COLLECTIVE BEHAVIOR

When less is more: Robot swarms adapt better to changes with constrained communication

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To effectively perform collective monitoring of dynamic environments, a robot swarm needs to adapt to changes by processing the latest information and discarding outdated beliefs. We show that in a swarm composed of robots relying on local sensing, adaptation is better achieved if the robots have a shorter rather than longer communication range. This result is in contrast with the widespread belief that more communication links always improve the information exchange on a network. We tasked robots with reaching agreement on the best option currently available in their operating environment. We propose a variety of behaviors composed of reactive rules to process environmental and social information. Our study focuses on simple behaviors based on the voter model—a well-known minimal protocol to regulate social interactions—that can be implemented in minimalistic machines. Although different from each other, all behaviors confirm the general result: The ability of the swarm to adapt improves when robots have fewer communication links. The average number of links per robot reduces when the individual communication range or the robot density decreases. The analysis of the swarm dynamics via mean-field models suggests that our results generalize to other systems based on the voter model. Model predictions are confirmed by results of multiagent simulations and experiments with 50 Kilobot robots. Limiting the communication to a local neighborhood is a cheap decentralized solution to allow robot swarms to adapt to previously unknown information that is locally observed by a minority of the robots.

INTRODUCTION

Monitoring an environment through a swarm of minimalistic robots can be useful in adverse scenarios that impose constraints on the individual robots' capabilities (*1–3*). Examples are biodegradable devices—simple by design constraints—to monitor remote locations, such as ocean floors or in-body blood vessels (*4*), or disposable devices—simple by budget constraints—deployed in hazardous search and rescue missions with a high risk of damage (*5*). This type of application may not allow for centralized control or human supervision, whereas controlling the robots via minimalistic decentralized behaviors can be a viable solution. Minimal computing provides the advantage of higher transferability to simpler platforms, such as nano- and microrobots (*6*, *7*). Here, we investigate the general scenario in which the environment has n alternative target sites, each with an intrinsic importance (or quality), and the swarm is tasked with reaching a consensus in favor of the most important site, the so-called best-of-n problem (see Fig. 1).

Considerable work has been dedicated to the design of decentralized robot behaviors to solve the best-of-n problem (*8–10*). Compared with previous work, we solve a more general variant of the problem using simpler robots in terms of required capabilities. Whereas most studies have investigated solutions of the best-of-n problem in static and binary ($n = 2$) setups, here, we provide minimal behaviors to reach consensus decisions in a dynamic environment in which the number of target sites n and their quality vary over time. Despite previous studies having shown qualitative changes in the system dynamics for $n > 2$ (*11*), only a few studies have considered the best-of-n problem with more than two options. The proposed solutions typically used robots with higher requirements than ours in terms of computation, memory, and communication capabilities and assumed prior knowledge of the number and location of the alternatives (*12–16*) (see also text ST1). Exceptions are our previous works (*17*, *18*), which relied on similar minimalistic behavior and the absence of prior knowledge but were limited to static environments. There were other minimal behaviors, e.g., (*19*), that could potentially be modified to remove limiting assumptions on a robot's prior knowledge; however, it has been shown that they were unable to adapt to environmental changes (*19*, *20*). The few studies on best-of-n decisions in time-varying environments were limited to $n = 2$ binary decisions with robots knowing a priori the options (*21*) or their location (*20*, *22*) and only agreeing on the one with the highest quality. Requiring prior knowledge about the number of alternatives n may reduce the applicability of such solutions. As well as collectively selecting the best alternative, a decentralized process of decision-making should also include the phase of decentralized discovery of the available alternatives (*23*, *24*). Behaviors that proved successful in the voting phase may suffer a drastic reduction of their performance when both discovery and voting phases are considered (*18*). We study collective behaviors to operate in time-varying environments; therefore, they include both mechanisms to discover environmental changes and to spread information. Time-varying environments are an intrinsic characteristic of several application scenarios, and efficient solutions that consider this aspect are therefore necessary for the deployment of robot swarms into the real world.

In this study, the robots have no prior knowledge of the problem. Instead, a robot can only know about a target site either via individual exploration of the environment (it discovers the site) or through social interactions with other robots (it receives the site's location). We consider robots that have minimal sensory, memory, and communication capabilities. In terms of sensory capabilities, robots in close proximity to a target site are able to make noisy estimates of its quality. In addition, because the task requires the

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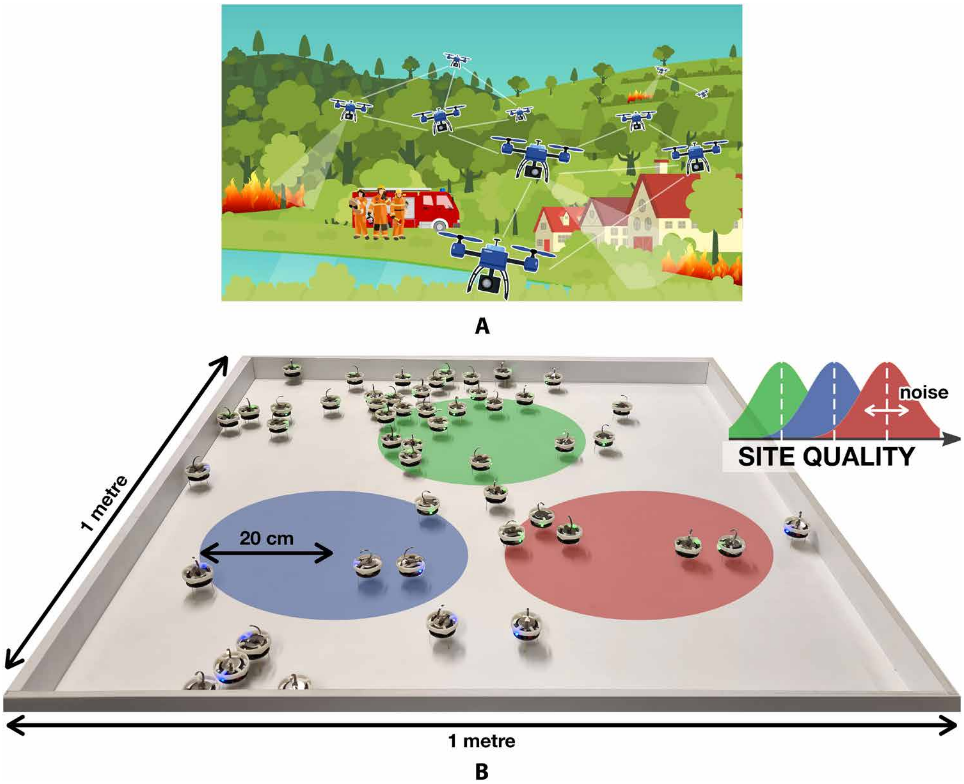
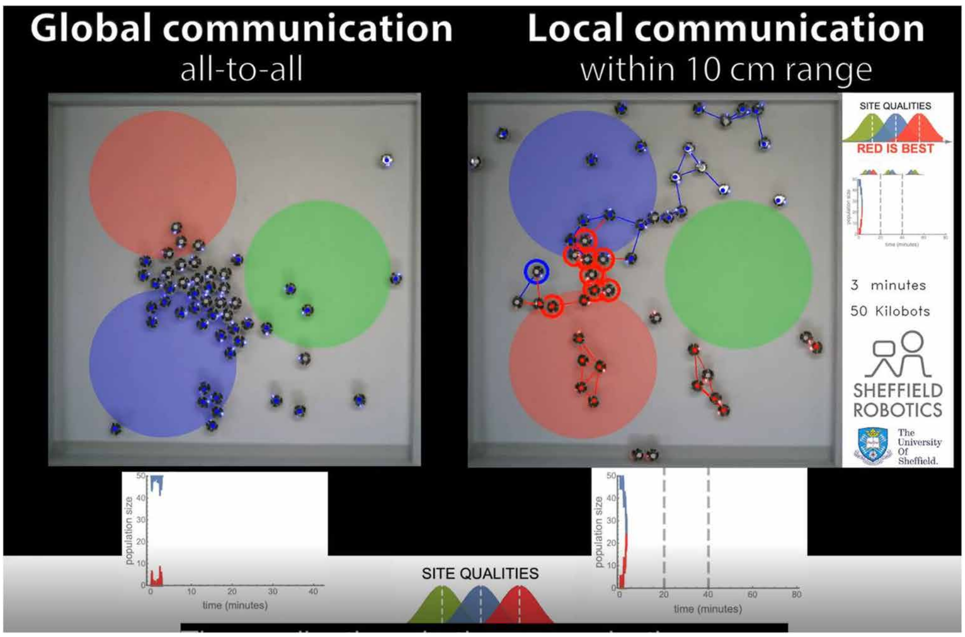


Fig. 1. Adaptive monitoring of time-varying environments. (**A**) The robot swarm may be deployed to monitor a forest fire and collectively select the best site (e.g., most urgent) where immediate action of firefighters on the ground is necessary (*100*). Robots explore the environment to acquire individual information and communicate with each other to exchange opinions. (**B**) We test the behavior on a swarm of 50 Kilobots, which are simple robots with limited capabilities. The target sites, here superimposed on the image as colored circles, are perceived by the robots through the ARK system (*95*), which allows the robots to perceive a simulated time-varying environment. Over time, new sites appear, and existing sites change in quality or disappear. The swarm adapts accordingly. Videos of the experiments are available as Movie 1 and movies S1 and S2.



