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Enhancing Robustness of Swarm Robotics Systems in a Perceptual Discrimination Task

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Abstract: The automation of tasks such as environmental monitoring, toxin detection, and mineral resource identification requires artificial agents with perceptual discrimination capabilities to identify the predominant features in environments much larger than their sensing range. The key challenge is developing collective decision-making methods that allow agents to predict a global perspective of the environment from local observations. Our research explores the effectiveness of collective decision-making for binary perceptual discrimination tasks, controlled by an artificial neural network synthesised using evolutionary computation techniques. We focus on strategies that generalised better to environments with patchy, clustered feature distribution. We investigate three communication strategies - *close-neighbour*, *rand-neighbour*, and *far-neighbour*- in which robots exchange opinions about the dominant colour of the environment based on the distance between sender and receiver robots. The results show that the *rand-neighbour* strategy significantly improves performance, particularly in unseen patchy patterns. The extensive analysis of the communication dynamics among the robots indicates that the effectiveness of *rand-neighbour* strategy is attributed to its efficient circulation of opinions among both close and distant robots. Our findings support the hypothesis that primordial communication between one receiver robot and a randomly chosen emitter robot is sufficient to develop an effective collective decision-making strategy for swarm of robots engages in perceptual discrimination tasks.

Keywords: Evolutionary robotics, Swarm robotics, Collective decision-Making, Communication strategies

1. INTRODUCTION

The automation of tasks such as environmental monitoring, toxin detection, and mineral resource identification requires artificial agents capable of perceptual discrimination capabilities to identify predominant features in unknown environments. A key challenge in these tasks is the size of the environment relative to the sensing capabilities of individual agents. This limited individual perspective can lead to an inaccurate evaluation and ineffective actions. Employing multiple agents to cover a larger area can make possible to gather more comprehensive information about the quality of environmental features or options. Nevertheless, effective mechanisms are needed to allow the group of agents to make autonomous collective decisions. Swarm robotics is the research domain that tries to identify the individual mechanisms underpinning collective decision-making as well as other complex collective responses. Generally speaking, swarm robotics systems address tasks that require collaborative efforts of a large number of agents interacting with each other to solve complex and extensive problems that would be otherwise impossible for a single agent to handle. Inspired to the behaviour of social insects, the distinctive characteristics of swarm robotics is self-organisation, distributed control, and local sensing, which endow the swarm with a higher level of fault tolerance, scalability, and adaptability to environmental disturbances [1].

The design methods in swarm robotics require roboticists to identify individual behaviours that generate the swarm desired collective response [2]. However, this is a particularly challenging design problem, since the collective response is a phenomenon that emerges from complex and difficult-to-predict dynamics involving both robot-robot and robot-environment interactions. This design problem can be found in the study of many swarm responses, including those requiring collective decision-making, which refers to a process in which the robots collectively choose an option among those available. The characteristics of collective decision-making is that once a consensus is

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reached, it cannot be attributed to any specific member of the swarm. Rather, it emerges from the complex spatial and temporal interactions involved in the opinion exchange process among swarm members [3]. In swarm robotics literature, collective decision-making mechanisms are generally investigate in a two-options scenarios in which the robots of the swarm have to find a consensus on the best option between the two available. This type of scenario are generally referred to as best-of-*n* (with $n = 2$ options) problems [4], [5]. A specific type of best-of-2 decision making problem is a perceptual discrimination task in which the two options are distributed within the environment, with the better quality option associated to the one that appears in a larger quantity than the alternative one. Since the perceptual capabilities of the robots are limited, a consensus on the best-quality option can be achieved only through a collective decision process in which robots explore different area of the environment, and interact in order to "integrate" their perceptual experiences to converge to a common opinion on the best option.

One effective method to design individual control mechanisms underpinning collective decision-making in perceptual discrimination tasks is the hand-coded approach. In this methodology, designers meticulously craft individual mechanisms that drive the collective response to the problem at hand. The literature has demonstrated the effectiveness of the hand-coded approach, especially when following the principles of the Voter model, where agents change their opinion based on selecting a random neighbour [6], [7], or the majority model, where the opinion aligns with the option held by the majority of a group of neighbours [8], [9]. However, the design of hand-coded controls often relies on strong assumptions made by designers regarding how the problem should be addressed. These assumptions can limit the ability of the swarm to exploit subtle irregularities in physical and social perceptual cues, which could otherwise enhance the collective decision-making process [10]. Recent research has highlighted weaknesses in the hand-coded approach, particularly its adaptability in dynamic environments where the optimal option changes over time [11], [9].

Recently, an alternative design approach based on evolutionary robotics (ER) has been introduced [12]. In this approach, the decision making unit generating the agents' opinion is an artificial neural network synthesised using evolutionary computation techniques [13]. A notable feature of the ER approach is the automation of the design process, which significantly reduces the influence of designer assumptions. Recent research work [14] provides evidence that the ER approach outperformed the hand-coded approach with respect to the robustness, adaptability, and scalability of the collective response of the group.

