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

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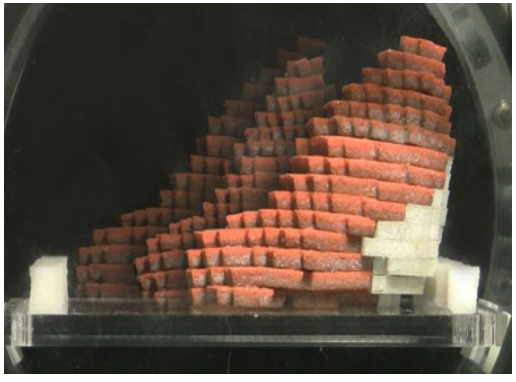
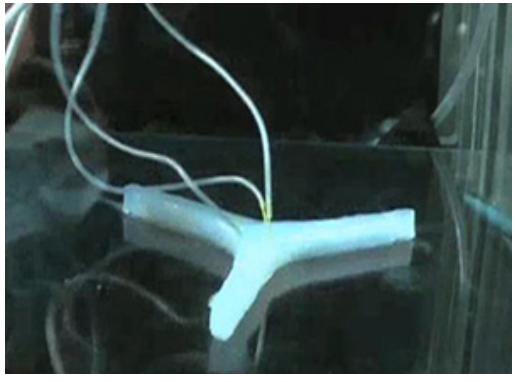
Introduction

Soft Robots

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

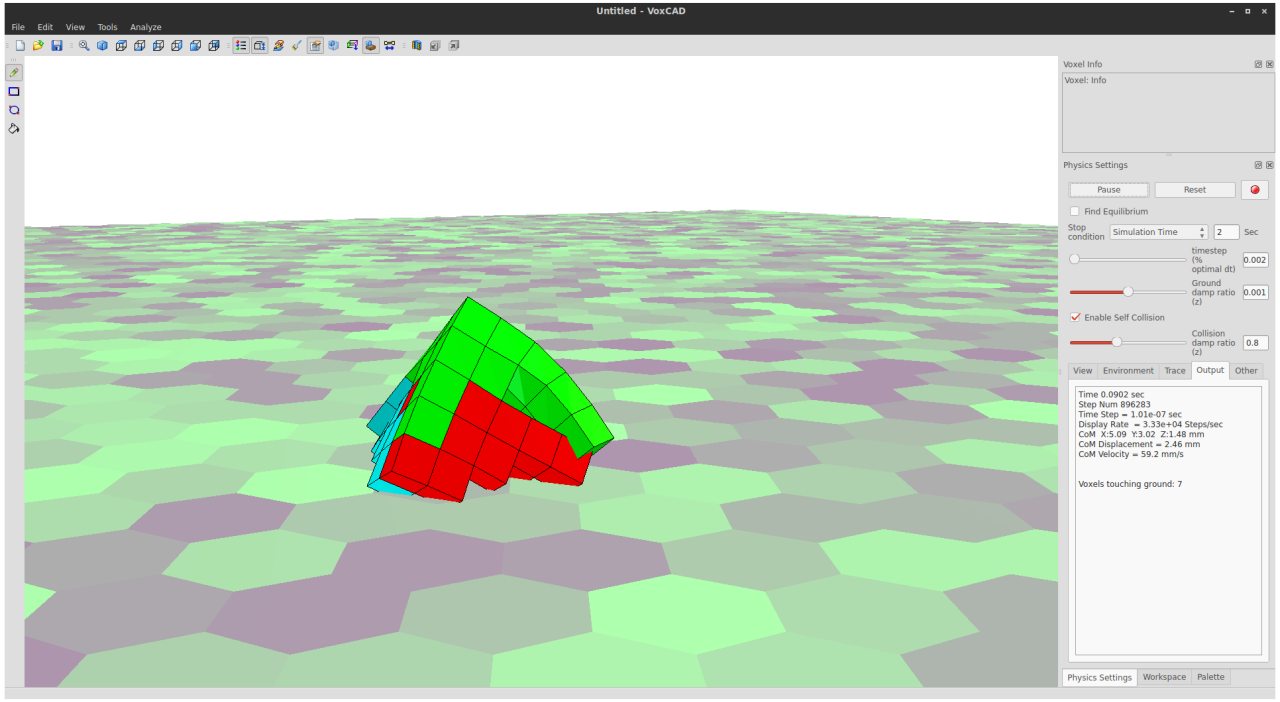
Soft robots can be actuated through air pressure tubes, environmental changes (temperature, pressure), even explosions.

Related Material

VoxCad Simulator [2]

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

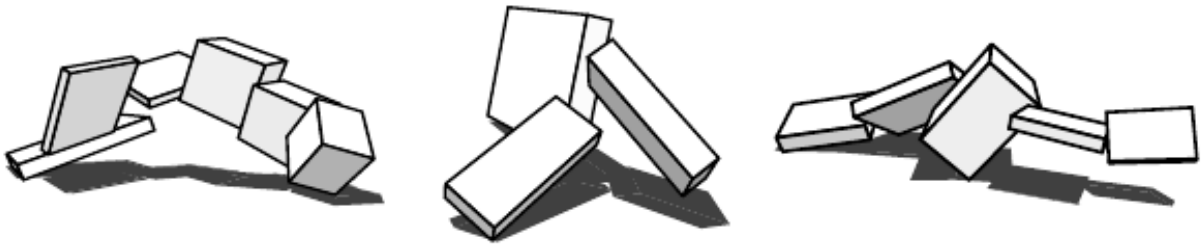
- Lattice
- Voxels
- Structure
- Materials



Related Work I

Evolving virtual creatures [5]

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



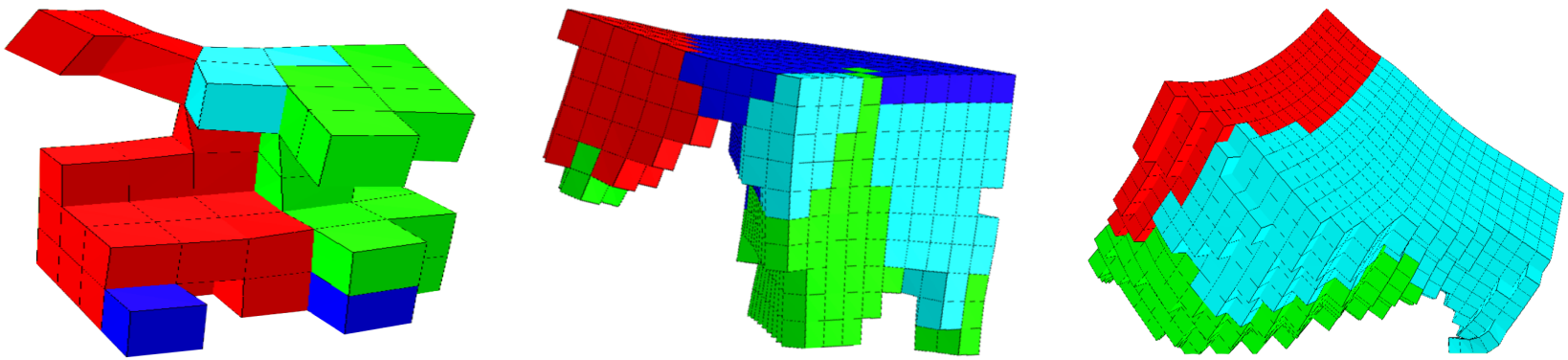
Evolving a diversity of virtual creatures through novelty search and local competition [4]

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

Related Work II

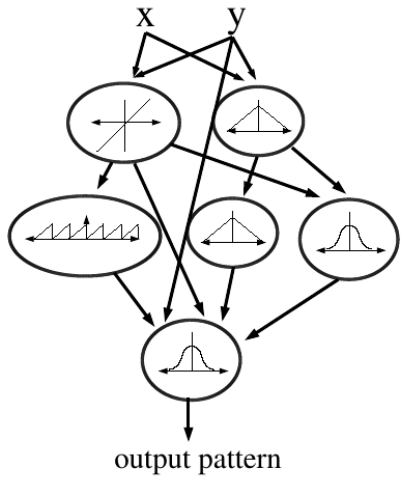
Evolving soft robots with multiple materials and a powerful generative encoding. [1]

- 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]

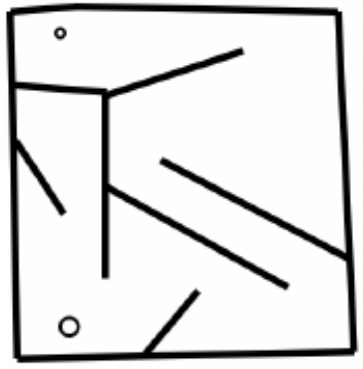
Some key points of this method are:

- 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

Random Soft Robots

Random

Assign materials to voxels randomly.

Generative 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.

Random CPPNs

Evolution with high mutation power and no fitness information.

