

Morphological change in machines accelerates the evolution of robust behavior

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Most animals exhibit significant neurological and morphological change throughout their lifetime. No robots to date, however, grow new morphological structure while behaving. This is due to technological limitations but also because it is unclear that morphological change provides a benefit to the acquisition of robust behavior in machines. Here I show that in evolving populations of simulated robots, if robots grow from anguilliform into legged robots during their lifetime in the early stages of evolution, and the anguilliform body plan is gradually lost during later stages of evolution, gaits are evolved for the final, legged form of the robot more rapidly—and the evolved gaits are more robust—compared to evolving populations of legged robots that do not transition through the anguilliform body plan. This suggests that morphological change, as well as the evolution of development, are two important processes that improve the automatic generation of robust behaviors for machines. It also provides an experimental platform for investigating the relationship between the evolution of development and robust behavior in biological organisms.

evolutionary computation | robotics | evolutionary robotics | biomechanics | locomotion

Using robots to study adaptive behavior is of interest as a basic intellectual pursuit, but it may also lead to machines that assist or replace humans in unstructured or outdoor environments. To date, however, limited success has been achieved in realizing machines that continually perform simple yet robust behaviors in unstructured environments. It is contended here that this is due to overemphasis on the proximate mechanisms (1) of adaptive behavior—copying specific morphological and neuro-morphological detail from organisms of interest into robots (2) in the hopes of replicating their behavior—and too little emphasis on the ultimate mechanisms of behavior—replicating the ontogenetic processes and selection pressures that gave rise to the behavior initially.

To demonstrate the value of incorporating the evolution of development (3) into robotics, here I show that the automated discovery of robot behaviors can be accelerated if their body plans progress from an infant to an adult form over their lifetime (Fig. 1*B*)—and this ontogenetic change itself changes over successive generations of robots (Fig. 1*D* and *F*) such that later robots exhibit only the adult form during their lifetime (Fig. 1*H*)—than if robots maintain the adult form throughout behavior optimization. Moreover, robots evolved with this evolution-of-development method were found to be more robust to environmental perturbation than robots evolved without it because the former robots' ancestors assumed a range of body plans and thus had to maintain the behavior over a wider range of sensor-motor relationships.

The method introduced here follows a biologically inspired approach to robotics in which populations of simulated robots undergo evolutionary pressure favoring some desired behavior (4, 5). In some approaches, only the robot's controller is optimized (6, 7) after which the best controller can be downloaded onto a physical robot (8). Alternatively, the robot's body plan can be evolved as well (9–12), after which the best body plan can be automatically manufactured (10). However, there are only two cases reported in the literature (13, 14) in which a simulated

robot's body was allowed to change while it was behaving. It was not clear though whether this ontogenetic morphological change facilitated the evolution of behavior.

Evolving Behavior

The system introduced here allows a robot's body plan to change while it behaves: Robots progress from anguilliform body plans (15) into upright, legged body plans while behaving in a simulated environment (Figs. 1*B* and Fig. 2*N*). Moreover, this morphological change itself changes over phylogenetic time such that later robots exhibit only the legged form.

This is accomplished by starting with an initial population of random neural-network controllers. Each robot is evaluated for a fixed time period using one of the controllers, and its ability to perform phototaxis is measured. The next generation is generated by probabilistically discarding controllers that produced poor behavior, creating randomly perturbed copies of the remaining controllers, and evaluating the new controllers. Generations elapse in this way until a controller evolves that successfully moves the robot to a light source placed in its environment during a fixed time period (Fig. 1*B*). Once this successful controller is found, each controller is reevaluated on a robot with an altered ontogeny: Morphological change is accelerated such that the robot begins with the anguilliform body plan and progresses to the adult, upright form over the first two-thirds of its evaluation period (Fig. 2*O*). Over the remaining third of the evaluation period it maintains the upright form. Usually, this degrades the behavior of the current controllers, so evolution continues until successful phototaxis is rediscovered (Fig. 1*D*).

