



Swarm Foraging Review: Closing the Gap Between Proof and Practice

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Abstract

Purpose of Review We review recent research on swarm robot foraging and contextualize it with foundational work. Recent work can be divided into two complementary camps: self-organizing algorithms that provide practical gains and analytical research focus on theoretical proofs.

Recent Findings Encouragingly, the convergence between theory and practice is evident in analytical work on the scaling of transportation networks and in behavioral grammars that give formal insight into emergent properties of foraging. Augmented reality has enabled virtual pheromones to be used with hardware, blurring the line between physical and simulation experiments.

Summary In this review we highlight bio-inspired and self-organizing approaches to swarm foraging and contrast them with approaches that can provide theoretical proofs, but which abstract away important features from foraging in real-world environments.

Keywords Swarm robotics · Swarm intelligence · Bio-inspired foraging · Foraging taxonomies · Central place foraging review

Introduction

Østergaard et al. [1] defined swarm foraging as “a two-step repetitive process in which (1) robots search a designated region of space for certain objects, and (2) once found these objects are brought to a goal region using some form of navigation.” Winfield [2] wrote that the foraging task is a powerful benchmark for three reasons: social insects provide a proof-of-concept, success requires the coordination of several physical tasks (searching, harvesting, transportation, homing, and deposition at a collection site), and optimality requires cooperation between robots.

One of the most cited applications of swarm foraging is the harvesting of resources on extraterrestrial bodies [2–4]. Efficient resource collection under these remote and harsh conditions requires the use of autonomous robots.

The fundamental challenge in swarm foraging is the complex and dynamic interaction between robots, the environment, and targets, given only limited and noisy local information. Several divergent lines of research have been developed to meet this challenge.

This review focuses on research published between 2015 and early 2020. We refer the reader to Senanayake et al. [5], Bayindir [6], and Zedadra et al. [7] for reviews of work before

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2015. We place recent research in context by discussing foundational papers, those primarily written in the 1980s and early 1990s when the various approaches to swarm foraging were forming. Foundational papers were selected by tracing references in recent work back to the first relevant ancestral publication (e.g., Baeza-Yates [8]) and frequently cited papers from that period (e.g., Brooks [9]), or papers that were representative of a highly cited author or research group (e.g., Deneubourg et al. [10]). See Efremov and Kholod [11] and Talamali et al. [12] for alternative points of view on recent foraging research.

Foundations

Swarm foraging has been a central robot task since the beginning of modern robotics in the 1990s. Drogoul and Ferber [13] in their 1993 swarm foraging paper described the “explorer-robots application” as popular because of its use in “the three most influential fields of Artificial life”: robotics where it motivated the subsumption architecture [9], evolutionary programming of simulated ants following the “Santa Fe Trail” [14], and behavioral simulations of social animals [10].

Almost as soon as robot foraging research began, the symbolic artificial-intelligence solutions that had dominated robotics were abandoned. Symbolic AI is a useful strawman because each of the above strategies is defined by how it overcomes the intractability of the model–plan–act solution that symbolic AI offered.

Steeles [3] found the logical planner approach to be wholly unreasonable because (1) the computational cost would be too high to reason effectively about the world and (2) creating an accurate model of the world is very difficult. Steeles’ argument that an intelligent robot would be infeasible because it would need megabytes of memory and the ability to perform thousands of logical inferences per second is anachronistic. However, recent work on swarm foraging still favors emergence, simple agents, and behaviors over reasoning explicitly from a constructed model of the environment.

Self-organizing strategies take advantage of emergent and dynamic interaction with the environment and necessarily provide empirical performance measures rather than proof. This branch is in the tradition of Brooks, Steels, and Mataric [3, 15, 16]. Self-organizing strategies treat the foraging process with its feedback cycles, contingency on environments and target configurations, and lack of global knowledge as a complex system. Solutions tend to be emergent, stigmergic, reactive, and based on scientific induction.

Ants have provided a behavioral model for robot foraging since the earliest publications [3, 13]. Our understanding of resource collection by animals has been largely shaped by optimal foraging theory [17, 18]. The work of ant researchers such as Hölldobler and Deneubourg [10, 19] quantified the efficiency

of ant foraging using mathematical models and by observation of real ants. Winfield [2] highlights the importance of social insect research “sophisticated foraging observed in social insects, recently becoming well understood, provides both inspiration and system-level models for artificial systems.”

