GECCO

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Novelty Search for Soft Robotic Space Exploration

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Soft Robotic Space Exploration

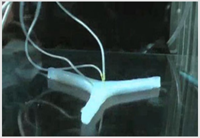
Exploration of extraterrestrial bodies

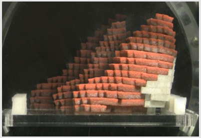
- One challenge, mobility
- Find ideas inspired by biology
- Locomotion strategy and morphology rarely connected

Soft Robots

- Inspired by nature
- Gravity-independent
- No restrictions in locomotion strategy

Soft Robots can have passive or active actuation



Soft Robots in Simulation

VoxCad Simulator[1]

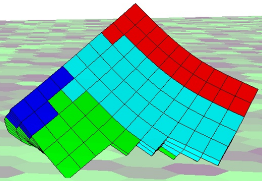
- Voxel modeling and analyzing software
- Physics engine extracted and used for the simulations

Simulation

- 3-D Grid, Voxels, Materials, Temperature

Possible solution space:

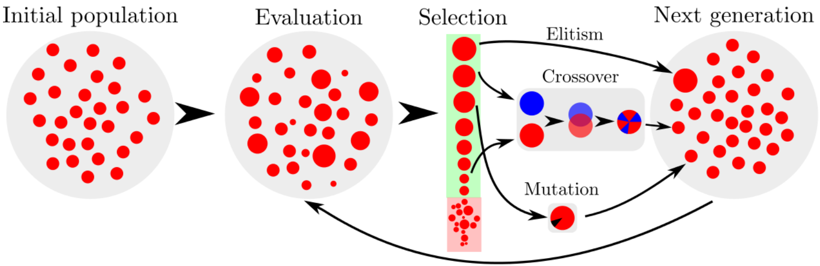
- for size 10^3: 9.3×10^{698}



[1] **hiller2012dynamic**.

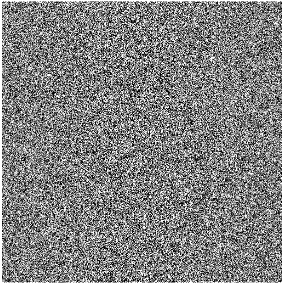
EVOLUTION OF SOFT ROBOTS BY NOVELTY SEARCH

Evolutionary algorithms



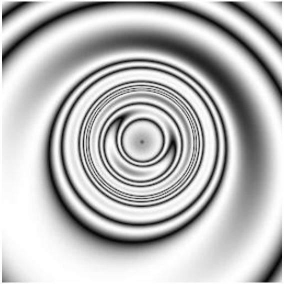
ENCODING SCHEMES

Direct Encoding



$$\underbrace{010101\ldots111101}_{\text{number of pixels}}$$

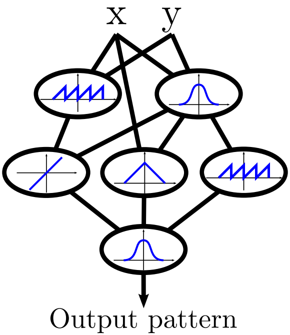
Generative Encoding



$$f(\underbrace{x\,,\,y}_{\text{coords.}}) = \text{pixel value}$$

COMPOSITIONAL PATTERN-PRODUCING NETWORK[2]

- Similar to artificial neural networks
- Large set of canonical activation functions



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

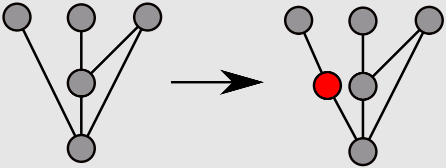
[2] **stanley2007compositional**.

NEUROEVOLUTION OF AUGMENTED TOPOLOGIES (NEAT)[3]

Some key points of this method are:

- Evolving neural network topologies along with weights
- Crossover between different topologies
- Structural innovation through speciation

Genetic Operations in NEAT:



[3] **stanley2002evolving**.

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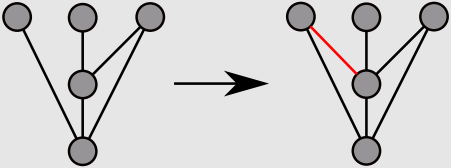

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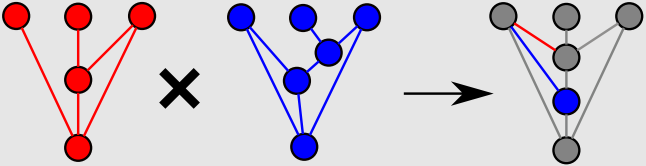

Evolution of Soft Robots by Novelty Search[4]

What is novelty search:

- Traditionally fitness measures how good an individual is.
- Objective function can prevent evolution reaching the target.
- Abandon the objective
- Define a behavior metric
- Try finding novelty in behavior space

How to define novelty: Sparsity

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

[4] **lehman2011abandoning**.