Ontogeny is again altered such that robots now reach the upright form after the first third of the evaluation period (Fig. 2*P*). Evolution again proceeds until phototaxis is rediscovered (Fig. 1*F*). In the fourth and final phase of evolution, each robot begins with the upright, adult form and maintains it throughout its evaluation in the simulated environment (Fig. 2*Q*). The experiment ends when an upright robot capable of phototaxis is discovered (Fig. 1*H*).

Impact of Morphological Change on Behavior

This process was found to produce successfully phototacting robots with the upright stance more rapidly, and the resulting behaviors were more robust, compared to four baseline algorithm variants in which morphological change is lessened or disabled. In all five variants, it is assumed that the final goal of the system is the automated discovery of a controller for an upright legged robot such that it locomotes toward a light source placed in its simulated environment (Fig. 1*H*). Thus, in all five algorithm variants, in the final generations controllers are evolved on robots that maintain the upright, legged form throughout behavior evaluation (Fig. 2*A*, *E*, *I*, *M*, and *Q*). Once such a controller is found

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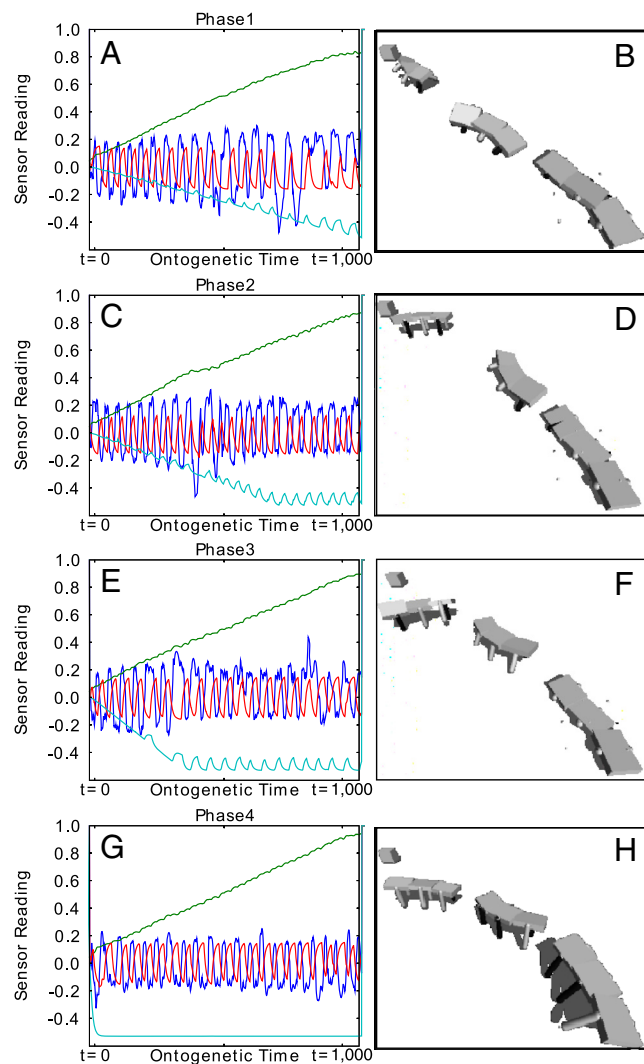


Fig. 1. Results from a typical experiment. (A) Sensor signals obtained from the first robot to evolve that successfully performs phototaxis in the first phase of evolution. (The blue line reports signals from one of two vestibular sensors in the robot's front segment, the green line reports signals from one of three photoreceptors located in the front segment, the red line reports signals from one of four proprioceptive sensors in the spine, and the light blue line reports signals from one of six proprioceptive sensors at the base of each leg.) The robot's behavior and morphological change is shown in B: It begins in the legless form (Lower Right); as it locomotes, it grows limbs (Center) and finally reaches the target object at the end of its "lifetime," at which point it has assumed the fully upright, legged form (Upper Left). The sensor signals (C) and behavior (D) of the successful robot found during the second phase: this robot reaches the fully upright, legged form two-thirds of the way through its lifetime. The sensor signals (E) and behavior (F) of the successful robot found during the third phase: this robot reaches the adult form one-third of the way through its lifetime. The sensor signals (G) and behavior (H) of the successful robot found during the fourth phase: this robot never assumes the infant, legless form; it maintains the legged form throughout evaluation.