Movie 1. Less is more. When simple robots have access to less social information, due to fewer communication links, they can adapt better to environmental changes.

selection of the best site, robots are able to estimate their own approximate position and move within the environment. In terms of memory capabilities, each robot can only memorize the location and quality of the selected site—that is, the robot has one opinion about the best site. In terms of communication capabilities, a robot can only locally broadcast one single piece of information: the location of the site it considers to be the best.

The robots combine information that they locally acquire in the environment with information that they receive from other swarm members. Our behaviors are based on the classical voter model (*25*) in which each robot is iteratively influenced by a single random neighbor. Individual and social information is combined through a behavior based on the cross-inhibition pattern (*9*, *17*) by which conflicting information between two communicating robots causes the robots to reset their own opinion and poll other robots' opinions. Via cross-inhibition, a swarm can reach a consensus on the best available option while avoiding decision deadlocks, as shown in theoretical models (*11*, *26*), honeybee nest-site selection (*27*), and robotic applications (*18*, *28*). A widely used alternative behavior is based on the direct-switching pattern (*29*). This, however, has the limitation of only breaking the deadlock of symmetric decisions—when options have the same quality—through noise (*30*–*32*) and therefore can be slow. Through a combination of experiments, simulations, and mathematical analysis, we study when behaviors based on cross-inhibition and direct switching can adapt to changes in the environment, particularly when the best site appears, disappears, or changes its quality. Through analysis at multiple description levels, we measure to what extent these behaviors are scalable to increasing swarm sizes, are sensitive to social information, and are robust to sensorial noise.

To precisely control the swarm behavior and predict its dynamics in different scenarios, we model the collective dynamics through a system of ordinary differential equations (ODEs). In swarm robotics, accurate models are necessary but generally hard to obtain (*1*, *10*, *33*). We show that our model accurately predicts the swarm dynamics and highlights a counterintuitive mechanism: By reducing the range of communication, the swarm can better adapt to changing environments. This result is general across our tested behaviors, and through the model, we can understand the cause of this effect. In our experiments, we observe that less, in terms of fewer communication links per robot, leads to more effective spreading of information within the swarm (Movie 1). This result is in contradiction to the widely accepted belief that more connected networks share information more effectively (*19*, *34*–*36*) and is instead congruent with works that document the emergence of the "slower is faster" effect (*37*). This effect occurs when increasing the performance at the individual level causes a decrease in the collective performance and has been found in several other contexts, such as ecology (*38*), voting dynamics (*39*, *40*), and collective animal behavior (*41*, *42*). In this study, by reducing the number of communication links, robots sacrifice the information-spreading speed, which is maximized in highly connected swarms, to facilitate adaptation. Such a solution is simple and highly effective.

RESULTS

We designed two collective robot behaviors to solve the problem of selecting the best site (best-of-n) in dynamic environments. We opted for minimalistic behaviors that can also run on minimal machines with limited capabilities. Both behaviors extend the classical voter model (*25*) in which, at each control step, a robot randomly selects one of the messages from its neighbors to update its opinion (see Fig. 2). The message only contains the location of the sender's preferred site i; thus, a robot, once informed about a previously unknown site, goes to assess its quality q_i. While doing so, the robot remains in a polling state in which it listens to incoming messages that it uses to update the location of the target site. Equipped with social information, the polling robot follows a biased random walk until a target site is reached and estimates its quality. During this biased random walk, the robot most often reaches the target site that has more support among its neighbors. Robots, to avoid the quick spreading of erroneous information, do not share the quality of their preferred site, but each makes an independent noisy estimate, a method that has been shown to improve collective decision accuracy (*18*, *43*). Nonpolling robots instead diffuse in the environment through a random walk to monitor the available target sites and to share their opinion with each other on the best site. When a robot does not have an opinion (i.e., it is uncommitted) and encounters the target site $\mathcal{T}_x$, it makes a noisy estimate of its quality q_x and selects $\mathcal{T}_x$ as the best site (commits to $\mathcal{T}_x$) with probability proportional to q_x. Every time a robot committed to $\mathcal{T}_x$ moves in the proximity of site $\mathcal{T}_x$, it updates the noisy estimate q_x to keep track of possible quality variations over time. The swarm converges toward the best option because each robot communicates with a frequency linearly proportional to the estimated quality (*44*). Such quality-dependent communication was inspired by the house-hunting behavior of social insects (*45*, *46*) and was successfully implemented in several swarm robotics systems (*17*, *19*, *43*, *44*, *47*).

The presented behavior implements the cross-inhibition pattern for the update of social information (*11*, *17*, *26*, *27*). The peculiarity of this social update pattern is the inhibition between robots committed to different sites (Fig. 2A). Upon inhibition, the robot enters a state of "indecision," the polling state, during which it temporarily suspends active recruitment and polls other robots' opinions until it gets recruited. The alternative social update pattern is the direct-switching pattern by which robots committed to different sites directly recruit each other (Fig. 2B). A recruited robot directly

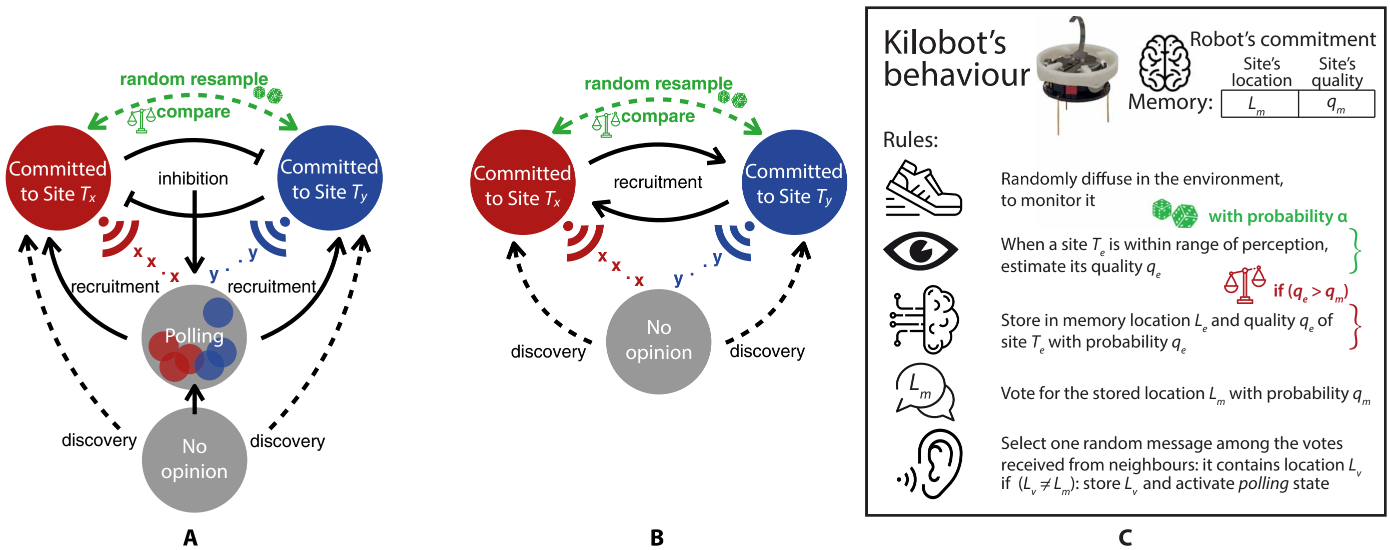


Fig. 2. Individual robot behavior. (**A** and **B**) The robot iteratively updates its opinion based on environmental (dashed transition lines) and social information (solid transition lines). The behaviors can include any of two alternative exploration rules (green dashed transition), compare and resample, and any of two alternative social interaction patterns (black solid lines), cross-inhibition (A) and direct switching (B). Through direct switching, any robot can get recruited and immediately changes its commitment state. Instead, through cross-inhibition, only polling robots can be recruited. Therefore, when a committed robot receives a message from a robot committed to a different site, it resets its commitment (inhibition) and activates the polling state. (**C**) Pseudo-algorithm of the robot behavior in the committed state (and in the uncommitted state when memory is void). The green and red conditions are mutually exclusive and indicate the effect of the resample and compare rules, respectively. These minimalistic behaviors can be potentially implemented on extremely simple devices. See more details in text ST2.

switches its commitment without activating the polling state. We tested both social information transfer patterns in theory and the cross-inhibition pattern, which analysis predicts is more robust (*11*, *26*), in physical robot swarms.

