Simultaneous Evolution of Morphology and Locomotion of Soft Robots by Novelty Search

Georgios Methenitis

University of Amsterdam

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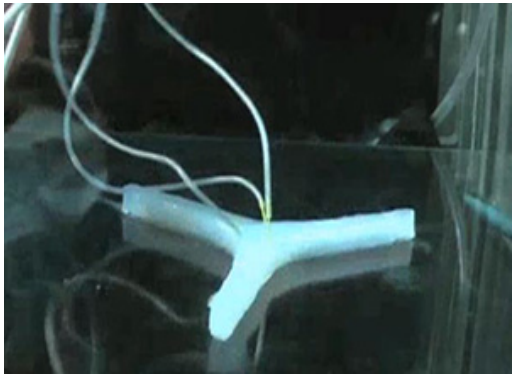
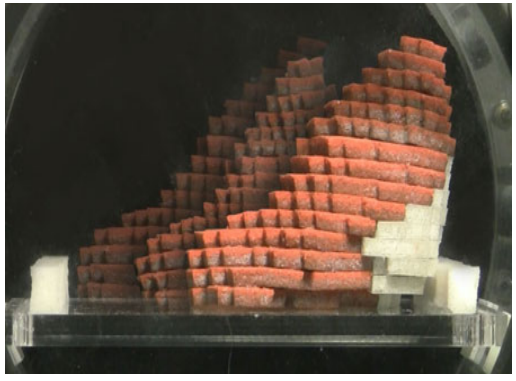
Introduction

Soft Robots

- Inspired by nature
- Completely soft bodies
- Capable of developing new kinds of locomotion

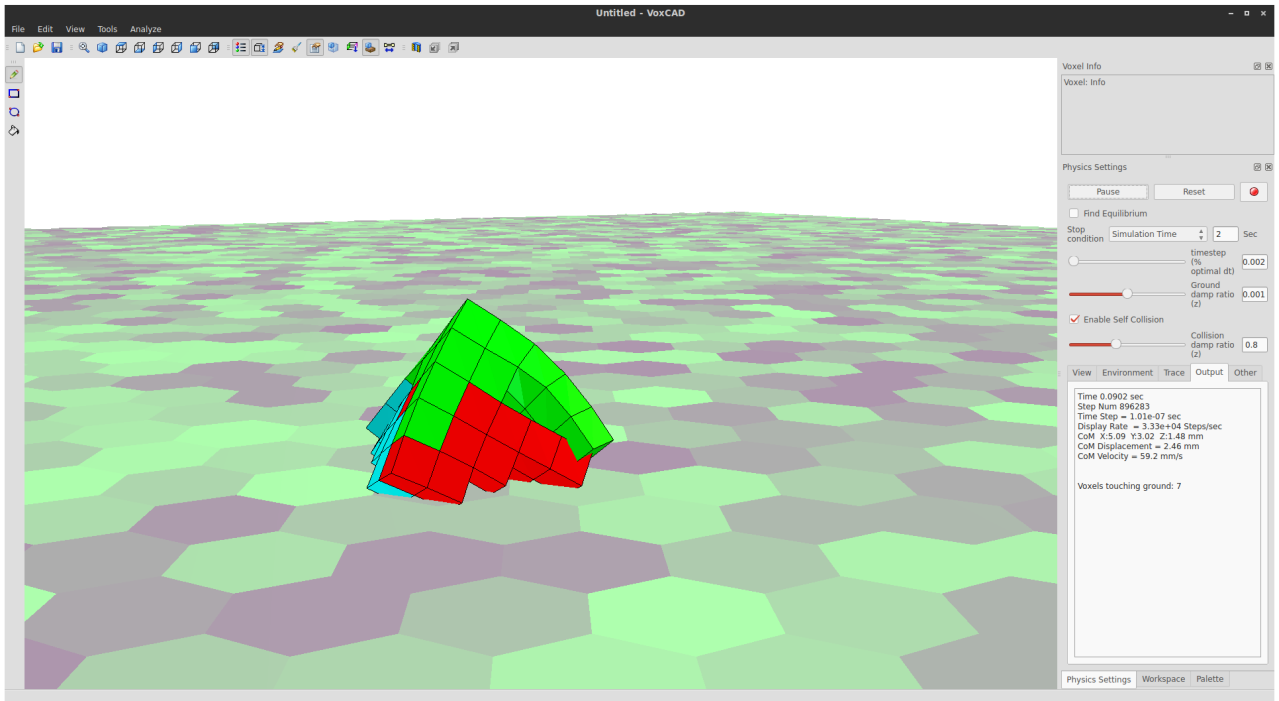
Soft robots can be actuated through air pressure tubes, environmental changes (temperature, pressure), even explosions.

Related Material

VoxCad Simulator (Hiller & Lipson, 2012)

- Created by Jonathan Hiller and Hod Lipson
- Voxel modeling and analyzing software
- Capable of developing new kinds of locomotion

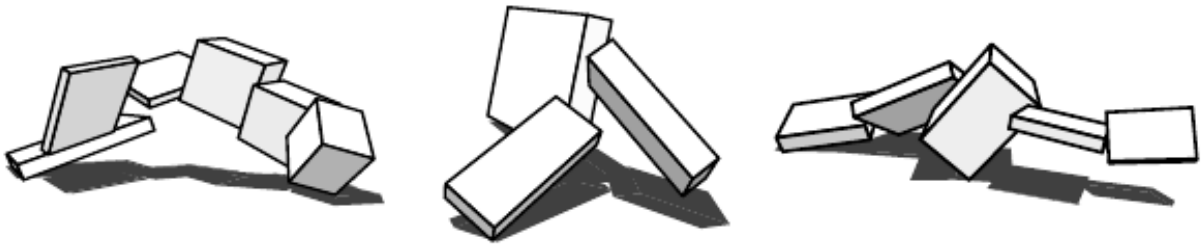
- Lattice
- Voxels
- Structure
- Materials