in any of these trials, it can be downloaded onto a physical robot with an upright quadrupedal form as shown in Fig. 2 U–W.

No Morphological Change. In the first baseline variant, the robots evolve using the same controller architecture, objective function, and optimization algorithm as before, but now no robots experience any morphological change: Each robot begins with the upright legged form and maintains it until the end of its evaluation period (Fig. 2A). Evolution continues until a robot is discovered that successfully exhibits phototaxis.

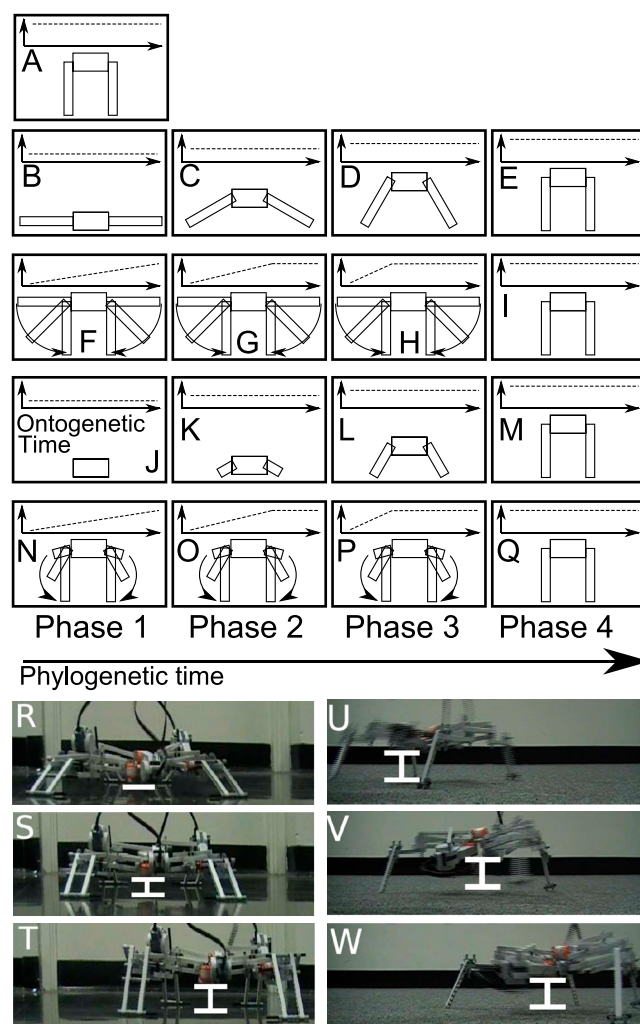


Fig. 2. Allowing morphological change during the evolution of robot behavior. (A) The first baseline algorithm variant in which all robots were evaluated in a fixed, upright stance. (Inset) Graph indicates how the height of the robot's center of mass changes during evaluation. (B–E) The second baseline variant, in which the robot's body plan changes parametrically from one evolutionary phase to the next but not while moving. (F–I) The third baseline variant in which ontogenetic morphological change is incorporated. (J–M) The fourth baseline variant in which anguilliform robots in the first phase evolve into upright legged robots in the final phase, but there is no morphological change during robot evaluation. (N–Q) The proposed method in which topological morphological change is combined with ontogenetic morphological change. (R–T) A physical robot was constructed that undergoes ontogenetic morphological change (as in F). This robot walks from left to right while transitioning from a prone to an upright stance. Once such a gait is found for the physical robot, the additional motors required to achieve ontogenetic morphological change can be removed, and the robot exhibits the same gait with a fixed, upright stance (U–W).

