Swarm Robotics: Past, Present, and Future

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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-organizing systems, such as social insects, fish schools, or bird flocks, characterized by emergent collective behavior based on simple local interaction rules [1], [2]. Typically, swarm robotics extracts engineering principles from the study of those natural systems in order to provide multirobot systems with comparable 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 behavior to changes in the environment.

Swarm robotics started out as an application of swarm intelligence [3], [4], that is, the computational modeling of collective, self-organizing behavior that has resulted in several successful optimization algorithms [5], [6] now being used in fields ranging from telecommunications [7] to simulation and prediction of crowd behavior [8]. However, it has quickly become evident that achieving swarm behavior 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, localization, 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 that demonstrated the potential of robot swarms, also contributing to a better understanding of how complex behaviors emerge in nature. Translating this research into practice represents a challenge that still needs to be appropriately tackled. As a matter of fact, as of today, only a few experiments have

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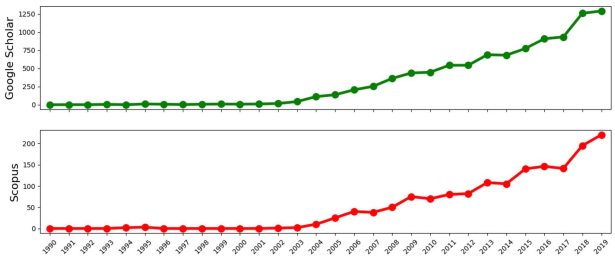

Fig. 1. *Citation count for the search "swarm robotics" in Google Scholar and in SCOPUS, showing an increasing trend after year 2000.*

managed to demonstrate a large number of autonomous self-organizing robots, and no real-world application of swarm robotics exists. More research is needed to establish the knowledge and practice required to bring robot swarms out of the lab and into the real world.

In the following, after a brief history of the field, we summarize the main lessons learned during the pioneering phase of swarm robotics, we analyze the main open challenges and provide examples of innovative and promising research directions. Finally, we suggest the most likely fields of application for swarm robotics and assess its potential impact on selected industries, by showing application scenarios that cannot be tackled by a single robot, or by a few robots controlled in a traditional, centralized way.

I. 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 [9]–[12] 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, and that its usage remained very limited until 2003 when it started to grow considerably. Similarly, a search with SCOPUS returns a comparable increasing trend (see Fig. 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.

Initially, the study of swarm robotics was aimed at testing the concept of stigmergy (see Table 1 for the definition of this and other concepts used in this article) as a means of indirect communication and coordination between robots. Following a few initial attempts [9]–[11], several studies appeared after 2000 focused on tasks such as object retrieval (foraging [13]; stick pulling [14]), clustering [15], and sorting of objects [16]. These studies started from known behaviors observed in social insects and deployed robot swarms demonstrating similar behavior. In a few cases, the robot swarm was exploited to closely replicate the dynamics observed in biological systems (e.g., aggregation in cockroaches [17]), leading to the first example of a mixed biological-robotic society [18]. In addition, swarms of robots have been used as a tool to address biological questions (e.g., what is the trail network geometry to find the shortest path between a food source and a nest [19]).

One of the first international projects to investigate cooperation in a swarm of robots was the Swarm-bots project funded by the European Commission 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 behaviors, such as collective transport, area coverage, and object search [25], [26]. The main result of the project was to demonstrate what—at the present day—remains the only example of self-organized teams of robots that cooperate to solve a complex task, with the robots in the swarm taking different roles over time [27]. 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 [28], [29].

In parallel with the successful demonstration of the swarm robotics paradigm, research on hardware miniaturization promised the deployment of hundreds, possibly thousands of cooperating robots (see Fig. 2). Robots became smaller and evermore minimalist, up to attempts of designs at the millimeter scale. 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 [30]. Kilobots were conceived to support the first demonstration of a large robot swarm designed for shape formation [31] and have been later used for several successful studies, allowing swarm robotics to be demonstrated in physical settings with hundreds of robots [32]–[34].

