Proceedings of the 2025 SICE Festival with Annual Conference
September 9-12, 2025, Chiang Mai, Thailand

Investigating Swarm Behavior through Group Compositions with Perceptual Variability in Evolutionary Swarm Robotics System

Asad Razzaq[1]†, Toshiyuki Yasuda [2]

[1]Graduate School of Science and Engineering, University of Toyama, Toyama, Japan
(E-mail: d2278003@ems.u-toyama.ac.jp)
[2]Faculty of Engineering, University of Toyama, Toyama, Japan
(Tel: +81-76-445-6806; E-mail: yasuda@eng.u-toyama.ac.jp)

Abstract: The swarm robotics system (SRS) uses multiple robots inspired by the self-organizing abilities of social organisms such as ants and bees. One of the methods for constructing SRS control systems is the evolutionary robotics (ER) approach, which automatically designs controller parameters. The ER approach is a method for automatically creating the artificial neural network controller parameters that often deal with homogeneous SRS. This study aims to investigate heterogeneity via perceptual variations between robots, primarily enabled by input acquisition sensors, which play an essential role in the acquisition of swarm behavior. Heterogeneous robots with different perceptual capabilities outperform homogeneous ones.

Keywords: Swarm robotics, Swarm intelligence, Evolutionary robotics, Artificial neural network, Perceptual variability

1. INTRODUCTION

A multi-robot system comprises a collection of autonomous robots designed to execute tasks collaboratively. One prominent subfield within this domain is swarm robotics (SR), which draws inspiration from collective behaviors observed in natural systems [1]. The self organization of social organisms such as ants and bees inspires this research field. It aims to establish collective behavior through local interactions among robots [2]. The SRS aims to accomplish tasks that are difficult for a single robot by having multiple robots cooperate. Since SRS uses autonomous robots, it does not require a central control mechanism [3].

Behavior-based design is commonly used in SRS, where robot actions are predefined by the designer. This method is effective in static environments but requires complex tuning when robot interactions are involved [4]. Alternatively, the ER approach uses evolutionary computation to automatically control, typically by optimizing ANN [5].

In general, the study of ER approaches in SRS often consists of teams of homogeneous robots with the same robot structure [6]. In SRS, few studies deal with heterogeneous robot performance and structure. However, many social organisms behave differently within a group due to individual differences in body structure and engage in division of labor [7]. Therefore, it is expected to generate advanced behaviors that cannot be realized in a homogeneous group by generating a group with different robot performance and structure for each robot instead of dealing with a homogeneous group. It is expected to generate advanced behaviors that cannot be realized by homogeneous swarms [8].

Several prior studies have employed homogeneous hardware configurations with consistent swarm compositions across all trials. For example, cooperative transport and foraging tasks in relied on identical robot types and fixed group structures [9, 10]. Similarly, the study on adaptive locomotion used a homogeneous setup without variation in swarm composition. Even in research involving heterogeneous hardware, the swarm composition remained fixed [11, 12]. In contrast, our approach introduces a manually designed heterogeneous swarm, enabling greater flexibility and behavioral diversity during cooperative exploration. This study aims to explore the role of perceptual heterogeneity in swarm robotics by introducing differences in sensor detection range among robots. We hypothesize that such heterogeneity enhances adaptability and efficiency in cooperative task.

2. PERCEPTUAL HETEROGENEITY DESIGN

In natural swarms, such as ant or bee colonies, individual differences in physical and sensory capabilities often lead to a division of labor, enabling efficient collective performance [13]. These biological insights motivate the introduction of heterogeneity in SRS, where robots with differing abilities may assume complementary roles during task execution. Inspired by the behavior of ants, which exhibit both physical and sensory-based division of labor during foraging, we hypothesize that perceptual heterogeneity will enhance adaptability and task efficiency compared to homogeneous swarms. The sensors serve as the primary input channel for the ANN controllers, evolved through an ER approach. Thus, perceptual differences directly influence the behavior acquisition process.

In this study, heterogeneity is introduced through variations in the robots' sensor detection distances, which serve as a proxy for perceptual ability. Specifically, we explore how individual differences in perceptual range affect emergent swarm behavior in a cooperative exploration task. The swarm is composed of robots equipped with either 4 m or 3 m range sensors, and group com-

---

† Asad Razzaq is the presenter of this paper.

