Energy and Complexity in Evolving Collective Robot Bodies and Brains

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***Abstract*—The impact of the environment on evolving increasingly complex morphologies (bodies) and controllers (brains) remains an open question in evolutionary biology and has important implications for the evolutionary design of robots. This study uses evolutionary robotics as an experimental platform to evaluate relationships between environment complexity and evolving body-brain complexity given energy costs on evolving complexity. We evolve robot body-brain designs for increasingly complex environments (difficult cooperative transport tasks) in a collective robotic gathering simulation. The impact of complexity costs on body-brain evolution is evaluated across such increasingly complex environments. Results indicate that complexity costs enable the evolution of simpler body-brain designs that are effective in simple environments but yield negligible behavior (task performance) differences in more complex environments.**

I. Introduction

An unsolved problem in natural and artificial evolutionary systems is determining the exact environmental and evolutionary conditions that enable complexity to evolve [1]. This is especially pertinent in evolutionary robotics [2] where possible problem-solving behaviors is constrained by brain (controller) and body (morphological) complexity [3]. This study addresses this via evaluating the impact of environments and complexity costs on robotic controller and morphology evolution across various evolutionary robotics task scenarios. We use evolutionary robotics as an experimental platform to test the *arrow of complexity hypothesis*, which states that the functional organization of the products of complex evolutionary systems increases over time [4]. This hypothesis has held true in other evolutionary robotics systems with complexity costs [5].

To evaluate the *arrow of complexity hypothesis* under a broader spectrum of robotic controller and morphology parameterizations, we use an alternate definition of controller and morphological complexity. In this study, morphological complexity accounts for possible sensor configurations of a counterpart *Khepera III* mobile robot [6], and controller complexity accounts for possible *Artificial Neural Network* (ANN) configurations coupled with a given morphology.

Evolutionary robotics was selected as the experimental platform since previous (especially collective behavior) work [7], [8], [9], [10] demonstrated that varying collective behavior task constraints as effective for tuning environment complexity and thus testing environmental impact on evolving robot controllers and morphologies. Evolutionary (collective) robotics thus represents a suitable platform for investigating the impact of environmental complexity on the artificial evolution of robotic controller and morphological complexity.

A key difference to related work [11], [7], [8], [9], [10] is that this study used complexity costs tantamount to mobile robot battery costs. Morphological cost was the battery cost of running robots configured with sensors of various types and sophistication [12]. Whereas, controller complexity was equated with controller efficiency (number of sensory-motor updates per simulation iteration). Using an evolutionary collective robotics system we thus evaluated the impact of imposing energy costs on robot neural (controller) and morphological (sensor) complexity evolved in increasingly complex environments (difficult tasks). This study's objective was thus to test if energy costs imposed on controller-morphology (body-brain) complexity enables the evolution of increasingly complex robotic designs in increasingly complex environments.

This objective's main motivation is the general lack of understanding [1], [13] for how environment complexity and energy requirements necessitates or enables the evolution of body-brain complexity. This study is also motivated by competing hypotheses and results in evolutionary robotics demonstrating that complexity costs imposed over increasingly complex environments enables the evolution of increased controller and morphological complexity [5] versus enabling the evolution of robots with simple designs [11], [9], [10].

From a practical perspective, the degree of controller and morphological complexity has important implications for engineering physical robots [14]. It is often necessary to minimize energy and fiscal expenditure on sensors and actuators by avoiding overly complicated and expensive designs. Robotic controller and morphology designs should thus be as efficient and effective as possible, allowing for optimal trade-offs between minimal controller computed behavior and maximal morphologically computed behavior [15]. This is especially pertinent in collective and swarm robotic systems where redundant behavioral and morphological complexity amplifies design costs as robot numbers increase [16].

