Modern Robots: Evolutionary Robotics

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Natural Selection Fails to Optimize Mutation Rates for Long-Term Adaptation on Rugged Fitness Landscapes

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Conclusions

• natural selection fails to optimize mutation rates for long-term adaptation on rugged fitness landscapes

• evolvability can involve short-term vs. long-term tradeoffs, and natural selection is short-sighted

• bad idea: self-adaptive mutation rates

• medical and practical implications
Background

• Evolvability
  • quickly adapting to new environments
  • important biological property

• Mutation rates
  • key driver of evolvability
  • ultimate source of genetic variation
  • evolve
  • medically important (e.g. viruses)
Question

• Are evolving mutation rates optimized?

• ...for long-term adaptation
Experimental Design

- Identify the optimum
  - evolve organisms with different, fixed (non-evolving) mutation rates in new environment

- Does evolution produce the optimum?
  - allow mutation rates to evolve
  - start well below and well above the optimum
Experiments

- sweep range of fixed mutation rates
- allow mutation rates to evolve
• natural selection fails to optimize for long-term
• ...in a complex fitness landscape (Avida default)
Hypothesis

Ruggedness of fitness landscape?

X (low mutation rate): higher avg. fitness
Y (high mutation rate): lower avg. fitness
• Optimized on smooth landscapes

• Not optimized when ruggedness above threshold

• Gap grows with valley size
Dynamics

- Lowering is a function of ‘waiting time’
- Optimal vs. Suboptimal for 300 gens
  - all below valley
  - one Optimal across valley
- Result
  - with waiting time: suboptimal fixes ~1%
  - without waiting time: suboptimal fixes 0% ($p=0.0082$)
- Note low probability of suboptimal fix
  - Valley crossed many times, but any delay = self-reinforcement
Same Results with Different...

- ancestors
- environments
  - complexity
  - static vs. changing
  - rate of change
- implementations of mutation rate evolution
  - size of changes
  - frequency of changes
  - increases more likely
  - self-reflexive
Discussion: Naturally high mutation rates?

Viruses, experimental evolution experiments

Sniegowski et al.
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• bad idea: self-adaptive mutation rates

• medical and practical implications
  • cancer
  • viruses
  • breeding
Co-Evolving Body and Brain

- Many believe co-evolving body and brain is better
  - Increases degrees of freedom
  - Allows co-adaptation

- But not much evidence for it
The utility of evolving simulated robot morphology increases with task complexity for object manipulation.

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Conclusions

- placing more degrees of morphological freedom under evolution
  - improves performance
    - as task complexity increases
  - improved robustness
  - and beats a anthropomorphic arm
Task

- manipulate objects
  - grasping
  - lifting
  - active categorical perception

- task complexity
  - number of objectives to accomplish simultaneously
Task Components

- How would you define/test/reward?
  - Grasping
  - Lifting
  - Active categorical perception
Task Components

- **Grasping**
  - minimize distance between fingers and object

- **Lifting**
  - vertical displacement

- **Active categorical perception**
  - away from the camera (spheres and cylinders)
  - towards the camera (cubes)
Morphology

- 0 to 3 body aspects can be evolved
  - finger length
  - finger thickness
  - spacing between fingers

- 3, 4, or 5 fingers
  - (not evolved, but not important)

- sensors
  - tactile in each finger segment & hand
Brain

- CTRNN

Figure 2. Architecture of the robot’s controller. Gray bars indicate body parts; black circles indicate actuated rotational joints connecting them. For the three-fingered hand, 10 motor neurons \((y_1, \ldots, y_{10})\) actuate the joints. Each motor neuron is fully connected to every other with a weighted connection \((w_{i,j})\). Each of the 20 sensors is also connected to every motor neuron with a weighted connection \((n_{i,j}; R = \text{range sensor}; T = \text{tactile sensor}; P = \text{proprioceptive sensor})\). Each distal and intermediate phalange is co-actuated by the same motor neuron \((y_8, y_9, y_{10})\).
Evolution

