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Dari Trendafilov[1,2✓], Ahmed Almansoori[1], Nicolas Bredeche[2], Timoteo Carletti[1] and Elio Tuci[1]

[1] *naXys, University of Namur, Namur, Belgium ; { dari-borisov.trendafilov, ahmed.almansoori, timoteo.carletti, elio.tuci } @unamur.be*
[2] *ISIR, Sorbonne University, Paris, France ; nicolas.bredeche@sorbonne-universite.fr*
✓ *Presenting author*

Abstract. We present an application of a recently introduced information-theoretic complexity measure for predicting the impact which obstacles to swarm communication have on swarm performance in the collective perceptual discrimination task. Our formalism is built on the notion of Empowerment – a task-independent, universal and generic utility function, which characterizes the level of perceivable control an embodied agent has over its environment. We conducted series of simulations with an empowerment model of the collective perception scenario, including simple communication obstacles of the same size and shape placed in varying positions and/or orientations in one particular environmental pattern used previously for assessing collective decision-making. The results indicate the potential detrimental impact communication disruptions in particular locations of the arena could have on swarm performance, while suggesting no effect when the same obstacles are placed elsewhere. Such analysis could provide a characterization of critical spots in the arena for a given environmental pattern.

Keywords. *Information theory; Complexity measures; Swarm robotics; Collective perception; Empowerment*

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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 [11]. The group-level response emerges from a self-organisation process [5], 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. Real-world contexts may include unexpected obstacles of different size, shape, position and orientation that affect the unrestricted movement and/or the effective communication of the swarm. 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. Generic theoretic measures of behavioural diversity could facilitate the assessment of the interactions and trade-offs between individual robots, swarm and environment, and could help predict swarm performance without resorting to costly empirical studies. In this regard, information-theoretic utilities have been proposed as potential generic measures, since they can abstract from implementation details and focus on the interactions and dynamics related to information processing only [23].

In this paper, we apply a recently introduced information-theoretic measure for the characterization of task difficulty in the collective perception paradigm. In this task, a swarm of robots aims to find a consensus on the most salient perceptual cue among those available in the environment, following a particular decision-making mechanism. We explore the potential of the empowerment measure [14] to capture and predict the effect of different communication obstacles in one particular environmental pattern in collective perception. The aim of the study is to demonstrate the ability of this measure to assess the impact of obstacles with a purely theoretical treatment. To our knowledge, this is the first study to consider the effect of communication occlusions on the behavioural dynamics and swarm performance in this task.

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 [see 15, 36]. Through the design of individual robot behaviour, swarm robotics aims to achieve locally coordinated interaction that results in a self-organized collective behaviour [10, 12]. Information theory has previously been applied to formalise guided self-organization [22, 21] in which complex global patterns emerge from relatively simple local interactions [see 20, 9]. Shannon entropy-based measures, used to characterise self-organized emergent robot behaviour, range from mutual information [25, 27] and transfer entropy [26], to predictive and integrated information [7, 2]. Information-theoretic methods allow for a quantitative study of robot-environment systems [29], and are fundamental in embodied systems research [19]. Generic information-theoretic complexity measures have been used to study system dynamics [16, 4], to characterise information flows in the sensorimotor loop [17], and to analyse robot behaviour [23], due to their ability to capture salient features of robot behaviour based on generic information processing principles, while abstracting from system-specific details [see 23]. The information-theoretic concept of empowerment [14] has been applied to problems in various domains, such as, dynamical control systems [13], robotics [24], and human-computer interaction [30, 31], and more recently in swarm robotics for providing a complexity (i.e., task difficulty) measure in the perceptual discrimination task [33]. The potential of the empowerment measure, demonstrated in initial investigations, provides motivation for its further exploration for facilitating the automatic design of robot swarms and the analysis of their behavioural dynamics.

