Effects of Neurological and Morphological Diversity on Robot Swarm Robustness

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Abstract

Using evolutionary robotics as a medium, we aim to determine if neurological and morphological intra-swarm diversity offers more robustness than other swarm types. Our methods involve the use of an evolutionary algorithm to evolve robot populations, exploring the landscape of possible control strategies and morphologies. We compared three types of robot swarms which can be differentiated by the type of intra-swarm diversity they exhibit: Case 1) No diversity, Case 2) Neurological diversity (diverse controllers), Case 3) Neurological and morphological diversity (diverse controllers and embodiments). We share the results of an experiment comparing the abilities of these three types of robot swarms to navigate a foreign environment post-evolution. Our results show that swarms with neurological and morphological diversity outperform those with neurological diversity, and those with no diversity. Our findings contribute insights into the potential for intra-swarm diversity to be leveraged for the navigation of unknown environments in the real-world.

Introduction

Foreign environments pose a substantial challenge in the field of robotics. They can contain unforeseen obstacles that require a level of robustness to navigate. In this context, we define robustness to be the ability of an agent to overcome unforeseen challenges. Environments with such challenges can range from extraterrestrial terrain to sub-aquatic caves – domains that might be too dangerous for direct human interaction. Furthermore, they can be difficult to map with precision, and potentially contain a multitude of dynamic factors that could hinder a robot from accomplishing its designed function.

Designing robots that are able to navigate challenging environments proves to be a non-trivial problem. Even with the employment of evolutionary algorithms (EAs) to automate robot design, making generally robust robots remains a difficult task. Even in deploying multiple robots for redundancy, an environment with a prominent type of obstacle might compromise robots of identical nature. However, in designing a variety of robots within a swarm, perhaps this issue can be circumvented. We hypothesize that swarms of diverse controllers and morphologies are more robust in foreign environments than swarms of diverse controllers, and swarms of no diversity at all. Figure 1 illustrates these competing robot swarms.

By designing a swarm of robots with diverse controllers and morphologies, we aim to embrace the unpredictability of a foreign environment. This shotgun approach departs from traditional methods of designing an "optimal" robot to explore a novel solution. We contemplate that diversity might play a key role in the navigation of an environment with unknown challenges.

Artificial Neural Networks

Artificial neural networks (ANNs) can govern the control policy of a robot. They aim to capture the basic makeup of an organic brain through a simplified model of artificial neurons and synapses that take the form of nodes and edges. This structure enables ANNs to be geared towards specific functions, like processing the sensory input from a robot's embodiment, and outputting corresponding motor commands – a sensorimotor control system. This control system functions by taking in information through the input layer of pre-synaptic neurons and processing it through synapses that perform mathematical calculations before it reaches an output layer of post-synaptic neurons. The calculations are dependent on the synaptic weights, which determine the factors by which the initial inputs are dampened before they reach the post-synaptic neurons. Such calculations are exemplified by the following equation, where a vector of input values $\vec{s}$ from pre-synaptic neurons is transformed into a value m_j for the corresponding post-synaptic neuron by their dot product with a vector of synaptic weights $\vec{w}_{:,j}$ from a matrix of synaptic weights W.

$$m_j = \vec{s} \cdot \vec{w}_{:,j} \tag{1}$$

Embodied Cognition

Where some agents might employ a neural network to learn from data sets or recognize patterns through solely cognitive training, other agents utilize a body to learn from physical