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

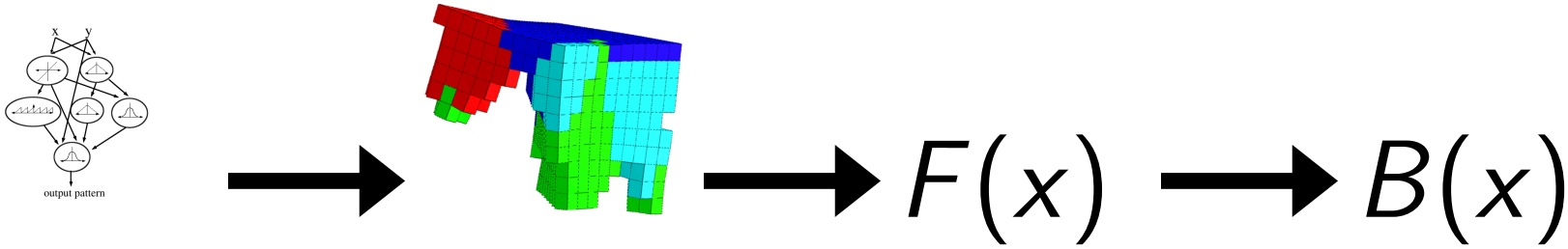
- HyperNEAT C++
- Each genome is represented by a CPPN.
- This CPPN is queried for each input coordinate to output the existance and the type of the material.
- NEAT evolves these CPPNs.
- In each generation, speciation. Population is split into species, new species can survive easier than old.

CPPN-NEAT with Novelty Search [3]

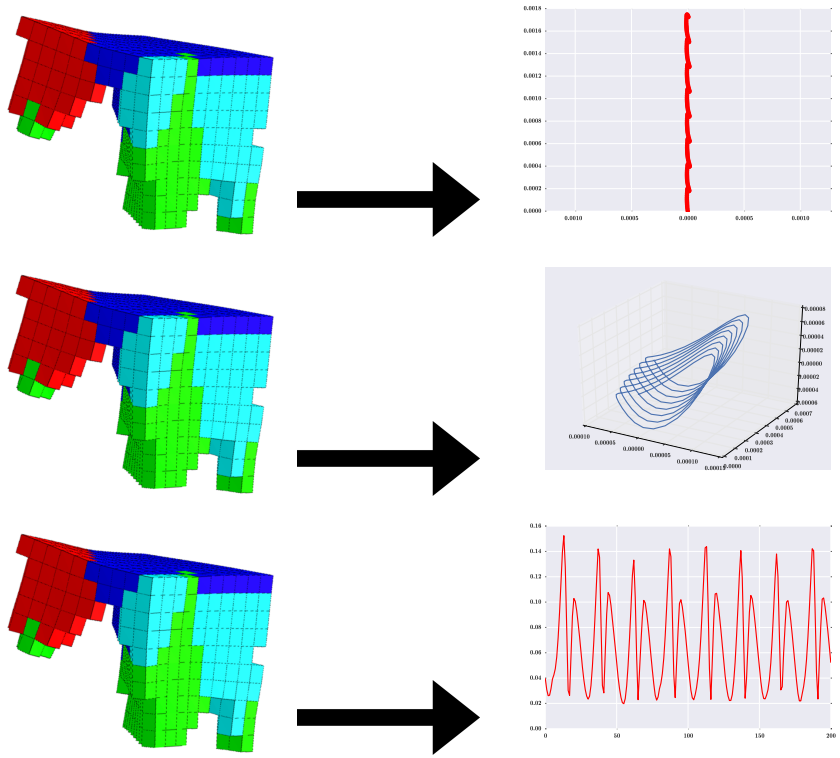
- Same code base
- Novelty takes the place of fitness
- Novel individuals stored in a list
- For each new individual in the population, check its novelty in respect to the stored novel individuals.
  - Sparsity

Behavior

How can we go from fitness to behavior:



Examples:



Behavior

Behavior types can be used:

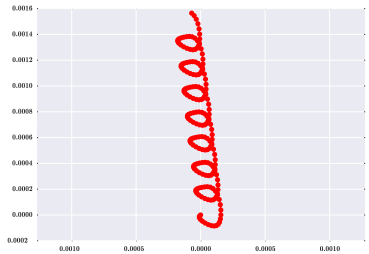
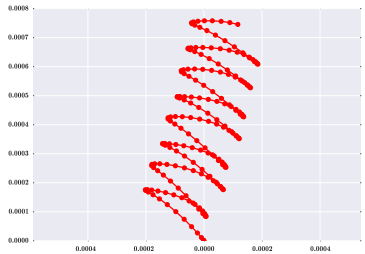
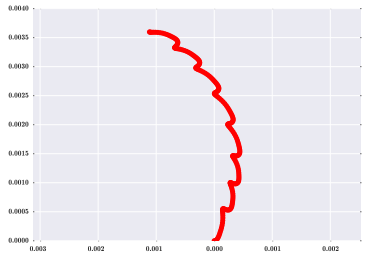
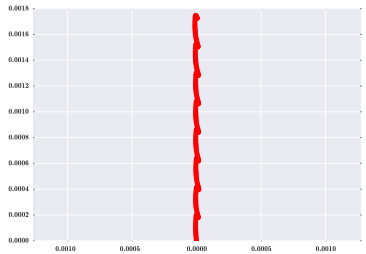
- Trajectory 3D, 2D
- Pace
- Voxels touching ground
- Kinetic energy
- Maximum pressure

Behavior similarity can be computed:

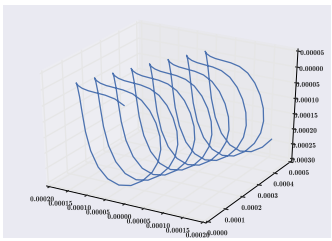
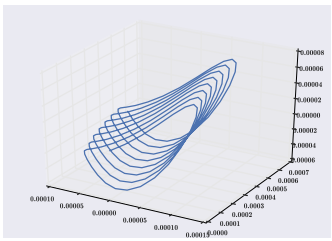
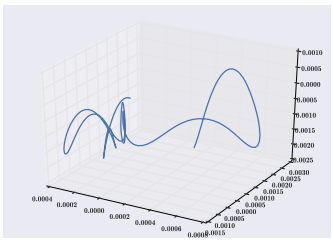
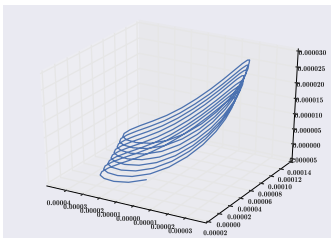
- Sum of Euclidean distances per timestep
- Cross-correlation

Behavior Examples I

2D - Trajectories:

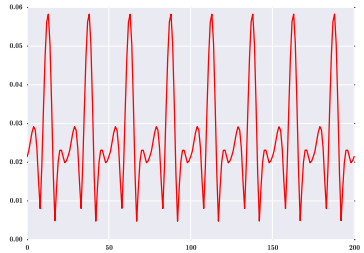
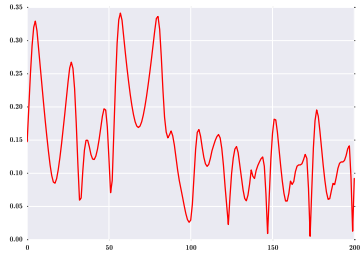
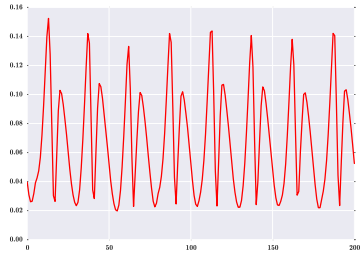
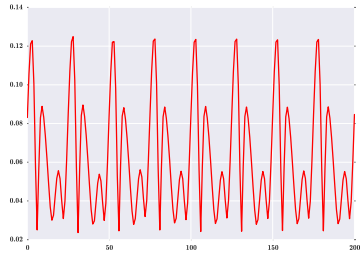





3D - Trajectories

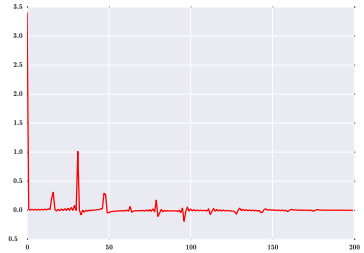
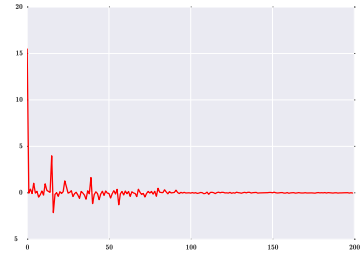
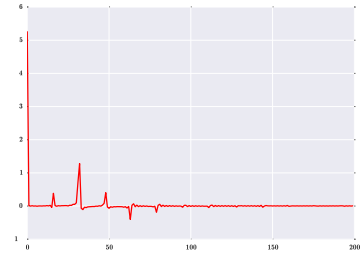
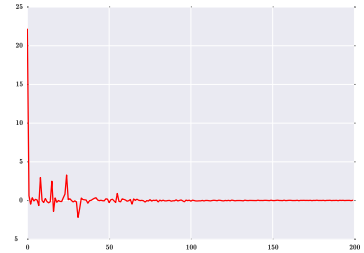