The study illustrated in [15] highlights that the challenge in perceptual discrimination tasks lies not only in the magnitude of the difference between the quality of the two options, but also in their distribution patterns. This result has been found in a type of perceptual discrimination task in which the options are two colours covering the floor of an arena that the robots explore with a random movement, and the quality refers to the proportion of floor covered by each option. In particular, the authors focused on nine benchmark environments with varying feature distribution patterns, as shown in Figure 1. The results of this study indicate that, regardless of the difference in quality, groups designed to perform optimally in the Random type of environments (see Figure 1, Random) experience a performance drop when they are post-evaluated in the Off-diagonal and Stripe environment (see Figure 1, Off-diagonal, and Stripe). This observation has been corroborated by other recent studies [12], [16], [17] which report the same type of performance drop in spite of the fact that they employ artificial neural network as robots controllers to improve the robustness of the collective response.

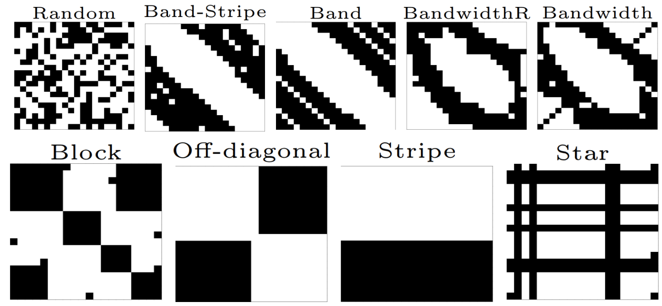


Figure 1. Images of the nine floor patterns used in this experiment. The Random is the floor pattern experienced by the robots during the design phase. The other eight floor patterns, originally introduced in [15], are used to test the robustness of the decision-making mechanisms used by the robots to perform this binary perceptual discrimination task.

The primary objective of this study is to overcome the limitations illustrated in [15], [12], [16], [17] by developing individual decision-making mechanisms underpinning a collective response that allow a swarm of robots to perform sufficiently well in all the nine types of floor distribution patters illustrated in Figure 1. In order to achieved this objective, We focus on multiple elements such as the type of individual random walk used by the robots to explore the arena, the structure of the neuro-controller, as well as on the characteristics of the communication strategy used to exchange individual opinions. We found out that, this latter element is the one that allowed us to achieve an important improvement in terms of robustness of the collective decision with respect to the floor patterns. In particular, we found out that only when the communication events happens between a robot receiver and a randomly chosen (rather than the closest as in [15], [12], [16], [17]) emitter among those within communication range, no performance drop is observed while moving from Random to all the other nine floor patterns. We show that the superior robustness observed in group in which the communication happens between a robot receiver and a randomly chosen emitter can be attributed to a more effective circulation of opinions among both the spatially close and distant robots, thereby maintaining a high accuracy rate in the decision process throughout the eight floor patterns not experienced by the robots during the design phase. We would like to bring to the reader's attention that this study is an extension of our previous study in [18], where we developed an effective collective decision-making strategy for a group of 20 e-puck robots. However, this research extends [18] by focusing on enhancing communications strategies to improve group performance that generalised better to environments with patchy, clustered feature distribution.

2. METHODS

The task the robots are required to perform in this experiment is a binary perceptual discrimination problem. The robots have to collectively choose which colour covers the largest proportion of a closed square arena (200×200 cm), tiled with black and white 10×10 cm tiles. We consider two scenarios: i) a simple scenario (hereafter, referred to as *S-env*), in which the difference in the proportion of black and white tiles is relatively large, since one colour (the dominant one) covers 66% of the arena floor, while the other colour covers the remaining 34% of the arena floor; ii) the hard scenario (hereafter, referred to as *H-env*), in which the difference in the proportion of black and white tiles is smaller than in *S-env*, since one colour (the dominant one) covers 55% of the arena floor, while the other colour covers the remaining 45% of the arena floor. For both the *S-env* and the *H-env* scenario, the robots experience both environments in which black is dominant (hereafter, referred to as *BD-env*), and environments in which white is dominant (hereafter, referred to as *WD-env*).

A swarm of 20 robots is initially placed in the arena with randomly chosen positions and orientations (see Figure 2a). The robots have to explore the arena and reach consensus on the best quality option (i.e., choosing which colour is the currently dominant colour) over a period of 400 seconds. While exploring the arena, the robots can communicate with spatially proximal neighbours their current opinion. Consensus to the correct option is attained whenever all the 20 robots shared the same correct opinion about which colour is currently dominant for at least 10 s.

Our simulation model the e-puck robot [19], a popular miniature robot commonly utilised in swarm robotic. The simulated robot is equipped with a floor sensor for binary colour detection (0 for black and 1 for white) and eight infrared sensors for obstacle detection. The robots communicate using Range and Bearing sensors, with the communication range limited to 50 cm. To bridge the simulation-reality gap, a uniform noise of 10% is added to all sensor readings, motor outputs, robot positions, and orientations.

