The Impact of Morphological Diversity in Robot Swarms

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ABSTRACT

In nature, morphological diversity enhances functional diversity, however, there is little swarm (collective) robotics research on the impact of morphological and behavioral (body-brain) diversity that emerges in response to changing environments. This study investigates the impact of increasingly complex task environments on the artificial evolution of body-brain diversity in simulated robot swarms. We investigate whether increasing task environment complexity (collective behavior tasks requiring increasing degrees of cooperative behavior) mandates concurrent increases in behavioral, morphological, or coupled increases in body-brain diversity in robotic swarms. Experiments compared three variants of collective behavior evolution across increasingly complex task environments: two behavioral diversity maintenance variants and body-brain diversity maintenance. Results indicate that body-brain diversity maintenance yielded a significantly higher behavioral and morphological diversity in evolved swarms overall, which was beneficial in the most complex task environment.

CCS CONCEPTS

• **Computing methodologies → Evolutionary robotics**.

KEYWORDS

Evolutionary Swarm Robotics, Morphology-Behavior Diversity

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1 INTRODUCTION

Social insect societies are biological hallmarks of self-organization and decentralized control [50], where complex interactions between evolving organism behavior, morphology, and environment, have resulted in the emergence of complex and diverse forms of sociality [16, 23]. Similarly, in artificial social systems such as swarm robotics, various forms of collective behavior arise from coupled dynamics between a robot's morphology (sensory-motor configuration), behavior (controller output) and environment (task) [8]. One perspective is that an agent's morphological and behavioral complexity must match its environment complexity [55]. However, with varying examples in biology [36], it remains an open question as to whether more complex task environments require agents with more complex behaviors and morphologies [13, 48, 67].

Studies on artificial morphology-behavior (body-brain) evolution using simulated [12, 29] and physical [48, 67] evolutionary robotics platforms have received significant research attention [15]. However, work investigating the impact of body-brain adaptation in collective (swarm) robotic systems is less prevalent [10, 20, 24], most likely due to the complexity of meaningfully distilling relationships between genotype (body-brain encodings) and phenotype plasticity (body-brain couplings) from emergent collective behaviors [43]. In this context, *phenotypic plasticity* refers to a single genotype producing multiple morphology-behavior couplings in response to environmental conditions [28, 58, 65, 66].

Even though previous evolutionary robotics work [5, 29] has demonstrated the importance of morphological adaptation (driven by phenotypic plasticity) for increasing the robustness of adapted behaviors, studies of how emergent morphological diversity impacts evolving swarm-robotic behavior has received little research attention [25]. Though, examples include self-assembly swarm robotics systems comprising many individual functionally simple robots that physically attach to each other [6, 34, 42] such as proof-of-concept demonstrations using hundreds of *Kilobots* [11, 56, 59], a *mergeable* nervous system [35] and a *group mind* [49], where swarm-robotic behaviors emerge from self-organising neural controllers interconnecting across hundreds of robots. Other examples include *multi-robot organisms* [32] that adapt morphology via self-organizing into various problem-solving forms, for example via evolving functional specialization in various interacting body-parts [2]. Within collective robotics (smaller swarm sizes), desired group behaviors have been evolved via morphological adaptation that switches sensors on and off, such that robots adapt to complementary sensory configurations [20, 24, 64]. Furthermore, while previous evolutionary robotics work [3, 37, 38, 60] has also studied the impact of the environment on body-brain co-evolution, there have been few studies that investigate environmental impact on body-brain evolution in swarm-robotics [21, 45, 46]. Existing studies on phenotypic plasticity in evolutionary swarm robotics is divisible into two categories. First, where robot morphologies are fixed and only controllers evolve and second, where each robot's controller and morphology is coupled and evolved [15]. Using fixed morphologies, there are few studies demonstrating that diverse environments conceivably produce diverse behaviors [17, 18].

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Otherwise, evolutionary swarm robotics work with evolvable coupled controllers and morphologies is scarce and limited in scope [52], where there is also a lack of studies on the impact of environment (task) complexity on phenotypic plasticity. Typically, experimenters set a specific environment and task and evolve robots for the given combination. For example, most swarm-robotics studies that include the task environment as an experimental parameter, evolve behavioral diversity using predefined morphologies to solve various collective behavior tasks [9, 18, 47, 61, 63]. This study is also motivated by the notion that morphological diversity enhances the overall problem-solving efficacy of swarm (collective) behaviors as observed in social insect colonies [19]. For example, different workers with different body shapes and sizes are more effective at solving particular tasks, boosting the robustness of collective behavior overall [26]. We thus hypothesize that morphological diversity within robotic swarms elicits similar benefits.

To investigate this we extend evolutionary swarm robotics research [62], that applies decentralized Quality Diversity [54] (QD) methods to evolve functional diversity (behavioral specialization [9]) across simulated swarms without requiring geographical isolation or division of labor mechanisms [22].