Swarm robotics is not limited to ground platforms: recent work has considered aquatic surface [38] and underwater robots [39], as well as swarms of flying drones [40], [41]. While aquatic and underwater technologies still need substantial development efforts to become mature, drones are instead already commercialized and represent a very promising platform for remote sensing applications in different domains, being currently hindered only by the lack of a legal framework authorizing 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

Table 1 Glossary of Key Terms Used in This Article

Term	Description
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 [20], [21]).
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 an explicit reference to the model of the environment.
Phase transition	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	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 [1].
Stigmergy	A form of indirect communication between natural or artificial 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 [22] and has played an important role in supporting self-organising mechanisms in swarm robotics [23], [24].

literature is beyond the scope of this perspective (but see [42]–[46]). The main directions taken so far include the following: the development of analytical models of swarm systems to guide the robotics implementation [47]–[49]; the adoption of (evolutionary) optimization approaches where robots are guided by minimalistic controllers (neural networks [50]; controllers without computation [51], [52]; finite-state machines [53]; and grammar-based controllers [54]); and the development of design and verification methodologies [20], [55]. As will be discussed in the following, 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.

II. LESSONS LEARNED AND OPEN PROBLEMS

Even though the ultimate goal of swarm robotics is to produce methodologies and tools that make possible the deployment of robot swarms for the solution of real-world problems, currently, the focus remains on the scientific understanding of the mechanisms that would inform such methodologies and tools. The first two decades of research have taught us a number of important lessons, also raising a few open problems that need to be addressed and solved.

First, we learned that the types of tasks that can currently be performed by robot swarms are strongly constrained by the still limited capabilities of autonomous robots. 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 them. This entails tailored hardware designs and specific sensing, processing, and interaction abilities. Current limitations in robot hardware and control have constrained the complexity of swarm robotics research in two different ways. On the one hand, specific robots have been developed to solve specific (toy) problems (e.g., termes [56] and kilobots [30]). These examples have opened new research directions but not always resulted in reusable components to be borrowed in different contexts. On the other hand, generic robots (alice [19], [57] and e-puck [37]) have been used to produce proofs of concept, often addressing tasks that are a direct transposition in the

Fig. 2. *Some of the robots largely used in swarm robotics research: (a) jasmine [35] (photo: WikiMedia Commons); (b) alice [36] (photo courtesy of Simon Garnier); (c) kilobots [30] (photo courtesy of Massimo Berruti); (d) e-pucks [37]; (e) swarm-bots [26]; and (f) swarmanoid [29].*

artificial world of analogous tasks performed by self-organized natural systems (e.g., foraging [13], [34]). 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 limited the number of robots in the tested swarms, reducing the breadth and significance of the demonstrations. Finally, it should be added that the miniaturization of hardware will be a key element for experimentation in the lab with large swarms and for many future applications. Still, downscaling hardware poses extremely hard problems that, so far, have not been solved [58].

To progress in swarm robotics research, we will need to develop tools that will make it easier for swarm robotics researchers to share results and replicate experiments. A few general-purpose robotic platforms would constitute valuable tools for the research community. The e-puck [37] is probably the most used swarm robotics platform to date, but research with more than 30 e-pucks remains complex and costly. The kilobot, being conceived for swarm robotics research, is widely used, but it is severely limited in its abilities, so much that virtualization environments have been proposed to increase the research possibilities [59], [60]. Crazyflies [61] are also becoming very much used as flying platforms for swarm robotics studies [41] even though they were not conceived for swarm robotics research. Substantial effort is still needed to deploy swarm robotics hardware that satisfies the needs of the research community. First, a good compromise between cost, size, and onboard features must be provided, ensuring a sufficiently rich set of sensors and actuators while keeping size limited to favor experimentation with hundreds of robots within a research lab. In this sense, a size between that of the kilobot and that of the e-puck (about 5-cm diameter) could be a good compromise. Modular approaches allowing to plug-in extensions with new sensors, actuators, or computational power proved successful with the e-puck but require a careful design. The possibility to program and recharge many robots in parallel—as done with kilobots—strongly simplifies the experimental activities when dealing with large numbers, especially when manual interventions to move robots around are not required (e.g., wireless recharging stations integrated into the experimental environment, or even electric floors for battery-less operation). A centralized system to automatize experimental activities, capable of observing the robots' state, moving them around, and logging data acquired by the robots, would be of great help to speed up research and would greatly benefit the community worldwide.