The robot's exploration of the environment is based on ballistic motion [20], a variant of random walk used in robotic swarm mapping. This movement pattern involves

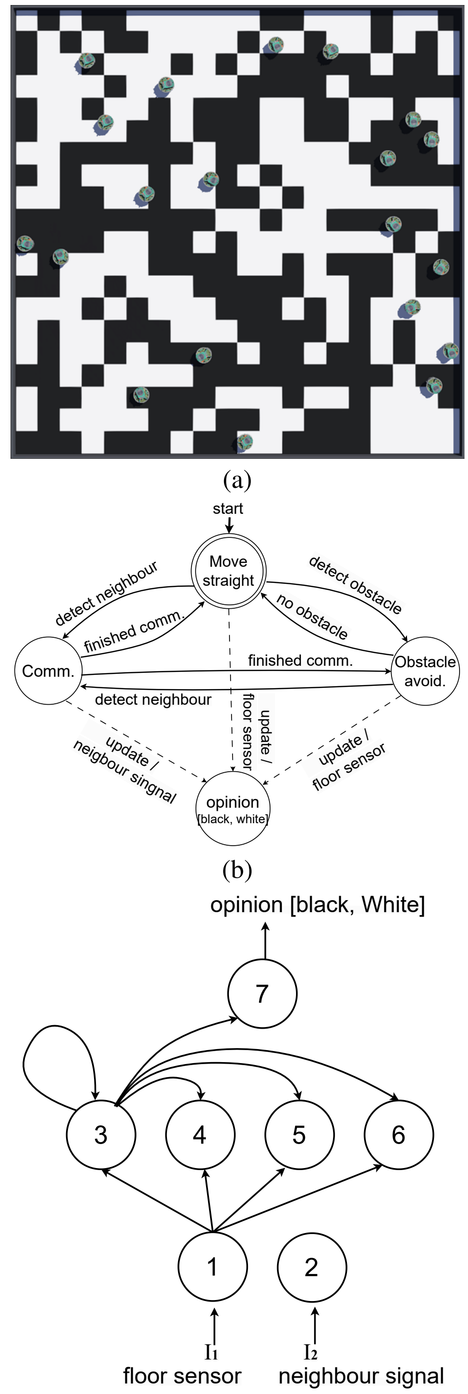


Figure 2. (a) The simulation environment. (b) The finite-state machine controlling the robots' movements. (c) Continuous-Time Recurrent Neural Network (CTRNN) generating the robots' opinion.

the robot travelling in a straight line (ballistic trajectory) until encountering an obstacle (other robots or the arena wall), at which point it randomly changes direction. Ballistic motion has proven to be effective in exploring enclosed environments [21]. Figure 2b illustrates the finite state machine controlling the robot's movement.

The decision-making process of the robot is controlled by a Continuous-Time Recurrent Neural Network (CTRNN) [22], synthesised using artificial evolutionary techniques. The CTRNN comprises 2 sensor neurons, 4 internal neurons, and 1 output neuron representing the robot's opinion. The topology of the CTRNN is depicted in Figure 2c. The network input includes readings from the floor sensor and a communication signal received from a randomly selected neighbour chosen from those at less than 50 cm distance from the receiver. The network outputs a binary value where 1 corresponds to the opinion that the dominant colour is white, and 0 corresponds to the opinion that the dominant colour is black. This binary value, corresponding to the current robot's opinion, is communicated among spatially proximal robots, as mentioned above. If, for a robot receiver there is no neighbouring robots within communication distance (i.e., $< 50\,\text{cm}$), the reading of the receivers sensor neuron for communication is set to 0.5. During communication, only one neighbour's opinion is selected from the set of available neighbours.

Equations 1, 2, and 3 illustrates how the sensory, internal, and opinion neurons are updated at every simulation cycle.

$$y_i = gI_i;\ i \in \{1, ..., N\}; \quad \text{with } N = 2; \tag{1}$$

$$\tau_i \dot{y}_i = -y_i + \sum_{j=1}^{j=N+4} \omega_{ji}\sigma(y_i + \beta_j);\ i \in \{N+1, ..., N+4\}; \tag{2}$$

$$y_i = \sum_{j=N+1}^{j=N+4} \omega_{ji}\sigma(y_j + \beta_j);\ i \in \{N+5\}; \tag{3}$$

with $\sigma(x) = (1 + e^{-x})^{-1}$. These equations incorporate terms reminiscent of real neuron functions: cell potential is denoted by y_i, τ_i is the decay constant, g represents a gain factor, and I_i with $i = 1, .., N$ is the activation of the i^{th} sensor neuron (refer to Figure. 2c for a mapping between sensor neurons and their corresponding sensors), ω_{ij} the strength of the synaptic connection from neuron j to neuron i, β_j the bias term, $\sigma(y_j + \beta_j)$ the firing rate. All sensory neurons share the same bias (β_I), and the same hold for opinion neuron (β_O). τ_i and β_i of internal neurons, β_I, β_O , all the network connection weights ω_{ij}, and g are genetically specified networks' parameters. When the network is initiated or reset, the cell potentials reset to 0. For integrating equation 2, the forward Euler method is employed with an integration time step of $\Delta T = 0.1$