Table 1: Heterogeneous group of robots

	het 1	het 2	het 3	het 4	het 5	het 6	het 7
4[m]	14	12	10	8	6	4	2
3[m]	2	4	6	8	10	12	14

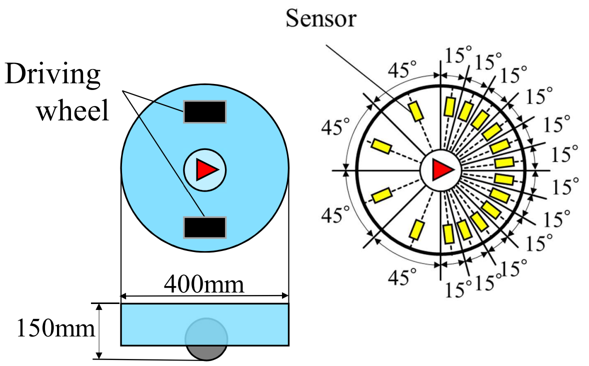


Fig. 1: Robot model

positions are manually designed to analyze performance across different heterogeneous ratios. Unlike earlier works that primarily used homogeneous swarms or fixed task allocations, our study focuses on perceptual diversity within manually designed heterogeneous groups shown in Table 1 for a cooperative exploration task.

3. EXPERIMENT

3.1. Robot Model

A schematic diagram of the robot used in this experiment is shown in Fig.1. Each autonomous robot is equipped with 16 distance sensors. An omnidirectional camera enables the robot to distinguish target types. The robot has left and right drive wheels and moves by differential drive.

3.2. Computational Experiment Environment

We use a (μ, λ)-ES algorithm with $\mu = 15$, $\lambda = 100$, evolving for 30 generations. Each encodes ANN parameters and mutation rates, initialized randomly. In each generation, individuals are evaluated over 30 seconds, and the top 5 elites are retained. New offspring are generated via mutation, with parent selection based on a truncated normal distribution. This process repeats through generation 30. The open-source 3D robot simulation program V-REP uses Bullet 2.78 as the default physics engine. This allowed us to study the behavior and performance of these systems in a controlled and repeatable manner.

In this study, we use a cooperative exploration task. The experimental environments are shown in Fig.2 and Fig.3. The 16 robots are randomly placed within the specified range to find 6 targets in 40 seconds. In addition, the robots are positioned at two distance ranges from the target: a long range (15 m–25 m) and a short range (7.5 m–15 m). A target is considered to have been found when two of the robots make contact with the target, and the target disappears from the area after it is found and appears back in the yellow circle. The targets are in different colors depending on the distance between the circle and the target.

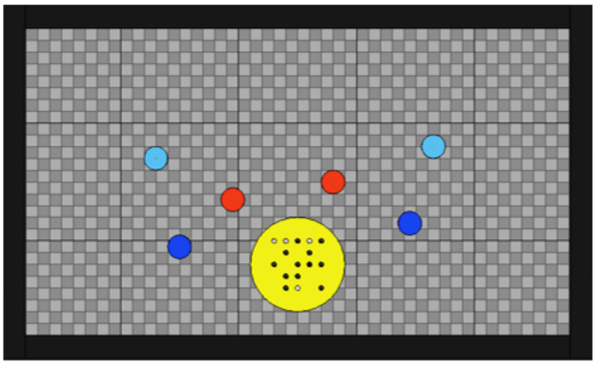


Fig. 2: Short-range experimental environment

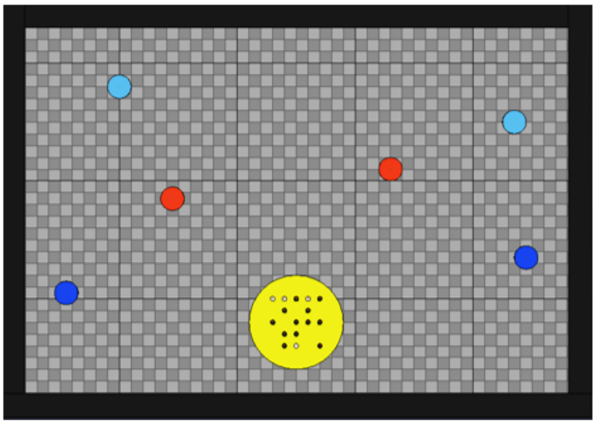


Fig. 3: Long-range experimental environment

We investigate the size effect of the exploration range on heterogeneous robots, where detection distances of 3[m] and 4[m] are used as differences in perceptual ability. The different combinations of the detection distance and the number of robots for the heterogeneous group of robots in our experiments are shown in Table 1. The effectiveness of heterogeneity is verified by comparing the two homogeneous groups of 3[m] and 4[m] robots with the seven heterogeneous groups of robots in Table 1.