Our focus is on the ability of the swarm to collectively select the best site and to adapt to environmental changes when a better site appears, the best site disappears, or a site's quality changes. After any of these changes, we want the swarm to converge to a stable consensus in favor of the best site, with a supermajority of the population (quorum 80%) having the same opinion. To let the swarm adapt, we introduce two alternative rules to allow individual robots to reconsider their opinion when exposed to new environmental evidence: compare and resample.

Minimal rules are sufficient to let the swarm adapt to dynamic environments

We propose the compare and the resample exploration rules to extend the base behavior of Fig. 2. These rules allow committed robots to constantly process the latest information that they acquire locally from the environment because, otherwise, the swarm may "freeze" into an absorbing state. The compare rule lets the robot compare the quality of its chosen site with the quality of any site found in the environment and probabilistically commit to the newly discovered site only if it has a higher quality. In this way, individual robots locally filter environmental information with a response threshold that dynamically changes with the current quality estimate (see Materials and Methods and text ST2) (*48*, *49*). The resample rule does not require any comparison, but committed robots process environmental information—upon discovery—with a small constant probability α (*50*). In this way, swarms that reached a consensus for the best location maintain on average a small proportion of robots reconsidering their opinion.

Comparing the performance of the two exploration rules—compare or resample—Fig. 3 shows the relationship between increasing individual robot capabilities and faster collective adaptation. On the one hand, when robots individually filter the environmental information (compare rule), the swarm shows a faster collective response to changes (Fig. 3B). However, filtering through comparison requires slightly more computation and the possibility to store the option's quality for subsequent comparison; such requirements may not be available at every degree of individual complexity or even necessary (*51*). On the other hand, the resample exploration

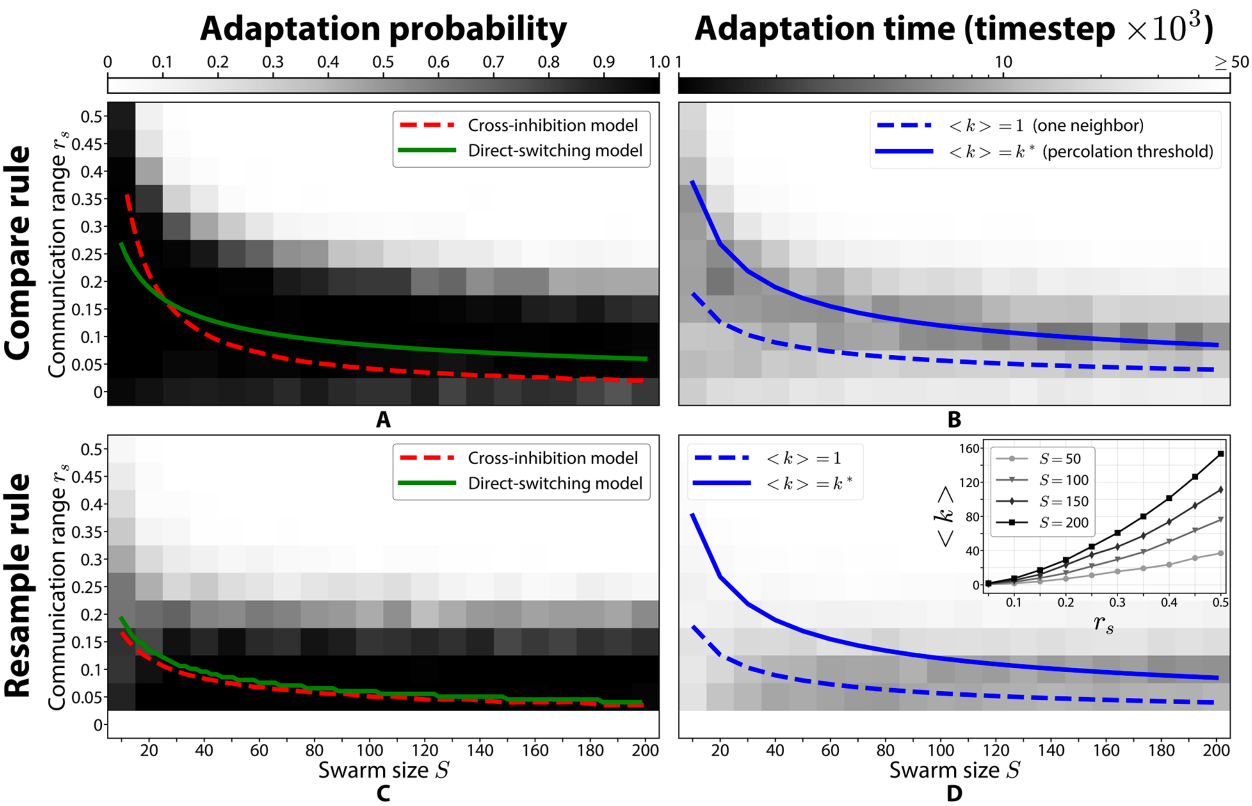


Fig. 3. Large communication ranges and swarm sizes are detrimental to swarm adaptability. The probability and speed of adaptation to a new better target site (with quality $q_x = 0.8$), when the swarm starts from a full commitment in favor of an inferior site (with quality $q_y = 0.7$), for the four analyzed behaviors. Grayscale maps show results for 100 multiagent simulations of $T_{max} = 6 \times 10^4$ time steps; simulated agents only use the cross-inhibition pattern. Superimposed lines are theoretical predictions; theory and simulations show good qualitative agreement. (**A** and **C**) Adaptation probability is the proportion of runs that adapted over the total number of simulations. Adaptation probability decreases for increasing swarm size S and increasing communication ranges; lines show the bifurcation point (see Materials and Methods) for both social interaction patterns. (**B** and **D**) Adaptation speed is high for low communication ranges and swarm sizes; superimposed lines show predicted connectivity transitions: The dashed curve predicts, on average, one neighbor per robot $\langle k \rangle = 1$ and the solid curve $\langle k \rangle = k^* = 4.51$ neighbors per robot [corresponding to the giant-component transition (*101*)]. The best performance in terms of both speed and ability to adapt can be achieved with intermediate values of $\langle k \rangle$. The inset shows that when increasing the robots' communication range r_s, or the swarm size S, the average number of communication links per robots per time step $\langle k \rangle$ increases accordingly.

rule is a reactive technique that does not require any additional individual computation nor capability at the cost of a slower collective adaptation to changes (Fig. 3D). In addition, the individual-level simplicity of this rule requires the selection of the parameter α for probabilistic environmental sampling. A very low α will not let the swarm adapt, whereas values of α that are excessively high can cause the swarm to remain undecided, with a considerable fraction of robots constantly changing opinion for any of the n alternative sites (see fig. S1). Therefore, the value of α needs to be appropriately selected depending on the scenario and individual characteristics (see sensitivity analysis in text ST3).

Communication range negatively correlates with swarm adaptability

Multiagent simulations show a counterintuitive result. Figure 3 (A and C) shows the probability of the swarm adapting for increasing communication range r_s and swarm size S. The swarm starts from a full consensus in favor of a target site $\mathcal{T}_y$ when a new target site $\mathcal{T}_x$ with better quality ($q_x > q_y$) appears. We observe that through both rules, resample and compare, the swarm has a lower probability of adapting with an increased communication range. In the extreme case of a fully connected network—attained with the maximum communication range $r_s = 0.5$—a simulated swarm of $S > 10$ robots is never able to adapt to new better sites. From the point of view of social interactions (not considering physical interactions), an increase in communication range is equivalent to an increase in robot density. Under dense conditions, the high number of neighbors per robot undermines the ability to adapt. Figure 3 (B and D) instead shows that extremely low values of the communication range can slow down the adaptation. There is therefore an intermediate value for which adaptation occurs at maximum speed. Qualitatively similar results can be obtained with more sophisticated mechanisms to sample the neighbors' votes. In text ST4, we show that collective behaviors based on the local majority rule (i.e., selecting the site that has been voted the most by the neighbors) (*52*) also benefit from a limited number of communication links per robot.

A strongly opinionated minority encounters competition among voters

To understand and predict the swarm behavior and the effect of the parameters on the performance, we modeled the collective decision-making process through a system of ODEs. Each equation describes how subpopulations (groups of robots with the same opinion) change over time as a function of environmental characteristics and robots' capabilities. Although we control the robots with individual-level behaviors (Fig. 2), we are interested in understanding and predicting the resulting collective behavior, which we describe with our models.