A simple evolutionary algorithm that uses tournament-based selection, as illustrated in [12] is used to optimise the parameters of the networks. This population comprises 64 genotypes. New generations emerge from a mixture of elitist selection, recombination, and mutation. Each generation preserves the six best performing individuals (i.e., 'elite') from the preceding generation without any change. The rest of the new generation is formulated by proportionally selecting the fittest 40 of the prior generation.

During the evolutionary phase, each group undergoes eight evaluations in the *S-env* condition (four in BD-env and four in WD-env), with each evaluation lasting 400 seconds (equivalent to 4000 simulation steps). In every evaluation, the genotype is decoded into a neuro-controller, which is then replicated in all 20 robots (considering a homogeneous swarm). The robots are placed randomly in the arena, both in terms of position and orientation. After the first 2000 simulation steps, the opinion of robot r is evaluated in every simulation step t (i.e., O^r_t). The average opinion of the 20 robots R is calculated and fitness assigned to the group according to Equation 4.

$$F_e = \begin{cases} \frac{T}{2} \sum_{t=\frac{T}{2}}^{T} \sum_{r=1}^{R} O^r_t & \text{in } \textit{WD-env} \\ \frac{T}{2} \sum_{t=\frac{T}{2}}^{T} \sum_{r=1}^{R} (1 - O^r_t) & \text{in } \textit{BD-env} \end{cases} \tag{4}$$

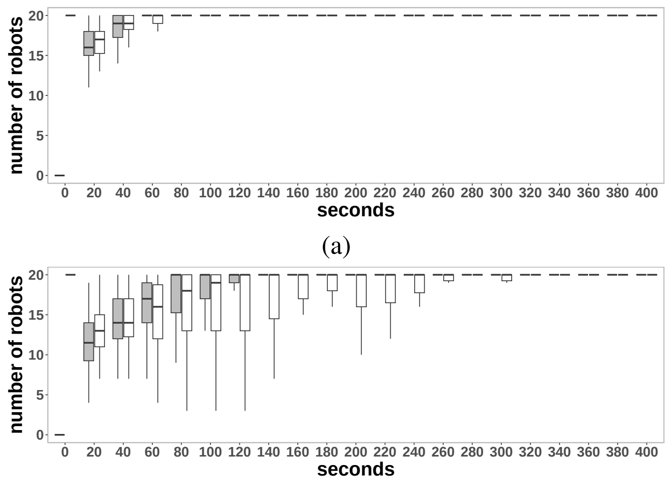
The evaluation of the fitness score in the latter half of the trial time is deliberate to avoid instability of opinion state during the initial exploration phase. In this early stage, robots have not yet accumulated sufficient physical and social experience of the environment.

Regarding computational complexity, the time required to complete a single evolutionary run, when executed on a Dell PowerEdge server equipped with 64 cores and 256 GB of main memory, is approximately 10 hours.

3. RESULTS

To design the robots' controller, we run five separate evolutionary simulations, each one lasting 2000 generations. We remind the reader that during the evolutionary phase, the robots experience only the Random floor pattern (see first image in Figure 1). In order to select the best group (i.e., the best genotype) The highest-ranked groups from the 1000^{th} to the 2000^{th} generation of each evolutionary run are re-evaluated 50 trials in *BD-env* and 50 trials in *WD-env* environment. The best group out of these re-evaluations is chosen to demonstrate that the neural-network based decision-making mechanisms allow a group of simulated robots to reach consensus in both types of environment (i.e., the *WD-env* and the *BD-env*). Moreover, we show that the group can adapt to different floor patterns to the one experienced during the design phase. In particular, we show the accuracy of the decision-making process on the best group in eight extra floor patterns shown in Figure 1.

