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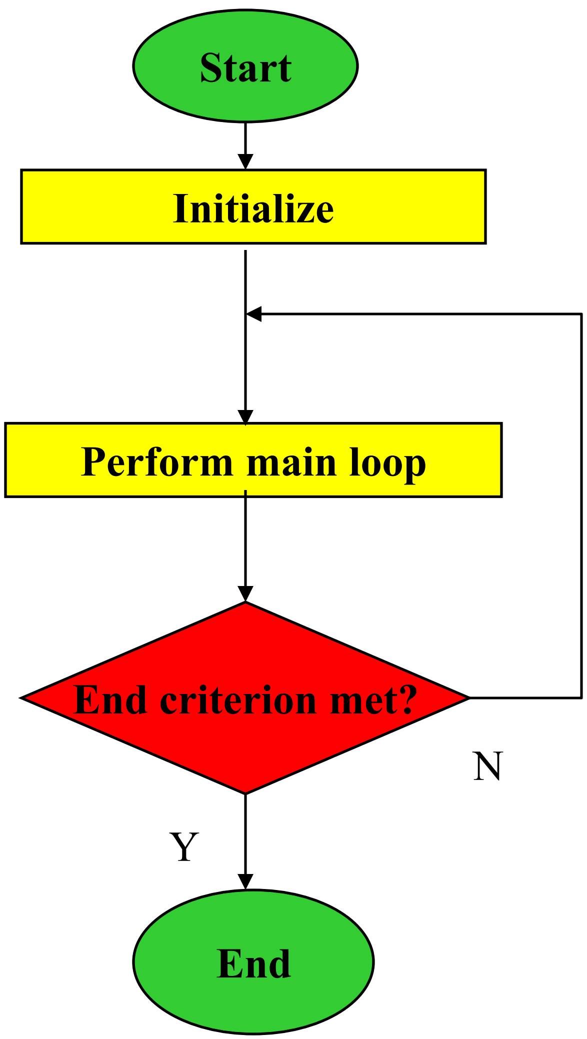
Disal

Introduction to Embedded and Real-Time Systems – W11:

An Introduction to Machine-Learning Techniques for Embedded Systems

Outline

- Rationale and motivation
- Classification and terminology
- Genetic algorithms as example of a metaheuristic
- Noise resistance and expensive optimization
- Examples
  - Standard functions
  - Control shaping
  - Hardware-software co-design



Machine-Learning for Embedded Systems: Rationale and Classification

Why Machine-Learning?

- Complementarity to a model-based/engineering approaches: when low-level details matter (optimization) and/or good models do not exist (design)!
- When the design/optimization space is too big (infinite)/too computationally expensive to be systematically searched
- Automatic design and optimization techniques
- Role of engineer reduced to specifying performance requirements and problem encoding

Why Machine-Learning?

- There are design and optimization techniques robust to noise, nonlinearities, discontinuities
- Individual real-time adaptation to new environmental conditions; i.e. increased individual flexibility when environmental conditions are not known/cannot predicted a priori
- Search space: parameters and/or rules

ML Techniques: Classification Axis 1

- Supervised learning: off-line, a teacher is available
- Unsupervised learning: off-line, teacher not available
- Reinforcement (or evaluative) learning: on-line, no pre-established training and evaluation data sets

Supervised Learning

- Off-line
- Training and test data are separated, a teacher is available
- Typical scenario: a set of input-output examples is provided to the system, performance error given by difference between system output and true/teacher-defined output, error fed to the system using optimization algorithm so that performance is increased over trial
- The generality of the system after training is tested on examples not previously presented to the system (i.e. a "test set" exclusive from the "training set")

Unsupervised Learning

- Off-line
- No teacher available, no distinction between training and test data sets
- Goal: structure extraction from the data set
- Examples: data clustering, Principal Component Analysis (PCA) and Independent Component analysis (ICA)

