Evolutionary Robotics: behavior oriented design

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Motivation:
Building automatic design methods for robotic systems that exploit at best their interaction with the environment to fulfill a task. Focus on the control design.

[Maris & te Boekhorst 1996]
Inspiration

Hypothesis of the Evolutionary Robotics approach

A search process based on a selection mechanism can fulfill the goal of autonomous design of robots controllers.
Example

Evolution of neuro-controllers for a flapping wings animat

Evolution of neuro-controllers for flapping-wing animats.

Incremental evolution of target-following neuro-controllers for flapping-wing animats.
In Nolfi, S., et al., editors, From Animals to Animats: Proceedings of the 9th International Conference on the Simulation of Adaptive Behavior (SAB), pages 606-618, Rome, Italy.
Khep. exp. [Floreano and Mondada 1998]

Locomotion [Filliat et al. 1999]

Loc. + Morph. [Lipson and Pollack 2000]

Swarm robotics
Symbion EU Project.

Resilient robotics
[Bongard et al. 2006]
Most evolutionary robotics applications today concern locomotion or one single reactive behavior at a time.

**Question**

How to scale in behavior complexity?
Outline

1. Evolutionary algorithms
2. Modularity
3. Multi-objectivization in Evolutionary Robotics
   - Incremental approach
   - Behavioral diversity
   - Transferability
4. Research project
Evolutionary algorithms
Artificial Evolution

Algorithmic principle
Darwinian natural selection: variation and differential selection over a set of candidate solutions.

Search space
Sequences of symbols, numerical values or structures.
Search operators: recombination and mutation.

Maximized function
fitness function, fitness landscape with peaks and valleys.

A long history...
- Evolution Strategies, I. Rechenberg, 1965
- Evolutionary programming, L. Fogel, 1966
- Genetic algorithms, J. Holland 1962
Optimization

Optimization formalism

Find $X \in \mathcal{F}$ that minimize/maximize $f(X)$ with the constraints:

$$
g_j(X) \leq 0, \quad j = 1, 2, \ldots, p
$$

$$
l_j(X) = 0, \quad j = 1, 2, \ldots, q
$$

Features of Evolutionary Algorithms

- stochastic, population based algorithms
- converge to an approximation of the optimal solution
- $\mathcal{F}$ need not be a subspace of $\mathbb{R}^n$
- $f(.)$ need not be continuous, nor differentiable
- $f(.)$ may even not be known analytically, but measured through a specific device
- $f(.)$ may be noisy, multi-modal
- $f(.)$ may be in $\mathbb{R}^n$
Evolutionary algorithms and multi-objective optimization

Mono-objective algorithms

Search space

Single optimal solution

maximization of $w_1 f_1 + w_2 f_2$

Result

Single optimal solution

Multi-objective algorithms

Search space

Non dominated solutions

Pareto front

maximization of $f_1$ and $f_2$

Result

Set of trade-off solutions
Multi-objective approach

Pareto dominance relation

Definitions

- $x_1$ dominates $x_2$ if:
  1. $x_1$ is as good as $x_2$ on all objectives
  2. $x_1$ is strictly better than $x_2$ on at least one objective

- the set of non dominated solutions is called the **Pareto set** (or Pareto front in 2D).

Reference

Deb, K. (2001)
*Multi-Objective Optimization Using Evolutionary Algorithms*
Evolutionary Robotics vs Evolutionary Algorithms

Evolution of a behavioral system

For robot control, use of neural networks whose structure and parameters are generated by the evolutionary algorithm.
For robot control, use of neural networks whose structure and parameters are generated by the evolutionary algorithm.
Modularity
On the importance of modularity

Importance of modularity

Widely present in both biology and engineering...
Parable of the watchmaker
[Simon 1962]

Hypothesis

The lack of modularity is the bottleneck of Evolutionary Robotics.

*Evolving PID-like neurocontrollers for non-linear control problems.*

*MENNAG: a modular, regular and hierarchical encoding for neural-networks based on attribute grammars.*
Evolutionary Intelligence. 1(3) 187–207
Back to the roots: what do biologists say?

