University Of Amsterdam

Master Thesis

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


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# *Abstract*

Faculty of Science
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**Simultaneous Evolution of Morphology and Locomotion of Soft Robots by Novelty Search**

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Soft robotics is a vivid research field on the science and engineering aspects of soft materials in mobile machines. Recent development in soft robotics and evolutionary optimization have shown the possibility to simultaneously evolve the morphology and locomotion of soft robots. Generative encoding coupled with neural evolution of augmented topologies shows promising results. Novelty search unlike traditional methods of search for optimization problems does not look to optimize the objective but instead looks for novelty, rewarding diversity and leading to a boundless variety of solutions, mimicking somehow natural evolution. Apart from the performance comparison between novelty and fitness based search it is of interest to show that new locomotion patterns can be produced by the former. Different types of selection algorithms for both evolutionary algorithms were studied, as well as, a method to combine both is proposed. Last but not least, the performance objective-wise is tested under variant gravity conditions leading into a taxonomy of possible locomotion strategies given different gravity levels.

# Contents

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# Chapter 1

# Introduction

## 1.1 Thesis Contribution

Actual introduction, an actual copy of abstract but with more details. For later stages of writing, maybe last.

## 1.2 Thesis Outline

Chapter 2 provides some background information on the field of soft robotics, an introduction to genetic algorithms, different encoding techniques for the genome, neuroevolution algorithms, finally, objective driven search is presented and compared to novelty search. In Chapter 3, related material about evolutionary techniques for evolution of soft-robots morphology and locomotion is presented. Chapter 7 serves as an epilogue to this thesis, where some important points of it are presented.

# Chapter 2

# Background

Papers taken from references of Unshackling evolution, maybe some of them are appropriate for introduction, related work:
[1]

## 2.1 Soft Robotics

Soft robotics [2, 3] is a vivid research field on the science and engineering aspects of soft materials in mobile machines. As the name suggests soft robots made completely of soft materials mimicking animals or animal-parts that consist of soft tissue (elephant trunk, tongue, worm, octapus, etc.). Having no rigid parts the degrees of freedom can be explode and the possible ways of motion can become very complicated. In traditional "hard" robotics joint and rigid parts can predefine a set of movements and sometimes restrict the robot's locomotion strategy for example in a specific gait. In soft robotics, the absence of rigid parts can on the one hand make it the design of a locomotion strategy extremely complicated, on the other hand though the gait alternatives are limitless. Considering also that soft materials can be more friendly than conventional robot materials to humans, human-robot interaction can become more safe [4].

Actuating soft materials can be done in many ways including pneumatic systems [5, 6], hydraylic, internal body explosions, pressure tubes, temperature changes and others [7, 8]. It may seem immature, nevertheless, soft robotics research field is growing fast.

More to add here...

**Interesting readings - Can be added later**

How the Body Shapes the Way We Think A New View of Intelligence [9] [10]

### 2.1.1 Soft Robotics in Simulation

VoxCad simulator [11].

## 2.2 Evolutionary Robotics

[12] [13]

## 2.3 Space Gaits

## 2.4 Genetic Algorithms

An introduction to genetic algorithms [14, 15].

[16]

[17]

### 2.4.1 Neuroevolution of Augmented Topologies

Paper for NEAT [18].

### 2.4.2 Generative Encoding

A Case Study on the Critical Role of Geometric Regularity in Machine Learning [19] Generating Large-Scale Neural Networks Through Discovering Geometric Regularities [20]

[21]

Main paper to compositional pattern producing networks [22].

##### 2.4.2.1 Compositional Pattern Producing Networks

[23]

##### 2.4.2.2 Hypercube NEAT

[24] [25] [26]

### 2.4.3 Novelty Search

Main paper of novelty search [27].
[28] [29] [30] [31]

# Chapter 3

# Related Work

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# Chapter 4

# Approach

GAlib c++ library [54]

# Chapter 5

# Results

## 5.1 Results

Figure 5.1 shows 10 indipendent runs for fitness based search, alongside the mean of these runs' fitness. Following the objective function's gradient fitness based evolution does small step towards better and more optimized individuals from generation to generation. What is more, fitness based evolution often sticks on shapes which then tries to optimize leading the evolution to stop at that local maximum.

Figure 5.2 shows 10 indipendent runs for novelty based search, alongside the mean of these runs' fitness. In comparison with the same figure for fitness based search we can see a clear difference. Evolving for novelty means that within the evolution only a novel behavior is rewarded instead of a good behavior or a behavior that leads to the optimization of the objective function. Big steps in the fitness value on all independent runs can be observed which can lead us to a conclusion that there is no such a function as optimization of current good individuals within the evolution process. Initially novel individuals are highly rewarded, these individuals could be very good in respect to the fitness or not, the algorithm does not consider how individuals can be measured in respect to the objective function and does not have any information regarding this either. On the next generation, mutations, crossovers, or even copies of these novel individuals are not going to be highly variant in respect to their genotype's topology from their ancestors, resulting to similar behaviors which are going to be unremarkably rewarded as far as their novelty is concerned. Thus, highly novel individuals are producing less novel children, meaning that these children, even though their fitness is high, will not have the chance to reproduce in the next generations and be improved eventually, as in fitness based evolution..

