Swarm Robotics: Robustness, Scalability, and Self-X Features in Industrial Applications

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Abstract

Applying principles of swarm intelligence to the control of autonomous systems in industry can advance our ability to manage complexity in prominent and high-cost sectors—such as transportation, logistics, and construction. In swarm robotics, the exclusive use of decentralized control relying on local communication and information provides the key advantage first of scalability, and second of robustness against failure points. These are directly useful in certain applied tasks that can be studied in laboratory environments, such as self-assembly and self-organized construction. In this article, we give a brief introduction to swarm robotics for a broad audience, with the intention of targeting future industrial applications. We then present a summary of four examples of our recently published research results with simple models. First, we present our approach to self-reconfiguration, which uses collective adjustment of swarm density in a dynamic setting. Second, we describe our robot experiments for self-organized material deployment in structured and semi-structured environments, applicable to braided composites. Third, we present our machine learning approach for self-assembly, motivated as a simple model developing foundational methods, which generates self-organizing robot behaviors to form emergent patterns. Fourth, we describe our experiments implementing a bioinspired model in a robot swarm, where we show self-healing of damage as the robots collectively locate a resource. Overall, the four examples we present concern robustness, scalability, and self-X features, which we propose as potentially relevant to future research in swarm robotics applied to industry sectors. We summarize these approaches as an introduction to our recent research, targeting the broad audience of this journal.

1 Introduction

Swarm robotics [20] is the application of swarm intelligence [3] to mobile robotics. Compared to other multi-robot approaches, swarm robotics comes with unique main advantages, which are above all: robustness and scalability [5]. Swarm robots rely exclusively on local information. Narrowcasts (local broadcasts) are allowed but no point-to-point communication across the whole swarm. Data is stored distributed across the swarm. Local communication and local information combined with decentralized control ensure a high degree of robustness. In a homogeneous swarm, no robot is specialized and each robot can replace any other robot. All these features provide a high degree of redundancy in the robot system and hence robustness.

Scalability in swarm robotics means that we can apply the same control algorithms unchanged to virtually any swarm and system size. Whether it is three, 100, or 1000 robots, the same algorithms should be applicable if the approach is truly decentralized and relies only on local information [20]. However, the swarm density (i.e., number of robots per area) needs to be kept constant when scaling and other resources should grow with the system size (e.g., number of charging stations). Scalability also means that the system may change dynamically at runtime. A swarm may be able to adapt to the changed system size, as discussed later. Scalability with a linear speedup would be $S = N$, where the speedup is $S = T_1/T_N$, and where T_1 is the time needed to complete the task with one robot, and T_N likewise with N robots. Each swarm system has an optimal swarm density and super-linear speedups are potentially possible in swarm robotics [19, 17]. The largest swarm robotics experiment reported so far used a swarm of 1024 robots for a self-assembly task [37].

Despite these advantages, robot swarms are not per se immune to detrimental effects due to malfunctioning robots or even targeted attacks by sabotaging robots. A damaged sensor may cause a robot to persistently send wrong messages to its neighbors. This may affect a large fraction of the swarm negatively by diffusing false information although all communication is local. Ongoing research in swarm robotics [34, 20] focuses on applications such as self-assembly, and on ensuring typical self-X properties, such as self-healing, self-adaptation, and self-reconfiguration.

2 Applicability to industry sectors

Approaches relevant to swarm robotics are represented in industry, although rarely. Related approaches, especially those of multi-agent systems, are more broadly seen. The commercially available Kiva system for the modern autonomous warehouse uses a multi-agent approach to control hundreds of autonomous robots simultaneously [52]. This distributed approach was selected because a centralized planning approach to coordinate trajectories of hundreds of robots would not be feasible [52]. Although not a commercial endeavor, and not making use of self-X features, an example of a demonstrated swarm system is the NASA Edison Demonstration of Smallsat Networks (EDSN), which uses a distributed approach to dramatically reduce the cost of deploying satellites, without sacrificing functionality [7].

We propose the application of swarm robotics approaches to industry sectors as a key open research challenge, and identify the following opportunities for future work. Our engineered systems are increasing in complexity, and failures of prominent and high-cost engineering projects are frequently attributed to unmanageable systems [2, 28, 6, 32]. As seen in the Kiva and EDSN systems, a distributed approach can greatly impact such sectors as logistics, transportation, and construction, for instance by simplifying organizational overhead, increasing robustness, or drastically decreasing cost. A system equipped with the necessary self-X properties could help manage the infrastructure and construction sectors' increasing—and sometimes prohibitive—complexity, for instance in the high-profile setbacks of the Berlin Brandenburg Airport [13]. If able to be recreated, the reduction in cost and overhead seen in the EDSN swarm would likewise greatly benefit complicated transportation mega-projects that are typically delayed and over-budget.

