Sim2Real of Soft-Bodied, Shape-Changing Robots

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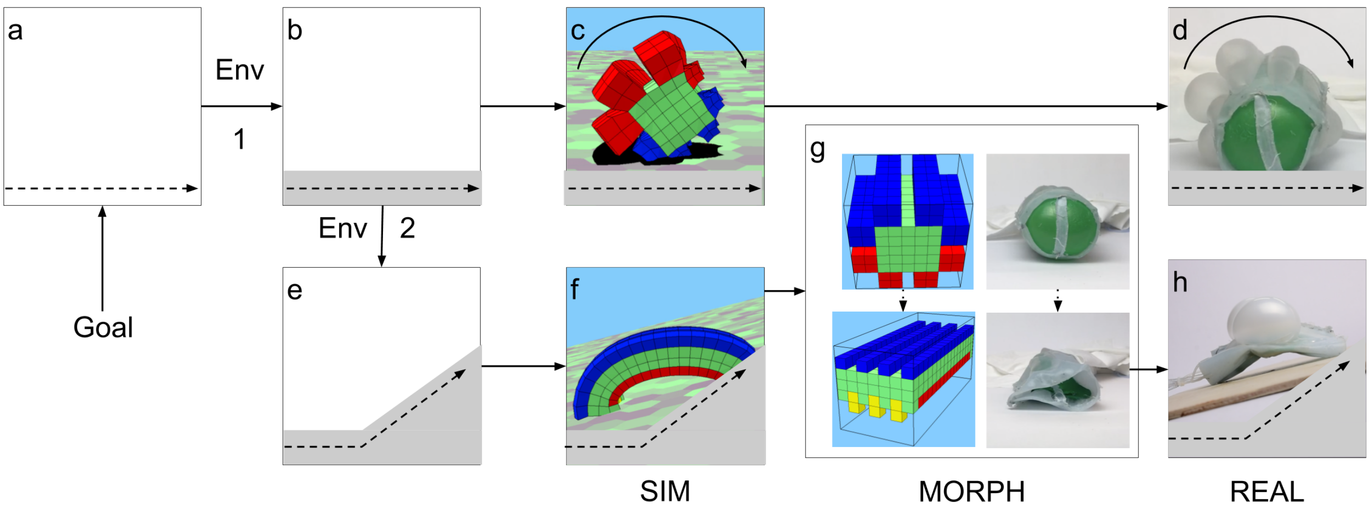

Fig. 1. **The sim2morph2real pipeline.** A goal behavior is supplied to the pipeline, such as forward travel (dotted arrow in **a**). A simulation of the robot's environment is then created (**b**), after which an optimization method automatically designs a simulated soft robot to achieve that behavior in that environment (**c**). It is then transferred to reality (**d**). If a new environment is added (**e**), a new shape and behavior is automatically designed for the robot in that environment (**f**) as well as a control policy that morphs the original shape into the new shape (**g**). The morphing plan and new controller are then sent to the physical robot (**h**).

***Abstract*—Soft robots provide a unique capability over rigid machines: the ability to continuously change their shape on demand. As demonstrated by organisms capable of shape change, this behavior has several desirable properties, including the ability to enter and operate in a wider range of environments, or manipulate objects with greater delicacy than a fixed-shape organism can. Introducing shape as a control variable leads to a rich yet complicated range of configurations, opening up a wide range of possibilities for multi-functional, shape-changing robots. Here, we present a target pipeline for the automatic design of soft-bodied, shape-changing robots to accomplish an input task, such as locomotion or grasping. We demonstrate working aspects of such a pipeline as we attempt sim2real transfer of morphing robots. In this context, we explore the current role of simulation, shortcomings of current soft robot simulators, and discuss methods for overcoming such shortcomings.**

***Index Terms*—Sim2Real, Reality Gap, Soft Robots, Shape Change, Simulation**

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I. Introduction

The emerging field of soft robotics holds promise for realizing machines capable of altering their shape to perform in changing environments. Shape change has allowed robots to crawl under low-hanging barriers [1], travel through different parts of the body [2], successfully operate in arboreal and underground environments [3], and — in simulation — exhibit large-scale deformations to squeeze through small apertures [4]. Collectively, this work shows how shape-change allows robots to adapt their functionality on-demand, for applications including locomotion, human-robot interaction, and grasping challenging objects.

