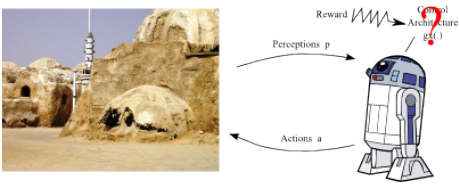
Selection pressures in evolutionary robotics

ISIR, UPMC - stephane.doncieux@isir.upmc.fr

06/09/2012 - Robot. et Neuro.

Introduction



$$\mathbf{a} = g_{\mathbf{X}}(\mathbf{p}),\ \mathbf{a} \in \mathbb{R}^n\ ,\ \mathbf{p} \in \mathbb{R}^k$$

Learning as an optimization problem :

Parameterized case, $g_{\mathbf{X}}(.)$ described by X :

Find $\mathbf{X} = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{Bmatrix}$ optimizing $f(\mathbf{X})$

General case :

Find $g_{\mathbf{X}}(.)$ optimizing $f(g_{\mathbf{X}}(.))$

with the constraints :

$$\begin{array}{rcll} h_j(g_{\mathbf{X}}(.)) & \leq & 0, & j = 1, 2, \ldots, p \\ l_j(g_{\mathbf{X}}(.)) & = & 0, & j = 1, 2, \ldots, q \end{array}$$

Context

- continuous state and actions
- non convex, non differentiable, discontinuous cost function
- minimizing a priori knowledge

Perspectives

Acquisition of cognitive abilities :

- memory
- action selection
- ...

Approach : neuroevolution

Learning in policy space

$\rightarrow$ stochastic optimization algorithms : **evolutionary algorithms.**

$\rightarrow$ control architecture : **neural networks.**

Context

- continuous state and actions
- non convex, non differentiable, discontinuous cost function
- minimizing a priori knowledge

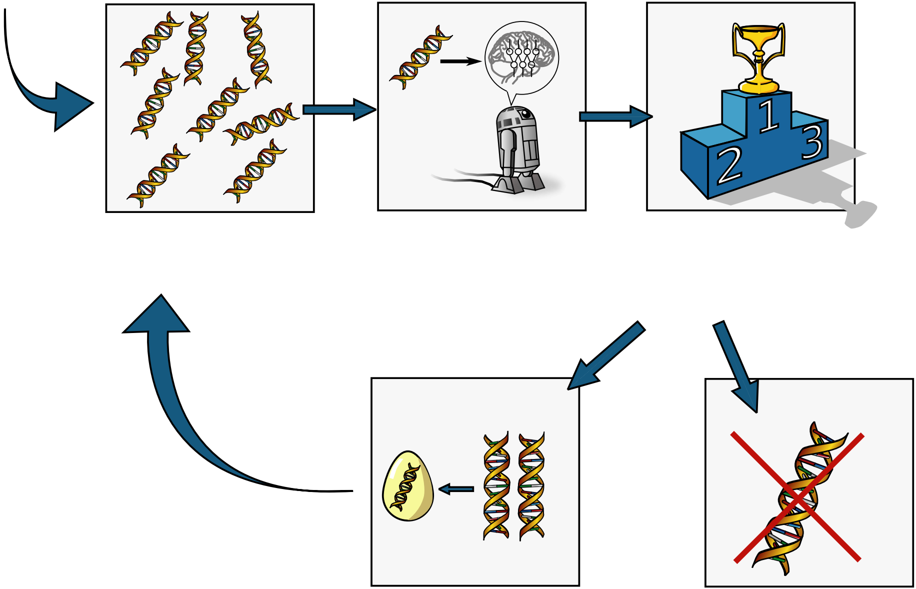
Perspectives

Acquisition of cognitive abilities :

- memory
- action selection
- ...

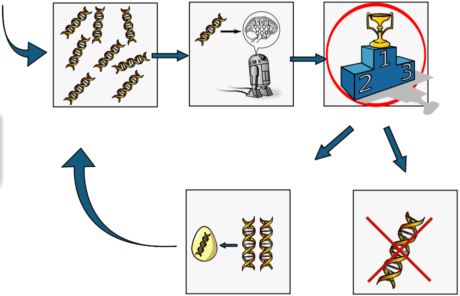
Approach : neuroevolution

Learning in policy space
$\rightarrow$ stochastic optimization algorithms : **evolutionary algorithms.**
$\rightarrow$ control architecture : **neural networks.**


1
2
3

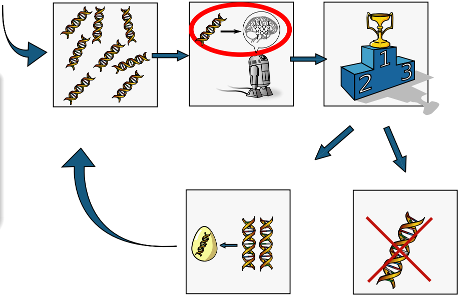
Question

- What selection algorithm ?