Reinforcement (or Evaluative) Learning

- On-line
- No pre-established training or test data sets
- The system judges its performance according to a given metric (e.g., fitness function, objective function, performance, reinforcement) to be optimized
- The metric does not refer to any specific input-to-output mapping
- The system tries out possible design solutions, does mistakes, and tries to learn from its mistakes

ML Techniques: Classification Axis 2

– In simulation: reproduces the real scenario in simulation and applies there machine-learning techniques; the learned solutions are then downloaded onto real hardware when certain criteria are met

– Hybrid: most of the time in simulation (e.g. 90%), last period (e.g. 10%) of the learning process on real hardware

– Hardware-in-the-loop: from the beginning on real hardware (no simulation). Depending on the algorithm more or less rapid

ML Techniques: Classification Axis 3

ML algorithms require sometimes fairly important computational resources (in particular for multi-agent optimization algorithms), therefore a further classification is:

- On-board: machine-learning algorithm run on the system to be learned (no external unit)

- Off-board: the machine-learning algorithm runs off-board and the system to be learned just serves as embodied implementation of a candidate solution

Selected ML Techniques Robust to Noisy Performance and Discontinuous Search Space

- Evolutionary computation
  - Genetic Algorithms (GA) → **This course**
  - Genetic Programming (GP)
  - Evolutionary Strategies (ES)
  - Particle Swarm Optimization (PSO) → **DIS course**
- Learning
  - In-Line Adaptive Learning → **DIS course**
  - Reinforcement Learning (RL) → **DIS course**

Genetic Algorithms

Genetic Algorithms Inspiration

- In natural evolution, organisms adapt to their environments – better able to survive over time
- Aspects of evolution:
  - Survival of the fittest
  - Genetic combination in reproduction
  - Mutation
- Genetic Algorithms use evolutionary techniques to achieve parameter optimization and solution design

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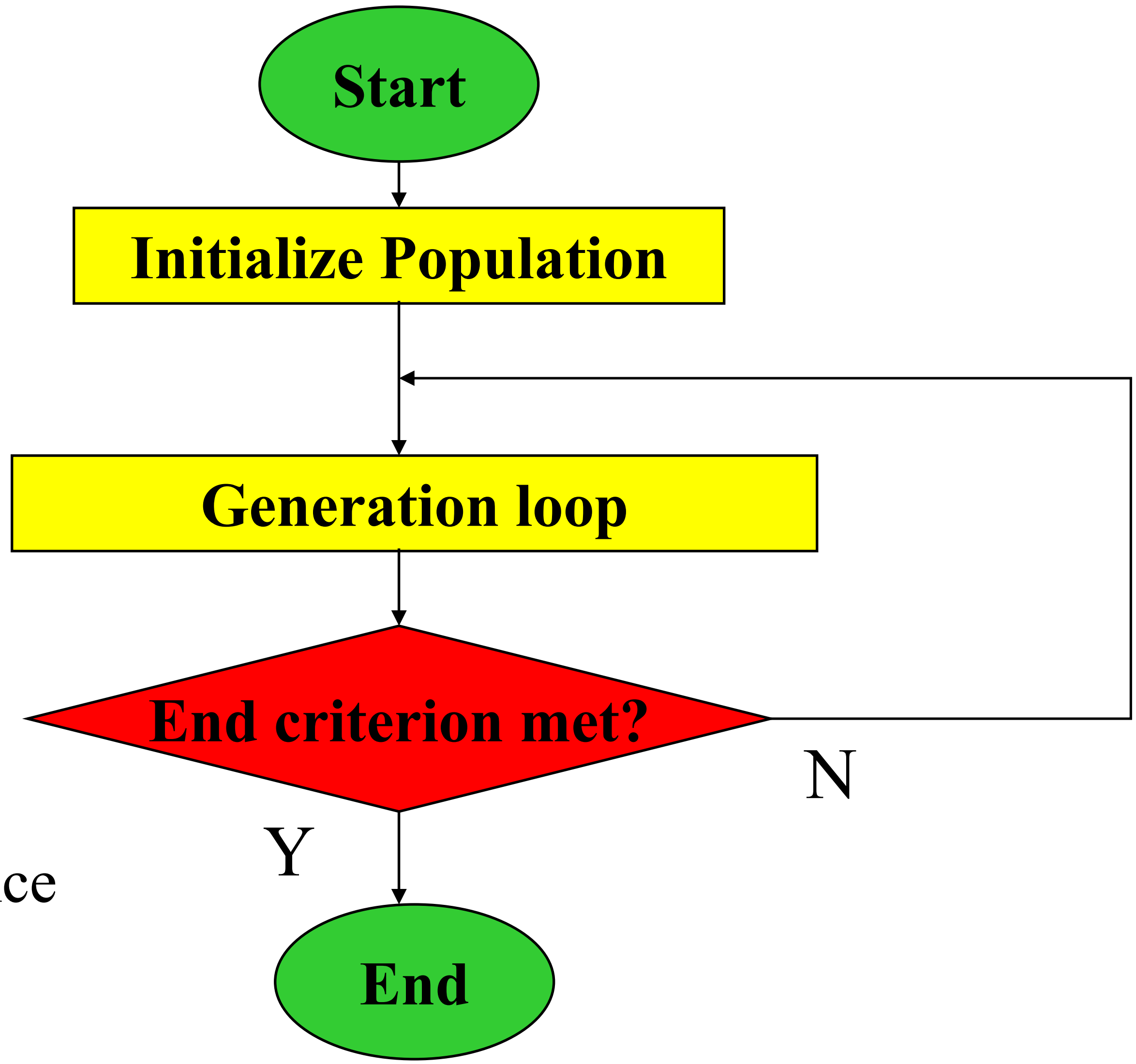
GA: Terminology

