The impact of environmental history on evolved robot properties

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Abstract

This paper studies the effects of changing environments on the evolution of bodies and brains of modular robots. Our results indicate that environmental history has a long lasting impact on the evolved robot properties. We show that if the environment gradually changes from type A to type B, then the evolved morphological and behavioral properties are very different from those evolving in a type B environment directly. That is, we observe some sort of “genetic memory”. Furthermore, we show that gradually introducing a difficult environment helps to reach fitness levels that are higher than those obtained under those difficult conditions directly. Finally, we also demonstrate that robots evolved in gradually changing environments are more robust, i.e., exhibit a more stable performance under different conditions.

Introduction

A widely acknowledged ground truth about natural evolution is that the environment largely determines the evolved lifeforms (Darwin, 2004; Sapolsky, 2017). However, within the field of artificial evolution, specifically robot evolution, things can be different and as of today there is not much evidence for this effect. As a potential explanation it can be noted that Evolutionary Robotics has a historical emphasis on evolving only the robot brains (controllers) and robot systems with evolvable forms (morphologies, bodies) have been paid relatively little attention, cf. (Floreano et al., 2008; Doncieux et al., 2015). Furthermore, existing studies on morphologically evolving robots focus on other aspects and only a few address the effect of the environment directly, e.g., (Auerbach and Bongard, 2014). Last, but not least, the effect might be hard to demonstrate with robots that have less complex morphologies and shorter evolution periods than the plants and animals observed in Nature.

Our own experience with a large number of different environments and various system setups seems to support the latter explanation. Specifically, we repeatedly found that even very different environments can lead to the same evolved robot morphologies. After many experiments we identified and investigated two environments that gave rise to measurably different morphological features in the evolved populations of modular robots (Miras and Eiben, 2019).

In this paper, we consider these two environments (described later on as “Plain” and “Tilted”) and define a couple of other ones that represent intermediary stages between them. This allows us to investigate the evolutionary dynamics when environment A is gradually transformed into environment B and compare this with evolving in constant environments A and B. In other words, we can research the effect of what can be called the environmental history. Our initial hypothesis is that starting evolution in a simple world (A) and smoothly transitioning into a difficult world (B) will make adaptation easier than starting directly in B. Hence, we expect a better adapted final population with more prominent B-type features and corresponding fitness values.

To be specific, we run experiments in constant worlds (A and B) and dynamically changing worlds (two systems that both gradually transform from A to B, but do this at a different pace) and investigate three questions regarding such a transformation from A to B:

- How does this affect the evolved morphologies?
- How does this affect the evolved behaviors?
- How does this affect the robustness of the evolved robots?

Related Work

Existing work related to morphological evolution of virtual creatures has been addressed in (Sims, 1994), put on a more solid footing later on (Pfeifer and Iida, 2005). The effects of different developmental mechanisms were studied in (Kriegman et al., 2018b), while a method for phenotypic plasticity of morphology and controller was proposed in (Kriegman et al., 2018a). Nevertheless, they did not experiment with different environmental conditions. In (Daudelin et al., 2018) reconfigurable robots were evolved to cope with actual changes in the environmental conditions as they moved about, but no quantification of this effect on the morphological level was provided. In (Auerbach and Bongard, 2014)
it has been demonstrated that increasing the complexity of the environmental conditions results in an increase in the morphological complexity of the creatures. Nevertheless, measuring complexity does not provide clear insights concerning intelligible morphological traits, as for instance the limbs of a robot. Moreover, in (Bongard, 2011a) it has been demonstrated that phylogenetic and ontogenetic morphological (and neurological) changes can not only accelerate the discovery of successful behavior but produce robots more robust to variations in environmental conditions. Finally, in (Bongard, 2011b) it was found that if environmental scaffolding is proceeded by morphological scaffolding, significant performance improvement can be achieved.