- This question was one of the main criticisms to Darwin
- "Conquest of the Earth":
  - legs are needed to walk
  - how did legs appear at first?

- Legs of tetrapods
  - useful in water
  - then opportunistically co-opted to walk on land
  → shift in the function of a trait during evolution

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Exaptation experiment

- Exaptation is useful to understand the evolution of life
- ... but is absent (or not analyzed) in artificial evolution

→ artificial evolution: only one (explicit) selective pressure (fitness)
→ exaptation: several selective pressures

→ adding selective pressures could enable exaptation
→ multiobjective evolutionary algorithms (MOEA)
Exaptation experiment

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Exaptation experiment

\[(a \oplus b) \land (c \oplus d)\]

- Neural network to compute: \((a \text{ xor } b) \text{ and } (c \text{ xor } d)\)
- Fitness: \(F_0 = \text{sum of errors (to be minimized)}\)
- Deceptive fitness: false for each input \(\rightarrow 75\%\) of success
- Modular structure

**Goal:**
- suggest that xor is a useful sub-function for a sub-module
- let xor be exapted to solve the main function
\[(a \oplus b) \land (c \oplus d)\] : setup

**Selection pressure on modules**
- Decomposition into modules [Newman 2008]
- Evaluation of the xor function for each module \((F_1)\)

\[\begin{align*}
F_0 &= \nu_0 \\
F_1 &= \nu_1 \\
F_2 &= \nu_2
\end{align*}\]

**Modular encoding**

Parcellation operator: isolation of modules [Wagner et al. 2005]
\[(a \oplus b) \land (c \oplus d)\] : setup

**Fitness**

**Control:** 1 objective
- \(F_0 = \text{sum of errors} \quad [(a \oplus b) \land (c \oplus d)]\)

**Multi:** 2 objectives
- \(F_0\)
- \(\min_{m}(F_1(m))\)

**Genotype**

**Direct encoding (DE)** Mutations only
- add/delete nodes
- add/delete connections
- change weights

**Modular encoding (M.E.)** op. DE +
- parcellation (isolation of a module)
- integration (duplication of a module)
- differentiation (cancel a parcellation/integration)
- cross-over: exchange of parcellated modules

**Other parameters**

- NSGA-II
- 400 individuals
- 1500 generations
- 32 experiments
Exaptation experiment

Results

Convergence rate

Average conv. gen.
Exaptation experiment

**Conclusion**

- modularity in the genotype only is useless
- **the selection pressure is of utmost importance** (N.B. : NEAT includes a specific selection algorithm)

Evolving modular neural-networks through exaptation.

work done during J.B. Mouret thesis
Multi-objectivization in Evolutionary Robotics
Introduction

Hypothesis
Selection pressure is the bottleneck of Evolutionary Robotics.

Multiobjectivization
“The term ‘multiobjectivization’ refers to the casting of a single-objective optimization problem as a multiobjective one, a transformation that can be achieved by the addition of supplementary objectives or by the decomposition of the original objective function.” [Handl et al. 2008]

Proposition
Defining new selection pressures to be used in a multi-objectivization scheme to solve problems of Evolutionary Robotics:
- multi-objective incremental approach to avoid the recourse to subtask ordering and the switch between subtasks
- evolution of “complex” behaviors by preserving behavioral diversity
- transfer from simulation to reality and reality gap
Multi-objectivization in Evolutionary Robotics

Incremental approach
How to solve a “complex” problem with ER?

What to do when it doesn’t work?

