

Evolving Behaviorally Diverse Soft Robots

Alvin Andino

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Abstract

Soft Robotics is an emerging field with many promising applications including the next generation of disaster first responders. One outstanding challenge in the field is finding ways to make soft robots move. A novel solution has been vibration, rather than linear or rotary actuation, as a means of locomotion. Soft Robots are complex enough systems where its unknown which specific motor frequencies produces specific behaviors. One could have trails of a soft robot until its full behavior is found. This can be inefficient and time consuming to do with every new design. Our research is to develop a more efficient method of evaluating behavioral diversity for soft robots with unknown behavior and incorporating it in an existing genetic algorithm used to evolve soft robots. We breed robots based on how differently they behave to various motor frequencies. The aim is figure out the frequencies to navigate a space with the minimum amount of trails.

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1 Introduction

Modern day robots have proven useful for a variety of tasks. These robots can perform tasks more quickly, accurately, and also in environments that are unsafe for humans. They are often made from rigid structures like motors and actuators. Soft robots can be made entirely from from a variety of flexible materials like plastic or silicon. The difficult part of using soft robots is creating designs and also modes of movement for these designs. We can use evolution in the form a genetic algorithm. We take a population and breed individuals that that perform the best. we represent the soft robots with a generative encoding which is analogous to DNA. We can use vibration to take advantage of the complex system to create motion. The persisting problem is that with every new design we must figure out the frequencies that correspond to certain behaviors liking moving straight, turning left, etc. so we must run tests to find these frequencies because they are different for every new design. This can be time and labor intensive but we can use the genetic algorithm to automate the process to find designs that are more likely to navigate an environment.

2 Background and Related Work

2.1 Soft Robotics

Robots composed of soft elastic materials are an alternative to the traditional rigid body robots. There are many advantages such as it robustness, deformability, the ability to change shape, and the ability to be dropped from great heights with out damage. This can allow a soft robot deform its shape to access hard to reach areas.

The benefits given by by the added flexibility and mobility are at the cost of design complexity. Broadly speaking, soft robotics research is cutting edge, and researchers don't know exactly how to design, build, or build soft robots. It is already a difficult task to design a controller that can coordinate a few degrees of freedom of a rigid robot. So when you encounter a robot with infinite degrees of freedom it is hard to control.

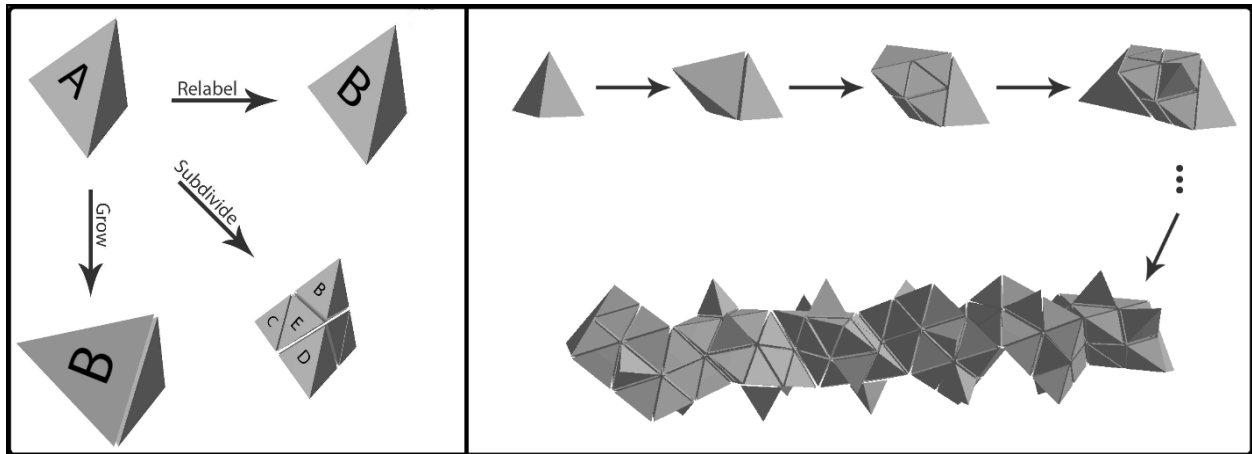


Figure 1: On the left is the tetrahedral face encoding grammar to design soft robots. On the right is a demonstration of evolution through repetitive iterations of the grammar.

