A Comparative Study on Decision-Making Mechanisms in a Site Selection Task

Almansoori, Ahmed; Trendafilov, Dari Borisov; Mohammed, Muhanad Hayder Mohammed; Tuci, Elio

DOI:
10.1007/978-3-031-93631-9_8

Publication date:
2025

Document Version
Early version, also known as pre-print

A Comparative Study on Decision-Making Mechanisms in a Site Selection Task

Ahmed Almansoori[1,2][0000−0002−2600−3344], Dari Trendafilov[1][0000−0001−5567−9784], Muhanad Alkilabi[1][0000−0002−6921−4993], and Elio Tuci[1][0000−0001−7345−671X]

[1] Faculty of Computer Science, University of Namur, Namur, Belgium
[2] Faculty of Engineering, University of Kerbala, Kerbala, Iraq
ahmed.almansoori@unamur.be

Abstract. In swarm robotics, it is crucial for swarm members to reach a consensus on a single option from a set of alternatives to complete complex tasks autonomously. Typically, individual mechanisms underpinning such collective behaviour are designed using either hand-coded or automatic approaches. In this paper, We aim to compare the performance of robotic swarms controlled by mechanisms designed using both types of techniques in a site-selection task. The evaluated hand-coded mechanisms are based on the voter model and majority rule, while the automatic design approach involves an evolved dynamic neural network mechanism. The evaluation is conducted in a simulated environment that represents different operating conditions and swarm sizes. The central hypothesis of this study is that evolved neural control in swarm robotics may lead to better behavioural responses, including more accurate decision-making and increased resilience to varying environments and group sizes, compared to traditional hand-coded approaches.

1 Introduction

In swarm robotics, collective behaviour is a global response arising, through a self-organisation process, from the local interaction of multiple simple agents with their physical and social environment. This emergent behaviour allows robotic swarms to achieve complex tasks beyond the capabilities of individual robots. While self-organisation offers undeniable advantages for designing adaptive and resilient systems, its inherent unpredictability and decentralised nature pose significant hurdles for system engineers [2]. To address the design problem, researchers have investigated a variety of controller design approaches, such as hand-coded and automatic design techniques. Hand-coded mechanisms produce behavioural strategies that can be easily described in operational terms. However, their capability to adapt to different sources of variability tends to be limited to the circumstances clearly predicted by the designer, which leaves the robots potentially unprepared to tackle unexpected events encountered in real-world settings [2]. In contrast, evolutionary robotics (ER), an automatic design strategy, employs evolutionary computation techniques to develop controllers based on artificial neural networks [6]. The primary advantage of ER lies in its use of evaluation functions that prioritise the performance of the swarm as a whole over the behaviour of individual robots. This approach allows for an automated design process that is adaptable to the specific requirements, however poses challenges for the analysis and the interpretation of such controllers [8,5,4,11].

Collective decision-making, one of the most studied collective behaviours in swarm robotics, refers to a decision problem in which natural or artificial agents collectively make a choice among two or more alternatives, with the final decision being a group outcome rather than an individual one [12]. Within the domain of collective decision-making, robot swarms demonstrated two fundamental abilities: task allocation and consensus achievement. Task allocation involves improving overall performance by splitting the swarm into subgroups focused on different tasks. While consensus achievement allows the swarm to adopt the same opinion about different options. The individual opinion formation process is influenced by direct sampling of the physical environment and by social interaction based on local communication. This paper is focused on consensus achievement in the site selection task.

To date, site selection research is based predominantly on hand-coded strategies. [15] studies a binary site-selection task using the voter model, which makes a robot switch to the opinion of a randomly chosen spatially close neighbour. [14,13] explore the majority rule, which makes a robot switch to the most frequent opinion among n spatially close neighbours. In these studies, robots alternate between exploring options and disseminating their current opinion for a time proportional to the option's quality. This modulation of the dissemination time is the main factor driving consensus achievement on the best quality option. Related research [7,3] on a binary site selection scenario investigates the effect of different opinion formation strategies on the decision dynamics. [10] explores the relationship between the maximum communication distance and the accuracy of the collective decision-making process in dynamic environments with three sites of different quality using the voter model with cross-inhibition, where conflicting information leads robots to reset their opinions and seek others.

