

The Cost of Morphological Complexity

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EXTENDED 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 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). Results indicate that imposing a cost of complexity induces the evolution of simpler morphologies with negligible differences in behavior (task performance) across increasingly complex environments (increasing task difficulty).

Robot Behavior-Morphology Evolution

This study evaluates the *NEAT-M-MODS* [7] multi-objective behavior-morphology evolution method extension of *NEAT-M* [6], 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 blocks into a *gathering zone*. Groups were homogeneous in that the same behavior-morphology adaptations were applied to all robots.

For *NEAT-M-MODS*, behavior-morphology evolution was directed by the maximization of collective gathering task performance and the minimization of morphological complexity (representing

a *complexity cost*). The second objective was thus to evolve a minimally effective sensory configuration that concurrently enabled the evolution of effective behaviors. To ascertain the impact of imposing a complexity cost, *NEAT-M* was comparatively evaluated where maximizing task performance was the only objective.

NEAT-M [6] and *NEAT-M-MODS* [7] evolved robots began with a minimal sensory configuration of five sensor types [7], where each sensor corresponded to an input node in the ANN controller. These input nodes were fully connected to two motor output nodes controlling robot movement. As with *NEAT* [8], ANN controller connection weights were randomly initialized and without any hidden layers. Controllers were then subject to *complexification* during the neuro-evolution process. All controllers used *Sigmoidal* units [5] for hidden and output nodes and all connection weights and sensory input values were normalized to the range: [0.0, 1.0].

Morphological Complexity Definition

*Morphological complexity*¹ is 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* [7]. Thus, morphological complexity M is minimized according to equation 1:

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

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

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

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

Experiments

Experiments² measured the impact of a fitness cost (*NEAT-M-MODS*) versus no cost (*NEAT-M*) on morphological complexity given neuro-morphology evolution of robots that must solve collective gathering tasks. *NEAT-M-MODS* used multi-objective evolution (task performance maximization and complexity minimization),

¹*Morphological simplicity* is also used given the goal of evolving morphologically simple robots with behaviorally effective controllers [3].

²The collective robotics simulator, *NEAT-M*, *NEAT-M-MODS* source-code is online at: <https://github.com/costcomplex/GECCO2019>

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and NEAT-M used single-objective optimization (task performance).

Experiments executed simulations of 20 robots in a bounded 2D continuous environment containing a distribution of *small*, *medium*, and *large* blocks. Block type distributions corresponded to increasing environment complexity (*simple*, *medium*, *difficult*) [7], to test the impact of task difficulty on controller-morphology evolution *with* and *without* a complexity cost. Two experiment sets evaluated the impact of a cost of complexity on behavior-morphology evolution. Experiment set 1 evaluated NEAT-M-MODS for all environments with a complexity cost and experiment set 2 evaluated NEAT-M for behavior-morphology evolution without a complexity cost in the same environments. Robot groups were behaviorally and morphologically homogeneous, meaning the same evolved behavior-morphology couplings were applied to each robot. For a complete description of the methods, experiments, neuro-evolution and simulation parameters, the reader is referred to Nagar et al. [7].

Results and Discussion

Evolved robots were evaluated in increasingly difficult collective gathering tasks and average task performance and evolved morphological complexity (evolved sensor-configurations) measured.

Results indicated that for *simple* and *medium* environments, NEAT-M evolved robots yielded comparable average task performances to NEAT-M-MODS evolved robots, where the best three *knee-points* [7] for NEAT-M-MODS were compared to the average best NEAT-M task performance. However, in the *difficult* environment, NEAT-M-MODS yielded a significantly higher average task performance, exceeding NEAT-M evolved robot task performance by approximately 15%. These results demonstrated 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.

In the difficult environment, 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. 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, independent two-tailed t-tests [4], $p < 0.05$), than the fittest NEAT-M robots evolved in the same environments.

This result elucidates that a morphological complexity cost imposed in less difficult task environments enables the evolution of simpler morphologies (fewer sensors) and effective controllers (behaviors). For the *simple* and *medium* environments, the corresponding average task performance of NEAT-M-MODS evolved robots was comparable to that of NEAT-M evolved robots. Thus, a complexity cost imposed during behavior-morphology evolution in increasingly difficult tasks resulted in the selection of simpler morphologies coupled with effective controllers.

This result was especially salient for 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 our definition of morphology). However, comparable average task performances were observed when compared to robots that evolved relatively more complex morphologies. For behavior-morphology evolution in the *difficult* environment, a complexity cost resulted in comparably simple morphologies. Though behavior couplings for these evolved morphologies achieved significantly higher task performances, when compared to behavior-morphology evolution without a complexity cost. Thus results indicated that, for all environments, robot morphologies evolved *with a complexity cost* (NEAT-M-MODS) were approximately 60% simpler, when compared to those evolved *without a complexity cost* (NEAT-M).

These results are consistent with related work [1, 9, 10], similarly demonstrating that increased morphological (sensor configuration) complexity does not necessarily evolve in response to increased task (environment) 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 [1, 2, 6] this study's results 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 [1] found that a *mechanical complexity* definition of evolved robot morphology, which was a function of mechanical degrees of freedom of robot joints and actuators, resulted in increasingly simpler morphologies in increasingly difficult task environments.

Thus, in summation, this study's results contribute to such previous work on robot morphology evolution [1, 2, 6] 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.

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