The Cost of Complexity in Robot Bodies

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***Abstract*—The evolutionary cost of morphological complexity in biological populations remains an open question. This study investigates the impact of imposing a cost on morphological complexity given co-adapting behavior-morphology couplings in simulated robots. Specifically, we investigate the environmental and evolutionary conditions for which morphological complexity can be evolved without sacrificing behavioral efficacy. This study evaluates the relationship between between task difficulty (environment complexity) and evolved morphological complexity. We use multi-objective neuro-evolution to evolve robot controller-morphology couplings in task environments of increasing difficulty, where the objectives are to minimize the cost of (morphological) complexity and to maximize behavior quality (task performance) over evolutionary time. Results indicate that imposing a cost of complexity induces the evolution of simpler morphologies with negligible differences in behavior (task performance) across varying task environments. That is, with a cost of complexity, evolution maintained a constant selection pressure for morphological complexity across all environments.**

I. Introduction

An open question in evolutionary robotics [1] and biology [2], is under what environmental and evolutionary conditions does complexity evolve. This is especially pertinent in evolutionary robotics where the range of possible (task accomplishing) behaviors is constrained by morphological complexity [3]. To contribute to this question, this study evaluates the impact of imposing a cost on morphological complexity for increasingly complex (difficult) evolutionary robotics environments (tasks). In nature, such a complexity cost is based in hypotheses that more complex environments facilitate the evolution of more complex organisms, where evolution is constrained by fitness costs on complexity [4], [5].

This study uses evolutionary collective robotics as an experimental platform to address this question. Collective robotics was selected as such systems are abstractions of natural communities of organisms in which varying degrees of morphological complexity has evolved across ecological niches [6]. Also, whilst significant work has been done on co-evolving behaviour and morphology for individual robots [7], [8], [9], [10], [11], much less has been done on behavior-morphology co-evolution in collective robotics [12], [13], [14], [15], [16], especially for investigating the evolution of complexity. Collective robotics thus represents a suitable experimental platform for investigating the evolution of morphological complexity.

Furthermore, from a practical perspective, the degree of morphological complexity has important implications for the engineering of physical robotic systems. That is, it is often necessary to minimise expenditure on sensors and actuators and avoid overly complicated or expensive robotic designs. Thus, where ever possible, morphologies should be as cheap and effective as possible whilst enabling as many (task accomplishing) behaviors as possible. This is especially pertinent in collective robotic systems where redundant morphological complexity amplifies design costs as robot numbers increase.

This research presents a comparative evaluation and analysis of the benefits versus disadvantages of imposing a morphological complexity cost during robot controller-morphology co-adaptation. Given the general evolutionary robotics aim of evolving robot morphologies suitable for enabling the co-evolution of task accomplishing behaviors in any given environment [1], we formulated the following research objective.

To better elucidate the relationship between increasing environment complexity (task difficulty), given co-adapting robot behavior and morphology with an imposed fitness cost on morphological complexity. Specifically, we aim to ascertain under what environment and evolutionary conditions does increasing environment complexity necessitate increased selection pressure for increasing morphological complexity.

Formulation of this objective was also motivated by previous evolutionary robotics research results describing how different forms of morphological complexity evolve as a function of the task and environment [17], [7].

For example, Auerbach and Bongard [17] demonstrated that increased *mechanical complexity*, was not selected for given behavior-morphology co-evolution in simulated robots adapted across increasingly complex task environments[1]. Related work on co-adapting controllers and morphologies in evolutionary collective robotics [13], [18], [12], [13], similarly reported that simpler robot morphologies were selected for as task complexity increased. However, subsequent research using another definition of morphology [7], demonstrated that a *morphological complexity cost* resulted in increasing morphological complexity during robot behavior-morphology co-evolution in increasingly complex task environments.

These studies demonstrated that increased environmental complexity does not necessarily imply a need for greater morphological complexity and that increased morphological complexity does not necessarily result in more effective evolved behaviors. Rather, the evolution of complexity depends upon the definition of morphology and the environment in which robot behavior-morphology is co-evolved [14], [18], [13].

To contribute to these results and our objective we use a

[1] *Task environment* and *environment* are used interchangeably.

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multi-objective extension of *Neuro-Evolution of Augmenting Topologies-Morphologies* (NEAT-M) [14] that minimises morphological cost whilst concurrently maximizing task performance during controller-morphology co-adaptation in a benchmark collective robotics task: *collective gathering* [1]. This evolved morphological complexity versus behavior efficacy trade-off is evaluated for increasing task difficulty (environment complexity), where we define *morphological complexity* as a function of a robot's sensory configuration. That is, morphological complexity is a function of the number and type of sensors on a given robot's chassis, whereas, evolved behavior efficacy is equated with the robots' collective gathering task performance [19].