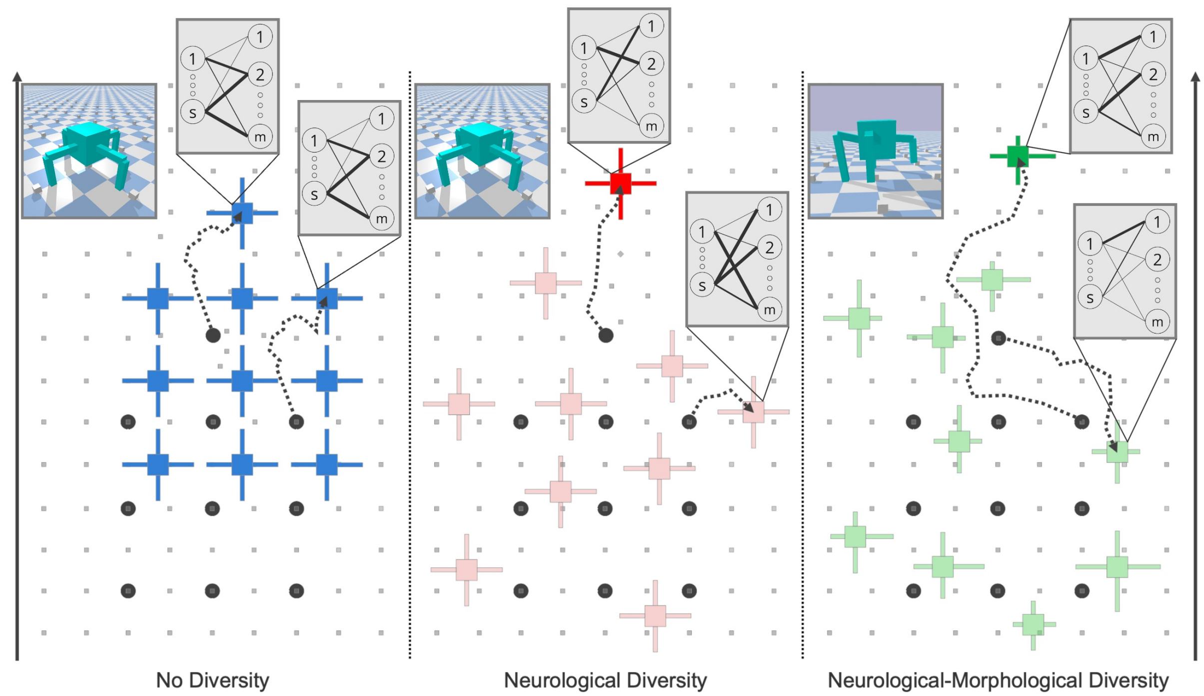


Figure 1: Cartoon depicting three types of robot swarms characterized by the intra-swarm diversity they exhibit. Each swarm is composed of 10 robots attempting to navigate a foreign cluttered environment, where swarm performance is measured by the displacement of the robot that travels furthest in the y-direction (see bordering black arrows). The robot of each swarm that has the largest y-displacement is shown with the highest opacity. Robot starting points are indicated by the black circles. Differences in neurology can be observed in the node-and-edge diagrams of a neural network that shows synaptic weights through line thickness. For each swarm, robots were simulated individually in the same relative environment. This visualization shows a superposition with staggered robot starting points to prevent any robots to appear overlapping.

interactions with their environment. In the context of embodied cognition, there are two key elements to consider: Whether an agent is *embodied*, and if it is *situated*. The former describes an agent that is in possession of a body with which it can affect and be affected by its environment, while the latter describes an agent that can learn about its environment through its sensory systems (Pfeifer and Bongard, 2006).

Agents that are imbued with both features have the capacity to circumvent issues that can arise within a more traditional framework of intelligence, utilized by disembodied agents. For a particular example of an embodied and situated agent, we can think of a stereotypical robot. Utilizing sensors and motors, it has the ability calculate its next action depending on its current state through a deterministic process. During this process, the robot thinks, senses, and acts, affording itself the ability to adapt its actions to unfamiliar environments.

This trait of adaptability inherently associates the controller with the morphology of the robot, as it is the medium through which the controller interacts with its environment. In situations where adaptability is required, like in navigating unknown terrain, robust behaviors and morphologies are necessary. EAs have been used to study the effects of various environments on the evolution of controllers and morphologies (Miras and Eiben, 2019). While previous work does not circumvent all issues in the virtual design of robust robotic systems, they do provide a knowledge base with which researchers can further their understanding.

Evolutionary Algorithms

The effectiveness of EAs on converging to a solution is predicated on stochasticity. The EA randomly explores a solution-scape using a number of initial solutions (parents) that are mutated over successive generations. The number of generations over which evolution occurs is referred to as *evolutionary time*. Similarly, the number of parents P and generations G over which they are evolved are collectively referred to as a system's *evolutionary resources*.

A mutation that occurs to a parent with a passing generation serves to modify an agent's *genotype*, a certain programmed attribute of the agent. The favorability of this genotypic change is evaluated according to a "fitness function" to quantify its favorability, yielding an agent's "fitness" metric. Researchers can use this metric to find solutions for specific capabilities. According to the EA, a mutated solution will replace the current solution if it has a higher fitness. This iterative process occurs over each passing generation until the end of evolutionary time, at the end of which the final descendents of all parents are compared, and the most fit is selected.

Genotype and Phenotype In the context of EAs, the genotype and phenotype of a virtual creature are analogous to that of a biological organism. The term "genotype", which refers to the genetic makeup of a biological organism, can describe attributes such as a set of synaptic weights of a neural controller, or the leg lengths of a robot's body. Using an EA, these genotypes can be evolved to achieve optimized components. Furthermore, a genome represents the basic structure that holds the genetic makeup. In the case of a biological organism, it describes the general genes that characterize a *type* of organism. In our analogy, the term describes the matrix that holds a set of synaptic weights, or a vector of a robot's leg lengths with measurements that have yet to be decided. Relatedly, the expression of a genotype is termed "phenotype". For example, an EA that evolves a robot's genotype to select for the ability to jump high can evaluate its fitness by measuring the height of its vertical jump – its phenotype. In this way, the phenotype of an organism is characterized by an agent's behavior.