Several papers in this review reference Lévy walks, which model the movement of biological organisms [20, 21] including ants [22] with a power-law distribution of movement lengths governed by the Lévy exponent. Viswanathan et al. [23] proved that for sparse, replenishable resources uniformly distributed in the plane Lévy walks are the optimal stochastic strategy. Though the underpinnings are analytical, recent papers have focused on how Lévy walks respond empirically to violations of those conditions, not on analysis.

In 1983 Baeza-Yates et al. [8] initiated “a new area of study dealing with the best way to search a possibly unbounded region for an object.” This work was extended in two further papers: a single robot searching for a single target [24] and multiple robots searching for a line [25]. This work formed the foundation of a branch of robot foraging research that tends to be highly abstract, interested in formal proofs of performance, often geometric, and does not include communication [26]. Alternatively, mean-field approaches model the feedback loops that contribute to the complexity of the foraging task. They can make strong statements about the statistical distribution of robot states, but they require infinite swarm sizes and generally assume only local interactions without communication [27].

Recently, Pitonakova et al. [28–30] proposed a framework that contextualizes many aspects of foraging in terms of information. Robot foragers succeeded or failed based on the amount and quality of information gathered during foraging and their ability to act on that information.

Taxonomy

Several taxonomies have been proposed for foraging robot swarms [1, 2, 31, 32]. Zedadra et al. [7] summarized these taxonomies and proposed a synthetic taxonomy: *environment*, *collective*, *strategy*, and *simulation* categories and applied them to simulated systems and real-world experiments. We classify recent work into *self-organizing* and *analytical* categories. Each category has the following features: *optimization methods*, *robot differentiation*, *hybrid control*, *communication*, and *implementation*. The classification of papers according to this taxonomy is in Table 1.

Optimization Method

We classify the optimization methods into three major categories: machine learning (ML) other than genetic algorithms, genetic algorithms (GA), and hand tuning. The ML and GA

Table 1 Taxonomy of foraging swarm

		Optimization method			Differentiation			Hybrid control	Communication				Implementation			
Paper	Year	ML	GA	HT	SS	DD	SD	Y		Dt	St	SM	None	Sim	Lab	Field
Self-organizing																
[33]	2020		×		×			×					×	100		
[34]	2020			×	×					×				3		
[12]	2020			×	×						×			500	200	
[35••]	2020		×			×		×				×		4864		
[36]	2020	×			×						×			20		
[37]	2019		×		×			×				×		4		4
[38]	2019			×	×					×				950		
[39]	2019			×	×						×			50		
[40]	2018		×			×		×				×		96		
[30]	2018			×	×					×				50		
[41]	2018			×	×						×			20		
[28]	2018			×	×					×				50		
[29]	2018			×	×					×					5	
[42]	2018			×	×						×				100	
[43]	2018			×	×					×				40		
[44]	2018			×	×						×		×	200		
[45]	2018			×	×								×			1
[46]	2018			×	×								×			1
[47]	2017	×	×		×						×			30		
[48]	2017		×	×	×						×			24		
[49]	2017			×	×						×				50	
[50]	2016		×		×							×		64		
[51]	2016			×	×					×				50		
[52]	2016			×	×			×		×				10		
[53]	2016			×	×					×				30	30	
[54]	2016	×					×	×					×	30		
[55]	2015		×		×							×		768	6	
[56]	2015		×		×						×	×		6		
[57]	2015			×	×						×			1000		
[58]	2015			×	×						×			30		
[59]	2015		×				×	×					×	20		
[60]	2015			×	×						×				6	
[61]	2015			×	×						×				15	
[62]	2015			×	×					×					20	
Analytical																
[35••]	2020		×			×		×				×		4864		
[63••]	2019				×								×	100		
[64]	2019			×	×								×		12	
[65]	2019			×	×								×	16,384		
[66]	2018			×			×	×					×	80		
[67••]	2020			×			×	×					×	1000		
[68]	2018		×		×								×	9		
[69]	2017			×	×								×	250		
[70]	2016			×	×			×					×	30		
[71]	2016	×			×					×				25		
[72]	2016			×	×								×	5	5	

The numbers indicate the maximum number of robots used

ML machine learning, *GA* genetic algorithm, *HT* hand tuning, Differentiation: robot and task differentiation (*SS* same robots for same tasks, *DD* different robots for different tasks, *SD* same robots for different tasks), *Dt* direct, *St* stigmergy, *SM* shared memory, *Sim* simulation, *Lab* physical robots in laboratory environments, *Field* physical robots in real-world environments.

methods are used to automatically find the optimal parameters of the foraging strategy. However, understanding automatically tuned solutions is challenging. In addition, sometimes ML optimization requires large computational resources and does not guarantee convergence to a solution. These drawbacks motivate many researchers to hand tune their strategies using heuristics.

