

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

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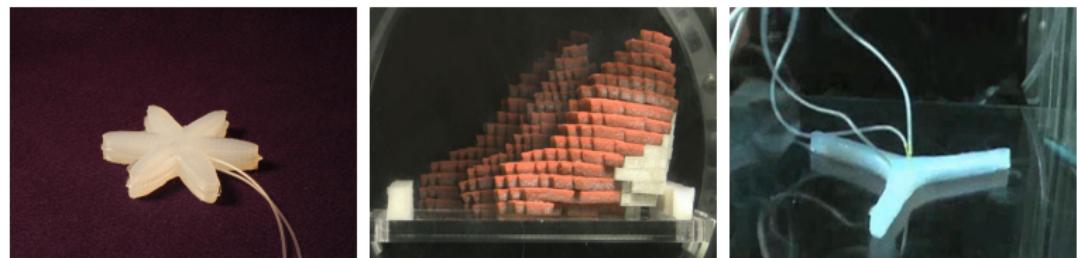
UvA, ACT

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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.

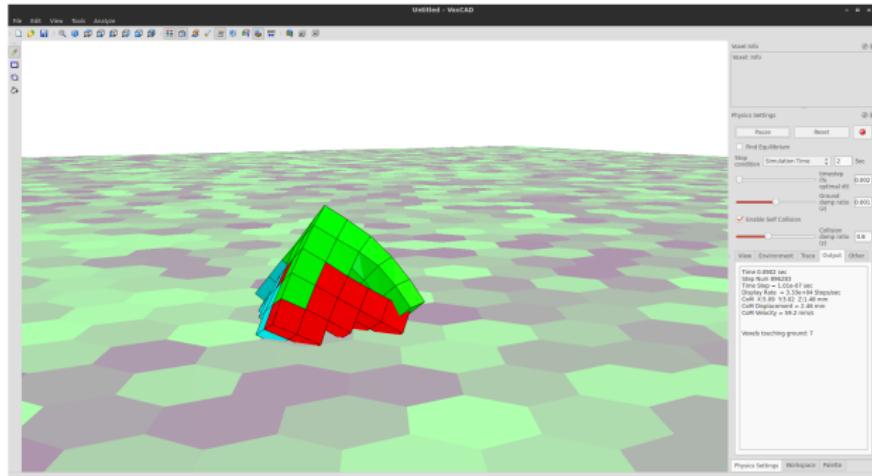
Related Material



VoxCad Simulator [2]

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

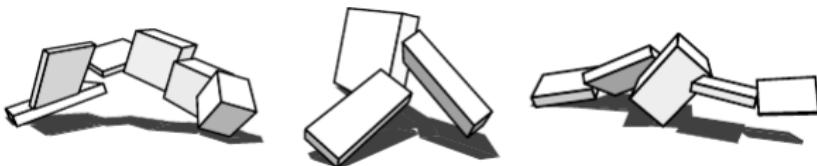
- ▶ Lattice
 - ▶ Voxels
 - ▶ Structure
 - ▶ Materials



Related Work I

Evolving virtual creatures [5]

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



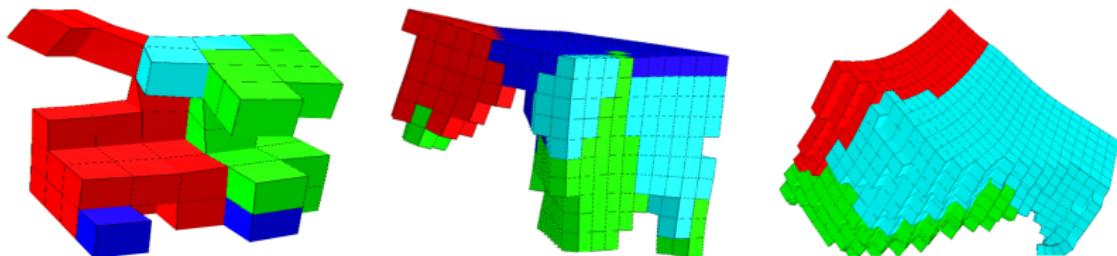
Evolving a diversity of virtual creatures through novelty search and local competition [4]

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

Related Work II

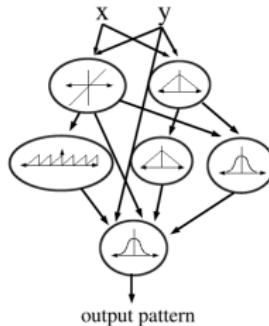
Evolving soft robots with multiple materials and a powerful generative encoding. [1]

- ▶ 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:

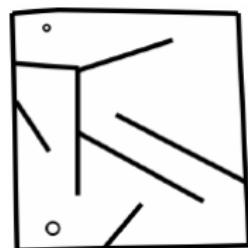
- ▶ Evolving neural network topologies along with weights
- ▶ Crossover between different topologies
- ▶ Structural innovation through speciation (New species have time to improve)

