Generalizations of Evolved Decision-Making Mechanisms in Swarm Collective Perception

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Generalize or perish: Communication range-Time-Accuracy trade-offs in swarm collective perception

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Abstract. We investigate the generalization characteristics of a recently proposed dynamical neural network as an individual decision-making mechanism, developed with evolutionary techniques for robotic swarms engaged in the collective perceptual discrimination task. To explore the performance of this neural model for opinion selection we conducted series of simulations with an artificial swarm of 20 epuck2 robots under various operating conditions. The controller, evolved in a randomly painted in two colours arena (in 55%–45% ratio) with a swarm communication range of 50cm, was evaluated in nine structurally different patterns representing environmental variability related to the spatial distribution of the options and in five levels of communication range – 10, 20, 30, 40, and 50 cm, respectively. The results reveal that our neural controller generalizes well in the collective perceptual discrimination task in a range of conditions with minor drops in consensus accuracy, however, the swarm performance degrades in conditions with patchily distributed perceptual cues and/or very short communication range.

Keywords: Swarm robotics · Collective perception · Evolutionary robotics.

1 Introduction

Swarm robotics studies multi-robot systems in which each robot has its own controller, perception is local and communication is based on spatial proximity [10]. The group-level response emerges from a self-organisation process [7], based on the interaction between the robots and their physical environment. However, the autonomous nature of this process poses a challenge for designers, since it is notoriously difficult to infer which set of individual actions leads to the emergence of a desired collective response. Moreover, traditional design methods lack the ability to tackle problems and swarms of increasing complexity in uncertain and unpredictable environments. This further intensifies the need for fundamental and generic automated methodologies for modulating collective behaviour, with the potential to circumvent tedious trial-and-error model tuning.

One type of widely studied paradigms in swarm robotics is the "best-of-n" problem set [18, 21], which requires the swarm to reach a consensus on the best among a number of available options. Consensus achievement is a process in which swarm members exchange their opinions with each other and eventually converge to a unique opinion. These studies instigate the search for controllers that perform robustly in different conditions, while at the same time optimize the utilization of critical device-operating resources. For example, emitting longer-range signals for swarm communication inevitably contributes to higher energy consumption and negatively impacts the autonomy of the robots. Since swarm communication is inherently local, it is important to establish the optimal bounds for the maximal communication range (and therefore constrain the energy consumption) and the exact trade-offs with respect to swarm performance in a particular task.

In this paper, we investigate the ability of one particular neural model [1] to generalize the opinion selection in a swarm of robots, engaged in the collective perceptual discrimination task, across a range of qualitatively and quantitatively different conditions, while preserving its effectiveness. We evaluate this previously developed neural model [1–3] over a set of test conditions in the collective perceptual discrimination task, while varying the environmental patterns with respect to the spatial distribution of the options and the communication range. We use the nine benchmark environments proposed in [4] in which the options are more patchily distributed than the environment experienced by the swarm during the control system design phase. The results of this study contribute to providing better awareness about the potential of the evolved controller for swarm robotics.

2 Background

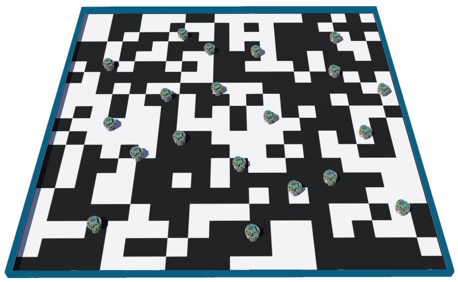
For designing large groups of robots, which coordinate and cooperatively perform a task, swarm robotics takes inspiration from natural self-organizing systems and attempts to recreate the emergence of collective behaviour from simple local interaction rules [12, 22]. Through the design of individual robot behaviour, swarm robotics aims to achieve locally coordinated interaction that results in a self-organized collective behaviour [9, 6, 11]. Collective decision-making mechanisms, designed by behaviour-based modular control systems, have demonstrated their effectiveness in a variety of scenarios [20, 19, 15]. However, the adaptability of these swarms to unexpected and unpredictable circumstances tend to be limited by the designer imposed bias. Further research is required to design collective decision-making mechanisms that allow swarms of robots to mimic natural swarms with respect to robustness, scalability, and flexibility [10].