Robot and Task Differentiation

Typically, in robot swarms, each robot is identical and works on the same tasks. However, in some heterogenous swarms, robots may have different specialized hardware or be responsible for specific tasks (e.g., task partitioning). In recent studies, most swarms have (1) the same robots for the same task

(SS) [52, 66], (2) different robots for different tasks (DD) [35, 40], or (3) the same robots for different tasks (SD) [54, 59, 73].

Hybrid Control

While all swarm foraging systems are inherently distributed, many approaches use some centralized global knowledge, for example, preplanned transportation routes [54, 59]. We call these hybrid control strategies.

Communication

Three major forms of communication appear in recent research: direct communication, stigmergy, and shared memory.

Direct Communication: Robots exchange information directly between each other.

Stigmergy: Stigmergy is communication through modification of the environment, exemplified by ant pheromones. In simulation studies changing the simulation environment is trivial. In physical instantiations stigmergy is difficult to achieve.

Three major approaches have been used to emulate ant pheromones: beacon robots [74–76], physical materials [77–79], and virtual pheromone [42, 49, 60, 61, 80]. Virtual pheromones may be implemented with augmented reality: Kilobots are capable of light stigmergy [12, 49] as are epucks [61]. Arvin et al. [60] implemented a series of low-cost robots capable of following light pheromones. Steels [3] proposed the use of radioactive materials to create physical trails and Alfeo et al. [39] suggested RFID tags.

Shared Memory: Robots can access and add information to a common memory. This mechanism is analogous to the broadcast communication in which each robot can exchange information with any other robots in the swarm.

Implementation

Foraging research used a variety of simulation and physical realizations of robots and their environments. These robots can be broadly divided into simulation, physical robots confined to laboratory environments, and field robots. We discuss commonly used robot platforms in the next section.

Robotic Platforms

Several hardware and simulation technologies have been developed, which underpin recent swarm foraging research.

Simulation: Many recent foraging robot experiments have been conducted using the Autonomous Robots Go Swarming (ARGoS) [81] and Gazebo simulators [82]. ARGoS is a swarm robot simulation environment that uses physics engines of varying fidelity to model various robots quickly.

Gazebo is a more accurate simulation but as a result cannot simulate large swarms. STAGE [72, 83–85], the Microsoft® Robotics Developer Studio (MRDS) [86], and the agent-based modeling Netlogo [87] have also been used in recent work.

Laboratory: Many studies simulated simple physical pick-up and drop-off of objects. For example, Castello et al. [72], Brutschy et al. [62], Pitonakova et al. [29] and Mondada et al. [88] use a group of e-puck robots; and Hecker and Moses [55] use iAnt robots, which detect targets but do not physically pick them up [89, 90]. Kilobots can operate autonomously to push items, but they have relatively limited mobility and only operate in controlled laboratory environments [91, 92]. Many physical foraging experiments have been conducted with foot-bots equipped with grippers, infrared sensors, and camera for omnidirectional vision [73] and customizable platforms like MinDART [93]. The Robotarium provides a testbed for remotely accessible physical robots, and localization is governed by an overhead camera [94].

Field: Many physical foraging experiments have been conducted in real-world environments. The Swarmanoid project demonstrates an innovative heterogeneous physical swarm robotic system in solving a complex object retrieval task in an environment containing a shelf and books [95]. The Cataglyphis robot, which won the NASA Sample Return Robot (SRR) Challenge, demonstrated robust robotic foraging in an outdoor environment.

One hundred Swarmie robots were used in the NASA Swarmathon competition. Swarmies were designed to operate outside of the lab in “parking lot” environments. They have a front web camera, three pairs of ultrasound range sensors, inertial measurement unit (IMU), GPS, wheels, onboard Linux computer, and a front gripper for collecting and transporting targets [4].

Self-Organizing Strategies

Hecker and Moses [55] developed the iAnt robot testbed and implemented a correlated random walk and pheromone foraging solution called the Central-Place Foraging Algorithm (CPFA). The system was optimized offline by a GA for different environments. Using ARGoS, Just et al. [48] built on the work in Hecker and Moses [55] to develop an online method of selecting the appropriate foraging parameters. Performance was compared with the Distributed Deterministic Spiral Algorithm (DDSA) [70] analytical approach and found to outperform it for dynamic distributions in which resource locations change over time but not for static resource locations.