II. Cooperative Transport Task

The cooperative transport task requires groups of robots to find resources distributed throughout a bounded environment, and to then cooperatively transport them to a *gathering zone* [17]. This task was selected given its pertinence to autonomous robotics applications in remote and hazardous environments

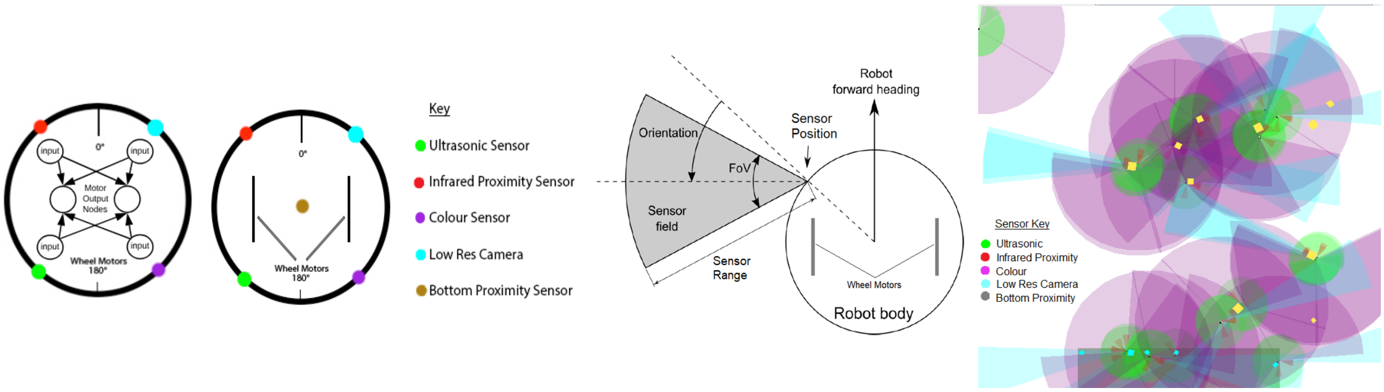

Fig. 1. LEFT: Initial robot neural controller connecting five sensors to two wheel motors. Robots were initialized with one ultrasonic, infrared proximity, color, bottom proximity sensor and low-resolution camera. CENTER: Example robot with one sensor. *Position* determined sensor location on the robot chassis with respect to its heading and *orientation* determined sensor direction. RIGHT: Example simulation containing 20 robots and different block types. *Gathering zone* (bottom) contained gathered blocks (blue squares). Varying sensor parameters (type, position, orientation, field of view, and range) are shaded semi-circles.

[18], and is an abstraction of other collective robotics applications such as environmental cleanup [19] and disaster management [20]. Cooperative transport is also an established evolutionary robotics benchmark task [2] and thus a suitable experimental test-bed for this study's experiments (section IV).

Cooperation was defined as the number of robots needed to push a given block type. Blocks types were: *small*, *medium*, or *large*, and could be pushed by one, two and three robots, respectively (table II). *Task difficulty* (*simple*, *medium*, or *difficult* environments) was a function of the *number of blocks* and *degree of cooperation* mandated for task accomplishment. Each environment type contained varying combinations of block types (table II). For example, the *simple* environment contained 10 small and 5 medium sized blocks, meaning robots could work concurrently with minimal cooperation to move all blocks into the gathering zone. Task performance (*fitness*, section IV-A) was the total number of blocks pushed into the gathering zone during the robots' *lifetime* (table II).

Environment complexity was thus abstracted as task difficulty, represented as the degree of cooperation required to solve the collective transport task. This parameterization of the environment in terms of task complexity, was selected as it was computationally tractable [9], [10] and found to be a suitable level of abstraction for evaluating the impact of environment complexity on evolving robot body-brain complexity.

III. Methods

To evolve controller (behavior) and morphology (sensory configuration) in robots, we used *Neuro-Evolution of Augmenting Topologies and Morphologies* (NEAT-M) [7]. NEAT-M co-adapts *Artificial Neural Network* (ANN) robot controllers and morphologies via evolving direct genotypic encodings of both controller and morphology (ANN connections to sensors).

NEAT-M equates the evolving topology of an ANN's input layer with a robot's adaptive sensory configuration, and as such includes evolutionary operators for adapting the *number* and *type* of sensors on a robot chassis as well as sensory *Field of View* (*FOV*), *range*, *bearing*, and *orientation* (figure 1). The NEAT-M method is described in related work [7].