II. Methods

This study evaluates the *NEAT-M-MODS* multi-objective behavior-morphology evolution method extension of *NEAT-M* [14], versus NEAT-M (single-objective evolution) for co-adapting robot *Artificial Neural Network* (ANN) controllers (behaviors) and morphologies (sensory-configurations) in various collective gathering task environments. The collective gathering task required groups of robots to locate and cooperatively push *resources* (blocks) into a *gathering zone* (section III). Groups were homogenous in that the same behavior-morphology adaptations were applied to all robots.

For NEAT-M-MODS, behavior-morphology (section II-B) evolution was directed by the maximisation of collective gathering task performance and the minimization of morphological complexity (representing a morphological complexity cost, section II-C). The second objective was thus to evolve a minimally effective sensory configuration that concurrently enabled the evolution of effective behaviors. In order to ascertain the impact of imposing a cost of complexity, NEAT-M was comparatively evaluated except that maximizing collective gathering task performance was the only objective.

A. NEAT-M-MODS Method Overview

Neuro-Evolution for Augmenting Topologies (NEAT)-M-MODS is a multi-objective optimization extension of NEAT-M [14] and NEAT-MODS [20]. However, NEAT-M evolves a direct genotypic encoding of both robot behavior (ANN controller) and morphology (ANN connections to an array of sensors that constitute the robot's sensory configuration).

NEAT-M-MODS supersedes the core functionality of NEAT-M [14] via including NEAT-MODS [20], an NSGA-II based *Multi-Objective Evolutionary Algorithm* that uses multiple objectives to direct the evolutionary process of NEAT [21]. NEAT-M-MODS initializes a genotype population, computes each genotype's score vector (multi-objective fitness), speciates the population and subsequently computes a *rank* for each genotype based on *non-dominated sorting* and *crowding distance comparisons* [22]. The NEAT-M-MODS evolutionary process is as follows (evolutionary operators and parameters settings used by NEAT-M-MODS are given in table I).

(1) Apply *mutation* and *crossover* operators to randomly paired genotypes within fittest $x\%$ of parent population (*size N*) to produce child population (*size N*).

(2) Evaluate child population in task and compute score vector (multi-objective fitness) for each child genotype.

(3) Combine fittest portions of parent and child genotypes into combined population of $2N$ genotypes.

(4) Speciate the combined population into S species.

(5) Compute a rank for each combined population genotype based on *non-dominated sorting* and *crowding distance*.

(6) Select (*phase 1, 2 selection*) genotypes from combined population to create the next generation population.

(7) Repeat steps 1 to 6.

Hence, the multi-objective evolutionary process is directed via augmenting the NEAT selection process to follow an elitist strategy that uses the combined parent and child populations of current solutions. Once this combined population is placed into respective species (*step 4*) and sorted via non-domination sorting and crowding-distance (*step 5*) as in NSGA-II [23], selection occurs in two phases:

Selection phase 1 (Select species): The combined population is traversed by genotype rank to select a list of species. A *limiting function* [20] ensures selected species are *genotypically diverse* and contain *pareto-optimal* genotypes.

Selection phase 2 (Select individuals): The species list is traversed via *serial progression* [20] to select *N* genotypes to constitute the new parent population. Serial progression ensures the list of selected genotypes is both genotypically diverse and elitist in the context of pareto-optimality.

A thorough treatment of the original NEAT-MODS method can be found in the associated paper [20].

B. Robot Behavior-Morphology Evolution

NEAT-M [14] and NEAT-M-MODS evolved robots began with a minimal sensory configuration of five sensors (one of each type), where each sensor corresponded to an input node in the ANN controller. These input nodes were fully connected to two motor output nodes (figure 1, left). As with NEAT [21], ANN connections were randomly initialized with weights within a pre-specified range (table II) and without any hidden layers. ANN controllers were then subject to *complexification* during the neuro-evolution process. ANN controllers used *Sigmoidal units* [24] for hidden and output nodes, all sensory input values were normalized to the range: [0.0, 1.0] for input nodes, and controller connection weights and hidden-layer topology was adapted with neuro-evolution (NEAT).

Figure 1 (center-left) presents the initial robot morphology (sensory-configuration) used as an evolutionary starting point for NEAT-M and NEAT-M-MODS. This initial sensory-motor configuration (motor outputs were fixed throughout behavior-morphology evolution) was selected to ensure that robots were initially able to accomplish the collective gathering task with some degree of success. The possible sensor types were: (1) *Ultrasonic*, (2) *Infrared Proximity*, (3) *Color*, (4) *Low Resolution Camera*, and (5) *Gathering Zone Detector* (table II). These sensors were selected as they are typically available for the Khepera III mobile robot [25].