Ericksen et al. [47] implemented a foraging algorithm using a neural network controller designed by Neuroevolution of Augmenting Topologies [96] named NeatFA and compared it against the CPFA in [55] and the DDSA [70]. Empirically, NeatFA can successfully forage for resources with comparable

performance without human-designed behavioral states and transitions.

The Swarmathon competition [4, 34, 97] was funded by NASA to develop foraging algorithms and evaluate them using Swarmie robots. In Fig. 1 robots use a spoke algorithm to gather target cubes and deposit them in a central location. Successful entries optimized their strategies empirically over many development trials. Solutions included geometric patterns such as expanding spirals, rotating spokes [63••], and zig-zags. Recruitment to target cluster locations was successfully employed in combination with these geometric patterns.

Wilson et al. [41] demonstrated online adaptation with a hormone inspired approach. Using ARGoS, emergent online adaptation was shown to do better than offline GA optimization.

Alfeo et al. [39] framed the problem of gathering refuse in a complex urban environment as a multiple-place foraging task. The authors used the structure provided by the environment along with stigmergy to develop a self-organizing solution that performs better than a preplanned strategy. Experiments were performed with the agent based urban planning tool Gama.

Using the iAnt simulation, Fricke et al. [98] motivated by the suggestion that T cells employ a Lévy search pattern [21], showed that the optimal Lévy exponent depends on both the degrees to which targets are clustered and on the size of the swarm. Nauta et al. [99] combined memory with Lévy walks. This improved performance in single objective foraging but reduced multi-objective efficiency. Memory also made the search pattern appear Brownian. Schroeder et al. [100] proposed a combination of pheromone following and Lévy walks. The combination was empirically demonstrated to be

more efficient, but “pop up” threats were more often avoided by Lévy walks alone. Dimidov et al. [53] investigated the parameterization of Lévy walks and correlated random walks (CRW). Using a customized simulation and Kilobots, the authors found that in bounded-foraging areas high-displacement CRWs outperform a Lévy walk, but the reverse was true for unbounded foraging areas.

Congestion is a negative feedback loop in foraging. To mitigate this, Isaacs et al. [34] implemented a reservation system, while Abdelaal et al. [69] used bias in pheromone following so that robots avoided each other on the way to the collection zone. Isaacs et al. performed experiments with a Gazebo [82] simulation developed for the Swarmathon [4]. Talimali et al. [12] and in follow up work Llenas et al. [44] used ARK [49] and ARGoS in a study informed by optimal foraging theory to show that congestion as a product of swarm size determines when swarms benefit from switching to alternate, lower quality, target clusters.

Zedadra et al. [57] implemented a pheromone strategy to avoid oversampling of the environment. Their system consisted of a subsumption architecture with 4 layers: exploration, target exploitation, recharging, and obstacle avoidance. Dadgar et al. [71] presented adaptive robot particle swarm optimization (A-RPSO), which they show improves upon previous PSO algorithms when applied to foraging.

Ferrante et al. [59] used a GA to evolve a foraging solution using a behavior grammar. The system evolved efficient foraging strategies with relatively little constraint on available behaviors. The authors emphasized the implications for evolutionary biology as well as swarm robotics. Experiments were performed using an ARGoS simulation of foot-bots.

Andrade and Boyle [33] investigated an energy constrained model of foraging in which robots use the energy from foraged resources to continue foraging. Evolutionary algorithms were used to tune a 6-parameter model over several environments. The authors reported that “reactive algorithms are ideal for minimalistic, low-cost or disposable robots as they do not demand complex or expensive hardware resources.”

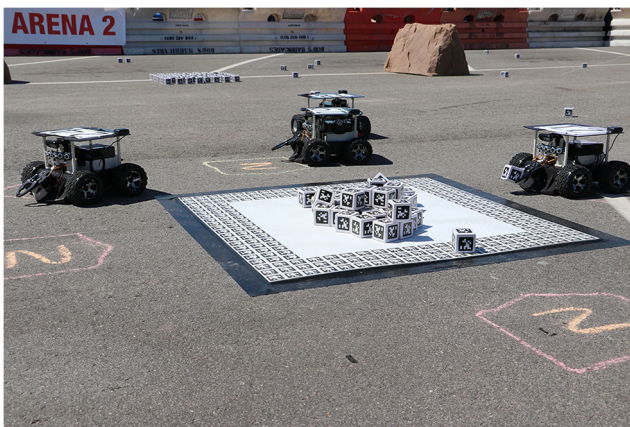


Fig. 1 Swarmie robot foraging. Teams of 6 robots utilized a spoke algorithm developed by the Southwest Indian Polytechnic Institute as part of the NASA Swarmathon III Competition at John F. Kennedy Space Center [4]. The arena is 20 × 20 m and contains several obstacles, one of which is visible at the top of the picture. Robot 21 on the right is carrying a target cube to the collection zone (white square). Previously foraged cubes are piled on the collection zone. (Credit: Beatriz Palacios, 2018)