- Population: set of m candidate solutions (e.g. m = 100); each candidate solution can also be considered as a genetic individual endowed with a single chromosome which in turn consists of multiple genes.
- Generation: new population after genetic operators have been applied (n = # generations e.g. 50, 100, 1000).
- Fitness function: measurement of the efficacy of each candidate solution
- Evaluation span: evaluation period of each candidate solution during a given generation. The time cost of the evaluation span differs greatly from scenario to scenario: it can be extremely cheap (e.g., simply computing the fitness function in a benchmark function) or involve an experimental period (e.g., evaluating the performance of a given control parameter set on a robot)
- Life span: number of generations a candidate solution survives
- Population manager: applies genetic operators to generate the candidate solutions of the new generation from the current one

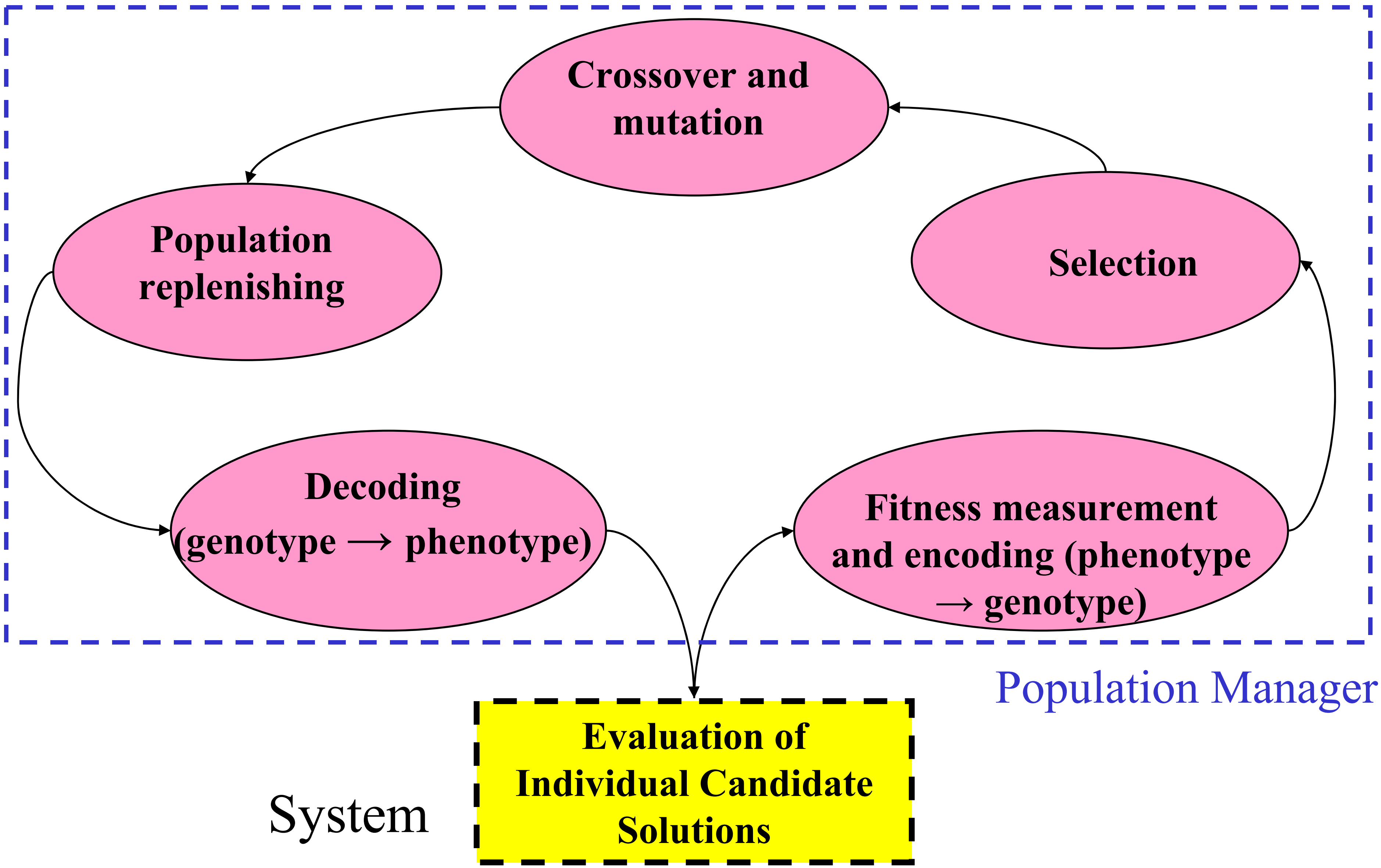
Evolutionary Loop: Several Generations