Our work applies three QD methods to evolve swarm behavior across increasingly complex cooperative tasks. First, behavior evolution with behavioral diversity maintenance, second, behavior and morphology evolution with behavioral diversity maintenance, and third, behavior and morphology with behavior-morphology diversity maintenance. The goal is to find the most suitable swarm controller design methods for the given task environments and thus gain insight into environmental impact on evolving behavioral and morphological diversity and the (task performance) benefits of such diversity. Specifically: *Is behavioral and morphological diversity beneficial for evolving collective behavior across increasingly complex task environments, where task complexity is the cooperation (between individual robots) required to achieve optimal performance.*

This question is also motivated by lack of behavior-diversity maintenance methods to automate body-brain design for swarm-robotics (collective behavior) tasks, where previous research has demonstrated the benefits of behavior-diversity maintenance [14, 27, 30, 31, 54]. We present the EDQD, EDQD-M and Double-Map EDQD-M methods (section 2), which hybridize the *MAP-Elites* [44] and *minimal Environment-driven Distributed Evolutionary Adaptation* (mEDEA) [7] methods, enabling swarm behavior evolution with behavioral diversity maintenance, behavior and morphology with behavioral diversity maintenance, and behavior and morphology with behavior-morphology diversity maintenance, respectively. The efficacy of Double-Map EDQD-M, EDQD-M and EDQD is compared with respect to collective behavior task performance, behavioral and morphological diversity elicited across increasingly complex task environments (section 3). The study's main contribution is the demonstrated effectiveness of the Double-Map EDQD-M method for evolving beneficial swarm behavior and morphologies across increasing task environment complexity.

2 METHODS

This study evaluates the EDQD (*Environment Driven Quality Diversity*) method [62] and also develops two extensions to EDQD in order to evaluate swarm-robotic controller and morphology evolution using a custom evolutionary embodied collective robotics simulator[1]. The two derivative methods developed were named: EDQD-M (robot morphology adaptation) and Double-Map EDQD-M (coupled robot behavior-morphology adaptation). We chose to extend the EDQD method as it has already been demonstrated for successfully evolving behaviorally diverse robot swarms without requiring explicit mechanisms for genotypic (reproductive) isolation or division of labor [62], and has not been tested on increasingly complex collective (swarm) behavior task environments.

2.1 Robot Controllers

Extending previous work [62], robots explore the environment for their *lifetime* duration (table 2), using *Artificial Neural Network* (ANN) controller behavior, where ANN behavior is adapted by either EDQD, EDQD-M or Double-Map EDQD-M (sections 2.2, 2.3, 2.4). Each robot in the swarm used the same controller topology, a fully connected feed-forward ANN comprising 33 sensory input nodes (proximity, color, target-area detection), a 20 node hidden layer, and 2 motor output nodes (table 2). Consistent with previous work [7, 62], all nodes in the ANN used Sigmoidal activation units. The two ANN outputs were the rotational and translational speed of each robot (normalised to the range: [0, 1]) at each simulation (robot lifetime) iteration. The sensory input nodes corresponded to three forward-facing proximity sensors, one backward-facing proximity sensor, and a bottom-facing target area detection sensor (constantly active). Proximity sensors were primed to detect the closest object in the environment, that is where the closer an object is to the robot, the higher the sensor activation value (normalised to the range: [0, 1]). For each forward and backward-facing proximity sensor, there were seven object type (color) detection sensors that would activate to discriminate between the colors of five resource types, walls and other robots (table 2). Thus the periphery of the robot comprised four sensor sets (each containing eight sensors), and one downward-facing target-area detection sensor, where these 33 sensors corresponded to the ANN input layer. The controller genotype adapted by EDQD, EDQD-M, or Double-Map EDQD-M thus comprised 700 connection weights. Specifically, 33 input nodes fully connected to 20 hidden nodes (33x20 connections), which in turn were fully connected to two output nodes (20x2 connections).

2.2 EDQD

The EDQD method hybridizes the MAP-Elites [44] and *minimal Environment-driven Distributed Evolutionary Adaptation* (mEDEA) [7] methods. EDQD, as in previous work [7], uses a fitness mechanism [51] to regulate the trade-off between fitness function exploitation and environmental exploration (in this study, collective gathering task behaviors). Differing from previous work [62], as robots explore their environment they periodically *broadcast* (table 2), their behavioral map which is received and stored by all robots within broadcast range. Such robot behavioral maps are termed *LocalMaps* (figure 1, left), and contain a list of the fittest genotypes

[1]The swarm-robotic simulator is available at: https://github.com/einstein07/AUTOFAC