Determining relevant shapes and effective control policies is difficult, both in simulation and in hardware. To address this limitation, we propose a pipeline that integrates advances in simulation, optimization, simulation-to-reality transfer, and physical soft robots to automate the design and manufacture of metamorphosing machines. This pipeline takes as input a desired goal state and target environments, and then automatically designs shapes, the transformations between them, and behaviors for each shape (Fig. 1). Importantly, this method automatically determines which shape/behavior pairs are appropriate for which environment. This is accomplished by training a variety of soft robots in different environments, selecting successful shape/environment combinations, and seeking transformations between all of those shapes. If transformations between all shapes can be be found, those shape/behavior pairs are output as instructions to the metamorphosing physical machine.

As a step toward realizing this complete pipeline, we present our own efforts to construct such a pipeline. A simplified task of locomotion was chosen; however, this work is a step toward a general-purpose simulator which can take tasks as seemingly different as locomotion and grasping, and find optimal robot designs and control policies. We then discuss current sim2real challenges and propose potential solutions.

II. Discussion

The capabilities of such a pipeline are inextricably tied to the chosen simulator. Particularly important for soft robot simulation is the trade-off between accurately modeling large continuum deformations, and using a computationally-efficient finite-element implementation to allow a greater number of simulations to be run. Current simulators for soft bodies are generally focused on specific tasks or specific robots. This works well for applications where there is a well-defined morphology. However, there are very few simulators which natively enable automatic design of dynamic soft robots' physical bodies.

One such simulator is the soft-bodied physics engine, Voxelyze, better known by its corresponding graphical interface: VoxCAD [5], which has been used in many other soft robotics experiments [6]–[8]. In this work, we used VoxCad due to its ability to simulate robots of a wide range of shapes with an API that is ideal for interfacing with evolutionary algorithms for automated design.

As a first test of the approach, we attempted to make a robot which operated in two highly dissimilar environments: a flat plane and an inclined plane (10°). In this "toy case", we sought to evaluate the suitability of the simulator for morphing and sim2real transfer, since the evolutionary algorithm portions of the pipeline are more established [6], [7], [9]. Evolutionary algorithms are well-suited to improve upon the basic shapes to adapt to complicated environments or difficult manipulation tasks. Rolling locomotion was chosen for the target shape for the flat environment; a flat shape was chosen for the incline (Fig. 1g). Robots are composed of cubic finite elements called voxels that can expand and contract in obeying given physical properties, including regions roughly corresponding to 8 pneumatic actuators that run along the length of its body.

While attainable in hardware, no solution was found to transition the robot from a rolling shape to a flat shape (Fig. 1g). This transition essentially corresponds to nearly complete shrinkage along a single dimension - collapsing a 3D robot into a 2D shape. As far as we are aware, no soft body simulators are set up to natively handle these types of transitions, even though many dramatic changes of functionality occur during such large-strain transitions. To test other aspects of the pipeline, we resigned to using a flat robot and a separate cylindrical robot. In preparation for the sim2real attempt, the robots were restricted to sufficiently slow "quasi-static" gaits (i.e., the robots couldn't trot or jump). Controllers were evolved for each simulated robot, and the robots indeed developed specialized functionality. The cylindrical robot evolved rapid rolling gaits for the flat terrain and was unable to roll up the hill. Meanwhile, the flat robot developed an inchworm gait which performed moderately well in both terrains. Thus, the ideal robot could normally locomote by rolling, and transition to a flat shape to inch up an incline.

The next step in the pipeline that we tested was sim2real. Due to the quasi-static nature of the controllers, the gait found for the inflated cylinder robot successfully transferred to reality, producing very similar behavior.

For the flat robot, the optimization algorithm found an inchworm motion. However, this did not properly transfer to reality due to differences in friction responses. Not only is there the typical error due to simulating Coulomb friction between two materials, but the friction coefficient can even change while the robot is at rest. In other words, the robot tends to stick to the ground when left motionless. Methods that may be best suited to overcome these types of problems include improving simulation, but will likely require approaches that attempt to increase the robustness of robot behaviors across change, such as Jacobi's radical envelope of noise [10].

Approaches for robustness also come with their own difficulties and hand designed features. One way to fix this in an especially enticing way for an automated pipelines includes improving a simulator based on data from reality. This could also include automatically tuning noise envelopes eliminating the difficulties from hand design. In the particular problem of friction one could imagine gathering real friction data on a soft robot and feeding that back into the simulator to update friction coefficients adding uncertainty (noise) in the simulation as part of it's optimization.

In our current version of this pipeline we are using locomotion as a toy example. Consequently the robot and it's two morphologies and environments are intuitive such that we can imagine and even hand design an optimal control policy. However, showing competency in this toy example implies that given a more arbitrary shape and goal a controller could be optimized to discover shapes and policies that are novel and non-intuitive. This could especially be applied to areas of manipulation of objects.

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