2.2 Designing Soft Robots with Grammars

Our solution for scalably designing soft robots is using grammars and an evolutionary algorithm. Grammatical encodings allows us to compactly represent a whole space of designs and are amenable to evolutionary search. This has proven effective to when applied to tetrahedral meshes. The evolutionary algorithm takes an initial population of tetrahedra, uses a grammatic encoding to grow them based on the label on each face, and then uses a fitness function to determine which travels further [2]. Tetrahedral meshes can be easily transformed into stereolithography (STL) files and directly printed on Union College’s Stratasys Connex500 printer.

2.3 Moving Soft Robots with Vibration

Grammars describes only how soft robots would look like by does not describe how they will move. The challenge is that conventional ways of moving robots require large rigid actuators that do not work for soft robots. The mechanism we chose is vibration because there are no solid structural components to manipulated it is easier to exploit the inherent resonance of the structure. This was inspired by related work on making tensegrity robots move [1].



Figure 2: A 3D printed robot designed using the above algorithm. Electrical components such as wires and vibrational motors will be inserted into the robot mid-print.

2.4 project foundation

The generative encodings represent Soft robots as tetrahedral meshes. Smith and Rieffel chose to have the soft robots represented as tetrahedral meshes because physics engines like Bullet Physics and PhysX represent soft robots as tetrahedral meshes. STL Files also represent soft robots as tetrahedral meshes, so designs can be easily printed in the future. Danise extended Smith and Rieffels research by writing a Bullet Physics simulation of soft robots. He also implemented a genetic algorithm that breeds the individuals with distance from the starting point as the fitness function. The work done as a part of his Senior thesis is the base of this work.

3 Methods and Design

The genetic algorithm used has a fitness function that has distance from the origin as a fitness function. These dont develop designs that are guaranteed to be behaviorally diverse. This research modifies the genetic algorithm to use behavioral diversity as a fitness function and using derived behaviors to quicken the process.

3.1 Behavioral Diversity

We define behavioral diversity as the level an individual reacts when vibrated at different frequencies. An individual that only has one reaction across all frequencies are deemed as least diverse. An individual that has a few reactions across all frequencies are semi-diverse. An individual that has a different reaction for every frequency are the most diverse and are the ideal candidates. Those who are behaviorally diverse are more likely to explore the whole environment. This approach is more favorable than having absolute distance as a fitness function.

3.2 Derived Behaviors

When you vibrate the soft robot at a specific frequency for a defined amount of time and reaches a location, the frequency is called a prime behavior. Prime behaviors can be repeated or combined in linear combi-

nations to make derived behaviors. These derived behaviors have not actually have been reached but are assumed reachable but using a pattern of prime behaviors. This can reduce time in finding the frequencies to navigate a space. A table a graphical representation are shown in Figure 3 and 4 respectively.

3.3 Behavioral Fitness

We need a way to determine which individuals are more behaviorally diverse and we call this the individuals behavioral fitness. To evaluate the behavioral fitness of an individual, we record the reached and derived locations and their associated behavior frequencies. We call this the behavioral envelope and it is then evaluated by a zoning technique where we divide the search area into zones and see if the locations fall into distinct zones. The number of distinct zones is the behavioral fitness of the individual.

4 Results and Discussion

4.1 Code Modification

Before changes can be made to the genetic algorithm features needed to be added to save and modify experiments. Code was added to write and read files containing experiments configuration settings, the generative encodings and fitness of individuals. The configuration settings were changed by file so experiments can be modified without recompiling. These modifications allowed for review and retest of individuals or experiments.

Data structures were then created to represent locations, behaviors, search space, and the behavioral envelope. The core genetic algorithm was then changed to evaluate an individual not only once but three times with each trial at a different frequency. The behavioral envelope was then created and the behavioral fitness calculated and used in the breeding step of the algorithm.

4.2 Current Status and Future Work

The new genetic algorithm successfully breeds more behaviorally diverse individuals as shown in Figure 5. Further experiments needs to be done with various search space, search depth, zone size, and other

Envelope	
Location	Behavior
(1,1)	A
(3,1)	B
(2,2)	AA
(3,3)	AAA
(6,2)	BB
(9,3)	BBB
(4,2)	BA
(7,3)	BAB

Figure 3: A table representation of the behavioral envelope.