Diverging from the previous body of research, a recent study demonstrates the potential of evolved dynamic neural networks as a more flexible and adaptable alternative for site selection [1]. By leveraging evolutionary computation techniques, the authors synthesised controllers enabling robotic swarms to effectively solve a ternary site selection task, without explicit assumptions on individual responses or group dynamics. The proposed approach does not assume a correlation between environmental features and robot behaviour, such as the positive correlation between option quality and dissemination time used in [15,14,13,7,3] or between option quality and the frequency of the individual's opinion update process used in [10,9]. Furthermore, this work avoids built-in assumptions on how robots process perceptual cues and communication signals to form their opinions, as seen in the voter or majority models. Instead, the evolutionary process develops individual mechanisms for integrating these signals

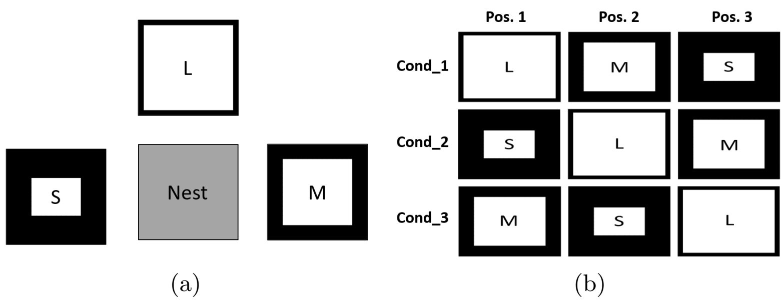


Fig. 1. a) The site-selection scenario with nest and three sites – L, M, and S [1]. b) The position of each site in the three experimental conditions [1].

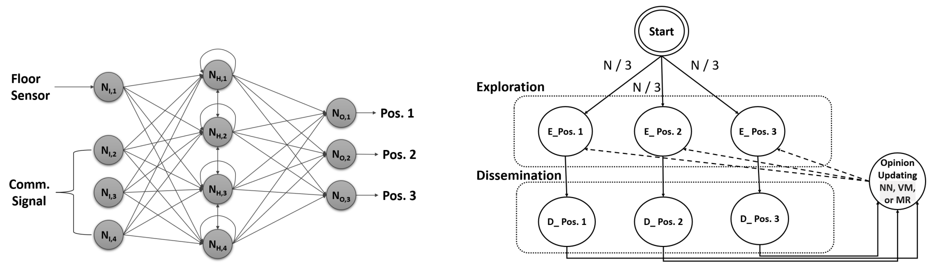
and creating the necessary relationships for generating modulations that break the initial equilibrium and push the group toward consensus on the best option.

The present study aims to replicate the site selection scenario illustrated in [1], in order to conduct a comprehensive comparative analysis of swarm performance under two distinct control paradigms: hand-coded mechanisms based on the voter model and the majority rule and evolved dynamic neural networks as described in [1]. The evaluation of these approaches across a range of operating conditions and swarm sizes aims to provide deeper insights into their relative strengths and weaknesses, eventually contributing to the development of more effective and adaptable collective decision-making strategies for robotic swarms.

2 Methods

We employ a simulated environment that closely replicates the site-selection scenario described in [1], in which 21 robots pseudo-randomly explore square arena of $2\,\mathrm{m} \times 2\,\mathrm{m}$ while avoiding collisions. The scenario features three sites (large (L), medium (M), and small (S)) with varying white floor proportions (80%, 50%, and 20% respectively) and a nest (see Fig. 1a). The swarm is evaluated in three experimental conditions (Cond_1, Cond_2, Cond_3) that differ in the position of the best quality site (see Fig. 1b). The task of the swarm is to determine which position hosts the highest quality site in all three conditions.

In both, hand-coded and neural network-controlled swarms, the development of individual opinions and the subsequent decision-making process follow a similar structure. The robots alternate between two phases: i) exploration phase, in which the robots perceive the cue signalling the respective site's quality, but they cannot communicate; and ii) dissemination phase, in which they are allowed to communicate their respective opinions on the best quality site to spatially close robots, but they cannot sample the site's quality. At the end of the dissemination state, each robot updates its opinion using either the VM or MM for the swarms controlled by hand-coded mechanism or the neural network controller for the swarm controlled by evolved mechanism. Finally, each robot moves to the exploration state that corresponds to its new opinion (see Fig. 2b).



(a) (b)

Fig. 2. (a) The decision module made of a dynamic neural network [1]. (b) The probabilistic finite-state machine. E_Pos 1, E_Pos 2, E_Pos 3, D_Pos 1, D_Pos 2 and D_Pos 3 represent the exploration and the dissemination state, respectively. Solid lines represent deterministic transitions, while dotted lines represent stochastic transitions.