The collective perceptual discrimination task for swarm of robots has been originally introduced by [18], who used a binary version of this task 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. Various individual mechanisms for opinion selection have been developed since, from the classical hand-crafted solutions, based on the voter model, the majority rule, and their variants [see 34], to more recent ones, based on the synthesis of artificial neural networks [1]. The performance of decision-making strategies has been investigated for varying options quality by [35], while multi-options scenarios have been studied by [8]. Some studies explored 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 [28]. Research in this domain generally considers situations where the robot movement is disturbed only by collisions with close neighbours and arena walls, and communication is unobstructed and effective in a range of up to 50cm based on the e-puck2 platform [32]. Typically, the unpredictable disturbances are modelled uniformly as a random additive noise perturbing both actuation (i.e., movement) and perception (i.e., floor sensing and communication). However, such uncertainty accounts only for sensor and actuator imprecision, while ignoring the possibility of encountering obstructive foreign objects in the field. Earlier research focused on the environmental feature ratio for modulating task difficulty, whereas more recently, [3] proposed that the key determinant of the difficulty in this task is the features' distribution and introduced a set of variations in the environmental topology. Building on their work, [33] introduced an empowerment-based universal and generic measure of task difficulty, which takes into account not only the environmental complexity (i.e., the features distribution), but also the agent's capabilities – arguably a key factor influencing swarm performance. Further extending this work, we demonstrate the ability of the empowerment measure to quantify salient features (i.e., obstacles) in the environment, independent from the task or goal of the swarm, which makes this approach directly applicable to various scenarios in this domain. This initial study provides important insights regarding the effect of communication obstacles in collective perception and sheds light on the interaction between obstacle placement and the predicted impact on swarm performance.

3 Collective Perception

This study is based on the collective perceptual discrimination task as described in [3, 1], which takes place in a square arena whose floor is covered by black and white tiles and where the dominant colour (black or white) covers 55% of the arena floor, while the other colour covers the remaining 45%. The goal of the swarm of robots is to reach a consensus on the dominant colour by randomly exploring the arena and by communicating their opinions on what is the dominant colour to spatially proximal robots. The most frequently used features' distribution in this task is the random distribution of colour patches (see Figure 1/left), which, however, has its limitations with respect to generalization of swarm behaviour; that is, decision-making strategies designed for randomly distributed patches are not equally successful in environments where features are distributed in a different way (for one such example see Figure 1/right). To study these limitations, [3] proposed a set of nine structurally different patterns, which revealed that swarm performance tends to deteriorate when the perceptual evidence is spatially arranged in distinctive clusters, regardless of the nature of control mechanisms (hand-coded [3] or neural network-based [1]). Overall, the less clustered the distribution of perceptual evidence, the higher the swarm accuracy in the collective decision-making [see 3, 1].

Figure 1: The Random environmental pattern, typically investigated in swarm collective perception research (left). The Stripe pattern, which was explored in our study (right).

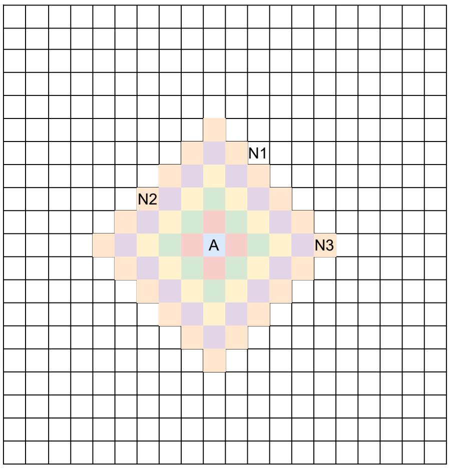


Figure 2: The experimental 2-D grid (20×20 cells) used in our study. The perceivable range of agent A is denoted with a colour map: range0 (blue), range1 (red), range2 (green), range3 (yellow), range4 (purple), and range5 (orange). E.g., neighbours $N2$ and $N3$ are in range5, and $N1$ is out of range.