Parametric Change. In the second baseline variant, only parametric morphological change was allowed. Topological morphological change is defined here as the growth of legs from an initially anguilliform body plan (Fig. 1). Parametric morphological change is defined as the angle between the robot's legs and its trunk, but the number of body parts and motorized degrees of freedom remain constant. In this variant robots begin with legs, but they are aligned horizontally such that the trunk of the robot is in contact with the ground plane. The controllers in the robots may then actuate the trunk and sweep the legs through the sagittal plane, thereby mimicking a reptilian body plan (Fig. 2B). In the initial generations of this variant, robots maintain this body plan throughout the evaluation period. When a successful robot is dis-

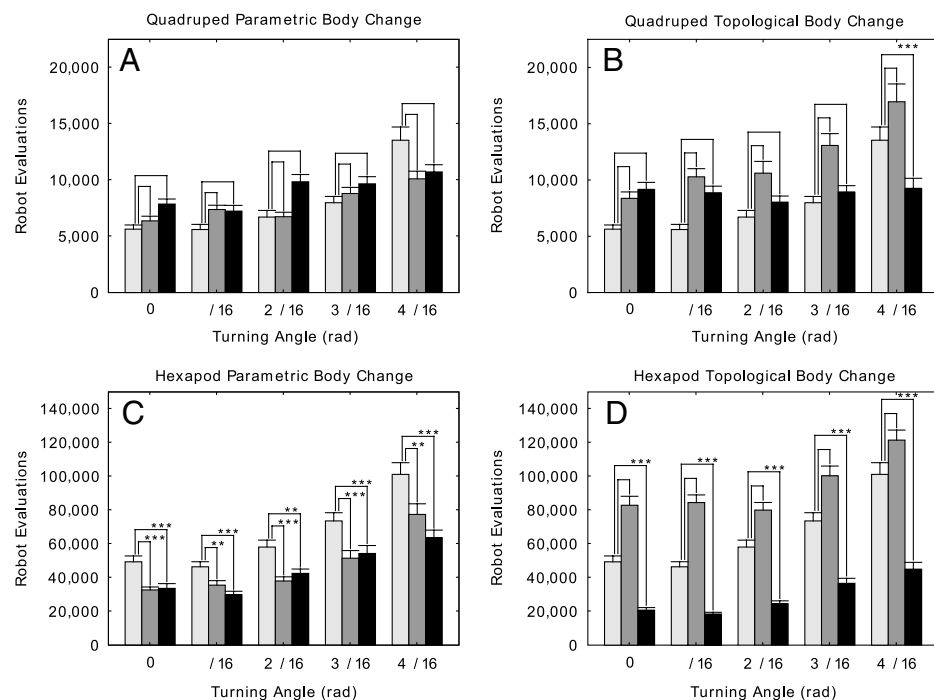


Fig. 3. How morphological change affects the time to discovery of the desired behavior in the quadruped (A and B) and hexapod (C and D) robot. Light gray bars indicate the number of controllers that had to be evaluated when no morphological change was allowed. Dark gray bars indicate the discovery time when the robots' body plans did not change during a robot's lifetime, but did change over evolutionary time. Black bars indicate the discovery time when body plans changed during each robot's lifetime, and also over evolutionary time. The dark gray and black bars in A and C report the impact of changing the robot's body plans parametrically; the dark gray and black bars in B and D report the impact of changing the robot's body plans topologically. Asterisks report statistically significant differences between no morphological change and topological, ontogenetic morphological change. Error bars report one unit of standard error of the mean.

change accelerates behavior discovery significantly compared to parametric change for all five task environments (Fig. 3 C and D): The p values obtained from the Mann-Whitney U test produced $p = 4.3 \times 10^{-6}$, $p = 1.7 \times 10^{-6}$, $p = 1.2 \times 10^{-8}$, $p = 8.7 \times 10^{-4}$, and $p = 4.4 \times 10^{-5}$ for the five increasingly challenging task environments, respectively.