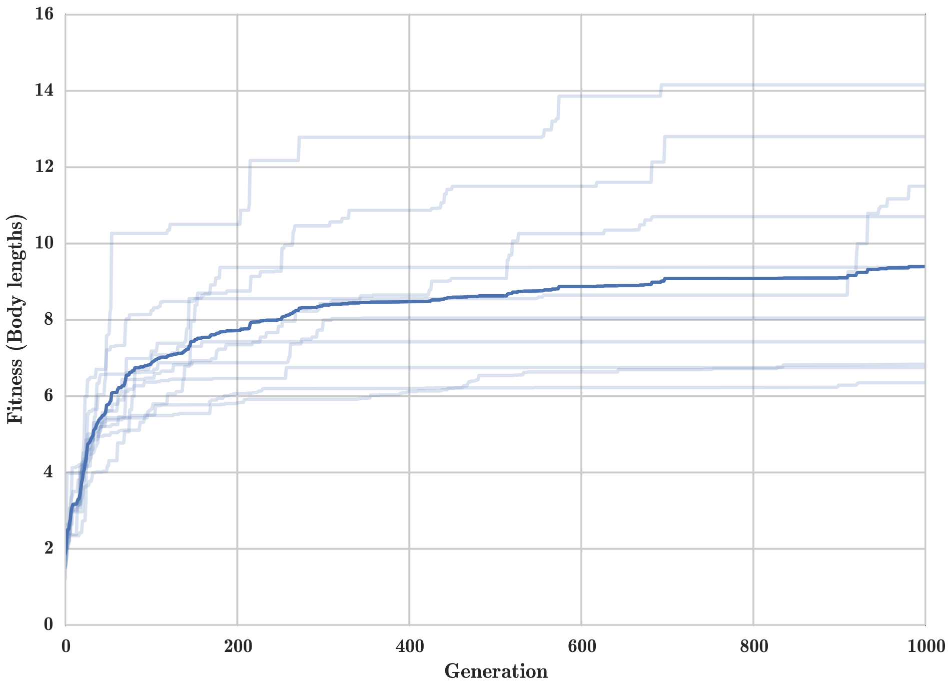


FIGURE 5.1: Best fitness so far, average fitness from 10 individual runs for fitness based search (see A.3.2).

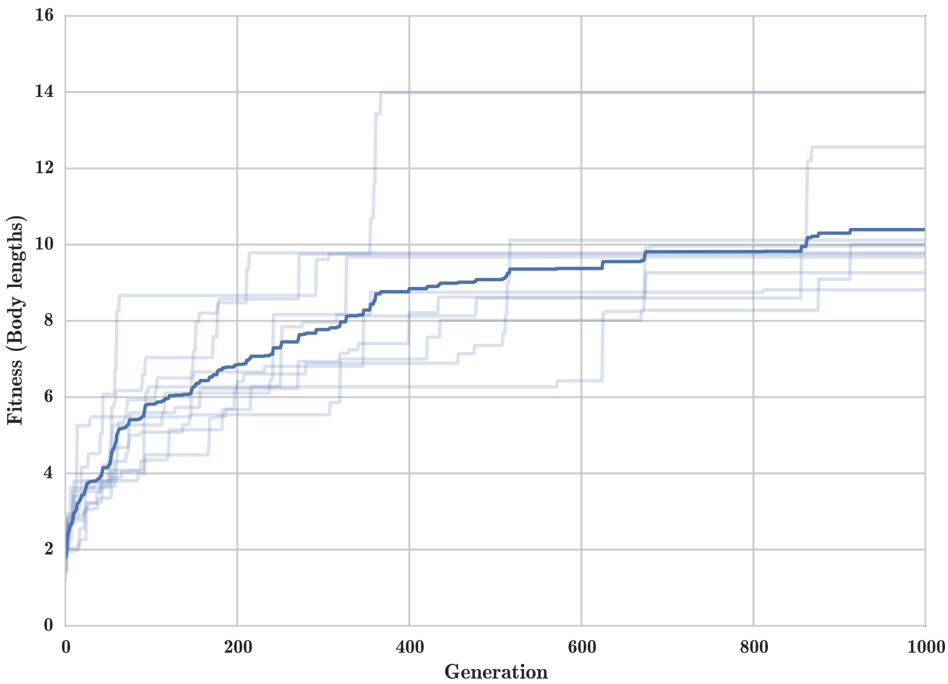


FIGURE 5.2: Best fitness so far, average fitness from 10 individual runs for novelty search (see A.3.2).