Drawing from this work, [33] proposed a generic way of measuring task complexity with respect to the distribution of features. This approach places a robot with a particular morphology into a specific environmental condition and attempts to quantify the complexity of the environment as perceived by the agent, which essentially depends on the agent's perception–action loop. For facilitating the analysis, the following simplifications with respect to the original robot-based scenario, as illustrated in [3, 1], were made. A single agent is placed in a discretized square grid of size of 20×20 cells in which each cell corresponds to a tile, that can be either black or white. The agent can perceive the colour of the cell in which it is located and the colours of neighbouring cells. The number of perceivable cells can vary from 5 (range 1) to 61 (range 5). The neighbourhood ranges of an agent A are illustrated in Figure 2. The access to the colour of neighbouring cells intends to simulate the information generated by social influence. Within this metaphor, different ranges correspond to different levels of the maximal robot–robot communication distance, which maps directly this model to studies based on the e-puck2 robotic platform with a communication range of 50 cm and an arena of $2m \times 2m$, patched with tiles $10cm \times 10cm$ each [see, for example 1].

To compute empowerment for each neighbourhood size (i.e., range), the agent is located in every cell of the grid. Thus, empowerment provides a measure of perceivable features with respect to the current position and range. By computing this measure for all possible positions of the agent in the arena, a task complexity estimate integrating both the environmental structure and the agent's sensory capabilities is obtained. This measure of task difficulty has shown its ability to predict swarm performance in collective perception using a number of different decision-making mechanisms for opinion selection and various environmental patterns (see [33]). We extend this work in the current study, by focusing on one particular environmental pattern – Stripe (see Figure 1/right) – while introducing communication obstacles in the arena at different locations. All obstacles have the shape of a straight thin line, three tiles long, placed between tiles and act as impenetrable walls, further restricting the communication range of 50 cm. To explore the effect of such communication obstacles, we varied the location and/or orientation according to the six layouts presented in Figure 3 and computed the empowerment levels for each one using the above approach.

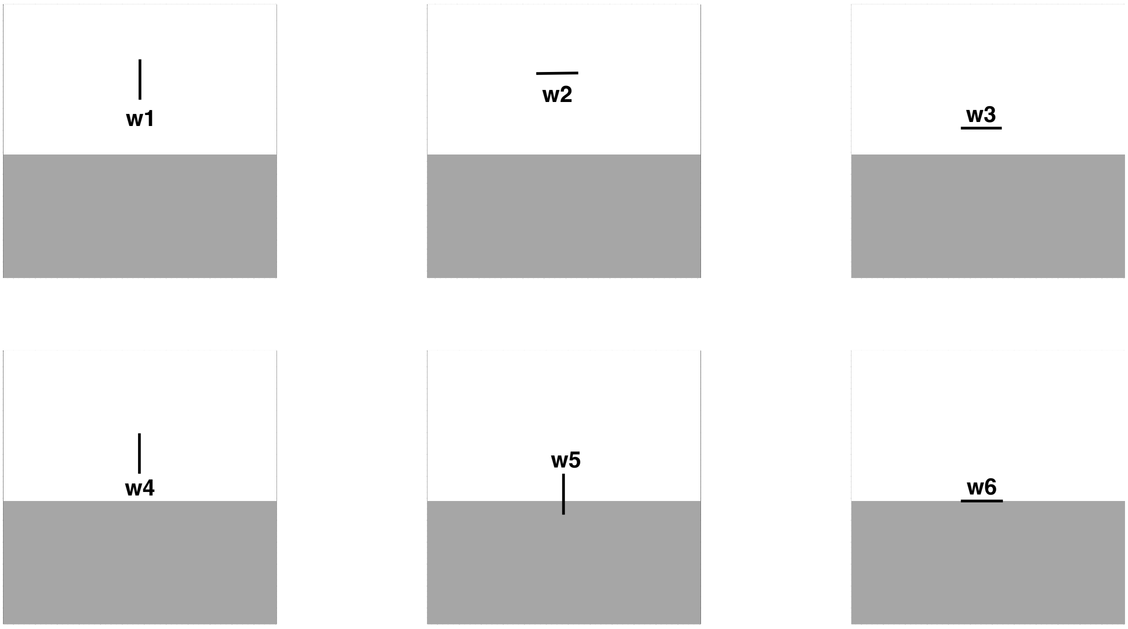


Figure 3: The six conditions investigated in this study, corresponding to six different placements (i.e., w1, w2, w3, w4, w5, and w6) of the communication obstacle (locations and/or orientations) in the discrete 2-D grid (20×20 cells) reflecting the Stripe environmental pattern.

