizing peers and the work done by others. This entails tailored hardware designs as well as specific sensing, interpretation and interaction abilities. Current limitations in robot hardware and control have constrained the complexity of swarm robotics research in a twofold way. On the one hand, specific robots have been developed to solve specific (toy) problems (e.g., termes, Werfel et al., 2014**;** kilobot, Rubenstein et al., 2014a). These examples have opened new avenues, but not always resulted in reusable components to be borrowed in different contexts. On the other hand, generic robots (alice, Garnier et al., 2009; 2013; e-puck, Mondada et al., 2005, 2009) have been used to produce proofs of concept, often addressing tasks that are a direct transposition in the artificial world of analogous tasks performed by self-organised natural systems (e.g., foraging, see Krieger et al., 2000, Talamali et al., 2020). However, when the hardware is not conceived for swarm robotics, daily work can become very cumbersome due to the need to deal with dozens or possibly hundreds of robots at the same time, making mundane activities such as recharging batteries or uploading software really tedious. This has often constrained the breadth and significance of the demonstrations, for instance forcing to use only a handful of robots, without unleashing the full power of swarm robotics. Finally, it should be added that miniaturisation of hardware will be a key element for experimentation in the lab with large swarms as well as for many future applications. Still, downscaling hardware poses extremely hard problems that so far have not been solved.

The second lesson we have learned is that addressing the micro-macro problem—how to design the swarm behaviour (macro-level) given we can only directly program the individual robots (micro level) that compose the swarm—is probably the most difficult aspect to be considered. In order to address this problem, there have been several attempts to propose design methodologies that are general-purpose and reusable in different application contexts—from design patterns (Reina et al., 2015) to automatic design methods (Trianni, 2008; Francesca et al., 2015). However, all these approaches are for the moment not powerful enough to address all the different aspects of the design of a robot swarm: they successfully address relatively simple or constrained problems, but rapidly show their limits as the problem complexity increases. Multiple aspects are linked with the absence of a solid design methodology. One, as mentioned above, is the lack of a standard and robust hardware platform for swarm robotics, which should be accompanied with efficient and reliable simulation tools (ARGoS, Pinciroli et al., 2012). Another issue is the lack of benchmarks that can measure the progress in a quantitative way (e.g., recent competitions like NASA Swarmathon[2]), and that can challenge the researchers on tasks that grow in complexity (e.g., as done in RoboCup, Hedberg, 1997).

The third lesson has been to understand that some of the properties that are given for granted in a robot swarm—e.g., fault tolerance and scalability—are not automatically provided by the swarm and require a careful design. The difficulties are even larger if one wants to provide other properties not intrinsically granted by self-organising robot swarms, such as robustness (continue to work efficiently in environmental conditions different from those considered at design time), flexibility (capacity to solve problems/perform tasks that depart from those chosen at design time), or adaptivity (ability to learn/change behaviour to respond to new operating conditions). Similarly, there are key aspects that did not receive sufficient attention so far, but that are required for deployment in real-world applications. Security against external attacks is needed to make swarms resilient to malicious users trying to sneak into and seize the swarm. Reliability is another requirement for concrete applications, as performance should be guaranteed at design time especially for domains with hard constraints. Finally, explainability is necessary to foster acceptance and trust of swarms by users and laypeople.

The fourth lesson we have learned is that the "biological inspiration tool" must be used with great care. Taking inspiration from the behaviour of social insects or group-living species has been very valuable in many cases because these natural swarms have properties and display behaviours that are fundamental for any robot swarm: they are "living proofs" of the fact that self-organisation can work in general, and they provide viable solutions for specific problems such as how a robot swarm can move in a coordinated way (flocking), allocate tasks, or make collective decisions. However, one should not forget that the long-term goal of swarm robotics research is to deploy in the real-world robot swarms that perform useful tasks. It is therefore unlikely that biological inspiration will be able to guide us when the behaviours required of the robot swarm becomes very application specific. Researchers should therefore avoid putting too much faith in the "biological inspiration tool" and be ready to devise ad hoc solutions whenever necessary. However, as discussed later, biology can still provide general guiding principles in the design of more complex, application-specific robot swarms.

