Growing Simulated Robots with Environmental Feedback: an Eco-Evo-Devo Approach

Kathryn Walker*
IT University Copenhagen
kwal@itu.dk

Helmut Hauser
University of Bristol
helmut.hauser@bristol.ac.uk

Sebastian Risi
IT University Copenhagen
sebr@itu.dk

ABSTRACT

Robots are still missing the ability to adapt to new environments. However, biological systems are able to adapt to new environments with ease; perhaps because they have the ability to react to environmental input during a growth phase with changes not only in behaviour, but also morphology. Yet within the field of robots, environmental based development of morphology is an under researched area. In this paper we use an evolutionary algorithm to evolve neural cellular automata capable of inducing environmental based developmental plasticity in robots. We use the kinetic energy of each cell and its neighbours as an input to our network, the output of which determines the position of new cell growth. We evolve our neural cellular automata first in three individual environments and then also for performance in multiple environments. We show that the networks that use environmental feedback outperform those that do not and that by introducing environmental feedback during development, more adaptive and better performing robots are potentially possible.

KEYWORDS

Evolutionary Robotics, Developmental Robotics, Morphology, Environmental Feedback

ACM Reference Format:

Kathryn Walker, Helmut Hauser, and Sebastian Risi. 2021. Growing Simulated Robots with Environmental Feedback: an Eco-Evo-Devo Approach. In *2021 Genetic and Evolutionary Computation Conference Companion (GECCO '21 Companion), July 10–14, 2021, Lille, France.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3449726.3459514

1 INTRODUCTION

When compared with biological systems, robots are currently simply not as adaptive. One possible reason is that nature has the ability to adapt over different time scales; i.e., instantaneous changes in the nervous system (learning), slower changes over the lifetime of the organism in both its morphology and behaviour (postnatal development), as well changes over numerous generations (evolution). Also, advances in biology have shown the importance of environmental feedback at every stage of adaption. For example, molecules found in the cells of plants can be activated by light, stimulating growth of the stem to position leaves away from shaded areas [3]. Depending on location of the light source the final "morphology" of the plant is different, it has adapted to its environment. The same mechanism is triggered by submergence of the plant in water, removing leaves from underwater. In these instances, the same plant genotype has been exposed to different environments and has used postnatal development to adapt accordingly.

The concept Eco-Evo-Devo (the combination of evolution and environmental based development) has been somewhat explored in robotics. It is more common in development of robot control but there are examples of morphological development. For example, Kriegman et al. [5, 6] showed the benefits of using even a small amount of morphological development, coupled with evolution, to create better performing voxel-based robots. Corucci et al. [2] investigated how individual voxels could alter their respective size to alter the overall morphology. Walker and Hauser [7] studied evolving simple rule sets that adapted the morphology and control of simulated robots based on the SLIP model to increase the robustness of locomotion in response to changes in the environment.

Additionally, other researchers have investigated development of simple 2D systems using other learning approaches. For example, Mordvintsev et al. [1], train neural cellular automata to generate a variety of images which are able to *regrow* after damage. Later, Horibe et al. [4], also use neural cellular automata to grow soft robots that have the ability to regenerate after damage, although these methods to do utilise environmental feedback.

In this paper, we evolve neural cellular automata that specify the morphological development of a simple voxel-based robot. We show that using specific feedback, in the form of kinetic energy, from the environment as an input to our neural network, we can evolve robots that significantly outperform those generated without environmental feedback. First, we let evolution take place in one of three vastly different environments. Then we show that our method generates better performing, and in some cases more morphologically adaptive robots, when evolved for performance in two different environments.

2 METHOD

Our hypothesis is that incorporating feedback from the environment (Eco-Evo-Devo) should increase the performance of the final generated robots. We also consider how changes in the environment have the potential to develop a single genotype into two different morphologies. To test this we have devised a set of experiments that involves evolving neural cellular automata capable of growing robots for locomotion.

Each experiment starts as a 1×4 line of active cells, at the center of a 3D grid of size 10×10×4, simulated using the software *Voxelyze*. An *active cell* is one with a mass, stiffness and the ability to increase

*This work was supported by Sapere Aude: DFF-Starting Grant (9063-00046B)

GECCO '21 Companion, July 10–14, 2021, Lille, France

ACM ISBN 978-1-4503-8351-6/21/07.
https://doi.org/10.1145/3449726.3459514

and decrease in volume in response to an external sinusoidal control signal. This is used as actuation for the locomotion. An active cell also has a phase shift property, allowing expansion to be offset between neighbouring cells. An *inactive cell* is an "empty space" for which an active cell has the potential to grow in.

Growth happens episodically; after each episode (10 seconds), the state of each cell position is queried. The kinetic energy from the cell in question is averaged across the episode, and inputted into the neural network, along with the average kinetic energy from its neighbours. If not incorporating environmental feedback, an active cell has an input to the network of 1 and an inactive cell has an input of 0. If including feedback, the input for an active cell is its average kinetic energy. Therefore, the robot is tested in its environment each episode. When growing without feedback, the robot is only tested in its environment when it has finished growing.