4 Empowerment Model

The information-theoretic model of the Collective Perception paradigm introduced in [33] is based on the empowerment formulation [14] of the perception–action loop of an embodied agent and its environment, represented as a communication channel. Using the causal Bayesian network representation of the perception-action loop (see Figure 4), empowerment is defined as the Shannon channel capacity from the sequence of actions $U_t, U_{t+1}, ..., U_{t+n-1}$ to the perception Y_{t+n} through the environment $X_{t+1}, X_{t+2}, ..., X_{t+n}$ after an arbitrary number of (n) time steps,

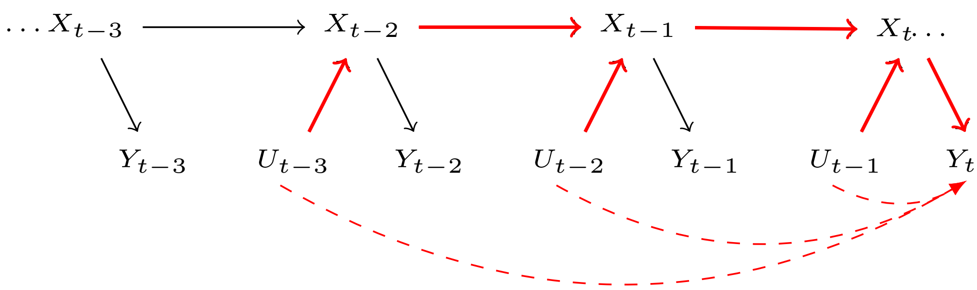


Figure 4: Perception–action loop as a causal Bayesian network – an agent performs an action U and injects information into the environment X, and subsequently reacquires part of this information via its sensors Y. Empowerment is the channel capacity from the action sequence (e.g., $U_{t-3}, U_{t-2}, U_{t-1}$) to the resulting observation (e.g., Y_t) after n (e.g., 3) time-steps.

using the following formulation

$$C(U_t, ..., U_{t+n-1} \rightarrow Y_{t+n}) = \sup_{p(\vec{u})} I(U_t, ..., U_{t+n-1}; Y_{t+n})$$

where $\vec{u} = (u_t, ..., u_{t+n-1})$ and the mutual information between two discrete random variables U and Y is defined by

$$I(U;Y) = \sum_u p(u) \sum_y p(y|u) \log \frac{p(y|u)}{p(y)}.$$

Empowerment is a task and representation independent utility function, fully specified by the dynamics of the perception–action loop of the agent–environment coupling unrolled over time. It reflects the capacity of an agent to control or influence its environment as perceived by its sensors. Empowerment depends on the agent's embodiment, i.e., its sensory apparatus and motor abilities, and on the degree of interaction between agents, i.e., agents need freedom to act and at the same time they need certain constraints imposed by other agents [6].

The decision-making mechanisms for collective perception are based on the agent's own perception and the opinions of its neighbours, which contain information about the environment at various remote positions and are transmitted from a distance within a specific communication range. This enables the agent to extend its sensing abilities and to acquire information about (perceive) the environment at distant locations. The collective perception scenario can be transformed into the empowerment formalism by re-framing the task into a communication problem, using swarm communication as an action space and representing the action horizon with the communication range. In this model, the state space consists of the position of a single agent in the grid. For simplicity, only the main four orthogonal directions are used from which neighbourhoods of a particular size are constructed with an action space $\mathcal{U}$ of the following five primitive actions

$$\mathcal{U} = \{north, south, east, west, idle\}.$$

The first four actions correspond to communicating with (i.e., polling the opinions of) the immediate neighbours in the four respective directions, while the last (*idle*) action reflects the agent's own sensor reading. N-step action sequences represent communication with agents in a neighbourhood of a particular range. The borders of the environment are hard and constrain the actions. Following this representation, Figure 2 depicts the perceivable range of agent A, in a blank 2-D grid, defined by a colour map – range0 (blue), range1 (red), range2 (green), range3 (yellow), range4 (purple), and range5 (orange).