The collective perceptual discrimination task for swarm of robots has been originally introduced by [14], who used a binary version of this scenario to design and evaluate individual mechanisms underpinning the collective decision-making process. In this task, the swarm explored a close arena patched with tiles, randomly painted in black and white, with the aim to collectively decide which colour is dominant. The two colours are the options or features, and the proportion with which each colour covers the arena floor corresponds to the option/feature quality. The goal is to design individual opinion selection mechanisms that allow the swarm to converge on the desired consensus state (i.e., all robots sharing the correct opinion about the arena colour dominance). Various individual mechanisms for opinion selection have been developed, from the classical hand-crafted solutions, based on the Voter model, the Majority rule, and their variants [21], to more recent ones, based on the synthesis of artificial neural networks [1]. More recently, an opinion selection mechanism based on artificially synthesised neural network using evolutionary algorithms [2] have proved effective for the collective perceptual discrimination task [19]. Further studies with evolved controllers [3] demonstrated that the neural network based opinion selection mechanism is more effective and scalable than the Voter model [19] in a set of environmental conditions. The perceptual discrimination task has been used by [19] to investigate the performance of various decision-making strategies for swarm of robots while varying the options quality (i.e., the features ratio) for controlling task difficulty. [16] explored further variations of this task, characterised by the presence of byzantine robots, i.e., robots that communicate deceptive messages with the intent to entice the swarm to converge on a consensus to a non-optimal choice. [8] investigated scenarios with more than two options/features. Arguing that the key determinant of the difficulty of the perceptual discrimination task for swarms of robots required to choose the best option is the features' distribution [4] proposed a set of nine structurally different variations in the environmental topology of the patterns (Fig. 1) and a set of measures for their characterization. Their work was further expanded by [17], who proposed a universal and generic measure of task difficulty, which takes into account not only the environmental complexity, but also the agent's capabilities. More recently, [1] used these patterns to evaluate the effectiveness of neural network-based decision-making mechanisms. This set of spatial distributions of the perceptual cues have been evaluated [5] with a decision-making mechanism tackling spatial correlations in unknown environments statistically.

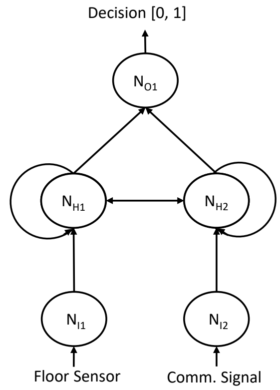
3 Methods

This study is based on the collective perceptual discrimination task as described in [1, 4], and is conducted in a simulation environment represented by a square arena of 2x2 m, whose floor is covered with black and white tiles (see Fig. 2a), 10x10 cm each, distributed according to one of the nine patterns presented in Figure 1. The dominant colour (either black or white) covers 55% of the arena floor and corresponds to the best quality option/feature, while the other colour

Fig. 1: All nine benchmark patterns used in our study, proposed by [4] and employed in perceptual discrimination tasks [1] to assess swarm performance.



(a)



(b)

Fig. 2: (a)Simulated arena of the collective perceptual discrimination task. (b)Multi-layer CTRNN underpinning the opinion selection of a single agent.

covers the remaining 45%. We used the widely popular in the research community e-puck2 robot [13], which is equipped with eight proximity infra-red sensors, a binary floor colour sensor, and a range&bearing board for local communication. Swarm communication consists of emitting a binary signal, which represents the robot's current opinion about the arena colour dominance. To compensate for the simulation–reality gap, 10% uniform noise is added to all sensor readings, motor outputs and robot position.

Initially, a homogeneous swarm of 20 robots is distributed randomly in the arena without knowing its colour dominance. During the evaluation they explore the arena with a random walk with a fixed step length (5 s., at 20 cm/s), and turning angles chosen from a wrapped Cauchy distribution, while avoiding obstacles (arena walls and neighbours) for up to 1000 s. On every iteration, the robots sample the arena under their body and communicate their opinion on the dominant colour to spatially proximal robots. The objective of the swarm is to reach a consensus (i.e., all robots sharing the same opinion) on the correct colour dominance. The process underpinning the development of the individual opinion is regulated by a continuous time recurrent neural network (Fig. 2b), synthesised using evolutionary algorithms [1].

Since the operational principles of our controller are not functionally symmetrical with respect to the dominant colour we performed the evaluation both in black-dominant and white-dominant environments separately and compare the outcome. The maximal robot–robot communication range, which allows a reliable implementation on the physical e-puck2 robot with the range&bearing board, is 50 cm, therefore we explore five communication range limits between 10 cm and 50 cm. In order to investigate the trade-offs between communication range, time-to-consensus and swarm accuracy, we analyze the performance of simulated robot swarms over 50 trials per each communication range for black-dominant and white-dominant floor distributions in all nine environmental conditions (patterns). To characterize swarm performance, we employ two measures – decision accuracy and time-to-consensus. The former quantifies the proportion of trials in which the swarm reached consensus on the correct opinion/option and the latter characterizes each successful trial.