OPEN PROBLEMS IN SWARM ROBOTICS

In order to push forward the state of the art and bring swarm robotics closer to real world deployment, a number of open problems needs to be addressed and solved. First, we will need to develop tools that will make it easier for swarm robotics researchers to share results and replicate experiments. As mentioned above, current research is fragmented and the used robots are often created in a very ad hoc fashion. This issue applies not only to hardware, but also to simulation software which is often developed from scratch for each new robot swarm demonstrator[3]. A common simulation tool shared by the research community would be a significant step forward as it would simplify the sharing and comparison of research results. However, to devise such a tool, we need to better understand the relation between simulation and the real world. The problem, known in robotics as the simulation-reality gap (Jakobi et al., 1995), is that differences between the models used in simulation and their real-world counterparts cause a drop in performance when robot controllers developed in simulation are used in the real world. This problem is particularly important in swarm robotics where it is exacerbated by the fact that many robots have to interact with each other (Francesca and Birattari, 2016). The ideal robot swarm simulator should make sure that such discrepancies are kept to a minimum, even though they cannot be completely eliminated.

Beyond simulation, a few general-purpose robotic platforms would also constitute valuable tools for the research community. The e-puck (Mondada et al., 2009) is probably the most used platform to date, but research with more than 30 e-pucks remains complex and costly. The kilobot, being conceived for swarm robotics research, is becoming a de facto standard, but is severely limited in its abilities, so much that virtualization environments have been proposed to increase the research possibilities (Valentini et al., 2018; Reina et al., 2017). Crazyflies (Giernacki et al., 2017) are also becoming very much used as flying platforms for swarm robotics studies (McGuire et al., 2019), but are not conceived for swarm robotics research. Substantial effort is still needed to deploy a swarm robotics hardware featuring the good compromise between cost, size, onboard features and support for experimentation: such an hardware would greatly benefit the community worldwide.

Having the right tools, the swarm robotics research community will need to provide solutions to the design problem, allowing to seamlessly move from specifications to implementation, testing and maintenance of swarm-based services. To this end, current practices need to scale up in different ways. First of all, any solution to the design problem also needs to address the above-mentioned reality-gap problem—allowing the use of simulations in an extensive way for the design, without severe impact on the transposition of solutions to the real world. We need design methodologies that can guarantee such a smooth transition despite possible inaccuracies of the simulation. Scaling up in the size of swarms, transitioning from small to large groups, is also an important requirement that a design methodology must explicitly consider. We need design methodologies that enable to program a robot swarm without being concerned with the swarm/problem size, which should instead be determined at configuration time. Providing performance guarantees is very much needed, but current practices do not address this point sufficiently, being limited to empirical assessments of performance statistics. We need instead design methodologies that provide performance bounds that can meet market verification and validation standards.

Swarm properties such as scalability, fault tolerance, robustness and flexibility have been a major concern of swarm robotics research from its very beginning. However, future design methodologies should also address issues such as security and human swarm interaction. Both these issues are particularly challenging in robot swarms as the presence of many robots and the lack of a central controller make it difficult to know what is happening within the swarm. From one side, this fact could be exploited by malicious robots to disrupt the swarm functioning and, on the other side, it makes it difficult for a human user to exchange information with the swarm.

Finally, an open problem is how to scale up in task complexity. A complex task is made of several subtasks that might require cooperation, and that have mutual dependencies and time constraints (Gerkey and Mataric, 2004; Nunes et al., 2017). A straight divide-and-conquer approach is not sufficient to deploy usable swarm robotics systems, and therefore design methodologies are needed that address the complex interrelations between subtasks via continuous integration and refinement.

The breadth of problems that needs to be solved suggests that, more than a single engineering methodology, what is needed is a set of design methods—automatic or not—that can generate modules that can be easily configured and integrated with each other.

To date, the design problem was mostly addressed by means of biological inspiration, where the study of biological systems provided guiding principles to be exploited for programming swarm robotics behaviours. The collaboration between biologists and roboticists has been very fruitful, but often uni-directional, with robotics taking more than what it gave back to biology. During the first two decades, as swarm robotics developed and hit new grounds, it was usual to replicate natural swarm behaviours into swarm robotics systems, providing proofs of concept that swayed between being artificial models of biological systems and artefacts addressing real-world applications. We believe that a more fruitful collaboration can be set by disentangling these two aspects. Robot swarms can truly help biologists, providing artificial, controllable models to study the effects of embodiment, perception, action and the individual cognitive requirements necessary to support collective behaviour (Garnier et al., 2013). Additionally, the possibility of integrating autonomous robots into natural swarms offers unique opportunities of study that are just starting to be exploited (Halloy et al., 2007; Krause et al., 2011; Mitri et al., 2013; Bonnet et al., 2019). On the other hand, robot swarms should be designed with an engineering-minded approach if we want them to be relevant for real-world applications. In this respect, we foster further contributions from biology to provide novel guiding principles, as fresh insights about the mechanisms underlying swarm intelligence will continue to fascinate and inspire swarm robotics practitioners. However, as mentioned above, biological inspiration should not be taken too literally, and applications should take centrality if we want robot swarms to get out of research labs.