A classical approach to model the collective behavior of a robot swarm is to build a mean-field model describing the average behavior of an infinite-sized swarm of fully connected individuals (*33*). Although this type of model has proved very useful in several scenarios (*53*–*55*), their assumptions make them of little utility to explain the dynamics observed in the scenario that we consider here. A model that assumes an infinite-size system cannot describe size-dependent dynamics. We observed above that the investigated swarm has a qualitative change in its environmental response depending on its size (see Fig. 3). In addition, in swarm robotic systems, local communication limits the interaction at each voting iteration to a limited neighborhood (a small fraction of the entire population); therefore, assuming a fully connected mean-field communication topology may typically be inaccurate. Therefore, we developed an ODE model that has explicit dependence on swarm size and robot density and is able to describe effects determined by a sparse communication topology.

Typically, at the start of every adaptation, the swarm has reached a consensus for the previously best site $\mathcal{T}_y$ when a new better site $\mathcal{T}_x$ appears. Therefore, subpopulations committed to different sites have sizes very different from each other, and the few-versus-many condition arises—that is, there is a small minority competing against a large majority. Depending on how frequently their members vote, subpopulations can be considered as strongly or weakly opinionated. Because communication frequency is proportional to site qualities q_x and q_y, with $q_x > q_y$, the small fraction of robots that spontaneously discover $\mathcal{T}_x$—the strongly opinionated minority of size S_x—will vote more frequently than robots committed to $\mathcal{T}_y$—the weakly opinionated majority of size S_y. However, under the few-versus-many condition, competition among voting messages may nullify the bias from quality-dependent communication frequency and lock the swarm into a consensus for the inferior site $\mathcal{T}_y$. Competition arises because robots select messages following the voter model approach (*25*). Therefore, a robot with m neighbors will select (and process the information of) one message among the m received messages (assuming that all m neighbors have sent their message). As a consequence, each neighbor (voter) of a robot (receiver) has a $1/m$ probability that its message would be read. It is therefore clear that increasing the number of neighbors that each robot has would dilute the impact of each voter. We model such a competition among voters via the Holling type II functional response of Fig. 4A, which was originally formulated in ecology to describe the interplay between populations of prey and predators (*56*). This functional response accounts for the fact that a predator requires time to consume prey. Therefore, the biomass of the consumed prey increases sublinearly with the biomass of the prey population. The same functional form has also been used in different fields with different names, for example, the Michaelis-Menten equation in chemical kinetics (*57*) and the Hill equation in biochemistry (*58*).

Borrowing the terminology from ecology, we show in Fig. 4A the extreme few-versus-many condition of a single "predator" (minority committed to $\mathcal{T}_x$ of size $S_x = 1$; red agent in Fig. 4A) and $S - 1$ "prey" (susceptible robots, majority committed to $\mathcal{T}_y$). The predator can "eat" (recruit) a number of prey that is a function of the majority size $S_y = S - 1$. In small swarms, the recruitment rate per voter is limited by the event of susceptible robots entering the communication range of the single committed robot (which occurs with rate proportional to the robot's communication area πr_s^2). By increasing the swarm size, the recruitment rate to $\mathcal{T}_x$ increases as the probability of committed-susceptible interaction increases, until it saturates at a maximum rate where the population density is high (Fig. 4A). In large swarms, the recruitment rate saturates because, in a high density situation, each message competes with several others to be read. Note that, in our system, the robots both receive and send messages, therefore increasing the number of susceptible robots (majority) also increases the competition among messages.

Through the functional response of Fig. 4A, our model introduces recruitment rates that are asymmetric with respect to the number of recruiters and susceptible robots. Figure 4B shows that asymmetry in the interactions can lead to a higher recruitment rate

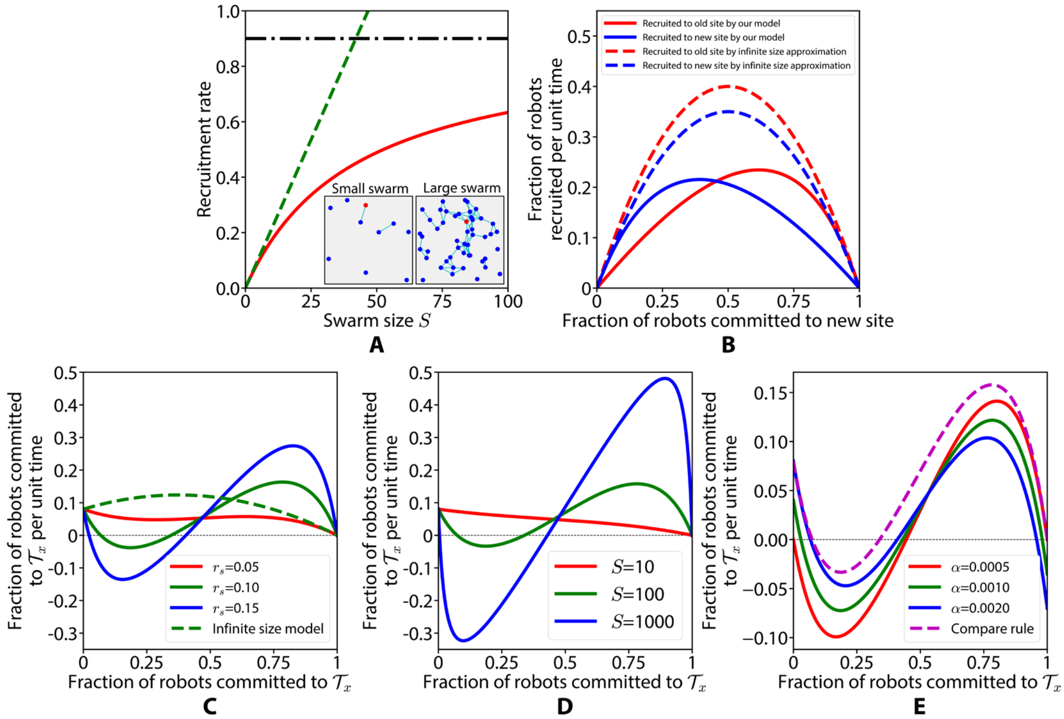


Fig. 4. Modeling asymmetric recruitment rates explains the interplay between a strongly opinionated minority and weakly opinionated majority. (**A**) A single robot committed to the superior site $\mathcal{T}_x$ (red agent in the insets) recruits susceptible robots (blue agents committed to the inferior site $\mathcal{T}_y$) at a rate that grows sublinearly with the number of susceptible robots (here $S-1$). The recruitment rate, based on the Holling type II functional response (red solid curve), increases with S when the number of susceptible robots is low and interactions sporadic. For high numbers, the rate saturates to the frequency of transmission (horizontal dot-dashed line). This is in contrast to the infinite-size approximation in which the recruitment rate (green dashed line) has linear dependence on the number of susceptible robots. (**B**) Recruitment rate to a superior (red $q_x = 0.8$) and an inferior (blue $q_y = 0.7$) site is asymmetric in our model (solid lines) and symmetric in infinite-size models (dashed lines). We fix $S = 100$ and vary the number of recruiters to $\mathcal{T}_x$ on the horizontal axis (where the recruiters to $\mathcal{T}_y$ are the complement to x-axis values, $S - x$, for direct switching). (**C** to **E**) Rate of change of robots committed to site $\mathcal{T}_x$ (y axis) against the proportion of robots committed to $\mathcal{T}_x$ (x axis), as from Eq. 1, for varying communication range r_s (C), swarm size S (D), and for the compare (C and D) and the resample rules (E).

for the inferior site than for the superior one, when $S_x \ll S_y$. Instead, with the standard infinite-size approximation (*33*), the mean-field model always has symmetric recruitment rates (with the red curve of Fig. 4B always higher than the blue). Asymmetric recruitment rates cause a nonmonotonic commitment rate to $\mathcal{T}_x$ and thus a bistability of consensus (Fig. 4, C to E). The asymmetry vanishes as robot density is decreased (Fig. 4, C and D), restoring monostability for the best site. As a consequence, in low robot densities, there is a small difference between ours and the infinite-size models. This difference increases as either swarm size S or communication range r_s increases. Stability analysis reveals, for both the compare and resample rules and both the cross-inhibition and direct-switching patterns, the presence of a bifurcation as the robot density is increased (see Fig. 3). Before bifurcation (small S and small r_s), the single stable fixed point corresponds to the entire group adapting to the best option, in agreement with infinite-size approximations. After the bifurcation, a second stable fixed point appears that corresponds to the swarm being unable to adapt to the new better option, remaining instead trapped in the current consensus on $\mathcal{T}_y$ (fig. S6). Using classical mean-field approximation, no bifurcation would be present, and it would fail to describe the robot swarm dynamics.

