Self-adaptive mutation in on-line, on-board evolutionary robotics

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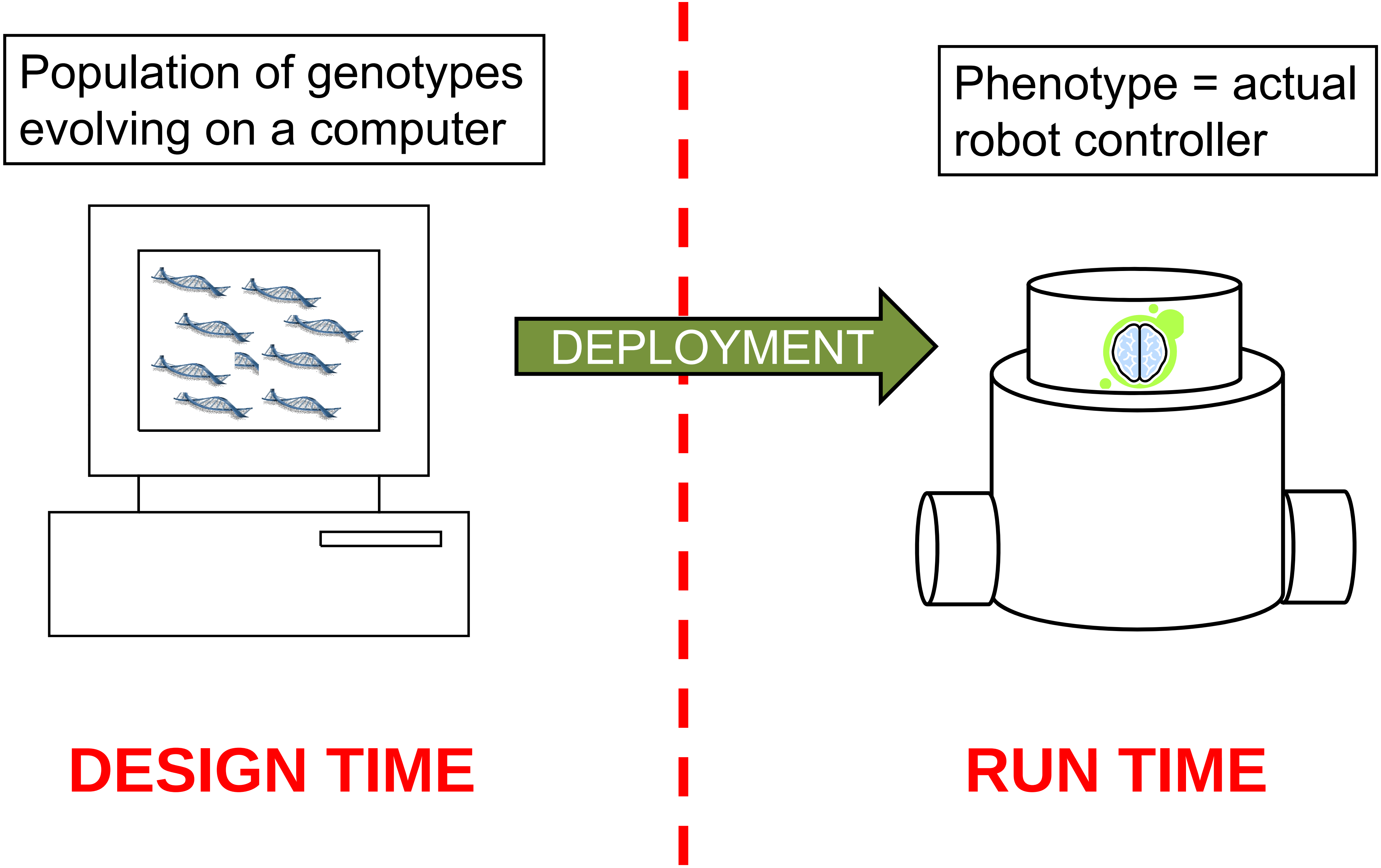
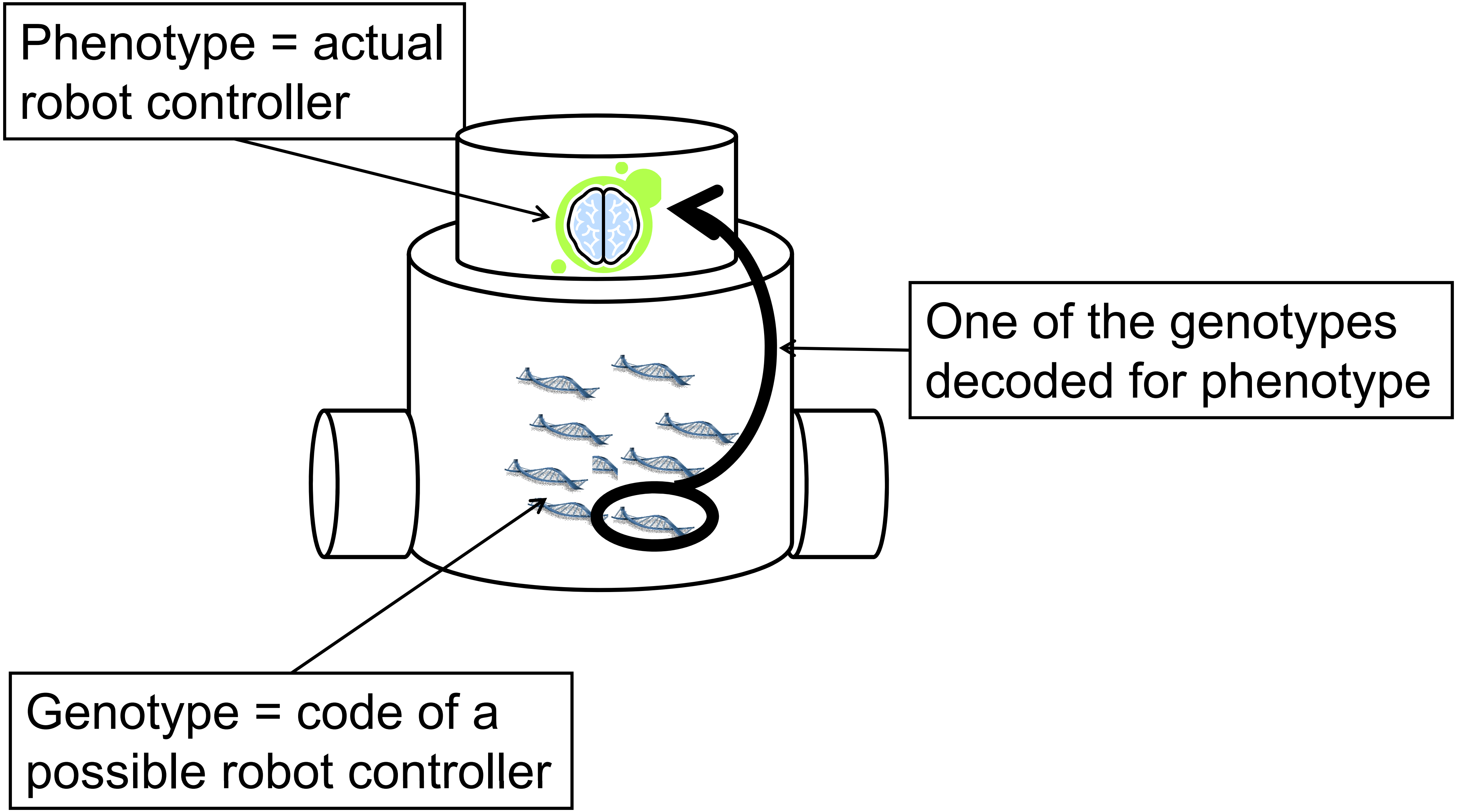
Talk overview

