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

Georgios Methenitis

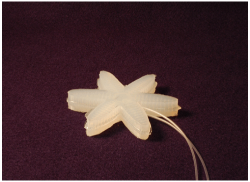
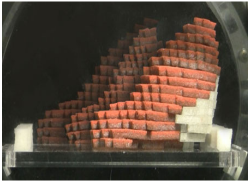
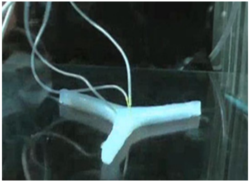
UvA, ACT

June 27, 2014

Introduction

Soft Robots

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

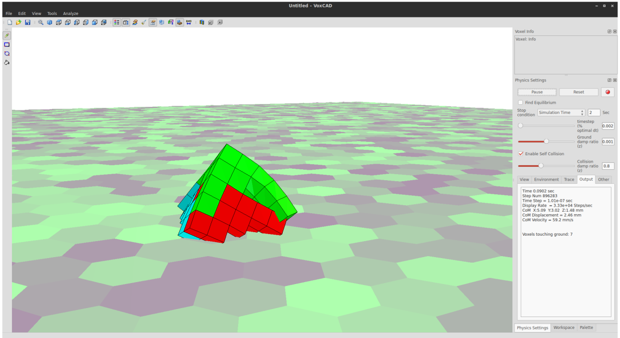
Soft robots can be actuated through air pressure tubes, environmental changes (temperature, pressure), even explosions.

Related Material

VoxCad Simulator [2]

- Created by Jonathan Hiller and Hod Lipson
- Voxel modeling and analyzing software

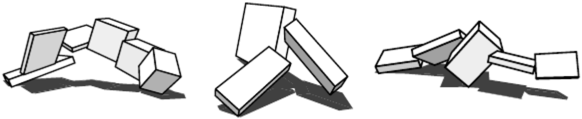
- Lattice
- Voxels
- Structure
- Materials



Related Work I

Evolving virtual creatures [5]

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



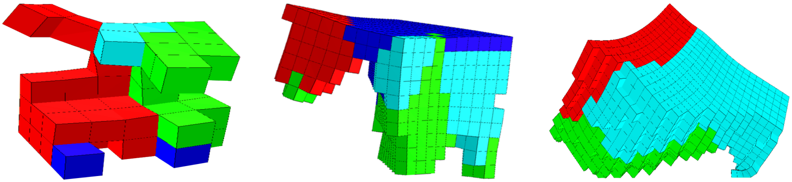
Evolving a diversity of virtual creatures through novelty search and local competition [4]

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

Related Work II

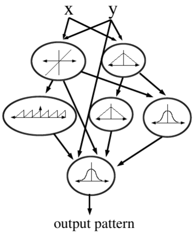
Evolving soft robots with multiple materials and a powerful generative encoding. [1]

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



Compositional pattern-producing network [7]

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



- Produce symmetrical and repetitive patterns
- Appropriate for problems with geometrical structure

NeuroEvolution through Augmented Topologies (NEAT) [6]

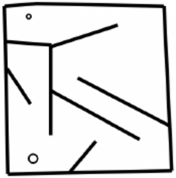
Some key points of this method are:

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

Novelty Search

What novelty means:

- Traditionally fitness measures how good an individual is (Objective function).
- Objective function can prevent evolution reaching the global maximum.
- Thus we can abandon the objective.
- Try finding novelty in behavior space.
- Random?



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
  - Covariance Matrix Adaptation Evolution Strategy (CMA-ES)
  - Differential Evolution (jDE)
- Can we evolve CPPNs with other evolutionary algorithms?

Things completed so far...

- Replication of the results from [1]
- 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

- GAlib C++ library
- 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 $10 \times 10 \times 10$ and 4 materials the length of the genome is 5000.
- Simple genetic algorithm fails to produce locomotion.
- No structure knowledge.

CPPN-NEAT

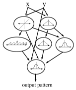
- HyperNEAT C++
- Each genome is represented by a CPPN.
- This CPPN is queried for each input coordinate to output the existance and the type of the material.
- NEAT evolves these CPPNs.
- In each generation, speciation. Population is split into species, new species can survive easier than old.

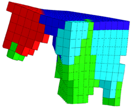
CPPN-NEAT with Novelty Search [3]

- Same code base
- Novelty takes the place of fitness
- Novel individuals stored in a list
- For each new individual in the population, check its novelty in respect to the stored novel individuals.
  - Minimum distance from a novel individual
  - Average distance from K nearest individuals
- Store novel enough individuals

Behavior

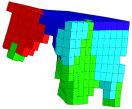
How can we go from fitness to behavior:

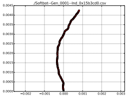


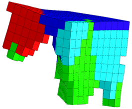


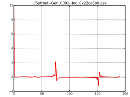
$$\longrightarrow F(x) \longrightarrow B(x)$$

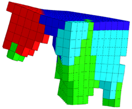
Examples:

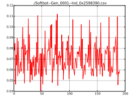












Behavior

Behavior types used are:

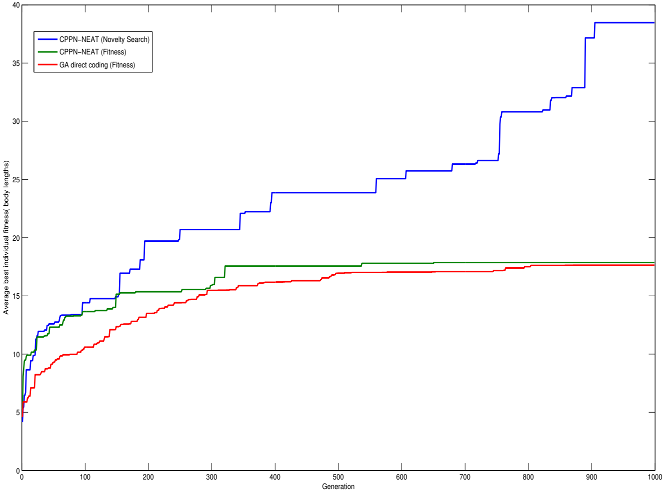
- Trajectory 3D, 2D
- Pace
- Voxels touching ground
- Kinetic energy
- Maximum pressure

Behavior similarity can be computed:

- Absolute difference between normalized trajectories
- Cross-correlation of discrete Fourier transformation

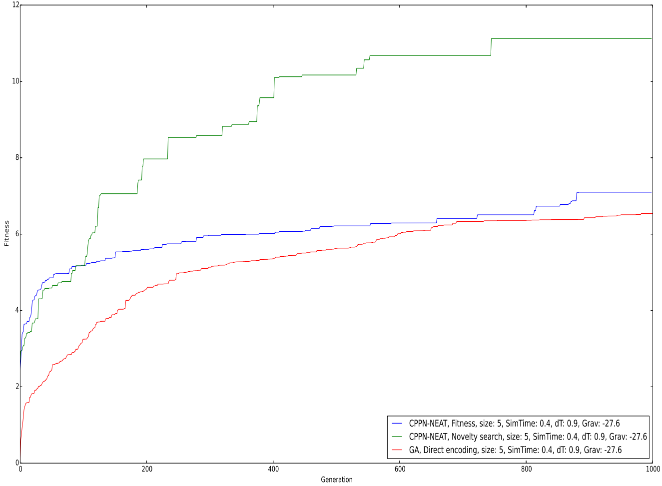
Primilinary results I

$5 \times 5 \times 5$



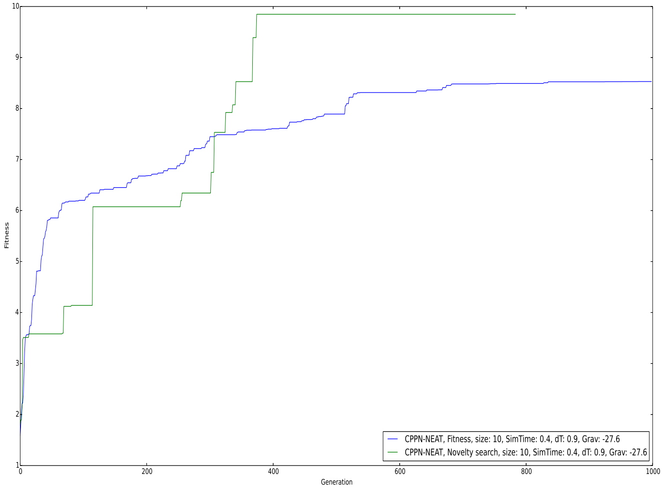
Primilinary results II

. . . same experiment, more stable simulation settings, 5 runs



Primilinary results III

. . . same settings but size: $10 \times 10 \times 10$



References I

Nick Cheney, Robert MacCurdy, Jeff Clune, and Hod Lipson.
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*, pages 167–174. ACM, 2013.

Jonathan Hiller and Hod Lipson.
Dynamic simulation of soft heterogeneous objects.
arXiv preprint arXiv:1212.2845, 2012.

Joel Lehman and Kenneth O Stanley.
Abandoning objectives: Evolution through the search for novelty alone.
Evolutionary computation, 19(2):189–223, 2011.

References II

Joel Lehman and Kenneth O Stanley.
Evolving a diversity of virtual creatures through novelty search and local competition.
In *Proceedings of the 13th annual conference on Genetic and evolutionary computation*, pages 211–218. ACM, 2011.

Karl Sims.
Evolving virtual creatures.
In *Proceedings of the 21st annual conference on Computer graphics and interactive techniques*, pages 15–22. ACM, 1994.

Kenneth Stanley and Risto Miikkulainen.
Evolving neural networks through augmenting topologies.
Evolutionary computation, 10(2):99–127, 2002.

References III

Kenneth O Stanley.
Compositional pattern producing networks: A novel abstraction of development.
Genetic programming and evolvable machines, 8(2):131–162, 2007.