MorphWorld: A State Transition Simulator

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Abstract

Digital simulation enables a wide variety of research and applications underlying the study of artificial life. In evolutionary robotics applications, the focus is often on maximizing *performance* of an animat for a specific task. Analyzing evolved behaviors can be challenging, however, given the complex coupling of morphology and brain. In this paper, we introduce a simulation environment built to investigate animats capable of smoothly transitioning between operating modes (e.g., from cautious to aggressive or from one physical form to another). The simulator provides functionality for logging sensory information as well as animat state enabling a deep analysis. Although more abstract than soft-body or rigid-body physics engines, it is lightweight and efficient, allowing for a high number of simulations in a small amount of time. The simulation supplements other more complex physics-based environments providing for greater inspection of sensor information and animat behavior. Furthermore, it is designed to provide an extensible test bed beyond just gait transitions to assess new artificial intelligence and evolutionary algorithms and more importantly the combination of these techniques.

Introduction

Simulation environments enable testing and verification of new robotic systems and adaptive controller designs (6; 12). However, simulation and animat complexity can make it challenging to analyze new controller behaviors as well as to assess algorithm characteristics (10). Interactions between morphology, controller, and task complexity make it challenging to isolate what aspects of brain, body, or problem formulation might contribute to the effectiveness of a solution (11). In addition, simulators do not always have full monitoring capabilities, which often necessitates a custom solution to help elucidate "why" a controller makes a decision. Even high fidelity simulators more often than not fail to produce behaviors that cross the reality gap (7; 8).

In this paper, we present a simulator for bench-marking artificial intelligence and evolutionary algorithms against an animat in a three dimensional voxelized world. The simulator, shown in Figure 1, was first and foremost designed to be as simple as possible while requiring morphological transformations as motivated by earlier controller design in (6).

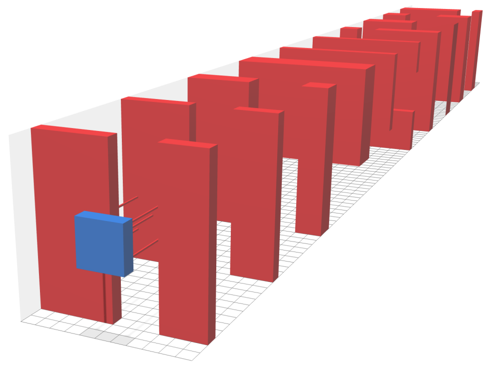
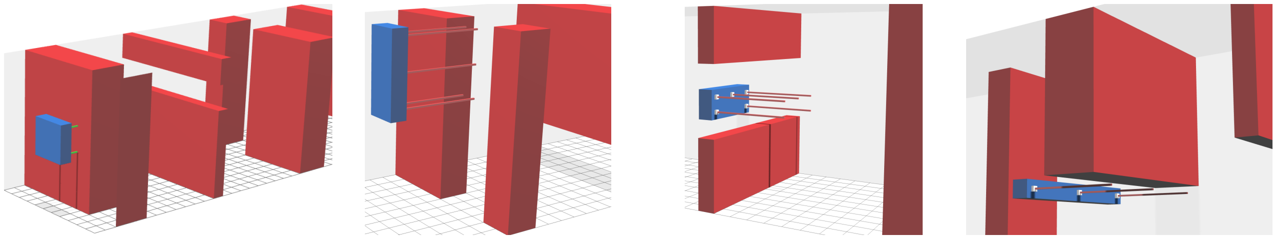


Figure 1: A view of the tunnel configuration of a simulation. The animat (blue) must navigate a series of obstacles by changing its shape to fit through gaps of varying sizes in zero gravity.

Specifically, building testable, robust controllers capable of transitioning between different gaits is an outstanding challenge that inspired this simulator. From a software perspective, walking and running are different modes of operation, and designing algorithms to identify modes and transition points is an ongoing challenge. Here, we focus on a related problem, the transition between different morphological states as a proxy for operating modes. The simulator simplifies the mode switching problem from a legged robotics domain to a voxel-based tunnel world. Movements are applied to the animat without the added complexity that joint actuation may introduce as observed in many robotics applications (5; 9; 14). Second, sensors (e.g., cameras or an array of distance sensors) allowing an animat to perceive its environment are implemented with full logging capability built-in, facilitating later analysis. The simplified world makes it easier to train vision-based deep learning algorithms (e.g., deep reinforcement learning and convolutional neural networks (Tai et al.)) and compare results with evolutionary algorithm approaches (e.g., ANNs and GPs). Finally, acknowledging the role morphology plays in robotics (4; 2; 1), the animat's morphology can change shape facilitating controller exploration in the face of changing morphology.



(a) (b) (c) (d)

Figure 2: (a) The 3D-maze navigation task requires that the animat to locate a gap to move through. (b) With an appropriate shape and no sensor collisions the animat navigates through a gap. (c) Wide, short gaps require a morphological change directed by the animat's controller to be short and wide. (d) The animat at its widest configuration to navigate a low, short gap.

Simulation Environment

The simulator is voxel-based, with a single voxel (1x1x1) representing the smallest possible object. Animats and obstacles are cuboids comprising one or more voxels forming a composite object. Each possible voxel for an object has a three-dimensional coordinate associated with it. The simulation proceeds in a discrete, step-wise manner with duration of a simulation measured in terms of the number of elapsed simulation steps. Collision checking is performed between steps of the simulation with two composite objects prohibited from inhabiting the same voxel simultaneously. If a movement would result in two objects occupying the same voxel, the movement is denied. The environment is also zero-gravity.

Example Task: Obstacle Navigation Figure 2 shows the animat in different morphological configurations over the course of an obstacle navigation task. Here, an animat with five possible shapes is tasked with navigating end-to-end through a tunnel populated with obstacles. A series of obstacles with randomly generated gaps is placed in front of the animat. Controllers are challenged to locate gaps, reconfigure the robot, and then navigate through to the next space.

The pictured animat has five possible shape configurations: one block tall by nine blocks wide, two by five, three by three, five by two, or nine by one. The animat has five forward facing distance sensors; one in the center and one on each corner voxel. The animat can move forward, backward, left, right, up, and down, and it can also choose to not move; the animat can also widen or narrow its body, which changes its width and height. If a widen or narrow command is given when the animat is already at the respective shape extent, a no movement operation is executed instead. The relatively simple control space is ideal for comparing, for example, a genetic program to a reinforcement learning policy.

Current Status and Future Improvements The software is currently built around the end-to-end navigation task. It is available under an open-source license at `https://github.com/jaredmoore/MorphWorld`. We plan several improvements, such as integrating the simulator with other initiatives as well as increasing the capabilities of the simulator itself. First, we are developing an interface with the OpenAI platform (3), allowing the simulator to readily be used with many existing algorithm implementations. Second, vision and lidar will be added as sensors enhancing the current sensor suite available to developers. Finally, we will implement interactions between animat and objects including rudimentary grasping and dynamically moving obstacles.

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