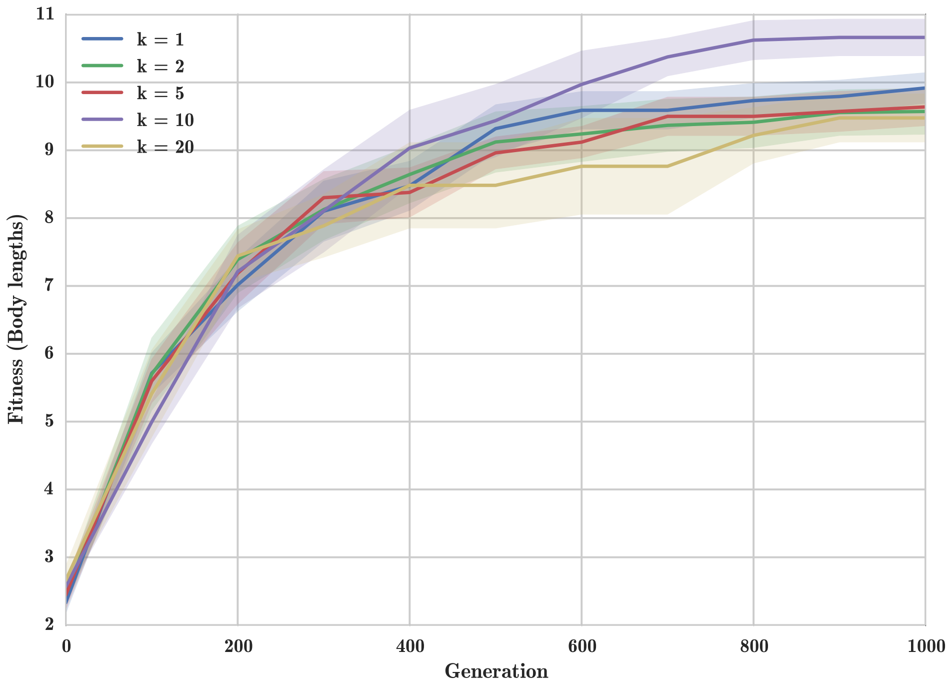


FIGURE 5.3: Best so far fitness averaged over 10 runs (see A.3.1), for different $k$ to sparsity computation of the behavior.

[1]Actuated materials penalize fitness:

$$f = (1 - (n_{actuated}/n_{total})^{1.5}) \times disp$$

, where $n_{actuated}$, is the number of actuated voxels, $n_{total}$ total number of voxels and $disp$ the displacement of the softbot's center of mass.

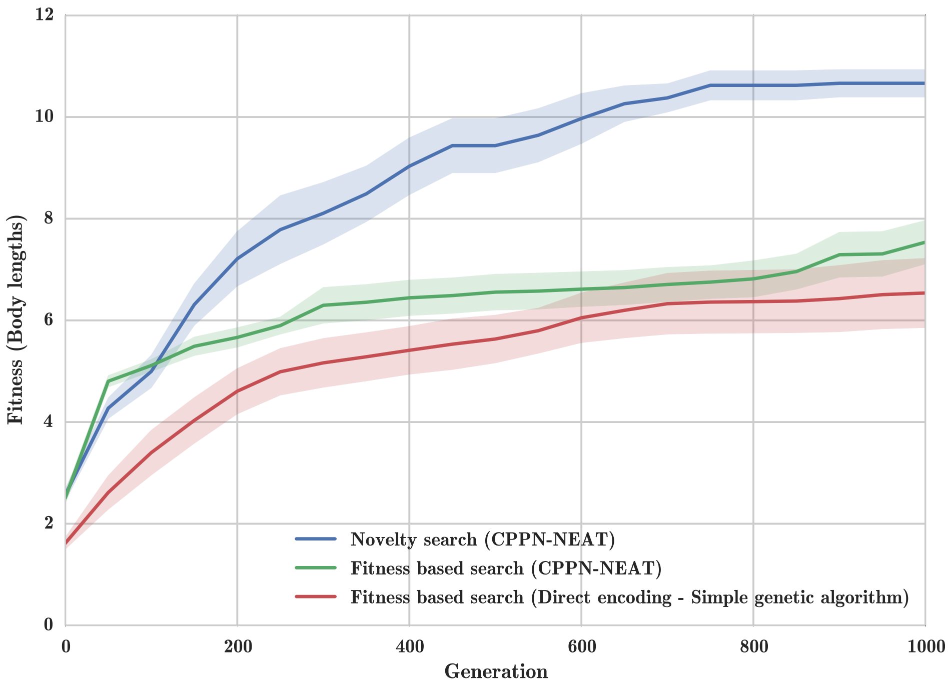


FIGURE 5.4: Comparison of simple genetic algorithm (direct encoding) against *fitness* - *novelty* search with generative encoding. Best so far fitness averaged over 10 runs (see A.3.1).

