The emergence of collective response to decisions in a group of physical agents

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Abstract

Robot swarms provide a potential solution to a wide range of collective decision problems due to their large scale, which enables them to explore large environments, and their local intensive communication, which allows information sharing. Despite this, the majority of decision-making processes are designed to solve a single-step decision process. The goal of this study is to design robot swarms that are able to develop proper collective responses to decisions that emerge in parallel in the robot group. We aim to challenge the collective dynamics in order to examine the extent to which it would be possible to allow two decisions correspondingly related to parallel development. We consider both best-of-n and symmetry-breaking decisions and investigate the performance of two well-known voting mechanisms: the majority rule and the voting model. Our results confirm the possibility to build up a proper response to an emerging decision and highlight the key parameters that influence its success.

Introduction

Collective decision-making (CDM) is fundamental for coordinating and synchronizing a large number of multi-agent applications Reina et al. (2015); Khaluf et al. (2017); Rausch et al. (2019b,a); Nauta et al. (2020c,b). It is mostly studied as a single-step decision process—i.e., forming consensus around one of the solutions (alternatives). However, in real-world scenarios, decisions are mostly coupled with responses. Designing collective systems that can demonstrate collective responses to their decisions is a very challenging process because of several factors, among the most important is the need to identify a proper time point at which the collective response should start to build up. In this study, we address a collective decision-response problem, in a simulated robot swarm that aims to solve both best-of-n Valentini (2017); Reina et al. (2017); Nauta et al. (2020a) and symmetry-breaking Khaluf et al. (2018) decisions. Best-of-n decisions deal with alternatives of different qualities and aim to find the best option out of n alternatives. The collective decision is represented by the establishment of a large majority of robots $K \geq (1-\delta)M$ that favor the *best* alternative (M is the total number of robots). δ is a design parameter that is defined as $0 \leq \delta \ll 0.5$. Having $\delta \ll 0.5$ enables the collective decision of the swarm to be highly coherent around a single alternative Valentini et al. (2017); Rausch et al. (2020). Differently, in symmetry-breaking decisions, all alternatives have identical qualities, thus the collective decision is represented by the establishment of a large majority of robots that favor the *same* alternative. The goal is, therefore, to converge on any of the available alternatives as quickly as possible.

In this study, we investigate both symmetry-breaking and best-of-n problems to model a collective evacuation problem in a 2D arena using a robot swarm of simulated footbots[1]. The mission of the robots is to collectively detect any ongoing fire, to decide on the most appropriate exit to be used, and to clear that exit. The collective decision is to decide on an appropriate exit, while the collective response is to clear the exit. Response is defined as appropriate when the exit cleared is the same as the one selected. The swarm consists of two sub-populations: (i) robots that are equipped with sensors to measure the environmental temperature. In our study, we model the temperature using the ground color, which is why this population of robots uses ground color sensors to measure the temperature intensity. These robots are referred to as temperature-sensing robots, and (ii) robots equipped with grippers to grasp and move objects around. We refer to those as the gripper robots. Robots from both populations use range-and-bearing sensor/actuator for communication (communication radius is set to 1.3 m), proximity sensors to sense obstacles, and an omnidirectional camera sensor to detect exits through their color highlight (exit A is blue, and exit A is red). One significant difference between this study and other collective decision-making studies is associated with the individual calculation of the alternative qualities. The alternative qualities are defined at the global (system level), e.g., exit B is better than exit A. In other studies Trianni et al. (2016); Khaluf et al. (2019), when a robot encounters any of these alternatives, it is able to measure its quality that aligns with the globally define one. In our study, the quality perceived by the robots when they encounter alternatives (i.e.,

[1] `http://www.swarmanoid.org/swarmanoid_hardware.php.html#`

an exit) changes based on the relative position of the robot in the 2D space—i.e., according to the temperature intensity at the robot's position and its relative distance to the two exits. This individualized quality measure is a major challenge for collective decision, as the problem to be solved goes beyond the spreading of information about better alternatives to also correct the opinions, if needed, that are formulated individually about the encountered alternatives.

In the collective-response process, robots explore the arena to detect ongoing fires and measure the quality of the exits in order to formulate their opinion about the best exit to clear. Simultaneously, they communicate their opinions to their local neighborhood to exploit the information collected by others. In order to combine the opinions received from the robot's neighborhood, we investigate two voting mechanisms: (i) the majority rule, in which the robot adopts the opinion that is represented by the majority (> 0.5) in its local neighborhood de Oca et al. (2011)—the robot's own opinion is counted. (ii) the voter model, in which the robot adopts the opinion of a randomly chosen neighbor in its neighborhood Valentini et al. (2014). The key challenge to tackle in our study is the design of a collective system that can develop a proper response in parallel to the decision emerging in the group.