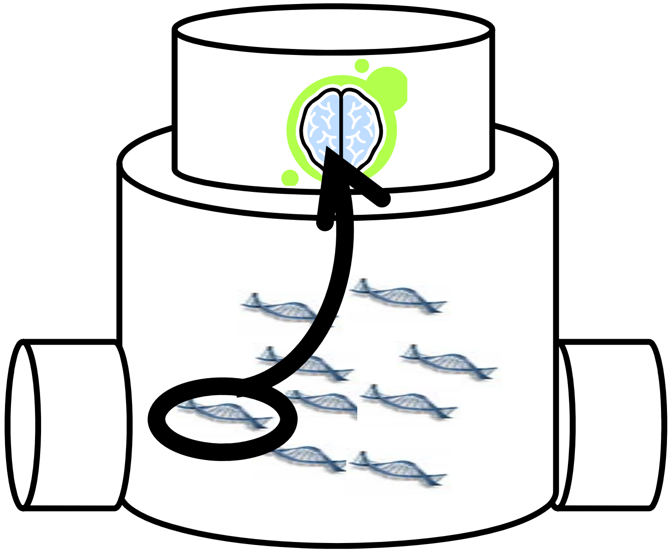
- Off-line vs. on-line evolutionary robotics
- (μ + 1) on-line EA and its parameters
- Experiments
  - Arenas and tasks
  - Self-adaptation of mutation step-sizes
  - Results
- Conclusions

