Sim2real of soft-bodied, shape-changing robots

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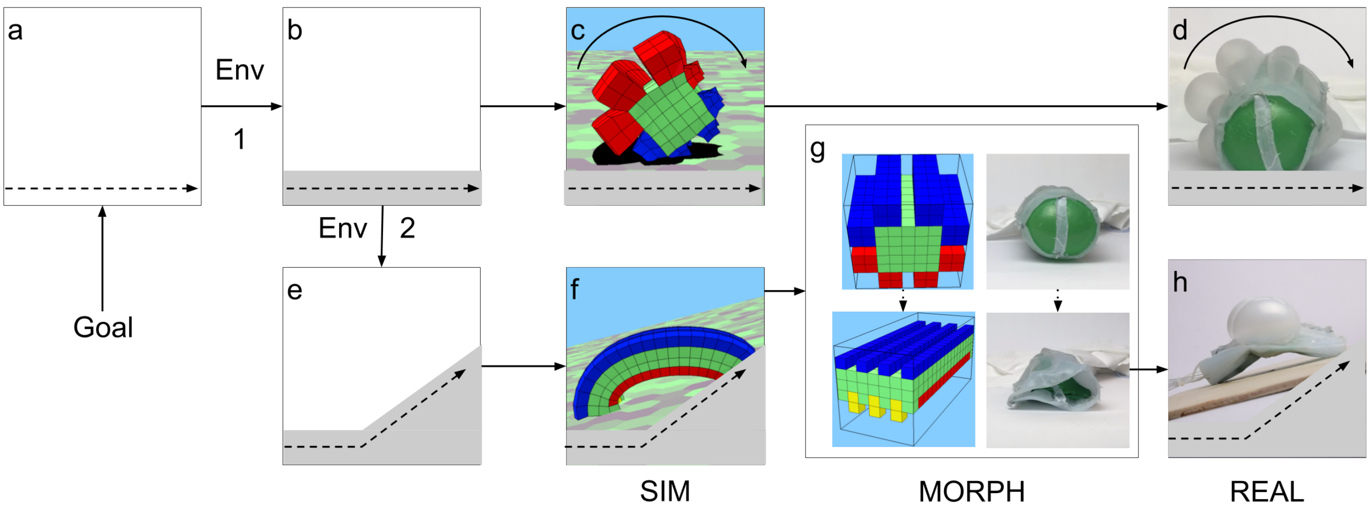

Fig. 1. **The sim2morph2real pipeline.** A goal behavior is supplied to the pipeline, such as forward travel (dotted arrow in **a**). A simulation of the robot's environment is then created (**b**), after which an optimization method automatically designs a simulated soft robot to achieve that behavior 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.**

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 grasp complex objects [4], recover from extreme structural damage [12], deliver temporary drug implants [20]; and successfully navigate below low-hanging barriers [18], over surface obstacles [17], through small apertures [6], and in challenging domains such as arboreal and underground environments [19]. Collectively, this work shows how shape-change allows robots to adapt their functionality to meet changing circumstances, and potentially mitigate some of the complications of controller adaptation (e.g., catastrophic forgetting; [15, 16]), for applications including locomotion, human-robot interaction, and object manipulation.

However, manually determining an effective shape and controller for a given environment, and how to transition to another shape when the environment changes, is extremely challenging in both simulation and in hardware [7]. 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.

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 more 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 [13].

One such simulator is the soft-bodied physics engine, Voxelyze, better known by its corresponding graphical interface: VoxCAD [9], which has been used in many other soft robotics experiments [5, 7, 8, 12]. 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 optimization algorithms for automated design [1].

As a first test of the approach, we attempted to make a robot which operated (locomoted) in two highly dissimilar environments: a flat plane (Fig. 1b) and an 10° inclined plane (Fig. 1e). In this "toy case," we sought to evaluate the suitability of the simulator for morphing and sim2real transfer, since the optimization portions of the pipeline are more established [7, 12]. Evolutionary algorithms are particularly well-suited to optimize shapes (in addition to their controllers) that are well-adapted to complicated environments or difficult manipulation tasks [3].

An elliptical cylinder (Fig. 1d) was manually chosen as the first target shape for the flat environment, and was manually flattened (Fig. 1g) into a second shape (Fig. 1h) to attack the incline. Simulated robots are composed of voxels—cubic finite elements that can expand and contract while obeying given physical properties—which are here constrained to mirror the (morphable) hardware of the real robot: eight, translucent pneumatic actuators wrapped around a green, inflatable core.

While attainable in hardware, no solution was found to transition the robot from an cylindrical to the flat shape (Fig. 1g). This transition essentially corresponds to nearly complete shrinkage along a single dimension—collapsing a 3D robot into a 2D shape. Soft body simulators are generally not equipped to natively handle these types of anisotropic transitions, even though many dramatic changes of functionality occur during such large-strain transitions.

To test other aspects of the pipeline, we temporarily sidestepped this limitation and hand designed two separate shapes: a flat robot, and a separate cylindrical robot. In preparation for the sim2real attempt, as in [14], the robots were restricted to sufficiently slow *quasistatic* gaits, in which the robot remains over its polygon of support at all times (i.e., no jumping or bounding gaits). 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 but 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, when necessary, transition to a flat shape to inch up an incline.