The software and hardware that could be utilized in these industry scenarios are an open challenge in the field of swarm robotics. Each sector is likely to require certain self-X properties of the system in combination with discipline-specific methods at the phase of final application. To progress toward these, basic research uses simplified setups—simplistic models that represent a mechanism as concisely as possible—to investigate key behaviors of robot swarms that can be generalized as foundations of future applications.

3 Self-reconfiguration

One self-X feature important for industry applications is self-reconfiguration. The robot swarms should be able to adapt to the uncertainty in typical application environments, while maintaining the efficiency of their performance. The robots can tackle this by self-reconfiguring their algorithm parameters according to the monitored environmental variations. Typically, each robot would individually measure the changes in the relevant features. Given that some features may only be detected by the swarm collectively [40], exchanging perspectives among the swarm members through local communication increases the efficiency and ensures behavioral consistency [47].

The most evident variable feature that has a significant impact on swarm performance is the swarm density. It may easily change during runtime if some robots break, get lost, are intentionally removed or added, or if the size of the operating area is altered. When swarm density increases over the optimum, the robots waste more time and resources avoiding collisions among each other (i.e., interference). This competition for physical space can significantly decrease the performance of the group [16, 19]. For example, in [30] the authors quantitatively investigate a performance decline due to interference in two foraging scenarios: a simple resource collection task, and a full foraging task. In the first scenario, they found that the collective performance of the swarm improves as density increases, but

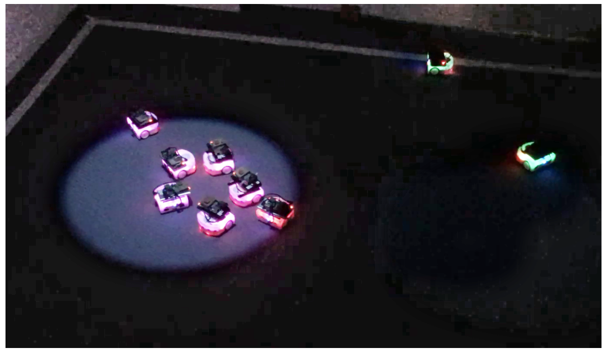


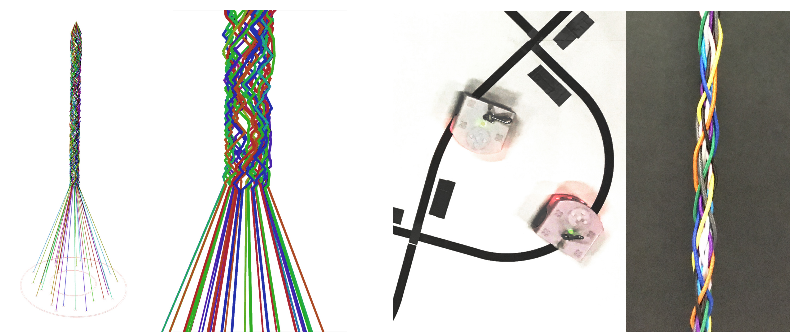
Figure 1: A swarm of nine robots running an adaptive BEECLUST algorithm. Robots in purple are in waiting state (i.e., clustering), and robots in green are in exploring state.

only sublinearly, due to interference—in other words, the performance of each individual robot decreases as the swarm density increases. In the second scenario, they found an optimal swarm density that maximizes performance. Increasing the swarm density beyond this optimum leads to declining performance. Optimal swarm density is task-dependant and varies according to many system parameters (e.g., size of operating area, number of charging stations in cases of autonomous charging, number of resources or homes in cases of foraging). If the robots are aware of the optimal and current swarm densities, then remedying actions can be taken when they differ. The robots can alter their swarm density, by for example retreating from the swarm, asking more robots to join, or adjusting the size of the operating area. Another approach would be adjusting the optimal density by altering the system parameters.