Helping evolution by defining intermediate steps:
- staged evolution [Harvey, Husbands and Cliff, 1994, Kodjabachian and Meyer 1997]
- environmental complexification [Gomez and Miikkulainen 1997]
- behavioral decomposition [Larsen and Hansen 2005]
- fitness shaping [Nolfi and Parisi 1995]

Proposition

considering each step as a separate objective in a multi-objective scheme.
Multi-objective approach

Experiment: Light seeking robot

Fitness: 8 objectives

- rewarding motion (for obstacle avoidance):
  \[ F_0 = \frac{1}{T} \sum_{t=0}^{T} \sqrt{(x(t) - x(t-1))^2 + (y(t) - y(t-1))^2} \]

- minimization of the time required to switch on a light:
  \[ F_i = \min_{n=1,2,3} \frac{-\varphi(n,i)}{T} \text{ for } i = 1, \ldots, 7 \]

Evolutionary algorithm: \(\epsilon\)-MOEA [Deb et al. 2005]
Multi-objective approach

Results

300 generations required on average to reach the sixth light.

The shortest path has been found.


*Incremental evolution of animat’s behavior as a multi-objective optimization*


work done during J.-B. Mouret thesis
Multi-objectivization in Evolutionary Robotics

Behavioral diversity
Behavioral diversity

**Intensification vs diversification in evolutionary algorithms**

- Exploration: stochastic search operators & population;
- exploitation: fitness function.

**Hypothesis**

The bottleneck of ER may be due to an exploration problem.

**Intensification vs diversification in EA**

How to keep a diverse population?

→ by penalizing similar individuals on the basis of their genotype or phenotype:

- fitness sharing [Goldberg and Richardson 1987]
- objective on diversity in a multi-objective scheme [Abbas and Deb 2003, de Jong et al. 2001]
- niches [Sareni and Krähenbühl 1998]
Behavioral diversity

3 neural networks $\rightarrow$ 1 behavior

Why not promoting diversity in the space of behaviors?
Diversity in Evolutionary Robotics experiments

Related work

- Novelty search [Lehman and Stanley 2008]
- behavior-based speciation [Trujillo et al. 2008]
- using behavioral information distance to sustain diversity in sequential decision tasks [Gomez 2009]
- considering the entropy of the sensori motor stream generated by the robot [Delarboulaus et al. 2011]

Using behavioral exploration objectives to solve deceptive problems in neuro-evolution.
In proc. of GECCO’09, pages 627–634. ACM.

Overcoming the bootstrap problem in evolutionary robotics using behavioral diversity.
In proc. of IEEE-CEC’09, pages 1161–1168.

Behavioral diversity measures for Evolutionary Robotics.
WCCI 2010 IEEE World Congress on Computational Intelligence, Congress on Evolutionary Computation (CEC). Pages 1303–1310.

Mouret, J.B. and Doncieux, S. (submitted)
Encouraging Behavioral Diversity in Evolutionary Robotics: an Empirical Study

work started during J.-B. Mouret thesis and pursued since then
Behavior

Behavioral diversity

Objectives to maximize:

\[
\begin{align*}
\text{maximize} & \quad F(x) \\
o_{bd}(x) = & \frac{1}{\text{size}(P)} \sum_{y \in P} \sigma(x, y)
\end{align*}
\]

How to describe and compare behaviors?

- **adhoc descriptions:**
  - final position [Lehman and Stanley 2008]
  - environment state [Mouret and Doncieux 2009]

- **generic descriptions:**
  - robot trajectory [Trujillo et al 2008]
  - measure based on an approximation of Kolmogorov complexity in a discrete world [Gomez 2009]
  - hamming distance [Doncieux and Mouret 2010]
  - entropy [Delarboulas et al. 2011]
Results

Example of evolved behavior

- Direct encoding of a neural network
- Fitness: 2 objectives
  - Number of collected balls
  - Behavioral diversity (trajectory based)
- NSGA-II
- Population size: 200
- 4000 generations
Behavioral diversity measures

**Hamming**

- **behavior descriptor** = discretized sensori-motor stream $\theta_{bin}$
- **behavioral diversity measure** $\sigma(x, y) = \text{hamming distance between } \theta_{bin}(x)$ and $\theta_{bin}(y)$