Fewer communication links make the swarm more flexible

Our results hint at a counterintuitive solution to the challenge of operating large-scale swarms: The adaptability of the swarm increases as the robots' communication range decreases (Fig. 3). That is, interacting with fewer robots at a time can improve the ability of the swarm to disseminate previously unknown information collected locally. We conducted a set of experiments (Fig. 5) with swarms of 50 Kilobots—small robots for collective intelligence studies (*59*). When the robots were able to communicate with any other robot—forming a fully connected topology—the swarm failed to adapt its decision to new better sites (Fig. 6). Once the swarm reached a consensus in favor of one alternative, robots that found new sites, even with a better quality than the previous, were a minority compared with the rest of the swarm. That minority immediately faced a large majority that quickly converted the minority to the consensus. When limiting communication, minorities with better opinions could gradually gain traction in the population and eventually steer the swarm toward the correct choice (Fig. 5, C to F). Figure 5 (A and B) shows the results from simulated and physical robot experiments.

Although a small number of communication links can bring advantages in terms of better adaptability, it is important to note that other types of processes can instead benefit from long communication ranges or even from no communication whatsoever. Text ST5 and fig. S3 show that the information-spreading speed is maximized in fully connected networks and decreases by reducing the number of links. Therefore, in processes where no voting among robots is necessary and information needs to spread quickly, large communication ranges are beneficial. Text ST6 and fig. S4, instead,

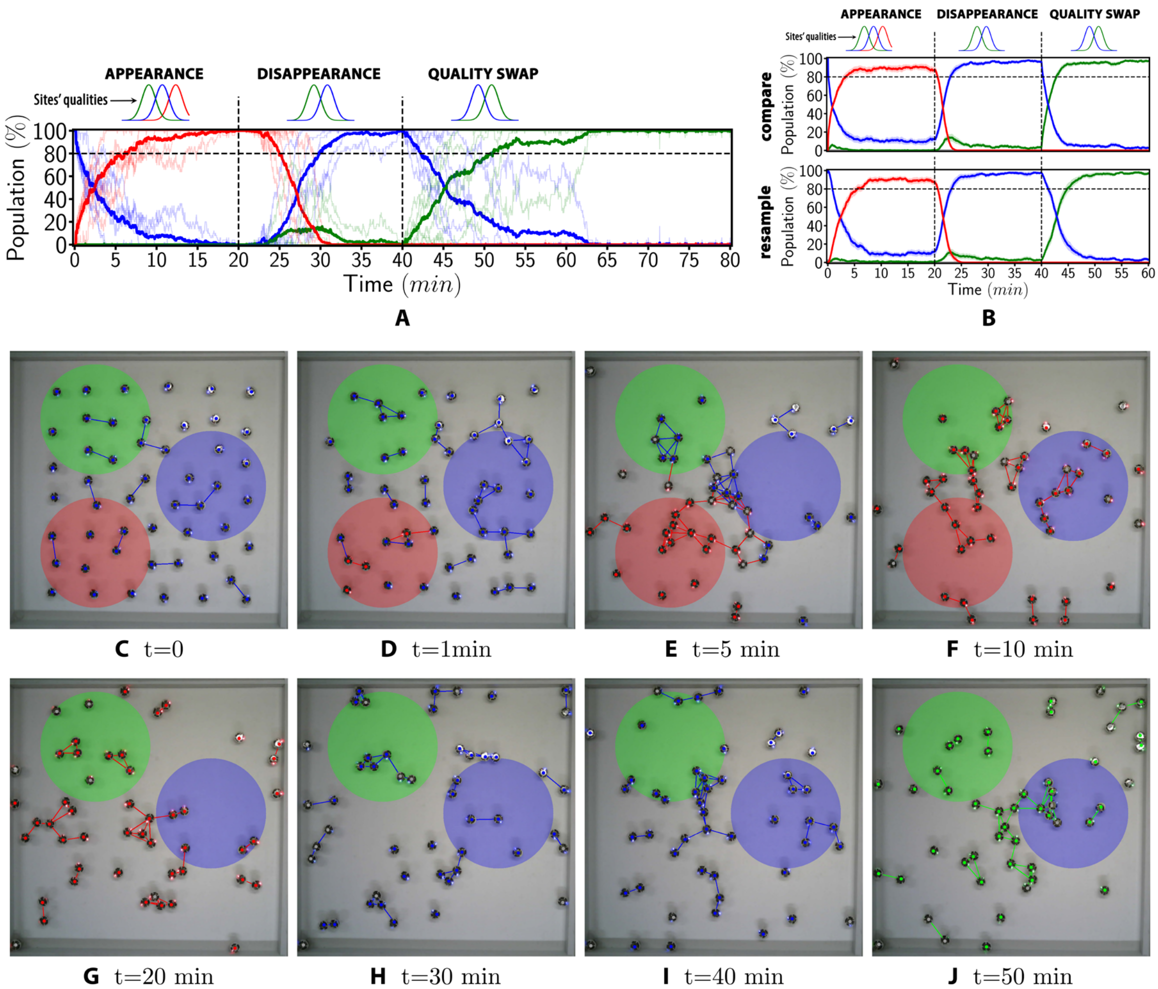


Fig. 5. The robot swarm can collectively select the best target site in a dynamic environment. (**A**) Timeseries of six experiments with swarms of 50 Kilobots monitoring time-varying environments with a collective behavior based on the compare rule and the cross-inhibition pattern (thick lines are the mean, and thin lines are single runs). The swarm successfully adapts in all three phases: appearance and disappearance of the best site and swap of quality between the best and second best site. (**B**) Similar results are obtained through physics-based simulations with behaviors based on both the compare (top) and the resample (bottom) rules (lines are the mean of 100 runs with 95% confidence interval as shades). (**C** to **J**) Overhead view of one experiment at salient moments; there are three target sites—here superimposed on the images as red, green, and blue circles—that can be locally perceived by robots through augmented reality [ARK (*95*)]. (C) The robots initially have a full consensus in favor of the previous best site (blue $q_B = 0.6$), when a new better site (red $q_R = 0.8$) appears. (D) A minority of the swarm discovers the new site. (E) Through local interactions, the red opinion spreads throughout the robot swarm. (F) The swarm converges to a consensus for red. (G) The red site disappears. (H) The swarm reverts to a consensus for blue. (I) The quality of the blue and green sites swaps ($q_B = 0.4$ and $q_G = 0.6$). (J) The swarm once again adapts its decision to the best available site. Full videos are available as supplementary electronic material in movie S1.

show that robots with noiseless sensors can achieve high performances without communicating with each other. However, both analyses indicate that a swarm of robots, which rely on noisy sensors and exchange votes to make a collective decision, maximizes the ability to adapt to environmental changes via short-range communication. The two proposed behaviors can also scale up to a large number of options. In the experiments of Figs. 5 and 6, we tested the swarm in collective decisions among up to $n = 3$ sites. In text ST7, we ran a set of simulations to test the swarm adaptability in an environment with an increasing number of alternative sites, up to $n = 9$. We show that both behaviors naturally scale to a higher number of options.

Value-sensitive collective adaptation

We can further extend our analysis to examine adaptation as a function of option values; the model predicts a value-sensitive adaptation as shown in Fig. 7. A swarm committed to site $\mathcal{T}_y$ with quality q_y will adapt to a new, better site $\mathcal{T}_x$ depending on both the quality q_y and the difference $\delta = q_x - q_y$. The minimum quality improvement δ required for adaptation increases with q_y. In other words, the swarm with a consensus in favor of a good location (high q_y) adapts to a better location only if it has a much higher quality (large δ), whereas adaptation in swarms with low-quality opinions (low q_y) also happens for small improvements (small δ). This value-sensitive mechanism is not directly encoded in the individual agent rules; rather, it is the observed emergent behavior of the collective (see also text ST8).

Value sensitivity has been predicted and observed in a variety of natural systems (*26*, *27*, *60*, *61*) and engineered in robot swarms (*9*, *28*, *62*) in a variety of processes, such as decision-making or foraging. Whereas most work on decision-making focuses on accuracy (*13*, *19*, *20*), in which only the best option is rewarded, a value-based