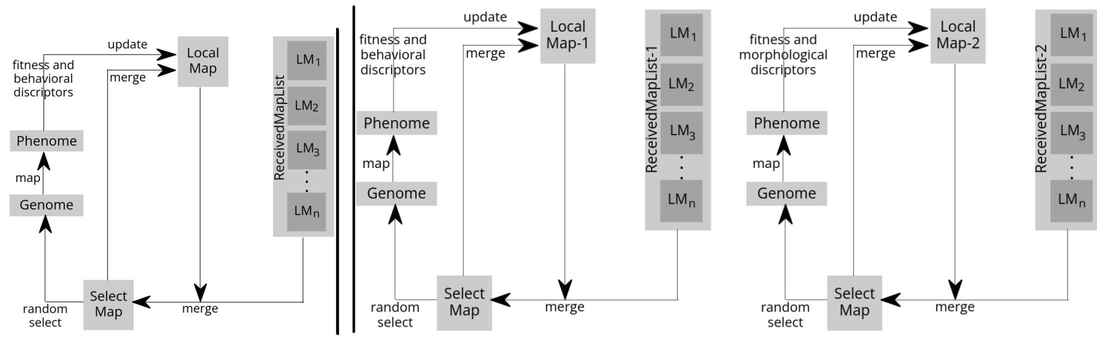

FIGURE 1. Left: *EDQD*: Each generation, a random genotype (controller encoding) is selected from *SelectMap* – merging the *ReceivedMapList* with the robot's *LocalMap*. Right: *Double-Map EDQD-M*: Robots maintain two *LocalMaps*. *LocalMap-1* is associated with behavior feature descriptors, *LocalMap-2* is associated with morphology feature descriptors.

(*genome*, figure 1, left) corresponding to specific robot behaviors (*phenome*, figure 1, left) previously evaluated for each robot. At the end of each robot's current *lifetime* (table 2), a genotype is randomly selected from the *SelectMap* (which is formed by merging the received maps with the robot's own *LocalMap*, figure 1, left), and a mutation operator (table 2) is applied to produce a new genotype which replaces the currently active genotype (robot behavior). Applying EDQD to our swarm, robots store a 2D behavior map (*LocalMap*, figure 1, left) defined by given behavioral dimensions of the collective gathering task (section 3). Specifically, resource type collected (table 2), and maximum Euclidean distance traversed by each robot (during its lifetime). The EDQD method and its extensions: *EDQD-M* and *Double-Map EDQD-M*, thus leveraged these behavioral dimensions to promote the evolution of behavioral diversity in terms of resource types collected and environment exploration.

2.3 EDQD-M

EDQD-M extends EDQD to enable morphological (sensor), in company with behavioral (controller), adaptation for each robot. Specifically, at the end of each generation, a random sensor type is selected to undergo mutation. The mutation operator reduces the range of a randomly selected sensor until it reaches a given *sensor-morpho* threshold (table 2). Once the range falls below this threshold then the given sensor becomes inactive, where sensor inactivity is realised by an input of zero to the corresponding ANN sensory input node. Similarly, if the mutation operator causes the sensor range to exceed the *sensor-morpho* threshold, then an inactive sensor will reactivate, reinstating the previous non-zero connection weight value for the given ANN sensory input node. Note that the bottom-facing target-area detection sensor (section 2.1) is excluded from morphological adaptation since robots must still be able to detect the target area and complete their task. The swarm is morphologically homogeneous meaning the same sensor adaptations (sensors switched on and off) are concurrently applied to all robots. Otherwise, the EDQD-M controller adaptation process using the *LocalMap* is identical to EDQD (section 2.2, figure 1, left).

2.4 Double-Map EDQD-M

Double-Map EDQD-M extends EDQD to enable co-adaptation of a robot's morphology and behavior. Double-Map EDQD-M thus uses two *LocalMaps*, where the first *LocalMap* is associated with controller (behavior) related feature descriptors, and the second *LocalMap* is associated with sensor (morphology) feature descriptors. This second map is also defined by two (morphological) dimensions, first the *ratio* of *active* sensor types, and second, the average *range* of *active* sensors. As in EDQD and EDQD-M, at each generation of the evolutionary process, parent genotypes are selected from each *SelectMap*, to undergo mutation (figure 1, right). The resulting offspring genotypes replace the robot's current active behavior (controller) and morphology (sensory configuration). However, the selected morphology determines the corresponding controller, in order that robot behavior and morphology are suitably matched. Hence, a selected morphology comprising A active and B inactive sensors, automatically re-configures the selected ANN controller so as A sensory input nodes are active and B are inactive. As in EDQD-M (section 2.3), ANN connection weights remain active, where robot sensory configuration (morphology) is adapted via switching specific sensors on and off, and zero values are input to ANN inputs corresponding to switched off sensors. Double-Map EDQD-M thus adapts both *LocalMaps* of each robot to encourage behavioral and morphological diversity. This differs from EDQD and EDQD-M, in that two maps are concurrently maintained and adapted, where both robot behavior and morphology are subject to diversity maintenance. Whereas, EDQD and EDQD-M, only accounted for behavioral diversity maintenance, and sensor adaptation in EDQD-M was not subject to morphological diversity maintenance.

3 EXPERIMENTS

Experiments were conducted using a collective gathering task simulation implemented on *RoboGen* [1]. Experiments evaluate the benefits of behavioral and morphological diversity in a robot swarm to solve increasingly difficult collective gathering tasks (section 1), where task difficulty is tuned by the number of robots required to cooperatively transport a resource (table 2). Each experiment compared the EDQD, EDQD-M, and Double-Map EDQD (sections 2.2, 2.3, 2.4) methods to adapt swarm behavior with behavioral diversity maintenance, behavior and morphology (with behavioral diversity maintenance), and behavior and morphology (with behavior-morphology diversity maintenance), respectively (table 1). For each experiment, a swarm of 100 robots and 50 resources were initialised

TABLE 1. Parameters for robot artificial neural network controllers adapted by Map-Elites component of EDQD, EDQD-M, Double-Map EDQD-M swarm behavior-morphology adaptation methods.