Our results show that the swarm was able to a high extent to build up a proper response in parallel to its collective decision. Among the key factors affecting the success of the collective response is the time point at which the robots (the gripper robots) react to the decision displayed in their local neighborhoods. Additionally, our findings illustrate a longer time to converge to both decision and response for symmetry-breaking problems compared to best-of-n. Finally, for our different configurations, the performance of the majority rule and the voter model show high similarity.

The Model

The Simulated Environment

To evaluate our collective-decision-response algorithm, we use the ARGoS simulator Pinciroli et al. (2012) to create a 15×15 m^2 arena. The arena has 2 exits A and B, each with a width of 3 m. The exits are blocked using 14 cylinders with a diameter of 0.1 m. To help the robot navigates towards the exits, exit A is marked with a red light, while exit B is marked with a blue light. These lights can be perceived by the robots across the arena using their omnidirectional camera sensors. Figure 1a shows the simulated arena with an example of an ongoing fire (ground color represents the fire intensity, black is the highest temperature). Figure 1b provides an example of the evolution of the robot opinions in both populations for the collective decision (solid line), and the collective response (dashed line).

The Robot Behavior

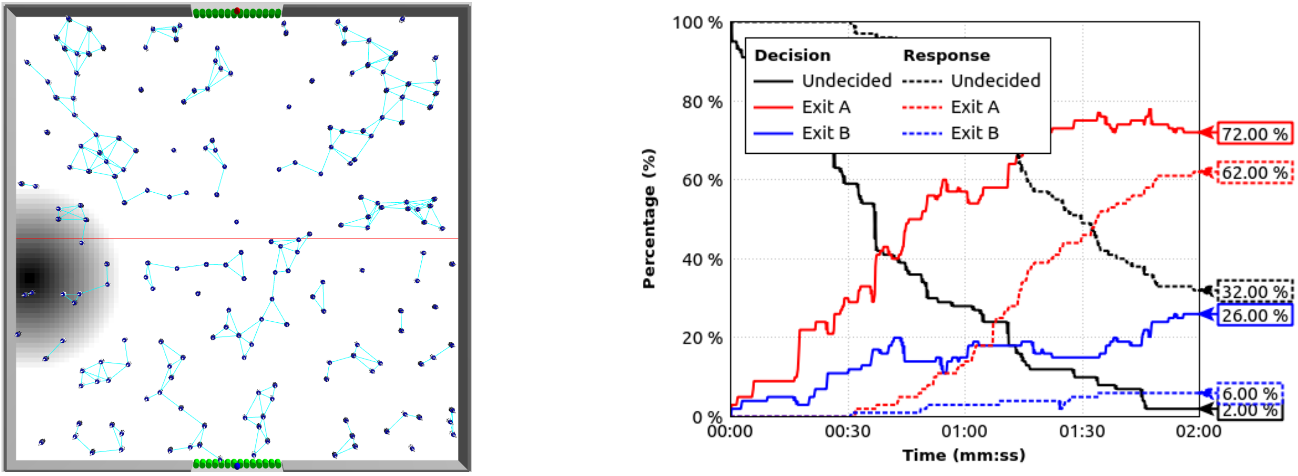
Robots from both populations perform a random walk in the arena for exploration and exploitation purposes. Our random walk algorithm exploits a pre-defined time interval, during which the robot keeps moving in a straight line if no obstacle avoidance is needed. At the end of that duration, the robot samples a new angle to change its heading direction. Limiting the time a robot moves in a straight line before changing direction increases the mixing of the system, which is an important feature for achieving better collective dynamics. During all experiments, we set the straight line duration to 100 time steps.

The temperature-sensing robots The temperature-sensing robots are engaged in the task of detecting any ongoing fire, and decide on the safest (the furthest) exit to be cleared. When a temperature-sensing robot i is not avoiding obstacles, it uses its ground sensors to measure the temperature at its current position. Additionally, robot i estimates its distance to each of the exits at time t: $\sigma_i(E,t)$ to exit E, using its omnidirectional camera sensor. After that, it weighs the distance to each exit by the intensity $\tau_i(F_k,t)$ of the fire F_k measured at time t at the current position of robot i. This weight is defined as $\tau_i(F_k,t) \in [0,1]$. $\tau_i(F_k,t) = 0$ for white ground where no fire, and $\tau_i(F_k,t) = 1$ for the highest temperature (black color). The quality of an exit E at time t is defined then by robot i as follows:

$$\eta_i(E,t) = \tau_i(F_k,t)\sigma_i(E,t) \tag{1}$$

As mentioned above, this is a key difference to other collective decision-making studies, how robots measure the alternative quality individually (i.e., local quality measure). In our study, $\eta_i(E)$ depends on both the position of the robot that impacts the current temperature intensity measure, and the distance to the exit measure. Therefore, $\eta_i(E)$ is not only different between robots but also for the same robot over different time points as the robot moves. These individual quality computations are shared in the robot's local neighborhood—i.e., all other robots within the communication radius of robot i—to formulate the robot's opinion.