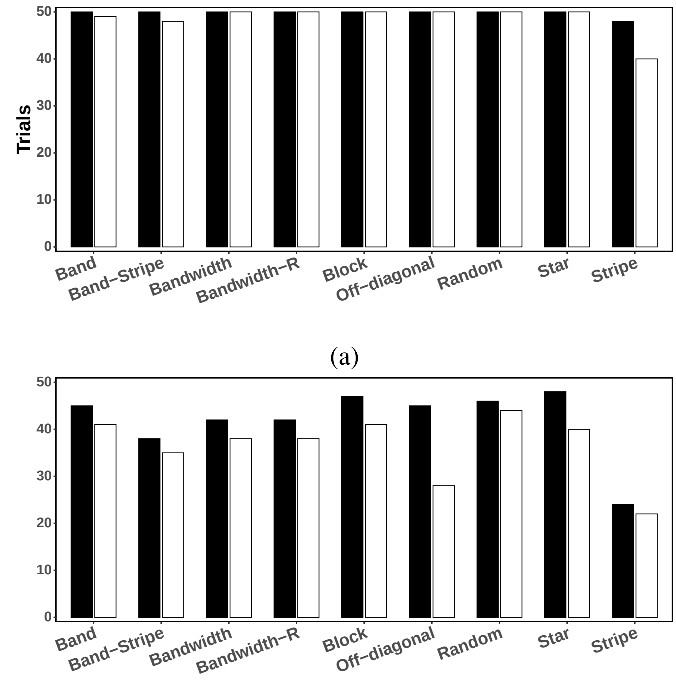
As far as it concerns the performances in the Random floor pattern, Figure 3 shows the development of the decision-making process by displaying the opinions of all the robots of the best group in both the *S-env* and in the *H-env* conditions, respectively. In both graphs, white boxes refer to the number of robots with the correct opinion in the *WD-env* environment, while black boxes refer to the number of robots with the correct opinion in the *BD-env*



(a)

(b)

Figure 3. Boxs plot showing the number of robots with the correct opinion in the *WD-env* environment (see white boxes) and in the *BD-env* environment (see grey boxes) at regular time intervals of 20 s until the trial end (400 s). (a) *S-env* condition; (b) *H-env* condition. Each box is made 50 points (corresponding to 50 differently seeded trials). Boxes represent the inter-quartile range of the data, while horizontal bars inside the boxes mark the median value. The whiskers extend to the most extreme data points within 1.5 times the inter-quartile range from the box.



(a)

(b)

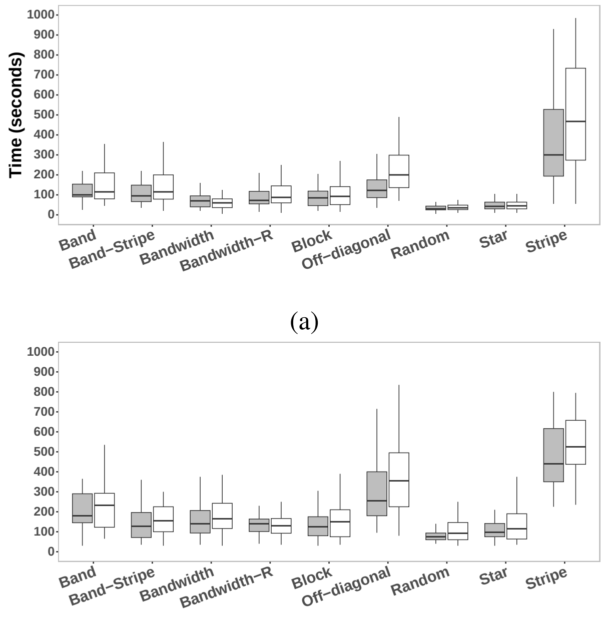
Figure 4. Bar plots showing accuracy, that is the number of trials (over 50 trials) in which the group reached the consensus state to the correct opinion for at least 10 s, in nine distinct floor patterns (see [?] and Section **??**). The white bars refer to accuracy in the *WD-env* environment, while the black bars refer to accuracy in the *BD-env* environment. Each trial lasts 1000 s. In (a), the graph shows the results in *S-env* (i.e., the proportion of the dominant colour tiles is %66) while in (b), the graph shows the results in *H-env* (i.e., the proportion of the dominant colour tiles is %55).

environment. Each box is made 50 points (corresponding to 50 differently seeded re-evaluation trials). Figure 3a refers to the robots' opinion in *S-env* (i.e., the dominant colour takes 66% of the arena floor), while Figure 3b to the robots' opinion in *H-env* (i.e., the dominant colour takes 55% of the arena floor).

The graphs indicates that the best group reaches a consensus on the correct option, in both types of environments and in both the *S-env* and in the *H-env*. Moreover, the consensus is reached more quickly in the *S-env* than in the *H-env* condition. The consensus on the correct option in the *H-env* condition is reached in approximately 200 seconds in both types of environments. Note that, the robots' control system has been designed in the *S-env*. Thus, the *H-env* represents a rather novel environmental condition for these robots. It should be noted that in Figures 3a and 3b, the group converges to the white opinion in *WD-env* at time 0. This is due to the genetic basis of the evolved controller which, even in the absence of any perceptual evidence—as it happens at the beginning of each trial—it selects opinion *WD-env*. The emergence of a genetic bias in binary collective and individual robot decision scenarios has been documented in previous research (e.g., see [23]), where robots are managed by analogous neural network architectures.