Fitness Landscape The solution-space that is explored by an EA is known as the fitness landscape. Each genotype is associated with a fitness value such that these two variables can be visualized, typically forming extrema that are traversed as an EA converges on a solution. The visualization of these extrema are formed by graphing fitness as a function of genotype. One important aspect to the fitness landscape is that as an algorithm converges on a solution, it is unknown whether it represents a local or global optimum. A greater amount of evolutionary resources enables an EA more variation between potential solutions, increasing the probability of finding maxima of higher fitnesses.

Robot Swarms

A robot swarm is a group of agents that often work together to accomplish a task. Early work on the topic by Holland and Melhuish (1999) was inspired by social insects. The research looked into the stigmergy and self-organization of robots in homogeneous swarms for a clustering and sorting task. As the applications of such robotic systems continued to be explored, they have become a popular choice of study for a variety of navigation-based applications ranging from object-transport to collective exploration in difficult environments (Schranz, 2020).

However, many of these studies focus on homogeneous swarms, in which each agent is identical. This lack of diversity in the swarm leaves robots susceptible to similar challenges – an obstacle that poses a threat to a single robot can present a hazard to every robot in the swarm. We investigate a possible solution by exploring the potential utilization of heterogeneous swarms for navigating challenging terrain, where the use of multiple robots is taken as a measure of hardware redundancy.

Heterogeneous Swarms A heterogeneous swarm is composed of multiple agents with some amount of diversity between them. This diversity can be expressed in neurological and morphological differences between robots, which are individually determined by their controllers (neurologies) and embodiments (morphologies).

Heterogeneous swarms have been studied to navigate cluttered environments to accomplish various tasks. Praneel Chand (2013) showed that a heterogeneous swarm can be hierarchically arranged such that computationally powerful robots delegate exploration tasks to robots with limited capabilities. In the same vain, Mkhatshwa and Nitschke (2023) showed that neurological-morphological diversity was beneficial in evolving collective behavior for complex tasks. However, collective behavior was a factor that was explored within the scope of this previous work, and it provided swarms an advantage when completing their tasks. In contrast, our research focuses on the potential advantage of heterogeneous robot swarms in navigating a foreign environment outside the scope of collective behavior.

A suitable analog for the type of system we explore is observable through swarms of marine turtle hatchlings. From their nesting sites, they aim for the sea, navigating sand dunes, debris, and predators. Through some degree of natural variation in genetic inheritance and gene expression, the turtles exhibit varying neurological and morphological traits. The journey from nesting site to sea serves as a selection process for the hatchlings, where each hatchling's unique attributes impact its odds of survival. For example, a characteristic like a large morphology, may positively impact a hatchling's ability to survive Janzen (1993). Thus, through genetic variance, some turtles are better equipped to complete their journey successfully. In essence, this variance between turtles serves to hedge nature's bet that at least one of the offspring will survive to continue its lineage and complete the swarm's function of genetic perpetuation. We aim to explore this fundamental framework to bolster the robustness of a swarm of virtual robotic agents.

Methods

Overview

To explore the impact of increasing diversity within a swarm of robots on their ability to navigate a foreign environment, we evolved three types of swarms in a familiar, empty environment, and then deployed them to a foreign, cluttered environment. We examined the fitness data of three types of swarms, which are characterized by their intra-swarm diversity: Case 1) No diversity, Case 2) Neurological diversity, Case 3) Neurological and morphological diversity. The resulting swarms were analyzed to compare their fitnesses post-deployment in a foreign environment. To support our findings, fitness data was also collected on evolved swarms in a familiar environment, and unevolved (random) swarms in a familiar and foreign environment. In each scenario, a total of 55 swarms were collected for each swarm type.

Swarm Design

The swarm size was arbitrarily chosen to include 10 robots, and they were simulated individually to capture the idea that their inter-robot spacing was sufficient to prevent interaction between them and their immediate environments. All robots were embodied using the same quadrupedal morphology except those of Case 3.

Case 1: No Diversity The first swarm we examined was lacking in any diversity. Each swarm of this type was created by evolving 10 controllers, and then assigning the controller of the highest fitness to each of 10 robots.

Case 2: Neurological Diversity The second swarm of interest was composed of robots with varying controllers. Each swarm of this type was created by evolving 10 controllers, and then assigning each to one of the 10 robots.