Ex. of end criteria:

- # of generations
- best solution performance
- …

Generation Loop



GA: Encoding & Decoding

phenotype $\xrightarrow{\text{encoding}}$ **genotype (chromosome)** $\xrightarrow{\text{decoding}}$ **phenotype**

- phenotype: usually represented by the whole system which can be evaluated; the whole system or a specific part of it (problem formulation done by the engineer) is represented by a vector of dimension D**;** vector components are usually real numbers in a bounded range
- genotype: chromosome = string of genotypical segments, i.e. genes, or mathematically speaking, again a vector of real or binary numbers; vector dimension varies according to coding schema ($\geq$ D); the algorithm search in this hyperspace

G_1	G_2	G_3	G_4	…	G_n

G_i = gene = binary or real number

Encoding: real-to-real or real-to-binary via Gray code (minimization of nonlinear jumping between phenotype and genotype)

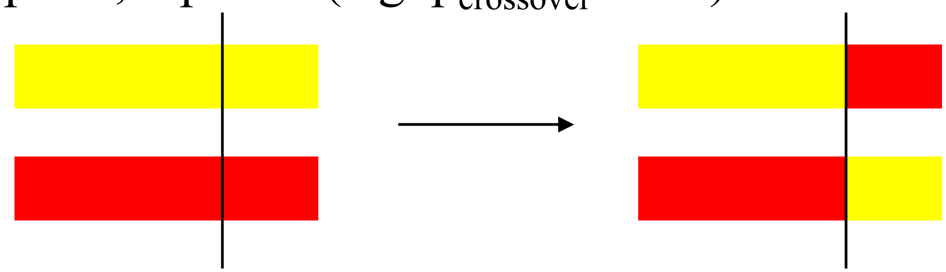
Decoding: inverted operation

Rem:

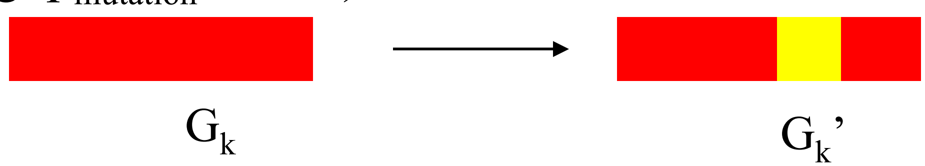
- Artificial evolution: usually one-to-one mapping between phenotypic and genotypic space
- Natural evolution: 1 gene codes for several functions, 1 function coded by several genes.

GA: Basic Operators

- Selection: *roulette wheel* (selection probability determined by normalized fitness), *ranked selection* (selection probability determined by fitness order), *elitist selection* (highest fitness individuals always selected)
- Crossover: 1 point, 2 points (e.g. $p_{crossover} = 0.2$)



- Mutation (e.g. $p_{mutation} = 0.05$)



Note: examples for fixed-length chromosomes!

GA: Discrete vs Continuous

- For default GA, all parameters discrete (e.g., binary bits, choice index)
- Common adaptation for continuous optimization:
  - Parameters are real values
  - Mutation: apply randomized adjustment to gene value (i.e. $G_i' = G_i + m$) instead of replacing value
- Selection of adjustment range affects optimization progress

Learning to Avoid Obstacles by Shaping a Neural Network Controller using Genetic Algorithms

