Behavioral Repertoires for Soft Robotics

John Rieffel (Union College)

Abstract Developing control systems for soft robots is challenging: the dynamics of soft materials often produce behaviors that are counter-intuitive and hard to model or predict. As a consequence, most behaviors for soft robots are discovered through the time-consuming process of empirical trial and error. This work seeks to develop data-efficient methods of exploring and exploiting the full range of soft robotic dynamical behaviors.

Quality Diversity Algorithms (QDA)

Quality Diversity Algorithms are a class of algorithm that seek out novelty instead of a singular optimality in a given space [2]. When applied to robotics, this translates to generating mappings between a robot's **parameter space** and its **behavior space** (Figure 2). When run on a soft robot QDAs produce a behavioral repertoire, which contains a diverse variety of behaviors the robot is capable of. QDAs have been successful when tested on both virtual agents [3] and physical robots [4].

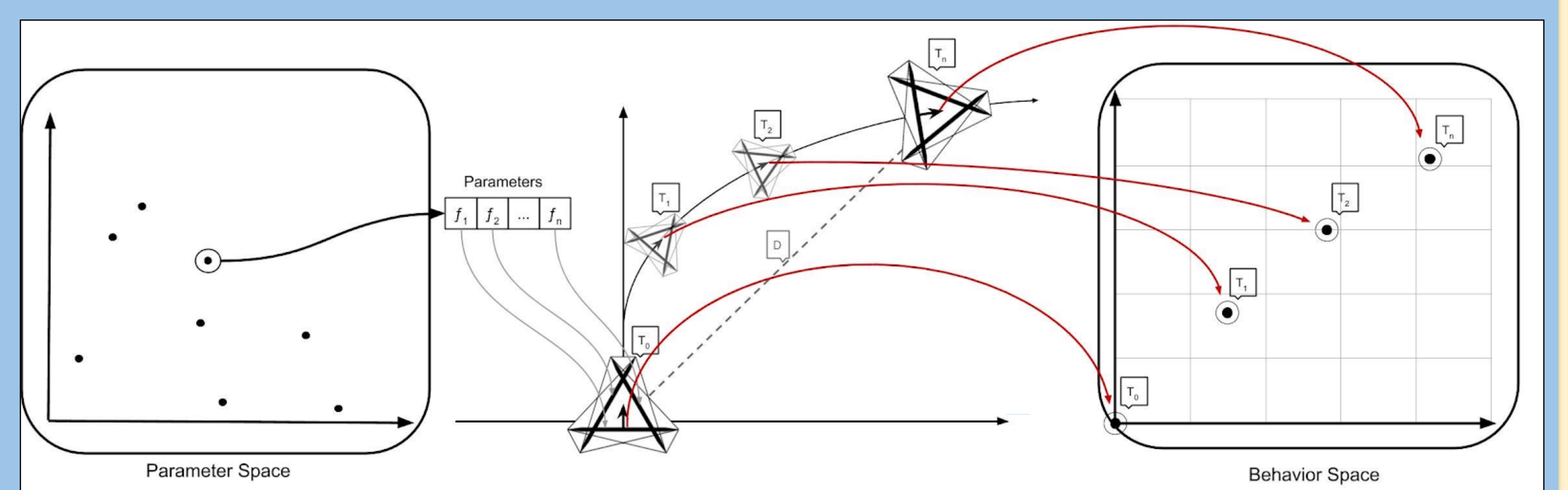


Figure 2: QDAs find a mapping between parameter space: the features a robot's controller manipulates, and its discretized behavior space: a description of the outcome of the controller's action.

Methods

We use a QDA called MAP-Elites [4] to construct a behavioral repertoire for our tensegrity robot. The **parameter space** is composed of the three speeds for the vibrating motors, and the **behaviors** are described by the robot's displacement in the x-y coordinate plane along with its rotation around the z axis (yaw). Formally a behavior $b = (\Delta x, \Delta y, \Delta\Phi)$.

Then we discretized the **behavior space** into twelve bins on the Δx and Δy axes with a 6cm width (-36cm:36cm), and six bins on the $\Delta\Phi$ axis with a 60° width (-180°:180°). We empirically determined these values by running tests to determined to what precision behaviors were repeatable.