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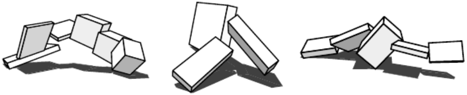
RELATED WORK

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[6]

- Novelty $<$ Fitness
- Novelty search with global fitness competition $>$ Fitness

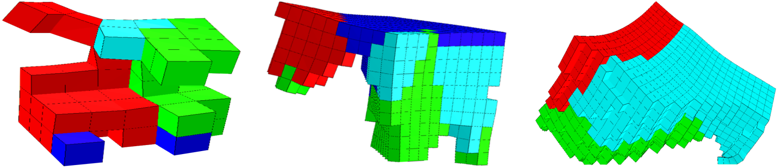
[5] **sims1994evolving**.

[6] **lehman2011evolving**.

RELATED WORK

Evolving soft robots with multiple materials and a powerful generative encoding[7]

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



Evolution of soft robots by novelty search

[7] **cheney2013unshackling**.

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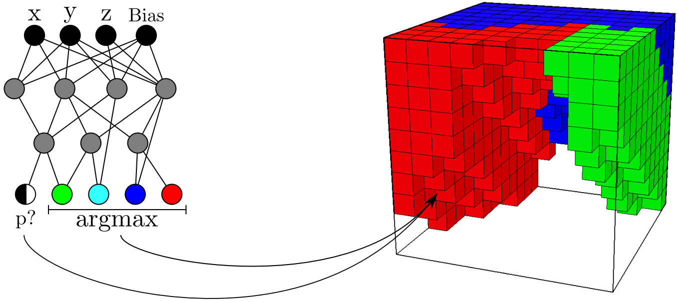
CPPN-NEAT

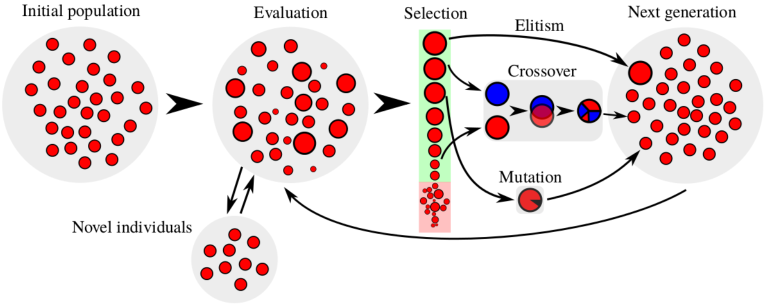
Evolving CPPNs with NEAT

- 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



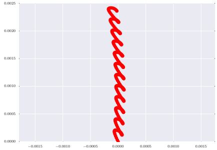
EXTENDING CPPN-NEAT WITH NOVELTY SEARCH

- 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.

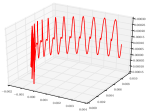


BEHAVIORS

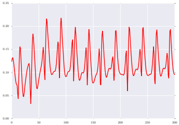
2D-traj.



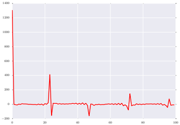
3D-traj.



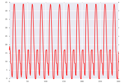
Pace



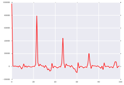
DFT-Pace



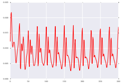
VTG



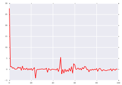
DFT-VTG



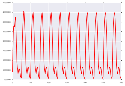
Pr



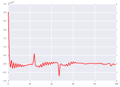
DFT-Pr



KE



DFT-KE



Experimental phase

Experiments:

- Population size: 30, Max. generations: 1000
- For lattice size/resolution: 5^3, 7^3, 10^3
- 10 different behavior metrics
- 4 variant gravity levels
- For both fitness and novelty search

Held at:

- $2 \times$ Servers (16-core & 8-core)
- $2 \times$ Desktops (4-core)

$\sim$ 22.500 hours of CPU time (single-thread)

