The Expense of Neuro-Morpho Functional Machines

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EXTENDED ABSTRACT

An unsolved problem in both natural and artificial evolutionary systems is determining the exact environmental and evolutionary conditions that enable complexity to evolve [16]. This is especially pertinent in evolutionary robotics [4] where possible problem-solving behavior is constrained by brain (controller) and body (morphology) complexity [12]. We evaluate the impact of environments and complexity costs on robotic controller and morphology evolution across various evolutionary robotics task scenarios. This study uses evolutionary robotics as an experimental platform to investigate the *arrow of complexity hypothesis* [3], previously demonstrated to hold in artificial evolutionary systems given an imposed complexity cost [2]. Specifically, we test whether energy costs imposed on evolving robot controller and morphology complexity enables the evolution of increasingly complex controller and morphological designs concomitant with increasing environment complexity. Morphological complexity was equated with possible sensor configurations for a physical counterpart *Khepera III* mobile robot [8], and neural complexity was equated to artificial neural network topological configurations that coupled with a robot's evolved morphology.

Methods and Experiments

To evaluate controller (behavior) and morphology (sensory configuration) evolution in robots, we use an extension of *Neuro-Evolution of Augmenting Topologies* (NEAT) [14], for controller-morphological adaptation: *Neuro-Evolution of Augmenting Topologies and Morphologies* (NEAT-M) [6]. NEAT-M co-adapts *Artificial Neural Network* (ANN) robot controllers and morphologies via evolving direct genotypic encodings of both robot behavior (ANN controller) and morphology (ANN connections to an array of robot sensors). Robot behavior-morphology adaptation was driven by *crossover* and *mutation* operators that evolved ANN connection weights and hidden nodes (behavior adaptation only), added or removed sensors or perturbed sensor parameters (morphology and behavior adaptation).

NEAT-M equated the evolving topology of an ANN's sensory input layer with a robot's adaptive sensory configuration[1]. 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*. These sensors were selected as they are typically available for the *Khepera III* mobile robot [8]. Two wheel motors were explicitly activated by the ANN controller, but fixed throughout evolutionary adaptation.

Controller-morphology evolution was driven by *crossover* and *mutation* operators 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 [6] were applied. For each sensor type, sensor parameters could be perturbed by mutation operators, 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*.

The *Morphological Complexity Cost*, (*MC*, equation 1), was defined as the sum of the energy costs associated with robot sensors.

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

Where, n was the number of sensors and $C(S_i)$ the energy cost for a sensor, S_i. The maximum sensors on a robot was 10, the bottom-proximity sensor was always active and the sensor type with the highest battery usage was the low-resolution camera. The maximum MC was $10 \times 0.001 + 0.0001 = 0.0101$, and minimum MC was $1 \times 0.0001 + 0.0001 = 0.0002$. The latter was for a robot with one infrared proximity sensor (the lowest energy consuming sensor).

For neural complexity, we measured the number of connections and neurons in an ANN controller [1]. *Neural Complexity* (*NC*) was thus the number of connections c ($c \in [4, 200]$) and sensory and hidden nodes n ($n \in [2, 23]$) in an ANN controller. The simplest sensory-motor configuration was two sensory input nodes directly connected to the wheel motors, meaning the controller contained four nodes and four connections. The most complex sensory-motor configuration was 11 sensory input nodes, 10 hidden nodes and

[1]Experiment parameter descriptions and values and simulator source-code is available online: github.com/robotcomplexity/2020

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two output nodes, meaning the evolved controller used 22 nodes and 200 node connections. Given this ANN topological complexity (*NC*), we calculated *Neural Energy Cost* (*NEC*) using equation 2:

$$NEC = \frac{NC}{c_{max} + n_{max}} * NM \quad (2)$$

Where, c_{max} = 200 (maximum connections for most complex ANN), n_{max} = 33 (maximum nodes for most complex ANN). *Neural Magnitude* (*NM*) = 10 (magnitude of difference in sensory-updates between robots running the simplest versus most complex ANN).

At each iteration of a robot's lifetime (10800 time steps) its battery level (equation 3) was decremented by the *MC* (equation 1) or *NEC* (equation 2), for experiments testing the impact of morphological and neural complexity costs, respectively.

$$B_{t+1} = B_t - MC(-NEC) \quad (3)$$

Where B_t was the battery level at time step t, and robots could have their active lifetime reduced given full battery drain.

Experiments measured the impact of *morphological* and *neural* complexity costs on robot controller-morphology evolution across increasing task complexity. Task complexity was the degree of cooperation needed for optimal task performance (to move all blocks into the environment's gathering zone). Experiments ran simulations of 20 robots in bounded two dimensional continuous environments containing distributions of *small*, *medium* and *large* blocks. *Simple*, *medium*, and *difficult* environments contained increasing numbers of medium and large blocks which increased task difficulty. Each experiment applied NEAT-M to evolve cooperative transport behavior for 250 generations, where one generation was five robot *lifetimes*. Each lifetime was a task trial simulation that tested different (random) robot starting positions, orientations, and block locations for all environments. Average collective transport task performance was calculated over 20 evolutionary runs.

Average task performance (T) was the number of blocks pushed into the gathering zone by robots over 250 generations and 20 runs. Where, v_c was the total value of resources in the gathering zone, v_t the total value of all resources in the environment, s_e the number of simulation time-steps in the robots' lifetime and s_t the number of trial evaluations per robot genotype (behavior-morphology coupling). T (equation 4) was thus maximized by behavior-morphology evolution (the same adaptations were applied to all robots).

$$T = 100 \times \frac{v_c}{v_t} + 10 \times (1.0 - \frac{s_e}{s_t}) \quad (4)$$

Where, 100 was the maximum number of blocks that could be gathered during an evolutionary run, and 10 was an experimentally determined weighting (boosting fitness for efficient gatherers).

Results and Discussion

This study's main contribution was the demonstrated benefits of complexity (energy) costs for evolving simple yet effective robots that function comparably to more complex designs. In the simple environment, complexity costs enabled the evolution of simpler controllers and morphologies, that elicited collective behaviors comparable to robots that evolved significantly more complex designs.

Robots evolved *with* energy costs had their lifetimes reduced by approximately 50% as a result of the imposed complexity costs. This has important implications for the evolutionary design of sensory-motor and controller systems of physical robots that must optimally solve tasks in minimal time. Minimization of neural controller complexity and maximization of behavioral efficacy is pertinent if such controllers are to be mapped onto physical controller hardware, such as PID controllers [7]. Also, evolutionary design of minimal controller-morphology designs eliciting effective behaviors, means engineering such physical designs can in turn minimize energy and fiscal expenditure on hardware. This is especially valuable in swarm-robotic systems comprising potentially thousands of robots that must work cooperatively [13, 15].

Overall, results suggest that contrary to intuitive hypotheses on the evolution of complexity [3], and in support of previous work [5, 6, 9, 10], that increased controller and morphological complexity is not necessarily required for evolving robot controller and morphology designs with more effective (higher task performance) behaviors as environment complexity (task difficulty) increases. For example, overly complex controllers have been demonstrated as containing unnecessary neural complexity that hinders behavioral performance as task complexity changes [11]. Ongoing work is using evolutionary robotics as an experimental platform to test various environment, controller and morphology complexity definitions at other levels of abstraction and thus evaluate complexity costs across a broad spectrum of evolutionary scenarios.

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