Analytical Strategies

Baeza-Yates et al. [24] proved that a spiral search pattern is optimal for guaranteed detection of a single target by a single searcher. Fricke et al. [70] built on that work to describe the DDSA which generates an interlocking pattern of spirals suitable for a robot swarm. The pattern was compared with a perfect foraging algorithm mathematically and to an ant-inspired self-organizing central place foraging algorithm (CPFA) in Hecker and Moses [55] in ARGoS. Pelc [101] considered an agent searching for a target using a square spiral strategy on a plane and proved that the time to find a target is

$O\left[\frac{D^2}{r}(\log D + \log \frac{1}{r})\right]$, where D is the initial distance between searcher and targets and r is the detection radius.

Aggarwal et al. [102] provided formal bounds on efficiency for three geometric CPFAs: (1) a distributed spiral algorithm [70], (2) a spoke algorithm [4], and (3) a random ballistic algorithm [103] when compared with an ideal foraging algorithm [70]. The spiral algorithm was proven to have an upper bound on performance closest to the ideal algorithm.

Lu et al. [35] described a hierarchical transportation network for swarm central place foraging. The formal analysis proved the scaling relationship of collection rate vs the number of robots for several variations on the strategy. The mathematical framework of biological scaling theory was leveraged in the proofs.

Mayya et al. [64] developed a model in which robots decided whether to continue an assigned task or leave the area based on local congestion. This strategy optimized the balance between allocating many robots to a task and overcrowding. The theoretical findings were tested in real robots [94]. This work employed a mean-field approach to the analysis of swarm foraging.

Ericksen et al. [104] developed algorithms for discovery and sampling of volcano plumes using UAV swarms. The authors presented the LOCUS algorithm and proved its resilience to UAV loss and verified theoretical predictions using the ARGoS simulator. Aggarwal and Saia [105] analyzed the Golden Foraging Algorithm (GoldenFA), which is reminiscent of a spoke algorithm [63••] entered into the Swarmathon competition [4], but the angle between spokes is taken from the golden ratio. The authors formally proved that the GoldenFA was fault tolerant.

In a series of papers Harwell and Gini presented a model for task allocation in swarm foraging [65–67]. Robots could choose dynamically based on local information whether to divide the foraging task into subtasks. Task allocation is governed by a graph structure. This network approach allowed the authors to develop formal proofs informed by simulation experiments about emergent behaviors. Specifically, the contributions of network structure to emergent behavior. Harwell and Gini have been closing the gap between analytical and self-organizing research.

Field Studies

Robot foraging is useful in smart farming. These applications range from crop monitoring [106, 107] fruit and vegetable harvesting [108–110] to exotic applications like robotic pollination [111]. Several studies developed viable solutions to collection problems in real-world environments. Due to the difficulty of integrating multiple requirements into a coherent robotic system, successful real-world demonstrations of foraging robots are still rare.

Albani et al. applied foraging techniques to agriculture in [112, 113] to produce a weed infestation map by using a swarm of Avular Curiosity UAVs with downward facing cameras. Building this map under strict flight time constraints of the small UAVs required a trade-off between exploration and exploitation to identify the location and density of weed clusters without exhaustive search. This approach used randomized search to identify possible clusters and virtual beacons to attract multiple robots to explore a location once a cluster is found.

Gu et al. [45, 46] described the Cataglyphis robot, which the authors entered the NASA Sample Return Robot (SRR) Challenge. This entry was the only robot to complete the real-world stage in 5 years and out of more than 50 entries. To succeed, the team leveraged a wide variety of technologies and techniques including 17 unique behaviors including hazard avoidance, image segmentation and classification, and a sophisticated robot. The team's success highlighted how difficult it is to perform robot foraging in the field.