The gripper robots The gripper robots are responsible for generating a proper response by clearing the exit that is collectively agreed on by the temperature-sensing robots. Therefore, when gripper robots are not avoiding obstacles, they are moving using the aforementioned random walk strategy and listening to the opinions exchanged among the temperature-sensing robots in their local neighborhood. The key challenge for gripper robots is to determine the time point at which they can consider that a collective decision was made and start acting upon that—i.e., navigating to the selected exit to clear it. An early response may lead to clearing the wrong exit, whereas a long waiting time to allow a mature-enough decision to emerge may lead to late response. Here our collective



(a) (b)

Figure 1: (a) The simulated 2D arena with an example of an ongoing fire, and two exits. Robots are depicted in dark-blue and lines illustrates their communication links. (b) An example of the evolution of a collective decision and its response.

response is facing a well-known challenge in collective systems, i.e., speed vs. accuracy Hamann et al. (2014).

To address this challenge gripper robots rely on two thresholds: (i) the opinion representation threshold ω, and (ii) the opinion duration threshold θ. The robots use a combination of two conditions to generate the collective response. The first condition is to have the percentage of neighbors voting for a particular exit E greater than ω ($N_i(E,t) > \omega$). The second condition is to have the duration, over which there is no change in the number of neighbors voting for exit E, greater than θ ($T(E, N_i > \omega) > \theta$). When both conditions hold, the gripper robot adopts exit E as the one to clear and starts to navigate towards it.

The swarm performance

We rely on two performance metrics to evaluate the efficiency of the collective decision and response: (i) the exit probability as a measure of accuracy, and (ii) the convergence time as a measure of speed. The exit probability is the probability at which the system convergences to the correct decision/response. In the case of the alternatives with different qualities—i.e., best-of-n—, the correct decision/response is defined in terms of the best alternative, this is the furthest exit from the center of the fire. When the exits are of the same quality—i.e. symmetry-breaking—, there is no correct decision/response. Therefore, the goal is to coverage to one of the available exits, and to avoid being undecided. Consequently, for symmetry-breaking decisions, the exit probability describes the probability of converging to any of the exits with a significant majority and not remain undecided. The swarm is considered to have been decided for an exit E if a fraction of robots voting for exit E stabilizes around a limit that is higher than a defined majority threshold. In our experiments, we set this majority threshold to 0.8. Consequently, we define the convergence time as the time elapsed from the beginning of the experiment to the time point at which a robot fraction of 0.8 agrees, and this fraction remains stable within an error margin of 0.05.

Results and Discussions

We run all experiments with a population of 200 robots. Each experiment runs for 4000 simulated seconds and results are averaged over 30 simulation runs for each configuration. We investigate the impact of key parameters on the collective decision and response in terms of their accuracy and speed. The investigated parameters are (i) the ratio of temperature-sensing to gripper robots, (ii) the opinion representation threshold ω, and (iii) the opinion duration threshold θ.

We consider 6 fire setups with different positions as shown in Figure 2. All setups model best-of-n problems, except for the configuration in Figure 2f that represents a symmetry-breaking problem as both exits A and B are at the same distance from the fire. Consequently, for Figure 2f both exits have identical qualities, whereas exit B has always a greater quality for the other best-of-n setups (Figure 2a to Figure 2e). For best-of-n setups, the difficulty degree of the decision increases when the position of the fire becomes closer to the center of the arena (Figure 2a through Figure 2e) as the qualities of the two exits becomes closer, but not yet equal. Figure 3a and Figure 3c reflect this increase in the decision difficulty in terms of the drop in the exit probability and the increase in the convergence time over the setups Figure 2a to Figure 2e. Exit probability drops for more difficult decisions, while it takes a longer time to converge to a decision, and this applies for both voting strategies: the majority rule and the voter model. Similar results have been obtained for the emerging response in terms of its exit probability and the convergence time across the different difficulty degrees of the best-of-n problem, see Figure 3b and Figure 3d.