**Robot Framework**

**Morphology**

We are using simulated robots based on RoboGen (Auerbach et al., 2014) whose morphologies (“bodies”) are composed of modules shown in Fig. 1. Any module can be attached to any other module through its attachable slots, except for the sensors, which can not be attached to joints. Our morphologies (Fig. 2) consist of a single layer, i.e., the modules do not allow attachment on the top or bottom slots, only on the lateral ones, but the joints can bend, so the robots can ‘stand’ in a 3D-shape. Each module type is represented by a distinct symbol in the genotype.

![Figure 1: Robot modules: Core-component with controller board (C); Structural brick (B); Active hinges with servo motor joints in the vertical (A1) and horizontal (A2) axes; Touch sensor (T). C and B have attachment slots on their four lateral faces, and A1 and A2 have slots on their two opposite lateral faces; T has a single slot which can be attached to any slot of C or B. The sequence of letters (T or n) in C and B indicate if there is a sensor on the laterals left, front, right and back (for C only), in this order.](image)

**Controller**

The controller (“brain”) is a hybrid artificial neural network, which we call Recurrent CPG Perceptron (Fig. 3, right). For every joint in the morphology, there exists a corresponding oscillator neuron in the network, whose activation function is calculated through a Sine wave with three parameters: Phase offset, Amplitude, and Period. The oscillators are not interconnected, and every oscillator may or may not possess a direct recurrent connection. Additionally, every sensor is reflected as an input for the network, which might connect to one or more oscillators, having the weights of its connections ranging from $-1$ to $1$. The CPG (Ijspeert, 2008) generates a constant pattern of movement, even if the robot is not sensing anything, so that the sensors are used either to suppress or to reinforce movements.

**Representation and operators**

We use an evo-devo style generative encoding to represent the robots. Specifically, our genomes –that encode both morphology and controller– are based on a Lindenmayer-System (L-system) inspired by (Hornby and Pollack, 2001). The grammar of an L-System is defined as a tuple $G = (V, w, P)$, where

- $V$, the alphabet, is a set of symbols containing replaceable and non-replaceable symbols.
- $w$, the axiom, is a symbol from which the system starts.
- $P$ is a set of production-rules for the replaceable symbols.

The following didactic example illustrates the process of iterative-rewriting of an L-System. For a given number of iterations, each replaceable symbol is simultaneously replaced by the symbols of its production-rule. Given $w = X$, $V = \{X, Y, Z\}$ and $P = \{X \rightarrow \{X, Y\}, Y \rightarrow \{Z\}, Z \rightarrow \{X, Z\}\}$, the rewriting goes as follows.

- Iteration 0: $X$
- Iteration 1: $XY$
- Iteration 2: $XYZ$
- Iteration 3: $XYZXZ$

In our system each genotype is a distinct grammar in the syntax specified by the types of modules we have. The alphabet is formed by symbols denoting the morphological modules and commands to attach them together, as well as commands for defining the structure of the controller. The construction of a phenotype (robot) from a genotype (grammar) is done in two stages. In the first stage (early development), the axiom of the grammar is rewritten into a more complex string of symbols (intermediate phenotype), according to the production-rules of the grammar. (Here we set the number of iterations to 3). In the second stage (late development), this string is decoded into a phenotype. The second stage of this process is illustrated in Figure 3.
The first stage was omitted because it is somewhat extensive, but it follows work flow shown in the example above. During the second stage of constructing a phenotype two positional references are always maintained in it, one for the morphology (pointing to the current module) and one for the controller (pointing to the current sensor and the current oscillator). The application of the commands happens in the current module in the case of the morphology, while for the controller it happens in (or between) the current sensor and the current oscillator. More details about the representation can be found in (Miras et al., 2018c,b).

Once it is possible that only the rules of one single parent end up being expressed in the final phenotype, and also as it is not rare that one mutation happens for non-expressed genes, both crossover and mutation probabilities were set high, to 80%, aiming to minimize this effect. ²

For practical reasons (simulator speed and physical constructability) we limit the number of modules allowed in a robot to a maximum of 15.