Sensory input nodes	25
Hidden layer nodes	20
Motor output nodes	2
Node activation function	Sigmoidal
Sensory input-Motor output weight range	[0.0, 1.0]
Neuron weight range	[-400, +400]
Mutation operator	Gaussian (tuned σ) [62]
Sigma range	[0.001, 0.5]
Update sigma step	0.35
Mutation probability	0.34
Sensor-morpho threshold	0 ($\leq$0: Sensor inactive; >0: Sensor active)
Map archive size	100
Number of dimensions per (behavior, morphology) map	2
Number of intervals per map-dimension	10

TABLE 2. Experiment parameters for EDQD, EDQD-M and Double-Map EDQD-M methods (applied to adapt swarm behavior-morphology) and Collective gathering task (evaluating swarm adaptation methods) parameters.

Resource-types (size: x, y, z: meters)	A	0.08 x 0.08 x 0.08
	B	0.50 x 0.50 x 0.08
	C	0.8 x 0.8 x 0.08
	D	1.0 x 1.0 x 0.08
	E	1.2 x 1.2 x 0.08
Sensor types: Range	Infrared Proximity	[0.0, 1.0]
	Color	[0.0, 1.0]
	Target-area detector	Bottom facing
Task environments (Resource types: A, B, C, D, E)	1: Simple	30, 5, 5, 5, 5
	2: Medium	10, 10, 10, 10, 10
	3: Difficult	5, 5, 5, 5, 30
Cooperation needed to move resource type	A	1 robot
	B	2 robots
	C	3 robots
	D	4 robots
	E	5 robots
Run length (per experiment)	100 generations	
Robot lifetime	10 000 (simulation iterations)	
Swarm size	100 robots	
Wait for assistance time (cooperative resource-pushing)	Remaining lifetime	
Initial robot & block position	Random (Outside target-area)	
Environment size | Target-area size (meters)	20 x 20 | 20 x 2	
Robot *LocalMap* broadcast range	Target-area size	
Robot *LocalMap* broadcast frequency	1 (per lifetime)	

in random positions and orientations in a 3D environment (*simple*, *medium* and *difficult* task environments, table 2). Robots and resources were initialized outside a *target-area* (where gathered resources were delivered to). The collective gathering task used to evaluate EDQD, EDQD-M, and Double-Map EDQD-M, entailed running the swarm for one *lifetime* (10000 simulation iterations), for 100 generations, where each generation represented a lifetime (table 2). At the beginning of each run, robots and resources were re-initialized in new random positions and orientations. The collective gathering task required robots to explore the environment, locate resources, and cooperatively move found resources to the target-area. Each resource type (A, B, C, D, E) was distinguished by its geometric size and thus required varying degrees of cooperation for robots to move to the target-area (table 2). For EDQD, EDQD-M and Double-Map EDQD-M, average (over 20 runs) swarm task performance (*quality*) was the portion of resources pushed into the target-area for all swarm lifetimes (per run: 100 generations). Average behavior quality was normalised to: [0.0, 1.0] (section 4.3).

Also, for EDQD, EDQD-M, we calculate the behavioral diversity as the number of distinct behaviors (occupied cells in the swarm's *LocalMap*) at the end of each run (100 generations). Average swarm

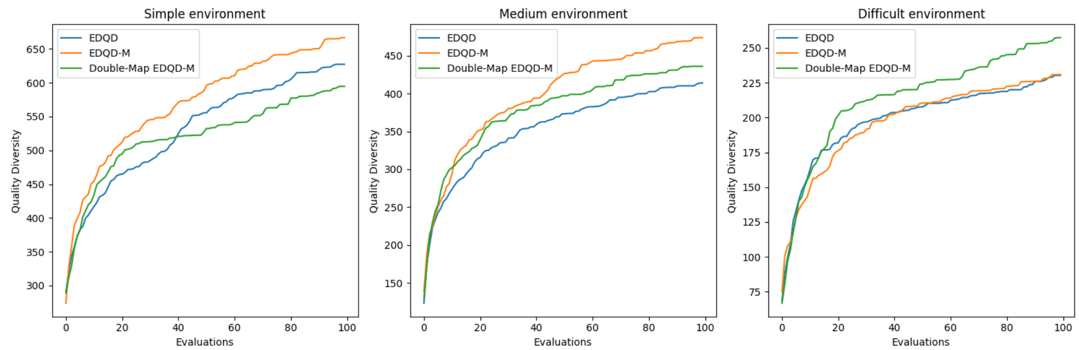

FIGURE 2. Average Quality-Diversity (QD) score calculated from EDQD, EDQD-M and Double-Map EDQD final (end of each run) behavior-maps for swarms evolved in *simple*, *medium* and *difficult* environments.

behavioral diversity is then taken over 20 runs of EDQD and EDQD-M (section 4.1). Additionally, for Double-Map EDQD-M, we calculate a swarm's average morphological diversity (over 20 runs) as the number of distinct morphologies (occupied cells in the swarm's second map) at the end of each run (section 4.2). To be consistent with previous work [53], we also calculate the average (over 20 runs) *Quality-Diversity* (QD) score for behaviors evolved by EDQD, EDQD-M and Double-Map EDQD-M. Since EDQD used fixed robot morphologies, we calculated the QD score for behavior maps only (EDQD, EDQD-M, and Double-Map EDQD-M, section 4.3).