Next, we investigate the frequency at which the response emerges in the population of the gripper robots agrees with the decision made by the temperature-sensing robots—i.e., free exit A/B when A/B is selected, or free no exit when the system does not converges. We test different values of our key parameters: (i) temperature-sensing to gripper ratios are in the set $\{3:1, 1:1, 1:3\}$, which for a population of 200 robots maps to the configurations of 150:50, 100:100, and 50:150. (ii) the opinion duration threshold θ in the set $\{10, 300, 1800\}$, and finally (iii) the opinion representation threshold ω in the set $\{0.6, 0.8, 1\}$. Figure 4a-c show the agreement frequency when robots vote according to the voter model, whereas Figure 4d-f show it when robots vote according to the majority rule. A very interesting result can be observed in Figure 4a, where for easy decisions (e.g., a and b on the x-axis) the lowest agreeing frequency is achieved for the 1:3 ratio, where the relatively small number of temperature-sensing robots (50), leads to a smaller robot's neighborhood, hence it becomes difficult to include a representative sample of the collective decision. Consequently, following the voter model, there is a low probability of selecting a robot that adapts the collective decision with a single pick. This doesn't happen for larger temperature-sensing populations. For the majority rule, the agreement frequency is relatively high for all ratios, see Figure 4d. When increasing the difficulty degree of the decision (along the x-axis), the agreement increases for both the majority rule and the voter model. This does not necessarily reflect a high success, however, it can result from not responding to an undecided system. Indeed, this high agreement aligns with the drop in the exit probability in Figures 3a and Figure 3c. Figure 4b and Figure 4e show how the frequency agreement is impacted by the opinion duration threshold θ. For both the majority rule and the voter model, we can notice high disagreement for large thresholds ($\theta = 1800$). This is due to the small time left for the gripper robots to converge to any response. For smaller thresholds, the agreement frequency is relatively high for both voting strategies. Figure 4c and Figure 4f show no impact of the opinion representation threshold ω on the agreement frequency that stays relatively high for all configurations and voting strategies.

In the following, we investigate the exit probability and the convergence time for best-of-n and symmetry-breaking problems. For the best-of-n setups, we average the results over the different degrees of difficulty (see Figure 2a-e).

Exit probability

Figure 5a-c show the exit probabilities obtained for the best-of-n setups, while Figure 5d-f show the exit probabilities obtained for the symmetry-breaking setups. Figure 5a and Figure 5d illustrate the robustness of the exit probability to changes in the ratio of the temperature-sensing to gripper robots. Figure 5b shows how large opinion duration thresholds $\theta = 1800$ result in low exit probability of the collective response (see narrow bars) regardless of the voting strategy used. This becomes worse when considering symmetry-breaking decisions as for $\theta = 1800$ in Figure 5e. The exit probability appears to be robust to the changes in the opinion representation threshold ω for all configurations. Also, for all configurations (Figure 5a-f), the exit probability for the best-of-n setups is lower (on average 0.8) than for the symmetry-breaking setup (on average 1). This is because both exits A and B are correct in the case of a symmetry-breaking problem, thus the exit probability sums up both probabilities of selecting exits A and B. This explanation is confirmed in Figures 5g-i, which shows the exit probability of each exit (A in blue and B in red) for the symmetry-breaking setup, and both voting strategies. We can notice that this probability adds up to 1 over the two exits, so the system never remains undecided. Finally, for all best-of-n setups, the majority rule performs slightly better than the voter model, this aligns with the results in Figure 3a and Figure 3b.

Convergence time

As mentioned above, the convergence time is calculated as the time at which the swarm (i) achieves a stable state of coherence (in our case this is 0.8 of the robot population agrees), and (ii) the swarm remains in that state within a specific margin of error (we set this to 0.05). Figure 6a-c show the convergence times obtained for the best-of-n configurations, while Figure 6d-f show the convergence times obtained for the symmetry-breaking setup. In both Figure 6a and Figure 6d, although the difference in the performance of the majority rule and the voter model is relatively small, there is a tendency to decrease the convergence time while decreasing the number of temperature-sensing robots, when using the majority rule. Whereas, the opposite tendency is observed when using the voter model. For large populations (3:1), this can be explained by the longer time it takes to have a majority in the robot's neighborhood that represents the collective decision compared to the time it takes to sample a random neighbor (i.e., voter model) whose opinion agrees with the collective decision. These dynamics reverse for low population sizes (1:3), where it becomes harder for a random neighbor selection (i.e. voter model) to stay stable due to the high chance of breaking up with that small neighborhood. Figure 6b and Figure 6e show the impact of the opinion duration threshold on the convergence time, hence the figures depict only the convergence time of the collective response. The findings shown in Figure 6e may suggest $\theta = 1800$ as the optimal value since it leads to the shortest convergence time. However, one should keep in mind that the time convergence findings should coordinate with the exit probabilities. This is because a short convergence time can be achieved also for the cases of undecided system. Therefore, based on Fig-