Simulating hardware is also a fundamental aspect of swarm robotics research but raises similar problems as with physical robots. Often, the simulation software is developed from scratch for each new robot swarm demonstrator. 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 [62], 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 [44]. The ideal robot swarm simulator should make sure that such discrepancies are kept to a minimum even though they cannot be completely eliminated.

Among the many simulation softwares available, ARGoS [63] stands out for the native support to swarm robotics research. ARGoS allows the real-time dynamical simulation of up to 10 000 robots due to a clever modular design and the possibility to parallelize the simulation. Moreover, it includes the models of some of the most used robots in swarm robotics (e-pucks and kilobots). Another interesting example is Flightmare [64], a (multi-)UAV simulator capable of photorealistic rendering of the environment, useful for studies of visual navigation and remote sensing. To improve over these experiences and provide a tool that responds to the needs of the swarm robotics community—also addressing the simulation–reality gap—several aspects need to be addressed and improved. For example, we will need to find ways to improve the simulation of perception and of physical (robot–robot and robot–environment) and nonphysical (communication) interactions. Simulations should be deployed at different levels of fidelity, allowing the user to choose the balance between speed and accuracy. In most cases, high-fidelity simulations are not mandatory, but their availability would largely simplify the transition from simulation to reality, supporting extensive tests before going live on real robots. It will also be necessary to improve the usability of the simulation by increasing the simulation speed and providing simpler means of handling and controlling the simulated robots and the environment in which they are deployed. Simulations should be highly configurable to respond to the needs of a diverse research community. At the same time, setting up a new simulation configuration should not require expert knowledge of the inner working of the software. Finally, it will be important for the simulation framework to be integrated with standard robotics tools and libraries (e.g., ROS) and to allow cross compilation with respect to the robotic platform, which would make it possible to test the code developed in simulation with the real robots without the need for any change or adjustment.

Having the right tools, the swarm robotics research community will need to provide solutions to the design problem. Indeed, the second lesson that we have learned is that addressing the micro-macro problem—how to design the swarm behavior (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—often guided by biological inspiration—that are general-purpose and reusable in different application contexts, from design patterns [20], [21] to automatic design methods [50], [53], [65] (see glossary in Table 1). However, all these approaches are for the moment not powerful enough: they successfully address relatively simple or constrained problems but rapidly show their limits as the problem complexity increases. A complex task is made of several subtasks that might require cooperation and that have mutual dependencies and time constraints [66], [67]. One might be tempted to apply available approaches to each subtask, obtaining building blocks to compose later. However, such a divide-and-conquer approach is not sufficient to deploy usable swarm robotics systems because this overlooks the many possible interrelations between tasks and the way in which these can be further partitioned and scheduled, leading to suboptimal solutions. We need design methodologies that address the complex interrelations between subtasks via continuous integration and refinement [55]. In addition, current practices need to scale up in the size of swarms, seamlessly transitioning from small to large groups. We need design methodologies that enable us to program a robot swarm without being concerned with the swarm/problem size, which should instead be determined at configuration time. Finally, 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 to meet verification and validation standards and that promote the reliability of robot swarms especially for application domains with hard constraints (e.g., space applications). To concretely support the research community, benchmarks are invaluable tools to measure the progress in a quantitative way and can be used to challenge the researchers on tasks that grow in complexity (e.g., as done in RoboCup [68]). To give an idea of the type of benchmarks needed to progress in swarm robotics research, consider a resource collection problem, as done in the NASA Swarmathon [69] competition. To move beyond current practices, one could set up the problem so that its complexity can be adjusted along several dimensions: environment size and topology, to test the capability of the proposed solution to adapt to different problem instances and to scale performance with group size; number and distribution of items to be collected, to test abilities for coordinated exploration and exploitation of resources; and type and persistence of items, to test the ability to collaborate for recognition and retrieval, and to adapt to a dynamic environment. Informational complexity should also be varied by allowing multiple alternative paths for task execution—this would require the swarm to gather and aggregate information about the problem and its dynamics, taking collective decisions when needed to optimize the task