State of the art

- Genetic algorithms [Goldberg 1989]
- Evolution Strategies [Beyer and Swefel 2002]
- Evolutionary Programming [Fogel 1995]
- Genetic Programming [Koza 1992]
- Evolutionary computation [De Jong 2006, Eiben and Smith 2007]
- CMA-ES [Hansen and Ostermeier 2001]

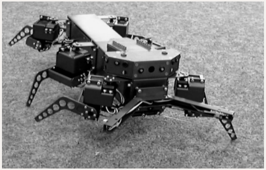


Question

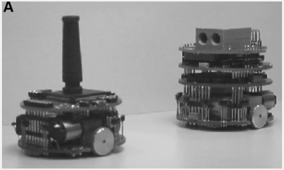
- How to represent the control architecture ?
- How to explore the structure ?

State of the art

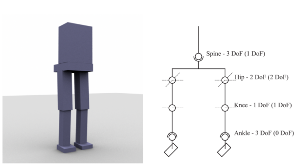
- Cellular Encoding [Gruau 1994]
- SGOCE [Kodjabachian and Meyer 1997]
- NEAT [Stanley and Miikkulainen 2002]
- MENNAG [Mouret and Doncieux 2008]
- HyperNEAT [Stanley et al. 2009]



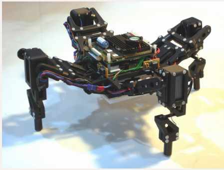
Filliat and Meyer, 1997



Floreano et al., 1998



Allen and Faloutsos, 2009

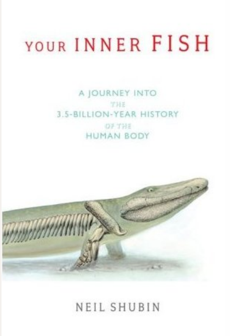


Bongard et al., 2006

Goal

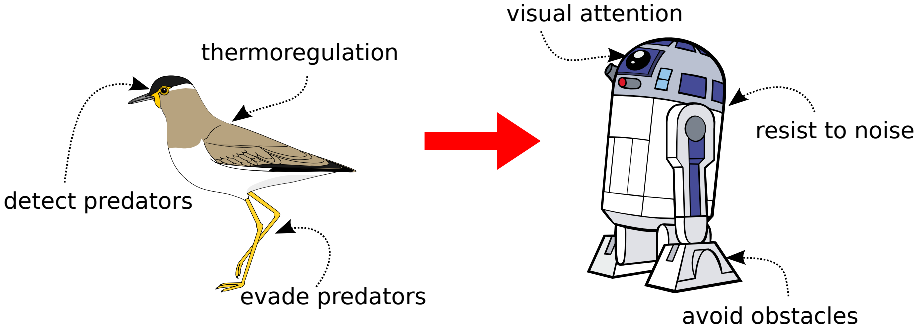
- Synthesis of several behaviors in one learning episode
- Synthesis of "cognitive" controllers.

Back to biology



Concept d'exaptation [Gould and Vrba 1982]

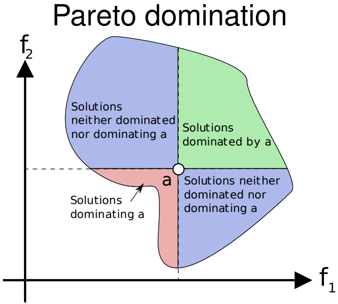
Proposition

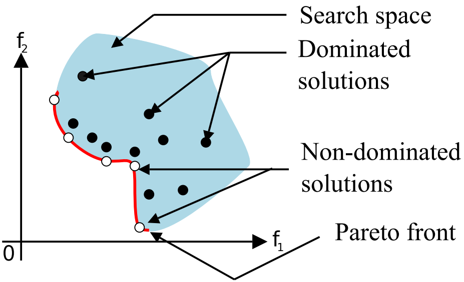


Critical question

- **What selection pressure ?**

Formalisation : multi-objective optimization





Proposition : formalizing learning as a multi-objective optimization problem

Find $g_{\mathbf{X}}(.)$ maximizing

$$\boxed{\mathbf{f}(g_{\mathbf{X}}(.)) = \begin{Bmatrix} f_1(\mathbf{X}) \\ f_2(\mathbf{X}) \\ \vdots \\ f_n(\mathbf{X}) \end{Bmatrix}}$$

with the constraints :

$$\begin{array}{rcll} h_j(\mathbf{X}) & \leq & 0, & j = 1, 2, \ldots, p \\ l_j(\mathbf{X}) & = & 0, & j = 1, 2, \ldots, q \end{array}$$