For each sensor type, sensor parameters could be perturbed by various mutation operators that add and remove sensors (of a given type), as well as modify, add and remove ANN connection weight values, add and remove weight connections to sensors, and change sensor positions and orientations (on the robot's periphery). These mutation operators are presented in table I, where the parameter-set for each sensory input node is: *Sensor Type*, *Field of View* (FOV), *Range*, *Position*, and *Orientation*. Figure 1 (center), presents an example robot with one sensor and an illustration of the sensor parameters subject to evolutionary adaptation.

Robot behavior-morphology evolution is driven by genetic (*crossover* or *mutation*) operators (table I) that adapt ANN connection weights and hidden nodes (behavior adaptation only), add or remove sensors or otherwise perturb sensor parameters (morphology and behavior adaptation). At each generation (of both methods), either crossover or mutation operators are applied. If mutation is applied then each of the mutation operators described in table I is applied with a given degree of probability. The crossover and mutation operators are fully described in previous work [21], [14].

Whenever a new sensor was added (*add sensor* operator) it was placed at a given minimum position distance (table I) between two randomly selected sensors already on the robot's chassis. In the case where there was only one sensor currently on the robot's body the new sensor was placed randomly to the left or right of this one sensor. The same procedure was followed for the *remove sensor* operator, where at least one sensor had to be positioned on a robot's chassis.

Only sensors were subject to mutation during behavior-morphology co-evolution. Robot movement actuators remained fixed during behavior-morphology co-adaptation.

1) Movement Actuators: Two wheel motors controlled a robot's heading at a constant speed. Movement was calculated in terms of real valued vectors (*dx* and *dy*). Wheel motors (figure 1, center-left, center-right) were explicitly activated by the ANN controller, where a robot's heading was determined by normalizing and scaling output values by the maximum distance it could traverse in one simulation time-step. That is:

$$dx = d_{max}(o_1 - 0.5)$$

$$dy = d_{max}(o_2 - 0.5)$$

Where, o_1 and o_2 are the motor output values. To calculate the distance between this robot (*v*), other robots and blocks in the environment, the squared *Euclidean norm*, bounded by a *minimum observation distance* was used (table I).

2) Controller (Behavioral) Heuristics: Given this study's research focus was on evaluating the impact of imposing a complexity cost on behavior-morphology evolution, behavioral heuristics from related work [14] were included to speed up the evolution of collective gathering behaviors.

C. Morphological Complexity Definition

Morphological complexity[2] is hereby defined as a function of the number of sensors n ($n \in [0, 10]$) on a candidate solution (robot) as well as the *Field of View* (FOV) value f_i and range value r_i of each sensor S_i in the set of n selected sensors. The values f_i and r_i are constrained by the *sensor type* of S_i. Namely, $\vee F_i$ and $\wedge F_i$, and $\vee R_i$ and $\wedge R_i$, are the maximum and minimum possible values of f_i and r_i, respectively, for S_i's *sensor type* (table II). Thus, morphological complexity M is minimized according to equation (1):

$$M = 5 \times \sum_{i=1}^{n} \left(\frac{f_i - \wedge F_i}{\vee F_i - \wedge F_i} + \frac{r_i - \wedge R_i}{\vee R_i - \wedge R_i} \right) \tag{1}$$

Where, there are five (5) points of complexity for the *range* and *FOV* of each sensor type, and we define the following:

$\frac{f_i - \wedge F_i}{\vee F_i - \wedge F_i}$: Fraction of total possible FOV used by S_i.

$\frac{r_i - \wedge R_i}{\vee R_i - \wedge R_i}$: Fraction of total possible Range used by S_i.

III. Collective Gathering Task

Collective gathering requires robots to locate distributed resources (blocks) in a bounded environment and transport them, via cooperative pushing, to a *gathering zone* [27]. This task was selected given its pertinence to various collective robotics applications in remote and hazardous real-world environments such as space exploration [28], toxic waste clean-up [29] and mine-field sweeping [30]. Also, collective gathering is an established collective evolutionary robotics benchmark task and is thus a suitable experimental platform for evaluating new evolutionary design methods [1].

Cooperation was defined as the number of robots required to push a given block type. *Task difficulty* (environment complexity) was defined as a function of the *number of blocks* and *degree of cooperation* mandated for task accomplishment. Blocks types were: *small*, *medium*, or *large*, which could be pushed by at least one, two and three robots, respectively (table II). Thus, task difficulty was calibrated via initializing environments (simple, medium, difficult) with varying combinations of block types (table II).

For example, in the *simple* environment, containing 10 small and 5 medium sized blocks, robots could work concurrently with minimal cooperation needed to move all blocks into the gathering zone. Collective gathering task performance (*fitness*, section IV-A) was the total number of blocks pushed into the gathering zone during the robots' *lifetime* (table II).