A. Robot Controller-Morphology Adaptation

Experiments applied NEAT-M rather than cooperative co-evolution [5] to controller-morphology evolution as NEAT-M requires significantly less computational expense [7]. Robots began with a minimal sensory configuration of five sensors (one of each type) as an evolutionary starting point for NEAT-M. The five sensor types were: *Ultrasonic*, *Infrared Proximity*, *Color*, *Low Resolution Camera* and *Bottom Proximity* (table II). These sensors were selected as they are typically available for the *Khepera III* mobile robot [6]. Two wheel motors (figure 1, left, center) were explicitly activated by the ANN controller, but fixed throughout evolutionary adaptation. A robot's heading was determined by normalizing and scaling output values by the maximum distance it could traverse in one simulation time-step (table I). This initial sensory-motor configuration was selected to ensure that robots initially exhibited some basic task accomplishing behavior.

Each sensor corresponded to an ANN input node, where each input was initially fully connected (no hidden nodes) to two output nodes (figure 1, left). ANN weight connections were randomly initialized within a given range (table II). Controllers were then subject to *complexification* where connection weights and hidden-layer topology was adapted with NEAT-M. Controllers used *Sigmoidal units* for hidden and output nodes and all sensory inputs were normalized to the range: [0.0, 1.0].

Controller-morphology evolution was driven by *crossover* and *mutation* operators (table I) adapting ANN connection weights and hidden node topology (behavior adaptation), adding or removing sensors or perturbing sensor parameters (morphology and behavior adaptation). At each generation of NEAT-M, crossover and mutation operators [7] were applied (mutation operators with a given probability, table I). For each sensor type, sensor parameters could be perturbed by mutation operators (table I), that add or remove sensors, as well as modify, add or remove ANN connection weight values, add and remove weight connections to sensors, and change sensor positions and orientations (on the robot's periphery).

The mutable parameter set for each sensory input node was: *Sensor Type*, *FOV*, *Range*, *Position*, and *Orientation* (table I). Figure 1 (center), presents an example robot with one sensor and an illustration of this mutable parameter set.

B. Morphological Complexity Cost

The morphology complexity metric was derived from experiments that evaluated battery[1] drain from running a *Khepera III* mobile robot [6] with one of five given sensor types (table II) onboard and constantly active for three hours. Running a *Khepera III* robot with a complement of 10 infrared proximity sensors gave the robot an approximate run-time of four hours. However, a maximum run-time of three hours (10800 simulation iterations, table II), was selected given the extra battery cost of robots that used multiple low-resolution cameras [6].

To estimate energy costs for each sensor type, battery drain was measured every second (for each sensor type), where the robot executed heuristic wall following behavior in a physical reconstruction of the simulation environment (figure 1, right). Given this, we calculated per second (60 simulation time-steps) sensor energy costs, as a portion of total initial energy for a fully charged battery (set to an initial normalized value of 1.0). Per simulation time-step battery drain was then calculated as one $60th$ this for each of the five sensor types.

The *Morphological Complexity Cost* (MC, equation 1), was thus the sum of energy costs for all onboard robot sensors.

$$MC = \sum_{i=1}^{n} C(S_i) \tag{1}$$

Where, n was the total number of sensors and $C(S_i)$ the energy cost for sensor S_i, of a particular type. Since the maximum number of sensors allowable on a robot chassis was 10, the bottom-proximity sensor was always active (not subject to evolutionary adaptation). The sensor type with the highest energy cost (battery usage) was the low-resolution camera.

The maximum value for MC was: 10 $\times$ 0.001 + 0.0001 $=$ 0.0101 (table I), and the minimum value for MC was: 1 $\times$ 0.0001 + 0.0001 $=$ 0.0002. The minimum MC equated to a robot using one infrared proximity sensor (lowest energy cost sensor type), whereas the maximum MC equated to a robot using 10 low-resolution cameras (highest energy cost sensor type). Each simulation time-step of a robot's lifetime its battery level was decremented by the *morphological complexity cost* (equation 2) or the *neural complexity cost* (section III-C).

$$B_{t+1} = B_t - MC \tag{2}$$

Where, B_t was the battery level at time step t. Since a robot's battery could fully drain before the end of its *lifetime*, a robot could have its *active lifetime* reduced, which reduced the robot's given time to interact with its environment and contribute to solving the *collective transport task* (section II).