For MAP-Elites, we needed to determine a fitness metric that ranked the 'goodness' of a behavior. When multiple configurations of parameters map to behaviors in the same behavior bin, we keep the behavior with a better fitness score. Our fitness metric is $f(b) = |\Delta x| + |\Delta y| + |\Delta\Phi|$. This metric prefers behaviors with greater absolute displacement, as this guarantees the most active behaviors of the robot are not discarded.

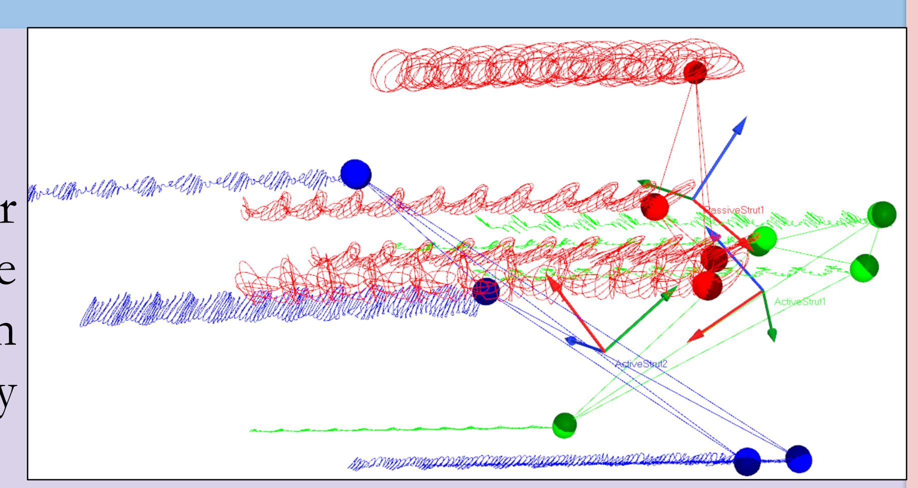


Figure 3: Four markers are placed on each of the three tracked tensegrity struts. These markers are tracked using a 20-camera Qualisys Oqus 700+ system and the QTM Tracking Software at a frame rate of 300 frames per second, which provides 6DOF position and rotation data for each marked strut.

Tensegrity Robots

Tensegrities (Figure 1) are relatively simple mechanical systems, consisting of several rigid elements (struts) joined at their endpoints by tensile elements (springs), and kept stable through a synergistic interplay of pre-stress forces [1].

Unlike many other soft robots, tensegrity structures are inherently modular and are therefore relatively easy to design and build, while still exhibiting many of the complex properties of more fully soft robots. They are therefore a compelling platform with which to explore the challenges of soft robot control.