Morphological Descriptors

For quantitatively assessing morphological properties of the robots, we utilized the following set of descriptors:

1. **Size**: Total number of modules in the body.
2. **Number of Joints**: Total number of active joints (motors) in the body.
3. **Number of Limbs**: The number of extremities of a body.
4. **Length of Limbs**: The number of modules with exactly two attachments.
5. **Relative Number of Joints**: The number of active joints relative to a practical limit ³.
6. **Relative Number of Limbs**: The number of extremities of a body relative to a practical limit.
7. **Relative Length of Limbs**: The length of limbs relative to a practical limit.
8. **Proportion**: The length-width ratio of the rectangular envelope around the body.

The exact formulas for descriptors 5 to 8 can be found in (Miras et al., 2018c,b). Additionally, a complete search space analysis of the utilized robot framework and its descriptors is available in (Miras et al., 2018c,b,a), demonstrating the capacity of these descriptors to capture relevant robot properties, and proving that this search space allows high levels of diversity.

Behavioral Descriptors

**Speed** Describes the speed (cm/s) of the robot along the $x$ axis as defined by Eq. 1.

$$s_x = \frac{e_x - b_x}{t}$$

where $b_x$ is $x$ coordinate of the robot’s head in the beginning of the simulation, $e_x$ is $x$ coordinate of the robot’s head at the end of the simulation, and $t$ is the duration of the simulation.

²This means that around 80% of the offspring will be result of crossovers, and also that around 80% of the offspring will suffer the above explained mutation.

³The practical limits definitions can be found in (Miras et al., 2018c,b).
Balance We use the rotation of the head in the $x$–$y$ plane to define the balance of the robot. In general, the rotation of an object can be described in the dimensions roll, pitch, and yaw. Thus, we consider the pitch and roll of the robot head, expressed in degrees between 0 and 180 (because we do not care if the rotation is clockwise or anti-clockwise). Perfect Balance belongs to $p = r = 0$, so that the higher the Balance, the less rotated the head is. Formally, Balance is defined by Eq. 2.

$$b = 1 - \frac{r + p}{t \times 180 \times 2}$$  \hspace{1cm} (2)$$

where $r = \sum_{i=1}^{t} | r_i |$, representing the roll rotation accumulated over time, $p = \sum_{i=1}^{t} | p_i |$, representing the pitch rotation accumulated over time, and $t$ is the duration of the simulation.

Experimental Setup

Environments

All environments we use are based on a flat terrain, distinguished by the angle of inclination $\alpha$ running from 0 to 15 with increments of 5 degrees. Thus we have four environments: Plain ($\alpha = 0$), Tilted 5 ($\alpha = 5$), Tilted 10 ($\alpha = 10$), and Tilted 15 ($\alpha = 15$). The tilted environments are more difficult than Plain because the robots must tackle gravity and we use a fitness function based on uphill locomotion. These choices are based on foregoing work that showed that Plain and Tilted 15 are really different in the sense that the robot populations evolved in them exhibit clear differences. Tilted 5 and Tilted 10 are introduced here as intermediary environments to allow a gradual transition between the two extremes, Plain and Tilted 15. Therefore, in the sequel we refer to Tilted 15 simply as Tilted. The environments are shown in Figure 4.

![Figure 4: The Plain and Tilted 15 environments.](http://tinyurl.com/yxry52ge)

Environmental scenarios

We carried out four experiments using the same experimental setup, except for the environments in which the robots were evolved. The four environmental scenarios are depicted in Figure 5 and explained below.

