Uninformed individuals enhance decision making in a noisy dynamic environment

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Abstract

In this study, we explore the adaptability of heterogeneous swarms in solving the *best-of-n* problem in dynamic environments, where robots must continuously update their opinion on the most abundant color. We employed both a Multi-Agent Simulation and the ARGoS simulator to evaluate swarm performance ϕ, considering varying levels of sensor and communication noise. Our findings reveal that heterogeneous swarms, composed of informed and uninformed agents, outperform homogeneous swarms under certain noise conditions. Specifically, swarms achieve higher accuracy when communication noise is lower than sensor noise, though this advantage diminishes as noise increases. A speed-performance trade-off was observed, with heterogeneous swarms achieving higher agreement at the cost of slower adaptability to the changing environment. These results highlight the potential benefits of swarm heterogeneity in dynamic decision-making tasks, providing a foundation for future research on parameter exploration in more realistic settings.

1 Introduction

Swarm robotics is a field of study combining robotics and collective behavior inspired by social animals. It involves studying and developing multi-agent systems comprising numerous simple robots capable of interacting with one another

and their environment to accomplish complex tasks. Drawing inspiration from the decentralized and self-organized nature of natural swarms, such as those observed in bees or ants, swarm robotics focuses on the design and coordination of autonomous robots to exhibit collective perception, intelligence, and decision-making. The key principles include local interactions, scalability, robustness, and adaptability. Computationally simple algorithms are developed to run on these simple robots. Collective behavior emerges from these simple interactions while ensuring the swarm is robust and resilient to dynamic environments.
In this study, we investigate an approach to the *best-of-n* problem in a dynamic environment. The objective is for the robots to agree on the optimal choice from the n options available in the environment. The optimal choice n also changes at a regular interval and the robots should be able to adapt to these changes. The important aspects of the system are communication noise and sensor noise. Communication noise affects the signal reception among the robots. Specifically, it occurs on the receiving end, meaning that robots may sometimes interpret the received signals incorrectly. Sensor noise affects the robot's ability to perceive the correct option. This may lead the robot to perceive one of the inferior options as the correct one.
We focus on the *best-of-n* problem with $n=5$, using Kilobots [Rubenstein et al., 2012] as the agents in a dynamic environment. The Kilobots operate on a floor composed of tiles of different colors, called the Kilogrid [Valentini et al., 2018]. The majority color of the tiles changes at regular intervals. Our goal is to investigate the ability of the swarm to incorporate new information, reject now inferior information, and adapt to the changing environment. Zakir et al. [2024], in their study on the *best-of-n* problem, demonstrate that a heterogeneous swarm can prevent opinion stagnation in swarms, a characteristic necessary for a swarm in a dynamic environment as integrating new environmental evidence is crucial. Another study by Salahshour [2019] highlights the significance of communication noise, demonstrating that a certain level of noise increases the swarm's responsiveness to environmental changes and is essential for collective decision-making. The study also shows that optimal performance is often achieved at the edge of bistability—where adding more noise would disrupt the decision-making process.
Unlike the study by Zakir et al. [2024] that explore the performance of heterogeneous swarms composed of voter-rule and majority-rule robots, we take inspiration from the work of Couzin et al. [2011]. In their study, Couzin et al. [2011] demonstrate that uninformed individuals (individuals who do not have the environmental knowledge required for decision-making) promote democratic consensus in animal groups. They show that when a minority group has the capability to dictate group outcomes, adding some uninformed individuals can make the swarm more democratic and return the control back to the numerical majority, they also show this with experiments using actual schooling fishes.
Our approach involves a swarm divided into informed and uninformed individuals. The informed individuals have access to both social information, which they gather through communication with their neighbors and personal information, which they obtain through sensors that detect the color of the floor beneath them. These robots incorporate both sources of information—social and personal—into their decision-making process, weighing their own observations alongside the opinions of the group. On the other hand, uninformed individuals rely solely on social information from their neighbors and do not

incorporate any personal observations about the environment. Their decisions are based entirely on the majority opinion of the robots around them, without any personal validation of the environmental conditions.
All robots in the swarm employ a majority-voting mechanism to form their social information, where each robot determines the majority opinion within its local neighborhood. This process is repeated as the robots communicate and update their opinions based on the information they gather from their peers.
The goal of the study is to examine how well the swarm can adapt to changing conditions in the environment, specifically in terms of agreeing on the correct majority color as it dynamically shifts over time. We examine how a heterogeneous swarm consisting of informed and uninformed individuals influences the swarm's performance in the best-of-n problem as compared to a homogeneous swarm, for different values of communication and sensor noise. We aim to identify the conditions under which a heterogeneous swarm is advantageous compared to a homogeneous swarm.

2 The Model

Our model takes inspiration from the model by Couzin et al. [2011] and from the works of Zakir et al. [2024] and Salahshour [2019]. The individuals live in a time-varying dynamic environment that changes at regular intervals. There are n options (or colors) in the environment and at any given moment one of them is the majority (or correct) option. After a defined number of timesteps, the environment switches and another one of the *n-1* options becomes the majority, this cycle repeats until the simulation ends. A few examples can be seen in screenshots in Figure 1. The robots are initialized with random color commitment at the start, this is called their color opinion. The color opinion is the color the robot believes to be the higher quality option from the $n = 5$ options.