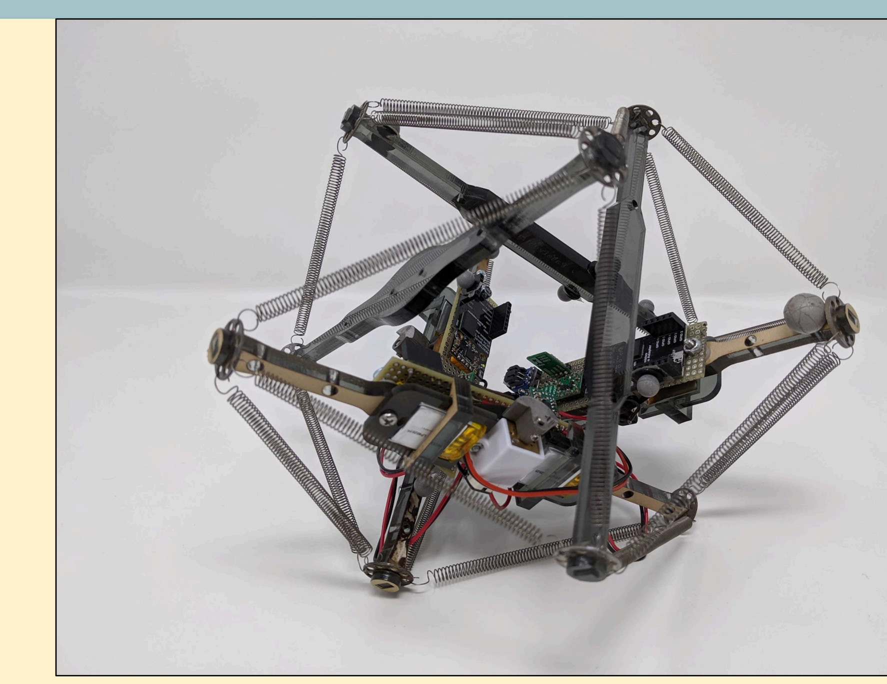
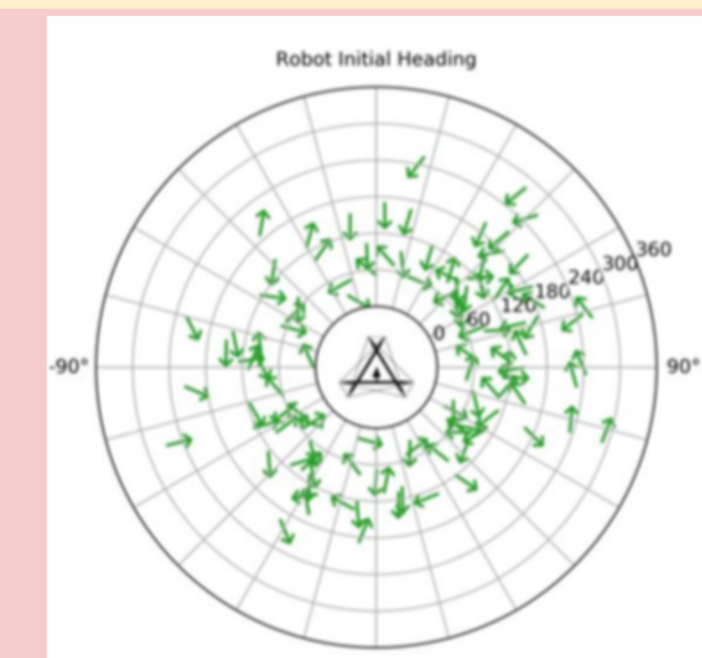


Figure 1: A 6 Strut Vibrational Tether-Free Tensegrity Robot

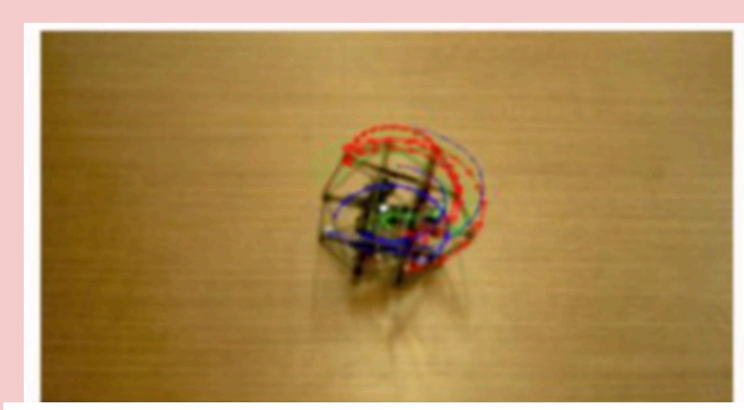
Results

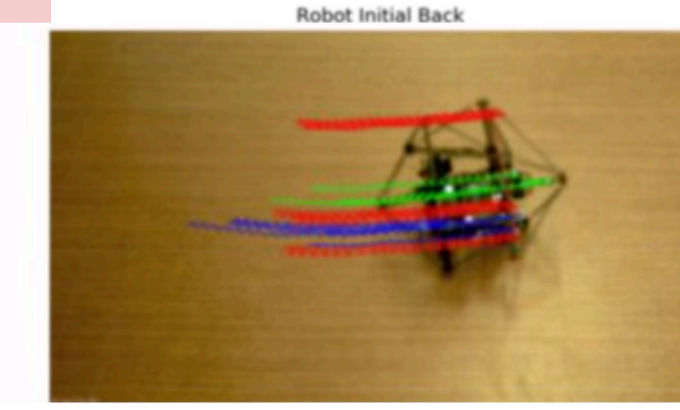
These results [5] were generated by first running an initial 100 trials of the robot with random parameters. This was then used as the 'seed' behavioral repertoire that MapElites mutated. Then 400 trials of MapElites were run and 400 more random trials were run to produce a control.