IV. Experiments

Experiments measured the impact of a fitness cost (NEAT-M-MODS) versus no cost (NEAT-M) on morphological complexity given behavior-morphology evolution for robots that must solve collective gathering tasks. In NEAT-M-MODS, multi-objective controller evolution (task performance maximization and complexity minimization) is used and in NEAT-M, single objective optimisation (task performance) is used.

The experimental platform was an extended collective-robotics simulator [14] implementing the collective gathering task (figure 1, right), where robots were modeled after the Khepera III [25], with co-adaptable ANN controllers and sensor configurations[3]. Experiments executed simulations of 20

[2]The term *morphological simplicity* is also used in this study's results and discussion (section V) given the evolutionary robotics goal of evolving morphologically simple robots with behaviorally effective controllers [26].

[3]The collective robotics simulator, NEAT-M and NEAT-M-MODS source-code is online at: https://github.com/costcomplex/CEC2019

TABLE I. NEURO-EVOLUTION PARAMETERS

Crossover rate		0.32
Probability to apply a mutation operator		0.34
Mutation Operators : Selection rate	Sensor weight perturbation	0.08
	Add / Remove sensor	0.07
	Sensor position / Orientation perturbation	0.10
	Sensor FOV / Range perturbation	0.07
	Add / Remove hidden node	0.05
	Add / Remove connection weight	0.05
	Connection weight perturbation	0.335
Generations per experiment / Experiment replications (runs)		250 / 20
Trial (robot lifetime) evaluations per generation		5
Population size		150
ANN connection weight range		$[-1.0, 1.0]$
ANN Hidden, output nodes		Sigmoidal
ANN Input nodes		Sensor input: $[0.0, 1.0]$
Initial Connection Density		0.5
Initial Sensory Input Nodes / Output Nodes		5 / 2
Output Nodes		2
Minimum sensor placement distance (Portion of chassis circumference)		0.01

TABLE II. EXPERIMENT AND SIMULATION PARAMETERS

Block size	Small	0.01 x 0.01
	Medium	0.015 x 0.015
	Large	0.02 x 0.02
Sensor types : Range / FOV	Ultrasonic	$(0.0, 1.0]$ / $(0.0, \pi)$
	Infrared Proximity	$(0.0, 0.4]$ / $(\pi/6, 5\pi/6)$
	Color	$(0.0, 0.4]$ / $(\pi/6, 5\pi/6)$
	Low Res Camera	$(0.0, 0.8]$ / $(\pi/9, 8\pi/9)$
	Gathering Zone Detection	Bottom facing
Sensor bearing range	$[-\pi, \pi]$ Radians	
Sensor orientation range	$[-\pi/2, \pi/2]$ Radians	
Robot *lifetime* (Time-steps per simulation task trial)	10000	
Robot group size	20	
Robot size (Diameter) / Gripping distance / Speed (per time step)	0.004 / 0.002 / 0.013 (As portion of environment size)	
Initial robot / block positions	Random (Outside gathering zone)	
Environment width x height / Gathering zone size	1.0 x 1.0 / 0.5 x 0.2	
Minimum / Maximum number of sensors	1 / 10	
Task environments (Blocks: small, medium, large)	Simple	10, 5, 0
	Medium	5, 5, 5
	Difficult	0, 5, 10
Cooperation needed for block pushing	Small	1 Robot
	Medium	2 Robots
	Large	3 Robots

robots in a bounded two dimensional continuous environment containing a distribution of *small*, *medium*, and *large* blocks (table II). Blocks were randomly distributed throughout the environment, excluding the *gathering zone*, whereas robots were initially randomly placed in the gathering zone. The three block type distributions given in table II correspond to increasing environment complexity (simple, medium, difficult), necessary to test the impact of task difficulty on controller-morphology evolution with and without a complexity cost.

To test the research objective (section I) we designed two sets of experiments. To evaluate the impact of a cost of complexity on behavior-morphology evolution, experiment set 1 evaluated NEAT-M-MODS for all three environments (table II). For comparison, experiment set 2 evaluated NEAT-M to evaluate behavior-morphology evolution without a cost on complexity for the same task environments.

Only homogenous teams were tested, meaning that at each NEAT-M and NEAT-M-MODS generation, the selected genotype was copied 20 times (to represent the robot group size of 20). In all experiments, groups were behaviorally and morphologically homogenous, meaning that the same evolved behavior-morphology couplings were applied to each robot.

A. Fitness Function

In experiment set 1, task performance was maximized and morphological complexity minimized, where this second objective placed additional selection pressure towards lower morphological complexity, thereby imposing a *fitness cost* on morphological complexity. In experiment set 2, only *task performance* was maximized, thereby only placing selection pressure on the evolution of effective collective behaviours.