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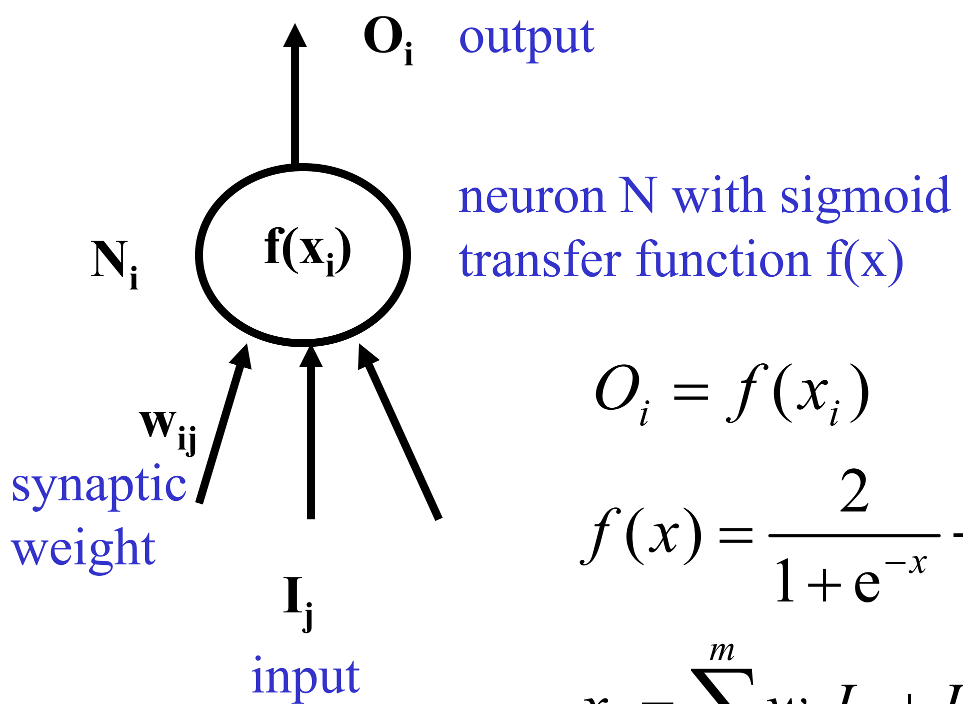
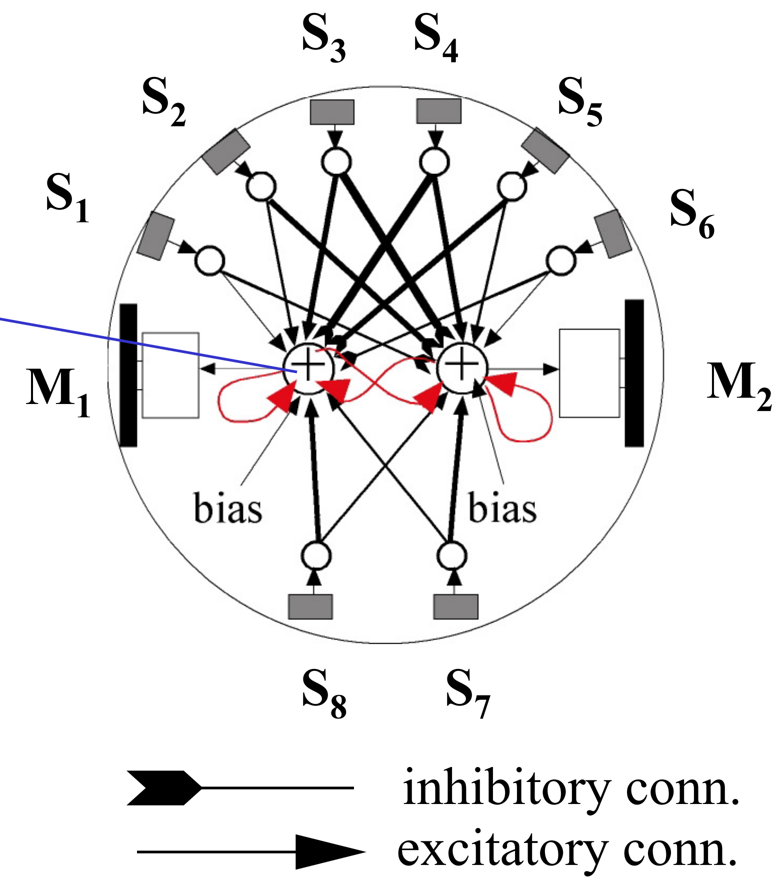
Evolving a Neural Controller



$$O_i = f(x_i)$$

$$f(x) = \frac{2}{1+e^{-x}} - 1$$

$$x_i = \sum_{j=1}^{m} w_{ij} I_j + I_0$$



Note: In our case we evolve synaptic weigths but Hebbian rules for dynamic change of the weights, transfer function parameters, … can also be evolved (see Floreano's course)

Evolving Obstacle Avoidance (Floreano and Mondada 1996)