This advantage can be explained as follows: When parametric body plan change is employed, evolution must shape controllers that orchestrate the spine and all four (or six) legs in the initial generations. When topological change is employed, however, only the spine motors must be orchestrated initially: the legs, while growing, have relatively little impact on the displacement and heading of the robot. Subsequent evolution aligns the legs' motions with the trunk's motion. This result corroborates observations from learning theory (18, 19) that manually clamping some degrees of freedom in a robot with a fixed body plan, and then gradually releasing them during learning, can accelerate behavior acquisition (20).

It was found that in general (Fig. 3) as the task thus became more challenging, the benefit of employing topological and ontogenetic morphological change during behavior optimization became more pronounced, compared to not allowing morphological change, for both robots. In short, the infant body plans scaffold behavior acquisition: Maintaining balance does not become an issue until robots in later evolutionary phases must begin and maintain an upright form during locomotion. It is known that environmental and social scaffolding accelerate the rate of learning in humans (21) and robots (22). Here, the robot's own body scaffolds behavior acquisition.

Impact of Different Developmental Trajectories. It is possible that the advantage conferred by morphological change is an artifact of the particular evolution-of-development trajectory employed: Robots grow from an infant to an adult form gradually, but this change is accelerated such that later robots transition increasingly rapidly, and the final robots begin evaluation with the adult form. To test this a different developmental trajectory was formulated: Initial robots transition from the infant to adult form as before, but in the second phase robots begin with a form one-third of the way from the infant to the adult form and progress to the full adult form (Fig. S2 J and N). In the third phase they begin with

a form two-thirds of the way to the adult form (Fig. S2 K and O), and in the fourth phase begin and end in the adult form.

This trajectory was tested on both robots, in all five task environments, and using parametric (Fig. S2 I–L) and topological (Fig. S2 M–P) change. These trials were contrasted with another set of trials in which robots maintain the infant form throughout evaluation in the first phase (Fig. S2 A and E), robots transition from the infant to the adult form in the second phase (Fig. S2 B and F), robots begin evaluation with a form midway between the infant and adult form and transition to the adult form in the third phase (Fig. S2 C and G), and finally begin evaluation with the adult form in the fourth phase.

It is predicted that this latter developmental trajectory should perform poorly as controllers will suffer a large decrease in fitness when they experience the adult form for the first time in the second phase. The former trials, however, should perform well as controllers experience all forms of the body plan during the first phase. Fig. S3 shows that this is indeed the case. As for the first developmental trajectory, when topological and ontogenetic change is allowed using the new developmental trajectory, and robots in the first phase experience the infant and adult forms, phototaxis is discovered more rapidly for the final, upright robot (Fig. S3, green bars) than it is if robots do not experience the adult form during the first phase (Fig. S3, red bars) or no morphological change is allowed (Fig. S3, light gray bars).

Robustness of Evolved Behaviors. It was found that not only did the right kind of morphological change accelerate the discovery of successful behavior, but the discovered controllers were more robust to novel environmental perturbations than controllers discovered when morphological change was disabled. This was accomplished by taking the final controllers from each trial, which successfully produced phototaxis in the upright robot, and reevaluating them in the same robot but applying slight random perturbations to the robot while it behaved. One hundred of these noisy reevaluations were performed for each of the controllers, and the mean difference in performance was measured as a percentage decrease in the overall fitness of the noisily evaluated robots (Fig. 4).

Robustness can arise as a result of modularity (23), but no increased structural (24) or functional (25) modularity was detected in the controllers evolved within the morphologically changing

methods such as the one presented here that simulate phylogenetic and ontogenetic change to body plans and neural networks could serve as unique tools for investigating such hypotheses.