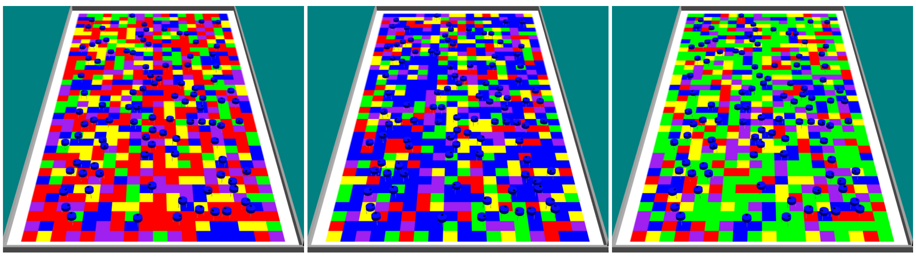


Figure 1: Screenshots of the simulation environment from ARGoS with one dominant color on the Kilogrid.

The robot can make environmental observations by measuring the color of a subset of tiles and estimating the most abundant color, this is called their *personal information*. Each robot broadcasts its color opinion to its neighbors. The robot also uses the information provided by their neighbors, this is called their *social information*.
Two types of noise are incorporated into the simulation: communication noise $\eta \in [0, 1]$ and sensor noise $\zeta \in [0, 1]$. Communication noise affects the transmission of information between robots, while sensor noise impacts the robots' ability to perceive the correct color accurately. With probability $1 - \zeta$, a robot

correctly senses the color of the tile, but with probability ζ, a noisy observation occurs, where one of the $n-1$ incorrect options is selected uniformly at random. Communication noise is implemented on the receiving end, with probability $1-\eta$ the message (which has the color opinion) received by the robot is interpreted correctly and with probability η it is interpreted as one of the other $n-1$ options.
For the decision-making, a method similar to Zakir et al. [2024] is used, for each option i in n, a score (or count) C_i is calculated. This is done by

$$C_i = M_i + \omega M \delta_i \tag{1}$$

where M_i is the number of neighbors sending messages for the option i, ω is the personal information weighing factor; when $\omega = 0$ the personal information (from the sensor readings) is ignored, M is the total number of neighbors, and $\delta_i = 1$ if the individual's personal information is i otherwise it's 0. The individual adopts the color i with the highest score C_i as its color opinion, if multiple options have the same score, one is chosen from them uniformly at random. In this way, social and personal information are combined together for decision-making.
There are two kinds of robots, the informed and the uninformed. The informed robots are those who use a combination of *personal information* and *social information* for the decision-making process (i.e. $\omega \neq 0$). The uninformed individuals are those who rely entirely upon social information, they collect opinions from their neighbors and switch to the majority opinion of the neighbors using the majority voter rule. In essence, they act as "blind" robots that do not observe the environment, this is equivalent to having $\omega = 0$.
We have a heterogeneous swarm consisting of a mix of informed and uninformed individuals. The heterogeneity is defined by the informed ratio $\rho \in [0, 1]$ where the ρ is the fraction of informed individuals while the $1-\rho$ is the fraction of uninformed individuals (see Table 1). Given the swarm size S, the number of informed individuals is $S_{informed} = \rho \cdot S$, and the number of uninformed individuals is $S_{uninformed} = (1-\rho) \cdot S$. For example, if the swarm size is $S = 100$ and $\rho = 0.6$ then $S_{informed} = 0.6 \cdot 100 = 60$ informed individuals and $S_{uninformed} = 0.4 \cdot 100 = 40$ uninformed individuals are present in the swarm. The swarm is homogeneous for $\rho = 0.0$ and $\rho = 1.0$.

3 Simulations

We run multi-agent simulations which are an abstract implementation that allow an easy and fast exploration of the parameters. After selecting the most interesting cases from the multi-agent simulation results, we also run a set of robot simulations using the ARGoS simulator [Pinciroli et al., 2012], a state-of-the-art robotic swarm simulator with plugins to run Kilobots [Pinciroli et al., 2018] and the Kilogrid [Aust et al., 2022]. Our swarm is of size $S = 100$ in both types of simulations. The environment consists of $n = 5$ options with one option having the highest quality (i.e. the majority color) and the other four options having an equal lower quality (i.e. the minority color).

3.1 Multi-Agent Simulation

In the multi-agent simulation, the robots do not move. Each robot has $M = 10$ neighbors, randomly assigned at initialization. Communication between robots is restricted to this predefined neighborhood throughout the simulation. There exists a correct color from the $n = 5$ possible options. The correct color switches every $t = 1000$ timestep, changing to one of the other $n - 1$ remaining options. The robots can read the correct color, subject to sensor noise ζ (*personal information*), and receive their neighbors' color opinion, subject to communication noise η (*social information*). The robots are either informed or uninformed based on the informed ratio ρ. The informed robots use both of these information for the decision-making and the uninformed robots use only social information.
Robots update their opinions asynchronously. At each timestep, only one robot executes its decision-making process, and this occurs sequentially, ensuring each robot gets an equal chance to update its opinion over time. The robot calculates a score (or count) C_i for each color i based on the information received from its neighbors and its own sensor reading using Equation (1). The color with the highest score is picked as the color opinion of the robot. The simulation runs for 6000 timesteps, with 5 color changes occurring at regular intervals. As there are 1000 timesteps between these changes and $S = 100$ robots, each robot gets to update its opinion 10 times.
We evaluate the swarm's performance ϕ (see Table 1) based on the fraction of robots committed to the correct color opinion. To ensure robust results, 40 independent simulation runs were conducted for each parameter combination (i.e. informed ratio, the personal information weight, sensor noise, and communication noise). The performance values from these 40 independent runs were then averaged to determine the overall swarm performance for each scenario.