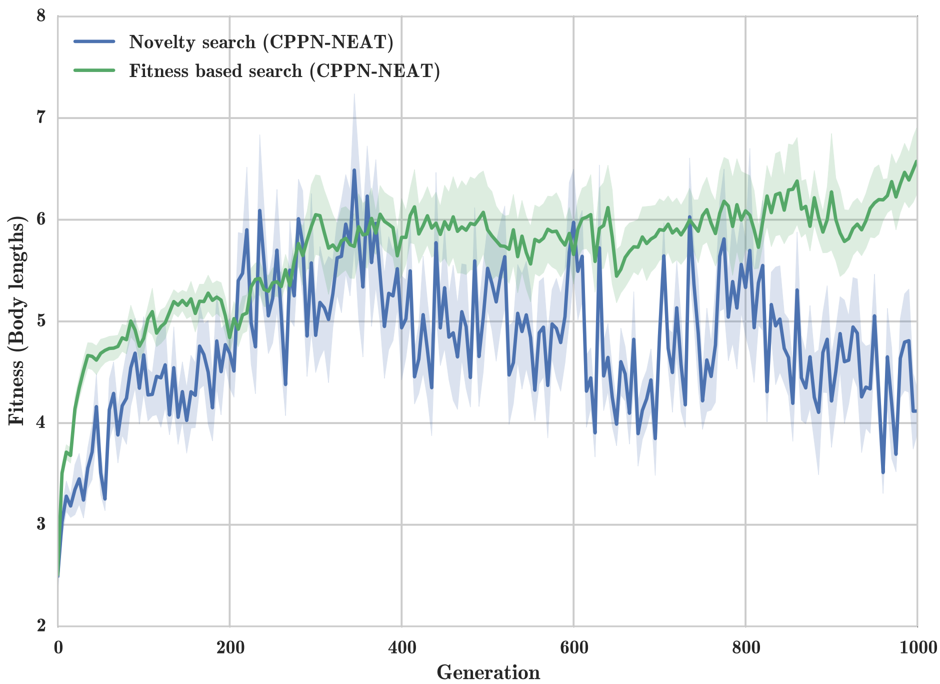


FIGURE 5.5: Fitness of the generation's champion (best individual) for *fitness* - *novelty* search averaged over 10 runs (see A.3.1).

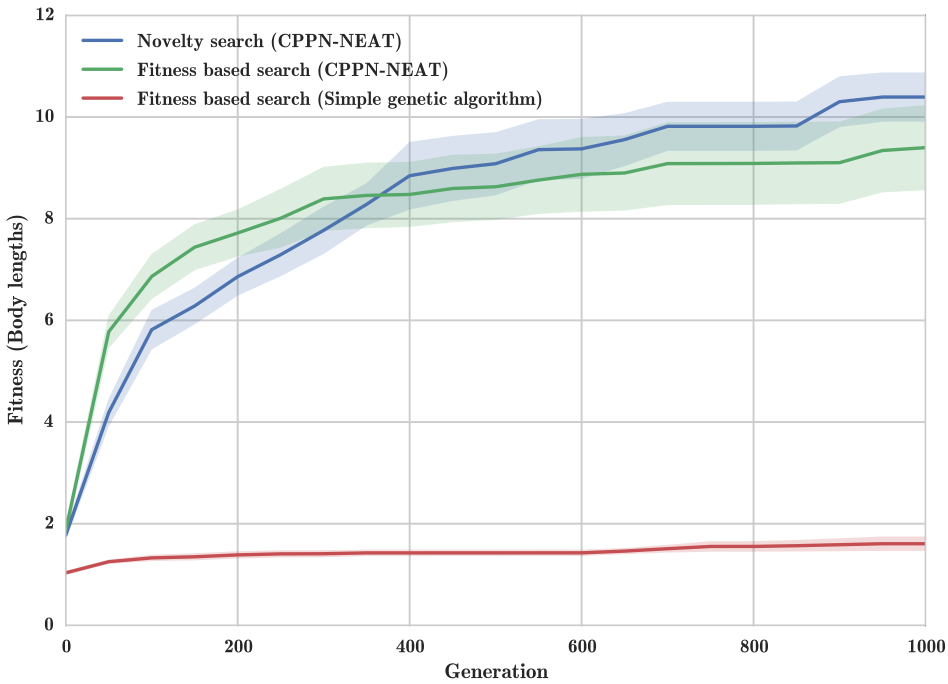


FIGURE 5.6: Comparison of simple genetic algorithm (direct encoding) against *fitness* - *novelty* search with generative encoding. Best so far fitness averaged over 10 runs (see A.3.2).