NEW DIRECTIONS AND NEW PROBLEMS

In the near future, most swarm robotics research will likely be devoted to finding solutions to the above mentioned open problems. Such research will be very important for the furthering of the field and for pushing forward the state of the art. There are however some research directions that might allow a larger jump forward as they would investigate either completely new approaches or areas that, even though already identified as open problems, have been understudied. These research directions are discussed in the following.

Nano-robots and biological robots

One of the tenets of swarm robotics is the ability to design and control thousands of simple robots, achieving swarm-level complex tasks resulting from simple individual behaviours and numerous interactions. An aspect that can maximise the impact of the domain in the future is the exploitation of thousands of miniature robots, with sizes scaling down to millimetres and even micro- or nanometres. Such swarms could access small confined spaces (e.g., microfluidic channels as well as the human body), could manipulate microscopic objects (e.g., microplastics or individual cells) and self-organise to support localised treatments (e.g., targeted drug delivery). To date, research has only scratched the surface of a domain with a huge potential. However, downscaling the robot size brings about new challenges that need to be addressed for swarm robotics to be able to offer practicable solutions. Micro and nano-robots are confronted with different physical laws than in the macroscopic scale, requiring novel models of collective behaviour. Also, integrating conventional ways of perception and action is extremely challenging, demanding a rethink of the strategies for designing and controlling such swarms. Indeed, current approaches to micro- and nano robots are not exploiting conventional hardware, but are rather made of active colloidal particles (Xie et al., 2019), soft-bodied (biological) robots (Kriegman et al., 2020), bacteria-powered nano-machines (Di Leonardo et al., 2010) and even controllable genetically-engineered organisms (Rabinowitch et al., 2014). Achieving and controlling collective behaviour in such systems will require novel paradigms, as the ability to precisely governing the individual behaviour will be forcedly limited. Hence, steering self-organisation can be more rewarding than attempting a direct control.

Heterogeneity

The homogeneity assumption still pervades research in swarm robotics: all robots are identical and all run the same control software, they are all replaceable and only the individual history of interactions with the (social) environment can lead to the expression of a somewhat specialised behaviour. This assumption stems from theoretical models of collective behaviour, which often simplify a complex phenomenon to gain in tractability. As a matter of fact, self-organisation in homogeneous systems has been often sufficient to explain experimental observations to a great degree (Camazine et al., 2001). However, individuals within natural swarms can be very different from each other, both physically and behaviourally, with individual personalities affecting the response to environmental and social cues (Jeanson & Weidenmüller, 2013). Heterogeneity is considered fundamental to grant collectives with flexibility of behaviour, adaptivity to new conditions, and resilience to external perturbations. All these features would benefit robot swarms, but heterogeneity is not exploited as much as it should. The already mentioned *Swarmanoid* project demonstrated one possible direction, by studying coordinated collective behaviours in physically heterogeneous groups of robots (Dorigo et al., 2013). Other powerful forms of collaboration allow initially-homogeneous robots to learn different behaviours, getting specialised to tasks when this leads to group performance benefits (Ferrante et al., 2015). Taming the complexity of the self-organised behaviour displayed by heterogeneous entities is however still very challenging, as well as finding viable approaches to multi-agent learning (Busoniu et al., 2008).

Decentralisation vs hierarchy

From its very beginning, swarm robotics has adopted the self-organisation paradigm, where the swarm control is obtained via simple (stochastic) rules that define the way the robots interact with each other and with the environment without exploiting any form of centralised control or of global knowledge. One could however argue that in many cases centralised or hierarchical forms of control could make the problem of designing and controlling a robot swarm easier. The introduction of some form of hierarchical control might also be justified by the fact that hierarchies are observed in many animal societies where they often go side by side with self-organisation (Chase, 1980). Unfortunately, these approaches would require the introduction of machinery that would make the system vulnerable (single point of failure) and difficult to scale.