3.3. Experimental Results

Evaluation of perceptual heterogeneity in swarm robot groups under two cooperative exploration scenarios: long-range (15-25 m) and short-range (7.5–15 m). Fitness was used as the performance metric across evolutionary trials. Kruskal-Wallis test employed, a nonparametric method for detecting differences in median ranks across multiple groups. Significant results were followed by pairwise comparisons using Dunn's test.

Fig.4 presents the results of the short-range condition where N_S denotes the number of robots equipped with the $3\,\mathrm{m}$ sensor range, and N_L denotes the number of robots equipped with the $4\,\mathrm{m}$ sensor range. The test confirmed a statistically significant difference among group medians ($H = 26.67$, $p = 7.06 \times 10^{-4}$). The $(2, 14)$ group had the highest rank mean and significantly out-

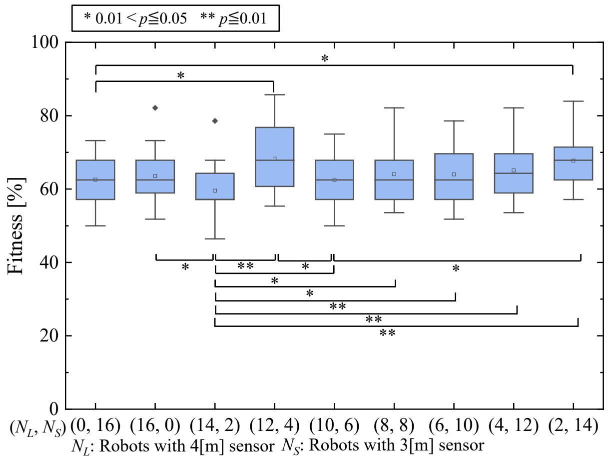


Fig. 4: Short-range environment: Fitness performance of homogeneous and heterogeneous robot groups

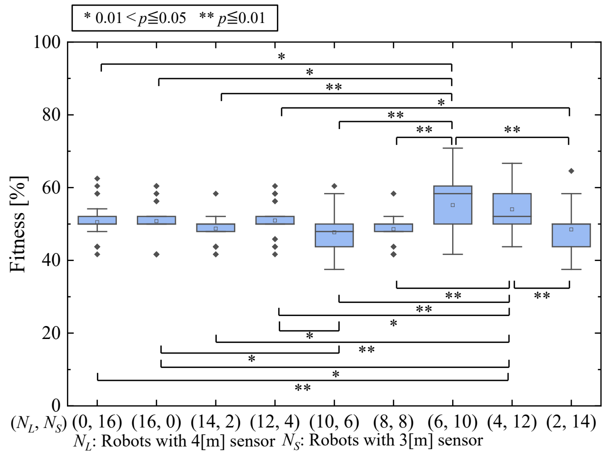


Fig. 5: Long-range environment: Fitness performance of homogeneous and heterogeneous robot groups

performed multiple other groups. The $(12, 4)$ group also ranked among the top performers and showed statistically significant advantages over lower-ranked configurations. In contrast, the $(14, 2)$ group had the lowest rank mean and was outperformed by most other groups.

As shown in Fig.5, heterogeneous groups demonstrated superior performance over homogeneous ones in the long-range exploration task. The test revealed a significant difference among group medians ($H = 40.82$, $p = 6.48 \times 10^{-7}$). Pairwise test showed that the groups $(6, 10)$ and $(4, 12)$ significantly outperformed most other group combinations. These groups included a higher proportion of 3-meter sensor robots and exhibited more effective coverage of the large search area. Homogeneous configurations such as $(0, 16)$ and $(16, 0)$ ranked lower in performance compared to these heterogeneous groups.

