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12 Evolving Morphological Computation

Abstract: *It has been argued that a robot's morphology (rather than its controller) may "compute." We hypothesize that there may be circumstances under which there is some advantage for a robot to compute using its body rather than its brain. If this is true, and if we use an evolutionary algorithm to improve the bodies and brains of robots under these circumstances, it should sometimes discover morphological computation and make use of it. Here we argue that morphological complexity may be correlated with morphological computation, and demonstrate a system in which morphological complexity evolves. We also hypothesize about how such a tool could be used to investigate how and when morphological computation is useful.*

Complexity and Morphological Computation

Imagine an artificial neural network that controls a robot. This controller computes in the sense that it transforms incoming sensor signals into outgoing motor commands. Controllers can perform more or less computation: a neural network composed of linear nodes and lacking a hidden layer can only perform linear transformations from sensing to action; networks with one or more hidden layers can perform both linear and nonlinear transformations.

What about the complexity of such controllers? A common measure of complexity is entropy. Consider two neural networks with the same number of neurons and synaptic connections, but in the first network all of the synaptic weights are identical and in the second network all of the weights are different. The latter network has a higher entropy associated with it compared to the former network. Intuitively, the former network is compressible: if all of the synaptic weights are the same, each hidden node in the network will compute the same function, so the network could be replaced with a smaller network composed of one hidden neuron that computes this function.

What then can be said about the relationship between computation and complexity in an artificial neural network? The exclusive or (XOR) function requires more computation than either the AND or OR function in an artificial neural network because a hidden layer is required to compute intermediate results. Also, the entropy of an ANN with a hidden layer has a higher entropy than an ANN without a hidden layer (assuming the hidden layer is employed to compute a nonlinear function). So, an ANN that computes XOR performs more computation, and has higher entropy, than an ANN that computes the AND or OR function.

Although the above example does not prove that there is a correlation between the amount of computation and complexity of an artificial neural network, it does suggest, anecdotally, that such a relationship may indeed exist.

Now consider the morphology of a robot. More specifically, let us consider just one aspect of its morphology: its three-dimensional shape. We can characterize the complexity of the robot's shape using shape entropy [4]. Shape entropy measures the variation in local curvature of an object: a sphere obtains a shape entropy measure of zero; a wadded-up piece of paper obtains a very large value. Indeed shape entropy seems to correlate with human designations of simple- and complexly-shaped objects [5].

We now have a common complexity measure – entropy—for both the neural network and the morphology of a given robot. If we now imagine two robots that perform the same task (such as moving over rough terrain), yet one robot has higher shape entropy and lower ANN entropy than the other robot, we could denote the former robot as performing more morphological computation than the latter robot. This approach to quantifying morphological computation bears some similarity to the work of Williams *et al.* [7] who showed that information theoretic measures can be used to determine whether information about the task at hand is stored in an agent's controller or in the relationship between the agent and its environment. Here however, instead of asking whether information is stored in the agent or in the environment we can measure the relative amount of information in the robot's morphology and in its controller.

Evolution and Morphological Computation

Consider now that an evolutionary algorithm is employed to improve a population of random robots such that they perform some given task. Consider further that both the three-dimensional shapes and controllers of the robots can be modified by evolution. Finally, assume that there exist multiple robots that can solve the task, but have differing degrees of morphological and control complexity. Which (if any) of these optimal robots will the evolutionary algorithm find? Which paths will evolution take? Will evolution first increase control complexity and then morphological complexity, or will it do so in the reverse order? Or will morphological complexity gradually increase over evolutionary time in step with control complexity? If a child robot is slightly more capable, morphologically more complex and simpler in terms of control than its parent robot, has evolution 'traded' control complexity for morphological complexity? In other words, has it evolved a more capable robot by taking advantage of morphological computation?

The answers to these questions depend of course on many factors, including the make up of the evolutionary algorithm, the task the robots are evolved to perform and the environment in which they must do so.

The Environment and Morphological Computation

In recent work [1] we have explored not so much the relationship between morphological and control complexity, but rather the relationship between morphological and environmental complexity. Robots were evolved to move in two different environments. The first environment was composed of a flat, featureless high-friction plane; the other environment also contained several closely-spaced low-friction blocks of ice (see Figure 1). In order to succeed in the latter environment, robots must evolve the ability to 'reach down' into the crevices between the blocks, gain purchase on the high-friction ground below and propel themselves forward.