Task performance was the average number of blocks

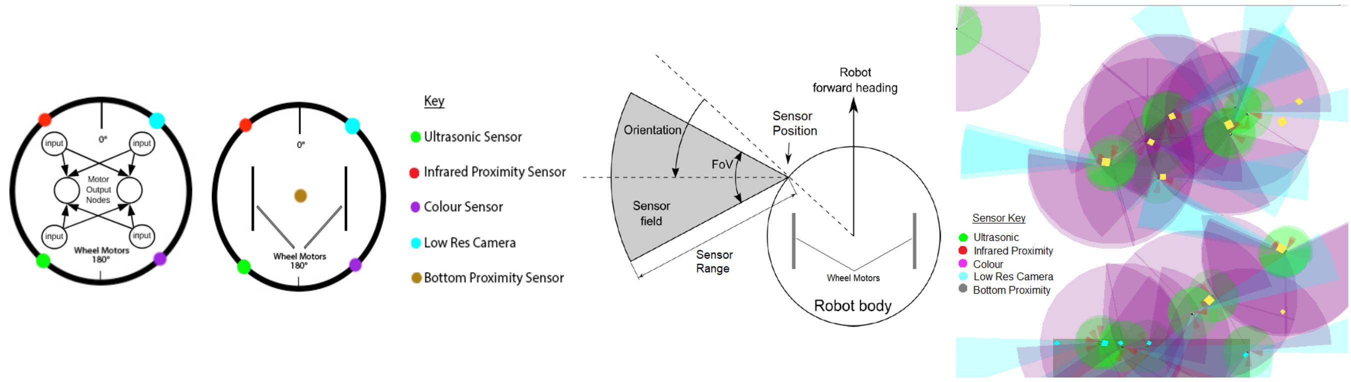

Fig. 1. LEFT: Initial robot ANN controller connecting 5 sensors to 2 actuators. CENTER-LEFT: Robots were initialized with one ultrasonic, infrared proximity, color, gathering zone detector (bottom proximity) sensor and one low-resolution camera. Wheel motors were fixed throughout behavior-morphology evolution. CENTER-RIGHT: Example robot with one sensor. Position determines sensor location on the robot's chassis with respect to the robot's heading. Orientation then determines the direction the sensor faces with respect to this position. By default, a robot's heading is forward facing (parallel to its wheels). RIGHT: Example simulation environment containing 20 robots and a distribution of different block types. The *gathering zone* containing gathered blocks (blue squares) is highlighted at the bottom. Varying sensory parameters (sensor type, position, orientation, field of view and range) are highlighted as shaded semi-circles.

pushed into the gathering zone by robots over five simulated task trials (*lifetimes*) in a given generation (table I). We defined v_c as total value of resources in the gathering zone, v_t as total value of all resources in the environment, s_e as the number of simulation time-steps in the robots' lifetime and s_t as number of trial evaluations per genotype (representing a given behavior-morphology configuration). As such, task performance T was maximised according to equation (2):

$$T = 100 \times \frac{v_c}{v_t} + 20 \times (1.0 - \frac{s_e}{s_t}) \tag{2}$$

In equation (2), 100 was the maximum number of blocks that could be gathered during an experiment run, and 20 was an experimentally determined weighting (boosting fitness for efficient individual and cooperative gatherers).

Each experiment applied NEAT-M or NEAT-M-MODS to evolve collective gathering behavior for 250 generations. A generation comprised five robot lifetimes, where each lifetime was 10000 simulation iterations. Each lifetime was a simulated collective gathering task scenario that tested different robot starting positions, orientations, and block locations in either a *simple*, *medium* or *difficult* environment (table II). Average collective gathering task performance was calculated at the end of each run and averaged over 20 runs. Tables I and II present (experimentally determined) evolution and simulation parameters used for all experiments. All other parameters used the same settings as in previous work [31], [20], [14].

V. Results & Discussion

Experiments (section IV) evaluated the impact of a morphological complexity cost versus no complexity cost (NEAT-M-MODS, NEAT-M, section II) in groups of robots for controllers (behaviors) and morphologies were co-adapted. Evolved robots were evaluated in increasing difficult task environments: *simple*, *medium* and *difficult*, in terms of collective gathering task performance (section III) and morphological complexity (evolved sensor-configurations, section II-C).

Figure 2 presents average *morphological complexity* and *task performance* results, and figure 3 presents *Pareto-front* and evolutionary progression of morphological complexity. All results compare NEAT-M-MODS and NEAT-M for evolving robot behavior-morphology couplings across increasingly difficult tasks and averages were calculated (for respective environments) over 20 evolutionary runs for each method.

Figure 2 (left) presents results of average morphological complexity[4] evolved by NEAT-M and NEAT-M-MODS. Behavior-morphology evolution in NEAT-M had a *Single Objective* (SO) of maximizing task performance, whereas, NEAT-M-MODS had the *Multiple Objectives* (MO) of maximizing task performance and minimizing morphological complexity.