<table>
<thead>
<tr>
<th>Environment</th>
<th>Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plain</td>
<td>Tilted</td>
</tr>
<tr>
<td>Tilted 5</td>
<td>Tilted 10</td>
</tr>
<tr>
<td>Tilted 15</td>
<td></td>
</tr>
</tbody>
</table>

• **Plain**: robots evolve in the Plain environment.
• **Tilted**: robots evolve in the Tilted 15 environment.
• **Equal Scaffolding**: robots evolve for an equal number of generations (25) in a sequence of environments Plain, Tilted 5, Tilted 10, and Tilted 15.
• **Incremental Scaffolding**: robots evolve for increasing numbers of generations in a sequence of environments Plain, Tilted 5, Tilted 10, and Tilted 15. The numbers are 10, 20, 30, and 40 respectively. The rationale behind this scenario is giving more time to the more difficult environments.

Evolution

We are using overlapping generations with population size $\mu = 100$. In each generation $\lambda = 50$ offspring are produced by selecting $50 \mu$ pairs of parents through binary tournaments (with replacement) and creating one child per pair by crossover and mutation. From the resulting set of $\mu$ parents plus $\lambda$ offspring, 100 individuals are selected for the next generation, also using binary tournaments. The evolutionary process is stopped after 100 generations, thus all together we perform 5050 fitness evaluations per run. For each environmental scenario the experiment was repeated 10 times independently.

Fitness function

In all environments the same fitness was utilized. It only concerns the speed of the robots along the $x$ axis to push for uphill movement in the tilted environments. Locomotion along the $y$ axis is ignored and not moving at all is penalized. The fitness function is defined by the following equation

$$f_x = \begin{cases} 
  s_x & \text{if } s_x > 0 \\
  \frac{s_x}{10} & \text{if } s_x < 0 \\
  -0.1 & \text{if } s_x = 0 
\end{cases}$$

where $s_x$ is the speed of the robot as defined by Eq. 1. The duration $t$ of the evaluation periods was set to 50 seconds in all environments.

Results

Behavior

In this section we review the evolved behaviors by considering speed, balance, and the actual gaits the robots exhibited.
Since fast uphill movement is our targeted quality, we start by analyzing the development of speed $s_x$ across the generations for each environmental scenario (Fig. 6, left). The robots achieved a much higher speed in the Plain scenario than in Tilted, confirming the intuition that the Tilted environment constitutes a greater challenge to the robots than the Plain environment. The results for Equal Scaffolding are not significantly different from Tilted, having a lot of variance among the runs. (See Table 2 for the exact $p$-values.)

Interestingly, Incremental Scaffolding achieved significantly higher speed than Tilted, proving helpful to succeed in the task, in accordance with our initial hypothesis. Let us note that four of the ten runs of Tilted stagnated in a local optimum, where the robots are small and hardly move. This seems like an avoiding strategy, that prefers reducing movement to risking a fall during the climbing attempt. Since this never occurred in a scaffolding scenario, we can observe that they help avoid such suboptimal strategies during the search.

Aiming to assess the emergent behavior beyond what is reflected in the fitness function, we measured the balance of the robots. Figure 6 (right) shows that while robots in the Tilted scenario converge to a high balance, in the two scaffolding scenarios they converge to a low balance, which is the same behavior emergent in the Plain scenario. The statistical tests in Figure 6 are shown in Table 2 confirm that these effects are significant. Thus, we found that in both scaffolding scenarios the robots evolved behavior that is similar to what is achieved in Plain and different from that in Tilted. This is in contrast with our initial hypothesis outlined in the Introduction.

As for the evolved gaits of the robots we could distinguish three prominent strategies, rolling, rowing, and standing still. Rolling is characterized by rotating over the roll or pitch dimension with the whole extension of the body. Rowing is characterized by simultaneously boosting with one or more parts of the body, keeping the head somewhat balanced. Standing still refers to robots that almost did not move. Table 1 shows the counts (out of the 10 independent runs) for each of these gaits in each of the four environmental scenarios. The distribution of these counts shows the same effect as the balance values: most runs of the scaffolding scenarios converged to the predominant gait for Plain (rolling), while all the Tilted runs that avoided the stand still strategy converged to another gait (rowing).