Novelty Search

What is novelty search:

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

Definition (Sparsity)



$$s(x) = \frac{1}{k} \sum_{i=0}^k dist(x, b_i)$$

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
- ▶ Implementation of CPPN-NEAT experiment
(HyperNEAT C++ library)
- ▶ Novelty search
- ▶ Competition between species (novelty, fitness)
- ▶ Combination of novelty and 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

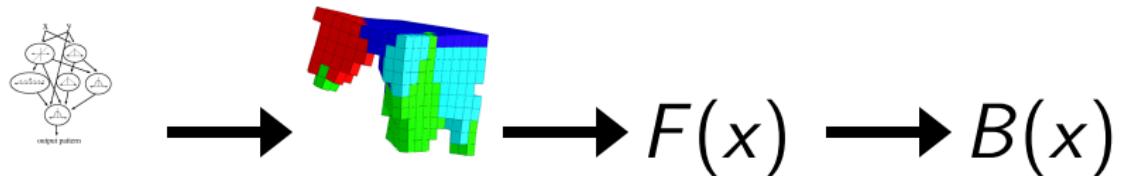
- ▶ HyperNEAT C++
- ▶ Each genome is represented by a CPPN.
- ▶ This CPPN is queried for each input coordinate to output the existance and the type of the material.
- ▶ NEAT evolves these CPPNs.
- ▶ In each generation, speciation. Population is split into species, new species can survive easier than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

CPPN-NEAT with Novelty Search [3]

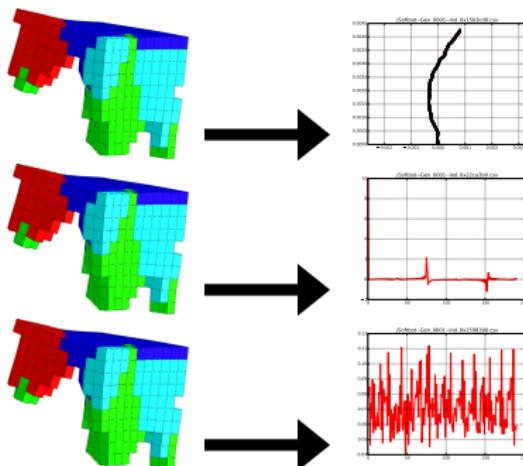
- ▶ Same code base
- ▶ Novelty takes the place of fitness
- ▶ Novel individuals stored in a list
- ▶ For each new individual in the population, check its novelty in respect to the stored novel individuals.
 - ▶ Sparsity
- ▶ Store novel enough individuals

Behavior

How can we go from fitness to behavior:



Examples:



Behavior

Behavior types used are:

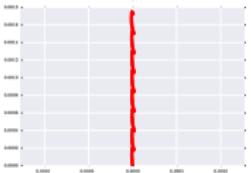
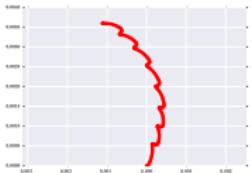
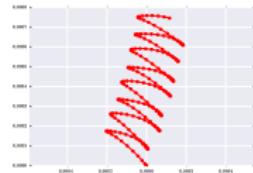
- ▶ Trajectory 3D, 2D
- ▶ Pace
- ▶ Voxels touching ground
- ▶ Kinetic energy
- ▶ Maximum pressure

Behavior similarity can be computed:

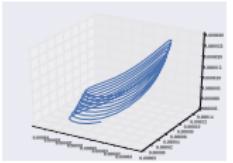
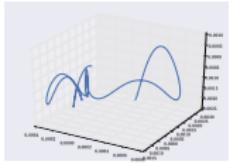
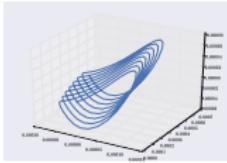
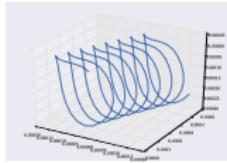
- ▶ Sum of Euclidean distances per timestep
- ▶ Cross-correlation

Behavior Examples I

2D - Trajectories:

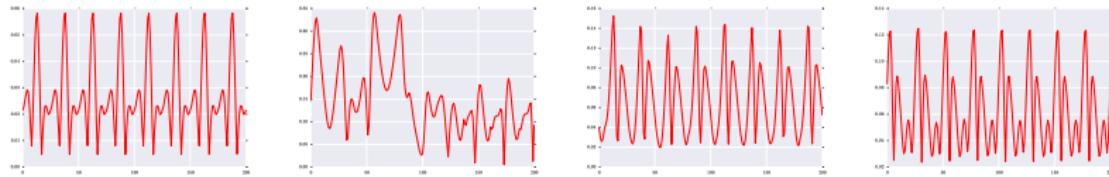


3D - Trajectories

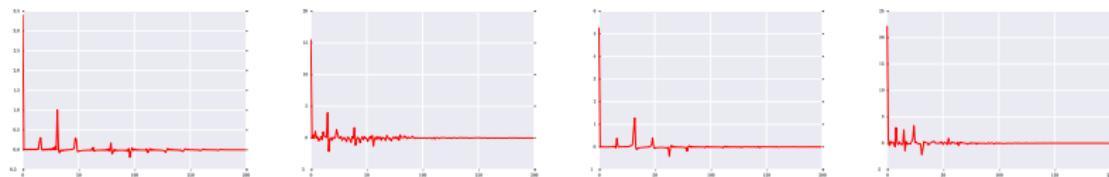


Behavior Examples II

Pace per timestep

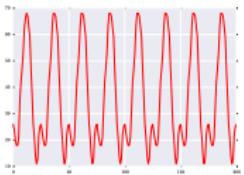
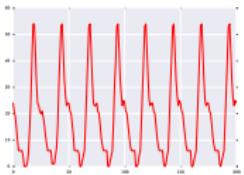
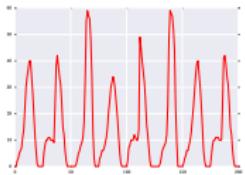
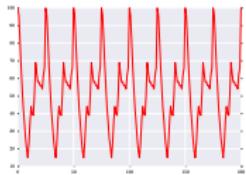


Pace - DFT

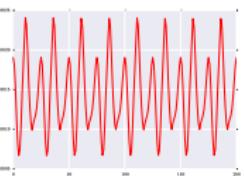
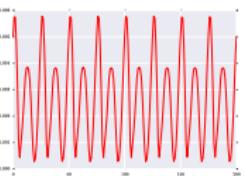
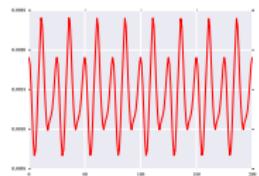
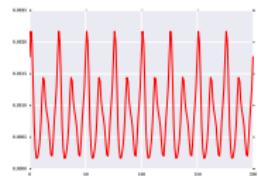


Behavior Examples III

Voxels touching ground per timestep

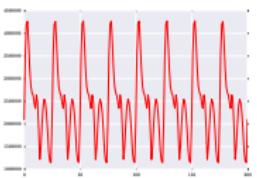
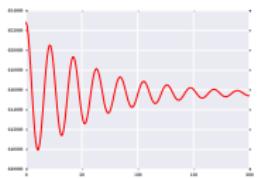
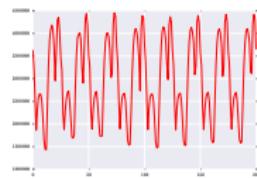
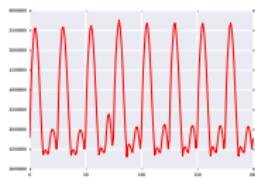