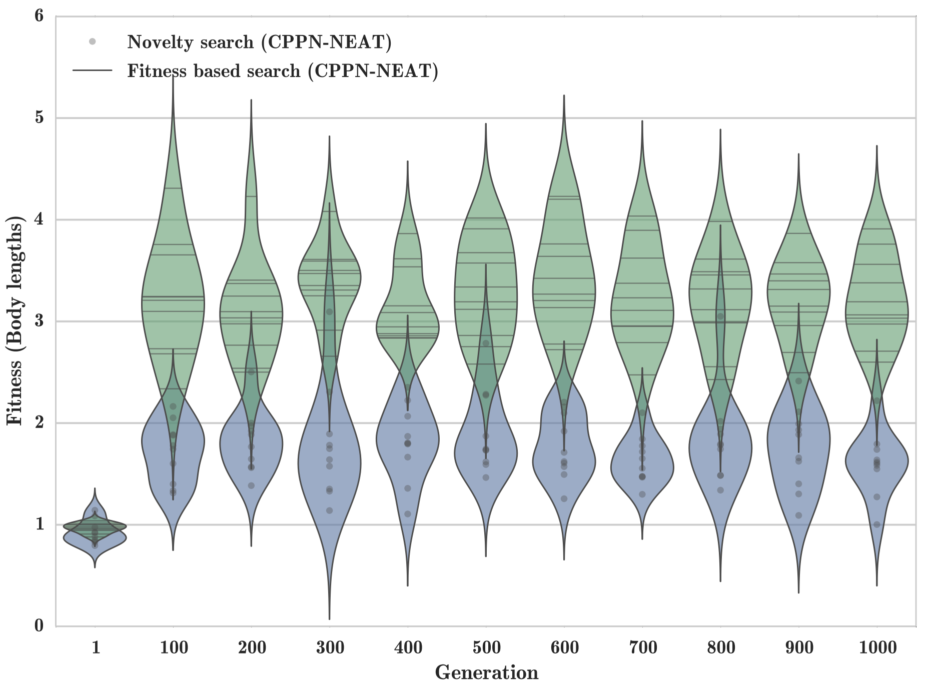


FIGURE 5.7: Distributions of average population fitness per generation over 10 runs for *fitness*(green) - *novelty* (blue) search with generative encoding (see A.3.2).

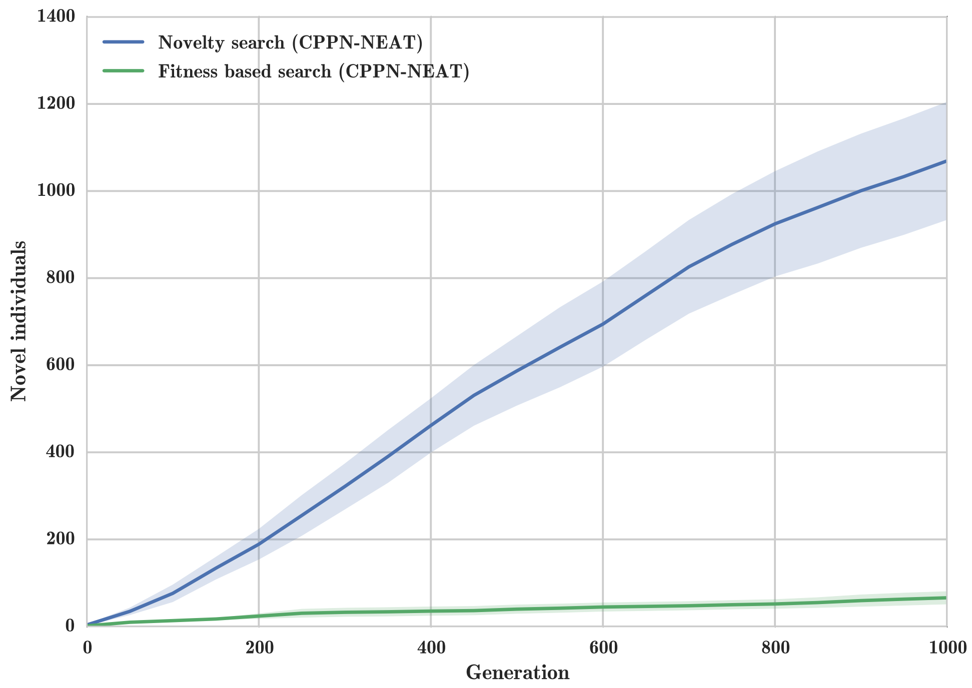


Figure 5.8: Number of novel behaviors up to generation number, averaged over 10 runs. The novelty measure is computed as the average distance from the 10-nearest behaviors for *fitness* - *novelty* search with generative encoding (see A.3.1).

