Ecological Modularity as a Means to Reduce Necessary Training Environments in Evolutionary Robotics

Collin Cappelle
The University of Vermont
Burlington, VT, USA
collin.cappelle@uvm.edu

Anton Bernatskiy
The University of Vermont
Burlington, VT, USA

Josh C. Bongard
The University of Vermont
Burlington, VT, USA

ABSTRACT

Due to the large number of evaluations required, evolutionary robotics experiments are generally conducted in simulated environments. One way to increase the generality of a robot's behavior is to evolve it in multiple environments. These environment spaces can be defined by the number of free parameters (f) and the number of variations each free parameter can take (n). Each environment space then has n^f individual environments. For a robot to be fit in the environment space it must perform well in each of the n^f environments. Thus the number of environments grows exponentially as n and f are increased. To mitigate the problem of having to evolve a robot in each environment in the space we introduce the concept of *ecological modularity*. Ecological modularity is here defined as the robot's modularity with respect to free parameters in the its environment space. We show that if a robot is modular along m of the free parameters in its environment space, it only needs to be evolved in n^{f-m+1} environments to be fit in all of the n^f environments. This work thus presents a heretofore unknown relationship between the modularity of an agent and its ability to generalize evolved behaviors in new environments.

KEYWORDS

Artificial Intelligence, Robotics, Modularity, Embodied Cognition

ACM Reference format:
Collin Cappelle, Anton Bernatskiy, and Josh C. Bongard. 2017. Ecological Modularity as a Means to Reduce Necessary Training Environments in Evolutionary Robotics. In *Proceedings of GECCO '17 Companion, Berlin, Germany, July 15-19, 2017,* 2 pages.
DOI: http://dx.doi.org/10.1145/3067695.3076027

1 INTRODUCTION

In many situations in evolutionary robotics, it is necessary to have a robot be fit in multiple different environments. However, because of catastrophic forgetting [4], it is not usually possible to evolve robots in one environment, discard that environment, continue evolving them in a different environment, and have them retain their ability to succeed in the first environment. Thus, robots must be trained in multiple environments. Matarić and Cliff [6] pointed out convergence time explodes in such multiple-environment contexts because of the combinatorics of parametrically-defined environments. Matarić and Cliff [6] showed that if we wish evolved robots to succeed in all environments defined for a given number of free parameters (f) and variations on those free parameters (n) then the robots will have to be evolved in n^f environments.

Previous work into modularity has mostly focused on non embodied agents using the Q-metric as the primary measure of modularity [2, 3, 5]. Recent work has shown that modularity in both body and control of embodied agents can reduce the necessary number of training environments when only n is scaled [1]. We extend this work by introducing ecological modularity.

We define ecological modularity as the robot's modularity with respect to it's environment. A robot which is ecological modular can more easily break down its environment into separate percepts which can be recognized independently of other percepts the robot has. Specifically if the robot can recognize m of the f free parameters independently, it will only be necessary to evolve the robot in n^{f-m+1} environments.

2 METHODS

We constructed a $2\times2\times2$ environment space for a tree-morphology (Treebot) robot to be evolved in (Fig. 1). The task was categorization of cylinders on the left and right of the robot. The robot was rewarded for having its leaves pointing at groups of two cylinders and away from groups which only had one cylinder.

Two types of Treebot were compared: the modular ($\mathcal{M}$) robot and the non-modular ($\mathcal{NM}$) robot. Each robot consisted of a root node and two leaf nodes. Each leaf node consisted of distance sensors. The $\mathcal{M}$ robot could move its leaf nodes independently of one another while its root was fixed in place. The $\mathcal{NM}$ robot had its leaf nodes fixed and could move about its root. The robots were controlled via neural networks whose weights were optimized through evolution.

The $\mathcal{M}$ network contained a modular network where the left sensor only affected the motor neuron of the left leaf node and similarly the right sensor only affected the right motor. In the $\mathcal{NM}$ network both sensors could affect the sole motor neuron.

3 RESULTS

Robots were evolved in a subset of the total environment space until they reached a target threshold fitness in each individual environment they were trained in. The robot was then tested in the remaining unseen environments and their fitness was recorded. Figures 2a and 2b shows the results of the $\mathcal{M}$ and $\mathcal{NM}$ evolved in a four environment subset and Figure 2c shows the $\mathcal{M}$ robot evolved in a two environment subset.