Kinetic energy per timestep



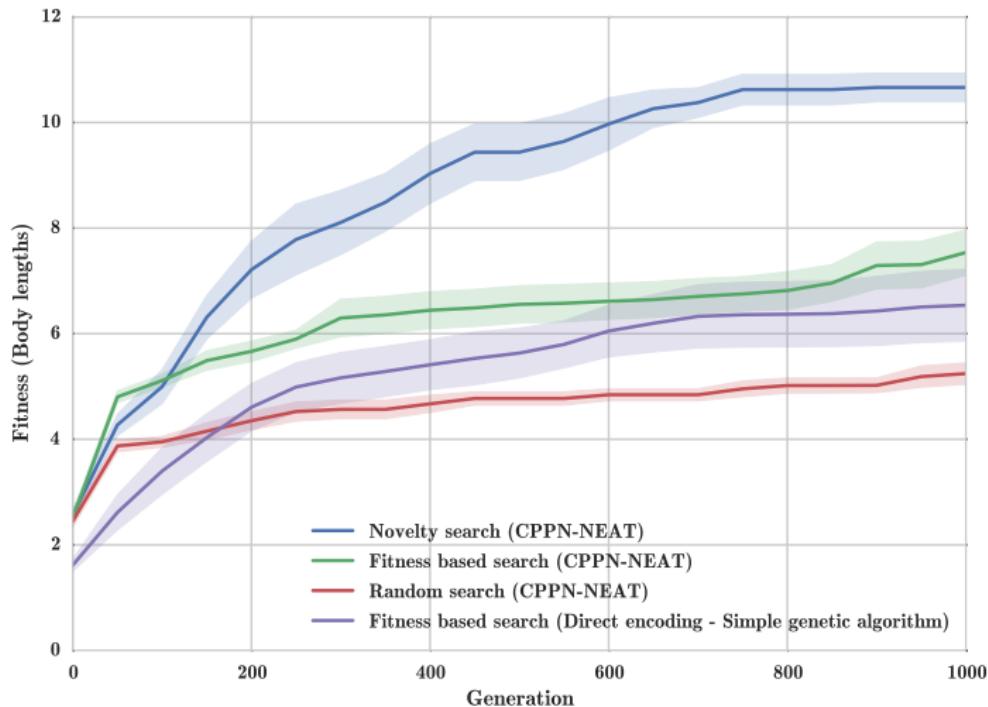
Behavior Examples IV

Maximum pressure per timestep



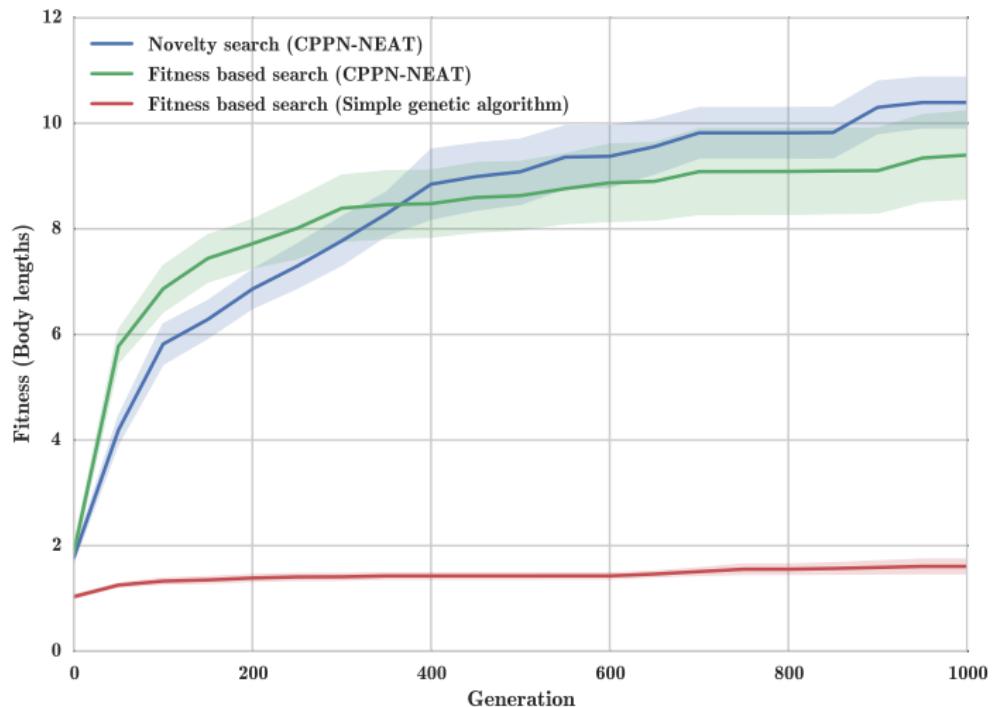
Results I

Fitness, Novelty, Random, Direct GA



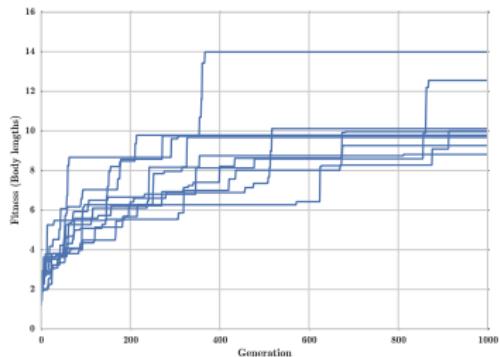
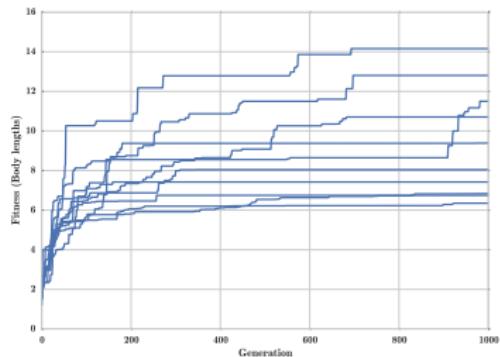
Results II

Fitness, Novelty, Direct GA



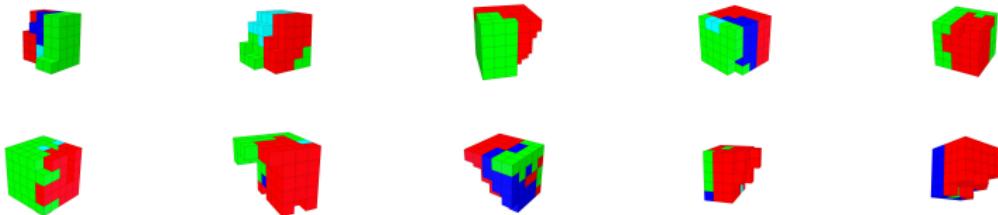
Results III

Best so far fitness in body lengths displacement of softbot's center of mass from 10 individual runs for fitness-novelty based search.