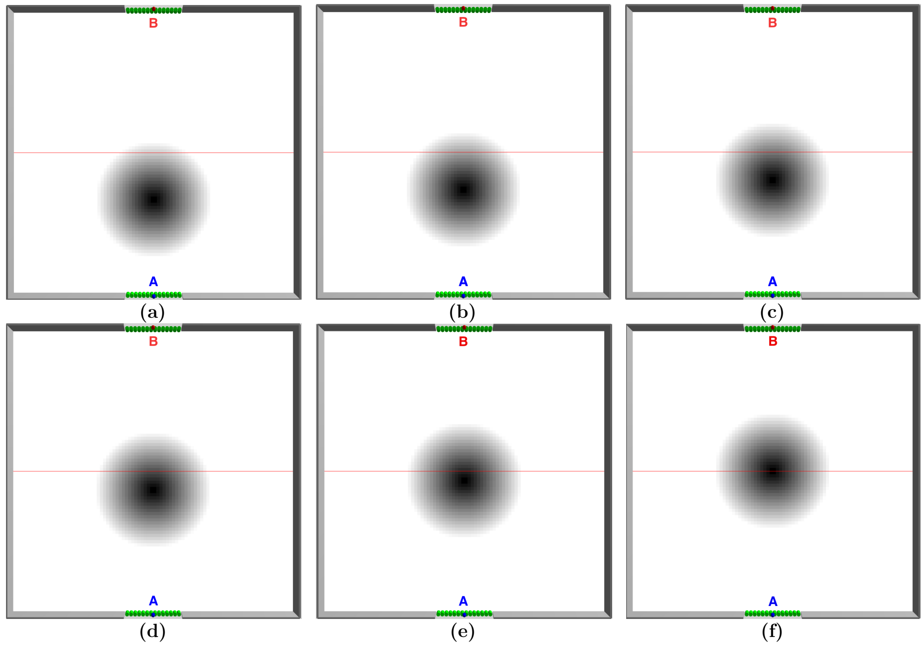


Figure 2: Setups with variable fire position: (a) to (e) show a sequence of best-of-n problems with an increasing degree of difficulty. (f) is a symmetry-breaking problem in which both exits are of equal quality.

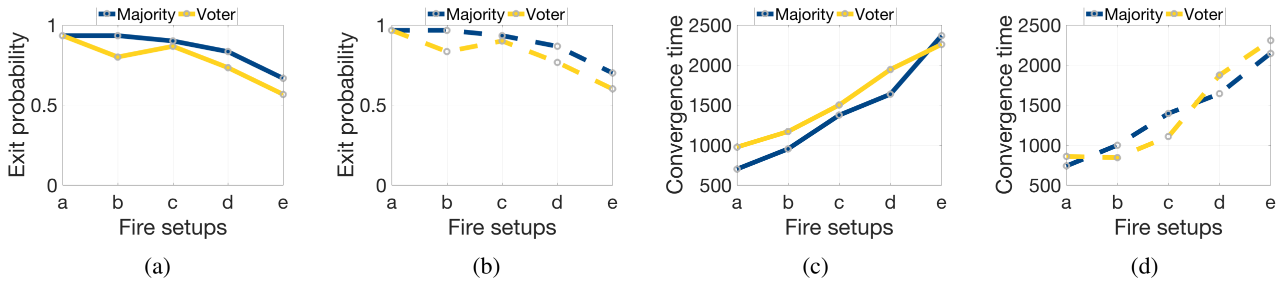


Figure 3: The increasing degree of difficulty for the different best-of-n setups expressed in terms of the exit probability and the convergence time for the collective decision and response, using the majority rule or the voter model.

ure 5b and Figure 5e the highest exit probability for both the collective decision and response is achieved for small values of $\theta \in \{10, 300\}$. For these values, the shortest convergence time is achieved for $\theta = 10$. Finally, the convergence time of the collective response seems robust to changes in the opinion representation threshold ω, similar to the response's exit probability.

Conclusions

We studied the emergence of a proper response in parallel with the decision made in a group of physical agents. We used a swarm of simulated robots to solve a collective evacuation task. The swarm has two populations: the temperature-sensing robots, who wander in a 2D arena to explore and detect ongoing fires, then to select a proper exit, and the gripper robots, who are responsible for generating the collective response, i.e., to clear the selected exit. Depending on the fire and exit positions, we modeled our decision-making problem as a best-of-n—exits have different qualities—or a symmetry-breaking—exits have the same quality—problem. For the best-of-n problem, we investigate 5 setups with an increasing degree of difficulty. We increased the decision difficulty by bringing the fire position closer to the center of the arena, thus making the quality of the two exits closer to each other. We use two of the widely-studied voting strategies in collective decision-making processes: the majority rule and the voter model to investigate the impact of the following parameters on the collective decision and response: (i) the ratio of temperature-sensing to gripper robots, (ii) the opinion representation threshold ω, and (iii) the opinion duration threshold θ. The efficiency of both the collective decision and response is evaluated using two metrics: the exit proba-