Case 3: Neurological and Morphological Diversity The third and final swarm was composed of robots with varying controllers and morphologies. Similar to the other heterogeneous swarm, each robot of this swarm type utilized an individually evolved controller. However, robots were also allowed to evolve their morphologies in conjunction with their controllers. The resulting swarm was composed of 10 robots of varying controllers and morphologies.

Controllers The controllers used by our robots were governed by a neural network designed to process tactile sensory input to produce motor command outputs. The neural network establishes fully connected synaptic connections between the input and output layers of neurons, and only consists of one layer. During simulation, the network undergoes updates, where motor neurons compute their values based on incoming signals from synapses, which carry information from the sensor neurons. The value of each neuron is thresholded by the activation function characterized by the hyperbolic tangent (tanh) to the range [-1.0, 1.0]. Each controller relies on 4 sensor neurons and 8 motor neurons.

Morphologies All morphologies used by our robots are based on the same quadrupedal architecture chosen for its simplistic nature. Robots for Case 1 and Case 2 swarm types used a consistent morphology, while robots of the Case 3 swarm type were allowed parametric variance. The general morphology is composed of 9 components, each with a mass of $1.0\mathrm{kg}$. It consists of a central cube-shaped torso, and four two-jointed legs divided into upper and lower sections. Upper and lower leg sections are each connected by a revolute joint. Revolute joints are also used to connect each leg to the torso in radially-symmetric fashion. The joints are all allowed a maximum rotation of $0.8\mathrm{rad}$ relative to their resting positions perpendicular to their connections, and proprioceptors keep track of the joint angles at each time step of the simulation. Lower leg sections each contain a tactile sensor, which yields values of +1 when observing physical contact and -1 otherwise.

For Case 1 and Case 2 robots, the quadruped features legs of dimensions $1.0\mathrm{m}$ x $0.2\mathrm{m}$ x $0.2\mathrm{m}$. For Case 3, the quadruped utilizes leg section lengths constrained within the range of $0.5\mathrm{m}$ to $1.5\mathrm{m}$ instead of $1.0\mathrm{m}$. Screenshots of robots in silico are shown in Figure 3.

Genome The genome design is consistent for Case 1 and Case 2. It only consists of the controller, which is represented by an $N \times M$ matrix of synaptic weights. N and M are representative of the number of sensor neurons and motor neurons, which are 4 and 8 respectively. For the Case 3 swarm, the genome consists of both the controller, and a vector of leg section lengths $\vec{L}$ of size 8.

Evolution For each swarm type, the controller of a robot is evolved for one generation by choosing a single element of the $N \times M$ matrix at random, and mutating the contained synaptic weight to a value defined by the range [-1.0, 1.0). Specifically for Case 3, the morphology of a robot can be evolved for one generation by choosing a single leg section at random, and mutating the contained length within the range of [0.5, 1.5]. For each generation of a Case 3 robot, a choice is made to mutate either the controller or the morphology with equal probability.

To optimize robot genotypes, we used a parallel-hillclimber evolutionary algorithm. 10 random parents were evolved over the course of 75 generations, where the most-fit offspring at the end of evolutionary time was selected according to the following fitness function.

$$f = y \tag{2}$$

Here, y represents the robot's y-displacement relative to its initial position at the origin at the end of simulation-time.

Swarm Performance

After their evolution, evolved genotypes were assigned to robots of their corresponding swarm types and deployed to the familiar or foreign environment for performance evaluation. This was done by calculating swarm fitness as seen in the following equation. F is determined by calculating the maximum of all robot fitnesses f_b within a 10-bot swarm.

$$F = \max\{f_0, f_1, ..., f_9\} \tag{3}$$

Environments

Familiar Environment The familiar environment consisted solely of a plane onto which robots were spawned at the origin. An overview of this environment is depicted as a cartoon in Figure 2, while Figure 3 shows images of it.

Foreign Environment The foreign environment was composed of a plane, onto which a field of obstacles was spawned. Obstacles were cube shaped, with a volume of $0.2\mathrm{m}^3$ and mass of $1.0\mathrm{kg}$. The obstacles were spawned in a grid-like pattern according to their centroids. They were spawned with a spacing of $2\mathrm{m}$ apart at x-coordinates ranging from -$8\mathrm{m}$ to $8\mathrm{m}$, and at y-coordinates ranging from -$10\mathrm{m}$ to $14\mathrm{m}$. It was assumed that the immediate surroundings of each robot were identical, so each robot was spawned at the origin. Obstacles were not spawned if their position was within $0.2m$ of a robot to prevent potential spawn overlap. As with the familiar environment, the foreign environment is depicted in Figure 2, and Figure 3.