A. Robustness to Different Floor Patterns

To evaluate the robustness of the best group to environments with floor patterns different from those experienced during the design phase, we estimated the accuracy in the decision-making process of this group in eight extra floor patterns shown in Figure 1. The results are shown in Figure 4. The graphs show accuracy, that is the number of trials (over 50 trials) in which the group reached the consensus state to the correct opinion for at least 10 s, in nine distinct floor patterns. That is the Random pattern, already experienced during the evolutionary design phase, and eight extra patterns never experienced before. In this post-evaluation test, each trial lasts 1000 s. Figure 4a shows the results in *S-env* (i.e., the proportion of dominant colour tiles is 66%). The graph demonstrates good performances with a relatively high success rate in all the floor patterns. In particular, its is worth noticing the accuracy in the Off-diagonal and Stripe, which remains above 80% in both floor patterns and for both the *WD-env* (see Figure 4a, white bars for Off-diagonal and Stripe) and the *BD-env* (see Figure 4a, black bars for Off-diagonal and Stripe). This is a significant performance improvement with respect to previous related works [16], [17], in which the authors report a significant performance drop, in term of accuracy, of robots required to operate in those patchy floor patters (i.e., the Off-diagonal and the Stripe) without having experienced them



(a)

(b)

Figure 5. Box plots showing time to converge to consensus calculated over successful trials only (out of 50 post-evaluation trials), in nine distinct floor patterns (see [?] and Section ??). The white boxes refer to time to convergence in the *WD-env* environment, while the black boxes refer to time to convergence in the *BD-env* environment. Each trial lasts 1000 s. In (a), the graph shows the results in *S-env* (i.e., the proportion of the dominant colour tiles is %66) while in (b), the graph shows the results in *H-env* (i.e., the proportion of the dominant colour tiles is %55).

during the design phase. In the next Section, we provide further evidence which illustrates the significance of the communication strategy in allowing the best group to extend its good accuracy rate to those eight floor patterns not experienced during the design phase. Figure 4b presents the results in *H-env* (i.e., the proportion of dominant colour tiles is 55%). When the difference in the proportion of floor covered by the two colour reduces, a slight performance degradation is observed across all the environment patterns, particularly in the Stripe environment. This accuracy drop can be, in large parts, accounted for by considering that the criteria for defining success in our experiment setup (i.e., all 20 robots must agree on the correct option for at least 10 s) is very stringent. It is worth mentioning that in many unsuccessful trials in the *H-env*, the majority of the robots (e.g., 18 or 19 robots) shared the same opinion about the correct option. However, in spite of the large convergence of the robots to the correct opinion, given our definition of consensus, those trials are not considered successful. Generally speaking, the performance shown in Figure 4a and 4b represent a significant improvement compared to the results reported in recent research works [16], [17], where poor performance was reported even in *S-env* condition, particularly in patchy environments (e.g., Off-diagonal and Stripe).

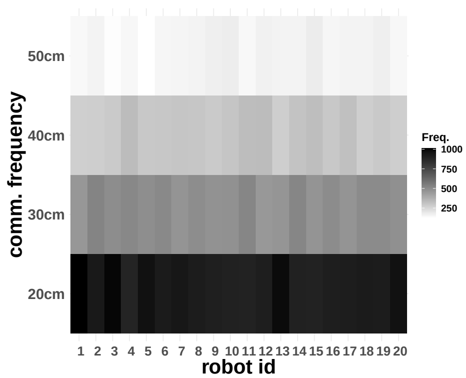
Figure 5 shows the time to converge to consensus calculated over successful trials only (out of 50 post-evaluation trials), in nine distinct floor patterns. The white boxes refer to time to convergence in the *WD-env*, while the black boxes refer to time to convergence in the *BD-env*. Each trial lasts 1000 s. In Figure 5a, the graph shows the results in *S-env* (i.e., the proportion of the dominant colour tiles is %66) while in Figure 5b, the graph shows the results in *H-env* (i.e., the proportion of the dominant colour tiles is %55). Similar trends are observed in both graphs, with slightly longer time to convergence to consensus in *H-env*. An obvious increase in the time to convergence is observed in the Stripe environment in both graphs. This explains why the trial duration was increased from 400 s during the design phase, to 1000 s for this post-evaluation tests.

B. Further Investigation On the Communication Strategies

In the previous Section, we have shown that our experimental setup allowed us to design decision-making mechanisms using evolutionary-designed neuro-controllers, that allow a group of robots to accurately choose the correct options between two alternatives in a perceptual discrimination task. More importantly, we have shown that our best group manages to generalise its performance to floor patterns not experienced during the design phase. This result is particularly relevant because it represents a step forward compared to the results of previous research works [16], [17], which all reported a large drop in decision accuracy in patchy distributed floor patterns (i.e., the Off-diagonal and the Stripe). In order to achieve the good accuracy rate at the robustness test shown above, we have modified several elements of the original experimental setup as illustrated in [16], [17]. In particular, we have modified the type of random walk with which the robots explore the arena, the structures of the neuro-controller by increasing the number of neurons in the hidden layers, and the communication strategy allowing a robot receiver to receive communication signals from a randomly chosen robots among those in the communication range. These three modifications have been introduced progressively, one after the other with the intent to improve the accuracy at the Robustness test. However, a significant improvement in accuracy performance in the patchy distributed floor patterns has been observed only after having introduced the modification concerning the communication strategy. Thus, this indicates that the new communication strategy has the largest merit in improving the accuracy rate.