4 RESULTS AND DISCUSSION

4.1 Quality-Diversity (QD) of Evolved Behaviors

Figure 3 (right) presents the average (over 20 runs) number of unique behaviors in the swarm discovered per experiment. This was calculated as the number of occupied cells in the *LocalMap* per run (for EDQD, EDQD-M, and Double-Map EDQD-M). Statistical tests (Mann-Whitney U-tests [33]) indicate no statistical significance ($p \geq 0.025$) between the methods in the *simple* environment. Both EDQD-M and Double-Map EDQD-M outperform EDQD in the *medium* environment ($p < 0.025$), with no statistical difference between EDQD-M and Double-Map EDQD-M. Double-Map EDQD-M outperforms the other methods in the *difficult* environment, with no statistical difference between EDQD and EDQD-M. QD behavioral maps (figures 4, 5, 6) evolved by the highest performing swarm at the end of each run (table 2), provided an indication of the swarm behavior and the quality of such behaviors, for gathering each resource type in each task environment. Swarm behavior (and thus diversity) was measured as the *distance traversed*, and portion of each *resource type gathered* (transported) to the target-area (in one robot lifetime, table 2). For each resource type, per environment, the average distance traversed (exploration behavior) has an associated average task performance. Such QD maps thus provide an indication of how effective evolved gathering behaviors are for varying task difficulty (simple, medium, difficult).

In the *difficult* environment, swarms evolved by all methods (figure 6), explore a low to medium distance (range: [0.05, 0.55]) and gather relatively low portions of type C, D, and E resources (range: [0.0, 0.2]), while a relatively higher portion of type A and B resources (range: [0.10, 0.95]) are gathered. Such swarms elicit a diverse behavior overall (exploring up to 55% of the environment, gathering each resource type), where the highest quality swarm behavior was in gathering resource types A and B (requiring no and two robot cooperation, table 2). A high quality-diversity was especially evident for Double-Map EDQD-M (figure 6, right), where the distance range explored for type A and B resources was: [0.35, 0.55], and resource types A and B gathered was: [0.65, 0.95]. Comparatively, for resource types A and B, EDQD and EDQD-M evolved swarms yielded a quality range: [0.10, 0.60] for an explored area: [0.05, 0.45]. The behavioral diversity of Double-Map EDQD-M evolved swarms is also evident in figure 3 (right), where a significantly (Mann-Whitney U, $p<0.025$) higher average behavioral diversity was calculated in comparison to EDQD and EDQD-M evolved swarms for the *difficult* environment. The capability of Double-Map EDQD-M for evolving diverse behaviors effective in the *difficult* (versus *simple* and *medium*) environments is also supported by no significant difference (Mann-Whitney U, $p>0.025$) between behavioral diversity of EDQD, EDQD-M, and Double-Map EDQD-M evolved swarms in the simple and medium environments (figure 3, right). This is supported by QD maps for *simple* and *medium* task environments (figures 4, 5). In simple and medium environments, evolved swarms explored environment portions in the range [0.05, 0.95], with type A and B resources gathered (range: [0.1, 0.95]), and type C, D, and E resources gathered (range: [0.05, 0.65]).

4.2 Quality-Diversity of Evolved Morphologies

Given that EDQD and EDQD-M did not include explicit morphological diversity maintenance mechanisms, the average morphological diversity of Double-Map EDQD-M evolved swarms was significantly higher (Mann-Whitney U, $p<0.025$) than EDQD and EDQD-M evolved swarms (figures 7, 8, 9). However, the efficacy of Double-Map EDQD-M, for evolving morphological diversity yielding high-quality swarm behavior was evidenced for all task environments. That is, Double-Map EDQD-M evolved swarms elicited average active sensor portions and ranges from 0.1 to 1.0. The highest quality (>90%) was yielded for 65-95% sensor activity with sensors operating between 85% and 100% of maximum range (figures 7, 8, 9, right). Verifying Double-Map EQDD-M evolved sensor