- Direct encoding
- Multi-Objective algorithm
- Shaping
  - one object type at a time
Figure 1. A sample evolved robot. This robot can successfully grasp, lift, and actively distinguish between spheres of different sizes (a–d, radius $r = 35$ cm; e–h, $r = 31.5$ cm), cylinders of different sizes (i–l, $r = 35$ cm, length $l = 70$ cm; m–p, $r = 31.5$ cm, $l = 63$ cm), and cubes of different sizes (q–t, l.w.h = 70 cm; u–x, l.w.h = 63 cm). Black and white indicate finger segments in which the tactile sensor is on or off, respectively. White lines denote the range sensors. Videos of this and other robots can be found at www.cs.uvm.edu/~jbongard.
Results

- One objective
  - non-evolving morphology = evolving morphology

- Two objectives
  - evolving morphology helps some

- Three objectives
  - evolving morphologies helps more
Robustness (Generality)

- Give them spheres, cylinders and cubes of different sizes than they were trained on
- More DOF = more generality

Figure 7. Performance impacts for the evolved four-fingered hands when confronted with novel environments. (a) Mean performance impacts when confronted with target objects of previously unseen sizes, grouped into regimes in which zero, one, two, or all three morphological aspects were evolved. (b) Mean performance impacts when a single sensor fails. (c) Mean performance impacts when pairs of sensors fail.
General Impressions

• What did you think of this paper?
Co-Evolution

- arms races
- holy grail?
- problems
  - cycling
  - detachment
  - not holy grail
The Hierarchical Fair Competition (HFC) Model for Parallel Evolutionary Algorithms

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CEC 2002

FIGURE 2: HFC model extends the search horizontally in search space and vertically in fitness dimension and kills bad individuals at appropriate times while allowing promising young individuals grow up continuously.

a) 6-eigenvalue problem

Standardized fitness of Best Individual of run

- OnePop
- MuPop
- HFC-GP

b) 8-eigenvalue problem

C) 10-eigenvalue problem

Standardized fitness of Best Individual of run

- OnePop
- MuPop
- HFC-GP

d) 12-eigenvalue problem

Standardized fitness of Best Individual of run

- OnePop
- MuPop
- HFC-GP
Not All Physics Simulators Can Be Wrong in the Same Way

[Extended Abstract]

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ABSTRACT

Transferring designs in evolutionary robotics from simulation to reality remains problematic. It has been addressed by using quasi-static physics simulators, adding noise to encourage robustness, and evolving primarily in simulation then evolving on actual hardware for fine-tuning. This paper experiments with this idea: All physics simulators have errors, but if the errors are distinct, one might profitably use multiple simulators to detect unrealistic physical behavior in simulation. Two physics simulators are used to evolve a controller for quadruped locomotion. Preliminary results validate some assumptions and further work is suggested.

Figure 1: Quadruped in a) Open Dynamics Engine and b) Bullet Physics Library
Ethics/Dangers/SkyNet

- Why the future doesn’t need us. By Bill Joy
  - What is he saying?

- Are you worried?

- Should we stop?
You have learned a lot
- Natural evolution
- Evolutionary Algorithms
- Fitness landscapes
- Evolvability
- Encodings
- Regularity
- Modularity

- Neural networks
- Novelty search
- Diversity
- HyperNEAT
- Multi-Objective Algos
- Self-modeling
- Evolutionary Robotics
Class

• Harder than other classes?
  • Too hard?

• Did you enjoy swinging for the fences?

• Do you understand science more?

• What could I do better?
Closing Thought

“It is not the critic who counts; not the man who points out how the strong man stumbles, or where the doer of deeds could have done them better. The credit belongs to the man who is actually in the arena, whose face is marred by dust and sweat and blood; who strives valiantly; who errs, who comes short again and again…; who does actually strive to do the deeds; who knows great enthusiasms, the great devotions; who spends himself in a worthy cause; who at the best knows in the end the triumph of high achievement, and who at the worst, if he fails, at least fails while daring greatly, so that his place shall never be with those cold and timid souls who neither know victory nor defeat.”

- Theodore Roosevelt, The Man in the Arena, 1910