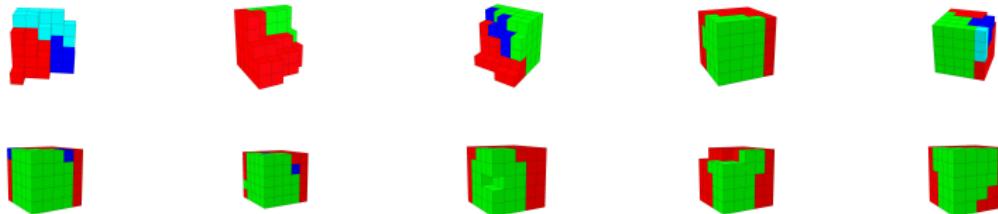


Results IV

Novelty Search - Best individuals every 100 generations:

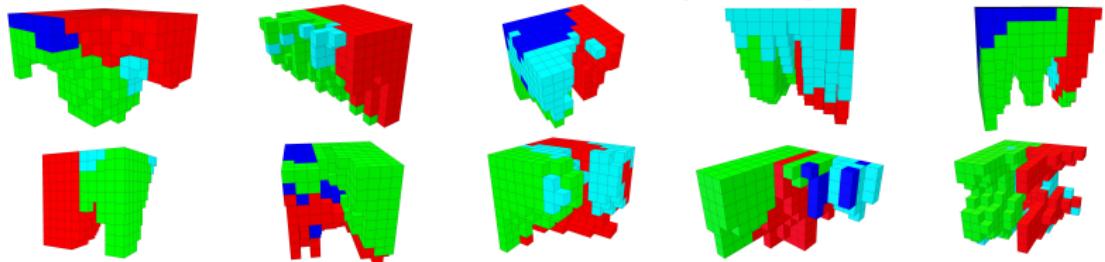


Fitness-based Search - Best individuals every 100 generations:

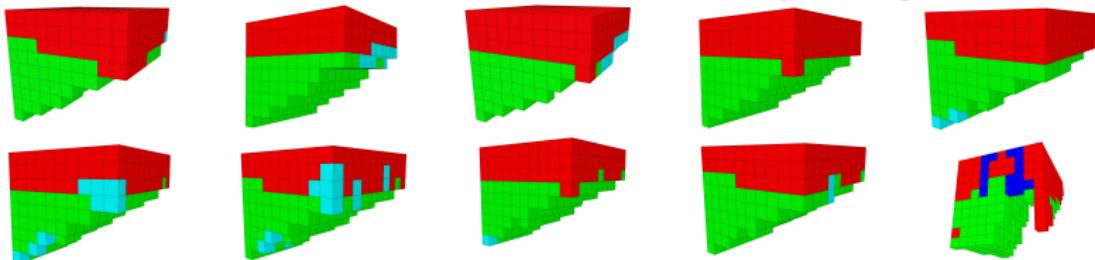


Results V

Novelty Search - Best individuals every 100 generations:

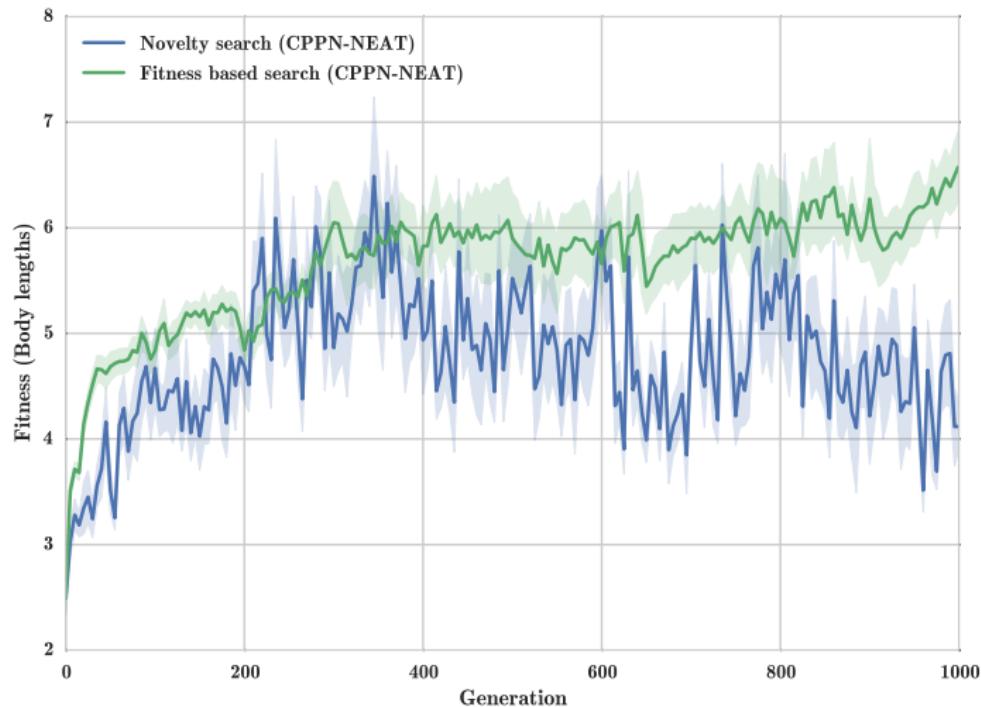


Fitness-based Search - Best individuals every 100 generations:



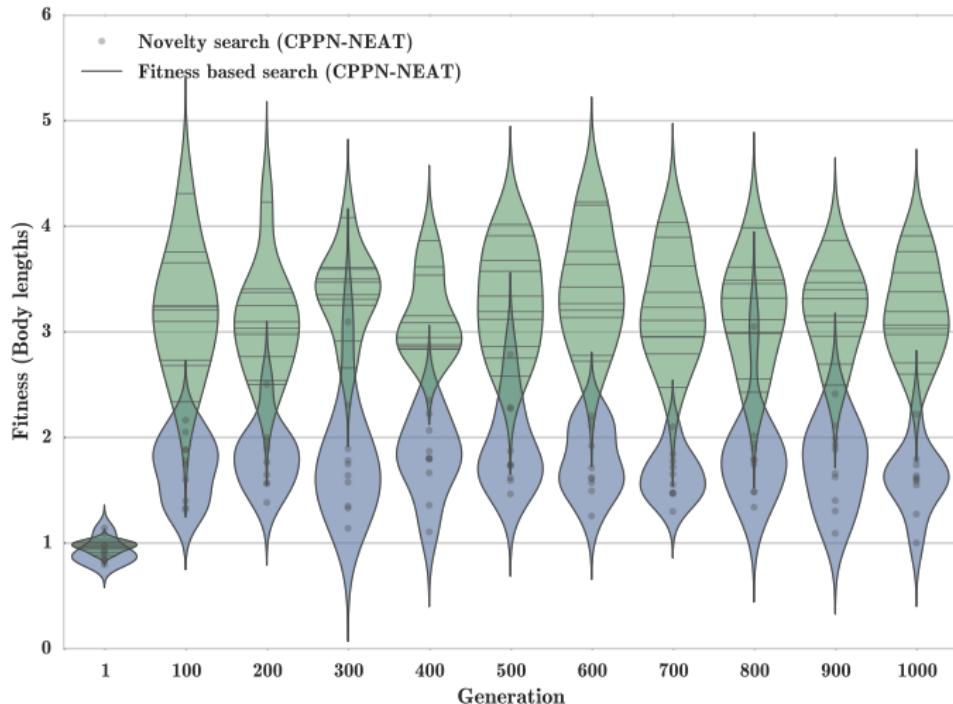
Results VI

Fitness of the generation champion (best individual) per generation



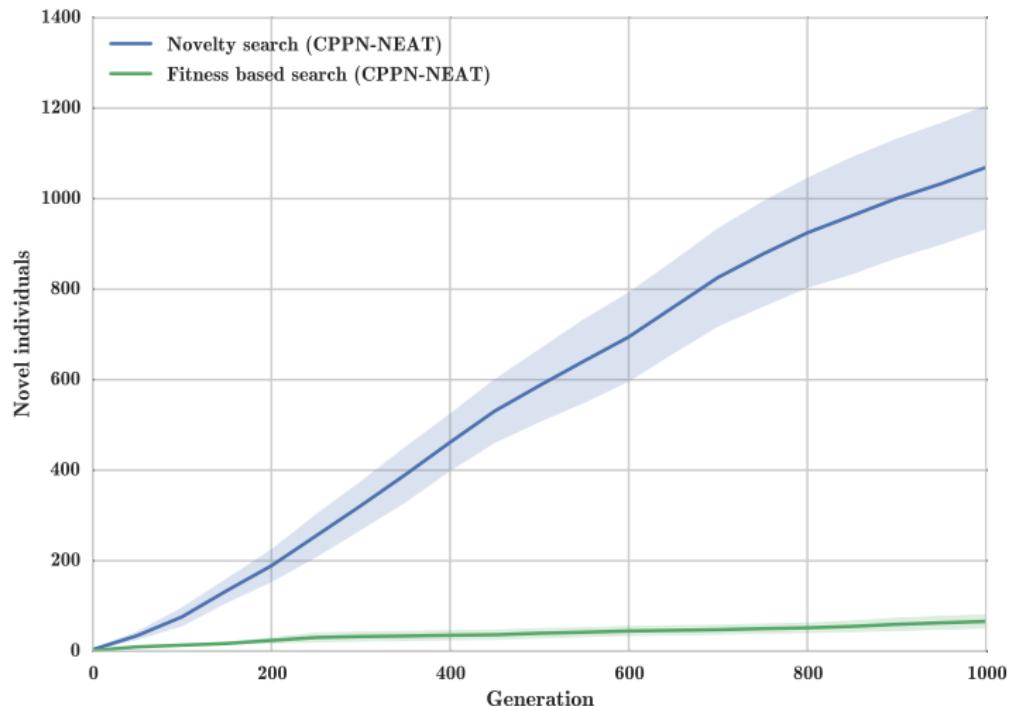
Results VII

Novelty Vs. Fitness, distributions of average population fitness per generation



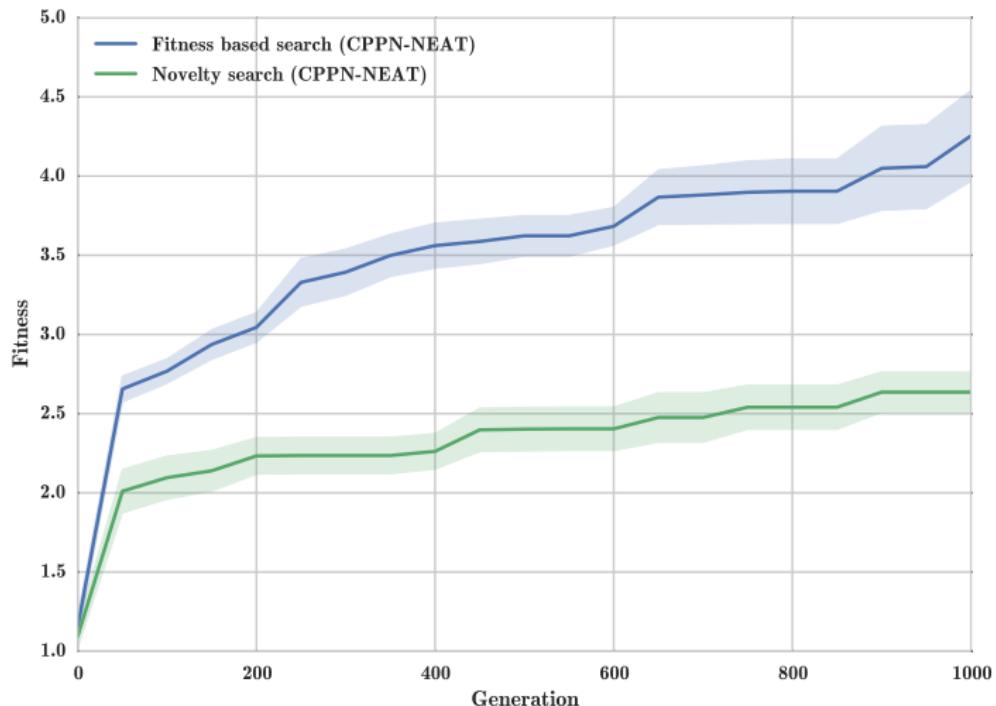