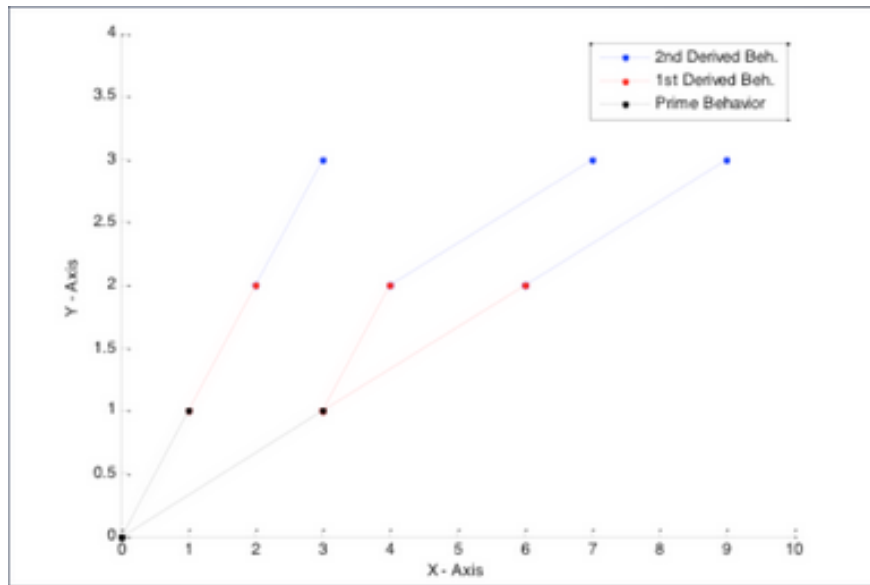


Figure 4: A graphical representation of the behavioral envelope.

variables in order to discover trends and patterns. If we are able to find the configuration necessary to be able find the set of frequencies to navigate a space we then can 3D print favorable candidates and have real-world testing. We also need to visualize the reached space of individuals to see if there are pattern in reached and unreachable zones.

References

- [1] Mark Khazanov, Ben Humphreys, William Keat, and John Rieffel. Exploiting dynamical complexity in a physical tensegrity robot to achieve locomotion. In *Advances in Artificial Life, ECAL*, volume 12, pages 965–972, 2013.
- [2] John Rieffel, Davis Knox, Schuyler Smith, and Barry Trimmer. Growing and evolving soft robots. *Artificial Life*, tba(tba), 2012.

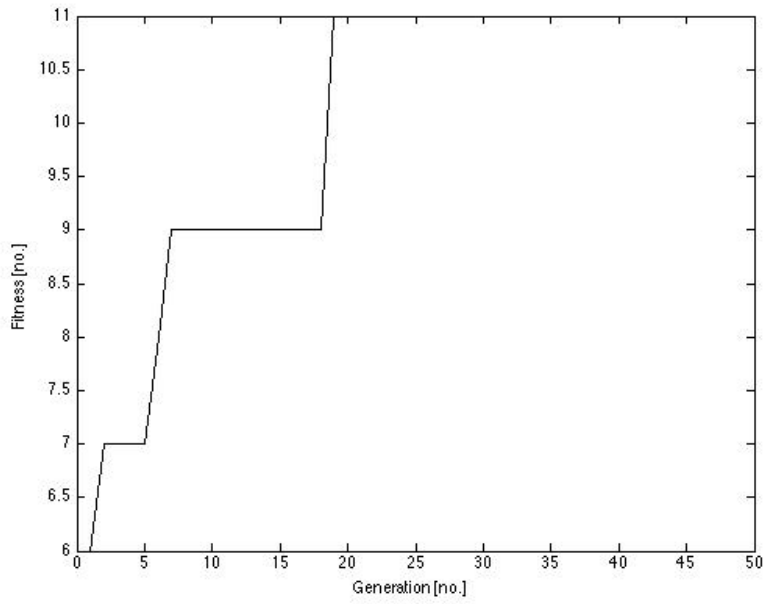


Figure 5: This graph shows the best fitness values per generation over the course of an experiment. At Generation 19 The best fitness value is found for the whole experiment.