Behavior Examples II

Pace per timestep

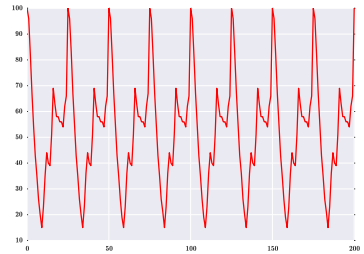
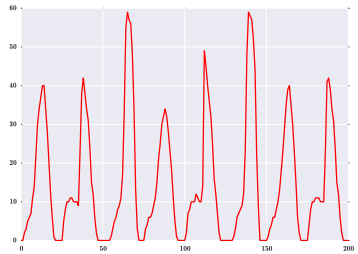
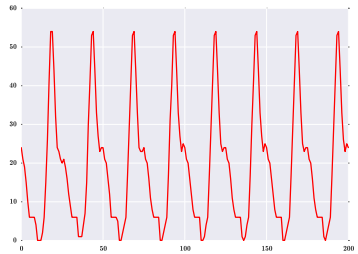
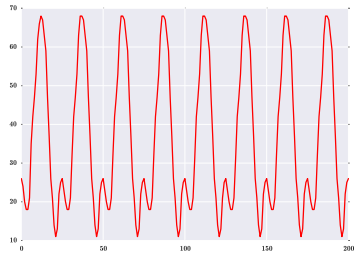





Pace - DFT

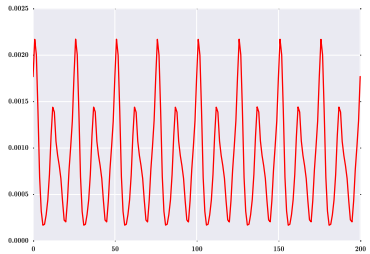
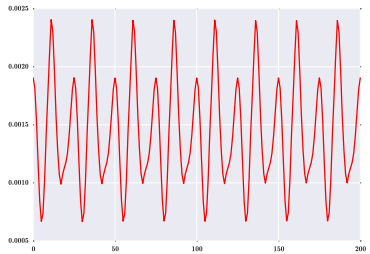
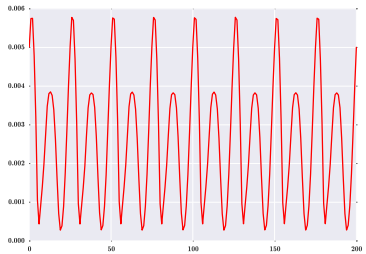
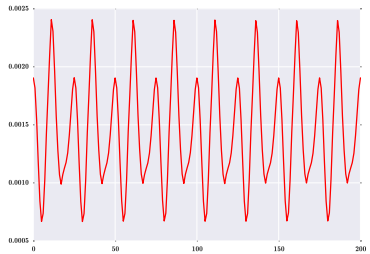





Behavior Examples III

Voxels touching ground per timestep

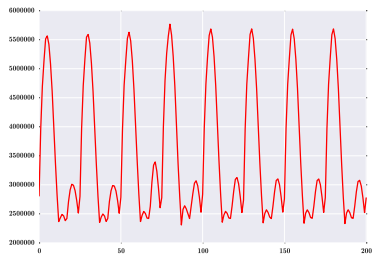
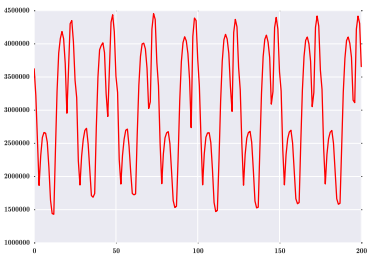
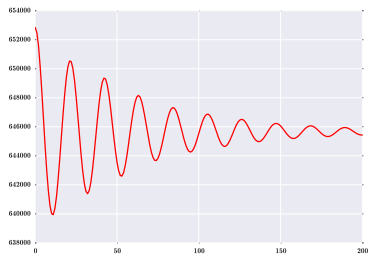
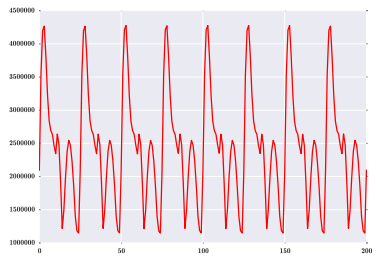