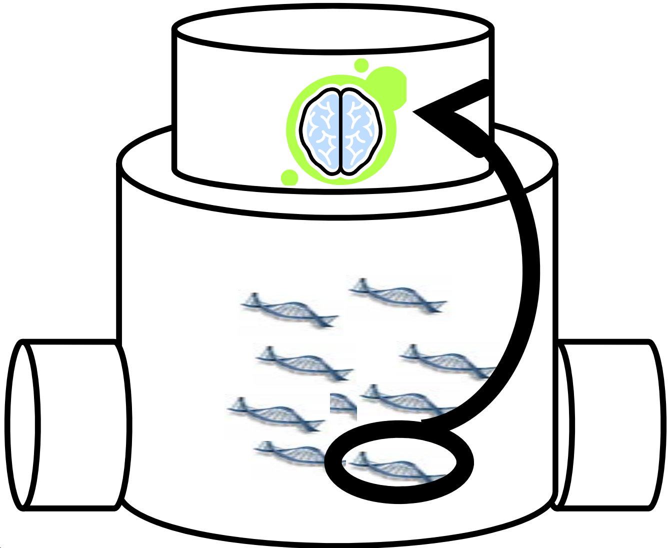
Traditional (off-line) approach

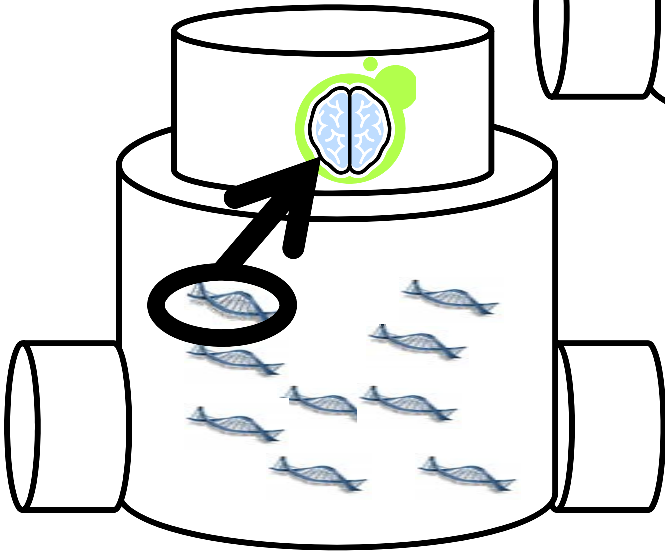


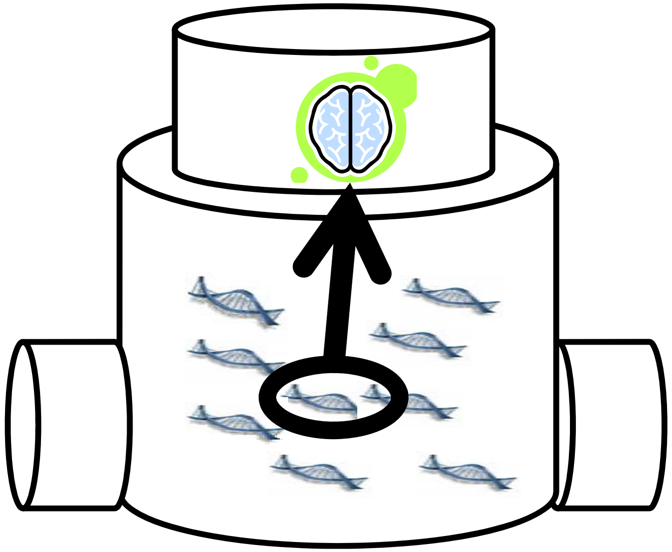
Encapsulated (on-line) evolution

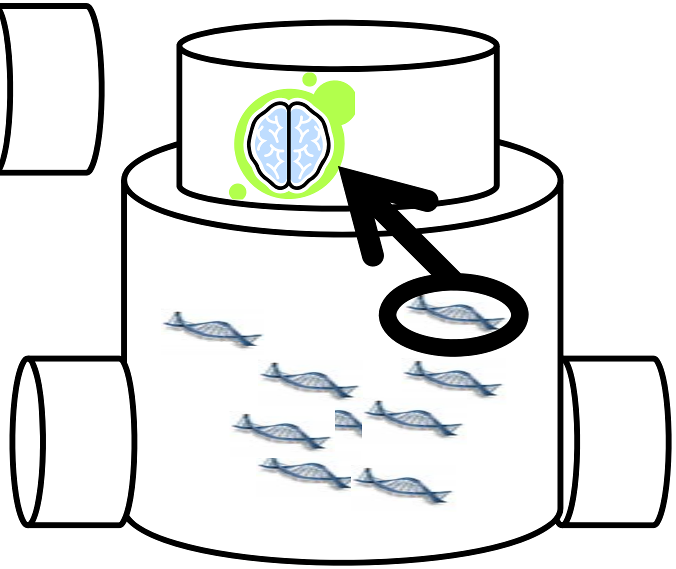




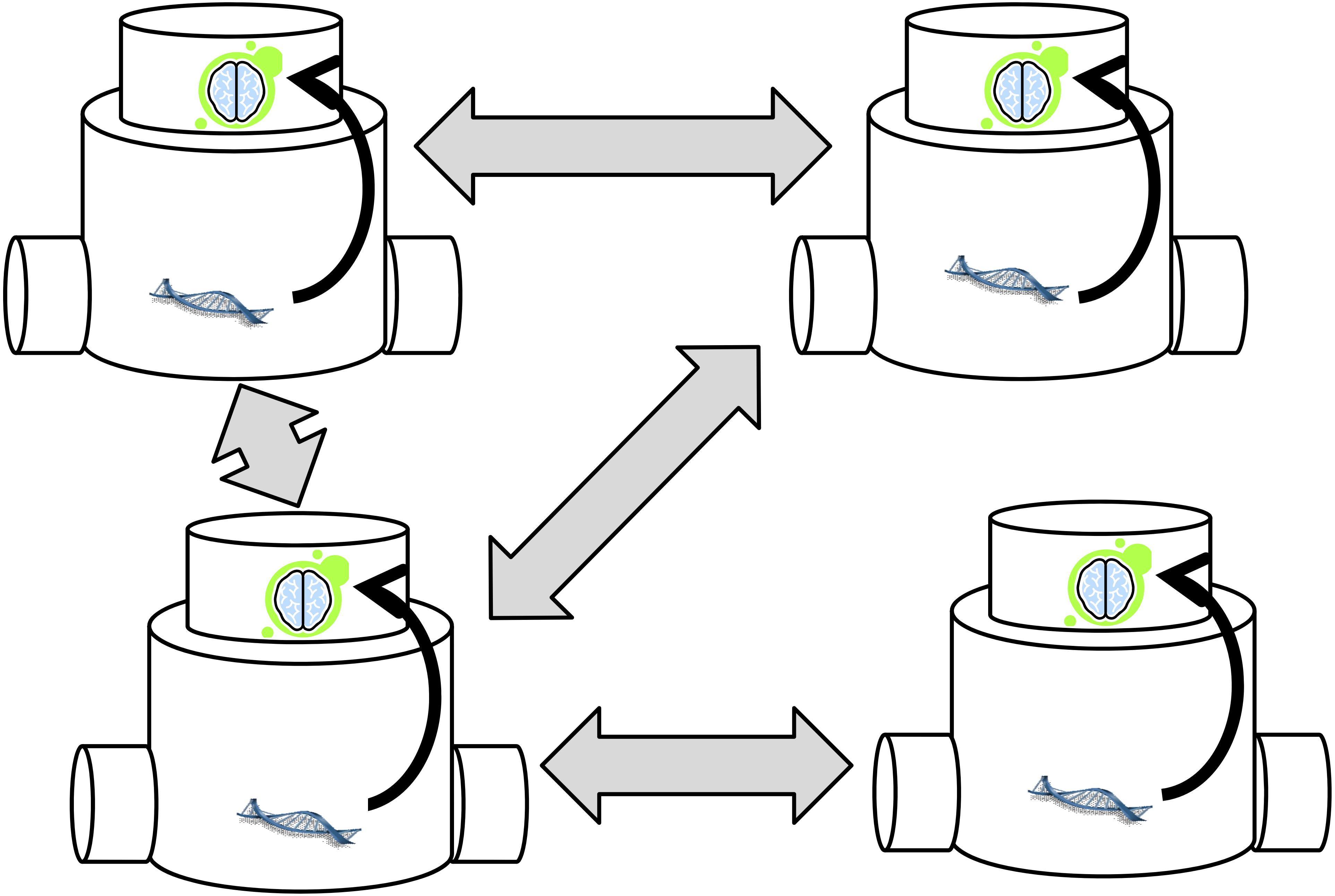








Distributed (on-line) evolution



Special issues for on-line ER

- (extremely) few evaluations
- noise
- actual performance counts

μ + 1 on-line EA

Encapsulated type:

- based on evolution strategies
- very small μ
- tournament selection
- recombination
- re-evaluations

μ + 1 on-line EA pseudocode

- Initialize the Population
- **DO** until current_time < simulation_time
  - **IF** random() < ρ **THEN**
    - Don’t create Offspring but Re-evaluate Selected Parent
  - **ELSE**
    - ParentA = SelectParentA();
    - ParentB = SelectParentB();
    - Challenger = Crossover(ParentA, ParentB);
    - Mutate the Challenger
    - Run and Evaluate the Challenger