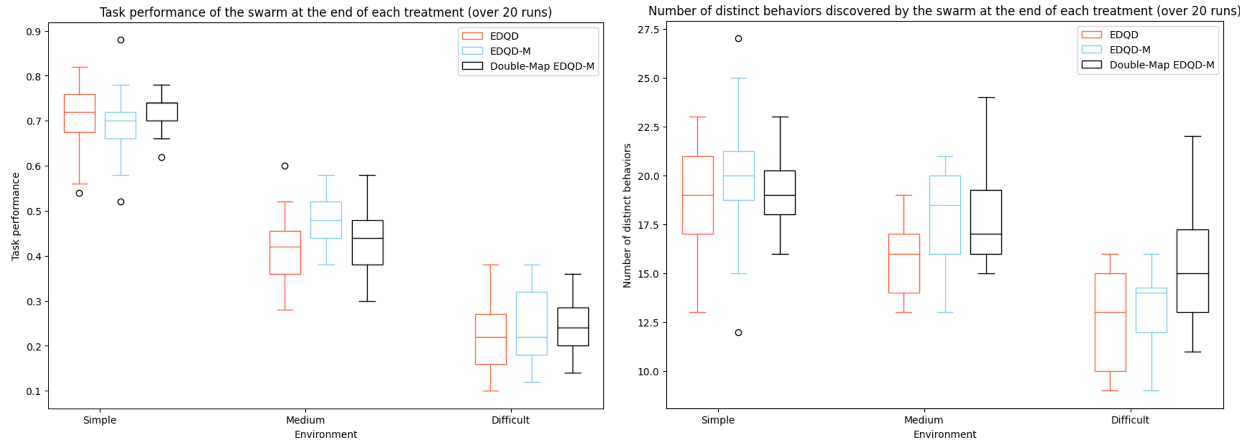

Figure 3. Left: Average task performance (quality) for swarms evolved by each method per environment. Right: Average behavioral diversity of swarms evolved by each method per environment.

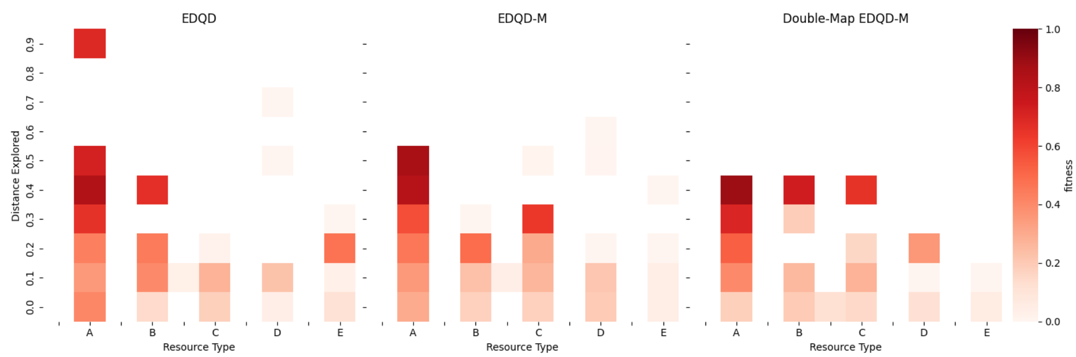

Figure 4. Quality-diversity of evolved behaviors in the *simple* task environment. *Quality* is swarm task performance. Behavioral *diversity* is the portion of environment explored to gather each resource type.

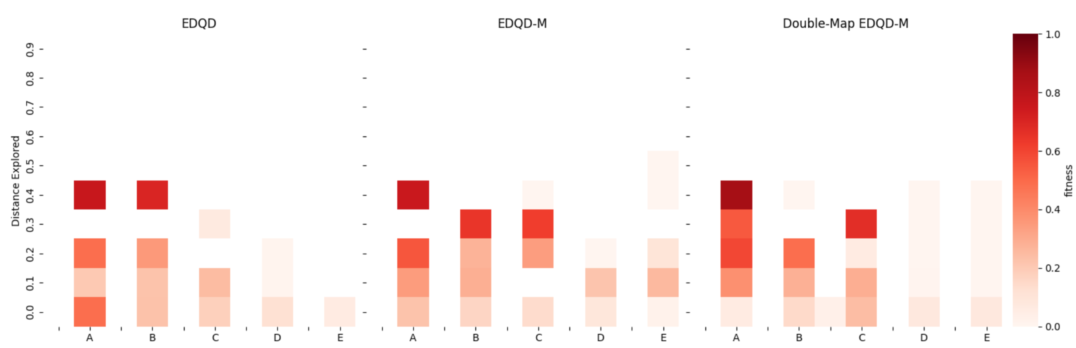

Figure 5. Quality-diversity of evolved behaviors in the *medium* task environment. *Quality* is swarm task performance. Behavioral *diversity* is the portion of environment explored to gather each resource type.

activity and ranges enabled effective swarm behaviors, comparable morphological diversity was observed in EDQD-M evolved swarms in all environments (figures 7, 8, 9, middle). Relating morphological and behavioral diversity elicited for Double-Map EDQD-M evolved swarms, the sensor configurations (active sensors and average ranges) presented in figures 7, 8, 9 elicited the behavioral diversity presented in figures 4, 5, 6. Where, for a given task environment, the highest quality of a specific sensory configuration (morphology) is the highest quality elicited by a specific behavior