Kinetic energy per timestep

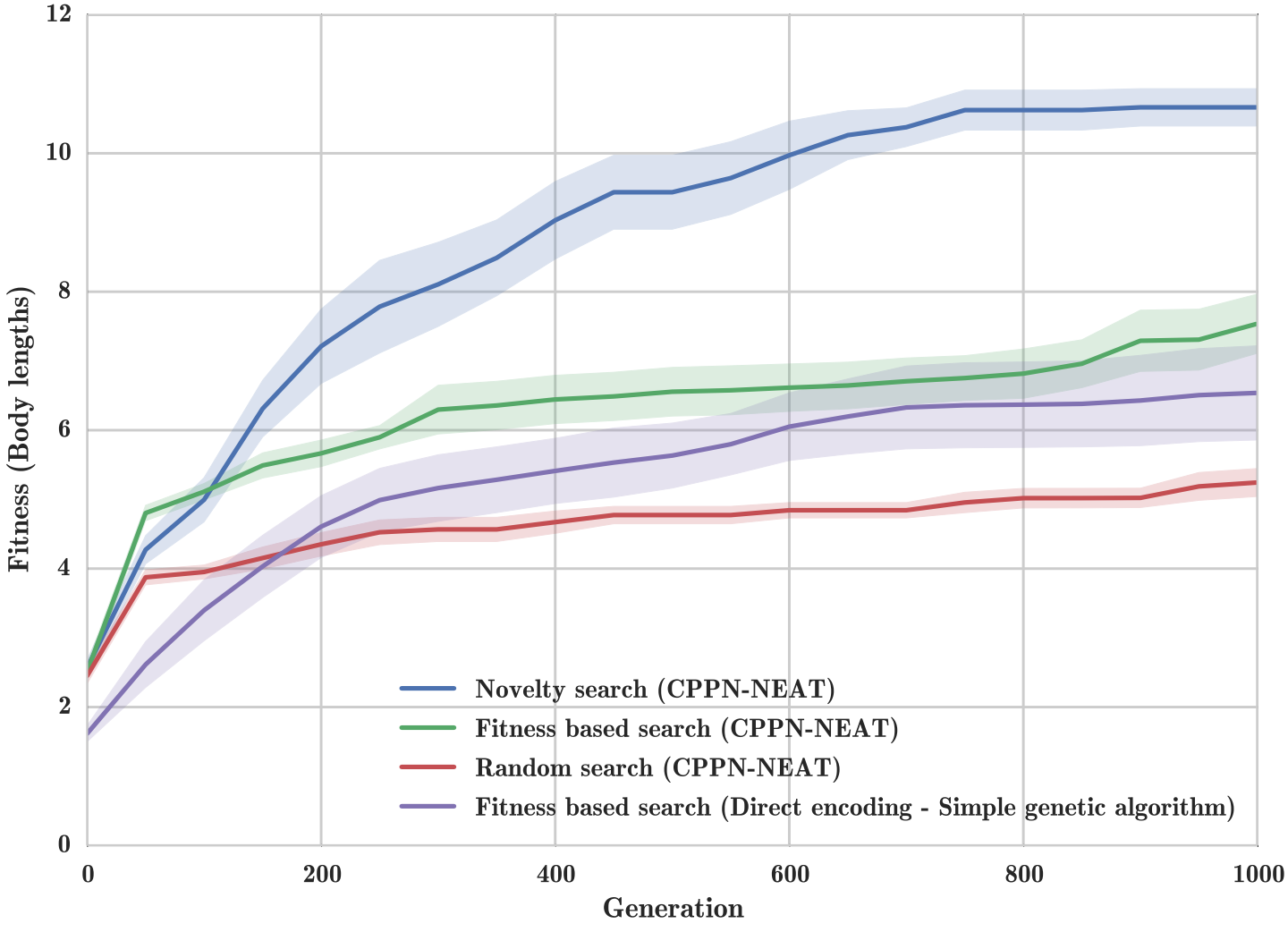
Behavior Examples IV

Maximum pressure per timestep

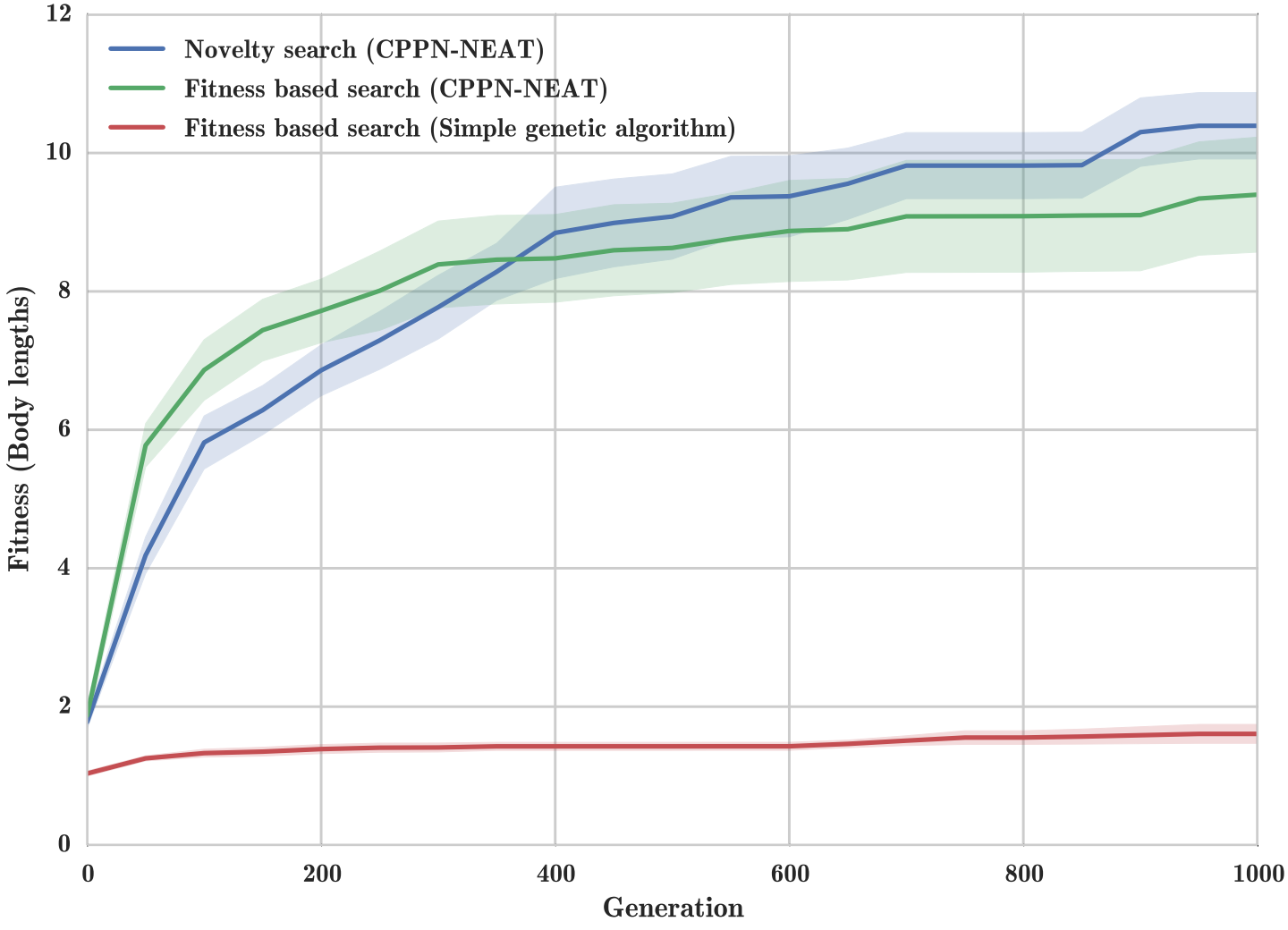
Results I

Fitness, Novelty, Random, Direct GA



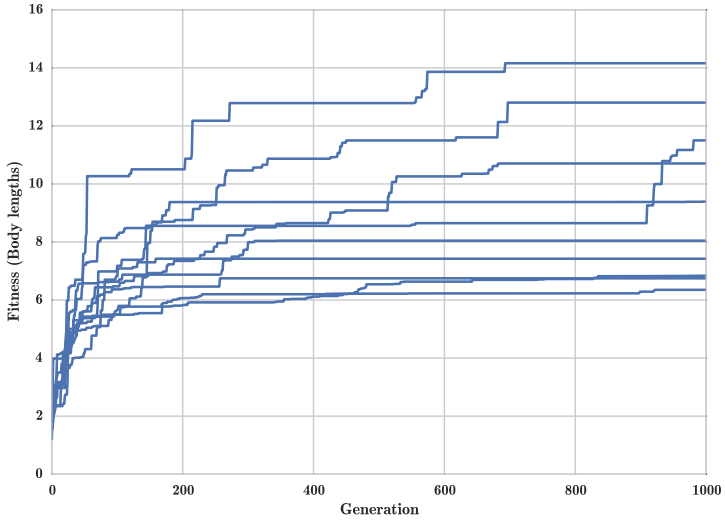
Results II

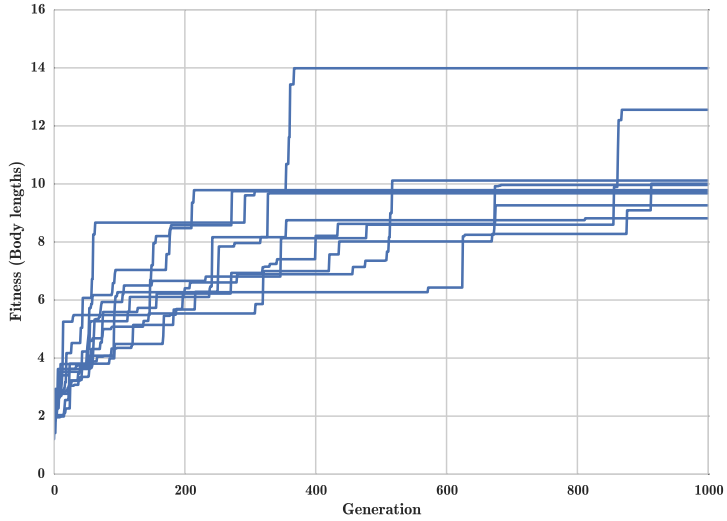
Fitness, Novelty, Direct GA



Results III

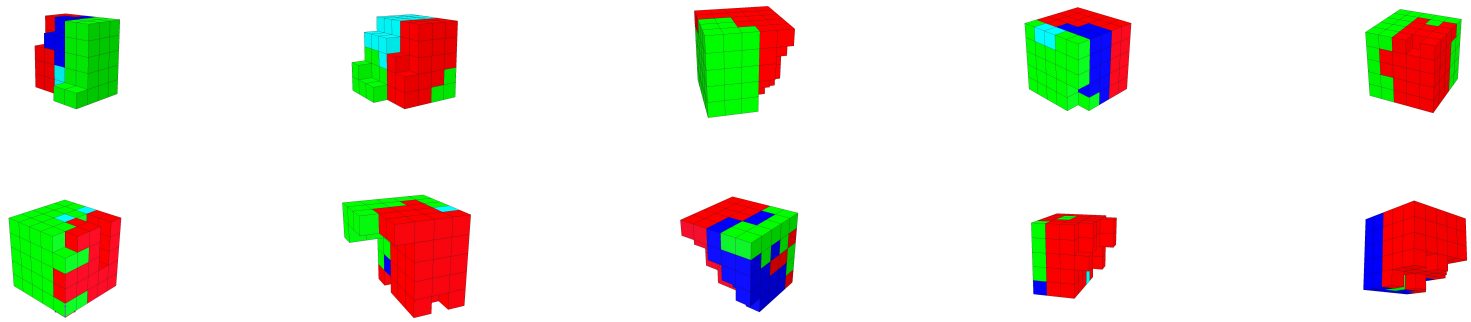
10 individual runs for fitness-novelty based search.



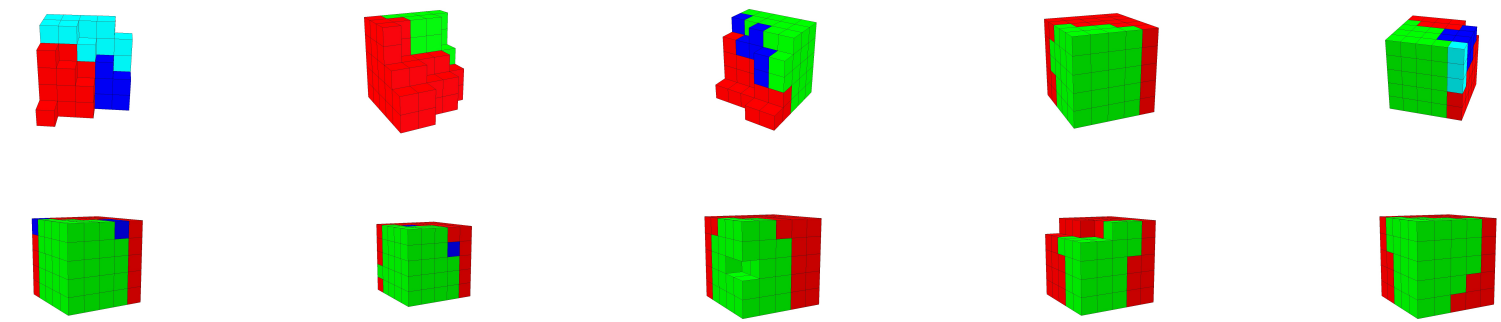


Results IV

Novelty Search - Champions every 100 generations:

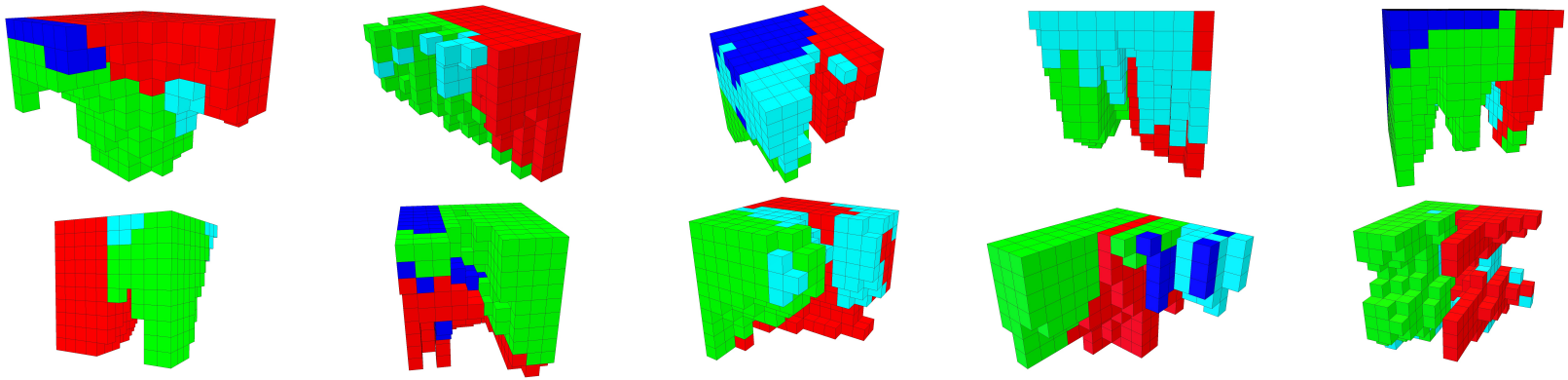


Fitness-based Search - Champions every 100 generations:

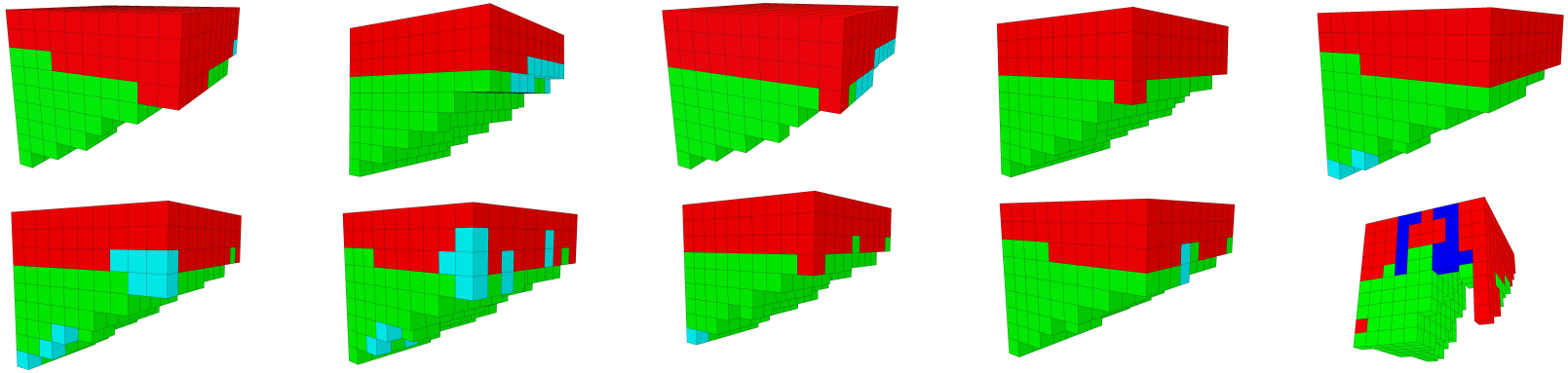


Results V

Novelty Search - Champions every 100 generations:

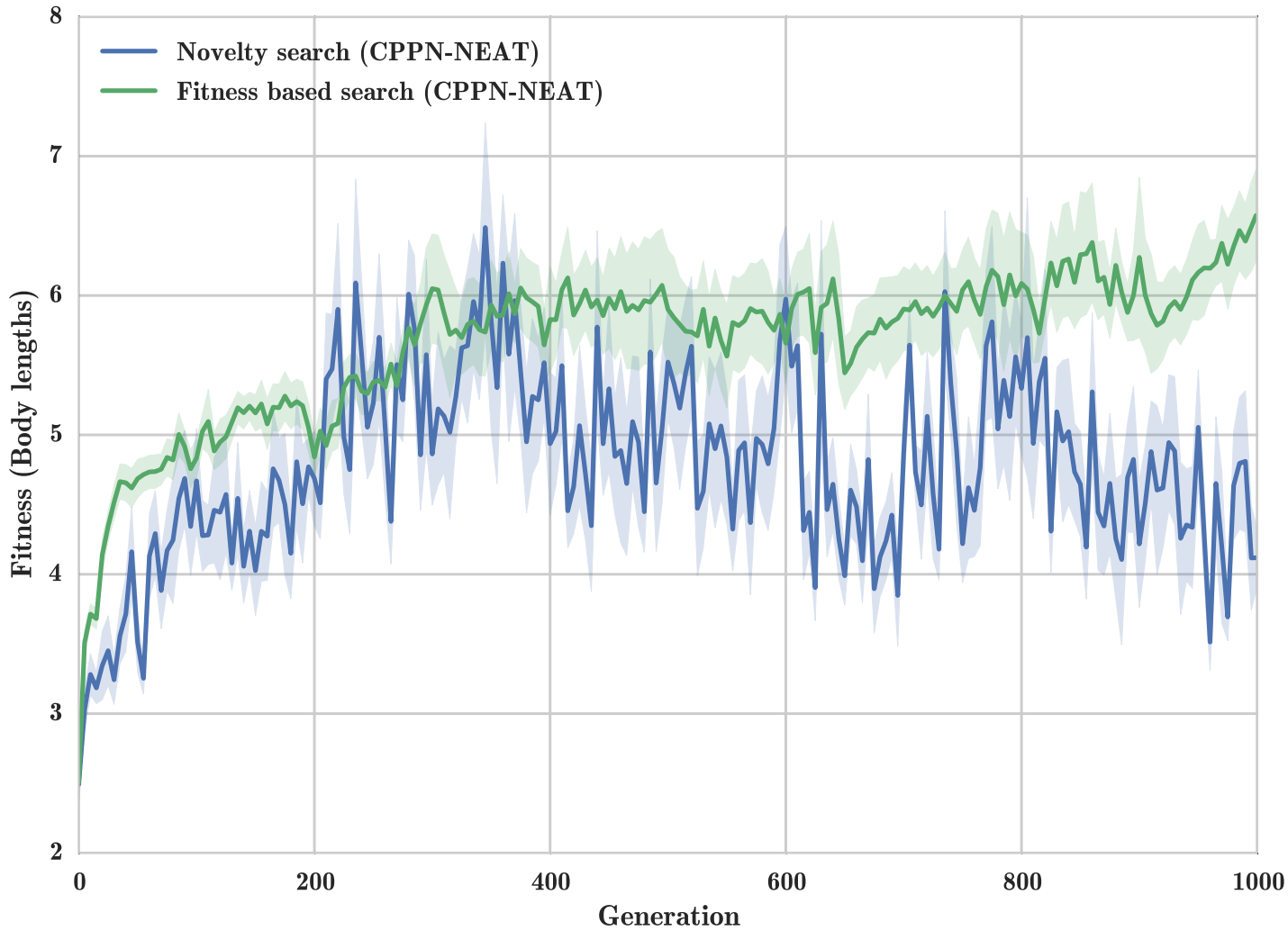


Fitness-based Search - Champions every 100 generations:



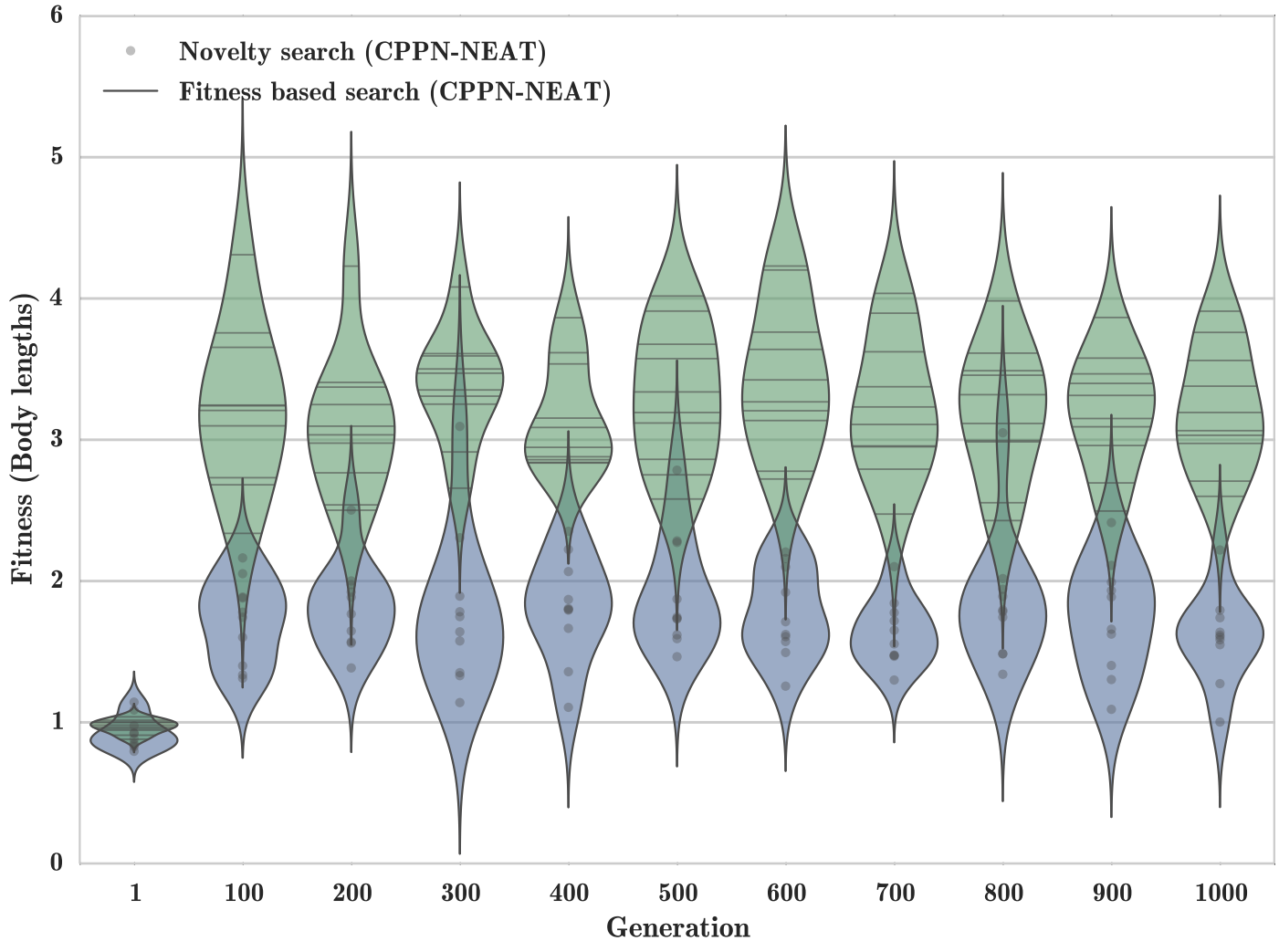
Results VI

Fitness of the generation champion (best individual) per generation



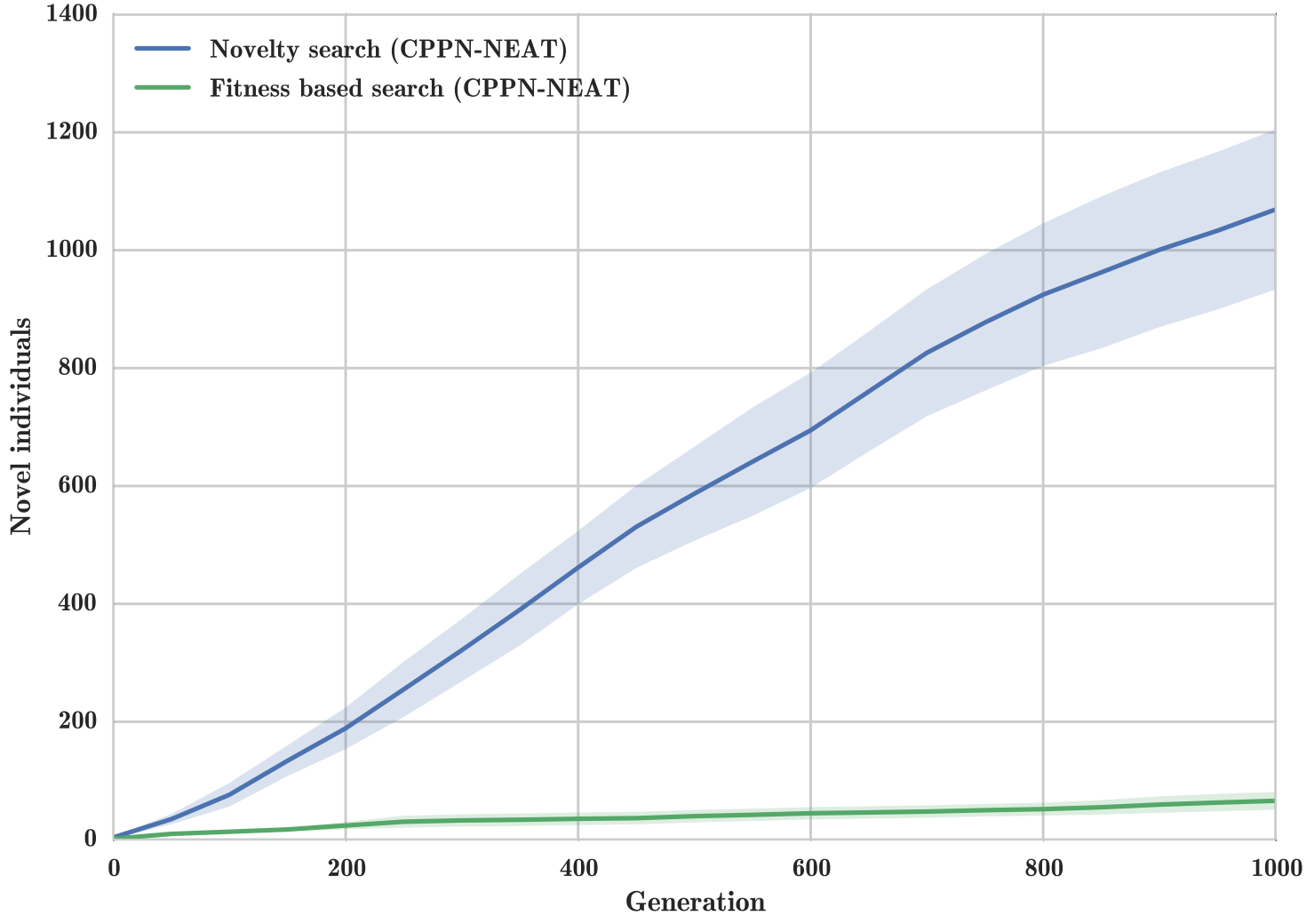
Results VII

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



Results VIII

Novelty Vs. Fitness, number of novel behaviors