    - Remove Worst Individual from the Population
  - **END IF**
  - Sort (Population);
- **END DO**

μ + 1 on-line EA parameters

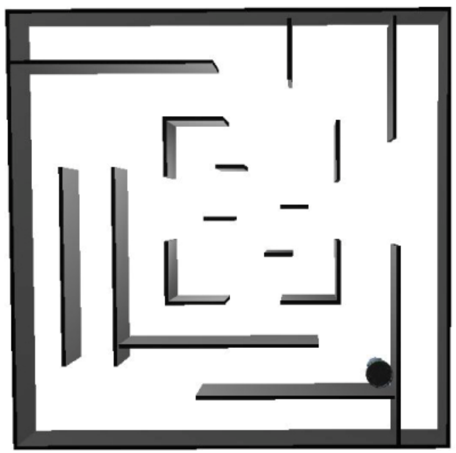
- ρ re-evaluation rate
- τ duration of controller evaluation
- μ population size
- σ mutation step-size

CEC 2010 paper: σ is the most influential parameter

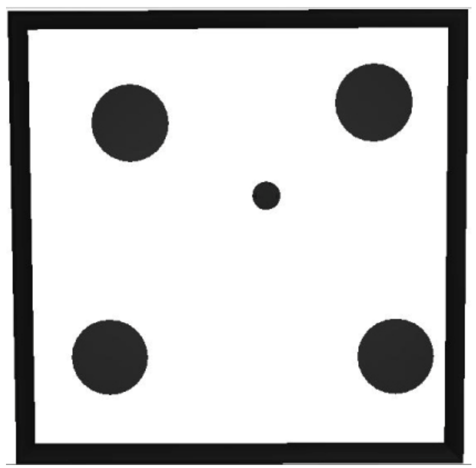
Experimental setup

- Simulator: Webots, robot: e-puck
- Controller: NN with 18 weights
- One single robot in these tests
- Tasks:
  - Fast forward (1)
  - Phototaxis
  - Resource gathering (3)

(1)



(3)



Mutation and step-size self-adaptation

- Main mechanism: changing value by adding random noise drawn from normal distribution
- $x'_i = x_i + N(0,\sigma)$
- Key idea:
  - σ is part of the chromosome $\langle x_1,\ldots,x_n, \sigma \rangle$
  - σ is also mutated into σ' (see later how)
- Thus: mutation step size σ is coevolving with the solution x