3.2 ARGoS Simulation

While the multi-agent simulations offer a computationally efficient framework for exploring various parameter combinations and assessing the relative performance of different swarm configurations, it is fundamentally a theoretical model that abstracts many real-world physical constraints. Its simplicity makes it ideal for rapidly probing the parameter space and identifying optimal swarm behaviors under different conditions. However, to assess the swarm's performance in more realistic, physics-based scenarios, we turn to ARGoS [Pinciroli et al., 2012]. ARGoS enables more detailed simulations by incorporating physical interactions and communication dynamics, making it a better tool for validating the swarm's adaptability in real-world environments.

Simulation Setup The agents lie on a Kilogrid [Antoun et al., 2016], an electronic table of size $1 \times 2m^2$ that has 800 cells in total, the cells (or tiles) are colored and transmit an infrared (IR) signal with their color. The agents can receive these IR signals to read the color of the tile they are on. The bordering cells are colored white which indicates a high wall flag, this triggers the wall avoidance behavior in the agent.
Of the 800 total tiles, 684 are colored either red, blue, yellow, green, or purple, while 116 are white and used for wall avoidance. At any given time, one of the

five colors represents the majority, with 256 tiles, while the remaining 428 tiles are distributed evenly among the four minority colors, with 107 tiles each. Thus, the majority of color occupies 37.4% of the total colored area of the Kilogrid. We also have another setting where 216 tiles form the majority color and the four minority colors have 117 tiles each. Here majority color occupies 31.7% of the total colored area of the Kilogrid.
Unlike the multi-agent simulation, in the ARGoS simulations, we do not include any simulated sensor noise. Instead, sensor noise occurs from the fact that Kilobots have limited sensor capability and can explore only a limited part of the Kilogrid. As the robots navigate the multicolored environment, they perceive the majority color from the Kilogrid but also sometimes one of the minority colors, causing occasional erroneous personal information.
The Kilobot Library provides kilotics as a unit for measurement of time for the Kilobots [Pinciroli et al., 2018]. There are 31 kiloticks per second for our simulation. The simulation runs for a total of 160,000 kiloticks, each run spans approximately

$$\frac{160,000}{31} \approx 5,161\,\text{seconds}\,(\sim 86\,\text{minutes})$$

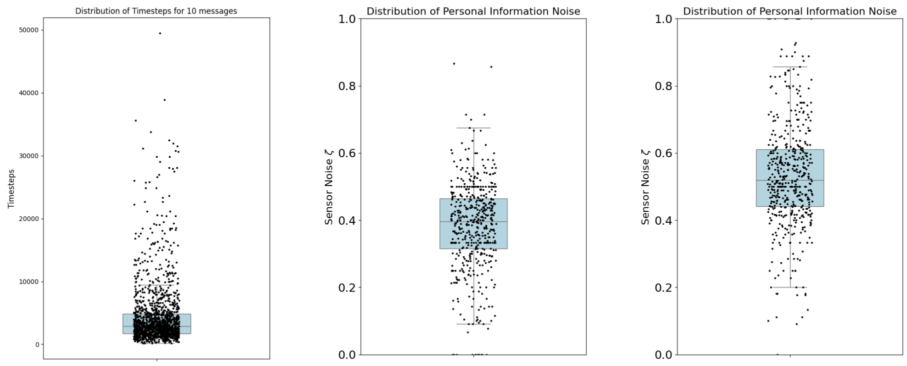
The majority color changes every 40,000 kiloticks, which corresponds to:

$$\frac{40,000}{31} \approx 1,290\,\text{seconds}\,(\sim 21\,\text{minutes})$$

Thus, there are 4 color switches per run, occurring at regular intervals of approximately 21 minutes. This setup allows us to observe the swarm's adaptability across multiple environmental changes during each simulation. TO ensure robust results, 10 independent runs were done for each combination of parameters and the results were averaged out.

Robot Behaviour We utilize Kilobots [Pinciroli et al., 2018] as agents in our simulation, which are small, 3.3 cm tall, low-cost robots designed specifically for swarm robotics experiments. The Kilobots can move at a speed of $1cm/s$ and communicate via infrared (IR) messages with a payload size of 9 bytes, within a communication range of $10cm$. Our swarm consists of 100 Kilobots, each of which is initialized with a random color commitment.
To explore the environment, the Kilobots employ a random walk strategy. They move forward for 300 kiloticks, then randomly execute either a left or right turn for 150 Kilotics, after which they resume moving forward. When a 'high wall' flag is detected (from the white border tiles), the Kilobot initiates a wall-avoidance behavior, randomly turning left or right for 130 kiloticks and then moving straight for 260 kiloticks.
Each robot tracks the color it detects from the Kilogrid at every timestep and maintains a count of these observations. The color with the highest count is considered the majority color for the robot, this forms its personal information (for which $\delta_i = 1$ in Equation (1)). For communication, each robot is said to have $M = 10$ neighbors. Communication between robots occurs via infrared (IR) signals, similar to the communication with the Kilogrid. Each robot broadcasts its color opinion along with its unique ID. The received color opinion is subject to communication noise η. Once a robot has received color opinions from 10 unique neighbors, it updates its opinion.