performance. Possibly, multiple interrelated tasks should be identified with variable constraints in their temporal execution (e.g., giving precedence to some item types to enable retrieval of other types). Clear performance metrics must be assigned to track progress and support comparison between different approaches. If a benchmark along these lines were proposed and associated with standard tools—both hardware and simulation, as discussed above—an open community could gather and flourish, learning from best practices and continuously improving over the achieved results.

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-organizing robot swarms, such as robustness, flexibility, or adaptivity (see the glossary in Table 1 for a definition of these terms). Attempts to design robot swarms featuring such properties have been made by means of theoretical approaches that neglect the embodiment of the robots and their specific functional aspects in terms of sensors and actuators. The abovementioned properties have been demonstrated using mathematical models, abstract particle systems, or multiagent systems in the context of swarms performing different behaviors (e.g., aggregation [70], collective motion [71], collective decision-making [20], and pattern formation [72]). However, translating theoretical findings into working robotic systems often requires a complete rethink of the approaches to introduce features and constraints not considered in the necessarily simplified theoretical models and to account for the specificity of the target application domain. In addition, there are key aspects that did not receive sufficient attention so far but 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. How to command and control a swarm is also extremely important, in order to let users interact with the robotic system in a meaningful and effortless way. This also requires a high level of explainability, which is necessary to foster acceptance and trust of swarms by users and laypeople. Properly addressing these aspects will largely strengthen swarm robotics and will promote its transition from research to concrete applications.

The fourth lesson that we have learned is that the "biological inspiration tool" must be used with great care. Taking inspiration from the behavior of social insects or group-living species has been very valuable in many cases because these natural swarms have properties and display behaviors that are fundamental for any robot swarm: they are "living proofs" of the fact that self-organization can work in general, and they provide viable solutions for specific problems, such as how a robot swarm can move in a coordinated way, allocate tasks, or make collective decisions. 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 inform swarm robotics practitioners. 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. Consequently, robot swarms should be designed with an engineering-oriented approach if we want them to be relevant for real-world applications. It is, therefore, unlikely that biological inspiration will be able alone to guide us when the behaviors required of the robot swarm become 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.

It is also interesting to note that, although the collaboration between biologists and roboticists has been very fruitful, it has often been unidirectional, with robotics taking more than what it gave back to biology. We believe that this situation can be improved and that robot swarms could truly help biologists, providing artificial, controllable models to study the effects of embodiment, perception, action, and the individual cognitive requirements necessary to support collective behavior [19], [73]. In addition, the possibility of integrating autonomous robots into natural swarms offers novel research directions that are just starting to be explored [18], [74]–[76].

III. NEW DIRECTIONS AND NEW PROBLEMS

In the near future, most swarm robotics research will likely be devoted to finding solutions to the abovementioned 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. We first discuss how to design and control robot swarms when dealing with novel and challenging situations, such as extreme constraints given by small sizes and large numbers of individuals (III-A), or the opportunities given by heterogeneous robot swarms, either in hardware/behavior (III-B) or in their organizational structure (III-C). We then move to consider new directions for designing robot swarms, either mimicking biologically inspired examples of responsiveness and adaptability (III-D) or adopting machine learning approaches to provide swarms with the ability to learn and improve their performance (III-E). Finally, we discuss the need for further research in robot swarm security (III-F) and in human–swarm

interaction (III-G) that will be of paramount importance for real-world deployments.