We found that robots evolved in the icy environments exhibited higher morphological complexity than robots evolved in the flat-ground environment. One can argue that the icy environments are more complex than the flat-ground environments based on the higher Kolmogorov complexity of the icy environments: a larger program is required to define the icy environments than one required to defined the flat-ground environment.

The observed relationship between morphological and environmental complexity is constrained to the kinds of robots and environments we investigated. However, this is the first work to investigate the conditions under which morphological complexity increases – or fails to increase – over evolutionary time. In future experiments one could investigate how the total amount of morphological and control complexity (and the ratio between the two) changes during evolution.

The robots in both kinds of environments were controlled with fixed-complexity artificial neural networks, so it was not possible to determine whether these different environments selected for different ratios of control and morphological complexity. However in a companion paper [2] we allowed the number of mechanical degrees of freedom – and

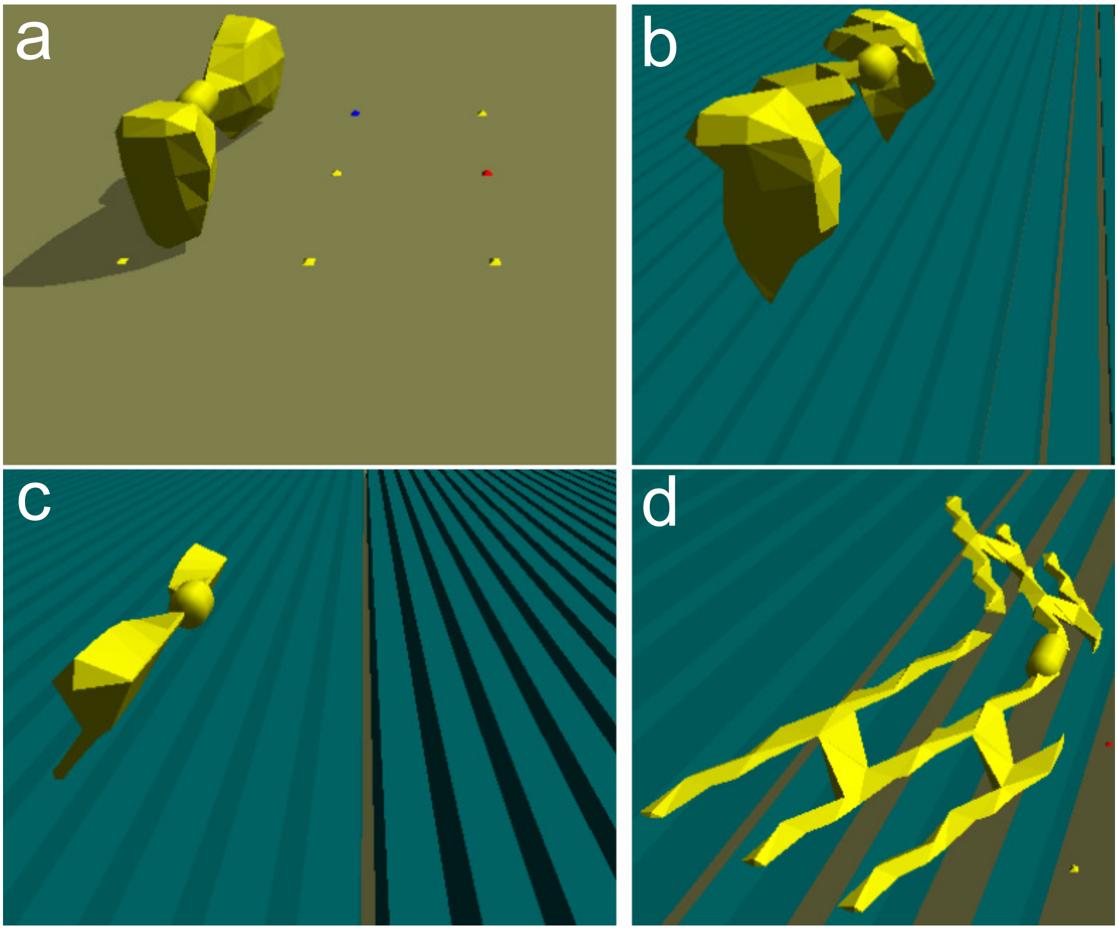

Figure 1: *A sample of four evolved robots.* ***a:*** *A simple-shaped robot that evolved to locomote over flat ground.* ***b-d:*** *Three sample robots, more morphologically complex than the robot in (**a**), that evolved in the icy environments. The figures has been taken from [3]. View videos of these robots here.*