C. Neural Complexity Cost

The neural complexity metric computes controller complexity as the number of connections and neurons [22]. This complexity metric selected since it accounts for the size of the robot sensory-motor system connected to the controller and was demonstrated as effective metric in related work [23].

Neural Complexity (NC) was the number of connections c ($c \in [4, 200]$) and (sensory and hidden) nodes n ($n \in [2, 23]$) in an evolved ANN controller. The simplest controller configuration was one sensory input node directly connected to two output nodes (wheel motors), meaning the controller contained three nodes and two connections. The most complex controller was 11 input nodes, 10 hidden nodes and two output nodes, meaning the controller used 22 nodes and 200 connections.

A controller's energy cost was a function of it's network topology (the number of connections and nodes) and the number of possible sensory-motor updates per simulation time-step. Experiments running a *Khepera III* robot with 10 infrared proximity sensors indicated that all sensors needed approximately $30ms$ to be read. Specifically, a controller's motor outputs directly connecting an input layer of 10 nodes could be updated 30 times per second (or per 60 simulation iterations, table II). However, a controller using only one proximity sensor needed only $3ms$ to be read, and could thus process 300 sensory-motor updates per second. Hence the simplest controller was an order of magnitude more efficient than the most complex controller. This provided a comparable estimate of the factor of difference (NM) in neural complexity between the simplest and most complex evolvable controllers.

Given neural network controller complexity (NC), and this factor of difference in efficiency of sensory-motor updates between the simplest and most complex evolvable controllers (NM), equation 3 estimates the *Neural Energy Cost* (NEC), at each simulation time-step of a robot's lifetime.

$$NEC = \frac{NC}{c_{max} + n_{max}} * NM \tag{3}$$

Where, c_{max} = 200 (maximum node connections), n_{max} = 33 (maximum number of nodes). *Neural Magnitude* (NM) = 10 (magnitude of difference in update efficiency of simplest versus most complex controller). NEC (equation 3) is indicative of a robot's battery drain associated with its controller's sensory-motor update efficiency per 60 simulation time-steps. Per time-step cost was then calculated as one $60th$ of NEC.

Consider that, per 60 simulation iterations (one second of actual *Khepera III* run-time), the simplest controller (one sensory input node) runs approximately 10 times as many sensory-motor updates as the most complex controller (200 inter-node connections and 33 nodes). The most complex controller costs more due to added sensory complexity. This cost is manifest as increased energy usage (equation 3), where such an energy cost represents a penalty for evolving complex controllers. That is, complex controllers have less chance to discover and adapt to beneficial sensory-motor patterns (behaviors) [24], due to their lower sensory-motor update efficiency.

For experiments testing the impact of a neural complexity cost (section IV), a robot's battery level was decremented each simulation iteration by the *neural complexity cost* (equation 3).

$$B_{t+1} = B_t - NEC \tag{4}$$

Where B_t is the battery level at time step t of the 10800 simulation iterations comprising a robot's lifetime.

[1]The *Khepera III* mobile robot uses a battery pack composed of two Li-Ion Polymer elements with a 7.4V volt battery and a 1400 mAH capacity [6].