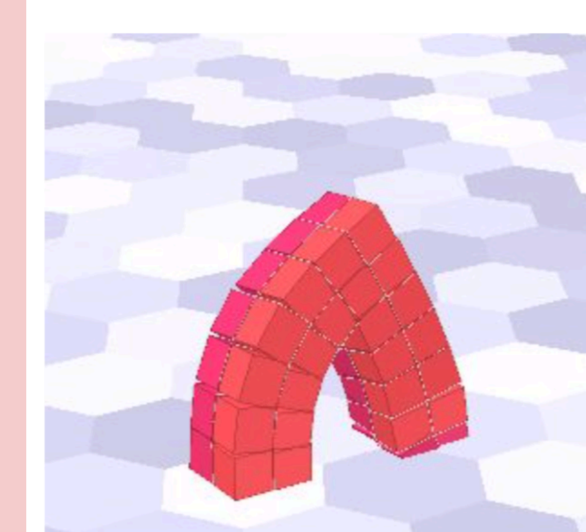
Key Takeaways:

- **MapElites Behaviors have higher average fitness**
- **MapElites discovered new behaviors twice as fast as random search**

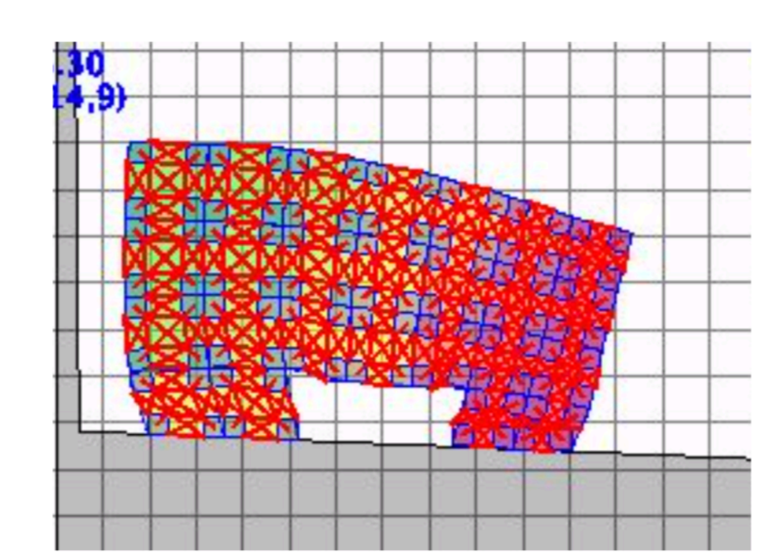




Current Work: applying QDA to voxel-based soft robots



Voxcraft



2dhsmr

Next Steps

- **Behavioral repertoires for voxel-based soft robots**
- **Policy networks and damage recovery**

[1] K. Snelson, "The art of tensegrity,"International Journal of SpaceStructures, vol. 27, no. 2-3, pp. 71–80, 2012.

[2] J. K. Pugh, L. B. Soros, and K. O. Stanley, "Quality diversity:A new frontier for evolutionary computation,"Frontiers inRobotics and AI, vol. 3, p. 40, 2016. [Online]. Available:https://www.frontiersin.org/article/10.3389/frobt.2016.00040

[3] M. Duarte, J. Gomes, S. M. Oliveira, and A. L. Christensen, "Evo-lution of repertoire-based control for robots with complex locomotorsystems,"IEEE Transactions on Evolutionary Computation, vol. 22, no. 2, pp. 314–328, 2018.

[4] A. Cully, J. Clune, D. Tarapore, and J.-B. Mouret, "Robots that canadapt like animals,"Nature, vol. 521, no. 7553, pp. 503–507, 2015.

[5]K. Doney, A. Petridou, J. Karaul, A. Khan, G. Liu and J. Rieffel, "Behavioral Repertoires for Soft Tensegrity Robots," 2020 IEEE Symposium Series on Computational Intelligence (SSCI), Canberra, ACT, Australia, 2020, pp. 2265-2271, doi: 10.1109/SSCI47803.2020.9308218.

2Q21 National Robotics Initiative (NRI) Principal Investigators' Meeting

Award ID#: 1939930 & 1827495