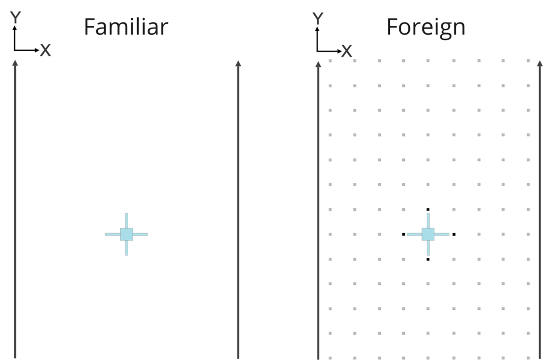


Figure 2: **Cartoon of familiar (left) and foreign (right) environments.** A Case 1 / Case 2 quadruped robot is present at its initial position at (0,0) for illustrative purposes. An obstacle is situated underneath the robot at coordinates (0,0) (not visible). The black-filled squares represent the obstacles that may not spawn into the environment in the event that they are too close to mutated leg of a Case 3 robot. The black bordering arrows represent the direction in which the robot attempts to locomote (y-direction).

Simulation

All simulation was done via PyBullet, an open-source 3D physics engine that is popular in the field of robotics for its capability to simulate robotic systems (Coumans and Bai, 2021). In addition, the simulations utilize Pyrosim, a robotics simulator developed by Bongard (2022) to facilitate the construction of robot bodies, their environments, and the communication between PyBullet and the robot's neural network. Small alterations were made in order to allow robot sensors to acknowledge their interaction with obstacles in the foreign environment. Each simulation consisted of 1000 timesteps, with a downward acceleration due to gravity of $9.8\frac{\mathrm{m}}{\mathrm{s}^2}$. Default PyBullet physics engine parameters were used, with the exception of the use of 500 solver iterations. Each step of the simulation consisted of three key stages performed in a closed loop: *sense*, *think*, and *act*. Thus, each step informs the subsequent step.

The *sense* stage updates the robot's physical state by reading in tactile sensory data from its four lower leg sensors.

Next, in the *think* stage, the sensor data is collected by the input neurons, where they are updated. Their new values were then sent through the neural network. Output neurons then calculate new target angles for each of the robot's joints. The formula used in this calculation can be viewed in Equation 1.

Finally, in the act state, the robot's joints move according to the activation of their corresponding motor neuron. A robot joint exerts a force that is proportional in magnitude to the difference between its current angle and desired angle. The maximum force possible was set to $50N$.

As the *sense*, *think*, *act* loop iterates, it results in the robot's movement. At the end of simulation time, the resulting y-displacement of the robot is utilized as its fitness, which is saved for subsequent analysis. An example of the trajectories of movement for each swarm type are shown in Figure 4.

Results

Swarm Fitness in a Foreign Environment

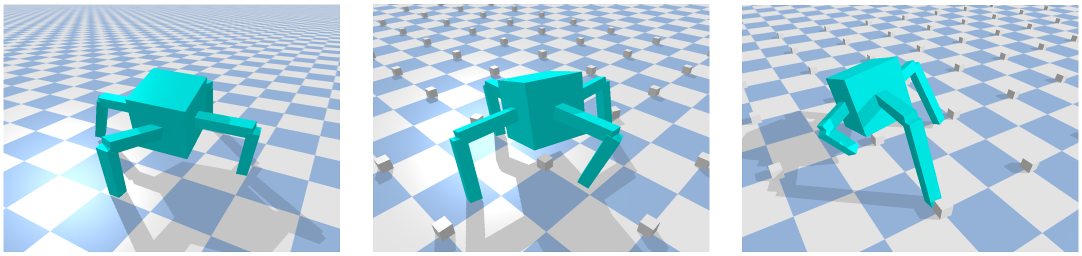
Swarm Comparison	Evolutionary Resources (P x G)	Environment	p-value
Case 1 vs. Case 3	10 x 75	Foreign	3.024e-13
Case 2 vs. Case 3	10 x 75	Foreign	5.375e-04

Table 1: **Statistical comparisons of mean swarm fitness between swarm types within the foreign environment.** Each robot of a swarm utilized 10 parents and 75 generations for its evolution. Swarm fitnesses were averaged over 55 trials. Each comparison revealed a statistically significant difference using a Mann-Whitney U test ($\alpha = 0.025$).

From the data presented in Figure 5 and Table 1, we found that swarms of neurological and morphological diversity showed a higher mean swarm fitness in the foreign environment than those of no diversity, and those of solely neurological diversity ($p < 0.025$).