Materials and Methods

This material describes in more detail the simulated robots and their controllers.

The Simulated Robots. A 10-degree-of-freedom (DOF) quadrupedal and 16-DOF hexapedal robot were employed in this work. Both have actuated spines and employ the same sensor modalities. The trunk of the quadrupedal robot is composed of a front and back segment; the segments are attached by a 2-DOF actuated rotational joint that allows the segments to yaw and roll relative to one another. The segments may yaw through $[-50^\circ, 50^\circ]$ and roll through $[-20^\circ, 20^\circ]$. The wider range of motion through the coronal plane helps the robot to turn when the light source is placed to its left. Each of the four legs is attached to the front or back segment by a 2-DOF actuated rotational joint. One DOF sweeps the leg through a transverse plane centered at the leg. The joint's range is defined as $[(-10+x)^\circ, (10+x)^\circ]$, where x is the angle of the leg relative to body. If the leg is absent or is horizontal to the body, $x = 0^\circ$; if the leg is vertical, $x = -90^\circ$. For those experimental regimes in which the robot undergoes ontogenetic morphological change, x changes as the robot behaves. For the second DOF in the leg, if the leg is horizontal the joint sweeps $[-50^\circ, 50^\circ]$ through the robot's coronal plane; if the leg is vertical, it sweeps through the sagittal plane; for other angles of the leg it sweeps through a plane intermediate between the coronal and sagittal plane. The hexapedal robot has a different mechanical construction to ensure the results were not specific to a given body plan. The hexapod's spine is composed of three segments, with each pair connected by two, 2-DOF actuated rotational joints. Both joints allow the segments to yaw and roll relative to one another, but unlike the quadruped each DOF can sweep through $[-30^\circ, 30^\circ]$. Each of the six legs is controlled by a 1-DOF rotational joint that sweeps the leg $[(-10+x)^\circ, (10+x)^\circ]$ through a transverse plane centered at the leg. As for the quadruped robot, x is the joint's set point that

can change from $x = 0^\circ$ if the leg is absent or horizontal through to $x = -90^\circ$ if the leg is vertical. Both robots are equipped with proprioceptive sensors at each DOF, a vestibular and photosensor at their centroids, and a second and third photosensor at the base of their front left and right legs, respectively. Each foot is also equipped with a binary tactile sensor.

The Controllers. Each of the two robots is equipped with a continuous time recurrent neural network (45). For each robot, a fully connected network is employed: Each degree of freedom is assigned a motor neuron, each motor neuron is connected with a synapse to every other motor neuron, and every sensor is connected to every motor neuron. At each time step of the simulator each motor neuron is updated according to

$$\tau_i y'_i = -y_i + \sum_{j=1}^m w_{ji} \sigma(y_j - \theta_i) + \sum_{j=1}^s n_{ji} s_j, \quad [1]$$

where m is the number of motor neurons in the robot ($m = 10$ and $m = 16$ for the quadruped and hexapod, respectively), s is the number of sensor neurons in the robot ($s = 5 + 10$ and $s = 5 + 16$ for the quadruped and hexapod, respectively), τ_i is the time constant associated with motor neuron i , y_i is the value of neuron i (with a range in $[0.0001, 1.0]$), $\sigma(x) = 1/(1 + e^{-x})$ is an activation function that brings the value of neuron i back into $[0, 1]$, w_{ji} is the weight of the synapse connecting neuron j to neuron i (with a range in $[-16, 16]$), θ_i is the bias of neuron i (with a range in $[-4, 4]$), n_{ji} is the weight of the synapse connecting sensor j to neuron i (with a range in $[-16, 16]$), and s_j is the value of sensor j . The optimizer was found to be insensitive to different settings for the ranges, so these ranges were adopted from previous reported values (45). This yielded 270 and 624 free parameters to be optimized by evolution for the quadruped and hexapod, respectively. Movies of the simulated and physical robots can be found in [SI Text](#).

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