4 Results

In order to explore the relationship between the time the swarm spent on the task, as a key performance indicator, and the swarm communication range, we averaged the execution time of all 50 trials per condition, including the time-to-consensus of successful and the time limit (1000s) of unsuccessful trials. The results reveal decreasing trends with the increase of communication range for all environmental patterns (Fig. 3), as expected, however with significant variability in the shapes and slopes. At one extreme, for the homogeneous Stripe pattern, the swarm achieved negligible success across conditions. At the other extreme, the curves for the Random pattern show consistent monotonic trends of execution time as communication range increases (Fig. 3/right), with one exception (Fig. 3/left), and largely outperform the rest. This is unsurprising, as the neural model was evolved on the Random pattern only. The generalization capability of this controller is best evidenced for the Star pattern, which approaches the

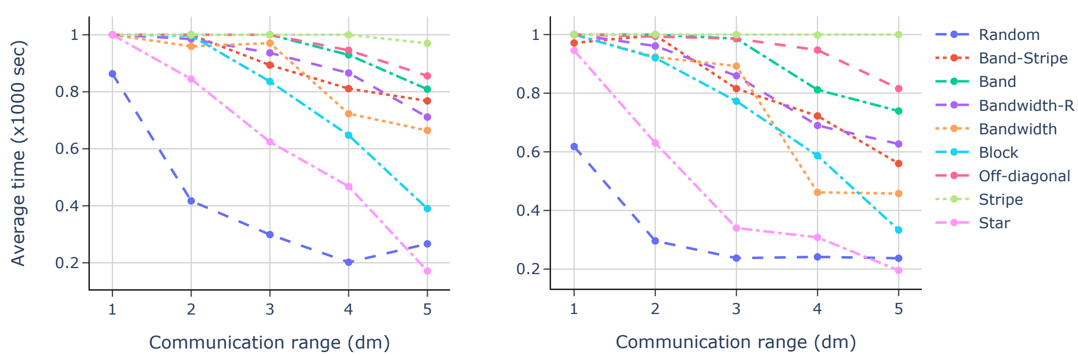


Fig. 3: Average execution time over 50 trials per communication range in all nine environmental conditions – black-dominant (left) and white-dominant (right). At one extreme (Stripe) the swarm achieved only negligible success across-the-board. At the other extreme, the curves for Random show a steady decrease of execution time as communication range increases, with one exception (left).

performance for Random pattern as the communication range increases and even exceeds that, surprisingly, in the largest range. However, the robustness of this controller shows its limitations for all patterns at the shortest range (10cm) and for all but the Random pattern at the range of 20cm.

In order to get a deeper insight into the performance trade-off between communication range, completion time and accuracy, we aggregated the number of successful trials with correct swarm consensus reached within 200, 400, 600, 800, and 1000s, respectively. Figures 4 and 5 show the corresponding curves,