In this section, we show the results of further post-evaluation tests which aim to provide elements to explain why the new communication strategy proven more effective than the previous strategy in making the collective decision process robust enough to deal with all different floor patterns shown in Figure 1.

To understand how effective communication contributes to collective performance, we studied communication strategies focusing on the distance between signal sender and



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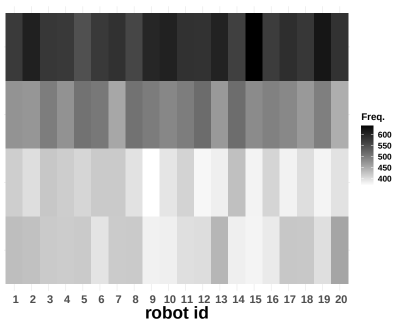

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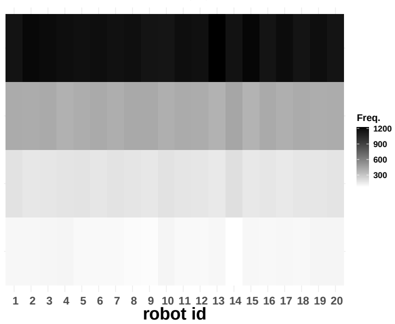


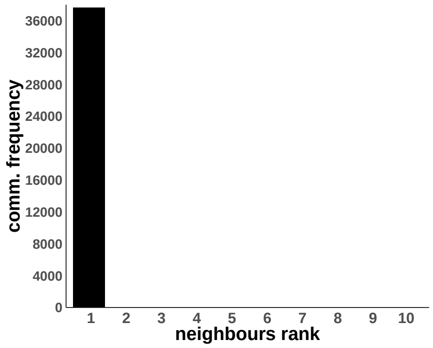
(c)

Figure 6. Heatmaps showing the frequency of communication events, over 50 trials, between two robots located at progressively longer distances. In particular, communication events are categorised into four categories (i.e., <= 20 cm, (20 cm, 30 cm], (30 cm, 40 cm], (40 cm, 50 cm]) based on the distance between the robot emitter and the robot receiver. In (a), the graph refers to the condition in which communication events are possible only between a robot receiver and a robot emitter located at the shortest distance to the receiver among those within the receiver communication range. In (b), the graph refers to the condition in which communication events are possible between a robot receiver and a randomly chosen robot emitter among those within the receiver communication range. In (c), the graph refers to the condition in which communication events are possible only between a robot receiver and a robot emitter located at the longest distance to the receiver among those within the receiver communication range.

receiver. In particular, we investigated three types of communication strategies: i) a strategy called *close-neighbour* in which the communication events are possible only between a robot receiver and a robot emitter located at the shortest distance to the receiver among those within the receiver communication range (i.e., 50 cm); ii) a strategy called *rand-neighbour* in which communication events are possible between a robot receiver and a randomly chosen robot emitter among those within the receiver communication range; iii) a strategy called *far-neighbour* in which communication events are possible only between a robot receiver and a robot emitter located at the longest distance to the receiver among those within the receiver communication range.

In this post-evaluation tests, we run 50 trials in which we recorded, for each type of communication strategy employed by the robots (i.e., the *close-neighbour*, the *rand-neighbour*, and the *far-neighbour*), the number of communication events falling in each of the following distance category: i) <= 20 cm, ii) (20 cm, 30 cm], iii) (30 cm, 40 cm], and iv) (40 cm, 50 cm]. This post-evaluation test is meant to provided better insights into how opinions are communicated within the group.

Figure 6 shows heatmaps of the communication frequency between the robots during 50 trials, with the communication frequency sampled every 10 s over a trial duration of 400 s. The darker the cell colour in the map, the higher the frequency of communication. Figures 6a, 6b, and 6c represent the frequency of communication in the *close-neighbour*, *rand-neighbour* and *far-neighbour* strategies, respectively. As expected, when the robots employ the *close-neighbour* strategy (Figure 6a), the most frequent interactions are those falling in to the category < 20 cm. On the contrary, when the robots employ the *far-neighbour* strategy, the most frequent interactions are those falling in to the category (40 cm, 50 cm]. This demonstrates that in *close-neighbour* and *far-neighbour* strategies, opinion exchange is spatially restricted to robots within a specific range of distances. That is, communication tends to concerns either spatially close robots (when the group employs the *close-neighbour* strategy) or the spatially distant robots (when the group employs the *far-neighbour* strategy). This bias affects the way in which opinions flows within the group, with a clear negative consequence on the accuracy in the patchy distributed floor patterns. Note that, those works that reported a significance performance drop in the patchy floor patterns (i.e., [16], [17]), the robots employ the *close-neighbour* strategy. When the robots employ the *rand-neighbour* strategy, we notice a frequency distribution similar to the *far-neighbour* strategy but definitely less biased towards the category (40 cm, 50 cm] (see Figure 6b). This indicates that, when the robots employ the *rand-neighbour* strategy, as in our experimental setup, opinions circulates more frequently than in the *close-neighbour* strategy among distant robots, and also more frequently than in the *far-neighbour* strategy among the nearest robots. This is an