Related Work I

Evolving virtual creatures (Sims, 1994)

- Rigid body parts, joints
- Evolution of the morphology and the control



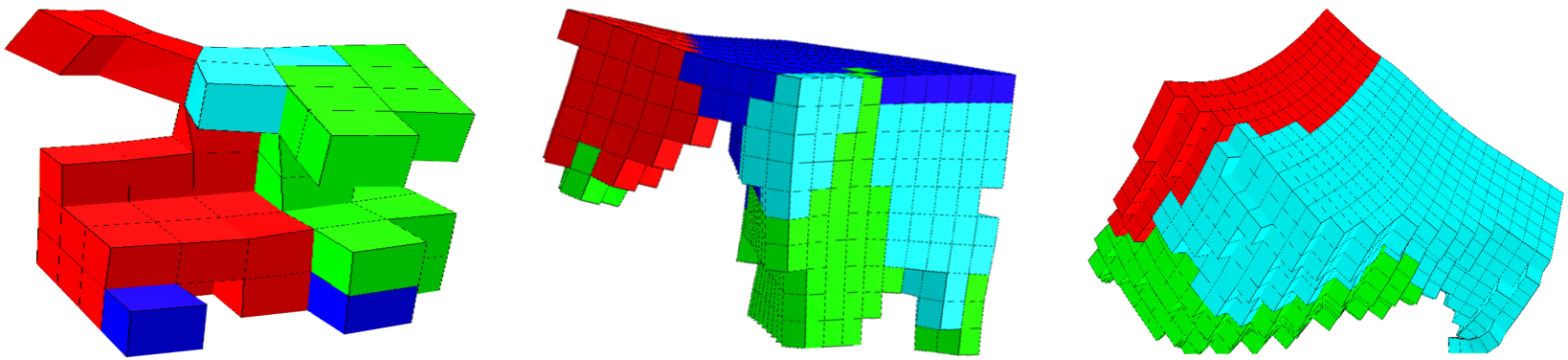
Evolving a diversity of virtual creatures through novelty search and local competition (Lehman & Stanley, 2011)

- Same experiment
- Novelty $<$ Fitness
- Novelty search with global competition has the best average fitness.

Related Work II

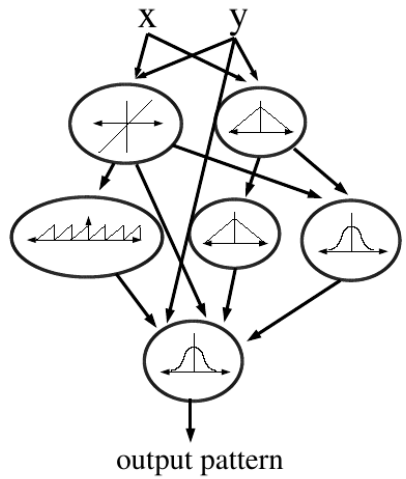
Evolving soft robots with multiple materials and a powerful generative encoding. (Cheney, MacCurdy, Clune, & Lipson, 2013)

- Generative encoding, Compositional pattern-producing network, CPPN.
- Neuroevolution of augmenting topologies, NEAT.



Compositional pattern-producing network (K. O. Stanley, 2007)

- Similar to artificial neural networks
- Different set of activation functions



- Produce symmetrical and repetitive patterns
- Appropriate for problems with geometrical structure (Board games).

NeuroEvolution through Augmented Topologies (NEAT) (K. Stanley & Miikkulainen, 2002)

Some key points of this method are:

- Evolving neural network topologies along with weights
- Crossover between different topologies
- Structural innovation through speciation (New species have time to improve)

Research Topics

- Gravity
  - Performance under different conditions of gravity
- Novelty search
  - Performance, in respect to the original fitness
  - Performance, in behavior space
  - Behavior, what is a good behavior metric?
- Other evolutionary algorithms
  - Genetic algorithm with direct coding
  - Random generative encoding
  - CMA-ES
  - jDE
- Can we evolve CPPNs with other evolutionary algorithms?

Things completed so far...

- Replication of the results from (Cheney et al., 2013)
- Generative random encoding
- Simple genetic algorithm
- Own implementation of CPPN-NEAT experiment (HyperNEAT C++ library)
- Novelty search
- Competition between species (novelty, fitness)

Generative Random Encoding

Only two parameters can change in this encoding.

1. The probability of adding a new voxel into the structure.
2. The probability that the new voxel introduced will use the same kind of material as its connection.

We start with a random voxel inserted into the lattice.

- Choose whether a new voxel is going to be inserted.
- Choose randomly its connection.
- Choose its material.
- Iterate

Simple genetic algorithm

- Each genome is represented by a stream of real numbers in $[0, 1]$.
- The length of this stream is equal to:

$$l = n \times (m + 1)$$

, where n, is the number of total voxels and m is the number of materials.

- For a lattice's dimensions of $10 \times 10 \times 10$, the length is 5000.
- Simple genetic algorithm fails to produce locomotion.
- No structure knowledge.

References I

Cheney, N., MacCurdy, R., Clune, J., & Lipson, H. (2013). Unshackling evolution: evolving soft robots with multiple materials and a powerful generative encoding. In *Proceeding of the fifteenth annual conference on genetic and evolutionary computation conference* (pp. 167–174).

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References II

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