Multi-objective evolutionary algorithms

Deb, K.(2001).
Multi-objective optimization using evolutionnary algorithms.
Wiley. ISBN : 978-0471873396

Example : Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II)
Principle :

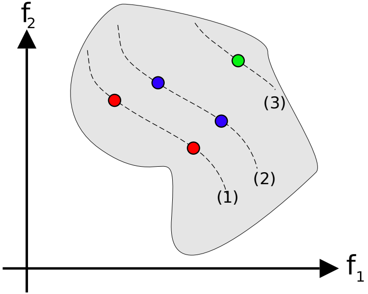
- elitist algorithm
- computes the fronts if non-dominated individuals
- new population = concatenation of the best fronts

K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan(2002).
A fast and elitist multiobjective genetic algorithm : NSGA-II.
IEEE Transactions on Evolutionary Computation, 6(2) :182–197.

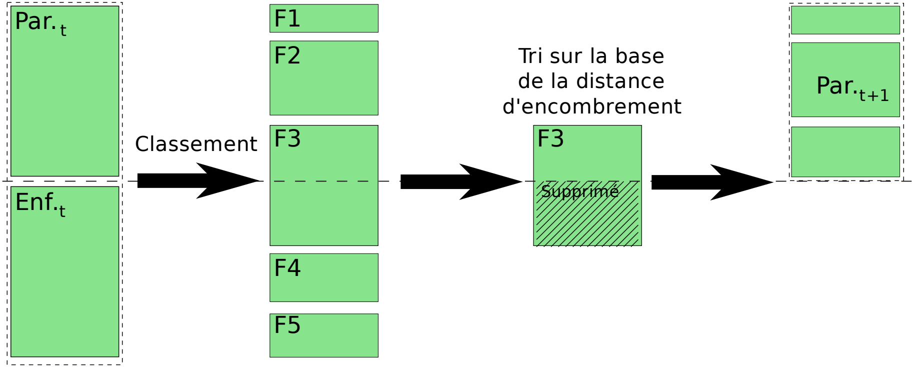
NSGA-II

Computation of the fronts :

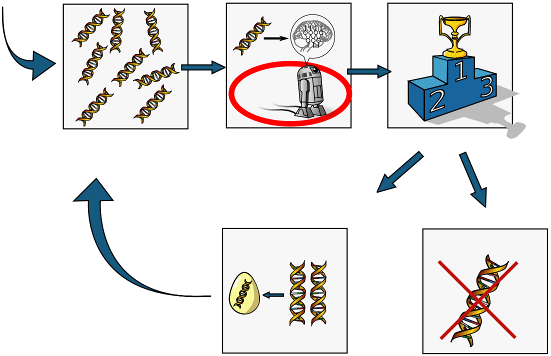
1. Pareto front : first front
2. temporally remove the front from the population
3. compute the new front of non-dominated individuals
4. go back to 2.



NSGA-II



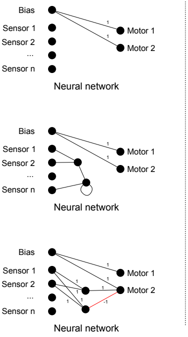
Par.$_t$
Enf.$_t$
Classement
F1
F2
F3
F4
F5
Tri sur la base
de la distance
d'encombrement
F3
Supprimé
Par.$_{t+1}$



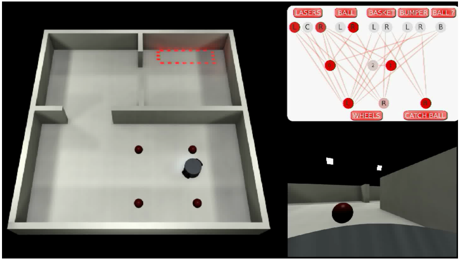
Features of our approach

- multi-objective optimization framework
- **goal-dependent objectives** : incremental app., modularity, consistency of behaviors, ...
- **goal-independent objectives** : exploration, reality gap, generalization, ...

Promoting exploration : behavioral diversity



Behavior



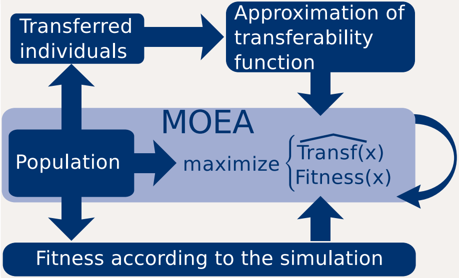
Proposed approach

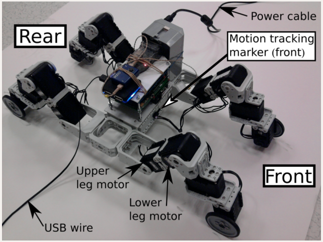
$$\text{Find } g_{\mathbf{X}}(.) \text{ maximizing } \begin{cases} f(g_{\mathbf{X}}(.)) \\ \frac{1}{N}\sum_{j=0}^{j=N} d(g_{\mathbf{X}}(.), g_{\mathbf{Y}}(.)) \end{cases}$$

with $d(\mathbf{X}, \mathbf{Y})$ behavioral distance between $\mathbf{X}$ and $\mathbf{Y}$