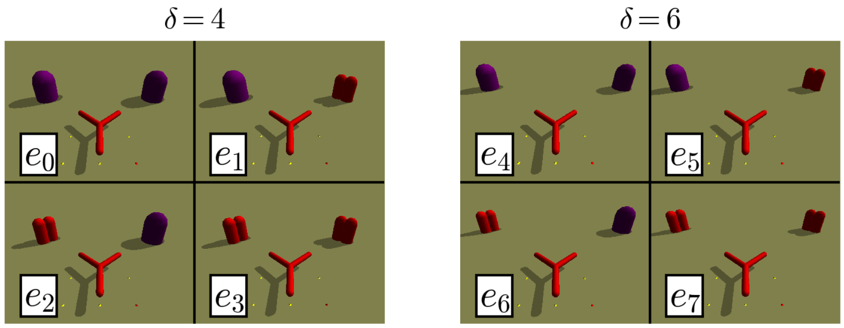
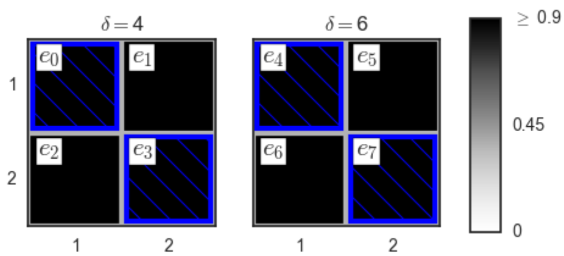
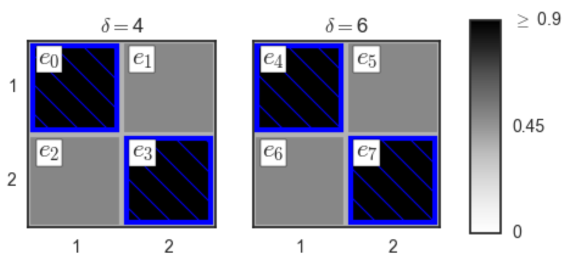


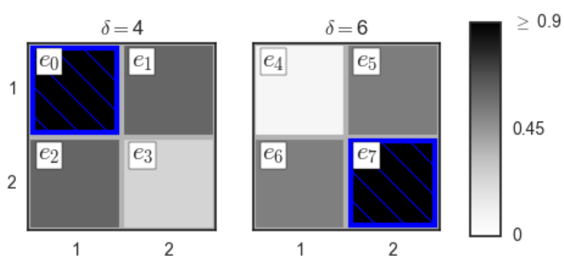
Figure 1: The starting point of the robots in simulation for each environment. The environment space is shown by all eight environments which make up the figure. Groups on the left and right could be made up of one or two cylinders and the groups could be $\delta = 4$ or $\delta = 6$ units away from the robot.



(a) $\mathcal{M}$ robot evolved in 4 environments



(b) $\mathcal{NM}$ robot evolved in 4 environments



(c) $\mathcal{M}$ robot evolved in 2 environments

Figure 2: Average fitness scores for $\mathcal{M}$ (2a) and $\mathcal{NM}$ (2b) robots in E_3 with training set $\{e_0, e_3, e_4, e_7\}$. 2c Shows the $\mathcal{M}$ robot in the training set $\{e_0, e_7\}$. Training sets are represented by the blue outlines around the environments.

4 DISCUSSION AND CONCLUSION

We have presented an environment space with $n = 2$ and $f = 3$ giving $2^3 = 8$ separate environments.

The $\mathcal{NM}$ robot could not separate the free parameters in the environment space so its modularity score is $m = 1$ and it is therefore necessary to evolve the robot in every environment in the space.

Because the $\mathcal{M}$ robot can break down the environment into right and left percepts, it was able to use what it had sensed before to inform how it should behave in future environments. However, the $\mathcal{M}$ robot could not separate the difference between objects at different δ values so it was not fully ecologically modular. Thus the $\mathcal{M}$ robot has an ecological modularity score of $m = 2$ meaning it is necessary to evolve it in $2^{3-2+1} = 4$ environments.

In the future we will explore how ecological modularity can arise through evolution instead of being baked in as in this paper and the difference in evolutionary time between ecologically modular and non-modular robots.

5 ACKNOWLEDGMENTS

We like to acknowledge financial support from NSF awards PECASE-0953837 and INSPIRE-1344227 as well as the Army Research Office contract W911NF-16-1-0304. We also acknowledge computation provided by the Vermont Advanced Computing Core.

REFERENCES

[1] Collin K Cappelle, Anton Bernatskiy, Kenneth Livingston, Nicholas Livingston, and Josh Bongard. 2016. Morphological Modularity Can Enable the Evolution of Robot Behavior to Scale Linearly with the Number of Environmental Features. Frontiers in Robotics and AI 3 (2016), 59.

[2] Jeff Clune, Jean-Baptiste Mouret, and Hod Lipson. 2013. The evolutionary origins of modularity. Procs of the Royal Society B: Biological sciences 280, 1755 (2013), 20122863.

[3] Kai Olav Ellefsen, Jean-Baptiste Mouret, and Jeff Clune. 2015. Neural modularity helps organisms evolve to learn new skills without forgetting old skills. PLoS Comput Biol 11, 4 (2015), e1004128.

[4] Robert M French. 1999. Catastrophic forgetting in connectionist networks. Trends in cognitive sciences 3, 4 (1999), 128–135.

[5] Hod Lipson, Jordan B Pollack, Nam P Suh, and P Wainwright. 2002. On the origin of modular variation. Evolution 56, 8 (2002), 1549–1556.

[6] Maja Matarić and Dave Cliff. 1996. Challenges in evolving controllers for physical robots. Robotics and autonomous systems 19, 1 (1996), 67–83.