<table>
<thead>
<tr>
<th>Scenario/Gait</th>
<th>Rolling</th>
<th>Rowing</th>
<th>Still</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plain</td>
<td>9</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Tilted</td>
<td>0</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>Equal Scaffolding</td>
<td>7</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Incremental Scaffolding</td>
<td>8</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1: Number of runs in which different gaits emerged within each environmental scenario.

**Morphology**

The morphological properties of the robots also present the same effect as observed for behaviors. Figure 7 contains the progression of the morphological descriptors for all the environmental scenarios. The scenario Tilted presents significant difference for several morphological descriptors when compared to all other scenarios. On the other hand, Plain, Equal Scaffolding, and Incremental Scaffolding present (almost) no cases of difference among themselves. These differences, i.e., induced properties on the evolved robots, between Tilted and Plain are evidence of the effects of the environmental conditions. In the case of Tilted, the selection pressure favored robots that are smaller, more proportional, less actuated and with more and shorter limbs in comparison with Plain. However, when introducing the context of a gradual change this pressure disappeared. What we see instead, is the gradualness of the changes causing the predominant robot traits of Plain to also emerge when scaffolding for Tilted. This phenomenon could perhaps be due to the scaffolding scenarios, once starting the evolution in the Plain environment, being driving the search to distinct areas which would be immediately favored when starting evolution directly in the Tilted environment. Statistical tests comparing the curves in Figure 7 are shown in Table 2.

To better illustrate the morphological differences and similarities in the last 10 generations we plotted the density maps for certain pairs of descriptors in Figure 8. These maps provide additional confirmation of the fact that the scaffolding scenarios end up with rather Plain-type populations.}

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6. A video showing some of the emergent robots in each environment can be found in http://tinyurl.com/y5deuh5

7. We additionally analyzed other morphological descriptors, but as they presented no significant differences, we did not include them in this paper.
Finally, we display the morphologies of the five best individuals of each run of each scenario for visual inspection in Figure 9. Looking at these forms, we can see that “snakes” are the winning morphologies in Plain and they are also very prominent in the scaffolding scenarios. The Tilted world is again the outlier, where only one run ends up with “snakes”, five runs lead to more complex shapes and four with small robots (that do not move).

**Robustness**

We performed a set of tests to check the robustness of the robots, i.e., their capacity to perform well in different environments. To this end, we looked at the speed of the final populations of each environmental scenario in both the Plain and in the Tilted environment. Figure 10 shows the box-plots summarizing these results.

As expected, robots evolved in the Plain scenario were much slower when tested in the Tilted environment. Nevertheless, when the robots evolved in the Tilted scenario were tested in the Plain environment, their speed was not different. Additionally, for both scaffolding scenarios, the fitness of the evolved robots tested in the Plain environment was better than or equal to the fitness in the Tilted environment. In summary, for all scenarios robots tested in the Plain environment always achieved higher or at least no different speed from the ones tested in the Tilted environment. This is curious because although the Tilted environment proved more difficult for the robots than the Plain environment, it could be the case that the properties of one difficult environment might not be “compatible” with the properties of an easy one.

## Table 2: Wilcoxon tests (p-values) for differences in the means (averaged over all runs) in the final populations. Significant differences (p < 0.05) are highlighted. P = Plain, T = Tilted, ES = Equal Scaffolding; IS = Incremental Scaffolding.