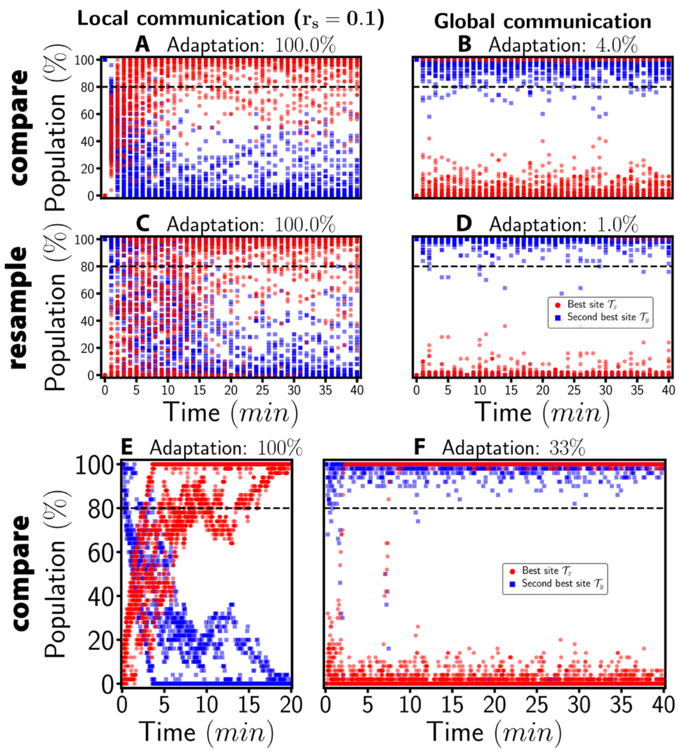


Fig. 6. The Kilobot swarm adapts to environmental changes when robots use short-range communication. Results from 100 simulations (**A** to **D**) and six physical robot experiments (**E** and **F**) with 50 Kilobots with a short (left column) and a long (right column) communication range. The swarm starts with a consensus in favor of the blue site (with $q_B = 0.6$) and is expected to adapt to the red site, which has a higher quality $q_R = 0.8$. Both simulations and physical robot experiments show that the swarm successfully adapts to changes when robots exchange messages locally (a short communication range grants a 100% success rate) but fails to reliably adapt when the communication is global. The proportions of successful adaptations are reported above each scatterplot. A run is considered successful when the average size of the population committed to red in the last 10 min is above 80% quorum (horizontal dashed line). Fluctuations are due to a relatively high level of noise $\sigma_q = 0.1$ in the robots' estimates of the site qualities. Global communication in the Kilobots is achieved through a virtual transreceiver implemented via ARK (*95*). Videos of the Kilobot experiments for both conditions (six repetitions each) are available with the paper in movies S1 and S2.

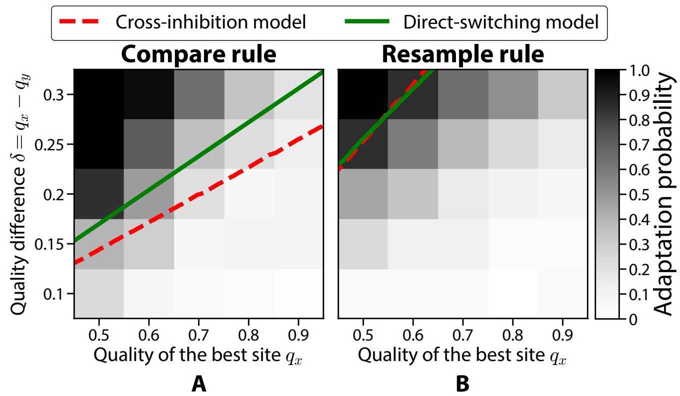


Fig. 7. Value-sensitive adaptation emerges. The swarm displays a value-sensitive response to environmental changes. This means that a new better site $\mathcal{T}_x$ is selected depending on both the quality of the previous site $\mathcal{T}_y$ and the difference $\delta = q_x - q_y$ between the qualities of $\mathcal{T}_x$ and $\mathcal{T}_y$. A consensus for a good site (high q_y) is changed only if the quality improvement is high (high δ). Instead, the swarm is less selective (small δ) when the current site's quality q_y is low. The grayscale maps show the proportion of 100 multiagent simulations that adapted within $T_{max} = 6 \times 10^4$ time steps using the compare (**A**) or the resample (**B**) exploration rules. The $S = 100$ agents only implement the social information pattern of cross-inhibition and use communication range $r_s = 0.3$. The superimposed lines are the bifurcation points for the ODE models based on the two alternative social information patterns.

metric has a reward dependent on the chosen option's quality, independently from it being the best (*63*); in such scenarios, value-sensitive decision dynamics can be beneficial (*26*). Our observations of value-sensitive collective adaptation align with previous analysis on costs for switching between options when consensus for one particular option is already established (*64*).

DISCUSSION

We propose two collective behaviors to allow swarms of minimalistic robots to track the best target site in a time-varying environment (the dynamic best-of-*n* problem). Robotic systems that aim to be deployed in the real world, where real-time changes can be the norm rather than the exception, need to be able to operate in time-varying environments. Our behaviors enable the robot swarm to successfully adapt to environmental changes, which can be the appearance or disappearance of a site or a change in sites' qualities. The requirements in terms of individual robot capabilities are minimal, making the implementation possible even in simpler robots than the ones used in our experiments, such as organic nanorobots or disposable devices (*4*, *5*). Despite the individual simplicity, the swarm is collectively able to track the site with the highest quality and show a value-sensitive response to changes (Movie 1).

Previous work that investigated simple voting behaviors to reach swarm consensus on the best option (*19*) has shown an increase in decision performance, in terms of consensus speed, when individuals use more social information (a result also confirmed by our analysis in texts ST4 and ST5). In particular, they replaced the voter model with the local majority rule (selection of the most voted site by neighbors). Their study also showed that such an increase of social information makes the swarm unable to adapt to changing environmental conditions once a consensus has been reached. Given the importance of adapting to time-varying environments, we focused our analysis on mechanisms that allow or prevent the swarm from effectively adapting the collective decision. Previous theoretical mean-field models based on the infinite-size assumption predicted that reducing social information—that is, replacing the majority rule with the voter model—would facilitate adaptation to the best available site (*19*, *47*). Finite-size simulations, however, conflicted with this prediction and showed that adaptation is not possible without strategies that keep the swarm from reaching full consensus (for instance, by using asocial agents) (*20*). In this study, we reconcile theory and application: Theoretical models allow us to understand the adaptation dynamics and design minimal behaviors that can adapt to changing environments. Physical robot experiments with a swarm of 50 Kilobots and extensive simulations confirm our findings.

Our analysis shows the counterintuitive result that reducing the connections between individuals improves the spreading of localized information and, in turn, allows an informed minority to effectively change the opinion of the entire group. This finding is opposed to the widely accepted and intuitive belief in network science that more connections lead to more effective information exchange (*19*, *34*–*36*, *65*, *66*). Although information-spreading speed may indeed increase (see text ST5 and fig. S3), we show that adaptation—the ability to modify the group's belief in light of new information—is impaired. Adaptation can be restored by reducing the average number of connections per robot; this can be achieved by reducing either the robot's communication range or the robot density (see Fig. 3). Through transition rates that depend on both the swarm density and the size of subpopulations committed to different sites, we model a form of "competition" among voters that stems from the voter model. The model is complex but tractable and allows us to study, via bifurcation analysis, the swarm's ability to adapt when the sizes of committed subpopulations are unbalanced—that is, when there is a large majority and a small minority. When robots have a limited number of communication links, the influence of just a few strongly opinionated robots (high-quality site) can succeed in recruiting other robots. Instead, when the communication can happen within large groups—due, for instance, to a large communication range—the minority's opinion is suppressed by the large majority, even when the latter is less opinionated (i.e., when the majority is committed to a lower-quality site). The minority's inability to spread better information is exacerbated in largely unbalanced subpopulations (few versus many) and vanishes when the two factions have comparable sizes (Fig. 4).

Our theory is in agreement with observations from previous swarm robotics studies that investigated the best-of-*n* problem in dynamic environments. In particular, Prasetyo *et al.* (*20*) showed that adaptation can be obtained by freezing a proportion of the swarm committed to every inferior site (through so-called stubborn robots). Our model explains the cause of their empirical observations because stubborn robots improve adaptability by reducing the imbalance between committed subpopulations (reduce the few-versus-many ratio; see also text ST16). Despite the promising results, their solution limits the applicability of the behavior because robots—as in other studies (*21*)—need prior knowledge of the alternative options (e.g., site locations). Therefore, these approaches may not scale to scenarios with options that dynamically appear and disappear. Our solution is more general because it includes the possibility and necessity of the spontaneous discovery of the options. Balancing the frequency of spontaneous discovery and social interactions is crucial to achieve coordinated responses to environmental changes in collective systems (*18*, *36*, *67*–*69*). Again, our model is now able to explain the mechanisms from previous empirical observations. For instance, we previously documented that relatively frequent social interactions speed up the decision but reduce the ability of the swarm to modify its decision once a consensus for an inferior option is made (*18*). The best empirically found solution comprised a first phase with spontaneous discovery only and a second phase of social interactions. Retrospectively, we can now understand the mechanism that is at the source of the success of such a collective behavior; it allows the swarm to split into committed subpopulations of comparable sizes before triggering quick consensus. In addition, we would like to reiterate the importance of having an adaptable system because adaptation can act as a means of correction of earlier mistakes and have a marked impact on accuracy. In summary, existing solutions achieved adaptability by avoiding largely unbalanced distributions of opinions in the population. Our understanding of the model allowed us to also propose alternative strategies, for instance, the communication range reduction, that allow adaptability even in case of extremely unbalanced starting conditions.