The neural network has 161 synaptic weights in total and is fully connected. There are 7 inputs nodes using the kinetic energy from the current cell in question and its 6 immediate neighbours. There are 3 hidden layers, each with 7 nodes, and there are no recurrent connections. The output of the neural network has two nodes: the state of the cell and change of cell phase shift. If the value from the first output node is greater than a threshold, the cell becomes active, and it is connected to at least one active neighbour. Once a cell is active it cannot become inactive. The threshold for state change is initially 0, it is increased by 0.05 each episode to control growth. The second output from the neural network determines how the value of the phase shift of an active cell should change. Initially a cell has a phase shift of 0.

The weights of the neural network are evolved using an evolutionary algorithm. For each experiment the evolutionary algorithm was run 12 times with a randomized starting population of 30 for 200 generations. A new population was formed as thus: the top 5% were automatically passed on to the next generation. 80% of the new genomes were generated by adding a jittered array of normal distribution (mean 0, std 0.05), to a randomly selected genome. The final 15% of genomes for the next generation were randomly generated. The fitness function for the evolution was the distance the robot travelled from its starting position in any direction. In the cases where we evolved for performance in multiple environments the fitness in the individual environments were ranked and then summed.

We investigated the evolution of the neural networks in three different environments: on a horizontal plane (flat land), in water, and on "bumpy" ground (bumped environment) both with and without environmental feedback. Also, optimal neural networks were evolved for both *flat Land and water* and *flat Land and bumpy ground* where a single neural network is required to grow robots that are successful in both environments.

3 RESULTS AND DISCUSSION

The mean fitness for the virtual creatures tested with and without environmental feedback for each environment are summarised in Table 1. The P values (calculated via T-tests with significant of 0.05) in Table 1 show that when environmental feedback is used to grow virtual creatures the overall final morphologies perform significantly better.

Environment	With Feedback		Without Feedback		*P Value*
	Mean	σ^2	Mean	σ^2	
Land	75	70	85	201	0.02
Water	25	9	28	7	0.001
Bumped	50	142	67	348	0.01
Land + Bumped	106	427	133	545	0.03
Land + Water	44	213	64	434	0.048

Table 1: Summary of the mean fitness for the virtual creatures tested with and without environmental feedback for each environment.

Not only do the robots that develop with environmental feedback outperform those that develop without, in some cases they are also able to change their morphology depending on the environment (e.g., Figure 1). Thus one neural network is able to produce two different morphologies. However, the change in morphology is relatively small and this is a limitation of our work.

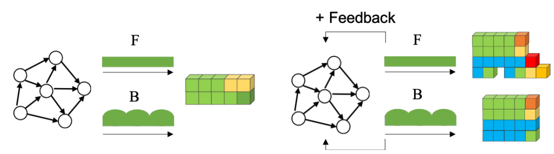

Figure 1: Our results show that using environmental feedback in the growth process allows robots to adapt during their lifetimes to different environments.

Our work demonstrates that robots capable of environmental-based growth are capable of outperforming those without this ability. It also lays some groundwork for a future of morphologically diverse and adapting robots.

REFERENCES

[1] Michael Alexander Mordvintsev, Ettore Randazzo, Eyvind Niklasson and Levin. 2020. Growing Neural Cellular Automata. (2020). https://doi.org/10.23915/distill.00023

[2] Francesco Corucci, Nick Cheney, Sam Kriegman, Josh Bongard, and Cecilia Laschi. 2017. Evolutionary developmental soft robotics as a framework to study intelligence and adaptive behavior in animals and plants. *Frontiers in Robotics and AI* 4 (2017), 34.

[3] Keara A Franklin. 2008. Shade avoidance. *New Phytologist* 179, 4 (2008), 930–944.

[4] Kazuya Horibe. 2021. Regenerating Soft Robots through Neural Cellular Automata. In *Genetic Programming: 24th European Conference, EuroGP 2021, Held as Part of EvoStar 2021, Virtual Event, April 7–9, 2021, Proceedings.* Springer Nature, 36.

[5] Sam Kriegman, Nick Cheney, and Josh Bongard. 2018. How morphological development can guide evolution. *Scientific reports* 8, 1 (2018), 1–10.

[6] Sam Kriegman, Francesco Corucci, Nick Cheney, and Josh C. Bongard. 2017. A minimal developmental model can increase evolvability in soft robots. *GECCO 2017 - Proceedings of the 2017 Genetic and Evolutionary Computation Conference* (2017), 131–138. https://doi.org/10.1145/3071178.3071296 arXiv:1706.07296

[7] Kathryn Walker and Helmut Hauser. 2019. Evolving optimal learning strategies for robust locomotion in the spring-loaded inverted pendulum model. *International Journal of Advanced Robotic Systems* 16, 6 (2019), 1729881419885701.