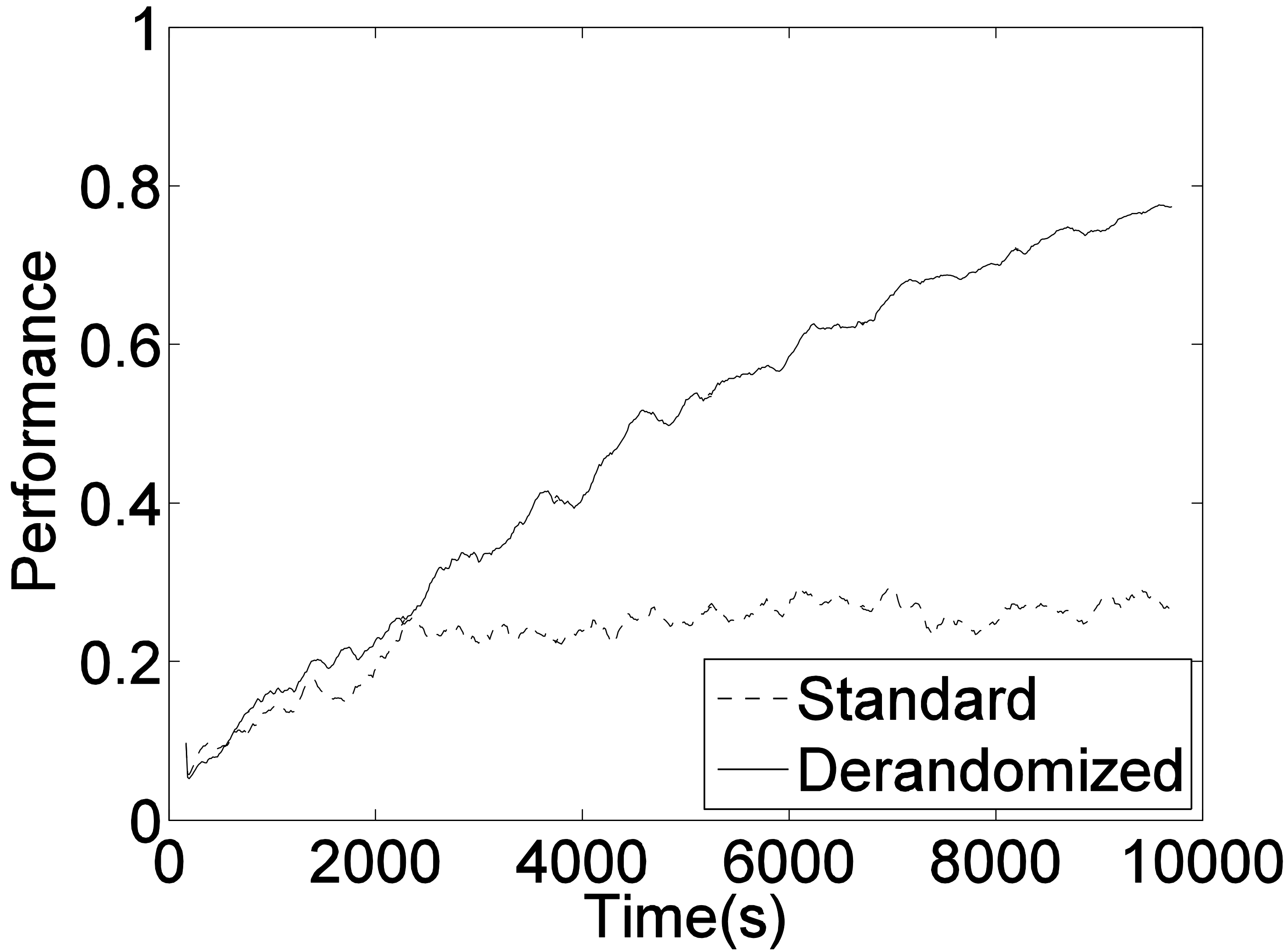
Usual self-adaptation of σ's

- Offered in the 70ies, "standard" in ES
- Chromosomes: $\langle x_1,\ldots,x_n, \sigma_1,\ldots, \sigma_n \rangle$
- $\sigma'_i = \sigma_i \cdot e\hat{}(\tau' \cdot N(0,1) + \tau \cdot N_i(0,1))$
- $x'_i = x_i + \sigma'_i \cdot N_i(0,1)$
- Two learning rate parameters:
  - τ' overall learning rate
  - τ coordinate-wise learning rate
- $\tau \sim 1/(2n)^{½}$ and $\tau \sim 1/(2n^{½})^{½}$
- and a boundary rule: if $\sigma_i' < \varepsilon_0$ then $\sigma_i' = \varepsilon_0$