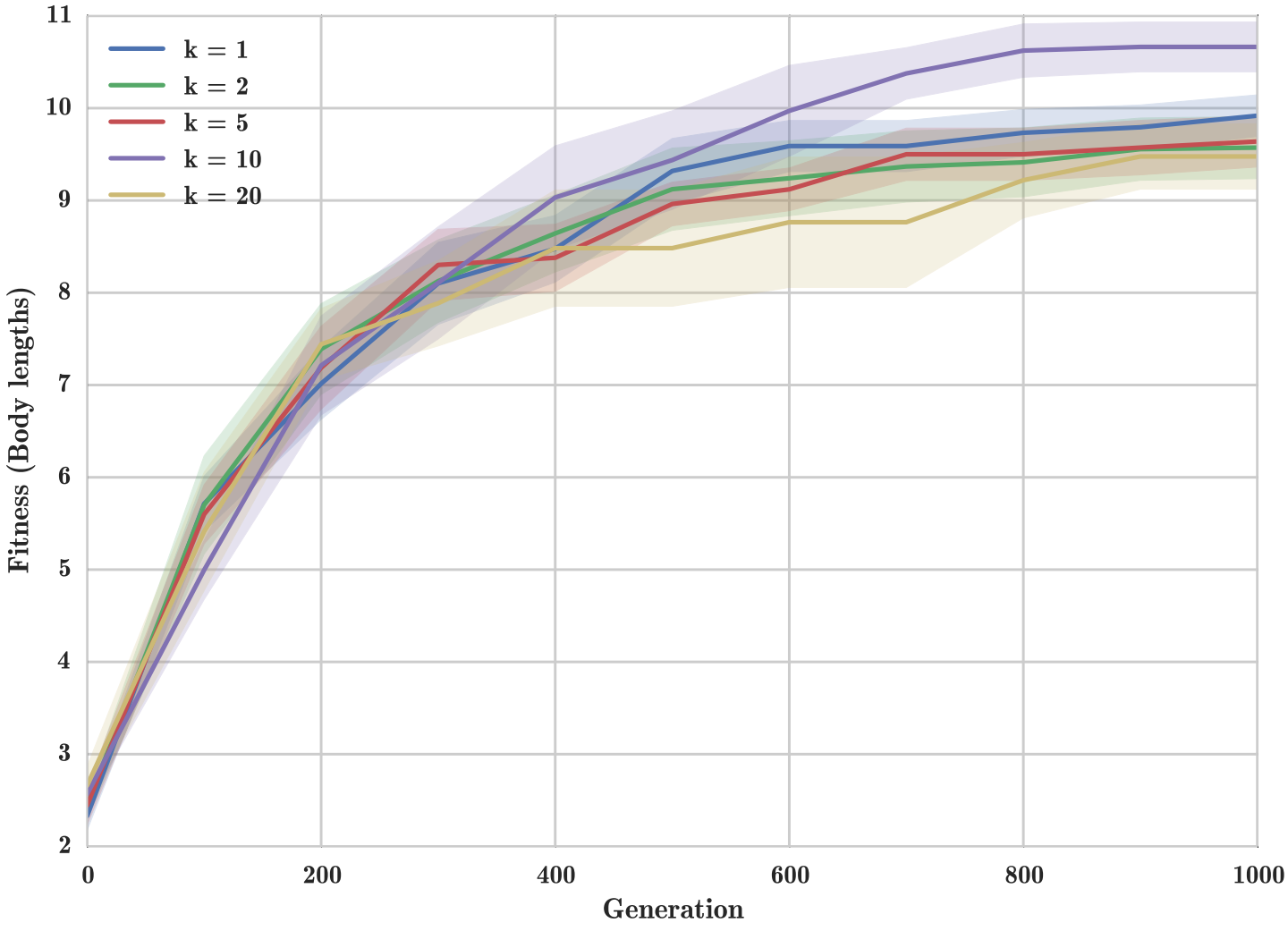


Results IX

Penalizing actuated materials, *Behavior*: 2D trajectories

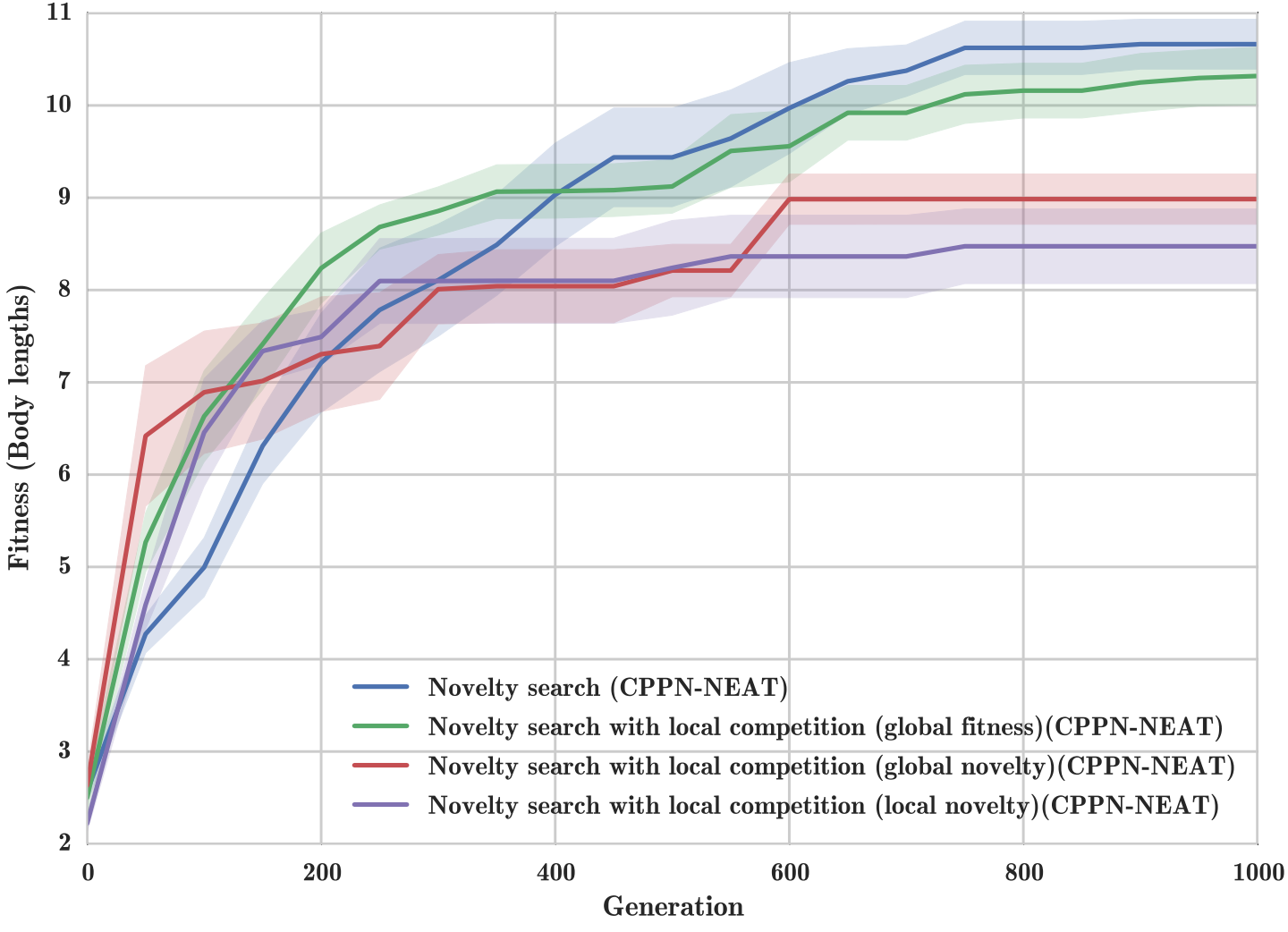
Results X

Novelty search - The novelty is computed as the average distance from the K-nearest behaviors.