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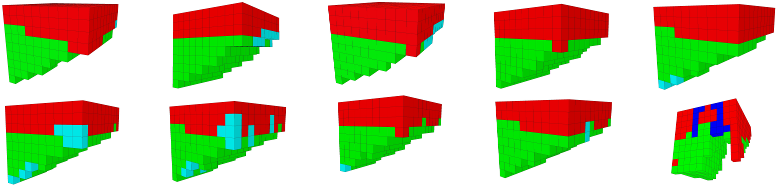
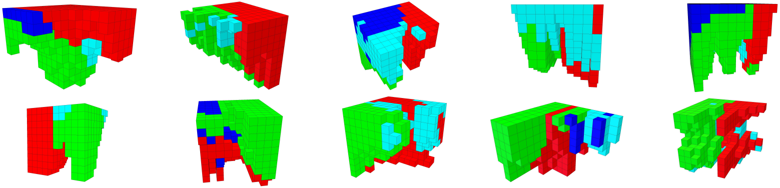
INCREASED DIVERSITY

Fitness-based Search - Champions every 100 generations:

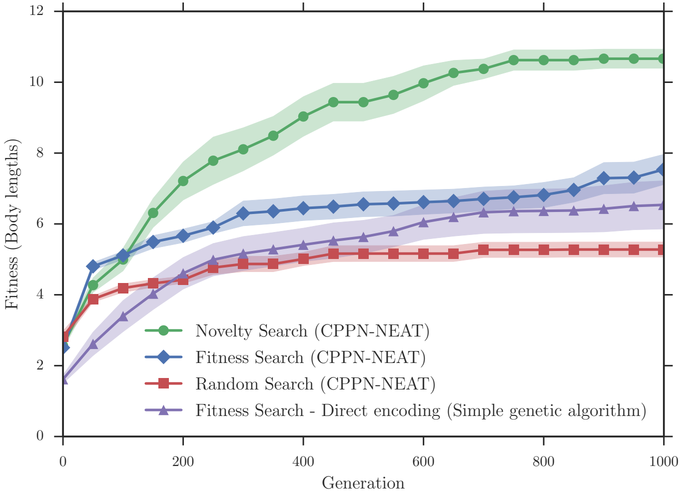


Novelty Search - Champions every 100 generations:



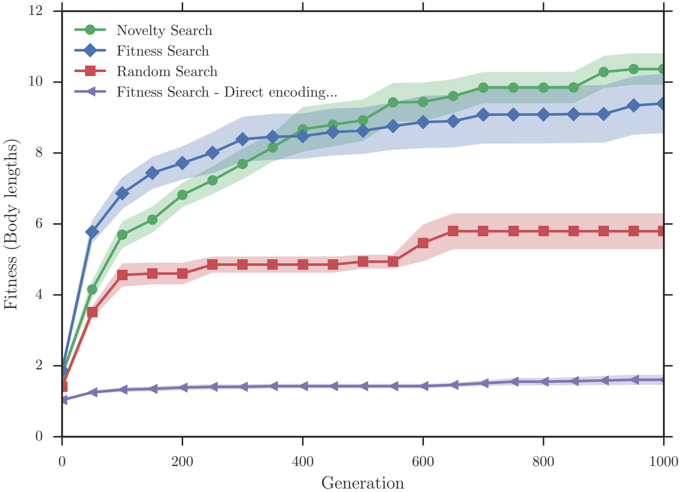
Increased Performance

Best fitness so far, low-res. 5^3



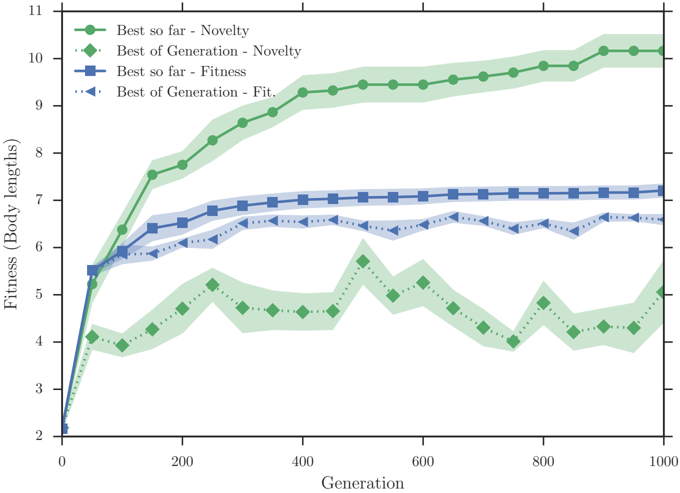
INCREASED PERFORMANCE

Best fitness so far, high-res. 10^3



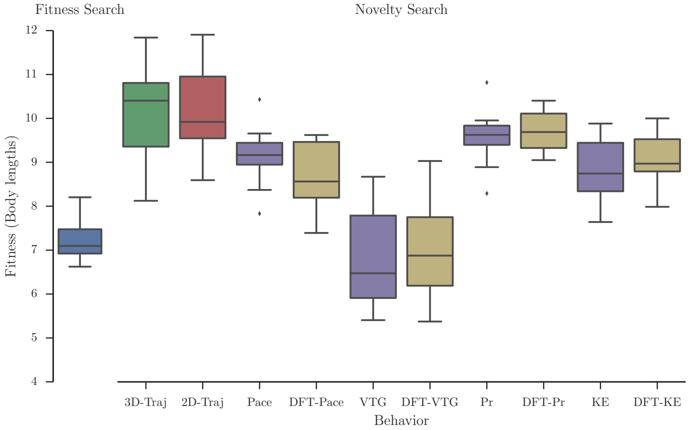
Population Comparison

Best fitness so far Vs. Generation best fitness, med-res. 7^3

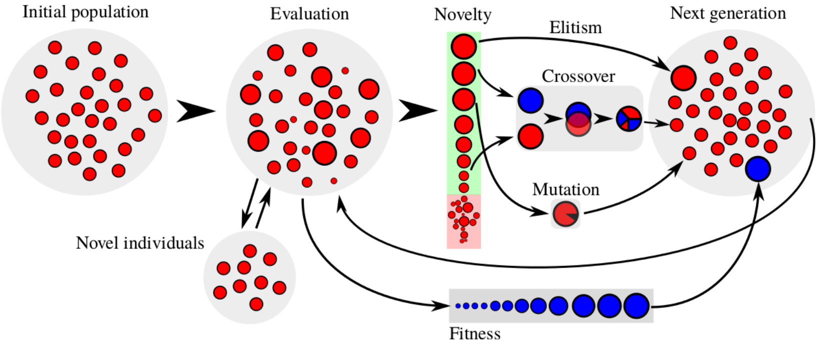


Behavior Selection

Novelty with 10-behavior metrics Vs. Fitness search, med-res. 7^3



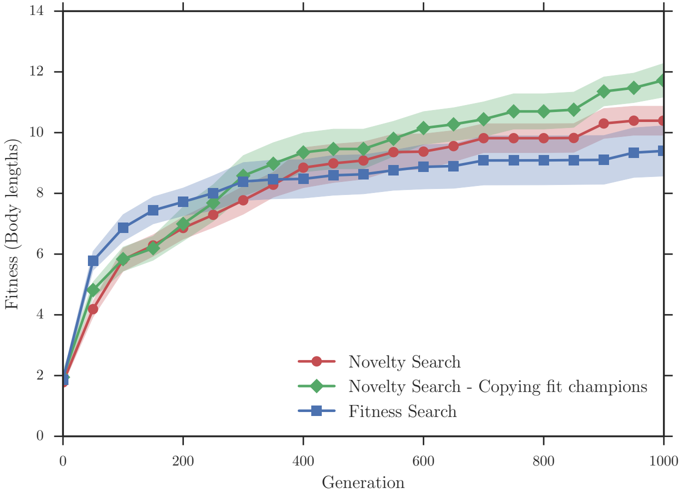
INCORPORATING FITNESS INFORMATION INTO NOVELTY SEARCH



- Keeping properties of novelty search

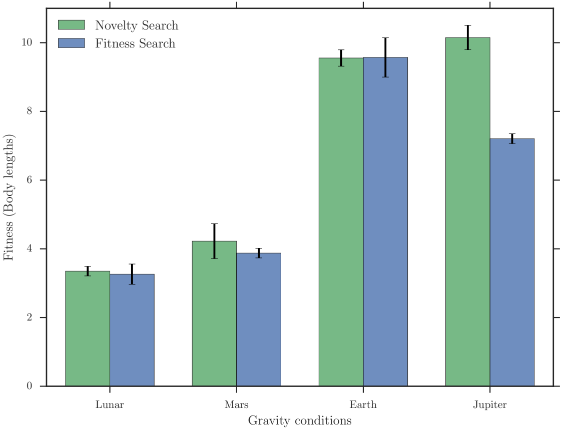
FITNESS ELITISM IN NOVELTY SEARCH

Best fitness so far, high-res. 10^3



Evolving Soft-Robots for Outer Space

Displacement achieved in variant gravity levels, med-res. 7^3



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CONCLUSION

- Novelty search performs better in respect to fitness
- Increased performance on different settings
- Performance is not much affected by the behavior metric
- Fitness elitism further improves performance

+ Co-evolution of materials alongside morphology
+ Develop methods to combine both searches

Thank you!