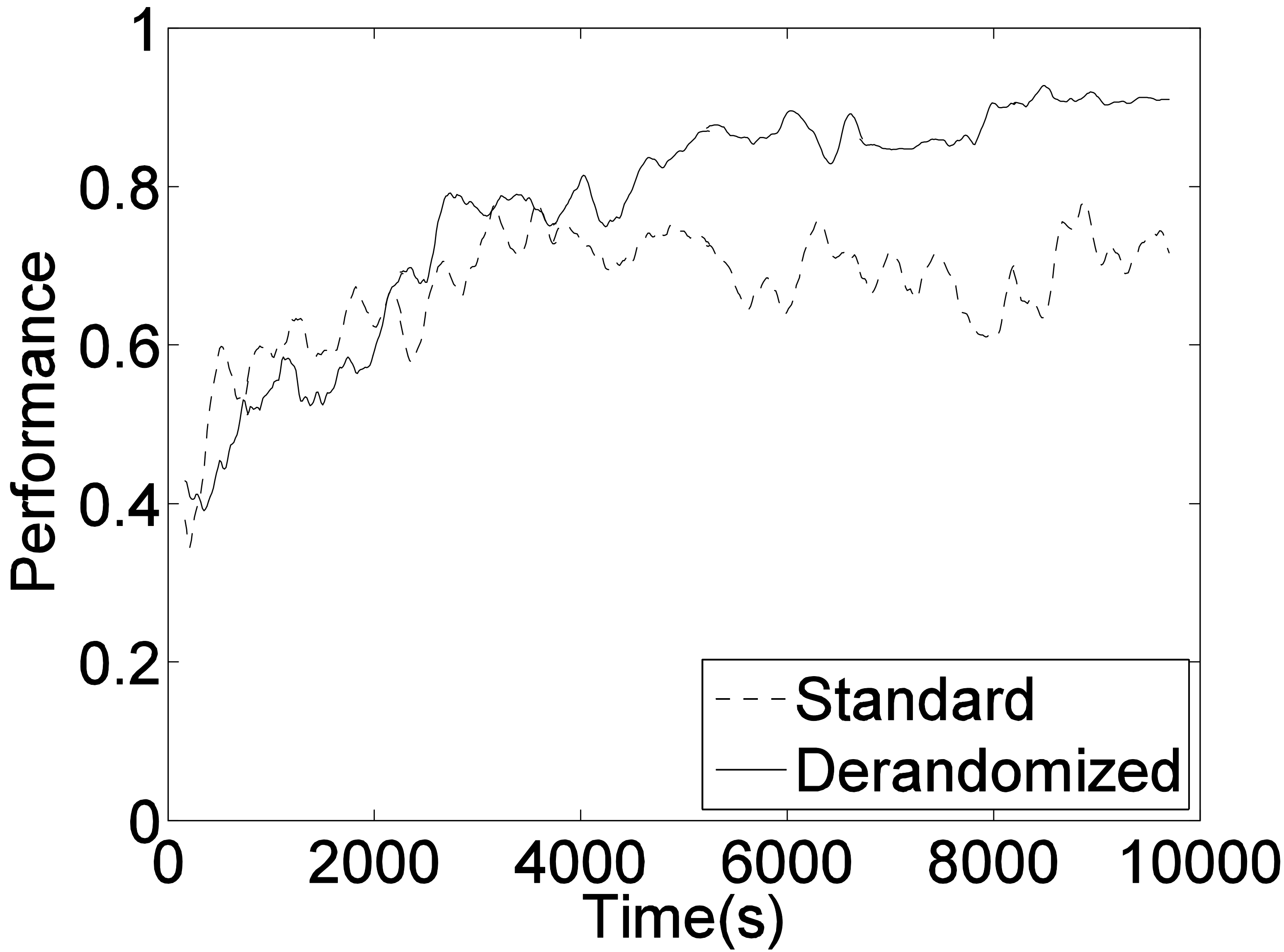
Derandomized self-adaptation of σ's

- Offered by Ostermeier et al. (1995), for small populations
- $\xi_i = \alpha; 1/\alpha$ with equal probability and $\alpha = 1.4$
- $z_i = N(0, \sigma_i)$
- $x'_i = x_i + \xi_i \cdot z_i$
- $\sigma_i = \sigma_i \cdot \xi_i$ ^ $(1/\sqrt{n}) \cdot e$ ^ $((|zi|-\sqrt{2}/\pi) / n)$