4. DISCUSSION

The experimental results presented in this study highlight the impact of varying the composition of heterogeneous robot groups on their adaptive capabilities under different environmental conditions. By using the detection distances of robots and analyzing their collective performance using evolutionary swarm robotics, we aimed to demonstrate the advantages of heterogeneity over homogeneity in cooperative exploration tasks.

Different patterns of adaptation were observed across exploration ranges. In a short-range environment, the robot groups with sensor ratios of (2, 14) and (12, 4) showed the highest levels of fitness. This was largely due to the ability of 3m robots to rapidly explore targets. Further analysis of heterogeneous group dynamics revealed that robots with 3m sensors frequently deviated from the main group to explore independently. This behavior contributed to a broader and more flexible exploration strategy, contrasting with homogeneous swarms, where robots typically followed synchronized, uniform movement patterns due to identical capabilities.

The study also investigated how exploration performance varied in a long-range environment. In environments with longer exploration areas, the robot groups with sensor ratios of (6, 10) and (4, 12) showed the highest levels of fitness. These groups, which included a higher proportion of robots with 3 m sensors, exhibited more exploratory and randomized search behavior. Such diversity allowed them to effectively cover larger areas and locate targets more efficiently than their homogeneous counterparts.

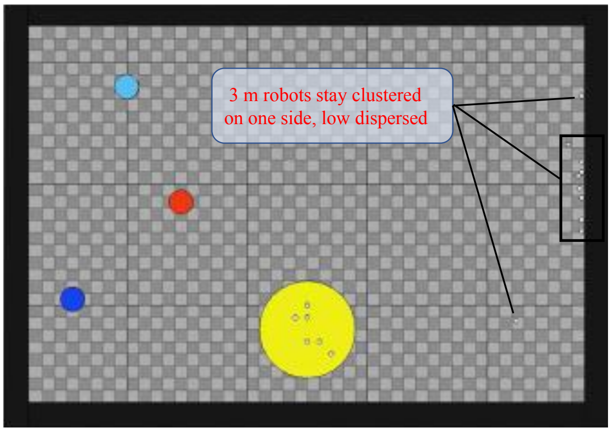
Fig. 6 compares the behavior of homogeneous and heterogeneous robot groups during the exploration task. In the homogeneous group composed entirely of 3 m sensor robots ($N_L, N_S = 0, 16$), the robots exhibit significant clustering, tending to remain on one side of the environment, which results in limited area coverage (Fig. 6(a)). A similar trend is observed in the homogeneous group with only 4 m sensor robots ($N_L, N_S = 16, 0$), where despite a longer sensing range, the group still stays clustered with minimal spread (Fig. 6(b)).

In contrast, the heterogeneous group consisting of both 4 m and 3 m sensor robots ($N_L, N_S = 6, 10$) shows a notably wider dispersion, particularly among the 3 m sensor robots (Fig. 6(c)). This diversity in sensing range leads to improved distribution, enhancing the overall exploration coverage.

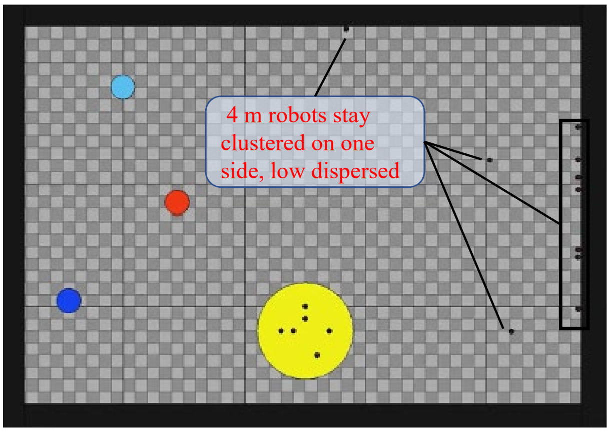
5. CONCLUSION

In conclusion, our experiments consistently demonstrated that heterogeneous robot groups outperformed homogeneous counterparts across both tested environments. This superiority underscores the adaptive advantage of leveraging individual differences in sensory capabilities within swarm robotics. Future research should explore further applications of heterogeneous robot groups in diverse tasks beyond cooperative exploration, potentially enhancing their collective intelligence in various environments.