We evaluate empowerment in all positions across the grid, using the environmental features as sensor readings. For any state $x \in \mathcal{X}$ in the grid empowerment is computed by

$$\mathfrak{E}(x) = \max_{p(\vec{u})} I(U_t, ..., U_{t+n-1}; Y_{t+n}|x),$$

where the action space $\mathcal{U}$ consists of the above five actions and the perception space $\mathcal{Y}$ is defined by a binary random variable

$$\mathcal{Y} = \{0, 1\},$$

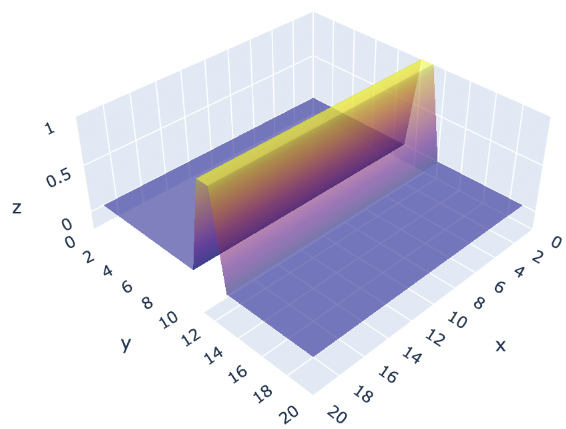
representing the environmental feature (black or white) in state $y \in \mathcal{X}$, where y is the resulting state after applying the action sequence $U_t, ..., U_{t+n-1}$ starting from x. Note that x is a starting position on the 2-D grid, while the perception $Y_{t+n} \in \mathcal{Y}$ is a binary value representing the feature in the final position.

5 Results

Employing the above model, we computed the empowerment levels for every starting position in the 2-D grid for all six conditions presented in Figure 3, with a range of empowerment horizons from one to five, which corresponds to a discrete communication radius of one to five cells and is in line with previous swarm robotics studies in this scenario [see 1]. Furthermore, to facilitate the assessment of the experimental conditions, we computed the empowerment for the baseline case consisting of the Stripe environmental pattern excluding obstacles.

For brevity, in this baseline condition, the evolution of the empowerment levels as the communication horizon increases is presented only for the minimal (1-step) and the maximal (5-step) horizon (see Figure 5). The results reveal an empowerment increase to its maximal level (in this case 1 bit) around the borderline between the black and the white patches, and is zero elsewhere. The larger the horizon, the wider the area of high empowerment is, as expected.

We found no difference in the empowerment levels between the baseline and the experimental conditions with two exceptions, namely conditions w3 and w6, which are presented in full details in Figures 6 and 7. For condition w3 (see Figure 6), the empowerment levels follow the trends of the baseline condition for 1-step and 2-step horizons, however, with the gradual increase of the horizon a drop from 1 bit to 0 bit in empowerment appears in the vicinity of the communication obstacle. For condition w6 (see Figure 7), this drop in empowerment is symmetrical, as expected, since the communication obstacle is placed exactly between the black and the white patches, and furthermore, affects all horizons from 1-step to 5-step. The impact for horizon steps 1 and 2 leads to zero empowerment on the borderline. We present the overall empowerment levels averaged across the grid for the baseline, w3 and w6 conditions in Figure 8. It reveals that the closer the obstacle is to the borderline, the stronger the overall effect on empowerment is. The impact may appear negligible, however, one should keep in mind the rather modestly sized obstacle used in this study. These results indicate that both the position and the orientation of the communication obstacles are crucial for maintaining optimal empowerment levels across the arena and suggests that swarm performance may be affected to a different degree by such obstacles depending on their particular placement. This insight highlights the intricate relationship between communication obstacles and specific environmental patterns, and calls for more thorough future investigations.



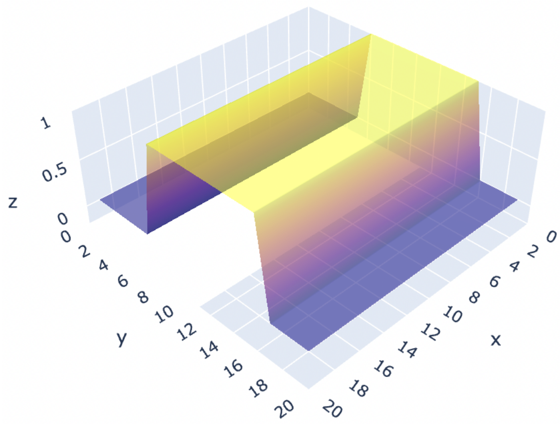


Figure 5: 1-step (left) and 5-step (right) empowerment levels computed across the 2-D grid in the Stripe condition without communication obstacles. Empowerment is at its maximum of 1 bit around the borderline between black and white patches, and zero elsewhere.