**Example:**

<table>
<thead>
<tr>
<th></th>
<th>$t=0$</th>
<th>$t=1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor 1</td>
<td>0.34</td>
<td>0.36</td>
</tr>
<tr>
<td>Sensor 2</td>
<td>0.52</td>
<td>0.49</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Sensor n</td>
<td>0.26</td>
<td>0.28</td>
</tr>
<tr>
<td>Effector 1</td>
<td>0.79</td>
<td>0.68</td>
</tr>
<tr>
<td>Effector 2</td>
<td>0.42</td>
<td>0.51</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Effector m</td>
<td>0.32</td>
<td>0.44</td>
</tr>
<tr>
<td>$\theta_{bin}$</td>
<td>01...010...0</td>
<td>00...011...0</td>
</tr>
</tbody>
</table>
Results

Statistics

Maze

Lights

Collectball

out of 30 runs for each setup with a population of 200 and for 5000 generations.
Multi-objectivization in Evolutionary Robotics

Transferability
Transferability

Crossing the reality gap

Proposed approach:

- perform *some* tests on the real robot;
- maximize the transferability.

*Crossing the Reality Gap in Evolutionary Robotics by Promoting Transferable Controllers.*
GECCO’10: Proceedings of the 12th annual conference on Genetic and evolutionary computation ACM, publisher.

*The Transferability Approach: Crossing the Reality Gap in Evolutionary Robotics.*

ongoing work, S. Koos thesis
Research project
Research project: theoretical issues

Generalization
How to ensure that the behavior generalizes well to different environments?

to be done during T. Pinville thesis

Notion of behavior
- how to describe a behavior?
- how to evaluate the distance between behaviors?
- how to evaluate the exploration in the space of behaviors?

Expected use:
- better monitoring of an ER run
  - restart
  - more accurate comparisons
  - parameter setting
- new EA dedicated to ER
- new methodology for encoding design and study

to be done during C. Ollion thesis
The road ahead

The current situation...
The road ahead

... and the next step!

Ongoing work
Approach proposed in the ANR EvoNeuro project.

**Neuro→Evo**

Goal: designing robot controllers with cognitive abilities

Approach:
- cognitive abilities as identified by neuroscientists
- protocols to evaluate them
- neural network primitives of neuroscience models to:
  - generate networks with similar abilities
  - compare results to well known models
Evolution of a labeled graph

Labels → connection type, weight, neuron type, ...

Mutations:
- add/remove a node
- add/remove a connection
- change parameters

No cross-over
First results

EvoNeuro encoding: applications

- Basal ganglia model (part of):
  → better scalability: no statistical difference between exp. with 6 and 15 channels.

- working memory model (part of):
  → better versatility: in 4 out of 5 exp. the network weights can be optimized to memorize a new sequence while keeping the same structure.

learning mechanisms

Importing the Computational Neuroscience Toolbox into Neuro-Evolution—Application to Basal Ganglia.
GECCO’10: Proceedings of the 12th annual conference on Genetic and evolutionary computation ACM, publisher.

Neurocomp 2010.

work done during T. Pinville and P. Tonelli thesis
Goal: using Evolutionary Robotics methods in a neuroscience context

Approach:
- multi-objective optimization
- multi-objective analysis
Multi-objective analysis

Principles

1. Select the search space;
2. Define objective functions;
3. Compute the Pareto front (or at least an approximation of it);
4. Analyze the results.

Questions that the approach can answer to

- What are the objective values within reach?
- What relations are there between the parameters and the objectives?
- How critical is a parameter?
- Are there singularities, e.g. discontinuities or plateaus, for instance, in the Pareto front or in the objective vs parameter relation?
- Are there a continuum or a set of qualitatively distinct solutions? In this case, where are the transitions and what are the features of the families of solutions?
- What characterizes a particular Pareto-optimal solution relative to the others?
Multi-objective analysis

Application to the analysis of Basal Ganglia models


work done during M. Hamdaoui thesis and since then.
The road ahead

Future work

Ongoing work

Future work
Questions ?

ER@ISIR
- J.-B. Mouret (MdC, ISIR/UPMC/CNRS)
- S. Koos (PhD stud.)
- P. Tonelli (PhD stud.)
- T. Pinville (PhD stud.)
- C. Ollion (PhD stud.)

Past post-doc students
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Past PhD students
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- R. Barate (EDF)
- ...