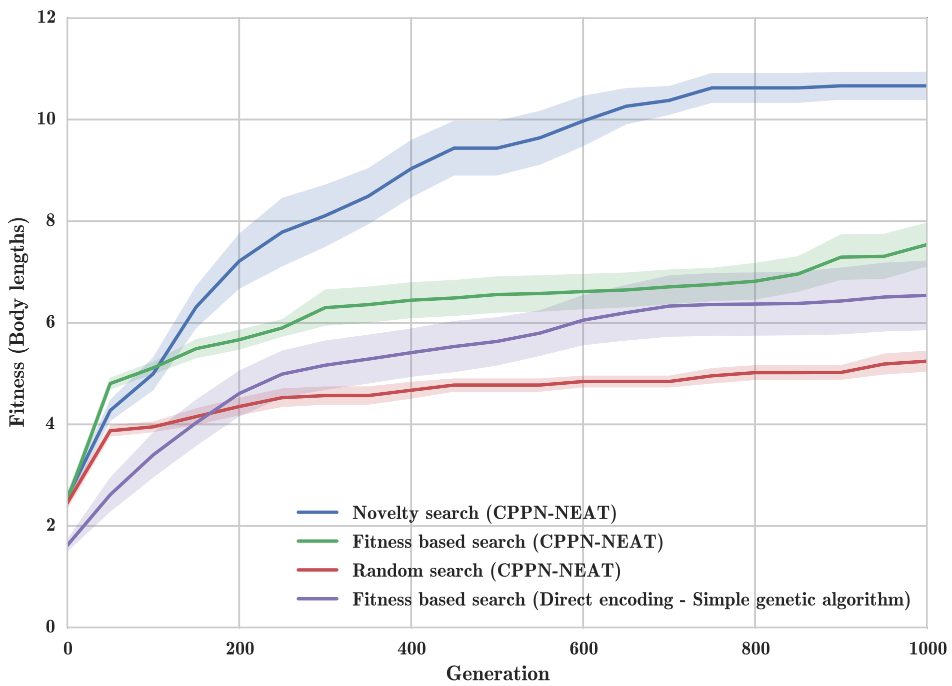


Figure 5.9: Comparison of simple genetic algorithm (direct encoding) against *random* - *fitness* - *novelty* search with generative encoding. Best so far fitness averaged over 10 runs (see A.3.1).

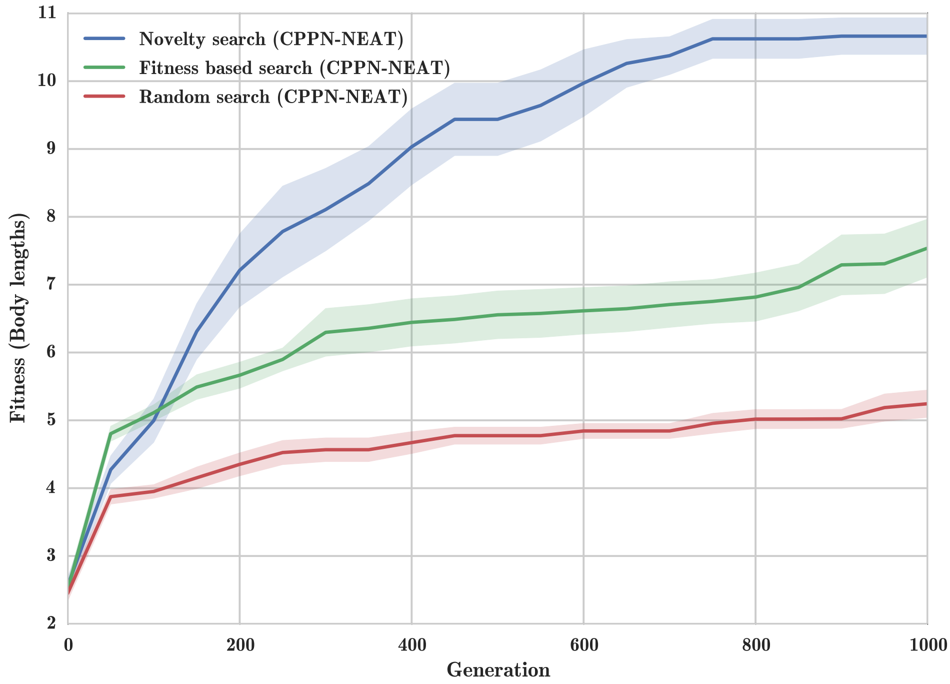


FIGURE 5.10: Comparison of *random* - *fitness* - *novelty* search with generative encoding. Best so far fitness averaged over 10 runs (see A.3.1).


FIGURE 5.11: Best so far fitness averaged over 10 runs, penalizing actuated materials[1]for *fitness* - *novelty* search with generative encoding (see A.3.1).