TABLE I. ROBOT MORPHOLOGY (SENSOR) & CONTROLLER (ANN) 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 Field of View (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 (evolutionary runs)		250 / 20
Task trials (robot lifetimes) 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 / Maximum Sensory Input Nodes		5 / 11
Minimum Sensory Input Nodes (Bottom proximity + another)		2
Output Nodes (fixed)		2
Minimum sensor placement distance (Portion of chassis circumference)		0.01

TABLE II. EXPERIMENT AND SIMULATION PARAMETERS

Block size (As portion of environment size)	Small	0.01 $\times$ 0.01
	Medium	0.015 $\times$ 0.015
	Large	0.02 $\times$ 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 Resolution Camera	$(0.0, 0.8]$ / $(\pi/9, 8\pi/9)$
	Bottom proximity sensor	Bottom facing
Sensor types : Energy cost (As portion of initial battery level: 1.0)	Ultrasonic	0.0005
	Infrared Proximity	0.0001
	Color	0.0002
	Low Resolution Camera	0.001
	Bottom proximity sensor	0.0001
Environment width x height / Gathering zone size	1.0 $\times$ 1.0 / 0.5 $\times$ 0.2	
Sensor bearing range	$[-\pi, \pi]$ Radians	
Sensor orientation range	$[-\pi/2, \pi/2]$ Radians	
Robot *lifetime* (time-steps per simulation task trial)	10800 ($\sim$ 3 hours run-time) / 60 ($\sim$ 1 second run-time)	
Initial robot battery capacity (energy units)	100000	
Robot group size	20	
Robot size (Diameter) / Gripping distance	0.004 / 0.002 (As portion of environment size)	
Robot speed (per time step)	0.013 (As portion of environment size)	
Initial robot / block positions	Random (Outside gathering zone)	
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

IV. Experiments

Experiments measured the impact of imposing *morphological* (section III-B) and *neural* (section III-C) complexity costs on robot controller-morphology evolution in increasing difficult task environments. Task environment difficulty was equivalent to the degree of cooperation needed for optimal task performance (to move all blocks into the environment's gathering zone). The *simple*, *medium*, and *difficult* environments thus represented increasing task difficulty (section II).

Experiments used a collective robotics simulator[2] that implemented the cooperative transport task environment (figure 1, right). Robots were modeled after the *Khepera III* [6], with co-adaptable ANN controllers and sensor configurations. Experiments executed simulations of 20 robots in bounded two dimensional continuous environments containing distributions of *small*, *medium* and *large* blocks (table II).

Each experiment applied NEAT-M to evolve cooperative transport behavior for 250 generations. A generation comprised five robot *lifetimes* (10800 simulation iterations). Each lifetime was a cooperative transport task simulation testing different (random) robot starting positions, orientations, and block locations in *simple*, *medium* or *difficult* environments (table II). Average task performance (section IV-A) was calculated at the end of each run and averaged over 20 runs. Tables I and II present all experiment parameters. All other parameters are as in previous work [21], [7].

Experiments were defined by robot controller-morphology evolution *with* or *without* neural or morphological complexity measures in *simple*, *medium* or *difficult* environments. For each environment type, blocks were randomly distributed throughout the environment, excluding the *gathering zone*, and robots were randomly placed throughout the environment. The three block type distributions (table II), thus corresponded to increasing levels of cooperative transport task difficulty.

To evaluate the impact of *complexity (energy) costs* versus *no complexity (energy) costs* on the controller-morphology evolution in each of the *simple*, *medium* or *difficult* environments we devised four experiment sets. First, to test the impact of controller-morphology evolution given a *morphological complexity cost* (section III-B). Second, to test the impact of controller-morphology evolution given a *neural complexity cost*. The third and fourth experiment sets used the same setup as the first and second experiments, but did not apply the morphological and neural complexity costs (respectively) to robot controller-morphology evolution. Hence, the first and second experiments produced evolved morphological complexity (MC, section III-B) and evolved controller complexity results (NC, section III-C), respectively, Where, as a benchmark comparison, the third and fourth experiments yielded only cooperative transport task performance results (section IV-A).

For simplicity and to reduce experiment run-time, only homogenous robot groups were evaluated. At each generation of NEAT-M, the fittest genotype (controller-morphology coupling) was copied 20 times to represent a group of 20 robots. Thus, for all experiments, robot groups were behaviorally and morphologically homogenous, meaning the same evolutionary adaptations were applied to all robots at each generation.