The next step in the pipeline that we tested was sim2real. Due to the quasistatic 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 adding noise to certain aspects of the environment [10].

Approaches for robustness also come with their own difficulties and hand-designed features. One way to fix this, which is especially enticing for a design pipeline with real-to-sim feedback, includes improving a simulator based on data intelligently gathered from reality [2]. This could also include automatically tuning noise envelopes. 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 preliminary instantiation of the pipeline here, the robot and its environments are intuitive: we can imagine—and even hand design—effective resting shapes and controllers. However, competency in this toy example implies that given an arbitrary physical substrate, environment, and goal behavior, a pipeline could be optimized to discover resting geometries and controllers (and the settings of other adjustable attributes such as material stiffness [11]) that are novel and non-intuitive. Thus, although we only considered locomotion, the pipeline could equally be applied to shapeshifting robots in other domains such as the manipulation of novel, complex objects.

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References

[1] URL https://github.com/skriegman/evosoro.

[2] Josh Bongard, Victor Zykov, and Hod Lipson. Resilient machines through continuous self-modeling. *Science*, 314(5802):1118–1121, 2006.

[3] Josh C. Bongard. Evolutionary robotics. *Communications of the ACM*, 56(8):74–83, 2013.

[4] Eric Brown, Nicholas Rodenberg, John Amend, Annan Mozeika, Erik Steltz, Mitchell R Zakin, Hod Lipson, and Heinrich M Jaeger. Universal robotic gripper based on the jamming of granular material. *Proceedings of the National Academy of Sciences*, 107(44):18809–18814, 2010.

[5] Nick Cheney, Robert MacCurdy, Jeff Clune, and Hod Lipson. Unshackling evolution: evolving soft robots with multiple materials and a powerful generative encoding. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 167–174. ACM, 2013.

[6] Nick Cheney, Josh Bongard, and Hod Lipson. Evolving soft robots in tight spaces. In *Proceedings of the 2015 annual conference on Genetic and Evolutionary Computation*, pages 935–942. ACM, 2015.

[7] Nick Cheney, Josh Bongard, Vytas SunSpiral, and Hod Lipson. Scalable co-optimization of morphology and control in embodied machines. *Journal of The Royal Society Interface*, 15(143):20170937, 2018.

[8] Jonathan Hiller and Hod Lipson. Automatic design and manufacture of soft robots. *IEEE Transactions on Robotics*, 28(2):457–466, 2012.

[9] Jonathan Hiller and Hod Lipson. Dynamic Simulation of Soft Heterogeneous Objects. *Soft Robotics*, 1(1), 2014. ISSN 2169-5172. doi: 10.1089/soro.2013.0010.

[10] Nick Jakobi, Phil Husbands, and Inman Harvey. Noise and the reality gap: The use of simulation in evolutionary robotics. In *European Conference on Artificial Life*, pages 704–720. Springer, 1995.

[11] Sam Kriegman, Nick Cheney, Francesco Corucci, and Josh C Bongard. Interoceptive robustness through environment-mediated morphological development. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 109–116. ACM, 2018.

[12] Sam Kriegman, Stephanie Walker, Dylan Shah, Michael Levin, Rebecca Kramer-Bottiglio, and Josh Bongard. Automated shapeshifting for function recovery in damaged robots. In *Robotics: Science and Systems*, 2019.

[13] Hod Lipson. Challenges and opportunities for design, simulation, and fabrication of soft robots. *Soft Robotics*, 1(1):21–27, 2014.

[14] Hod Lipson and Jordan B Pollack. Automatic design and manufacture of robotic lifeforms. *Nature*, 406(6799):974, 2000.

[15] Joshua Powers, Sam Kriegman, and Josh Bongard. The effects of morphology and fitness on catastrophic interference. In *Artificial Life Conference Proceedings*, pages 606–613. MIT Press, 2018.

[16] Joshua Powers, Sam Kriegman, and Josh C Bongard. Embodiment can combat catastrophic forgetting. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, pages 119–120. ACM, 2018.

[17] Dylan S Shah, Michelle Ching-Sum Yuen, Liana G Tilton, Ellen J Yang, and Rebecca Kramer-Bottiglio. Morphing robots using robotic skins that sculpt clay. *IEEE Robotics and Automation Letters*, 2019.

[18] Robert F Shepherd, Filip Ilievski, Wonjae Choi, Stephen A Morin, Adam A Stokes, Aaron D Mazzeo, Xin Chen, Michael Wang, and George M Whitesides. Multigait soft robot. *Proceedings of the National Academy of Sciences*, 108(51):20400–20403, 2011.

[19] Barry A Trimmer, Ann E Takesian, Brian M Sweet, Chris B Rogers, Daniel C Hake, and Daniel J Rogers. Caterpillar locomotion: a new model for soft-bodied climbing and burrowing robots. In *7th International Symposium on Technology and the Mine Problem*, volume 1, pages 1–10, 2006.

[20] Sehyuk Yim and Metin Sitti. Shape-programmable soft capsule robots for semi-implantable drug delivery. *IEEE Transactions on Robotics*, 28(5):1198–1202, 2012.