Our work has the potential to affect various disciplines. The investigated problem—that is, how an opinionated minority can spread its opinion throughout a large population that holds a different belief—is relevant in biology (*70*), social sciences (*71*), and swarm robotics (*72*). The underlying mechanism of our collective behavior—that is, individuals have social interactions based on the voter model (*25*)—is also widely used to model opinion dynamics in humans (*73*), collective behavior of animals (*74*), and natural evolution in ecosystems (*75*), as well as to design robot swarms (*8*). The results are not limited to the voter model because we also tested collective behaviors with social interactions based on the local majority rule and observed the same dynamics (text ST4). The number of communication links per individual determines when a more opinionated minority is able to persuade a less opinionated majority. We conjecture that any voting system, in which probability of adoption of an opinion by a voter is a sublinearly increasing function of its representation among the voter's neighbors, will exhibit the less-is-more pattern reported here. Reducing the interaction range at the individual level to collectively adapt to changes is a cheap solution that might be exploited by both natural and artificial swarms. Recent studies have indeed observed that animal groups reduce their interaction network to effectively respond to environmental changes (*41*, *42*). The behaviors proposed in this study also have similarities with the decision-making behavior of social insects in terms of quality-dependent communication protocols (*45*, *46*) and individual rules to adapt to environmental changes (*76*). Although it has been shown that direct comparison of alternatives is not necessary to reach a consensus in favor of the best site (*50*, *77*), it remains unclear in which contexts an experience-dependent filtering—similar to our compare rule—is adopted by individual insects when reconsidering their choice (*48*, *78*). Although more demanding at the cognitive level, the compare rule shows better performance than the cognitively simpler resample in terms of both adaptation speed and robustness to parameter variations (Fig. 3, B and D, and texts ST3 and ST8). In the same way, when the individuals have more capabilities to process more social information via the local majority rule, the swarm adapts faster (text ST4). Our study therefore shows a link between the collective performance and the individual cognitive abilities in terms of both environmental sampling and social interactions.

The simplicity of our approach is one of its strengths because it reduces the complexity both at the individual level, granting a wider applicability, and at the group level, allowing a better understanding of the emergent dynamics. The performance of our behaviors can be improved by increasing the requirements at the individual level. Robots capable of storing probabilities on multiple opinions and updating them recursively could improve the accuracy and speed of collective decisions (*12*, *13*, *15*, *16*). Recent theoretical analysis has also shown that distributed learning by computationally more demanding agents can benefit from limited communication (*79*). It will be interesting to test how the same mechanism can be applied to a robot swarm. The exploration of the environment could also be made more efficient by replacing the diffusive random walk with more elaborated collective search strategies (*80*, *81*) that, for example, use Lévy walks and larger individual memory (*82*) or include a constant probability to return to a site and reestimate its quality (*83*). Furthermore, we can envision that the use of a time-varying communication range—varied by individual robots that increase and decrease it depending on how old or recent their environmental information is—could further improve the collective behavior. Such a solution could exploit the benefits of both a quick consensus by highly connected individuals and effective adaptation to environmental changes by individuals that reduce their response to social influence when they have recent information. Temporarily exploiting more knowledgeable individuals by modifying the communication network is an effective strategy that provides adaptive benefits in animal groups (*84*, *85*) and could be "exported" to engineered solutions. However, even without such refinements, a simple strategy of less is more allows for sophisticated group adaptation in time-varying environments.

MATERIALS AND METHODS

Formalization of collective adaptation in a time-varying environment

The robot swarm operates in an environment $\mathcal{E}$ that is a plane with n target sites that can vary over time. A target site $\mathcal{T}_i$ is characterized by its location $L_i \in \mathcal{E}$ and its quality $q_i \in [0,1]$. When L_i is within the robot's sensing range r_e, the robot can individually estimate the site's quality $\hat{q}_i \sim \mathcal{N}(q_i, \sigma_q)$ with noise σ_q, truncated to line in the interval [0,1]. We investigate three types of sudden and instantaneous environmental changes: First, a new site appears with a higher quality than any other site in the environment; second, the best site disappears; or third, the best and the second-best sites switch their quality. The robot swarm is tasked to react to these changes and to always converge to a consensus in favor of the currently best target site in the environment. We consider the swarm to have adapted to the best site $\mathcal{T}_i$ when the average size of subpopulation S_i committed to $\mathcal{T}_i$ in the last 5000 temporal steps is above the quorum of 80%. We choose this metric to avoid counting random fluctuations as decisions (see text ST9) because this could impair the subsequent phase of decentralized measuring of the decision state (*86*–*88*).

Individual behavior for a collective response

Robots combine environmental exploration with social interactions to reach agreement with others on the best site. Each robot uses the information that it obtained through exploration and interactions to iteratively update its commitment state—every 2 s—through the finite state machines of Fig. 2. Robots in any commitment state explore the environment, except for the robots in the polling state, which move toward the site that they have been recruited to.

Environmental exploration is implemented through random diffusion on the plane $\mathcal{E}$ to allow robots to both discover target sites and change their interaction neighborhood. Agent mobility is important because limited mobility can jeopardize the ability to reach a consensus (*28*, *89*, *90*). In the Kilobots, we implemented the random diffusion via the random waypoint mobility model (see further details in text ST2) (*91*).

Social interactions consist of the exchange of messages between neighboring robots that are within the range of communication r_s. Robots committed to site $\mathcal{T}_i$ send their message every 500 ms with probability equal to the estimated quality $\hat{q}_i$. The message only contains the location L_i of the site $\mathcal{T}_i$ but not $\hat{q}_i$. Therefore, robots that receive a recruitment message and change their commitment state do not know the value of $\hat{q}_i$. These robots change their state to polling during which they do not communicate because they lack information about the site's quality. Polling robots move through a biased random walk toward the most frequently voted site. Once the target site is reached, they estimate $\hat{q}_i$, change their state to committed, and start to periodically broadcast their vote message (Fig. 2C). Therefore, both polling and committed robots have an opinion in favor of one site; however, the former do not broadcast their opinion, whereas the latter do. We differentiate these two states in terms of individual behavior, as shown in Fig. 2A; however, we count both populations when measuring the collective opinion and swarm consensus.

Adaptability is obtained by allowing robots to integrate information from the environment after they have committed to a site. The robot changes its commitment in favor of the site $\mathcal{T}_i$, that it finds through exploration, with probability $d \propto \hat{q}_i$. The relationship between the probability d and the site's quality $\hat{q}_i$ favors the selection of the best site and is determined by the function $f(\hat{q}_i)$, which, in our experiments, we set as $f(\hat{q}_i) = \hat{q}_i$, as $\hat{q}_i \in [0,1]$. Through the compare rule, a robot committed to $\mathcal{T}_j$ makes this probabilistic change of commitment only if the last encountered site's quality $\hat{q}_i$ is better than $\hat{q}_j$, i.e., $\hat{q}_i > \hat{q}_j + \epsilon$. The parameter ϵ sets the minimum difference for which adaptation is worthwhile (see fig. S1A) because changing consensus may have a cost (*64*). Therefore, the resulting probability of committing to the newly discovered site T_i is $d = f(\hat{q}_i)\, H(\hat{q}_i + \epsilon - \hat{q}_j)$, where H is the Heaviside step function. Through the resample rule, instead, a committed robot considers newly discovered environmental information with a constant probability α. Therefore, when a committed robot encounters the site $\mathcal{T}_i$, the total probability of committing to it is $d = \alpha f(\hat{q}_i)$. The probability term α balances the trade-off between a large stable consensus and the ability to react to changes (see fig. S1B). A small α value makes the robots' use of environmental information rare, whereas a high α value makes the swarm more undecided and the consensus subject to large fluctuations.

Kilobot augmented reality experiments

Kilobots are simple robots widely used for studies of collective robotics and swarm intelligence (*19*, *59*, *62*, *92*–*94*). Kilobots move on a plane by modulating the vibration frequency of two motors. The robot moves forward at a speed of about v = 1 cm/s and rotates at about 40°/s. The robots communicate with one another via infrared messages of 9 bytes. The maximum communication range is about r_s = 10 cm. Last, the Kilobot has a multicolor light-emitting diode light to show us its internal state, which, in our case, is its commitment. The Kilobots' capabilities are increased by the Augmented Reality for Kilobot (ARK) system (*95*) that is described in text ST10.

In our experiments, the Kilobots are augmented via two virtual sensors: a position and a site sensor. Through the position virtual sensor (see implementation details in text ST11), polling robots use their location and orientation to effectively move to the target sites they want to estimate. Robots also use the position sensor to perform random waypoint exploration and to avoid collisions with the boundary walls. Although we resort to the position sensor, efficient robot navigation can also be attained with other methods that do not rely on any global positioning system, such as social odometry (*96*) or self-organized navigation (*97*). Through the site virtual sensor, instead, robots estimate the site's quality $\hat{q}_i \sim \mathcal{N}(q_i, \sigma_q)$ when the site's location is within the perception range r_e = 0.2 m of the robot's virtual sensor. When the quality estimate is outside the sensing range [0,1], the estimate $\hat{q}_i$ is set to the nearest boundary value. Whereas in local communication experiments (r_s = 10 cm), robots exchange messages via an onboard infrared transreceiver, in the experiments with the global communication range, the Kilobots are also equipped with a virtual transreceiver to exchange messages with the entire swarm as illustrated in detail in text ST12.