Here we describe our approach (for more details see [48]) for online reconfiguration of system parameters, to maintain high performance during an aggregation task in a dynamic environment. Based on the BEECLUST algorithm [39, 41, 26], a swarm of Thymio II robots [33] aggregates at the brightest spot in the arena (see Fig. 1). A waiting function manages the waiting times when the robots stop at robot-to-robot encounters, eventually forming a cluster at the desired location. We expose the swarm to challenges by changing the light conditions two to four times per experiment, in 25 experiments. The swarm size was also halved in the middle of 10 of these experiments. In each case, the key measure of success is mapping the current environmental condition correctly to the optimal waiting time. The robots collect light sensor readings and measure the average time between consecutive robot-to-robot encounters, which is proportional to the mean free path. Supported by the analysis conducted on kinetic gas theory in [27], we assume that the swarm density scales inversely proportional to the mean free path. Collectively, the robots estimate the current swarm density and the interval of experienced light intensities, without necessarily visiting all relevant locations. They use this information to adjust the waiting function accordingly, and successfully find the brightest spot.

4 Self-organized construction

The construction sector handles expensive and high-profile mega-projects [32] that often have unmanageable complexity [2, 28]. Self-organization in construction automation could be a useful feature, and the relevant technologies are being developed [15]. A key challenge is the use of nondeterministic control when the associated industries rely on known results that are pre-approved for certain traits, such as structural performance under live loads. One solution to this expectation of known results—proposed by Werfel et al. [51, 50]—is that each robot is given a full map of the desired structure, which it compares to the actual current structure to determine where to place its next block. Alternatively, architecture and engineering approaches propose to guarantee only key performance traits, not a full configuration description [22, 24]. A limited performance demonstration may be sufficient for regulatory approval of new construction technologies (cf. [38]).



(a) Simulation in a semi-structured environment.

(b) Experiment setup and result for a structured environment [23].

Figure 2: Self-organized deployment of fibres is potentially applicable to carbon fibre composites, an established manufacturing method [36] and broadening construction method [29].

We consider simple models where a group of mobile robots uses limited self-organization approaches to deploy fibre, steered by environment conditions. One use of fibre deployment is in the production of composites, where industrial braid machines organize carbon fibre into a biaxial interwoven tube, for instance around a rigid core [36]. The machinery is often limited in flexibility and slow to reconfigure. In an effort to improve this, there have been advances toward distributed hardware that is more flexible. Implementing swarm robotics approaches to control this hardware could facilitate scalability and robustness, for instance allowing the size and pattern of braid to adapt online, for a complex multilayer braid [31] or for winding a non-uniform cross-section core. Using

Thymio II robots [33] as a stand-in for patented production-ready robots for trackless industrial braiding [21], we have investigated self-organized deployment in structured and in semi-structured arenas.

In a semi-structured arena, the robots move between two concentric circular walls. They organize their deployment only by avoiding any obstacle they encounter—whether neighboring robot or wall—and by alternating the side on which they prefer to pass an obstacle. The patterns deployed by the robots have a tendency to be regular biaxial braid, due to their alternating preference for passing. The concentric walls provide an environmental cue that steers the robots toward an overall circular shape, thereby forming a tubular braid. The semi-structured nature of the arena is such that, although the robots reliably execute alternating passes, there is quite some randomness to the order in which robots are encountered. This produces a braid with an irregular pattern (see simulation results in Fig. 2a; cf. experiment results in [23]).

To also deploy fibres according to a regular pattern, we investigate a structured, trackless arena [23]. The robots use ground-facing sensors to follow 2D printed lines (see Fig. 2a) that oscillate according to the track layout often seen in industrial braid machines (cf. [43]). The robots do not have access to any global information about the environment or task. They use only locally sensed information and local communication with neighbors to deploy a braid, augmenting their line-following with a self-organized approach to intersection events. When one robot encounters a line intersection, it waits there until it meets another robot. Once the two meeting robots have communicated their presence to each other, they pass on a given side, and then switch to the opposite preference for the next intersection. This reliably deploys a regularly patterned braid (see Fig. 2a). Although the printed lines in this setup cannot be reconfigured, the patented industrial mobile braiding robots [21] can be run for instance in an LCD screen arena, allowing dynamic paths rather than static ones. Because the robots in our approach navigate the lines and intersections without any global information, our method could be directly implemented in a rapidly reconfigurable arena. In an extended approach, we use projection of a more abstracted arena, and robots self-organize adaptive paths (for details see [12]).