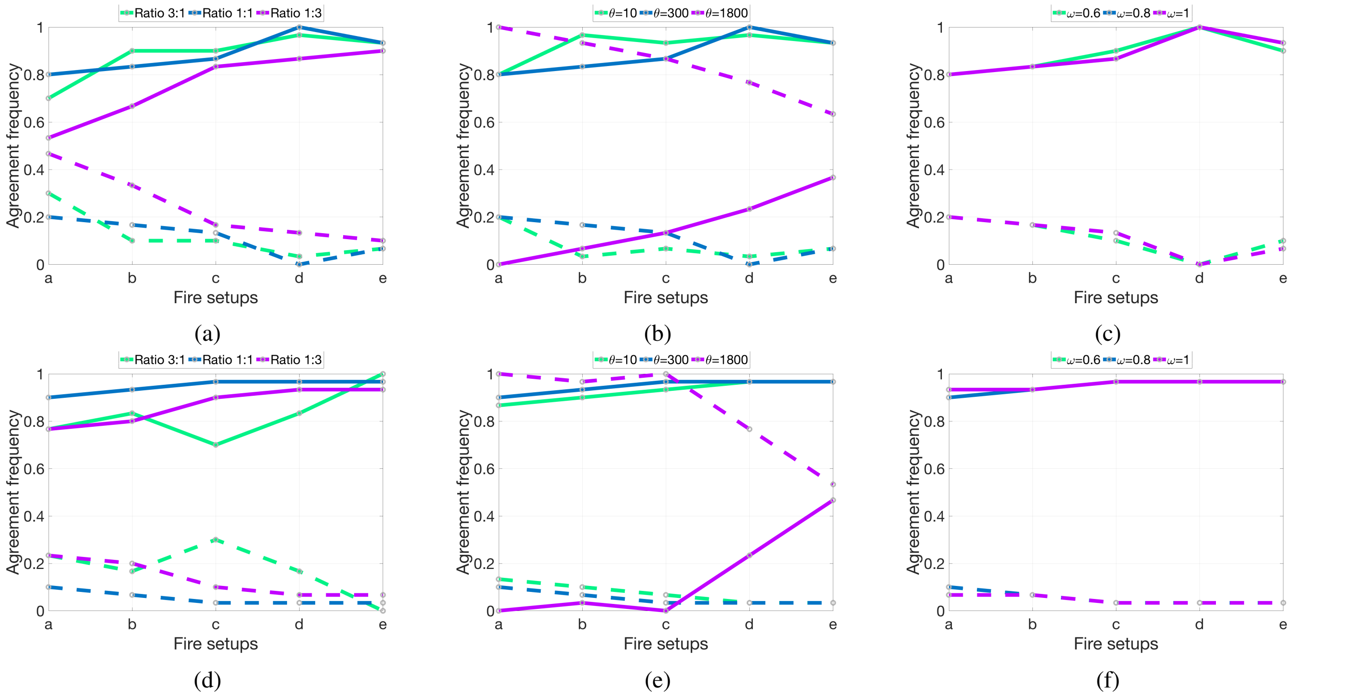


Figure 4: The frequency at which the collective response agrees with the decision made in parallel, for the best-of-n setups. (a)-to (c) obtained using the voter model, while (d) to (f) obtained using the majority rule. The x-axis labels indicate the different difficult degrees of the decision.

bility and the convergence time. Additionally, we used the agreement frequency to examine to which extent the emerged response agrees with the collective decision.

Our results have shown that for the best-of-n problems, the exit probability of both the decision and response drops with the same factor while increasing the difficult degree of the decision. This is accompanied by an increase in their convergence time. We have also shown that the agreement frequency between the decision and response drops in particular cases due to the challenge facing the voter model to select a representative neighbor in a small population of the temperature-sensing robots and for best-of-n problems. It also drops in both symmetry-breaking and best-of-n problems when the opinion duration threshold is set high. Our results reflect an important role of this threshold on the collective response, as setting it to high values can lead to a significant drop in the exit probability of the collective response or to no collective response at all. Differently, the collective response seems to be quite robust to changes in the opinion representative threshold. Finally, both the majority rule and the voter model showed lower performance in the cases of best-of-n than in symmetry-breaking problems. This is due to the higher exit probability when both exits are correct (i.e., symmetry-breaking).

References

de Oca, M. A. M., Ferrante, E., Scheidler, A., Pinciroli, C., Birattari, M., and Dorigo, M. (2011). Majority-rule opinion dynamics with differential latency: a mechanism for self-organized collective decision-making. *Swarm Intelligence*, 5(3):305–327.

Hamann, H., Valentini, G., Khaluf, Y., and Dorigo, M. (2014). Derivation of a micro-macro link for collective decision-making systems. In *International Conference on Parallel Problem Solving from Nature*, pages 181–190. Springer.

Khaluf, Y., Pinciroli, C., Valentini, G., and Hamann, H. (2017). The impact of agent density on scalability in collective systems: noise-induced versus majority-based bistability. *Swarm Intelligence*, 11(2):155–179.

Khaluf, Y., Rausch, I., and Simoens, P. (2018). The impact of interaction models on the coherence of collective decision-making: a case study with simulated locusts. In *International Conference on Swarm Intelligence*, pages 252–263. Springer.

Khaluf, Y., Simoens, P., and Hamann, H. (2019). The neglected pieces of designing collective decision-making processes. *Frontiers in Robotics and AI*, 6:16.

Nauta, J., Khaluf, Y., and Simoens, P. (2020a). Hybrid foraging in patchy environments using spatial memory. *Journal of the Royal Society Interface*, 17(166):20200026.