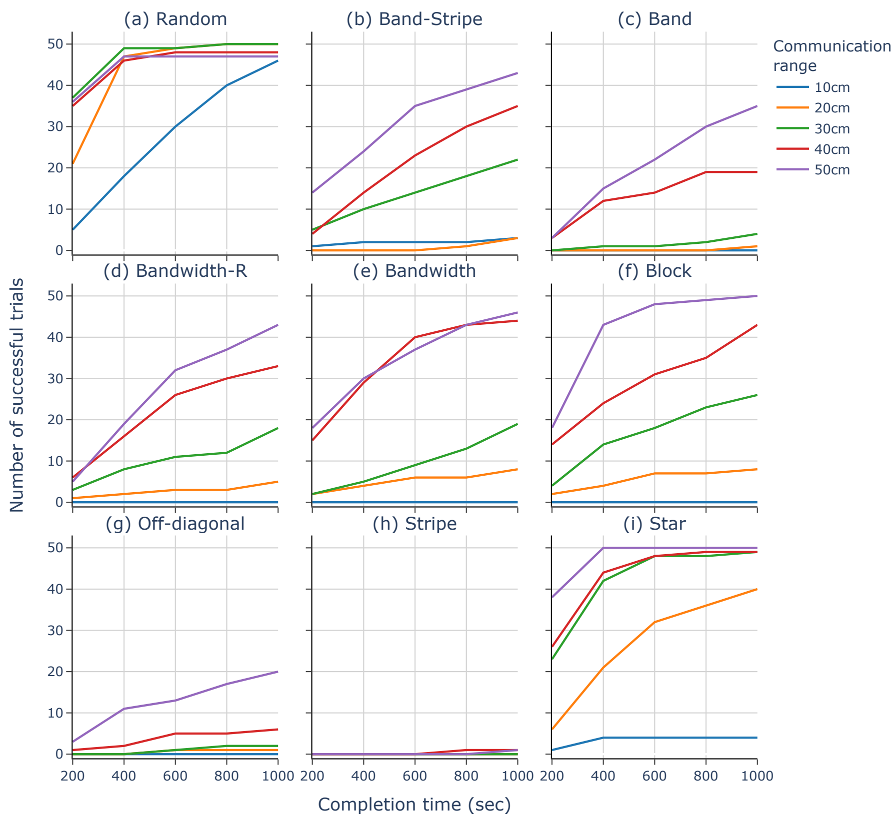


Fig. 4: Time-Accuracy trade-off (white-dominant). Number of successful trials with correct swarm consensus reached within 200, 400, 600, 800, and 1000s. Saturation is reached for (a) Random and (i) Star at 400s in the longest communication range, while (e) Bandwidth and (f) Block require 600–1000s to attain their peaks. Increasing the limit from 400 to 1000s allows (g) Off-diagonal to double the performance in the largest communication range.

representing the number of successful trials as a function of completion time for white-dominant and black-dominant arenas, respectively. The figures reveal important details regarding the time span required by a specific condition (environmental pattern, communication range and colour dominance) to achieve a certain level of performance. The curves indicate that for most patterns the typical time limit of 400s is not sufficient, as performance continues to increase well beyond that mark. Fig. 4 demonstrates that saturation is reached for Random (a) and Star (i) patterns at the 400s mark in the longest communication range,

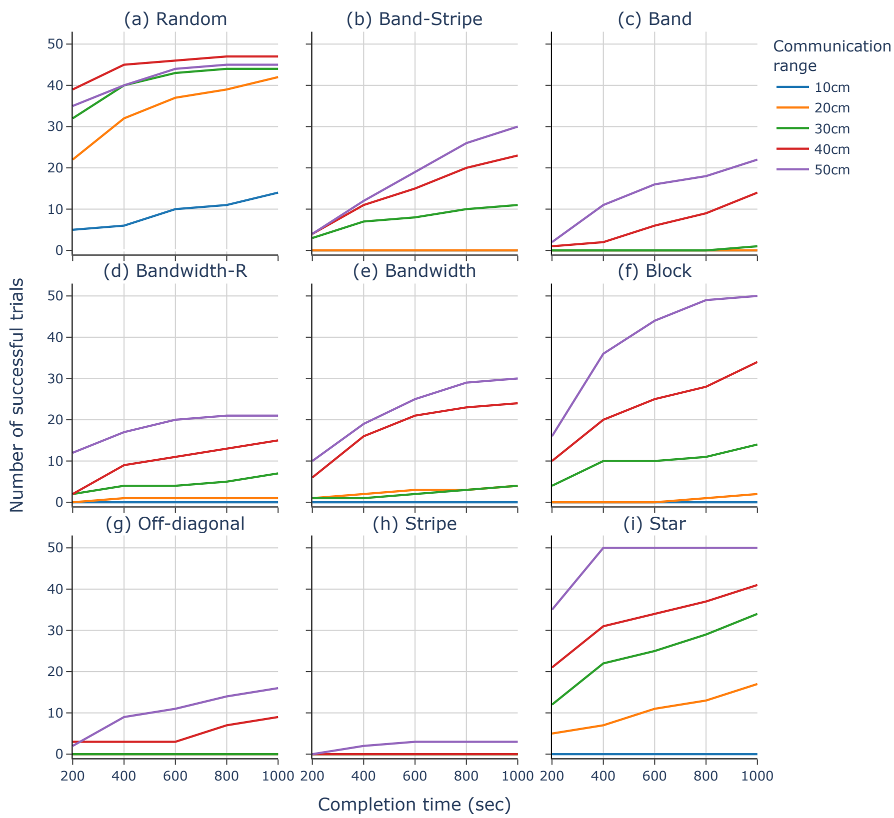


Fig. 5: Time-Accuracy trade-off (black-dominant). Generally similar trends to Fig. 4 with specific exceptions due to evolutionary bias. In the shortest communication range, the (a) Random pattern achieves close to optimal performance at 1000s in white-dominant, while staying significantly lower for black-dominant. Similarly, for communication ranges 40cm and 50cm, (d) Bandwidth-R doubles the performance in white-dominant compared to black-dominant at 1000s.