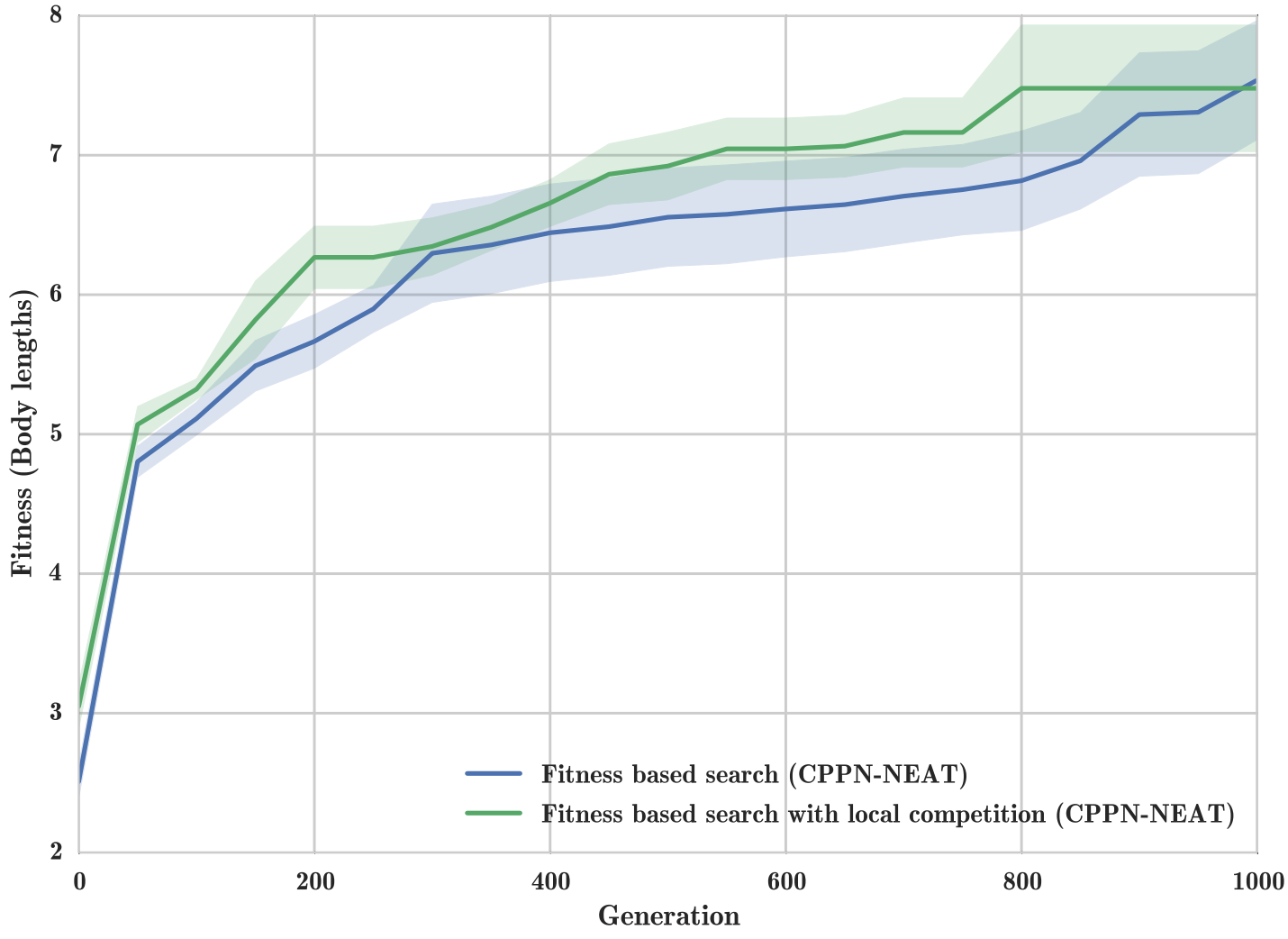
Results XI

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

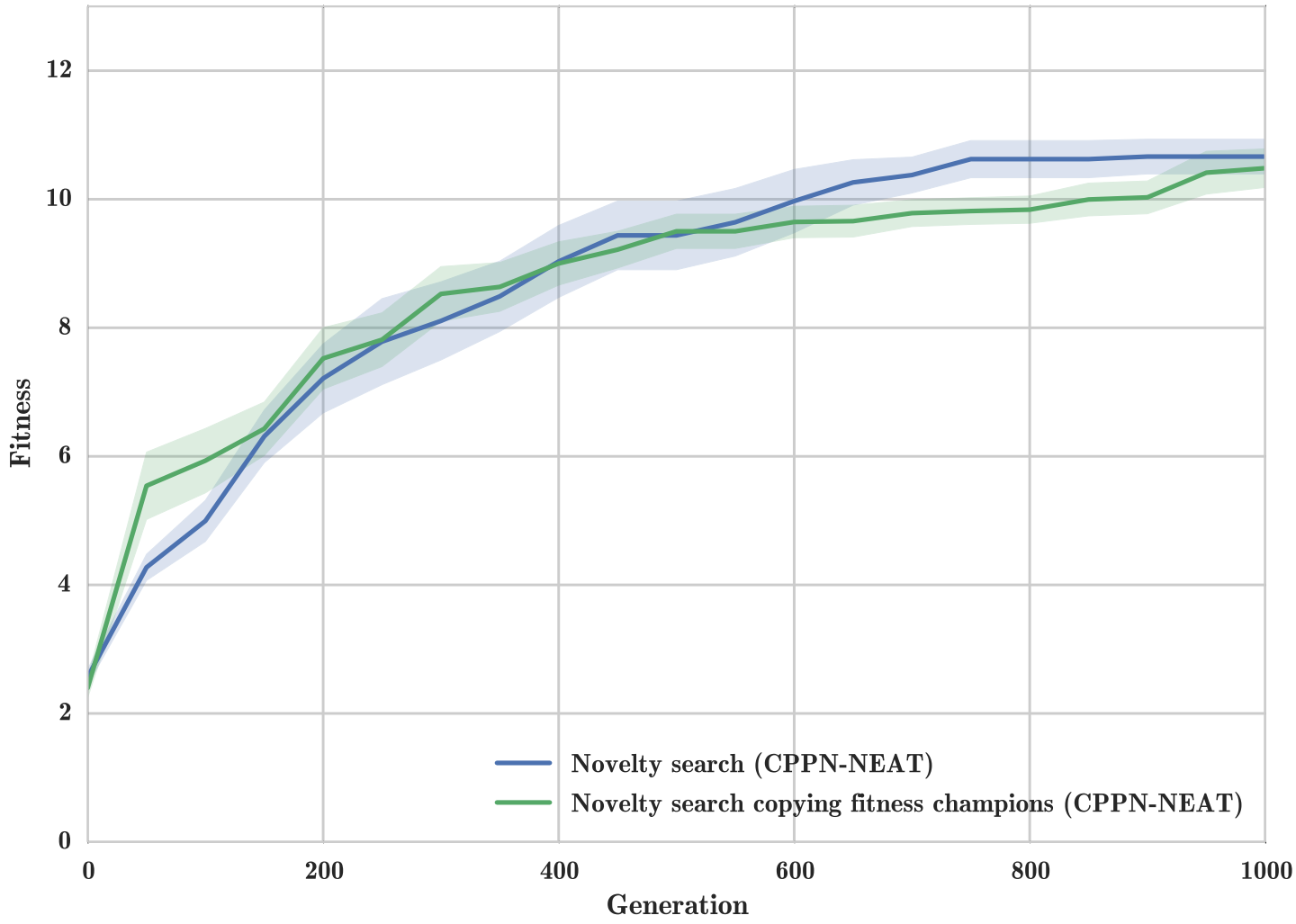


Results XII

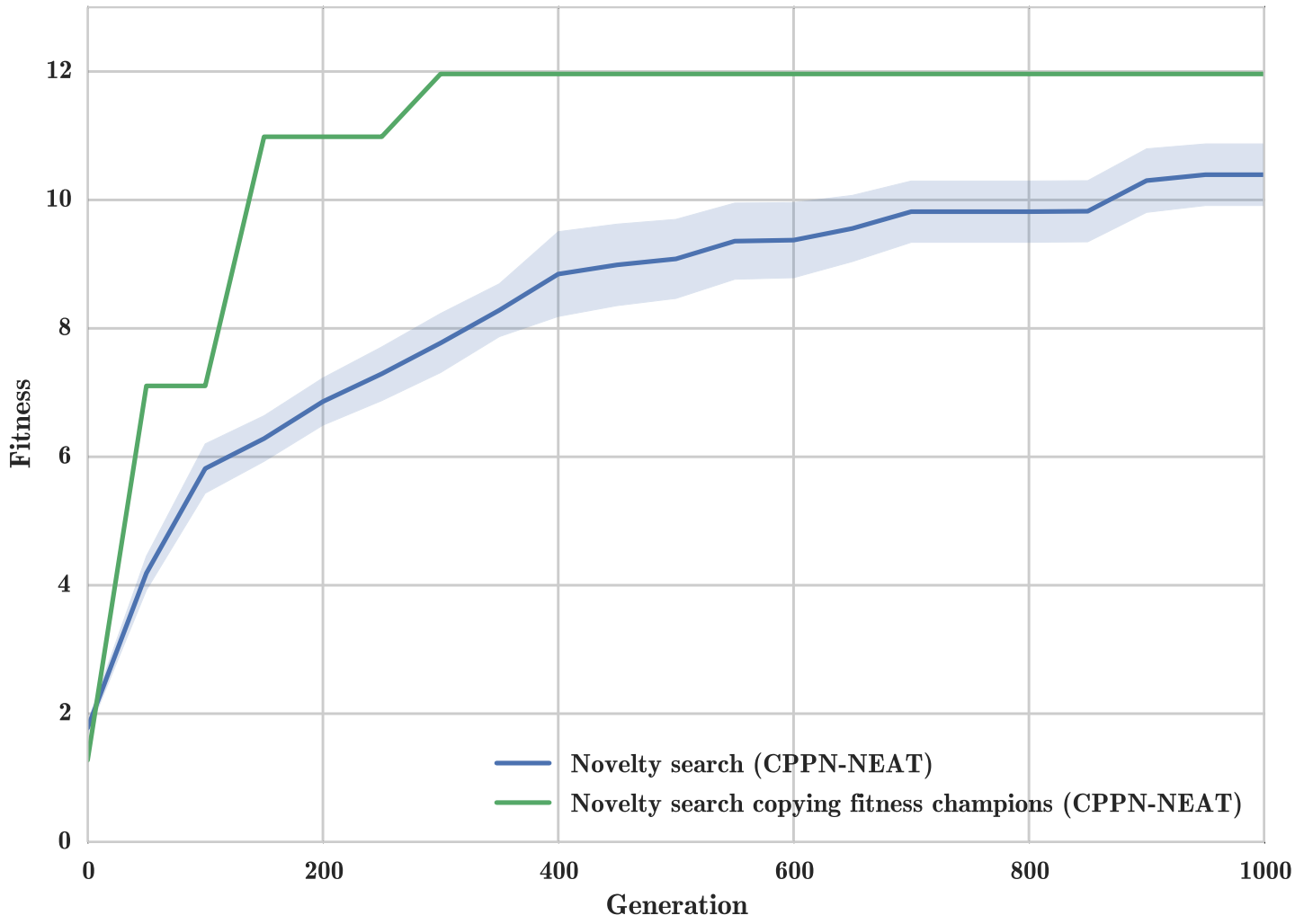
Local competition is held among the complete population of each species.



Results XIII



Results XIV


12
10
8
6
4
2
0
Fitness
0
200
400
600
800
1000
Generation
Novelty search (CPPN-NEAT)
Novelty search copying fitness champions (CPPN-NEAT)

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