[2]Simulator and experiment source-code: github.com/robotcomplexity/2020

A. Cooperative Transport Evaluation

Cooperative transport task performance was the average number of blocks pushed into the gathering zone by robots over five simulated task trials. 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 task trial evaluations per genotype (representing a given behavior-morphology configuration). As such, NEAT-M evolved genotypes that maximized task performance T (equation 5):

$$T = 100 \times \frac{v_c}{v_t} + 10 \times (1.0 - \frac{s_e}{s_t}) \quad (5)$$

Where, 100 was the maximum number of blocks that could be gathered in a given task trial and 10 was a task performance weighting that boosted fitness for efficient gatherers.

V. Results and Discussion

Figure 2 (left) presents average maximum *task performance* (fitness) for robot groups evolved *with* and *without* morphology complexity (energy) costs in the *simple*, *medium* and *difficult* environments. Figure 2 (right) presents the corresponding average (normalized) *morphological complexity* (section III-B) for robot groups evolved *with* and *without* morphological complexity costs in the same environments. From each run, we selected the evolved morphology (sensor configuration) corresponding to the fittest controller and calculated the average *morphological complexity* across all evolutionary runs.

Figure 3 (left) presents average maximum *task performance* for groups evolved *with* and *without* neural complexity (energy) costs in *simple*, *medium* and *difficult* environments. Figure 3 (right) presents the corresponding average (normalized) *neural complexity* (section III-C) for groups evolved *with* and *without* neural complexity costs in the same environments. For each run, we selected the fittest evolved controller from each run and calculated average *neural complexity* across all runs.

Independent two-tailed t-tests [25] ($p < 0.05$) were applied to test for significant differences in average task performance between comparative result data-sets (for robot groups evolved in each environment, *with* and *without* complexity costs). These t-tests indicated that in the *simple* environment, robots evolved *with* either morphological or neural complexity costs yielded statistically comparable average task performances compared to those evolved *without* an energy cost (tables III and IV). In *medium* and *difficult* environments, robots evolved *without* complexity costs yielded significantly higher average task performances. Such task performances exceeded those evolved *with* morphological and neural complexity costs by 25% and 27% in the *medium* environment and 20% and 23% (respectively) in the *difficult* environment (tables III and IV).

This study's contributions are thus two-fold. First, the demonstration that if the task requires a low-degree of cooperative behavior between robots to optimally solve (*simple environment*, section II), then homogenous robot groups using simple controllers and morphologies are suitable [7], [8], [10], [9]. Specifically, in the *simple environment*, 10 of the 15 blocks could be pushed by individual robots and five blocks required at least two robots to cooperatively transport (table II).