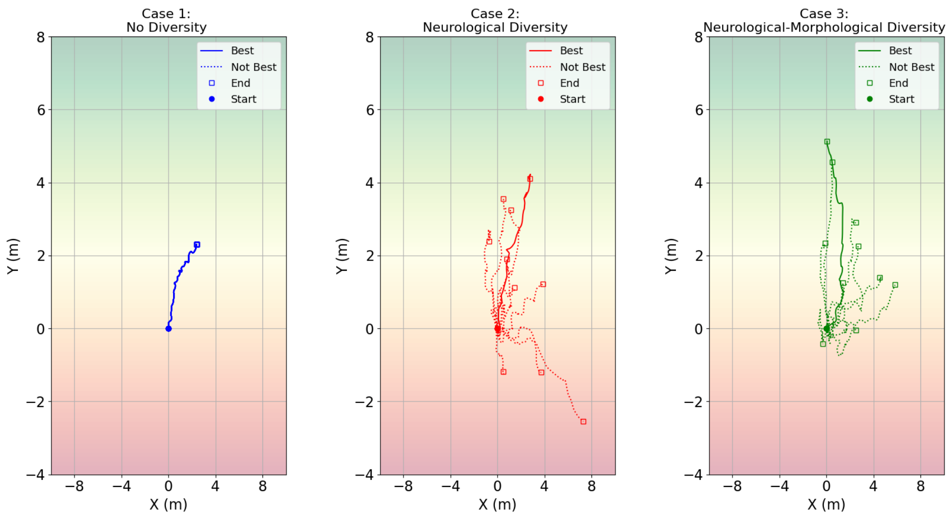
Assessment of Environmental Rigor

To substantiate the validity of our findings, we demonstrated that the swarms faced significant hindrances by the obstacles in the foreign environment by contrasting their performance with that in the empty, familiar environment. Figure 6 and Table 2 show that the mean swarm fitness was significantly



(a) (b) (c)

Figure 3: **Screenshots of robots in simulation.** **(a)** shows a Case 1/Case 2 robot in the familiar environment. **(b)** shows a Case 1/Case 2 robot in the foreign environment. **(c)** shows a Case 3 robot in the foreign environment.



(a) (b) (c)

Figure 4: **Trajectory plots of each swarm type in the foreign environment.** Each plot shows the trajectories of a single swarm. Data was collected from individual simulations, and are superimposed for visualization. All robots start at position (0,0), denoted by a colored circle. An empty square indicates a robot's final position at the end of its simulation. The background is colored from red to green to indicate the direction of favorable locomotion (y-direction). The robot of a swarm with the largest y-displacement is denoted by a solid line, and all other trajectories are plotted with a dotted line.

higher in an empty environment than in our foreign one for each swarm type ($p < 0.05$).

Assessment Of Sufficient Evolutionary Resources

Finally, Figure 7 and Table 3 show that the robots were all evolved with sufficient evolutionary resources such that their mean swarm fitness would be significantly greater than those of unevolved (random) swarms in the foreign environment ($p < 0.05$). Providing the robots within the swarms with sufficient evolutionary resources to do this serves the purpose of benchmarking their performance such that swarms are compared under the notion that they can all successfully navigate the foreign environment.

Swarm Comparison	Evolutionary Resources (P x G)	p-value
Case 1 (Foreign) vs. Case 1 (Familiar)	10 x 75	1.176e-08
Case 2 (Foreign) vs. Case 2 (Familiar)	10 x 75	1.257e-15
Case 3 (Foreign) vs. Case 3 (Familiar)	10 x 75	2.471e-15

Table 2: **Statistical comparisons of mean swarm fitness for evolved swarms of the same type within the foreign versus familiar environment.** Each robot of a swarm utilized 10 parents and 75 generations for its evolution. Swarm fitnesses were averaged over 55 trials. Each comparison shows a statistically significant difference using a Mann-Whitney U test ($\alpha = 0.05$)

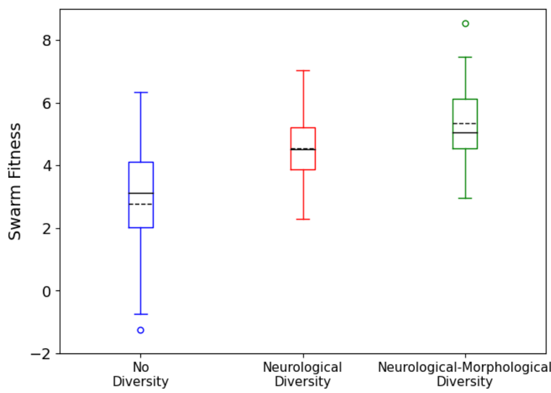


Figure 5: **Boxplots comparing fitnesses of different swarm types for evolved swarms within the foreign environment.** The black dotted line indicates the mean, and the black solid line indicates the median. Each robot of a swarm utilized 10 parents and 75 generations for its evolution. Swarm fitnesses were averaged over 55 trials.