Nauta, J., Simoens, P., and Khaluf, Y. (2020b). Memory induced aggregation in collective foraging. In *International Conference on Swarm Intelligence*, pages 176–189. Springer.

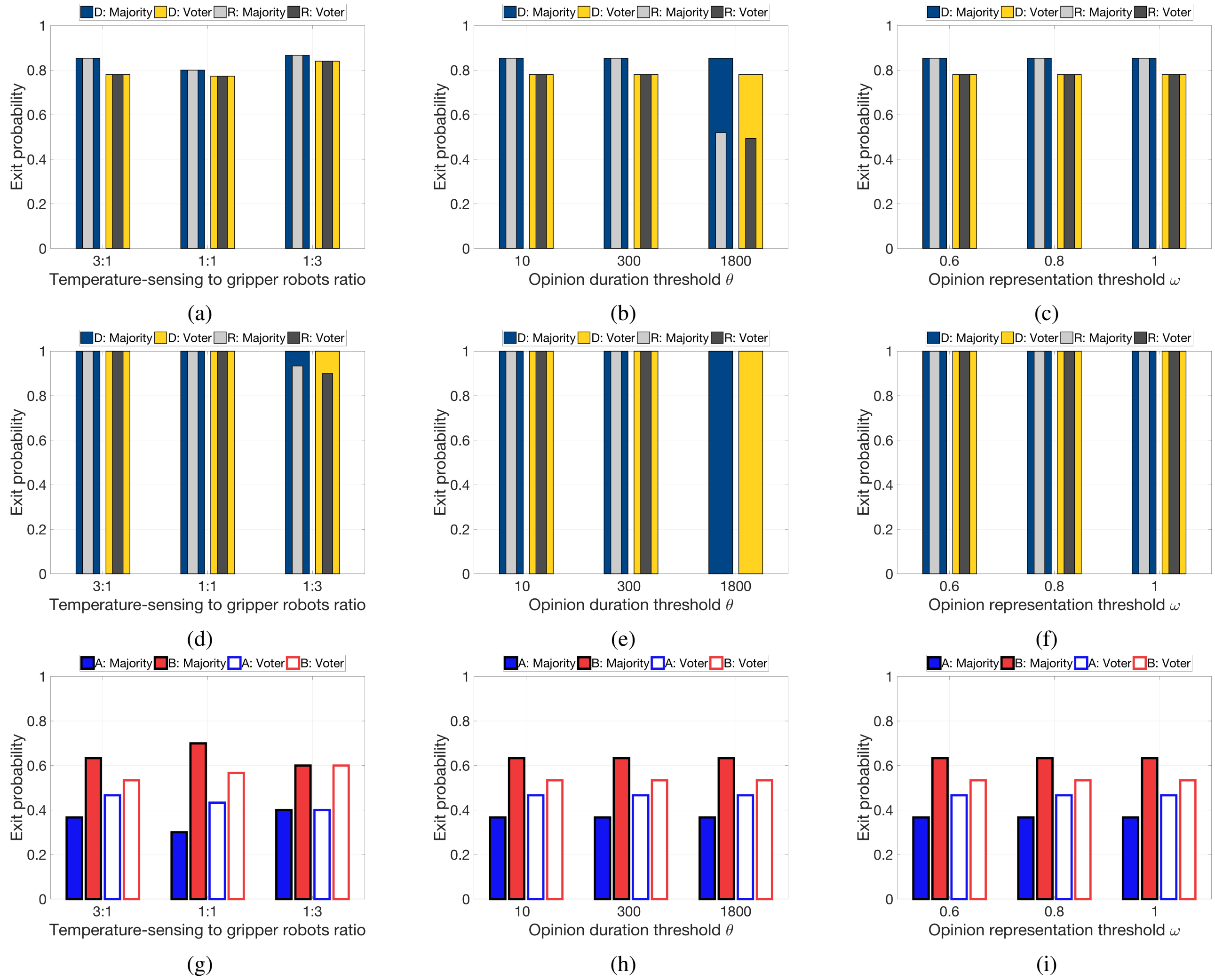


Figure 5: The exit probability: (a) to (c) for the best-of-n setups and (d) to (f) for the symmetry-breaking setups. Wide bars show the exit probability for the collective decision, while narrow bars show it for the collective response. (g) to (i) show the detailed selection of exits A and B in the case of symmetry-breaking problem.

Nauta, J., Van Havermaet, S., Simoens, P., and Khaluf, Y. (2020c). Enhanced foraging in robot swarms using collective lévy walks. In *ECAI2020, the 24th European Conference on Artificial Intelligence*, volume 325.

Pinciroli, C., Trianni, V., O'Grady, R., Pini, G., Brutschy, A., Brambilla, M., Mathews, N., Ferrante, E., Di Caro, G., Ducatelle, F., et al. (2012). Argos: a modular, parallel, multi-engine simulator for multi-robot systems. *Swarm intelligence*, 6(4):271–295.