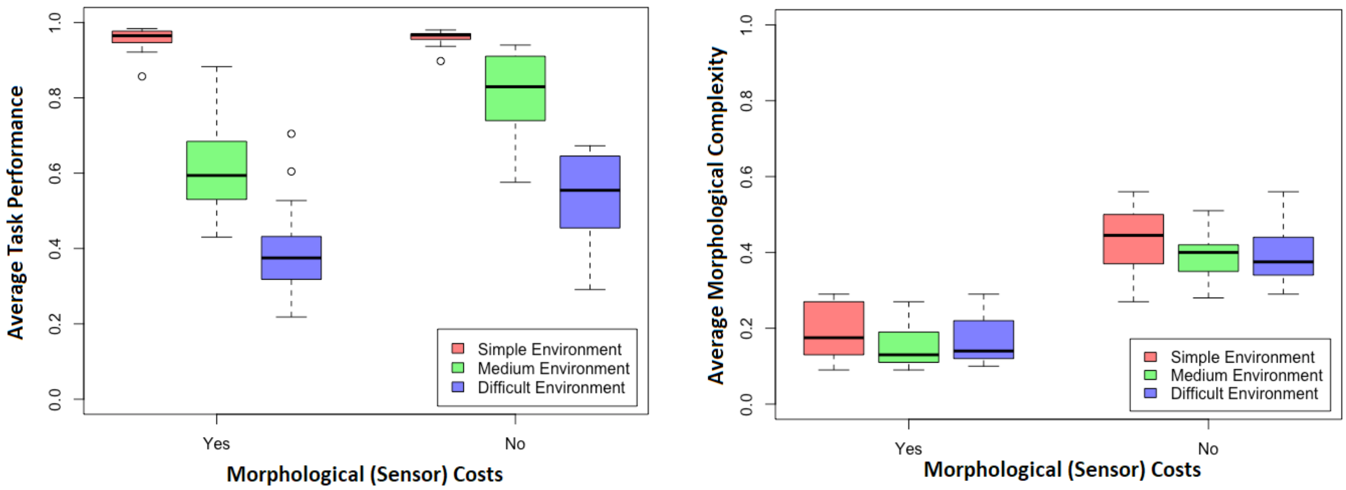

Fig. 2. Normalized average maximum *task performance* (left) and corresponding *morphological (sensor) complexity cost* (right) for robots evolved *with* and *without* sensor energy costs (left and right in figure, respectively) in each of the three environments: *simple*, *medium* and *difficult*.

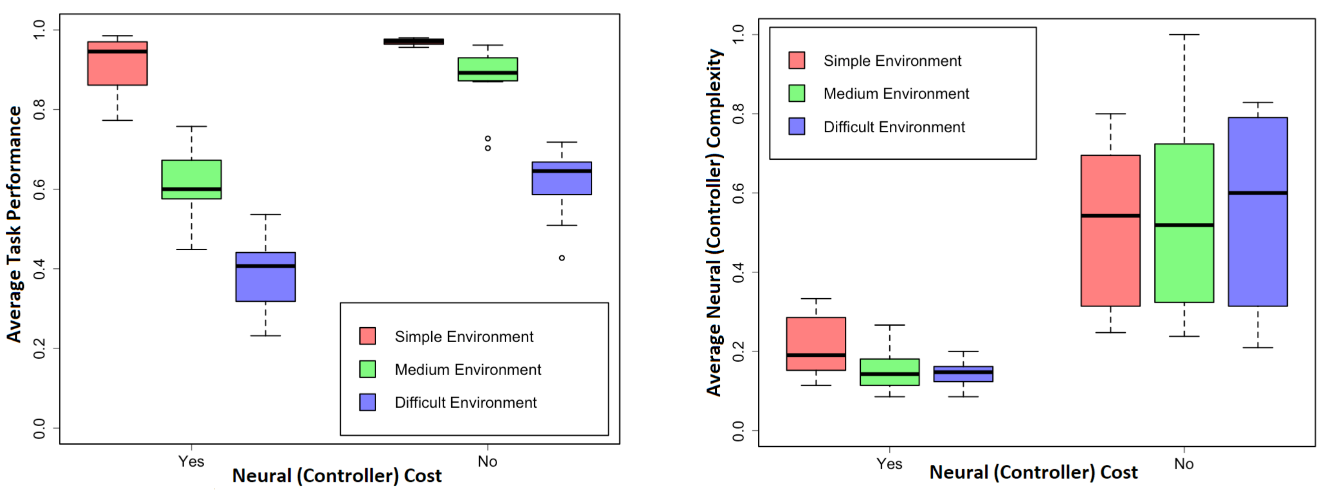

Fig. 3. Normalized average maximum *task performance* (left) and corresponding *neural (controller) complexity cost* (right) for robots evolved *with* and *without* sensor energy costs (left and right in figure, respectively) in each of the three environments: *simple*, *medium* and *difficult*.

TABLE III. STATISTICAL *task performance* AND *morphological complexity* COMPARISONS OF BEST NEAT-M EVOLVED ROBOTS WITH *No (energy) Cost* (NC) VERSUS THOSE WITH AN *Energy cost* (EC). == : STATISTICALLY COMPARABLE. MORPHOLOGICAL COMPLEXITY IS DEFINED IN SECTION III-B.