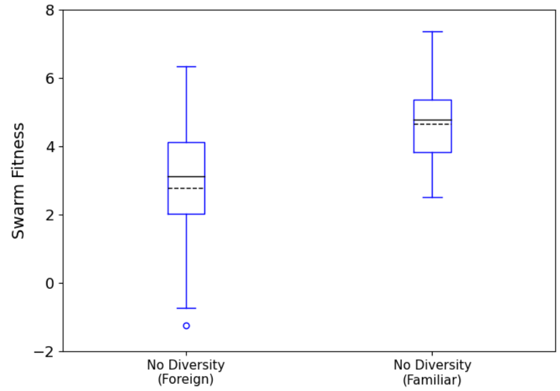
Swarm Comparison	Environment	p-value
Case 1 (Evolved) vs. Case 1 (Random)	Foreign	4.206e-08
Case 2 (Evolved) vs. Case 2 (Random)	Foreign	6.835e-19
Case 3 (Evolved) vs. Case 3 (Random)	Foreign	2.195e-19

Table 3: **Statistical comparisons of mean swarm fitness for evolved versus random swarms of the same type within the foreign environment.** Each robot of an evolved swarm utilized 10 parents and 75 generations while robots of a random swarm utilized 1 parent and 0 generations. Swarm fitnesses were averaged over 55 trials. Each comparison revealed a statistically significant difference using a Mann-Whitney U test ($\alpha = 0.05$).

Discussion

In this paper, we outlined a method for evaluating the fitness of robot swarms. We then applied it to assess the performance of three types of robot swarms with varying intra-swarm diversity in a foreign environment post-evolution. Our results indicate that the swarms with both neurological and morphological diversity were more robust to the foreign environment than those with only neurological diversity, and those with no diversity at all.

While these findings support our hypothesis, a direct explanation as to why neurological and morphological diversity was correlated with greater swarm robustness was not established. One possible explanation could be that the introduction of inter-robot differences increased the variance of inter-robot fitnesses. Since our metric for swarm fitness chooses the maximum fitness of all robots in a swarm, they can benefit from increased variance without being negatively impacted at all. This would account for the statistically significant differences in mean swarm fitness between Case 1



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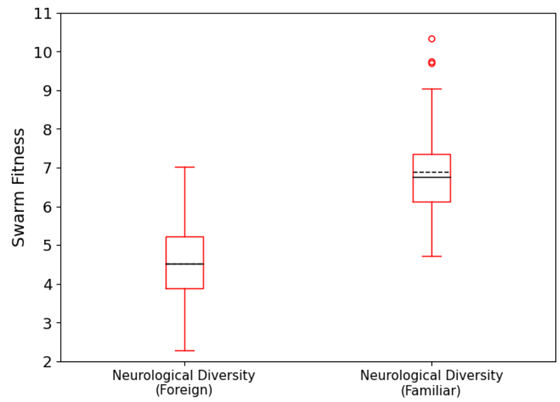

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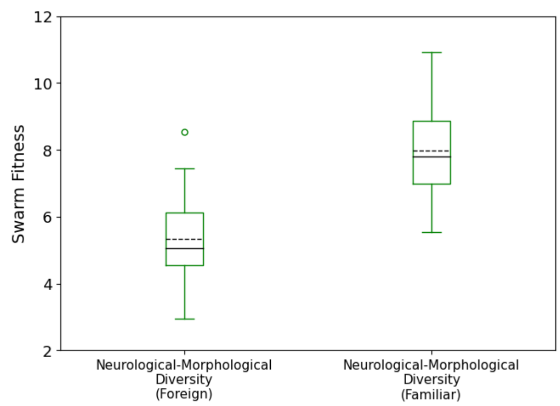
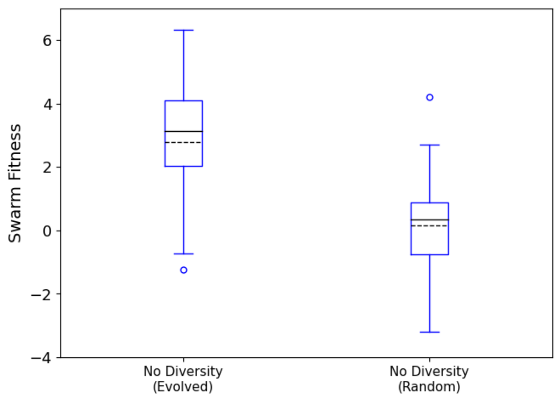


(c)

Figure 6: **Boxplots comparing the fitnesses of evolved swarms of the same type in the foreign versus familiar environment.** The black dotted line indicates the mean, and the black solid line indicates the median. Each robot utilized 10 parents and 75 generations for its evolution. Swarm fitnesses were averaged over 55 trials. Figures **(a)**, **(b)**, and **(c)** represent the comparisons for Case 1, Case 2, and Case 3 respectively. Each comparison shows a statistically significant difference.