To quantify the sensor noise (or personal information noise) ζ, we assess the observations from the Kilogrid. After receiving messages from 10 unique neighbors, we check if the most frequently observed color from the Kilogrid by the robot matches the actual majority color in the environment. If not, this is recorded as a noisy observation. We estimate the personal information noise of the entire swarm by averaging these noisy measurements across all robots throughout the run. Hence here the noise does not only depend on the fill ratio of the Kilogrid but also on the time spent collecting environmental information. As described above, the collection time (i.e., the time between two opinion updates by the robots) depends on the time to receive messages from $M = 10$ unique neighbors. Therefore, requiring receiving information from a higher number of neighbors would also result in a lower personal information noise. Similarly, a lower density of robots (i.e., fewer robots per meter squared) would also lead to longer times between robot updates, hence lower personal information noise. We determined that the system exhibited an average personal information noise (or sensor noise) of 38.2% for conditions when 256 tiles formed the majority, this data is presented in Figure 2b. When 216 tiles formed the majority the sensor noise was estimated to be 53.61%, this is presented in Figure 2c.



(a) Timesteps required for to receive 10 messages

(b) Sensor noise with 256 tiles of the majority color

(c) Sensor noise with 216 tiles of the majority color

Figure 2: (a) Number of timesteps required for a robot to receive 10 messages, each dot shows the timestep needed for a robot to receive 10 messages. On average it takes 3850 timesteps. (b),(c) Boxplot shows sensor noise data collected from 5 independent runs from the simulated Kilobot, each dot shows average noise for a robot.

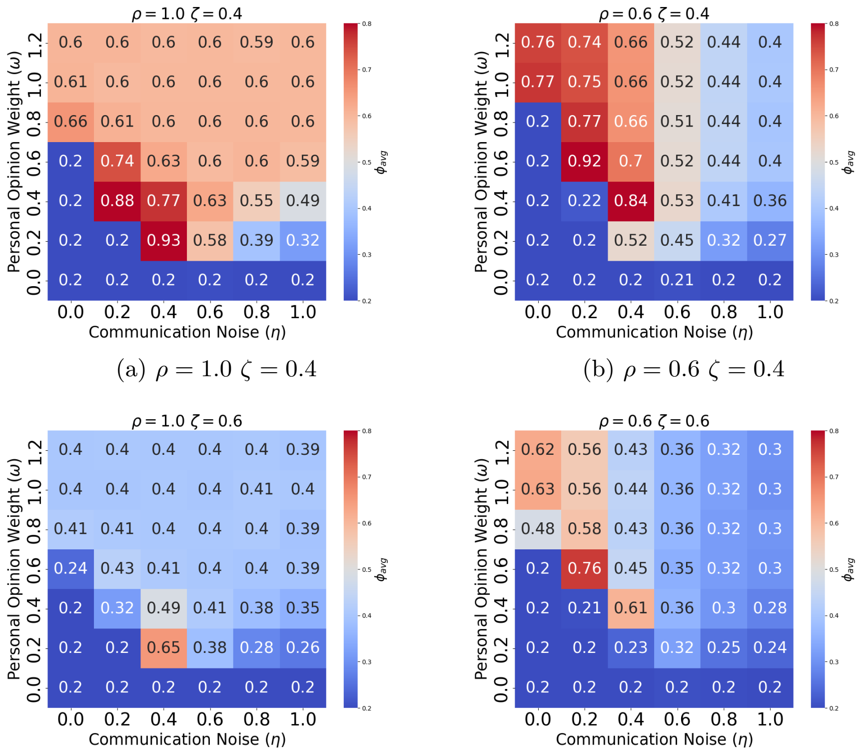
Given the characteristics of our scenario (environment size, number of robots, motion speed), robots take on average approximately 4000 kiloticks to receive messages from $M = 10$ unique robots, Figure 2a shows this distribution. Therefore, we decided to have an environmental change (switch of the majority color) every 40,000 timesteps so that each robot would execute the decision-making process 10 times on average, inline with the MA Simulations.
There are informed and uninformed robots, defined by the informed ratio ρ. The informed robots use a combination of personal and social information ($\omega \neq 0$), and the uninformed use only social information ($\omega = 0$). To update the opinion the robot calculates score C_i for each color i using Equation (1). The color with

the highest score C_i is adopted as the color opinion of the robot.

4 Result

We evaluate swarm performance ϕ (see Table 1) across various conditions to identify regions where performance is enhanced or diminished. 40 independent simulation runs are conducted to ensure robust results, and the outcomes are averaged.