while Block (f) and Bandwidth (e) patterns require between 600 and 1000s for attaining their peaks. Increasing the time limit from 400s to 1000s allows the challenging Off-diagonal (g) pattern to double its performance in the largest communication range. Fig. 5 exhibits mostly similar trends to Fig. 4 with certain exceptions due to evolutionary bias. In the shortest communication range, the Random pattern succeeds in reaching nearly perfect performance at the limit of 1000s in white-dominant (Fig. 4(a)), while remaining significantly lower for black-dominant. Likewise, in the two largest communication ranges Bandwidth-R pattern reaches twice as high accuracy in white- than in black-dominant at the 1000s mark (Figs. 4(d) and 5(d)). These results elucidate further the bias in swarm behavior in black- vs. white-dominant environments of the same type and ratio, scrutinized through the lens of the communication range.

Figure 6 presents the accuracy and time-to-consensus distribution for all conditions (pattern, communication range, dominant colour), which provide further insights about the performance of our controller. It reveals high accuracy for both Star and Random patterns across the range of 20cm (b), 30cm (c), 40cm (d) and 50cm (e), which is a strong indicator for the generalisability of the model. The performance (Fig. 6/left) reveal strong generalisability for most patterns in 50cm range, with gradual decrease in 40cm and more significant drop in 30cm, whereas in 10cm range the only performance still in-line is for Random pattern (white-dominant). The time-to-consensus distributions exhibit large variability across patterns and communication ranges (Fig. 6/right). The exception is confined to Random pattern and to some extent to Star patterns, with more compact time distributions. Varying the communication range does not provide an evidence for a pronounced strong influence on the time distribution, except for the Star pattern, which shows a consistent monotonic relationship between time and range. Strikingly, the performance in 10cm range for the Random pattern requires a fourfold time increase compared to 50cm. Increasing the time limit to 1000s appears to allow the convergence to consensus for certain patterns as the communication range decreases, but only to a certain degree, as the figure suggests that in 10cm and 20cm range it is highly unlikely to achieve further consensus gains if the time limit is increased beyond 1000s.

5 Discussion

The results of this study complement the findings reported in [1] by extending the scope of the test conditions. Both studies employ the same neural network controller, evolved for the Random pattern with communication range of 50cm. While the earlier study evaluated the controller in the collective perceptual discrimination task on nine environmental patterns using communication range of 50cm overall, this study evaluates it on all nine patterns in five communication settings, ranging from 10cm to 50cm, with the aim to explore the limits of generalizability of the controller. Anticipating slower than typical convergence to consensus, in this study, we have increased the cut-off time from 400s to 1000s, which proved productive overall. Certain patterns required longer (600-800s)