Simulators

We analyzed the effect of the various parameters of the system through simulations at two levels of abstraction: self-propelled particles and accurate physics-based models. In the former, robots are modeled as point-size agents that move in a two-dimensional space with periodic boundary conditions. Movement and communication are synchronous and noiseless, rotation in place is instantaneous, and collisions are not taken into consideration. The multiagent simulation is not tailored to the specific robotic platform that we use, the Kilobot, but rather describes a generic and simplified agent with capabilities equivalent to our robots. The physics-based simulation, instead, accurately simulates the Kilobot's sensors and actuators, as well as collision and friction between embodied robots. The Kilobots and the ARK systems are both simulated through a dedicated plug-in for ARGoS (*98*), which is a fast and accurate simulator for swarm robotics. ARGoS has been configured to simulate noise in motion and communication that quantitatively matches with the noise of the real Kilobots (*98*). In addition, ARGoS uses the identical code that runs on the robot, which improves the fidelity of the simulations and facilitates testing and development. All simulation and robot code are available with the paper (*99*).

Implementing the same behavior at two or more levels of abstraction is the best practice for the analysis of collective systems. Collective systems are typically difficult to model and fully understand. The effect of certain parameters on swarm dynamics can be counterintuitive (as this study shows), and modeling assumptions may hide emerging patterns (as for infinite-size approximations, for example). Therefore, the implementation of the same behavior at various levels of complexity can help in the understanding of the system and the generality of the obtained results.

Experimental setup

We conducted a series of experiments to understand the robot swarm behavior and validate the modeling results. Experiments in simulation used parameters that agree with the real counterpart tested with the Kilobots (e.g., motion speed $v = 1$ cm/s, environment size $\mathcal{E} = 1 \times 1$ m^2, sensing range $r_e = 20$ cm, and communication range $r_s = 10$ cm). All parameters are indicated and discussed in text ST13; here, for completeness, we only briefly report an overview of the parameters and their values. The environment includes $n = 3$ target sites with quality $\{q_x, q_y, q_z\} = \{0.8, 0.7, 0.1\}$ for multiagent simulations and $\{q_x, q_y, q_z\} = \{0.8, 0.6, 0.4\}$ for robot experiments, if not indicated otherwise. In both multiagent simulations and robot experiments, noise in individual estimates is relatively high: $\sigma_q = 0.1$ (see inset of Fig. 1B). Exploration rules' parameters are $\epsilon = 0.05$ and $\alpha = 0.01$ for the compare and resample rule, respectively. In the multiagent simulations, the three events of appearance, disappearance, and quality exchange have been studied in isolation with dedicated experiments. Instead, the robot experiments are long demonstrations (80 min; Fig. 5) comprising three phases, in each of which an environmental change occurs (see text ST13).

Dynamical systems analysis

The collective behaviors that we investigate in this study comprise one exploration rule among compare and resample and one social interaction pattern among direct switching and the cross-inhibition. The combination of exploration rules and social interaction patterns led to four distinct, yet related, systems of ODEs that describe the behavior of the robots. The ODE systems describe the macroscopic dynamics of swarm subpopulations committed to the different sites. In text ST14, we formulate a system of ODEs for each of the four investigated behaviors. These models substantially simplify when describing the collective adaptation process. The simpler models allow us to compute the bifurcation point as a function of the system's parameters, as detailed in text ST15. Here, we report the simplified models that describe the adaptation process.

Let S be the swarm size. Let x and y be the fraction of robots committed to the new best and the previously best target sites, with quality q_x and q_y, respectively. Also, let z be the fraction of polling robots. Our system has finite size (that is, a constant number of robots); therefore, we have $x + y + z = 1$ for the cross-inhibition patterns and $x + y = 1$ for the direct-switching pattern (as $z = 0$). This implies that, in case of adaptation, the dynamics reduces to one dimension in case of direct switching and to two dimensions for cross-inhibition. In particular,

For compare rule with direct switching

$$\dot{x} = k\pi r_e^2 q_x y + \frac{k\pi r_s^2 S y}{1 + k\pi r_s^2 S y} q_x x - \frac{k\pi r_s^2 S x}{1 + k\pi r_s^2 S x} q_y y \quad (1)$$

For compare rule with cross-inhibition

$$\begin{aligned} \dot{x} &= k\pi r_e^2 q_x y + \gamma \frac{k\pi r_s^2 S z}{1 + k\pi r_s^2 S z} q_x x - \frac{k\pi r_s^2 S x}{1 + k\pi r_s^2 S x} q_y y \\ \dot{y} &= -k\pi r_e^2 q_x y + \gamma \frac{k\pi r_s^2 S z}{1 + k\pi r_s^2 S z} q_y y - \frac{k\pi r_s^2 S y}{1 + k\pi r_s^2 S y} q_x x \end{aligned} \quad (2)$$

For resample rule with direct switching

$$\begin{aligned} \dot{x} = k\pi r_e^2 \alpha q_x y - k\pi r_e^2 \alpha q_y x + \frac{k\pi r_s^2 S y}{1 + k\pi r_s^2 S y} q_x x \\ - \frac{k\pi r_s^2 S x}{1 + k\pi r_s^2 S x} q_y y \end{aligned} \quad (3)$$

For resample rule with cross-inhibition

$$\begin{aligned} \dot{x} &= k\pi r_e^2 \alpha q_x y - k\pi r_e^2 \alpha q_y x + \gamma \frac{k\pi r_s^2 S z}{1 + k\pi r_s^2 S z} q_x x \\ &\quad - \frac{k\pi r_s^2 S x}{1 + k\pi r_s^2 S x} q_y y \\ \dot{y} &= k\pi r_e^2 \alpha q_y x - k\pi r_e^2 \alpha q_x y + \gamma \frac{k\pi r_s^2 S z}{1 + k\pi r_s^2 S z} q_y y \\ &\quad - \frac{k\pi r_s^2 S y}{1 + k\pi r_s^2 S y} q_x x \end{aligned} \quad (4)$$

In these equations, α is a proportionality constant representing the rate at which committed robots resample; γ is the proportion of polling robots that get committed to a target site; and k is a proportionality constant for the probability per unit time of a robot encountering a target site or being in communication range with another robot. These probabilities can be expressed as $P_e = k \pi r_e^2$ and $P_m = k \pi r_s^2$, respectively. In our model, the proportionality constant k depends on factors such as the speed of motion of the robots and their movement patterns and is indicative of the speed of the collective dynamics. Full details on the derivation and analysis of the models are available in texts ST14 to ST16; we also include with the paper a Jupyter notebook to reproduce our analytical results (*99*).

SUPPLEMENTARY MATERIALS

robotics.sciencemag.org/cgi/content/full/6/56/eabf1416/DC1
Movies S1 and S2
Texts ST1 to ST16
Algorithm S1
Figs. S1 to S6
References (*102*, *103*)

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Acknowledgments: We thank M. Port whose technical support has been vital for the success of this project. **Funding:** This project was funded by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement number 647704) and by the Office of Naval Research Global (ONRG) under grant number 12547352. A.R. also acknowledges funding by the Belgian F.R.S.-FNRS, of which he is a Chargé de Recherches. **Author contributions:** M.S.T. and A.R. conceived the original idea. M.S.T. and A.R. implemented the multiagent simulator and the robot control code and conducted the robot experiments. M.S.T. conducted the simulation experiments. A.S. performed the dynamical

system modeling and analysis. A.R. directed the project. All authors interpreted results and wrote the manuscript. **Competing interests:** J.A.R.M. is a shareholder in Opteran Technologies Limited. The other authors declare that they have no competing interests. **Data and materials availability:** All the code to generate the data reported and discussed is available online on GitHub at (*99*). The 12 videos of the robot experiments are available as movies S1 and S2. All data needed to evaluate the conclusions of the paper are available in the paper, the Supplementary Materials, or available online at https://doi.org/10.5522/04/c.5478558.

Submitted 7 October 2020
Accepted 28 June 2021
Published 28 July 2021
10.1126/scirobotics.abf1416

Citation: M. S. Talamali, A. Saha, J. A. R. Marshall, A. Reina, When less is more: Robot swarms adapt better to changes with constrained communication. *Sci. Robot.* **6**, eabf1416 (2021).

Science Robotics

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Sci. Robotics **6**, eabf1416.
DOI: 10.1126/scirobotics.abf1416

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