Rausch, I., Khaluf, Y., and Simoens, P. (2019a). Scale-free features in collective robot foraging. *Applied Sciences*, 9(13):2667.

Rausch, I., Khaluf, Y., and Simoens, P. (2020). Collective decision-making on triadic graphs. In *Complex Networks XI*, pages 119–130. Springer.

Rausch, I., Reina, A., Simoens, P., and Khaluf, Y. (2019b). Coherent collective behaviour emerging from decentralised balancing of social feedback and noise. *Swarm Intelligence*, 13(3):321–345.

Reina, A., Marshall, J. A., Trianni, V., and Bose, T. (2017). Model of the best-of-n nest-site selection process in honeybees. *Physical Review E*, 95(5):052411.

Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., and Trianni, V. (2015). A design pattern for decentralised decision making. *PloS one*, 10(10):e0140950.

Trianni, V., De Simone, D., Reina, A., and Baronchelli, A. (2016). Emergence of consensus in a multi-robot network: from abstract models to empirical validation. *IEEE Robotics and Automation Letters*, 1(1):348–353.

Valentini, G. (2017). *Achieving Consensus in Robot Swarms*. Springer.

Valentini, G., Ferrante, E., and Dorigo, M. (2017). The best-of-n problem in robot swarms: Formalization, state of the art, and novel perspectives. *Frontiers in Robotics and AI*, 4:9.

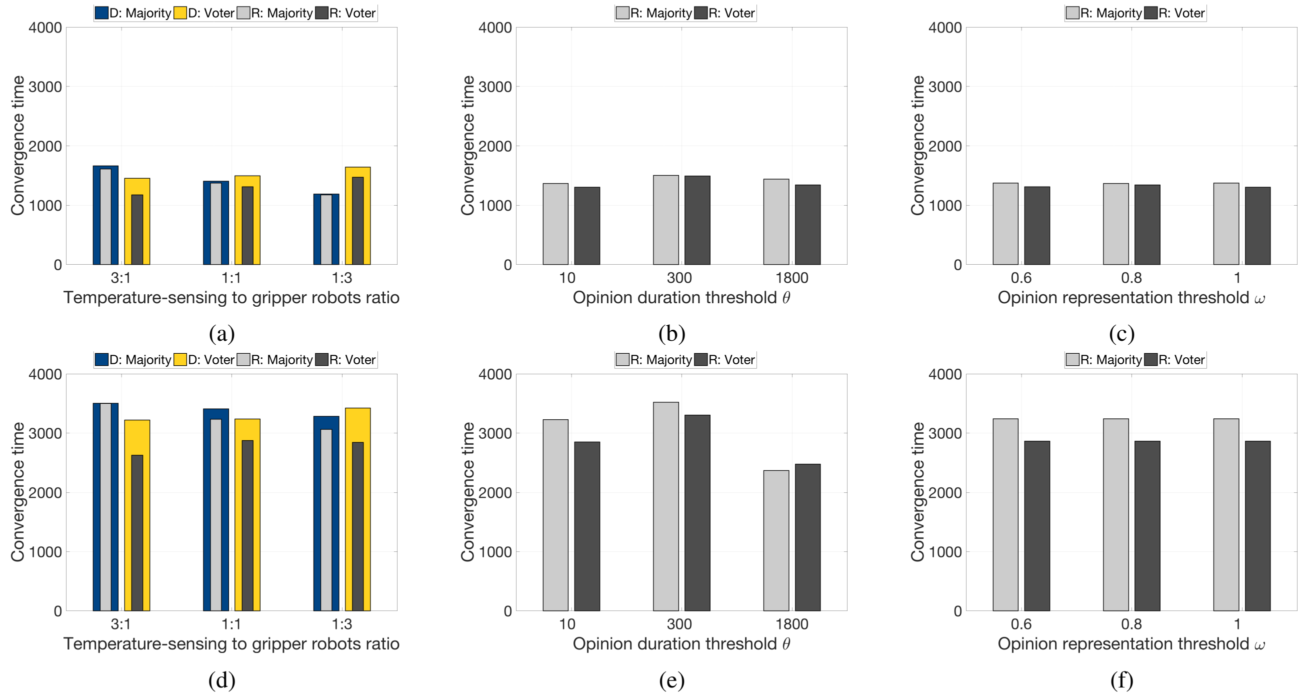


Figure 6: The exit probability: (a) to (c) for the best-of-n setups and (d) to (f) for the symmetry-breaking setups. In (a) and (d) Wide bars show the exit probability for the collective decision, while narrow bars show it for the collective response. The rest of the figures show the convergence time for the collective response only.

Valentini, G., Hamann, H., Dorigo, M., et al. (2014). Self-organized collective decision making: the weighted voter model. In *AAMAS*, pages 45–52.