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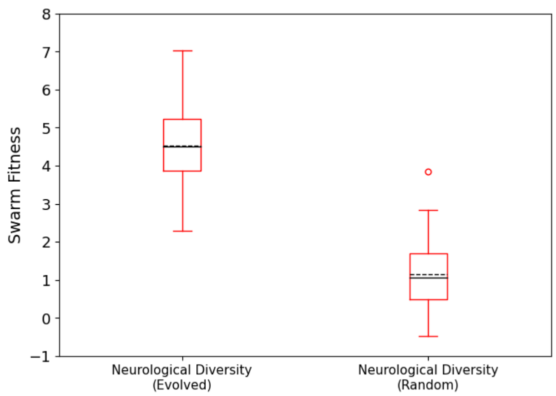

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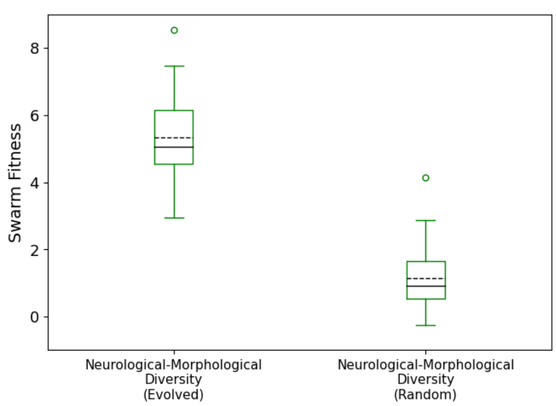

(c)

Figure 7: **Boxplots comparing the fitnesses of evolved versus random swarms of the same type in the foreign environment.** The black dotted line indicates the mean, and the black solid line indicates the median. Each robot utilized 10 parents and 75 generations for its evolution. Swarm fitnesses were averaged over 55 trials. Figures **(a)**, **(b)**, and **(c)** represent the comparisons for Case 1, Case 2, and Case 3 respectively. Each comparison shows a statistically significant difference.

and Case 3, and between Case 2 and Case 3. Furthermore, it would also explain why Case 3 showed a larger difference in mean swarm fitness when compared to Case 1 than to Case 2, as the difference in capacity for inter-robot differences is greater between Case 1 and Case 3 than between Case 2 and Case 3.

Notably, we did not explore the swarm type of solely morphological diversity. This was because we could not choose a random controller to hold constant for this swarm type, as it would have been difficult to know if it provided a reasonable neurology onto which morphology could be evolved. We could also not evolve the controller of a given morphology to then remain constant, because it would bias subsequent morphological evolution towards the morphology of the body in which the controller was evolved.

Overall, the results obtained here were expected, and it aligns with the findings of a similarly motivated study done by Mkhatshwa and Nitschke (2023), who found that neurological-morphological diversity in robot swarms was beneficial in evolving collective behavior across complex task environments. However, collective behavior was a factor that was explored within the scope of their study, and it played a role in the swarms' ability to complete tasks. In contrast, our research suggests that neurological-morphological diversity offers an advantage for swarms outside the scope of collective behavior.

Nevertheless, further exploration would be useful in uncovering the extent to which our results hold. One suggestion for future work would be to randomly vary obstacle size and placement in the foreign environment to confirm that swarms of neurological-morphological diversity remain superior in foreign environments that are different from the one studied here. In addition, our experiments could be altered to further explore the fitness landscape of morphological evolution, and to determine if experiments involving base morphologies outside of quadrupedal robots result in consistent findings.

It has been established by previous work that intra-swarm diversity offers enhancements to robot swarms in certain contexts. In particular, recent investigation has suggested that neurological and morphological diversity offers advantages in complex gathering tasks. However, there are a lack of studies that analyze swarms with varying degrees of diversity in navigating unknown environments. The environments of interest may contain a myriad of challenges for robot swarms to overcome, necessitating exploration into solutions for their navigation. In such challenging environments, our results suggest that neurological and morphological intra-swarm diversity provides a potential solution.

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