Evolutionary Algorithms & Robotics: from Optimization to Creativity

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Overview

• Evolutionary robotics
• Selective pressures
• From convergent to divergent search
• Creativity & robotics
• Perspective: analysis of computational models
Evolutionary Robotics


Mouret, J.B., Bredeche, N. et Doncieux S. La robotique évoluoniste Pour la science n°87, Avril-Juin 2015
Beyond the cost function

Fitness = $n_{ball}$

https://github.com/doncieux/collectball
The fitness function has two roles:

- It defines the goal ✔
- It drives the search ✗
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- It defines the goal
- It drives the search

The graph shows a fitness landscape with peaks and valleys, illustrating the concept.
Solution:
add « process helpers »

A process helper intends to increase the efficiency of the search process without changing the optimum(s) of the fitness function.

Solution: add « process helpers »


Behavioral diversity: 

\[ f_{bd}(i) = \frac{1}{N} \sum_{j \in Pop} d(beh_i, beh_j) \]
Collect ball experiment

Fitness:
1. \( \text{nb}_{\text{ball}} \)
2. \( f_{bd}(i) = \frac{1}{N} \sum_{j \in Pop} d(beh_i, beh_j) \)

Multi-objective EA:
NSGA-II

Neuroevolution

https://github.com/doncieux/collectball
Process helpers

• **Task specific:**
  - Fitness shaping [Dorigo and Colombetti, 1994] [Nolfi 1997]
  - Incremental evolution [Harvey et al. 1994]
  - Incremental MOEA [Barlow et al. 2004]
  - Staged MOEA [Mouret et al. 2006]

• **Task agnostic:**
  - Competitive coevolution [Cliff and Miller 1996]
  - Coevolution environment/controller [Berlanga et al. 2000]
  - Behavioral diversity [Mouret and Doncieux, 2009]
  - Novelty objective [Mouret 2011, Lehman et al. 2013]

Novelty search

- Objective to maximize: distance towards the k nearest points in population+archive (novelty)

- Archive augmented with individuals having a high novelty


http://picbreeder.org
From convergent to divergent search

Looking for **the** optimal solution

Looking for **many** novel or original solutions


Adapting to failures

Robotics in open environments: challenge

How to acquire experience in a (partially) unknown environment?

How to generate « interesting » behaviors with little knowledge about the environment?
Robotics in open environments: challenge

Robots need to be creative!

- Creativity: effectiveness and originality (Runco et Jaeger 2012)

**Robotics**

- Creativity of a behavior (Doncieux 2016):
  - Efficiency of the behavior
  - **Originality w.r.t. knowledge available to the robot programmer**


Evolution and human creativity


DREAM overview

**Goal:** enable robots to gain an **open-ended understanding** of the world **over long periods of time**

**Main ideas:**

- evolutionary approach to bootstrap cognition
- redescription of acquired knowledge
- alternation between
  - « **daytime** »: active interaction
  - « **nighttime** »:
    - analysis of past events
    - knowledge consolidation
    - simulation of new behaviors

Deferred Restructuring of Experience in Autonomous Machines
**H2020 FET Proactive « Knowing, doing, being » 01/2015-12/2018**

http://www.robotsthatdream.eu/
https://twitter.com/robotsthatdream
DREAM Overview

Collective scale

No initial policy
No single task
Motivations:
- curiosity
- satisfying humans
- global mission

New situation:
- no reprogramming
- fast adaptation

Individual scale

Daytime
Sequence of learning episodes driven by motivations
Small batch
Behavior exploration
Knowledge improvement
Knowledge adaptation
Knowledge validation

Knowledge sharing between robots:
- better generalization
- faster learning

Nighttime
Dream
Knowledge restructuring
Transfer from STM to LTM

Consolidated knowledge
- task-relevant features
- task contexts
- abstract knowledge
- new motivations

Daytime experience (large batch)
Novelty to explore

DREAM, the work flow

1. Day 1: babbling

2. «night 1» Learning to grasp

3. Day 2: Back to reality

Unexpected behaviors
Identifying important features & transferring knowledge

Generates examples of behaviours
Discrete actions and sensors to consider

Learning
Direct policy search (neuroevolution)
Task-agnostic representations
Slow learning
Limited generalization

Passive analysis
Representation redescription

Learning
Discrete reinforcement learning
Task-specific representations
Fast learning
Good generalization


Results. IEEE Transactions on Cognitive and Developmental Systems
Non-robotic applications: Analysis of a computational neuroscience model

- Development of a basal ganglia model compatible with electrophysiological recordings and anatomical data
- Proposed approach:
  1. Mean field model of the whole basal ganglia
  2. Identification of fixed and optimized parameters.

Objectives:
1. Plausibility of the parameters wrt literature
2. Plausibility of the behavior wrt literature

Take home messages

• Importance of the selective pressure

• Potential of divergent search … even for converging to an optimal solution

• Beyond optimization, there is a lot to learn from divergent search results
Thank you!
Questions?

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