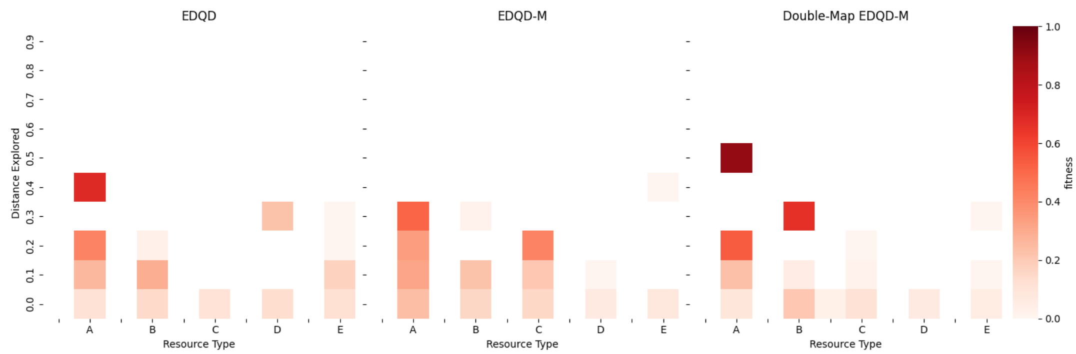

Figure 6. Quality-diversity of evolved behaviors in the *difficult* task environment. *Quality* is swarm average task performance. Behavioral *diversity* is the portion of environment explored to gather each resource type.

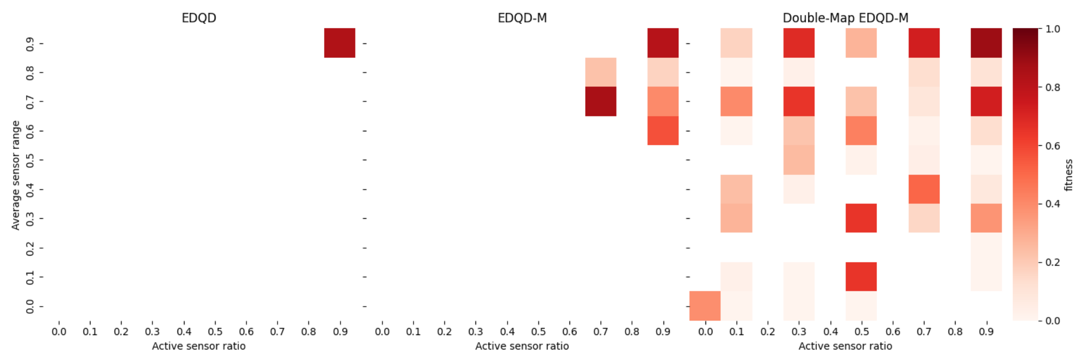

Figure 7. Quality-diversity of evolved morphologies in the *simple* task environment. *Quality* is swarm task performance. Morphological *diversity* is the number of sensors active and sensor range per robot in the swarm.

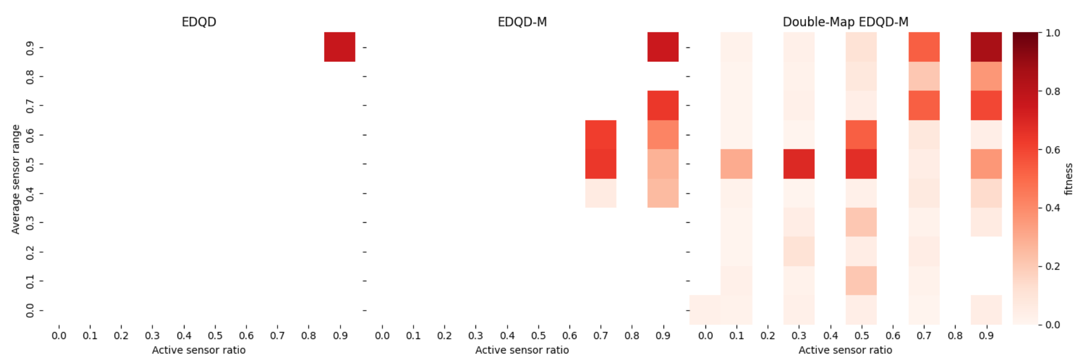

Figure 8. Quality-diversity of evolved morphologies in the *medium* task environment. *Quality* is swarm average task performance. Morphological *diversity* is the number of sensors active and sensor range per robot in the swarm.

(in the same task environment). For example, in the *difficult* environment, swarms evolved the behavior to gather ≈90% of type A resources via exploring ≈50% of the environment (figure 6, right), corresponding to a specific swarm sensory configuration: ≈70% of sensors active operating at 90% of maximum range (figure 9, right).

These results support the benefits of morphological and behavioral diversity maintenance in concert with behavior-morphology adaptation. Observing EDQD-M and Double-Map EDQD-M evolved sensory configurations, we note that, for the *simple* and *medium* task environments, the highest quality for specific morphologies is consistently higher than the highest quality for these same morphologies in EDQD-M evolved swarms (figures 7, 8, middle, right). For the *difficult* task environment, the higher quality morphology evolved by Double-Map EDQD-M was also higher than the highest quality morphology evolved by EDQD-M but slightly different