	Task Performance	**Morphological Complexity**
Simple Environment	NC == EC	NC >EC (Simpler by $\sim$ 55%)
Medium Environment	NC >EC (Lower by $\sim$ 25%)	NC >EC (Simpler by $\sim$ 61%)
Difficult Environment	NC >EC (Lower by $\sim$ 27%)	NC >EC (Simpler by $\sim$ 56%)

However, as the cooperative transport task is made more complex it requires less concurrent and more cooperative behavior (*medium* and *difficult* environments, section II), meaning robots with increased controller and morphology complexity are required for optimal task performance. This is supported by related work [7], [8], [10], [9] that similarly demonstrates increased environment complexity mandates increased controller and morphological complexity.

Notably this result held despite key differences in defining controller and morphological complexity and complexity costs. This study used an energy cost associated with evolving controller and morphological complexity (taking inspiration from evolutionary biology [26]), whereas previous work used multi-objective optimization to simulate complexity costs [10], [9], as well as other complexity definitions [11].

A second contribution was demonstrated benefits of complexity costs on evolutionary design in tasks requiring minimal cooperative behavior (*simple* environment, section II). In the simple environment, complexity costs enabled the evolution of low complexity controller-morphology designs eliciting collective behaviors of comparable efficacy to robots with more complex controllers and morphologies.

TABLE IV. STATISTICAL *task performance* AND *neural complexity* COMPARISONS OF BEST NEAT-M EVOLVED ROBOTS WITH *No (energy) Cost* (NC) VERSUS THOSE WITH AN *Energy Cost* (EC). == : STATISTICALLY COMPARABLE. NEURAL COMPLEXITY IS DEFINED IN SECTION III-B.

	Task Performance	**Neural Complexity**
Simple Environment	NC == EC	NC >EC (Simpler by $\sim$ 37%)
Medium Environment	NC >EC (Lower by $\sim$ 29%)	NC >EC (Simpler by $\sim$ 34%)
Difficult Environment	NC >EC (Lower by $\sim$ 23%)	NC >EC (Simpler by $\sim$ 44%)

From a practical perspective of engineering robot designs, consider that robots evolved *with* energy costs had their lifetimes (table II), significantly reduced as a result of battery drain associated with controller and morphology complexity costs. Thus, across all environments (*simple*, *medium* and *difficult*), imposed complexity costs resulted in robot lifetime (battery run-time) being reduced by approximately 50%. This corresponded to approximately 5400 simulation iterations or 1.5 hours of run-time in a physical *Khepera III* robot (section III-B). Hence the cooperative transport task could be completed in the simple environment, with comparable task performance to robots running for 10800 simulation iterations (approximately 3 hours of actual *Khepera III* run-time).

This has important implications for the evolutionary design of physical robots that must solve tasks in minimal time given minimally complex robot designs. Assuming complex sensory-motor configurations, complicated robot designs, and sophisticated sensors imply high fiscal costs to engineer and high energy costs to run, it is important that the engineering of robotic solutions use minimally complex controller-morphology designs. This is especially pertinent in swarm-robotic systems that comprise potentially thousands of robots [27], [28]. Furthermore, overly complex controllers have had demonstrated disadvantages such as containing unnecessary controller complexity that hinders behavioral performance as task complexity changes [23].

In summary, this study supports the *arrow of complexity hypothesis* (section I), demonstrating that increasingly complex environments enables the evolution of increasing robot complexity, but under the assumption that such increased complexity does not incur an evolutionary cost.

VI. CONCLUSION

This paper investigated the relationship between evolving body-brain architecture in robot groups and complexity of the evolution environment. Experiments evaluated the impact of imposing complexity (energy) costs on evolving controller and morphological robot complexity given increasing environment complexity (collective behavior task difficulty). The key contribution was that for simple tasks (requiring minimal cooperation), these complexity costs enabled the evolution of simpler controllers and morphologies, that elicited collective behaviors comparable to those of robots with more complex controllers and morphologies. However, this result did not hold for more complex task environments where increased degrees of cooperative behavior were required. In such environments, lower task performance was achieved by controller-morphology designs evolved with complexity costs. This indicates that the added controller and morphological complexity evolved without a complexity cost in these more complex environments was required in order for robots to achieve increased task performance.

Future work will continue to use evolutionary robotics as an experimental platform, to further evaluate the impact of varying environments on evolving controller and morphology complexity according to various complexity definitions.

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