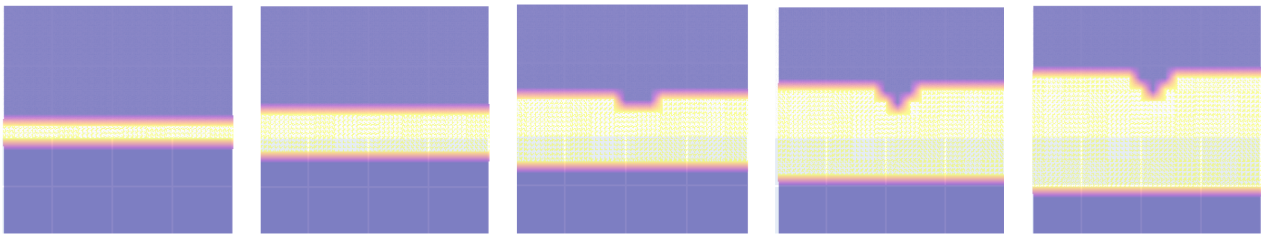


Figure 6: 1, 2, 3, 4, and 5-step (from left to right) empowerment levels, computed across the 2-D grid in condition $W3$ and projected on the X-Y plane. The close proximity of the obstacle to the borderline between black and white regions in this particular orientation leads to its detrimental effect on empowerment levels for 3, 4, and 5-step horizons.

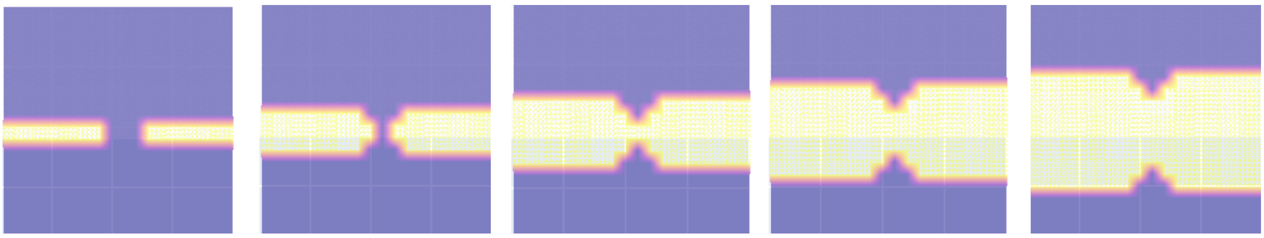


Figure 7: 1, 2, 3, 4, and 5-step (from left to right) empowerment levels, computed across the 2-D grid in condition $W6$ and projected on the X-Y plane. The placement of the obstacle exactly on the borderline between black and white regions explains the symmetry of the profiles and its detrimental effect on empowerment levels for all horizons.

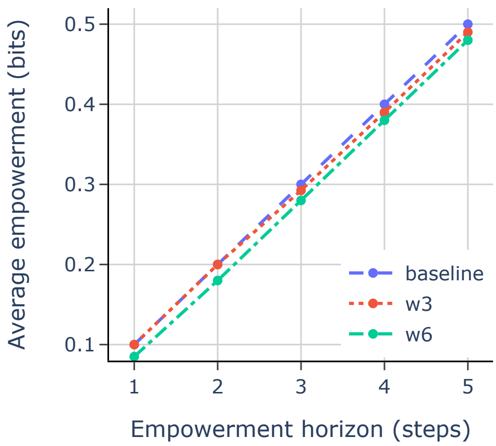


Figure 8: Average empowerment levels aggregated over the 2-D grid for five horizon spans in the baseline, w3 and w6 conditions. The drop in empowerment is minor for condition w3 with respect to the baseline and appears at larger horizons, whereas for w6 the drop is pronounced and affects all horizons. Note that the maximal empowerment level in this case is 1 bit.