The question of decentralisation vs hierarchy, or of how to integrate these two aspects, is currently understudied. A notable first step in this direction (Mathews et al., 2017) proposes to create hybrid systems where hierarchical control structures resulting from self-organising processes can appear on the fly in an ad hoc manner. This would be similar to what occurs in some wasp colonies where self-organising processes lead to the formation of a linear hierarchy and the emergence of a single reproducing individual (Theraulaz et al., 1995). Mathews et al. (2017) have created the infrastructure—middleware—that allows a robot swarm to autonomously switch from purely self-organised control to hierarchical control and back. While experiments have demonstrated the feasibility of the approach, much needs to be done to understand how the rules that allow the creation of the hierarchical control structure should be designed as a function of the task that the robot swarm has to perform, and how the passage from purely self-organised to hierarchical control and back can be activated as a function of the task and of the environment in which the robot swarm is acting.

Phase transition and adaptability

In a real-world environment, the main challenge faced by a swarm of robots is to adapt to unexpected events such as the presence of obstacles or changing atmospheric conditions (brightness, wind, rain). All these events may prevent the swarm moving forward or accomplishing some tasks. In these conditions, the swarm must collectively adapt its behaviour and automatically change its strategy. Such collective capabilities are observed in some species of group-living animals (swarms of midges, schools of fish, herds of sheep). In these species, the interactions between individuals give rise to group properties similar to those of a physical system close to a "phase transition" between two macroscopic states, resulting in an extreme sensitivity to changes in the behaviour of a small number of individuals (Attanasi et al., 2014; Muñoz, 2018). The reaction of a few individuals that have detected a change in the environment can then spread to all the other group members, allowing them to react efficiently to such disturbances such as a predator attack. Such collective adaptive capabilities do not only result from the particular form of interactions between individuals but also from a modulation of the relative intensities of these interactions (Calovi et al., 2015). The transposition of this type of properties in swarms of robots could significantly increase their level of autonomy and would be a promising line of research.

Security

The use of autonomous robots outside the lab will also introduce security issues. Robots need to be safe while doing their tasks, they should guarantee the privacy of the data they collect, and should also be resilient to external attacks by malicious users trying to get control. Such issues will be even more serious in the case of robot swarms (Higgins et al., 2009). Issues such as entity authentication, data confidentiality, data integrity, are amplified by the mere presence of potentially hundreds of robots interacting with each other. Additionally, disruption in the working of the swarm might be caused by just a few malicious robots sneaked into the group (Higgins at al., 2009). Research in robot swarm security is still in its infancy. Initial work is investigating how traditional (e.g., cryptographic Merkle trees, Castello et al., 2019) and less traditional (blockchain, Strobel et al., 2020) approaches to security can be exploited either to add security layers or to be fully integrated in the control architecture of robots swarms. These initial works allow to address issues such as how to keep information in a swarm private (Prorok and Kumar, 2018; Castello et al., 2019), how to avoid disruption due to the presence of malicious robots (Strobel et al., 2018), and how to counter Sybil attacks (Strobel et al., 2020). Much research will be needed to extend these simple, proof-of-concept solutions so that they can be ported to large swarms of robots acting in the real world.

Machine Learning and swarm robotics

As of today, the only prominent use of machine learning in swarm robotics has been the exploitation of evolutionary computation techniques for the development of simple neural controllers driving the behaviour of individual robots in the swarm. However, recent advances in machine learning and in particular the availability of new deep learning techniques could be leveraged both as a means to design the swarm behaviour and to provide additional capabilities to individual robots to be shared within the swarm. So far there has been little appreciation of these studies within the swarm robotics community. Machine learning as a design methodology suffers from the problems associated with the automatic design of robot swarms (Francesca and Birattari, 2016), with the additional constraints given by online learning of behaviours by trial and error (Busoniu et al., 2008), with episodic rewards and coordination problems. Model-free approaches may be very demanding in terms of computational requirements, although they can be very powerful in handling the complex, unpredictable contingencies that characterise swarm behaviour. Model-based approaches could be valuable, as learning a model of the (current) collective behaviour could lead to an efficient design of the individual policies. Combination of the two are currently sought for in several domains, and could be relevant also for swarm robotics research. Besides designing the swarm behaviour, machine learning and especially deep learning approaches could find space in swarm robotics research to provide advanced capabilities to individual robots that sustain the individual and collective behaviour. In this respect, it would be important to identify methods that can leverage the information available to the collective to support more efficient interpretation of the world. For instance, deep networks represent the state-of-the-art for image classification, a feature that is needed in many applications brought forth by robot swarms. By leveraging the presence of multiple robots observing the same scene, possibly from different perspectives and at different times, more accurate and computationally efficient solutions could be provided (Price et al., 2018; Magistri et al., 2019). Much work is needed to define the network architectures and learning paradigms to support swarm-level operations of this kind.