4.1 Multi-Agent Simulation Results



(a) $\rho = 1.0$ $\zeta = 0.4$ (b) $\rho = 0.6$ $\zeta = 0.4$

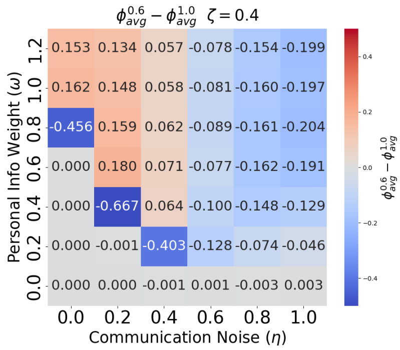
(c) $\rho = 1.0$ $\zeta = 0.6$ (d) $\rho = 0.6$ $\zeta = 0.6$

Figure 3: Heatmap of swarm performance ϕ_{avg} across varying η and ω, shown for select cases of ρ and ζ.

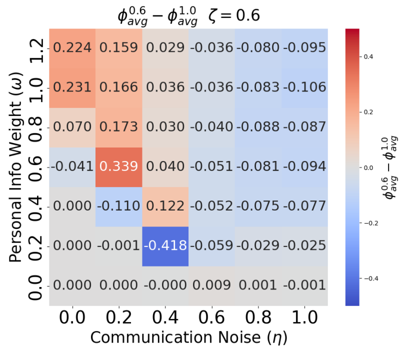
Figure 3 presents heatmaps of the averaged swarm performance, ϕ_{avg} (see Table 1), for two different levels of sensor noise: $\zeta = 0.4$ and $\zeta = 0.6$. For the lower sensor noise level ($\zeta = 0.4$), the homogeneous swarm (Figure 3a) exhibits relatively good performance across a wider range of parameter values. However, in certain cases, the heterogeneous swarm (Figure 3b) achieves a higher ϕ_{avg} compared to the homogeneous swarm with $\rho = 1$, indicating that a mixture of informed and uninformed individuals can lead to better outcomes under specific conditions.

As sensor noise increases to $\zeta = 0.6$, the performance of the homogeneous swarm (Figure 3c) declines significantly, with $\phi_{avg} > 0.5$ in only one of the parameter combinations. In contrast, the heterogeneous swarm (Figure 3d) shows good performance across more parameter configurations, suggesting that heterogeneity in the swarm becomes more beneficial as sensor noise increases, allowing for better adaptability to noisy environments. We also observe that as heterogeneity increases, the swarm performance declines with rising communication noise η. This is primarily because uninformed individuals rely solely on social information for decision-making. When communication noise is high, the accuracy and reliability of this information deteriorate, making it difficult for the swarm to make effective decisions.

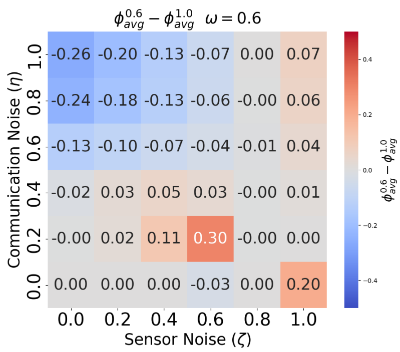
For the difference heat maps in Figure 4, we use ϕ^{ρ}_{avg} (see Table 1). $\phi^{1.0}_{avg}$ would mean average swarm performance (ϕ_{avg}) when $\rho = 1.0$. For each combination of parameters $\phi^{1.0}_{avg}$ was subtracted from $\phi^{0.6}_{avg}$. This gives us the difference of ϕ_{avg} when the swarm is homogeneous vs. heterogeneous. The higher the value (redder the cell) the more advantageous it was to have a heterogeneous swarm. These heat maps paint a better picture of where and by how much it is advantageous to have a heterogeneous swarm.



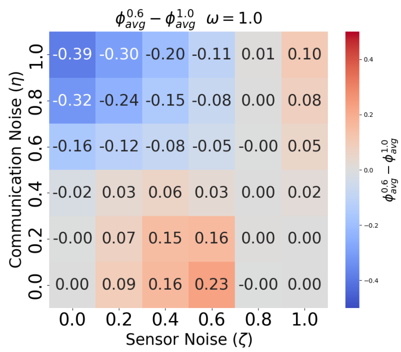
(a) $\zeta = 0.4$, $\phi^{0.6}_{avg} - \phi^{1.0}_{avg}$



(b) $\zeta = 0.6$, $\phi^{0.6}_{avg} - \phi^{1.0}_{avg}$



(c) $\omega = 0.6$, $\phi^{0.6}_{avg} - \phi^{1.0}_{avg}$

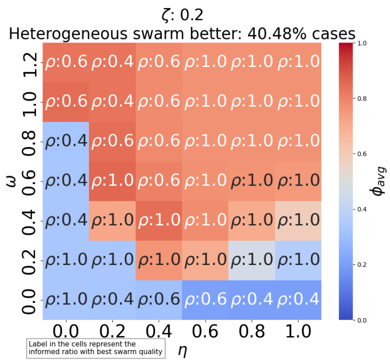


(d) $\omega = 1.0$, $\phi^{0.6}_{avg} - \phi^{1.0}_{avg}$

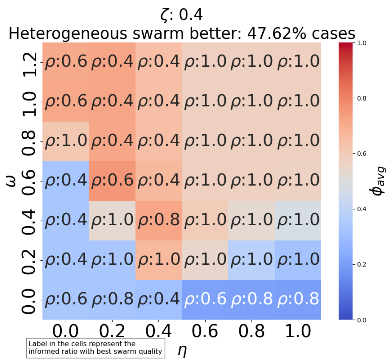
Figure 4: Heat maps taking the difference of the average swarm performance ϕ_{avg} at different informed ratio using ϕ^{ρ}_{avg}.