A. Hardware Miniaturization

One of the ambitions of swarm robotics is to design and control thousands of simple robots, achieving swarm-level complex behavior resulting from simple individual behaviors and numerous interactions. An aspect that can maximize the future impact of robot swarms is the exploitation of thousands of miniature robots, with sizes scaling down to millimeters or even micro- or nanometers. Such swarms could access small confined spaces (e.g., microfluidic channels and the human body), manipulate microscopic objects (e.g., microplastics or individual cells), and self-organize to support localized treatments (e.g., targeted drug delivery). To date, research has only scratched the surface of a domain with 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. Microrobots and nanorobots are confronted with different physical laws than at the macroscopic scale, requiring novel models of collective behavior. Current approaches to microrobots and nanorobots are not exploiting conventional hardware but are rather made of active colloidal particles [77], soft-bodied (biological) robots [78], bacteria-powered nanomachines [79], [80], and even controllable genetically engineered organisms [81]. Achieving and controlling collective behavior in such systems will require novel paradigms, as the ability to precisely governing the individual behavior will be forcedly limited. Also, integrating conventional ways of perception and action is extremely challenging [82], demanding a rethink of the strategies for designing and controlling such swarms. Overall, research should focus on control methods that exploit few unreliable sensors, minimal or completely absent computational abilities, and unreliable actions [51], [52]. Solutions that design the hardware to present self-organizing properties are also plausible [83], [84] although, in this case, it may be difficult to obtain flexible and adaptive behavior. In all these cases, steering self-organization can be more rewarding than attempting direct control.

B. 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 specialized behavior. This assumption stems from theoretical models of collective behavior, which often simplify a complex phenomenon to gain tractability. As a matter of fact, self-organization in homogeneous systems has been often sufficient to explain experimental observations to a great degree [1]. However, individuals within natural swarms can be very different from each other, both physically and behaviorally, with individual personalities affecting the response to environmental and social cues [85]. Heterogeneity is considered fundamental to grant collectives with the flexibility of behavior, 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 behaviors in physically heterogeneous groups of robots [29]. Other powerful forms of collaboration allow initially-homogeneous robots to learn different behaviors, getting specialized to tasks when this leads to group performance benefits [54]. Taming the complexity of the self-organized behavior displayed by heterogeneous entities is, however, still very challenging but promises great advances for the domain as a whole.

C. Decentralization Versus Hierarchy

From its very beginning, swarm robotics has adopted the self-organization 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 centralized control or of global knowledge. One could, however, argue that, in many cases, centralized 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-organization [86], [87]. 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 decentralization versus hierarchy, or of how to integrate these two aspects, is currently understudied. A notable first step in this direction [88] proposes to create hybrid systems where hierarchical control structures resulting from self-organizing processes can appear on the fly in an *ad hoc* manner. This would be similar to what occurs in some wasp colonies where self-organizing processes lead to the formation of a linear hierarchy and the emergence of a single reproducing individual [87]. Mathews *et al.* [88] have created the infrastructure—middleware—that allows a robot swarm to autonomously switch from purely self-organized control to hierarchical control and back. While experiments have demonstrated the feasibility of the approach [88], [89], 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-organized 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.

D. Phase Transitions 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 (e.g., brightness, wind, or rain). All these events may prevent the swarm from moving forward or accomplishing some tasks. In these conditions, the swarm must collectively adapt its behavior and automatically change its strategy. Such collective capabilities are observed in some species of group-living animals (swarms of midges, schools of fish, and 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 (see the glossary in Table 1), resulting in an extreme sensitivity to changes in the behavior of a small number of individuals [90], [91]. In such conditions, the reaction of a few individuals that have detected a change in the environment can spread to all the other group members, allowing them to react efficiently to such disturbances 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 [92]. 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.