In figure 2, a complexity value of 1.0 indicates the simplest possible morphology (one sensor) and a value of 0.0 indicates the most complex morphology (10 sensors, table II). Figure 2 (right) presents average maximum task performance results yielded by NEAT-M (SO) versus NEAT-M-MODS (MO point with highest task performance overall) in each environment.

Figure 3 (left) presents the best three *knee-points* for each *Pareto front*, where a knee-point has the highest value for both objectives (closest to the *utopia* point of the most effective controllers coupled with the simplest morphology[5]. For comparison, the best *single-objective* points (average maximum task performance and corresponding morphological simplicity) yielded by NEAT-M in each environment are also presented.

Figure 3 (right) presents the evolutionary progression of *morphological simplicity* for the NEAT-M-MODS and NEAT-M methods applied in each environment. Values close to 1.0 indicate low morphological complexity (few sensors), and values close to 0.0 indicate relatively high complexity (many sensors). Figure 3 (right) clearly illustrates, for all environments, that NEAT-M-MODS evolved morphologies were on average, half as complex as NEAT-M evolved morphologies.

For each environment, results data-set normality was confirmed using the *Shapiro-Wilk* test [32], and independent two-tailed t-tests [32] ($p < 0.05$) applied to test for significant

[4] *Simplicity* in figure 2 for clarity and consistency with previous work [7].

[5] The automated evolution of such robot behavior-morphology configurations is an end-goal in evolutionary robotics [26].

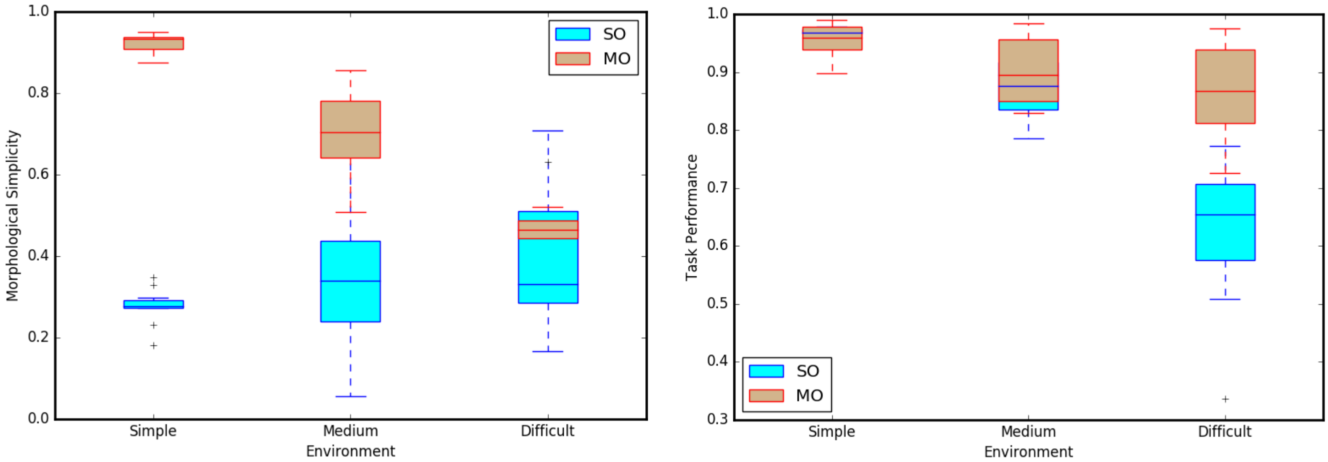

Fig. 2. LEFT: Average maximum morphological simplicity for *Single Objective* (SO): NEAT-M, and *Multi Objective* (MO): NEAT-M-MODS, knee-points for simple, medium and difficult environments, respectively. RIGHT: Average maximum task performance of the SO: NEAT-M versus MO points: NEAT-M-MODS with highest task performance overall. *Morphological simplicity* values close to 1.0 indicate low morphological complexity.