5 Self-assembly

Self-assembly enables groups of robots to accomplish tasks a single robot would not be able to carry out, such as crossing large gaps or navigating rough terrain [35, 46]. The approach draws inspiration from nature, where individual elements self-assemble into complex forms using only local interactions—for example, molecules forming crystals [37] or ant colonies creating bridges [1].

We use methods of machine learning to generate self-assembly behaviors for collective shape formation in a 2D torus grid world [25]. Our approach—‘minimize surprise’—targets the automatic creation of controllers for robot swarms, which despite recent improvements in machine learning is still a challenging problem [20]. We apply methods of evo-

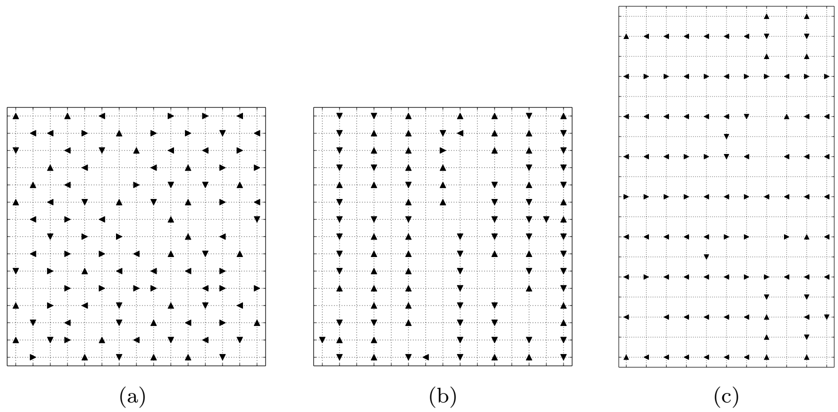


Figure 3: Samples of emergent patterns in a self-assembly scenario using minimal surprise: (a) triangular lattice and (b,c) lines (cf. [25])

lutionary computation, following the approach of evolutionary swarm robotics [45]. A pair of artificial neural networks is evolved, where one serves as a typical controller and the other serves as a world model predicting the sensor values of the next time step. As the design of a fitness function in evolutionary robotics is challenging [44], an intrinsic driver is provided instead of a task-specific reward. Fitness is given according the quality of the predictions, which is effectively minimizing the difference between real and predicted sensor values—thus, minimizing surprise (cf. [14]).

In previous works [4, 18, 53], we evolve four simple swarm behaviors in 1D and 2D torus environments. In our approach presented here [25], we increase the task complexity by using minimal surprise for the task of self-assembly in patterns. A variety of self-assembly behaviors evolved, including dispersing behaviors like triangular lattices (see Fig. 3a), squares and loose dispersion; grouping behaviors like aggregation, clustering and pairs of agents; and line structures. We engineer self-organized self-assembly using predefined sensor predictions, fixing the outputs of the world model to desired values. This guides evolution towards specific self-assembly behaviors, such as the formation of lines (see Fig. 3b). The resulting patterns can also be influenced by changing the shape of the environment. A rectangular grid for instance requires the formation of horizontal lines (see Fig. 3c) to reach a maximal fitness value. Details can be found in [25] and the code is available online.[1]

While this approach is not yet used in real world applications, it is promising for certain scenarios. Switching the grid-based self-assembly approach to a continuous world is the next step toward real implementation. The patterns evolved thus far are suggestive of tasks that can be solved by minimizing surprise. The dispersion behaviors, for exam-

[1] `https://github.com/msminirobot/minimal-surprise-self-assembly`

ple, could be used for area coverage tasks. Using robots with gripping capabilities, stable self-assemblages (cf. [37]) could be formed, potentially allowing the evolved line structures to cross gaps or traverse challenging terrain. After implementing on a swarm of real robots and aiming for increasingly complex tasks, our approach of minimizing surprise can help automatically generate swarm controllers for self-assembly and other tasks.