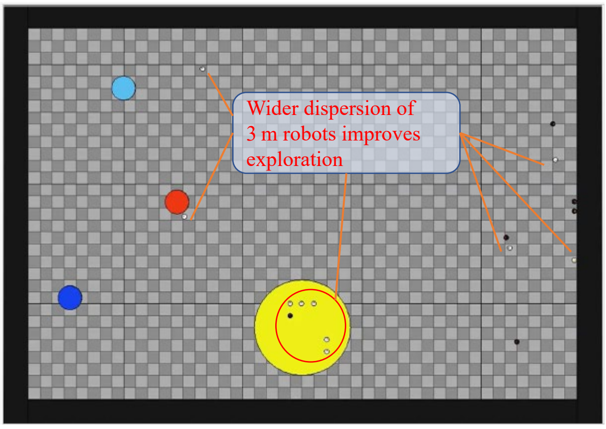
This study contributes to the growing body of research in evolutionary swarm robotics by highlighting the strategic benefits of heterogeneity.



(a) Homogeneous group with only 3 m sensor robots ($N_L, N_S = 0, 16$) exhibits strong spatial clustering



(b) Homogeneous group with only 4 m sensor robots ($N_L, N_S = 16, 0$) also shows limited spread



(c) Heterogeneous group ($N_L, N_S = 6, 10$) shows wider dispersion, particularly among 3 m sensor robots, leading to improved exploration

Fig. 6: Homogeneous and heterogeneous robot groups in terms of their behavior during the exploration task. N_L and N_S denote the number of robots with 4 and 3 m sensors, respectively

ACKNOWLEDGEMENT

This work was supported by JST SPRING, Grant Number JPMJSP2145 and JSPS KAKENHI Grant Number 25K15286.

REFERENCES

[1] M. Masár, “A biologically inspired swarm robot coordination algorithm for exploration and surveillance,” *IEEE 17th International Conference on Intelligent Engineering Systems*, 2013.

[2] S. Nouyan et al., “Path formation in a robot swarm: Self-organized strategies to find your way home,” *Swarm Intelligence*, Vol. 2, No. 1, pp. 1–23, 2008.

[3] E. Şahin, “Swarm Robotics: From Sources of Inspiration to Domains of Application,” *Swarm Robotics*, pp. 10–20, 2004.

[4] V. García-López et al., “Molecular machines open cell membranes,” *Nature*, Vol. 548, pp. 567–572, 2017.

[5] M. Dorigo et al., “Evolving self-organizing behaviors for a swarm-bot,” *Autonomous Robots*, Vol. 17, pp. 223–245, 2004.

[6] O. Soysal et al., “Aggregation in swarm robotic systems: Evolution and probabilistic control,” *Turkish Journal of Electrical Engineering & Computer Sciences*, Vol. 15, No. 2, pp. 199–225, 2007.

[7] E. Ferrante et al., “Self-organized flocking with a mobile robot swarm: A novel motion control method,” *Adaptive Behavior*, Vol. 20, No. 6, pp. 460–477, 2012.

[8] M. Brambilla et al., “Swarm robotics: A review from the swarm engineering perspective,” *Swarm Intelligence*, Vol. 7, No. 1, pp. 1–41, 2013.

[9] R. Groß and M. Dorigo, “Towards group transport by swarms of robots,” *International Journal of Bio-Inspired Computation*, Vol. 1, No. 1–2, pp. 1–13, 2009.

[10] Z. Wei et al. “Flexible foraging response of wintering hooded cranes (Grus monacha) to food availability in the lakes of the Yangtze River floodplain, China,” *Animals*, Vol. 10, No. 4, p. 568, 2020.

[11] H. Li et al., “Co-evolution framework of swarm self-assembly robots,” *Neurocomputing*, Vol. 148, pp. 112–121, 2015.

[12] A. Razzaq et al., “Evolutionary design of cooperative transport behavior for a heterogeneous robotic swarm,” *Journal of Robotics and Mechatronics*, Vol. 35, No. 4, pp. 1007–1015, 2023.

[13] M. Lehue et al., “Nest entrances, spatial fidelity, and foraging patterns in the red ant myrmica rubra: a field and theoretical study,” *Insects*, Vol. 11, No. 5, p. 317, 2020.