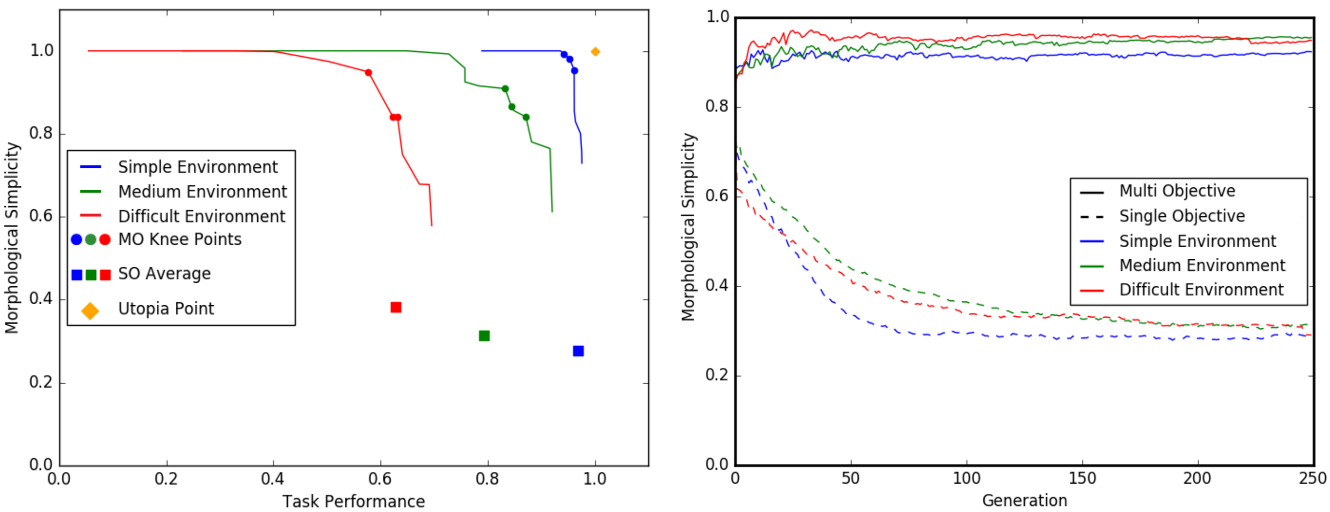

Fig. 3. LEFT: *Multi-Objective* (MO, NEAT-M-MODS) Pareto front and *Single Objective* (SO, NEAT-M) scores, where the SO point for each environment corresponds to the maximum task performance and corresponding morphological simplicity score (averaged across all experiment repetitions). RIGHT: Progression of average *morphological simplicity* for MO and SO over evolutionary time in each environment.

differences in average task performance. Specifically, between NEAT-M (SO) and NEAT-M-MODS (MO) evolved robots, where for the latter we used the average of maximum task performance knee-points from each evolved Pareto front.

These comparisons (table III) indicated that for *simple* and *medium* environments (section III), NEAT-M evolved robots yielded comparable average task performances to NEAT-M-MODS evolved robots, where the best three knee-points (figure 3) for NEAT-M-MODS were compared to the average best NEAT-M task performance. However, in the *difficult* environment (section III), NEAT-M-MODS yielded a significantly higher average task performance, exceeding NEAT-M evolved robot task performance by approximately 15%.

These results partially contribute to this study's research objective (section I), in demonstrating that as task complexity (difficulty) increases, imposing a cost on morphological complexity during behavior-morphology evolution (NEAT-M-MODS), results in evolved behavior-morphology couplings that more effectively accomplish difficult tasks.

Also, in the difficult environment, on average NEAT-M and NEAT-M-MODS evolved morphologies were comparably complex (table III and figure 2, left). However, some morphologies of the fittest (highest task performance) NEAT-M-MODS evolved robots comprised approximately 40% fewer sensors than the fittest NEAT-M evolved robots (figure 3, left).

This trend is more salient in behavior-morphology couplings evolved in simple and medium environments, where average morphological complexity of the fittest NEAT-M-MODS robots was approximately 60% and 25% simpler, respectively (with statistical significance, table III), than the fittest NEAT-M robots evolved in the same environments.

TABLE III. STATISTICAL TASK PERFORMANCE AND MORPHOLOGY COMPARISONS OF BEST EVOLVED NEAT-M (SO: HIGHEST TASK PERFORMANCE) AND NEAT-M-MODS (MO: 3 KNEE-POINTS ON PARETO-FRONT, FIGURE 3) ROBOTS. == : STATISTICALLY COMPARABLE. MORPHOLOGICAL SIMPLICITY (COMPLEXITY) IS DEFINED IN SECTION II-C.

	Task Performance	Morphological Simplicity
Simple Environment	MO == SO	MO >SO (simpler by approx. 60%)
Medium Environment	MO == SO	MO >SO (simpler by approx. 25%)
Difficult Environment	MO >SO (approx. 15%)	MO == SO

This result further contributes to the research objective (section I), via elucidating that a morphological complexity cost imposed in less difficult task environments enables the evolution of simpler morphologies (fewer sensors) and effective controllers (behaviors). That is, for simple and medium environments, the corresponding average task performance of NEAT-M-MODS evolved robots is comparable to that of NEAT-M evolved robots (table III). Thus, a complexity cost imposed during behavior-morphology evolution in increasingly difficult tasks, results in the selection of simpler morphologies coupled with effective controllers.