E. Machine Learning for Robot Swarms

As of today, the only prominent use of machine learning in swarm robotics has been the exploitation of evolutionary algorithms (see the glossary in Table 1) for the development of simple neural controllers driving the behavior of individual robots in the swarm. However, recent advances in machine learning, in particular the availability of new deep learning techniques, could be leveraged both as a means to design the swarm behavior 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 [44], with the additional constraints given by online learning of behaviors by trial and error [93], with episodic rewards and coordination problems. Model-free approaches (see Table 1) may be very demanding in terms of computational requirements although they can be very powerful in handling the complex, unpredictable contingencies that characterize swarm behavior. Model-based approaches could be valuable, as learning a model of the (current) collective behavior could lead to an efficient design of the individual policies. The combination of the two is currently sought for in several domains and could be relevant also for swarm robotics research. Besides designing the swarm behavior, 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 behavior. In this respect, it would be important to identify methods that can leverage the information available to the collective to support a 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 [94], [95]. Much work is needed to define the network architectures and learning paradigms to support swarm-level operations of this kind.

F. Security

The use of autonomous robots outside the lab will introduce security issues. Robots need to be safe while doing their tasks [96], they should guarantee the privacy of the data that they collect, and they 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 [97]. Issues such as entity authentication, data confidentiality, and data integrity are amplified by the mere presence of potentially hundreds of robots interacting with each other. In addition, disruption in the working of the swarm might be caused by just a few malicious robots sneaking into the group [97]. Research in robot swarm security is still in its infancy. Initial work is investigating how traditional (e.g., cryptographic Merkle trees [98]) and less traditional (blockchain [99]) 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 [98], [100], how to avoid disruption due to the presence of malicious robots [101], and how to counter Sybil attacks [99]. 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.

G. Human–Swarm Interaction

While the interaction with a single machine/robot is a very well-studied problem [102], the interaction with a robot swarm opens completely new avenues. The main difficulty is given by the fact that, with the swarm being self-organized, there is no clear entity with which a human could establish communication. Human–swarm interaction (HSI) will be necessary to provide the swarm with information about goals to be achieved or tasks to be performed [103], [104]. A swarm could be controlled indirectly by means of a few user-driven robots embedded within the swarm. Recent

research in several disciplines [92], [105]–[107] has shown that a minority of committed agents can determine the overall behavior 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 [108], [109] or EEG signals [110].

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. Therefore, explainability is crucial. Possible solutions might be built into the self-organizing mechanisms of the swarm, so as to make the current state and goal of the swarm visible to users. Interfaces to swarm behaviors, possibly enabled by augmented reality, may collect and visualize information from the swarm, while models of the collective behavior 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 HSI solution will also require an understanding of the psychological effects induced on humans who interact with a robot swarm in order to favor interaction modalities that reduce stress [111], [112] and improve usability and trust [113].

IV. HOW FUTURE APPLICATIONS WILL GUIDE RESEARCH

The great interest in swarm robotics research recorded to date [114]–[116] is due to the expected forthcoming ubiquity of autonomous robots in real-world applications and to the challenge of letting them cooperate with each other and with their human users avoiding the pitfalls of centralized control. The knowledge and practice produced by swarm robotics research will be key to address complex coordination problems of future robotics applications, taking into account both cooperative scenarios (i.e., robots coordinating for accomplishing a common task) and semicooperative scenarios (i.e., robots that are self-interested but benefit from a globally efficient organization of activities, such as autonomous vehicles). Hence, we firmly believe that pushing forward swarm robotics research will benefit not only the field in itself but also the domains of robotics, cyber–physical systems, and sociotechnical systems at large.