Human-swarm interaction

While the interaction with a single machine/robot is a very well-studied problem (Bartneck et al. 2020), interaction with a robot swarm opens completely new avenues. The main difficulty is given by the fact that, the swarm being self-organised, there is no clear entity with which a human could establish a communication link[4]. Human-swarm interaction will be necessary to provide the swarm information about goals to be achieved or tasks to be performed (Kolling et al., 2016, Brown et al., 2016). A swarm could be controlled indirectly by means of few user-driven robots embedded within the swarm. Recent research in several disciplines (Gautrais et al., 2004; Couzin et al., 2005; Calovi et al., 2015; Baronchelli, 2018) has shown that a minority of committed agents can determine the overall behaviour of a group. Similar mechanisms represent interesting means for the control of robot swarms, although they may introduce security challenges that must be dealt with, to avoid a few malicious robots taking control of the entire swarm. Alternatively, robot swarms could be controlled or steered directly by the user, and different ways have been proposed, such as through gestures (Podevijn et al., 2013; Nagi et al., 2014) or EEG signals (Mondada et al., 2016).

Direct control of a swarm by a user is complicated by the fact that understanding what the swarm is doing might be very challenging due to the multitude of interactions happening within the swarm, which might be hard to 'read' for a human observer. Possible solutions might be built-in within the self-organising mechanisms of the swarm, in a way to make the current state and goal of the swarm visible to users. Interfaces to swarm behaviours, possibly enabled by augmented reality, may collect and visualise information from the swarm, while models of the collective behaviour could be integrated in order to provide predictions that could support the user to take action (e.g., by issuing new commands to the swarm). The design of any human-swarm interaction solution will also require an understanding of the psychological effects induced on humans who interact with a robot swarm, in order to favour interaction modalities that reduce stress (Podevijn et al., 2016) and improve usability and trust (Nam et al., 2019).

How future applications will guide research

We are rapidly moving towards a society in which human beings will be more and more supported in their daily activities by robots. Soon robots will be everywhere and they will need to cooperate not only with humans but also with each other. It will therefore become of paramount importance to be able to program such robotic systems in a way that is secure, robust and flexible.

With these considerations in mind, potential application domains for swarm robotics should be critically evaluated for the benefits that a swarm robotics approach can concretely bring into play. For instance, **service robots** may not come in a swarm, although coordination of activities and allocation of tasks performed by each robot can be decentralised and self-organised to some extent. Still, the specific task itself may not require coordination or collaboration among robots. Similarly, **logistics** (e.g., in large warehouses, see D'Andrea 2012), **autonomous cars** and **smart mobility** in general can surely benefit from the decentralised coordination strategies studied in swarm robotics. It is however unlikely that these applications can guide future swarm robotics research. Conversely, applications like **precision**

agriculture or **infrastructure inspection and maintenance** require dealing with an unstructured, unpredictable environment—often covering extensive areas—and can benefit from collaboration among robots in a swarm. For instance, early identification of the outbreak of diseases within a crop field requires information sharing among robots to make global patterns emerge from coupled local views, supporting suitable responses and better strategic planning. Similarly, a reliable identification of defects in a large infrastructure requires active search abilities that could be best implemented by means of swarms, both in terms of efficiency and accuracy. In this respect, future research should focus on collective perception strategies to make sense of complex features by means of information fusion among multiple, possibly heterogeneous, robots. At the same time, tailored intervention and manipulation abilities need to be devised (e.g., for harvesting fruits or for maintenance), opening to new opportunities for collaborative activities.

The application of robot swarms is sought for by **defence** agencies worldwide, who find extremely appealing a system that cannot be easily shut down. A system that is fault-tolerant to external attacks can support operations in adversarial settings, especially when robots are replaceable and, to some extent, disposable. Here, however, the human component remains inevitably central. Hence, defence applications need to consider the human in the loop, and advanced human-swarm interaction strategies will be crucial for effective deployment. Also, security aspects need to be at the highest level to guarantee that robot swarms do not get out of control or maliciously seized. Similar aspects are fundamental in other application areas, such as **civil protection**, where the need to face natural disasters or anthropogenic hazards requires agile robots capable of dealing with emergency conditions, with no external infrastructure or reliable maps. Such applications set the bar very high, as robot swarms should be capable of guaranteeing the highest possible performance and reliability, because no victim should be left behind.