Figures 2 and 3 present complementary results providing further insights on the impact of a morphological complexity cost on behavior-morphology evolution across increasingly complex environments. Figure 3 (left) illustrates the result that a complexity cost, defined as an objective of NEAT-M-MODS behavior-morphology evolution, enables the evolution of comparable or significantly simpler robot morphologies when compared to behavior-morphology evolution with no complexity cost (NEAT-M by comparison, table III).

This result was especially salient in the case of evolution in the simple and medium environments where this complexity cost resulted in, on average, all evolved morphologies being 60% and 25% simpler, respectively (given the robot morphology definition, section II-C), though with comparable task performances when compared to robots that evolved relatively more complex morphologies (SO in figures 2 and 3: left). In the case of behavior-morphology evolution in the *difficult* environment, a complexity cost resulted in evolved robots with comparably simple morphologies (figure 2 left), but with behavioral couplings that achieved a significantly higher task performance (figure 2, right), when compared to behavior-morphology evolution without a complexity cost (table III).

As further evidence that a complexity cost enables evolutionary selection of simpler morphologies, figure 3 (right) presents the evolutionary progression of average morphological complexity given the application of NEAT-M-MODS and NEAT-M in each environment. These results indicate that for all environments, whilst initially all morphologies were relatively simple, those evolved by NEAT-M became increasingly complex over evolutionary time.

Thus, on average over all environments, robot morphologies evolved *with a complexity cost* (NEAT-M-MODS) were approximately 60% simpler (figure 2, left, and figure 3, right), given our morphology definition (section II-C), when compared to those evolved *without a complexity cost* (NEAT-M).

These results are consistent with related work [12], [13], [17], similarly demonstrating that increased morphological (sensor configuration) complexity does not necessarily evolve in response to increased task complexity. However, such simpler morphologies are often a sufficient substrate for the evolution of effective controllers, resulting in evolved robots yielding increased task performance.

Overall, and inline with related work [33], [7], [14] these results (table III and figures 2, 3) indicate that the evolution of robots comprising effective behaviors coupled with simple morphologies, is strongly impacted by the definition of morphology. For example, Auerbach and Bongard [33] found that given a *mechanical complexity* definition of evolved robot morphology, which was a function of the mechanical degrees of freedom of robot joints and actuators, then over the course of behavior-morphology evolution in increasingly difficult tasks, increasingly simpler morphologies were selected for.

This mechanical complexity definition of morphology was orthogonal to that defined in subsequent work [7], where morphological complexity was defined as a function of the curvature of an evolved robot's exterior (*Shannon diversity* [34]). In this later work, a complexity cost resulted in the evolutionary selection of increasingly complex morphologies in increasingly complex task environments.

In the case of this study, morphology was defined as a function of the number, type and properties of sensors (section II-C), where this definition of morphology supported previous work [33], [14], that similarly found that increasingly simple robot morphologies were selected for during behavior-morphology evolution across increasingly difficult task environments. However, this studies novel contribution was that a morphological complexity cost similarly results in the evolution of simple-morphologies coupled with effective behaviors. This contradicts the key result of previous work that similarly imposed a morphological complexity cost [7], though as also hypothesized in this related work, this is due to differing definitions of morphology and the nature of the evolutionary process and task environments.

Thus in summation, this study's results contribute to such previous work [33], [7], [14] providing additional insight into the relationship between task environment complexity, the definition of morphology and the impact of a complexity cost on the evolution of behavior-morphology couplings.

VI. CONCLUSION

This study investigated how imposing fitness costs on morphological complexity (sensory configuration evolution) impacts the evolution of robot behaviors and morphologies. Experiments evaluated collective gathering task performance and morphological complexity of robot *behavior-morphology* couplings evolved in increasingly complex task environments. Evaluation of evolved robot behaviors and morphologies was with respect to an imposed cost on morphological complexity versus no cost during behavior-morphology evolution.

Results indicated that imposing a morphological complexity cost enables the evolution of simpler morphologies (sensory configurations) coupled with effective controllers, when compared to behavior-morphology evolution with no complexity cost. This result held for evolution across increasingly complex (difficult) task environments. This suggests that, contrary to intuitive hypotheses on the evolution of complexity [35], increased morphological complexity is not necessarily required for evolving effective behaviors as task complexity increases. This result is supported by related work similarly indicating that increased environment complexity does not necessarily facilitate increased morphological complexity [17].

However, this study's key contribution was that a complexity cost enables the evolution of simpler morphologies that retain the capacity to support effective behavior couplings. This result was contrary to previous research [7], though this is hypothesized to be due to the differing definitions of morphology, task environments and the behavior-morphology evolution process used in this work. Hence, elucidating the relationships between complexity evolution given varying definitions of morphological complexity, environments and evolutionary processes remains the topic of ongoing research.

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