the attendant neural control – to be modified by evolution, suggesting that in future it would be possible to investigate the relationships between morphological, control and environmental complexity.

More specifically, the concept of morphological computation could be investigated in this experimental paradigm relatively easily. If the robot must travel over the tops of these icy blocks, there are two classes of robot that can succeed at this task. The first class is composed of robots that, using a complex controller that performs much computation, carefully reach down into crevices and push in the correct direction. The second class is composed of robots that have complex appendages that, through simple motions, manage to lodge in the crevices in the correct way to generate propulsion. If the evolutionary algorithm generates robots of the latter kind more often that it generates robots of the former kind, we could conclude that evolution discovers and exploits the concept of morphological computation for generating useful behavior.

Ultimate Causation and Morphological Computation

Nikolas Tinbergen made clear that in order to understand a behavioral or physiological trait of an animal, it is important to understand that trait's proximate as well as ultimate causes [6]. For example, the proximate causes of human bipedal locomotion include the various muscles, tendons and ligaments found in the leg. The ultimate cause of bipedal locomotion may be[1] that natural selection favored energy-efficient walking – enabled by our particular combination of muscles, tendons and ligaments – over less energy-efficient walking.

If in future work we evolve robots that exhibit morphological computation, investigating the ultimate causes that gave rise to it may shed unique light on this phenomenon. For example, we may evolve robots with complexly-shaped appendages yet simple controllers that are able to move over rough terrain. We may then find that there is a proximate cause for this robot's success: the particular curvatures of its appendages allow it to passively fit into crevices in the terrain to propel itself forward. The ultimate cause of morphological computation in this case may be that it was easier for evolution to fine-tune the appendage's curvature than it was to discover some complex controller that manoeuvered a simply-shaped appendage down into crevices.

Imagine then that we were to repeat such experiments using different robots, environments and tasks and that found the evolution of morphological computation in many of them. If we then investigated the proximate causes of morphological computation in each case we might build up a general theory of *how* this phenomenon arises; that is, how a particular morphology performs computation. If we investigate the various ultimate causes of morphological computation in each case we might learn *why* this phenomenon arises: that is, how morphological computation supports adaptive behavior.

Bibliography

[1] J. Auerbach and J. Bongard. On the relationship between environmental and morphological complexity in evolved robots. In *Proceedings of the 14th International Conference on Genetic and Evolutionary Computation*, pages 521–528. ACM, 2012.

[2] J. Auerbach and J. Bongard. On the relationship between environmental and mechanical complexity in evolved robots. In *Proceedings of the 13th International Conference on the Synthesis and Simulation of Living Systems (ALife XIII)*, volume 13, pages 309–316, 2012.

[3] J. E. Auerbach and J. C. Bongard. Environmental influence on the evolution of morphological complexity in machines. *PLoS Computational Biology*, 10(1):e1003399, 2014.

[1] There are several competing hypotheses regarding the evolutionary origins of bipedal locomotion.

[4] D. Page, A. Koschan, S. Sukumar, B. Roui-Abidi, and M. Abidi. Shape analysis algorithm based on information theory. In *Proceedings of the International Conference on Image Processing*, volume 1, pages I–229. IEEE, 2003.

[5] S. Sukumar, D. Page, A. Koschan, and M. Abidi. Towards understanding what makes 3D objects appear simple or complex. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1–8. IEEE, 2008.

[6] N. Tinbergen. On aims and methods of ethology. *Zeitschrift für Tierpsychologie*, 20 (4):410–433, 1963.

[7] P. Williams and R. Beer. Information dynamics of evolved agents. *From Animals to Animats 11*, pages 38–49, 2010.