Space missions—both with rovers for planet explorations and in-orbit satellites—introduce other constraints on robotics applications that might be successfully addressed by swarm robotics. In space, the computational power of computers has to remain limited because of cosmic radiation burning modern CPUs. A swarm of robots of limited computational power might therefore be a better design choice than a single more powerful robot. Robots that are sent out in space cannot be easily repaired or substituted, which is well addressed by the swarm robotics focus on redundant systems where the failure of one of the robots does cause only a graceful degradation of the swarm performance. Finally, in space it might be extremely costly or even impossible to build an external infrastructure to support the coordination of robots, again a typical situation that robot swarm can effectively deal with. The great challenge brought forward by space applications is the necessary autonomy of the swarm system, which cannot rely on reliable and constant intervention from human operators.

Finally, swarms of nano-bots might in the future become a new and powerful tool in **precision medicine**, making possible targeted interventions within the human body, such as minimally-invasive surgery or polytherapy delivery directly to cancerous cells. However, the coordination of huge numbers of robots with extremely limited computational and communication capabilities will stretch to the limits the swarm robotics approach and will require the development of new conceptual tools, let alone the development of microscopic hardware or bio-robotics devices (Sitti, 2017).

Overall, the relationship between the requirements from potential application domains and future research challenges for swarm robotics is indisputable. We therefore envisage a close collaboration between researchers and the relevant stakeholders from the various application domains, who can provide concrete examples to challenge novel developments, and contribute to set the agenda of swarm robotics research in the years to come.

CONCLUSIONS

The design and implementation of effective robot swarms is one of the greatest challenges that lie ahead for robotics, as well as one of the most promising research avenues, as acknowledged by Yang et al. (2018). In this perspective, we have briefly summarised the state of the art, and identified what we believe to be the most promising research directions and main open problems. Yet our overview is inevitably incomplete, because significant advances in swarm robotics will strongly depend on research carried out outside the field; in fact, advancements in many of the other grand challenges identified by Yang et al. (2018) will be decisive for the development of swarm robotics. For example, new materials, biohybrid solutions, new ways of storing and transmitting energy, could help address some of the current issues related to the hardware of robot swarms. The development of AI techniques, in particular of distributed learning algorithms that require limited computation and can work with the CPUs of small inexpensive robots, will allow robot swarms to gradually increase their autonomy. Swarms will have to ensure explainability, now a major issue for the whole field of robotics and artificial intelligence. In other words, the user will need to be able to understand the decision making of the swarm without a detailed knowledge of the underlying mechanisms—a paramount requirement to ensure the acceptability of robot swarms and to foster trust in them, hence creating the conditions for a massive real-world deployment. Even though many of these issues are being addressed more generally within the artificial intelligence field, their complexity might be increased by the high number of autonomous entities and by their numerous interactions with each other that are typical of swarm robotics systems.

If these challenges are faced, we expect swarm robotics could successfully transition from laboratories to real-world applications within the current decade (see box 2: “Timeline of the swarm robotics research domain”), with the first deployments taking place in agriculture, infrastructure inspection and maintenance, and non-offensive military applications. The use of robot swarms as part of space missions could come next, and play a key role in the exploration of the Moon and Mars by 2040. The last—and more challenging—frontier would be medical applications such as drug delivery inside the body, that require miniaturisation and advanced biocompatibility and where the first demonstrations could arrive by the mid- 21st century. The successful deployment of robot swarms in these and other applications could pave the way for collective, bioinspired robotics to become a mainstay of engineering in the second half of the century, possibly establishing itself as *the* standard way of designing complex robotic systems.

NOTES

(1) As a matter of fact, there is practically no application domain—apart from vacuum cleaners—that provides fully autonomous solutions.

(2) http://www.nasaswarmathon.com/

(3) A notable exception is the ARGoS simulator (Pinciroli 2012), which has not however been adopted by the whole community yet.

(4) It is interesting to note that research discussed above about introducing components of hierarchical control in a self-organised swarm can help provide a solution to this problem.

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