In this section, we first discuss what are the general criteria that would justify the use of robot swarms to solve problems or perform tasks in real-world applications, and then, we give an overview of what we believe to be the main potential application domains for swarm robotics. This overview is of a speculative nature since—as we said—real-world applications are still to come. We try, however, to motivate our choices by critically evaluating the benefits that a swarm robotics approach could concretely bring into play in the different application domains considered.

A. General Criteria for a Robot Swarm Solution

In principle, the first question to ask when considering the application of a robot swarm to the solution of a real-world problem is whether a robot swarm is indeed the best way to go. However, this is a very difficult question, especially so given that swarm robotics is a young discipline and that, as discussed above, there are still many open research questions. As a consequence, the current practice consists of evaluating the suitability of swarm robotics solutions on the basis of the expected advantages with respect to other solutions, factoring in the constraints imposed by available technologies.[1] Given the lack of working methodologies to move from problem specification to robot swarm implementation and deployment, in the following we discuss a few general guidelines that should direct the choice of swarm robotics solutions when dealing with a concrete application problem.

The first very general guideline is that the use of a multirobot system—and by extension, of a robot swarm—should be envisioned only if the problem considered cannot be (efficiently) solved via a single-robot solution because it is either too complex or too demanding considering the available technology and the application constraints. For instance, the surveillance of a large area with a single robot might not be feasible, and the only option might be to use many robots at the same time [119]. Another example is the exploration of a large collapsed building by UAVs in a search-and-rescue scenario: even though, in this case, a single UAV might perform the task, this might not be efficient enough due to the limited flight time and the need to fly back for recharging. In such conditions, a multirobot solution could be more efficient due to parallel operation [41].

Once the suitability of a multirobot system is established, one should consider what type of control approach would be the most appropriate for the considered problem. For example, when it is not possible or advisable to coordinate the robots in a centralized way [120], the use of a robot swarm might be the right way to go. In some cases, centralized replanning could be feasible to deal with task uncertainty and environmental unpredictability [121]. However, a strong demand for online recognition of features and adaptation to experienced contingencies might be better approached through decentralized, self-organized methods. Even in this case, however, one should consider if other approaches, such as distributed model predictive control [122], [123], could be used,

[1] A notable exception is the work of Kazadi [117], [118], who explicitly addresses the question of whether a robot swarm is an appropriate technology for a given problem; however, his methodology is still at the stage of proposal and has not been applied on any real robot swarm implementation.

which might not be the case when it is impossible or too difficult to create simple enough models of both the problem to be solved and the environment in which the robots are going to operate.

Another aspect to consider is whether the given problem is decomposable in a fixed number of well-defined tasks that can be addressed by a team of robots, each with a specific role, as is the case for instance in an assembly line or in robotic soccer [68]. Once again, if this is not the case, then a swarm robotics approach might be conceivable. In other words, even if a problem is better solved with a multirobot system, this does not necessarily imply the need for a robot swarm. The latter is better justified by tasks that have no predefined partitioning in subtasks or that allow diverse allocations of roles to the available robots [27], [29]. Finally, a swarm robotics approach might be the right choice if a beneficial collaboration between the robots is expected. In fact, due to collaboration, a swarm robotics system can aim for a superlinear increase in performance that would justify the overhead necessary to set up the collaboration [124].