6 Self-healing

Biological phenomena have inspired many approaches to robot morphology and control [49], including self-healing. There are for instance hexapod robots that adapt like animals after damage to some of their legs [8], and here we describe our method for structures that self-heal using a model inspired by plants. Here, we give an example experiment. For more details, see [10] that gives the results of several different experiment types and repetitions (over 30 in total).[2]

Plant growth is robust against many types of damage, via a feedback mechanism that drives vascular patterning to adapt to the distribution of resources in the environment [42]. Resources gathered by the plant are distributed to different organs through a vascular network. The vessel properties driving this distribution are impacted in part by transport of the growth hormone *auxin*. Higher auxin concentration, that is for instance impacted by stimuli at the plant tips, leads to thicker vessels that in turn facilitate resource transportation from the root to the tips. An abstract generative model of the plants' vascular system has been developed for bio-inspired growth of tree structures [54]. In our approach, we implement this model onto a robot swarm. As the robots form nodes in the graph—representing different organs of a plant—and the communication channels form the edges—representing the plant vessels—the whole plant can be modeled as a tree structure (i.e., directed acylcic graph). Each robot senses the local environment, here represented by light distribution. The branches of the tree that receive more light create thicker vessels and therefore receive higher virtual resources from the root, resulting in a higher chance to remain in the tree. The resource is distributed such that there is competition between branches. Therefore, if a branch becomes weaker the other branches gain more resource. This way the structure stays adaptive. If a part of the structure is cut, the tree adapts to the change and once there is a chance to regrow a branch the self-healing process begins.

We implement the vascular morphogenesis controller onto a robot swarm to achieve adaptation to a dynamic environment and collective site selection [9, 11]. In order to examine if the swarm is also able to self-heal when damaged, we conduct an experiment with 70 'Kilobots' [37]. Kilobots are small robots (33 mm width, 34 mm height) that communicate with a local neighborhood of up to three body lengths away via infrared [37]. A square arena (84 cm on each side) is used with a video

[2]Repository of experiment results: `http://doi.org/10.5281/zenodo.2538671`

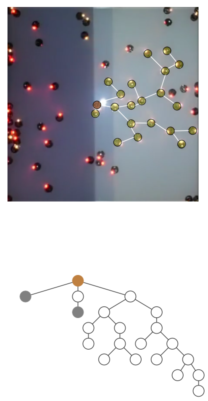


Figure 4: A dark bar on a self-assembled tree structure (‘cutting the tree’). Three time steps of a self-healing experiment. In the center frame, the robots under the dark bar depart the tree and as a result, all of their children disassemble too. This simulates damage. Once we stop projecting the dark bar, the tree repairs itself and rebuilds the structure. [9].

projector above, projecting different patterns of light. A robot in the center of the arena serves as the root of the tree structure, and it is the only robot in the tree at experiment initialization. The root robot informs the robots in its neighborhood that a tree is within their reach so that they can join the tree as well. The tree grows from the center of the arena towards the boundaries not in all directions necessarily. The robots at the bright side of the arena are able to provide more light to the tree. Therefore, they have a higher chance to successfully compete against the robots at the darker side of the arena.

As shown in Fig. 4, the right half of the arena is brighter than the left half. Each experiment lasts for 600 seconds. After the first 200 seconds (see Fig. 4, left), the tree on the right side develops long branches whereas the left part of the tree does not grow, as few robots join and those that do leave quickly due to lack of resource. During $200 < t \leq 400$ (see Fig. 4, center) a dark bar is projected that decreases the light values for the robots it hits. As a result, the robots receiving the dark bar cannot gain sufficient resource and depart the tree, along with all of their children nodes. This represents damage, as the tree is cut by the dark bar. During the last 200 seconds, the dark bar is lifted, allowing the structure to sense light in that area again. The result shows that the swarm was able to self-heal after being cut, growing back the damaged structure (see Fig. 4, right). The graph plots underneath the experiment frames in Fig. 4 show the tree structure of the respective experiment frame—before, during, and after the dark bar is projected.

7 Conclusion

We have described four works related to swarm robotics, advantages of scalability and robustness, and its applications. The increasing complexity of engineered systems may still be governed in the future by such strictly decentralized approaches. Two of our works present methods for achieving self-X properties, and the others demonstrate applications. Although each is conducted in a basic setup, they are representative and have the potential to be applied in real industry scenarios. Our method for self-reconfiguration can protect high performance in a swarm executing tasks such as foraging. Our self-organized construction approach can expand the reconfigurability possibilities in existing industry applications. Our machine learning method for self-assembly facilitates the execution of complex tasks that mechanically require the collaboration of multiple robots. Our self-healing approach can provide robustness even in challenging scenarios where a majority of robots are damaged. Although so far demonstrated in quite limited examples, these research topics are relevant to the execution of many tasks that may otherwise be prohibitively complex, an increasingly present problem across industry sectors.

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