Looking into Figure 4a we see that the advantage of having a heterogeneous swarm is greater mostly when the communication noise η is less than the sensor

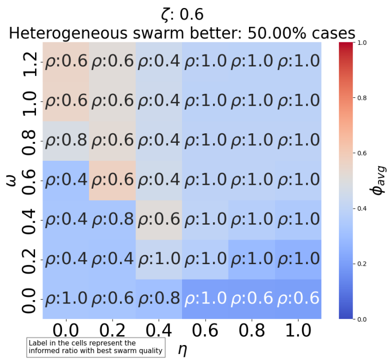
noise ζ. When the sensor noise is increased to $\zeta = 0.6$ in Figure 4b the effect of uninformed is even more enhanced. The presence of uninformed agents leads to a notable improvement in swarm performance under higher sensor noise conditions especially when $\eta < \zeta$.
To further illustrate the impact of the different noise types on swarm performance, in Figure 4c and 4d, we generated a difference heatmap with sensor noise ζ and communication noise η, for two fixed personal opinion weights, $\omega = 0.6$ and $\omega = 1.0$. In both cases, when $\eta < \zeta$ we see either a performance improvement by having some uninformed agents or an almost negligible difference in performance. This visualization emphasizes the regions where heterogeneity proves advantageous, particularly when the communication noise η is lower than the sensor noise ζ.



(a) $\zeta = 0.2$



(b) $\zeta = 0.4$



(c) $\zeta = 0.6$

Figure 5: These heat maps show changes in swarm accuracy as a function of personal opinion weight (ω) and communication noise (η). A redder cell indicates higher swarm accuracy. The label within each cell represents the informed ratio (ir) at which the highest swarm performance was achieved. (a) $\zeta = 0.2$. (b) $\zeta = 0.4$. (c) $\zeta = 0.6$.

In the heatmaps in Figure 5, we present swarm performance as a function of personal opinion weight ω and communication noise η for some fixed sensor noises ζ. The color in each cell reflects the swarm performance ϕ_{avg}, with redder shades indicating higher performance (here ϕ_{avg} is again averaged over $\rho \in [0, 1]$ in steps of 0.2). Additionally, each cell is labeled with the corresponding informed ratio ρ that yielded the highest performance for that particular combination of parameters. This visualizes swarm performance under various ω and η, while also highlighting the informed ratio ρ that maximizes performance under different conditions. We can see the swarm performance ϕ_{avg} reduces with increasing ζ but the effectiveness of having a heterogeneous swarm increases. With $\zeta = 0.2$ in 40.48% of cases having a heterogeneous swarm is beneficial (Figure 5a). This rises to 47.62% of cases for $\zeta = 0.4$ (Figure 5b) and reaches 50% of cases for $\zeta = 0.6$ (Figure 5c)although the swarm performance is lower at this point. This establishes that having a heterogeneous swarm is advantageous in certain cases.

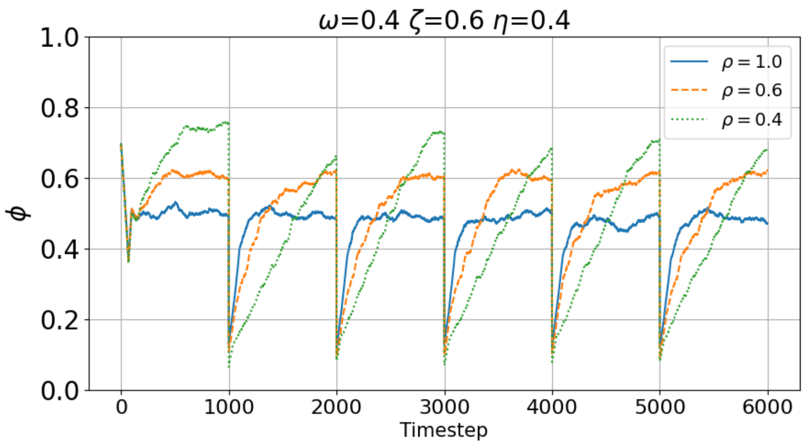
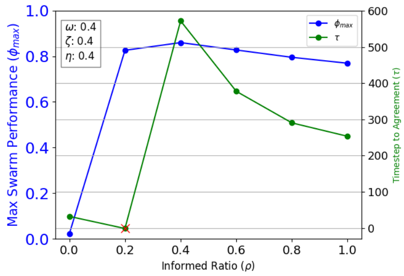
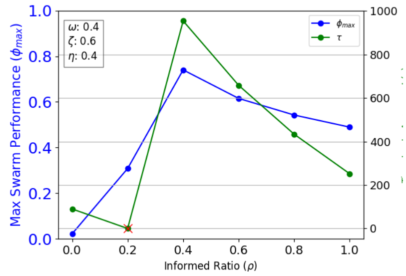


Figure 6: Swarm performance ϕ for different informed ratios ρ over timesteps. $\omega = 0.4$ $\zeta = 0.6$ $\eta = 0.2$