Mouret, J.-B. and Doncieux,S. (2012)
Encouraging Behavioral Diversity in Evolutionary Robotics : an Empirical Study
Evolutionary Computation. Vol 20 No 1 Pages 91-133.

Transfer between simulation and reality





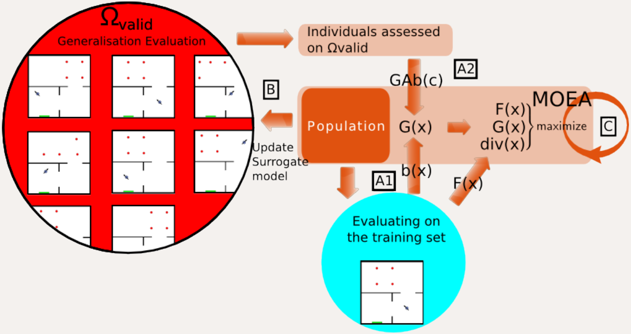
Proposed approach

$$\text{Find } g_{\mathbf{x}}(.) \text{ maximizing } \begin{cases} f(g_{\mathbf{x}}(.)) \\ \widehat{Transf}(g_{\mathbf{x}}(.)) \end{cases}$$

Koos, S. and Mouret, J.-B. and Doncieux, S. (2010).
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.

Koos, S. and Mouret, J.-B. and Doncieux S. (à paraître).
The Transferability Approach : Crossing the Reality Gap in Evolutionary Robotics.
IEEE Transaction on Evolutionary Computation.

Promoting generalization ability

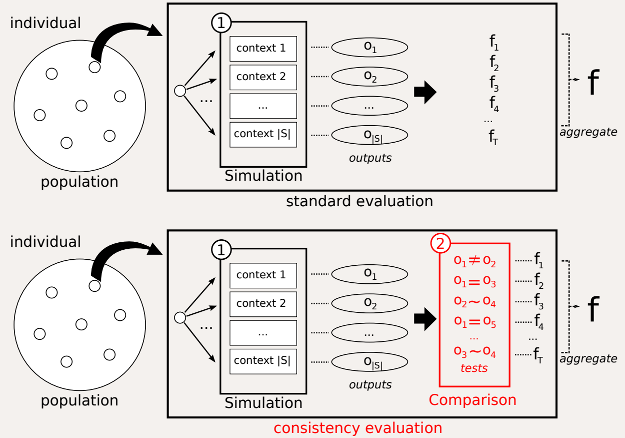


Proposed approach

$$\text{Find } g_{\mathbf{X}}(.) \text{ maximizing } \left\{ \begin{array}{l} f(g_{\mathbf{X}}(.)) \\ \widehat{G(g_{\mathbf{X}}(.))} \\ \frac{1}{N}\sum_{j=0}^{j=N} d(g_{\mathbf{X}}(.), g_{\mathbf{Y}}(.)) \end{array} \right.$$

Pinville, T. and Koos, S. and Mouret, J-B. and Doncieux, S. (2011).
How to Promote Generalisation in Evolutionary Robotics : the ProGAb Approach.
Proceedings of GECCO'11.

Promoting behavior consistency



Ollion, C. and Doncieux, S. (2012).
Towards Behavioral Consistency in Neuroevolution.
From Animals to Animats : Proceedings of the SAB 2012.

Ollion, C. and Pinville, T. and Doncieux, S. (2012).
With a little help from selection pressures : evolution of memory in robot controllers.
Proc. Alife XIII. Pages 1-8.

Conclusion

Take home messages

- **learning as an optimization problem**
- importance of the cost function/reward function/fitness function/selection pressure
- **multi-objective** optimization as a framework to study and define selection pressures
- definition of **goal-independent and control architecture independent** selection pressures to tackle learning problems

People involved

- Jean-Baptiste Mouret
- Sylvain Koos
- Paul Tonelli
- Tony Pinville
- Charles Ollion
- Stéphane Doncieux

Questions ?

`stephane.doncieux@isir.upmc.fr`
`mouret@isir.upmc.fr`

Implemented in the *SFERES*$_{v2}$ framework
(`http://sferes2.isir.upmc.fr`)

Source code of the experiments on
`http://pages.isir.upmc.fr/evorob_db`