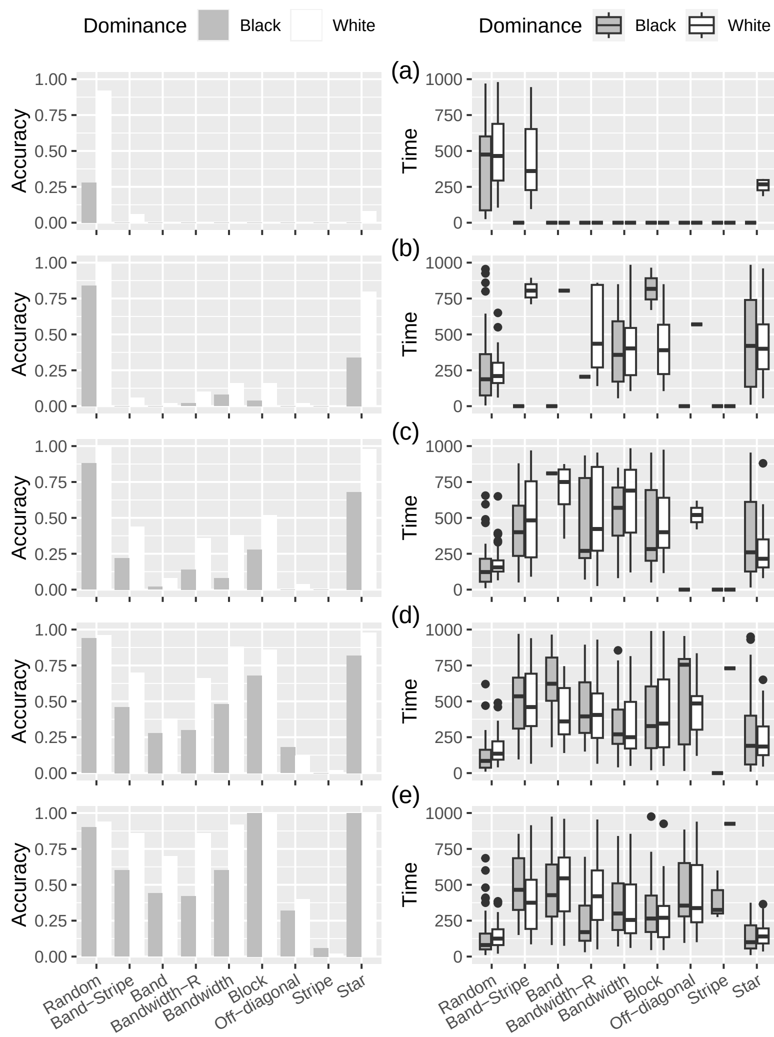


Fig. 6: Swarm consensus accuracy (left) and time-to-consensus distribution (in sec., right) of successful trials, recorded in 50 simulation trials per condition in all nine environmental patterns and five communication ranges: (a)10cm, (b)20cm, (c)30cm, (d)40cm, and (e)50cm. The success rate (left) reveals strong performance for most patterns in the 50cm range, with gradual decrease in 40cm and more significant drop in 30cm, whereas in 10cm range the accuracy is still in-line only for the Random pattern (white-dominant). The time-to-consensus distribution demonstrates large variability across patterns and communication ranges (right). Varying the communication range does not provide an evidence for a pronounced strong effect on the time distribution, except for the Star pattern, for which a consistent monotonic relationship between time and range is visible. Notably, the performance in 10cm range for the Random pattern requires a fourfold time increase compared to 50cm.

time to converge, especially with decreasing communication ranges. However, the results did not provide an evidence that further increasing the cut-off time (beyond 1000s) could provide considerable benefits. This insight is an important empirical benchmark, given that the typical cut-off time used by the research community in this type of studies is 400s.

The results demonstrate strong performance in the Star pattern across all but the shortest communication range, which provides an evidence that the controller generalizes well along that dimension at least in one pattern type. For larger communication ranges performance remains comparably high in multiple pattern types with gradual drops. The large variability of time-to-consensus reveal the difficulties this controller is facing in more clustered pattern types.

The results highlight that, with a few exceptions, performance drops with decreasing communication range across all environmental patterns, as expected, however at a different rate for different patterns. This study emphasized again the role of evolutionary bias, leading to a significant difference in performance between black-dominant and white-dominant environments of the same type and ratio, which calls for further research to unravel the foundations, control the levels or completely eliminate this bias.

Time-to-consensus increased gradually for all pattern types as the communication range decreased, as expected, however, the increase for the Random pattern was negligible and for the Star pattern moderately steeper (Fig. 6/right(c-e)), which highlights the robustness of the controller. Interestingly, the Star and Block patterns outperformed the Random pattern in the range of 50cm (Fig. 6/left(e)). Furthermore, in the white-dominant environment, the performance for the Random pattern was unexpectedly higher in the ranges of 20cm and 30 cm, compared to the ranges of 40cm and 50cm (Fig. 6/left(b-e)), an artefact of the evolutionary bias effect.

6 Conclusion

This paper presents an investigation into the performance of a neural network controller, recently developed for the collective perceptual discrimination task, evolved for a randomly distributed environmental pattern with a swarm communication range of 50cm. The controller was evaluated in a simulated homogeneous swarm of 20 robots in a set of conditions, varying the structural distribution of the arena floor pattern and the swarm communication range. The results indicate the ability of this type of neural models to generalize its decision-making behaviour towards swarm consensus in a range of test conditions, and highlight its limitations. This work elucidates the potential of the evolutionary approach to automatically design decision-making mechanisms for swarm robotics and represents an important milestone towards the development of robust controllers that adapt successfully to unexpected conditions while retaining their performance. Future research will focus on the evolution of controllers for various conditions in order to identify the optimal configurations and establish the precise performance bounds and trade-offs in swarm collective perception.

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