6 Discussion

We have explored the potential impact communication obstacles might have on swarm performance with respect to environmental topology, building on a recently introduced [33] generic information-theoretic approach for characterizing task difficulty in the collective perception paradigm. This approach does not characterise the topological structure of the environment based on number, size, shape and inter-connectivity of clusters, but instead, it explores the environment with the given agent morphology, which is critically relevant in determining task difficulty. Our earlier study [33] revealed a significant correlation between the empowerment levels and the accuracy of state-of-the-art decision-making strategies, which suggests the potential of the empowerment measure to predict swarm performance based solely on properties of the environment and independent of the particular task. Building on this insight, we investigated the effect communication obstacles have on empowerment levels across various horizons in one particular environmental pattern. We applied the empowerment formalism to characterise the effect various locations and orientations of linear obstacles imply on task difficulty. Two key parameters influencing swarm performance in this scenario are the environmental pattern type and the swarm communication abilities. For this – first of its kind study – we have selected the simplest environment reported previously in this field, which is composed of two coherent colour patches. For obstacle, we have chosen a straight line placed in six different locations and/or orientations with respect to the borderline between the two colour patches, which appears to be a performance-critical spot. The rational behind the simplistic configurations used in our initial study was grounded in the search for unambiguous and clear interpretations of the interactions between communication range, environmental pattern and communication obstacles. Different and more complex environments with multiple obstacles of various sizes and shapes would have had a less predictable effect on empowerment which is more difficult to interpret, however, is an important direction for future research.

The results demonstrate that obstacles located sufficiently far – with respect to the empowerment horizon – from the borderline have no effect on empowerment, as expected, since the communication exchanges in homogeneous areas carry no new information for the swarm. Therefore, such communication obstacles have no detrimental impact. However, when placed closer to the borderline, the same obstacles inflict a drop in empowerment levels for sufficiently large horizons with respect to the distance between an obstacle and the borderline. Obstacles on the borderline have the highest impact on empowerment for all horizons, as expected, and result in a symmetric empowerment profile with respect to the borderline. An interesting finding of this study is the fact that only obstacles parallel to the borderline have influence on empowerment levels, which opens up new questions with regard to obstacle orientation for future research.

The key benefits of the applied information-theoretic treatment are that it is universal, general and could enable the analytical comparison of scenarios with different computational models. The proposed approach elucidates the trade-off between task difficulty (i.e., swarm performance) and the cost of enabling particular agent capacities, and provides information-theoretic bounds, which are fundamental properties of agent–environment systems. The empowerment levels could reveal critical points in the environment (e.g., obstacles), which might inflict significant drops in swarm performance, and thus raise designer's attention for a more careful consideration. Empowerment captures in a uniform measure salient features of the agent–environment perception–action loop, such as topology, morphology, noise in the sensing, actuation and communication channels, with a generic information-theoretic model. We believe that theories and tools from complex systems and information theory can successfully be applied for facilitating the automated design of robot collectives and for the analysis of their dynamics.

7 Conclusion

This paper presents an initial study on the effects communication obstacles might have on swarm performance in the collective perceptual discrimination task. The analysis, based on an application of the information-theoretic capacity of empowerment to the field of swarm robotics, highlights the benefits of utilising such a generic utility measure. Our approach is task-independent and the same model could be applied to further scenarios in this domain, e.g., shortest-path or site-selection. Leveraging Shannon's information theory by way of creating generative mathematical models and artificial simulations, empowerment offers a novel perspective for swarm robotics, building on objective quantitative measures and analytical tools, which could support the automated design of robotic swarms. Our study opens up new directions for research into how environmental factors and communication obstacles influence swarm behaviour and decision-making. Future work will focus on developing more robust, empirically validated models of swarm intelligence that have direct implications for the design and optimization of swarm-based technologies in various domains. To bridge the gap between theoretical insights provided here and their practical applications, related domain-specific methodologies will be explored for contextualizing and enhancing the findings of this study in more realistic settings and scenarios that reflect the complexity of real-world applications.

8 Acknowledgements

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