Results VIII

Novelty Vs. Fitness, number of novel behaviors



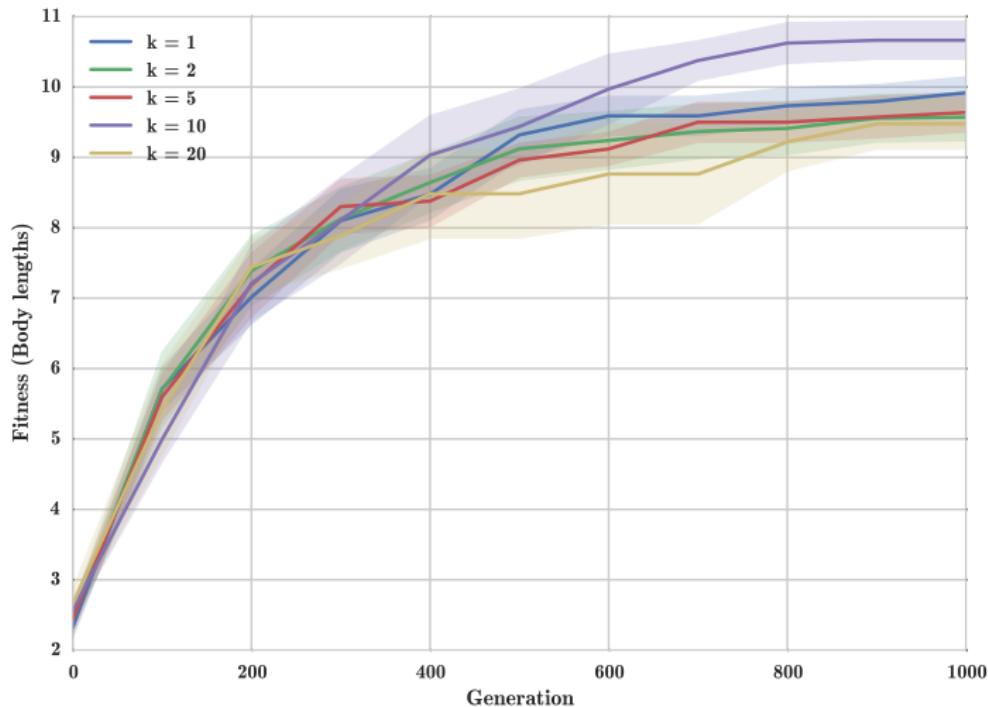
Results IX

Penalizing actuated materials



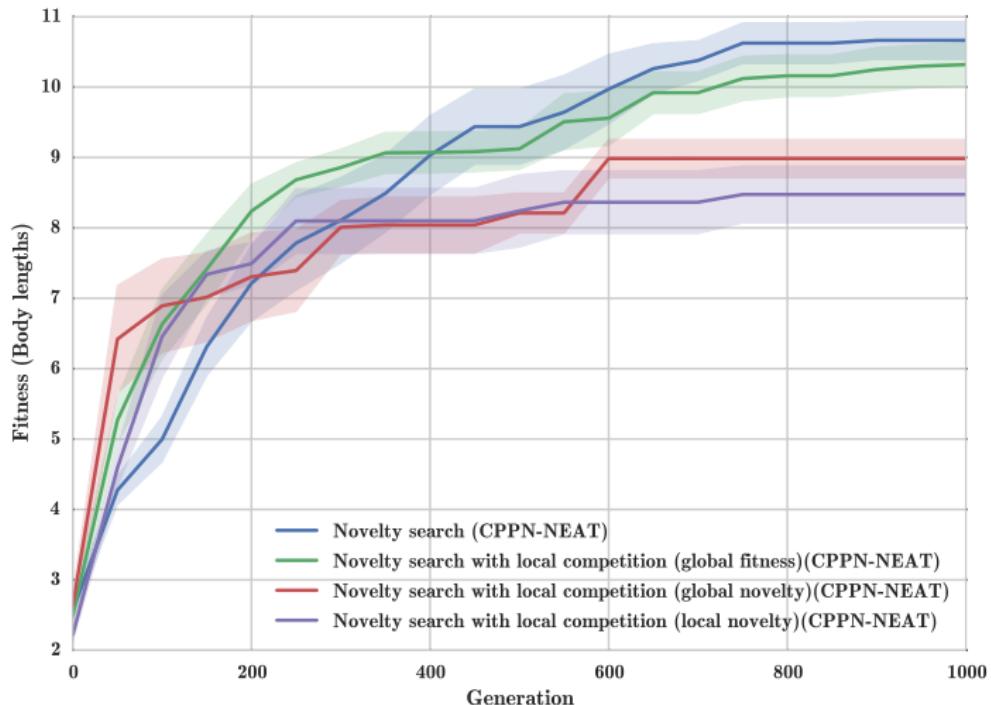
Results X

Novelty search - The novelty is computed as the average distance from the K -nearest behaviors for $K \in \{1, 2, 5, 10, 20\}$.