The main differences between hand-coded mechanisms (VM and MM) and the evolved neural network are in the dissemination time and opinion update mechanisms. In VM and MM, the dissemination time is directly proportional to the robot's estimate of site quality, promoting robots with higher site quality to propagate their opinions for longer duration. Following hand-coded mechanisms, the robots update their opinions based only on social information received from their neighbours. In the VM, this involves adopting a random neighbour's opinion, while in the MM, it involves adopting the majority opinion. Conversely, the evolved neural network does not impose a direct relationship between quality estimation and dissemination time. Instead, during the evolution phase, the network learns how to use the environmental bias among the available options to create both the indirect feedback modulation and opinion update mechanism needed to complete the task. This is done through a complex interaction of sensory inputs and communication signals.

As described in [1], the evolved dynamic neural network controller consists of a three-layer architecture with a fully recurrent hidden layer. The input layer receives sensory data (floor colour and communication signals), while the output layer generates the robot's opinion (see Fig. 1a). The network weights, biases, and decay constants are genetically encoded and optimised through a simple tournament selection evolutionary algorithm.

3 Conclusions

We will present the insights of a comparative analysis of two types of decision-making mechanisms: hand-coded, based on the voter model and majority rule and evolved, using a dynamic neural network [1]. The experimental task is the site selection, illustrated in [1] and described in section 2. The comparisons are based on performance criteria, such as accuracy and consensus time. The study evaluates the robustness to environmental variability and the scalability of solutions in a range of conditions.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101034383 and CERUNA doctoral fellowship by UNamur.

References

1. Almansoori, A., Alkilabi, M., Trendafilov, D., Tuci, E.: On the design of control mechanisms for a site selection task in a simulated swarm of robots. In: Swarm Intelligence: 14th International Conference. Springer (2024), in Press. Preprint available at: https://tinyurl.com/SS-ANTS2014
2. Brambilla, M., Ferrante, E., Birattari, M., Dorigo, M.: Swarm robotics: a review from the swarm engineering perspective. Swarm Intelligence **7**(1), 1–41 (2013)
3. De Masi, G., Prasetyo, J., Zakir, R., Mankovskii, N., Ferrante, E., Tuci, E.: Robot swarm democracy: the importance of informed individuals against zealots. Swarm Intelligence **15**, 315–338 (2021)
4. Mendiburu, F.J., Ramos, D.G., Morais, M.R., Lima, A.M., Birattari, M.: Automode-mate: Automatic off-line design of spatially-organizing behaviors for robot swarms. Swarm and Evolutionary Computation **74**, 101118 (2022)
5. Nelson, A.L., Barlow, G.J., Doitsidis, L.: Fitness functions in evolutionary robotics: A survey and analysis. Robotics and Autonomous Systems **57**(4), 345–370 (2009)
6. Nolfi, S., Floreano, D.: Evolutionary robotics: The biology, intelligence, and technology of self-organizing machines. MIT press (2000)
7. Prasetyo, J., De Masi, G., Ferrante, E.: Collective decision making in dynamic environments. Swarm intelligence **13**(3), 217–243 (2019)
8. Salman, M., Garzón Ramos, D., Birattari, M.: Automatic design of stigmergy-based behaviours for robot swarms. Communications Engineering **3**(1), 30 (2024)
9. Talamali, M.S., Marshall, J.A., Bose, T., Reina, A.: Improving collective decision accuracy via time-varying cross-inhibition. In: 2019 International conference on robotics and automation (ICRA). pp. 9652–9659. IEEE (2019)
10. Talamali, M.S., Saha, A., Marshall, J.A., Reina, A.: When less is more: Robot swarms adapt better to changes with constrained communication. Science Robotics **6**(56), eabf1416 (2021)
11. Tuci, E., Rabérin, A.: On the design of generalist strategies for swarms of simulated robots engaged in a task-allocation scenario. Swarm Intelligence **9**, 267–290 (2015)
12. Valentini, G., Ferrante, E., Dorigo, M.: The best-of-n problem in robot swarms: Formalization, state of the art, and novel perspectives. Frontiers in Robotics and AI **4**, 9 (2017). https://doi.org/10.3389/frobt.2017.00009
13. Valentini, G., Ferrante, E., Hamann, H., Dorigo, M.: Collective decision with 100 kilobots: Speed versus accuracy in binary discrimination problems. Autonomous Agents and Multi-Agent Systems **30**(3) (2016). https://doi.org/10.1007/s10458-015-9323-3, https://doi.org/10.1007/s10458-015-9323-3
14. Valentini, G., Hamann, H., Dorigo, M.: Efficient decision-making in a self-organizing robot swarm: On the speed versus accuracy trade-off. In: Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems. pp. 1305–1314 (2015)
15. Valentini, G., Hamann, H., Dorigo, M., et al.: Self-organized collective decision making: the weighted voter model. In: AAMAS. vol. 14, pp. 45–52. Citeseer (2014)