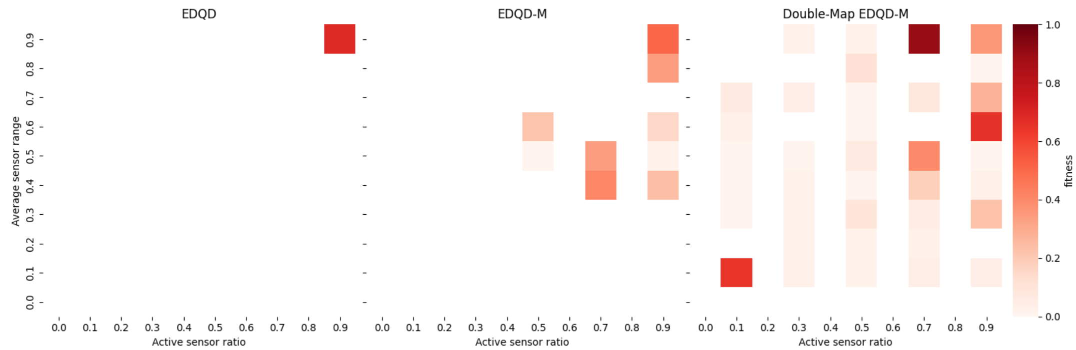

FIGURE 9. Quality-diversity of evolved morphologies in the *difficult* task environment. *Quality* is swarm task performance. Morphological *diversity* is the number of sensors active and sensor range per robot in the swarm.

(≈70% versus 90% of sensors active in EDQD-M, figure 9, middle, right). Also, in the *difficult* environment, the benefits of morphological diversity (Double-Map EDQD-M) are further evidenced by an accompanying significantly higher behavioral diversity (compared to EDQD and EDQD-M). That is, the highest quality Double-Map EDQD-M evolved behaviors (gathering resource type A) exceeded the highest quality EDQD and EDQD-M evolved behaviors (≈0.9 versus 0.6 versus 0.5 maximum task performance, respectively, figure 6). In the *medium* environment, Double-Map EDQD-M elicited similar (though less pronounced benefits) over EDQD and EDQD-M. Specifically, the maximum quality (for gathering resource type A) of Double-Map EDQD-M versus EDQD was ≈0.9 versus 0.75 versus 0.75, respectively figure 6). In the *simple* environment, the maximum quality of Double-Map EDQD-M versus EDQD versus EDQD-M (also for gathering resource type A), was comparable.

4.3 Task-Performance and Quality-Diversity

Task performance (quality) averages are calculated as the maximum portion of resources (range: [0.0, 1.0]) gathered over all swarm lifetimes (100 generations per run), averaged over 20 runs (figure 3, left). Statistical tests[2] (Mann-Whitney U-tests [33]) indicate that EDQD-M outperforms the other methods in the *medium* environment (Mann-Whitney U, $p<0.025$), while there is no statistical difference between methods in the *simple* and *difficult* environments. Figure 2 presents the average (over 20 runs) *Quality-Diversity* score of the final EDQD, EDQD-M, and Double-Map EDQD-M behavioral maps at the end of each run, where an average QD score is calculated for the 20 runs of each method. As in related work [53], the QD score is measured as the total quality across all filled grid-cells within the QD behavioral map (where higher quality means a higher portion of resources gathered during the swarm's lifetime). A high average QD score thus represents swarms with a high degree of both behavioral (EDQD, EDQD-M) or behavior-morphology (EDQD-M Double-Map) diversity and a correspondingly high average quality.

Specifically, we observe the benefits of Double-Map EDQD-M as task difficulty increases. That is, after 100 evaluations (generations) in the *simple* environment, Double-Map EDQD-M yields the lowest average QD score. In the *medium* environment Double-Map EDQD-M yields the second lowest average QD score. However, in the difficult environment Double-Map EDQD-M yields the highest average QD score (figure 2). This evidence supports the benefits of increased behavior (and morphological) diversity enabled by Double-Map EDQD-M, and the suitability of this method for evolving swarms in task environments of increased difficulty is also supported by the QD maps for evolved behaviors (section 4.1) and morphologies (section 4.2). Related evolutionary robotics work [4, 37–41, 57] supports this notion of increased behavior-morphology diversity that in turn elicits quality (task performance) benefits as the robot's task environment complexity (difficulty) increases. However, few studies have investigated the benefits of diversity in controller-morphology adaptation across increasingly complex environments and then only for simple single robot ambulation tasks [37, 38]. This study's key contribution was thus elucidating the benefits of behavior-morphology diversity in collective behavior (cooperative) tasks solved by robotic swarms.

5 CONCLUSIONS

The objective of this study was to ascertain the value of behavioral and morphological diversity in robot swarms. Overall results indicated that the Double-Map EDQD-M method, evolving both swarm behavior and morphology with mechanisms for behavioral and morphological diversity maintenance, was demonstrated as beneficial as environment complexity (task difficulty) increased. These benefits were demonstrated as a higher *Quality-Diversity* (QD) for the most difficult task, and the highest task performance overall (behavioral quality) for *medium* and *difficult* tasks. The study thus contributes evidence for the benefits of evolutionary swarm-robotic methods that include explicit mechanisms for behavioral and morphological diversity maintenance, where such swarms must adapt across increasingly complex task environments.

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[2]The p values for all statistical tests are available online: https://github.com/Impact-of-morphological-Diversity/GECCO2023.

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