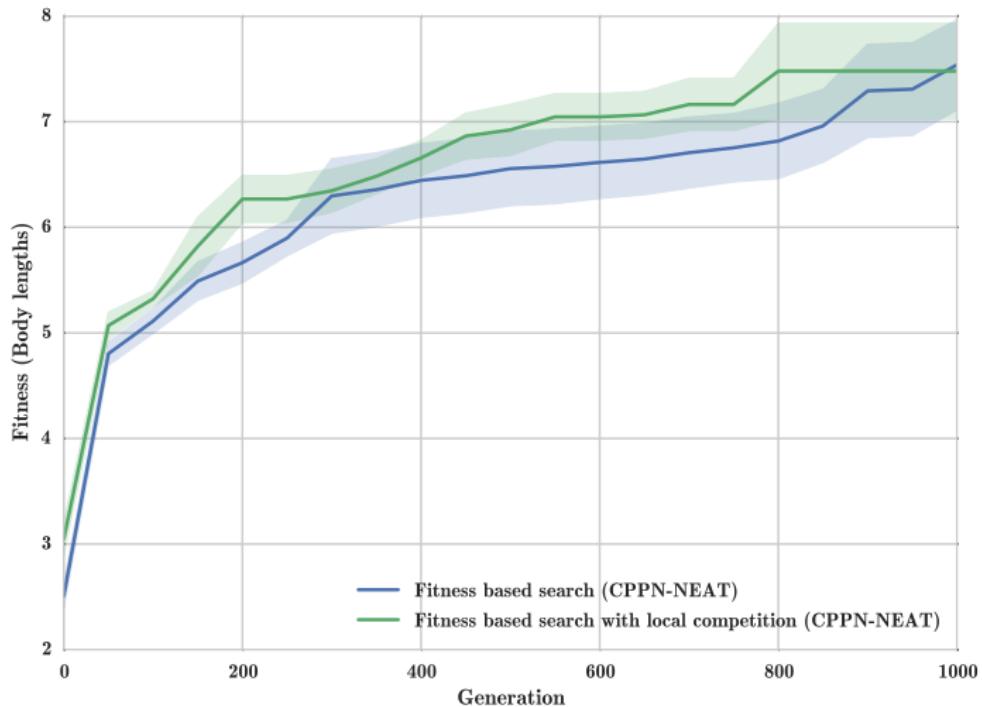
Results XI

Local competition (global fitness, global novelty, local novelty)



Results XII

Local competition is held among the complete population of each species.



References I

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