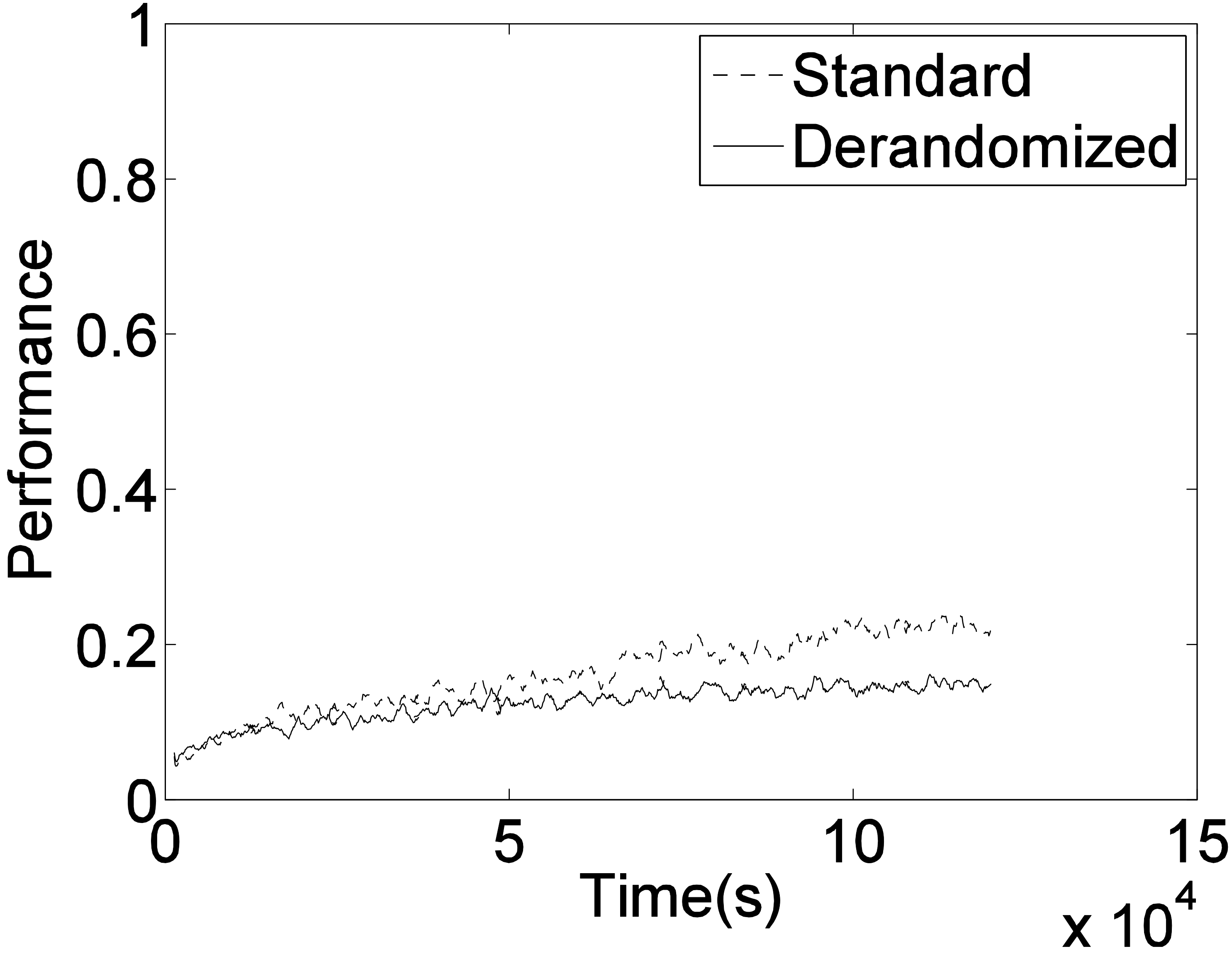
Results I (fast forward)



Results II (phototaxis)



Results III (resource gathering)



Conclusions

- 2 out of 3 problems:
  - Evolution solves the problem &
  - Derandomized self-adaptation is better
- 1 out of 3 problems:
  - Evolution cannot solve the problem &
  - Traditional self-adaptation is better
- In general: we still don't know, scoping is hard here
- Best bet = our recommendation: derandomized
- Ongoing and future work: more test problems