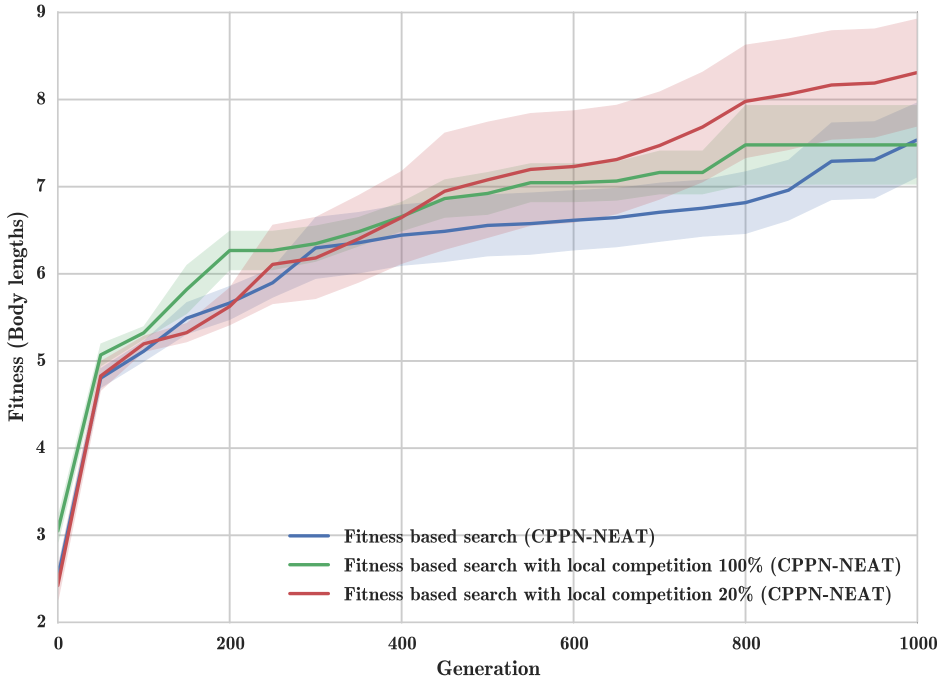


FIGURE 5.12: Best so far fitness averaged over 10 runs, with no competition, local competition among the top 20% and in the complete population of each species for *fitness* search (see A.3.1).

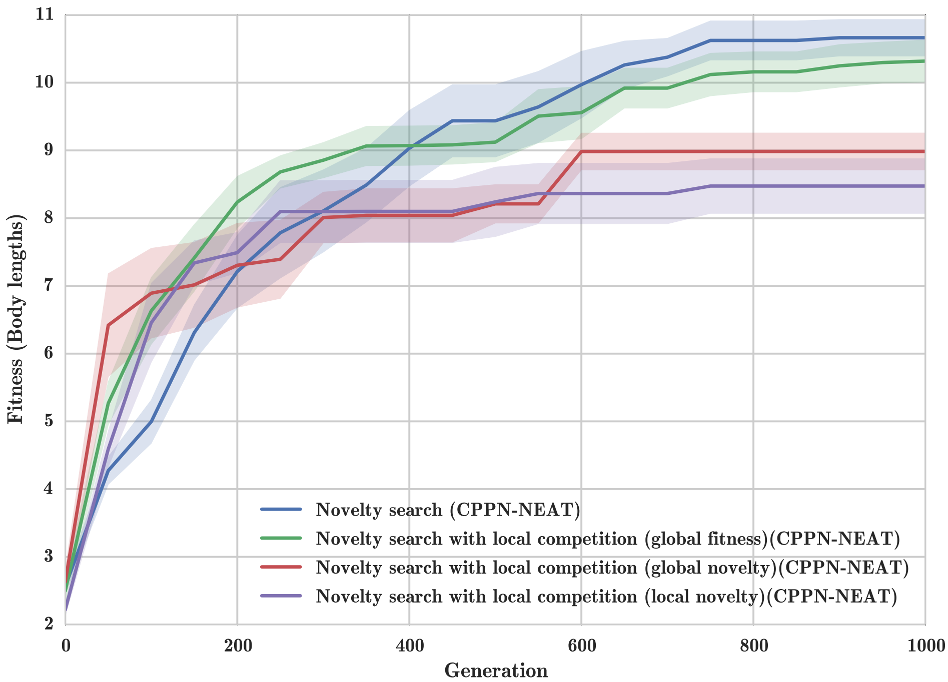


FIGURE 5.13: Best so far fitness averaged over 10 runs, for local competition held among the population of each species for *novelty* search with generative encoding (see A.3.1).