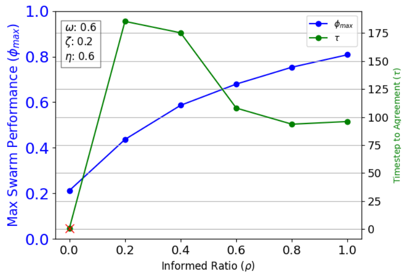
We also see the effect of heterogeneity on swarm dynamics, that is how quickly the swarm comes to an agreement over the correct color. In Figure 6 we compare ϕ for three different ρ values. We can see the existence of a speed-performance tradeoff where the highest performance is achieved with the lowest ρ but it is also slower to come to an agreement.
The number of timesteps required for the swarm to reach consensus is denoted by τ. This is calculated by using the maximum achievable swarm performance ϕ_{max}, Table 1 details these metrics. The higher the τ is, the slower the swarm is to reach consensus. We present both ϕ_{max} and τ plotted against $\rho \in [0, 1]$ in Figure 7.
In most cases, we see that peak ϕ_{max} is achieved when $\rho = 0.4$ or $\rho = 0.6$, and then it starts to fall off for higher ρ values. In all cases where a heterogeneous swarm performs better [Figures 7a,7b,7d], we observe that the peak ϕ_{max} corresponds to the peak τ, indicating that the swarm is slowest when maximum performance is achieved. The exception is Figure 7c, here $\zeta < \eta$ so ϕ_{max} keeps increasing with increasing ρ hence the homogeneous swarm performs best and also is fast. This corresponds with our previous findings that heterogeneity is advantageous when $\eta < \zeta$. For the case marked with a cross in Figures 7a, 7b, 7c, no decision-making occurred when switched to a dynamic environment hence $\tau = 0$ through the run.



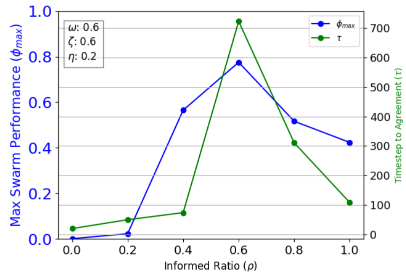
(a) $\omega = 0.4$ $\zeta = 0.4$ $\eta = 0.4$



(b) $\omega = 0.4$ $\zeta = 0.6$ $\eta = 0.4$



(c) $\omega = 0.6$ $\zeta = 0.2$ $\eta = 0.6$

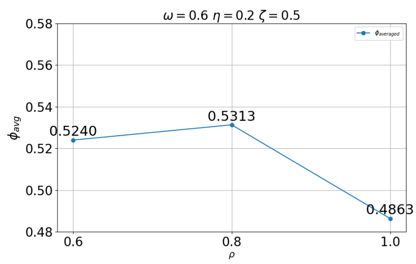


(d) $\omega = 0.6$ $\zeta = 0.6$ $\eta = 0.2$

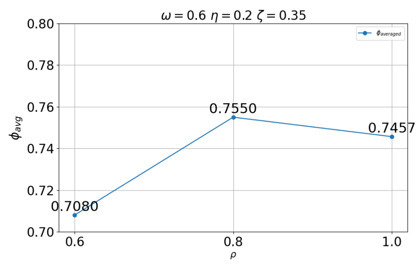
Figure 7: ϕ_{max} and τ plotted over informed ratio ρ for different selection of parameters.

4.2 ARGoS Simulation Results

Building on the insights gained from the Multi-Agent (MA) simulation, we now turn to the ARGoS simulator results. In this subsection, we examine the swarm's performance in a more detailed, physics-based simulator.



(a) $\omega = 0.6$ $\eta = 0.2$ $\zeta = 0.5$

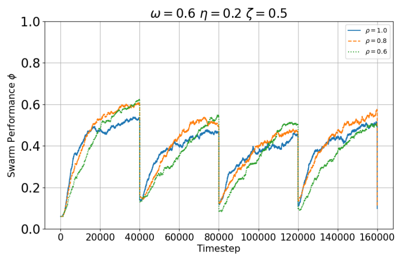


(b) $\omega = 0.6$ $\eta = 0.2$ $\zeta = 0.35$

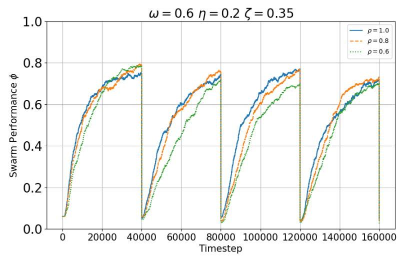
Figure 8: Variation of swarm performance with ρ in ARGoS

Figure 8 gives us insight into the how swarm performance ϕ_{avg} changes with increasing informed ratio ρ. In Figure 8a we see that swarm performance is $\phi_{avg} = 0.52$ for $\rho = 0.6$, a slight increase is seen in the performance ($\phi_{avg} = 0.53$) at for $\rho = 0.8$. The worst performance at $\phi_{avg} = 0.49$ is seen for a homogeneous swarm with completely informed individuals ($\rho = 1.0$). In Figure 8b we see peak swarm performance at $\rho = 0.8$, although the performance gain is just about 1%

from the swarm at $\rho = 1.0$, and the worst performance is seen at $\rho = 0.6$ hence adding more uninformed is not helpful.
In Figure 9, we present the swarm performance ϕ over timesteps (or kiloticks). In Figure 9a, a speed-performance tradeoff is observed, where swarms with lower informed ratio ρ exhibit higher performance ϕ but take longer to reach consensus. This is also present in Figure 9b when comparing $\rho = 1.0$ to $\rho = 0.8$, although it is not as apparent, the performance drops for $\rho = 0.6$ here. This mirrors the speed-performance tradeoff observed in the MA simulation, as shown in Figure 6 and more elaborately in Figure 7, further reinforcing the consistency of these results across both simulation platforms.