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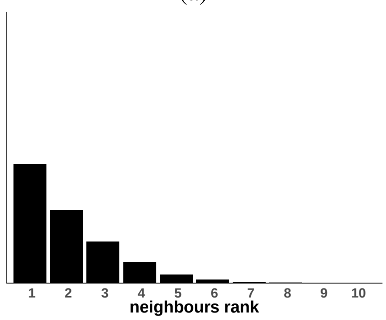

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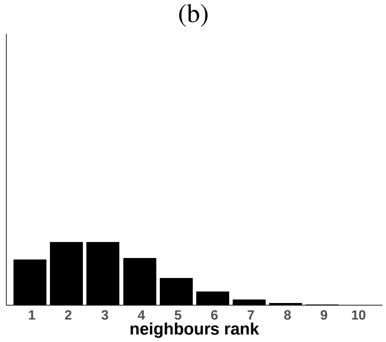

(c)

Figure 7. Bar plots showing the number of communication events between a receiver and senders, within communication range, ordered from closest to farthest. The x-axis refers to the ordinal number of the senders, while the y-axis refers to the number of communication events. These events are computed over 50 trials in post-evaluation tests in which the robots employ (a) the *close-neighbour* strategy, (b) the *rand-neighbour* strategy, (c) the *far-neighbour* strategy.

element that favours an opinion exchange process that turns out to generate decision-making strategies capable of dealing with the patchy floor distributions without a significant accuracy drop in the group performance (see Figure 4).

A final series of post-evaluation tests is run to further investigate how the opinions flow within the group for the three different communication strategies. In particular, we run 50 trials in which, for each type of communication strategy, we recorded the number of communication events between a receiver and senders, within communication range, ordered from closest to farthest. For example, the closest sender is considered the first 1, the second closest to second 2, and so forth. The primary focus of this test is to correlate the communication strategies with the number of available robots within communication range, aiming to understand how this number affects the performance of opinions exchanged between robots. Figure 7 shows the number of communication events between a receiver and senders, within communication range, ordered from closest to farthest. These events are computed over 50 trials in post-evaluation tests in which the robots employ the *close-neighbour* strategy (see Figure 7a), the *rand-neighbour* strategy (see Figure 7b), and the *far-neighbour* strategy (see Figure 7c). The number of communication events is sampled every 10 s over a 400 s trial. It is worth noticing that, as for the previous test, the *rand-neighbour* strategy generates distributions of events more similar to the *far-neighbour* strategy, while recording the highest number of communication events for the first robot.

Generally speaking, the *rand-neighbour* strategy seems to generate a circulation of opinions between both closest and farthest robots, while the *close-neighbour* strategy allows only communication between the closest robots among those within communication range, and the *far-neighbour* strategy only between the farthest robots among those within communication range. Thanks to this property, the *rand-neighbour* strategy, contrary to the other two, allows the group to maintain a high accuracy rate even in the patchy floor patterns.

4. Conclusions and Future Work

This study describes a series of experiments designed to develop effective and robust swarm robotics control mechanisms to allow the robots to perform a binary collective perceptual discrimination task, in which we vary not only the options' quality but also the way in which the perceptual cues are distributed within the environment. Our primary objective was to overcomes certain limitations observed in similar recent studies [15], [12], [16], [17], concerning the robustness of the collective decision making process. In particular, we focus on a task in which individual decision making mechanisms are first optimised to allow a swarm of robots to achieve a high accuracy rate in the collective decision in a type of environment in which cues are distributed randomly, and subsequently tested for their robustness in eight different environments where cues are distributed differently.

In order to improve the robustness, we modified three elements compared to [12], [16], [17]: the way in which the robots explore the arenas, the structure of the neuro-controller, and the communication strategy among the robots. In this paper, we illustrate the important improvements, in terms of robustness of the collective response with respect to [15], [12], [16], [17] emerged thanks to the introduction of an alternative communication strategy, in which the opinion are exchanged between a robot receiver and a randomly chosen (instead from the closest as in [15], [12],

[16], [17]) robot sender among those within communication range.

Our findings indicate that the control mechanism following the the new communication strategy significantly enhances performance, particularly in unseen patchy patterns of option distribution in the environment. The superiority of the random strategy over the previously used solutions is due to its more efficient circulation of opinions among both the spatially close and distant robots, thus ensuring high accuracy of opinion even in environments with patchy distributed features.

In the future, we plan to investigate the impact of communication strategies on the performance of larger swarm size. We also intend to transfer the developed controller to physical e-puck robots to validate our findings in a physical system.

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