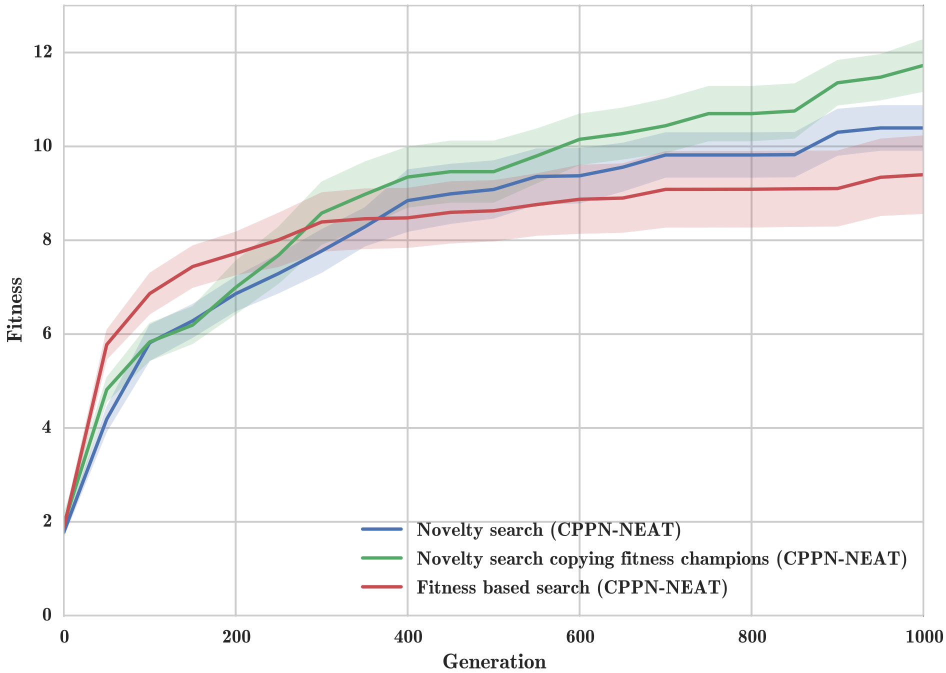


FIGURE 5.14: Best so far fitness averaged over 10 runs, for *novelty* search with and without copying *fitness* champions within species with generative encoding (see A.3.1).

# Chapter 6

# Future Work

# Chapter 7

# Conclusion

# Appendix A

# Simulation Settings

## A.1 Environment

Table A.1: Voxelyze simulation settings

| **Property** | **Value** | **Description** |
|---|---|---|
| *DtFrac* | 0.9 | The timestep of the simulation, currently $0.9 \times dt$, where $dt$ is the optimal timestep. |
| *ColSystem* | 3 | Hierarchical collision detection between all voxels. Updates potential collision list only when aggregated motion requires it[1] |
| *StopConditionValue* | 0.4 | Time in seconds simulation is stopped. |
| *TempBase* | 25.0 | Base temperature of the environment. |
| *TempAmp* | 39.0 | Temperature's amplitude of the environment. |
| *TempPeriod* | 0.025 | Period of the temperature cycle. |
| *Lattice_Dim* | 0.001 | Lattice dimensions, each voxel has length, height, and depth of 1mm. |

## A.2 Materials

In this section all materials' properties used during the simulations will be given. All materials used in the simulations have a set of shared properties which are shown in table A.2. Furthermore, unique characteristics of the materials are presented in table A.3.

[1]From VoxCad's documentation [11].

Table A.2: Universal material properties

| **Property** | **Value** |
|---|---|
| *Poissons ratio* | 0.35 |
| *Temporal phase* | 0.0 |
| *Static friction coefficient* | 1.0 |
| *Dynamic friction coefficient* | 0.5 |

Table A.3: Unique per material properties

| **Name** | **Color** | **Elastic Modulus** (MPa) | **CTE** ($1/deg\ C$) |
|---|---|---|---|
| *Active positive* (+) | Red | 10 | +0.01 |
| *Active negative* (-) | Green | 10 | -0.01 |
| *Passive soft* | Cyan | 10 | 0.00 |
| *Passive hard* | Blue | 50 | 0.00 |

## A.3 Experimental Settings

In this section the settings used for each experiment will be presented. For all the following experimental constants the simulation and material settings used are the ones described above, in case of other settings used, the new settings will be mentioned.

### A.3.1 Experiment 1

**Objective function** Displacement in body lengths (displacement divided by size of soft robot) of soft robot's center of mass.

**Gravity acceleration** $-27.6\ m/s^2$

**Lattice dimensions** $5 \times 5 \times 5$

### A.3.2 Settings

**Objective function** Displacement in body lengths (displacement divided by size of soft robot) of soft robot's center of mass.

**Gravity acceleration** $-27.6\ m/s^2$

**Lattice dimensions** $10 \times 10 \times 10$

### A.3.3 Settings

**Objective function** Displacement in body lengths (displacement divided by size of soft robot) of soft robot's center of mass.

**Gravity acceleration** $-27.6\ m/s^2$

**Lattice dimensions** $7 \times 7 \times 7$

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