(a) $\omega = 0.6$ $\eta = 0.2$ $\zeta = 0.5$



(b) $\omega = 0.6$ $\eta = 0.2$ $\zeta = 0.35$

Figure 9: Swarm performance ϕ with different informed ratios ρ for a set of parameters.

The findings from the ARGoS simulator, while showing a less pronounced effect of having uninformed individuals, remain consistent with the results from the Multi-Agent simulations, where heterogeneous swarms outperform homogeneous ones. Although the scope of testing in ARGoS was limited due to the long simulation times and time constraints, the results still demonstrate the potential advantages of incorporating uninformed agents in dynamic environments. These initial observations provide a solid foundation for future research, which could further explore under what conditions these effects become more pronounced in realistic, physics-based simulations.

5 Discussion and conclusion

In this paper, we explore an approach to the *best-of-n* problem in a dynamic environment. In this context, robots are tasked with evaluating the highest-quality option among multiple available choices. Previous studies have shown that having a heterogeneous swarm consisting of individuals employing different kinds of decision-making processes is potentially advantageous as compared to a homogeneous swarm [Ducatelle et al., 2010, Kengyel et al., 2015, Prorok et al., 2016].
Zakir et al. [2024] in their study of the *best-of-n* problem in a dynamic environment, demonstrated that a heterogeneous swarm composed of voter and majority rule robots exhibits greater adaptability, faster decision-making, and has a higher swarm performance compared to a homogeneous swarm. We draw inspiration from the work of Couzin et al. [2011] with regard to heterogeneity. Their

research demonstrated that the inclusion of some uninformed individuals—those lacking access to information necessary for decision-making—promotes equal representation of preferences within the swarm, thereby promoting a more democratic outcome.
Our swarm is heterogeneous, comprising informed and uninformed individuals. Informed individuals utilize a combination of personal and social information for decision-making, while uninformed individuals rely solely on social information. Personal information is obtained through direct environmental observations, whereas social information is gathered by communication with other robots and employing majority rule. Both communication and environmental observations may be subject to errors. We see that a heterogeneous swarm exhibits a higher swarm performance when there is lower communication noise in the system as compared to the personal observation noise.
We see the existence of the a speed-performance trade-off where maximum swarm performance (i.e. maximum consensus for the correct option) often occurs in the swarm that is also the slowest to come to the consensus. As the swarm becomes more heterogeneous the number of timesteps required for consensus goes up. As previous studies suggest this could be because more reliance on social information (which the uninformed do) can lead to group opinion stagnation making it difficult to integrate new information [Talamali et al., 2021, Pfister and Hamann, 2023, Soorati et al., 2019].
We validate our findings using the more robust, physics-based simulator called ARGoS. While the results generally align with those from the abstract multi-agent simulation, the influence of uninformed individuals is less pronounced. Further analysis is needed to determine whether more significant effects of uninformed individuals can also be observed in ARGoS, and if so, under what parameters and how these parameters are different from those in the multi-agent simulations.

6 Supplementary Resources and Key Metrics

The source code for the ARGoS Simulation and the Multi-Agent Simulation is available in the git repository.

Metric	Summary
S (Swarm size)	Total number of robots in the simulation
$S_{informed}$ (Informed swarm size)	The number of robots that are informed (can make environmental observations).
$S_{uninformed}$ (Uninformed swarm size)	The number of robots that are uninformed (cannot make environmental observations).
ϕ (Swarm performance)	Proportion of swarm size S committed to the correct/majority color. Averaged over all independent runs.
ϕ_{avg} (Average swarm performance)	Swarm performance, ϕ, is recorded just before each environmental change, and ϕ_{avg} represents the average of these recorded values over multiple changes.
ϕ_{max} (Maximum swarm performance)	In a non-dynamic environment, the value ϕ is recorded at the end of the simulation run. It represents the maximum achievable swarm performance for a given set of parameters.
ρ (Informed Ratio)	The ratio of the number of informed robots to swarm size. $\rho = \frac{S_{informed}}{S}$
ϕ^{ρ}_{avg} (Average swarm performance)	The average swarm performance ϕ_{avg} for a particular informed ratio ρ.
τ (Timesteps to consensus)	The number of timesteps required to reach 95% of ϕ_{max} after an environmental change, averaged over all environmental changes.
M (Neighbourhood size)	The number of robots, a robot communicates with before switching color opinion.
n (Number of options)	The number of options (colors) present in the environment. One of the n is the majority/correct color in the environment.
ζ (Sensor/Observation noise)	Probability of interpreting the majority/correct color erroneously as one of the other $n-1$ colors.
η (Communication noise)	Probability to interpret a received color opinion from another robot erroneously as one of the other $n-1$ colors.
ω (Personal information weight)	A measure of how highly a robot weighs its personal information about the environment.

Table 1: A table listing the different metrics and symbols used in the paper.

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