<table>
<thead>
<tr>
<th></th>
<th>P vs T</th>
<th>P vs ES</th>
<th>P vs IS</th>
<th>T vs ES</th>
<th>T vs IS</th>
<th>ES vs IS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>0</td>
<td>1e-04</td>
<td>0</td>
<td>0.247</td>
<td>0.007</td>
<td>0.63</td>
</tr>
<tr>
<td>Balance</td>
<td>0.002</td>
<td>0.25</td>
<td>0.58</td>
<td>5e-04</td>
<td>0</td>
<td>0.32</td>
</tr>
<tr>
<td>Number of Joints</td>
<td>2e-04</td>
<td>0.171</td>
<td>0.6</td>
<td>0.001</td>
<td>4e-04</td>
<td>0.15</td>
</tr>
<tr>
<td>Rel. Number of Joints</td>
<td>2e-04</td>
<td>0.231</td>
<td>0.903</td>
<td>0.008</td>
<td>0.002</td>
<td>0.405</td>
</tr>
<tr>
<td>Number of Limbs</td>
<td>0.73</td>
<td>0.96</td>
<td>0.803</td>
<td>0.654</td>
<td>0.962</td>
<td>0.803</td>
</tr>
<tr>
<td>Rel. Number of Limbs</td>
<td>0.002</td>
<td>1</td>
<td>0.16</td>
<td>0.002</td>
<td>4e-04</td>
<td>0.182</td>
</tr>
<tr>
<td>Length of Limbs</td>
<td>2e-04</td>
<td>0.91</td>
<td>0.052</td>
<td>8e-04</td>
<td>2e-04</td>
<td>0.06</td>
</tr>
<tr>
<td>Rel. Length of Limbs</td>
<td>0.022</td>
<td>0.96</td>
<td>0.803</td>
<td>0.02</td>
<td>0.03</td>
<td>0.803</td>
</tr>
<tr>
<td>Proportion</td>
<td>3e-04</td>
<td>0.384</td>
<td>0.382</td>
<td>0.001</td>
<td>0.003</td>
<td>0.161</td>
</tr>
<tr>
<td>Size</td>
<td>4e-04</td>
<td>0.97</td>
<td>0.035</td>
<td>0.002</td>
<td>2e-04</td>
<td>0.056</td>
</tr>
</tbody>
</table>

the meanwhile, the last generations in the Tilted environment are clustered in more distant areas.

Finally, we display the morphologies of the five best individuals of each run of each scenario for visual inspection in Figure 9. Looking at these forms, we can see that “snakes” are the winning morphologies in Plain and they are also very prominent in the scaffolding scenarios. The Tilted world is again the outlier, where only one run ends up with “snakes”, five runs lead to more complex shapes and four with small robots (that do not move).
can observe the following. For Incremental Scaffolding the differences in speed are not significant between the Plain and the Tilted environments. However, for Equal Scaffolding the evolved robots are significantly slower in Tilted, even though only the first 25 generations have been evolved in the Plain environment and 75 generations were exposed to tilted floors with different angles of inclination. This could be related to the fact that Equal Scaffolding, differently from Incremental Scaffolding, allows robots to evolve for the same amount of generations in all stages, regardless of their difficulty. Thus, once the Tilted environment is more challenging, there is not time enough for the robots to adapt to it as well as to the Plain environment. Finally, for robots tested in the Tilted environment, there was no difference between having been evolved with Incremental Scaffolding or Equal Scaffolding, and the same can be said about robots tested in the Plain environment.

**Conclusions and Future work**

We studied the effects of environmental histories by evolving modular robots using different environmental scenarios, a) flat terrain; b) inclined terrain; c) environmental scaffolding from flat to inclined, using an equal number of generations per stage; d) environmental scaffolding from flat to inclined, using increasing numbers of generations per stage. To assess the effects of these scenarios, we utilized a set of morphological and behavioral descriptors. Our results showed that 1) Both scaffolding scenarios helped in the dis-
covery of better (faster) robots; 2) While the Tilted scenario induced morphological and behavioral properties different from the ones induced by the Plain scenario, both scaffolding scenarios induced the same properties as Plain. 3) From the perspective of robustness, the advantage of using Incremental Scaffolding instead of Equal Scaffolding concerns obtaining a population of robots that performs the task with equivalent quality in both the involved environments. In summary, we can draw two main lessons from this study. First, we observe that populations have a “genetic memory” of properties evolved in environmental conditions from early stages. Second, we note that to evolve robots for difficult conditions it is beneficial to gradually increasing the difficulty.

For future work we propose to verify the effects of inverting the scaffolding to scenarios, starting with the most challenging environment, and ending with the easiest one.

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