B. Applications, Needs, and Future Research

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, although service robots are usually not organized as a swarm, the coordination of activities and allocation of tasks performed by each robot can be decentralized and self-organized to some extent. Still, the specific task itself may not require coordination or collaboration between robots. Similarly, logistics (e.g., in large warehouses), autonomous cars, and smart mobility can surely benefit from the decentralized coordination strategies studied in swarm robotics. It is, however, unlikely that these applications can guide future swarm robotics research. Conversely, applications such as precision agriculture or infrastructure inspection and maintenance require dealing with an unstructured, unpredictable environment—often covering extensive areas—and can benefit from parallelization and collaboration between robots in a swarm. For instance, early identification of the outbreak of diseases within a crop field requires information sharing between robots to make global patterns emerge from coupled local views, supporting suitable responses and better strategic planning [95], [125]. Similarly, reliable identification of defects in a large infrastructure requires efficient search abilities that could be best implemented by means of swarms [126]. Both precision agriculture and infrastructure inspection happen in somewhat static environments (the crop field or the infrastructure to inspect). Despite this, decentralization and self-organization can be useful in improving efficiency—thanks to parallel and coordinated operations—and accuracy—thanks to adaptive strategies for collective perception that allow to respond to the sensed contingencies and determine the optimal mission plan so as to maximize the likelihood that all relevant features are observed with care. In this respect, future research should focus on strategies to make sense of complex features by means of information fusion among multiple, possibly heterogeneous, robots. In addition, tailored intervention and manipulation abilities need to be devised (e.g., for harvesting fruits or maintenance), opening to new opportunities for decentralized, collaborative activities.

The application of robot swarms is sought by defense agencies worldwide, that find extremely appealing a system that cannot be easily shut down [127]. 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, defense applications need to consider the human in the loop, and advanced HSI strategies will be crucial for effective deployment [113]. Also, safety and security aspects need to be at the highest level to guarantee that robot swarms do not get out of control or maliciously seized [96]. Similar aspects are fundamental in other application areas, such as civil protection, where the need to face natural or anthropogenic disasters requires agile robots capable of dealing with emergency situations, 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 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 [128]. A swarm of robots of limited computational power might, therefore, be a better design choice than a single more powerful robot [69], [129], [130]. 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. Accordingly, space agencies, such as NASA and ESA, have started to show interest in swarm technologies, for example, with activities such as the already mentioned Swarmathon competition [69] and with research directed at the control of swarms of picosatellites [130]. 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.

The entertainment sector has also good potential for the employment of robot swarms. There are already several examples of light shows performed with drone swarms both outdoors and indoors [131], which, however, are generally based on centralized preorchestrated trajectories for the drones. In a similar way, other attempts to exploit multirobot systems for entertainment have relied on some centralized solution to finely control the system [132], [133]. New avenues are possible if a decentralized approach is considered, especially if users can actively participate in the entertainment activity by engaging with the robot swarm, changing its dynamics according to positions, movements, and even emotions [134]. In this context, research can experiment with radically new modalities for HSI that can be afterward borrowed by other application domains. For instance, all sorts of HSI interfaces can be imagined, from wearable devices [135], augmented and virtual reality [136], and brain–computer interaction modalities [110].

Finally, swarms of nanobots 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 [137], [138]. However, the coordination of huge numbers of robots with extremely limited computational and communication capabilities will stretch the swarm robotics approach to its limits and will require the development of new conceptual tools, in addition to the development of microscopic hardware or biorobotics devices [58].

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 push novel developments and contribute to set the agenda of swarm robotics research in the years to come.

V. CONCLUSION

The design and implementation of effective robot swarms is among the greatest challenges that lie ahead for robotics, as well as one of the most promising research avenues, as acknowledged in [116]. In this article, we have briefly summarized the state of the art and identified what we believe to be the most promising research directions and main open problems. It should, however, be considered that significant advances in swarm robotics are bound to progress made outside the field. For example, new materials, biohybrid solutions, and new ways of storing and transmitting energy would 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 processes without detailed knowledge of the underlying mechanisms—a paramount requirement to ensure the acceptability of new intelligent technologies and to foster trust in them, hence creating the conditions for 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 overcome, we expect swarm robotics to successfully transition from laboratories to real-world applications within the current decade, as suggested above. Such a transition will not be immediate but will progressively involve more and more application domains in the identification of new challenges and the creation of a demand for new technological solutions that will drive research and innovation in the years to come. ■

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