Lu et al. [37] showed how implementing an algorithm in a physical robot can change the relative performance of algorithms in simulation. They compared the CPFA [55] and the DDSA [70] using Swarmie robots. The experiments were performed in a “parking lot” environment outside with obstacles. In simulations the DDSA was shown to outperform the CPFA, but in physical robots this did not hold true. Furthermore, in the presence of obstacles and targets, the pattern of movement produced by the DDSA became indistinguishable from that of the CPFA. This was further evidence that bridging the *reality gap* [114] is very challenging.

Scalability

An effective foraging strategy should work in swarms ranging from tens to thousands of robots without reducing per robot foraging performance. This property is often called *scalability* [8–11]. Many complex systems confront the challenge of designing scale-invariant robot swarms. Harwell and Gini proposed a set of quantitative metrics for the scalability of simulated swarms over 10,000 robots as a design tool by solving a large object gathering problem [65]. Rausch et al. [38] investigated scale-free properties of artificial collective systems using simulated robot swarms. Many studies focused on mitigating the negative feedback-loop in foraging robot swarms caused by congestion [51, 69, 115]. Even without including collisions in simulations, Hecker and Moses [55] observed sub-linear foraging performance as more robots were added in a foraging task simulation. Rosenfeld et al. [49] also observed sub-linear performance increases for one of their simulation sets that simply allowed robots to pass through one another without colliding [116].

Two problems affect scalability. First, large swarms with many robots produce more inter-robot collisions, which result in diminishing returns [117]. Second, large foraging arenas require robots to travel further distances to find targets and transport them to the central collection point since over time target become rarer, and per target collection time increases exponentially [56].

Lu et al. [40] focused on improving the scalability of bio-inspired foraging robot swarms using a multiple-place foraging algorithm (MPFA). The foraging behavior is optimized by a GA in ARGoS. The experimental results indicated that the foraging performance increased with the number of collection zone since (1) collisions were distributed to multiple collection zones and (2) robots do not have to transport targets as far.

However, the foraging performance per robot of the MPFA still decreases when the swarm size is very large. Ideally, foraging performance per robot would be linear in swarm size. Lu et al. [35••] presented a bio-inspired hierarchical transportation network inspired by the mammalian cardiovascular network. Biological scaling theory predicts how quickly robots forage for unlimited swarm sizes and foraging areas. Experiments were performed with ARGoS using thousands of robots searching over thousands of square meters. The experimental results showed that the transportation network produces scale-invariant robot swarms.

Font Llenas et al. [44] successfully implemented a foraging robot swarm composed of up to 100 Kilobots. With the ARK system [49], Kilobots can deploy and sense virtual pheromones in physical environments. Talamali et al. [12] is the largest physical robot experiment in stigmergic foraging, with swarms of 200 physical robots. The results demonstrated an efficient and robust collective foraging process in a large physical robot swarm.

Conclusions

Central place foraging remains a grand-challenge problem in swarm robotics. It requires solving several important subtasks: search, harvesting, transportation, navigation, and localization [2], and to be effective, cooperation between robots [118]. We outlined recent approaches to foraging and highlighted two complementary strategies: self-organization and formal analysis. Self-organized, bioinspired approaches continue to dominate swarm foraging research, especially for more practical, though still aspirational, applications such as refuse collection [39], and resource collection [4]. Recent analytical approaches have provided theoretical bounds on efficiency [35, 63], fault tolerance [104, 105], and even the conditions required for emergent behavior [67••].

Increasingly, researchers have been able to reason analytically about swarm foraging while bridging the gap between proof and practice. Conversely, analytical solutions have been

tested in a practical setting [37]. Despite these advances, linking these two concepts together remains a challenge as is evident from recent fieldwork [45, 112].

Optimization of self-organizing strategies with machine learning techniques such as neural networks and especially evolutionary algorithms are commonly observed in the papers from the past 5 years. This is not an entirely new phenomenon with genetic programming having been used by Koza [14] in the 1990s to optimize trail following in simulations of ant-inspired robots, but it does seem to be increasingly common. It is still the case that machine learning optimization of foraging remains confined to simulation.

Swarm foraging hardware has been making incremental improvements. Some platforms such as the Kilobots and Robotarium provide a middle ground between simulation and practical robots, especially with the increasing use of the ARK system. The Swarmie robot, which is designed to operate outdoors, while still being limited to parking lots, is a step towards ground swarms that can operate in outside the laboratory.

Taken together, recent work has advanced swarm foraging on several fronts, from theoretical inroads to practical robots and has reduced the gap between them.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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