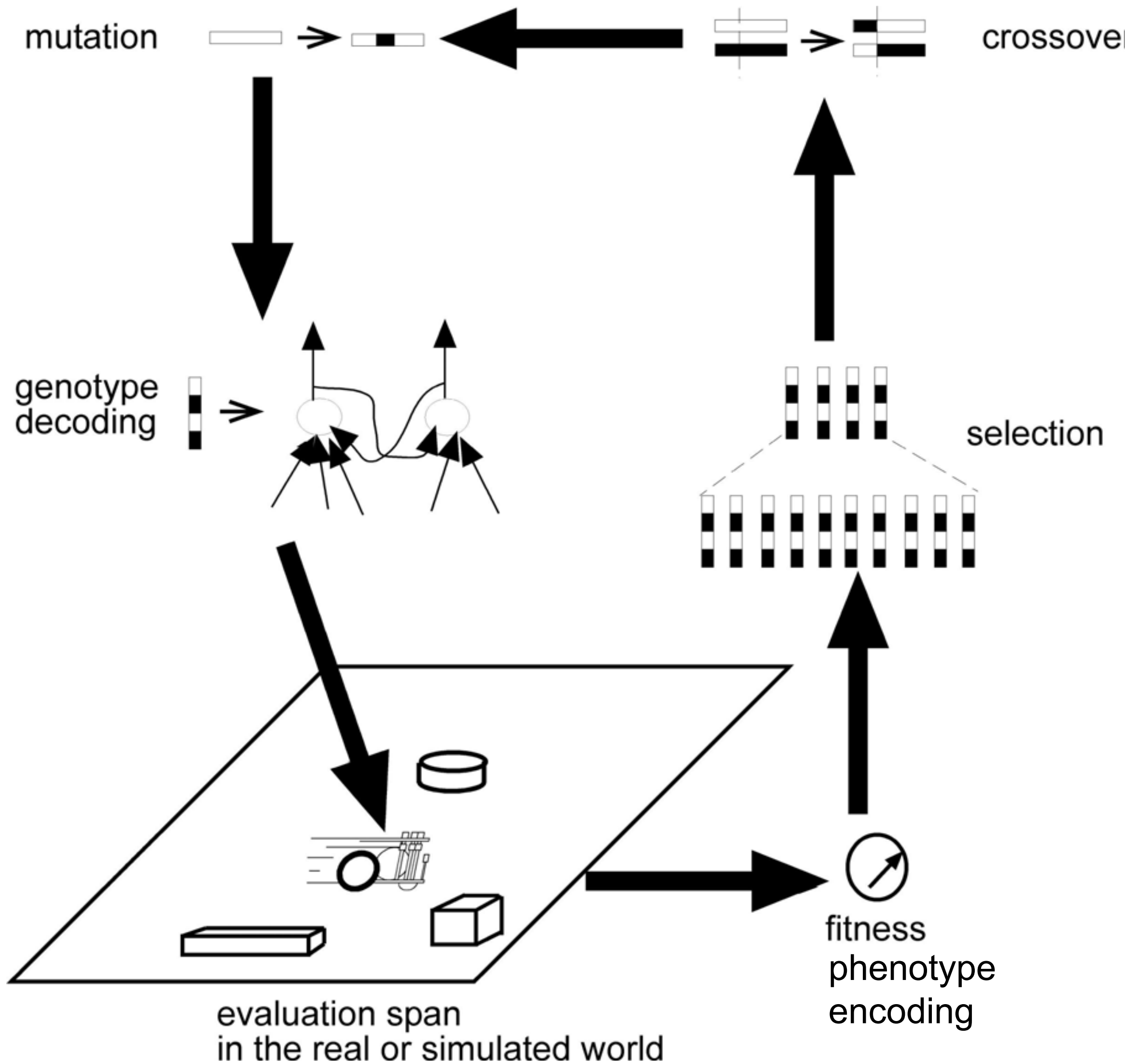
Defining performance (fitness function):

$$\Phi = V(1-\sqrt{\Delta V})(1-i)$$

- **V** = mean speed of wheels, $0 \leq V \leq 1$
- **Δv** = absolute algebraic difference between wheel speeds, $0 \leq \Delta v \leq 1$
- **i** = activation value of the sensor with the highest activity, $0 \leq i \leq 1$

Note: Fitness accumulated during evaluation span, normalized over number of control loops (actions).

Evolving Robot Controllers



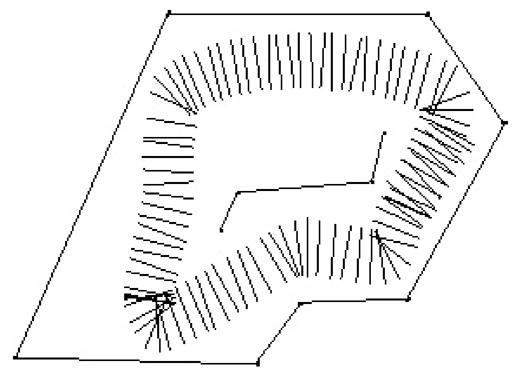
Note:
Controller architecture can be of any type but worth using GA if the number of parameters to be tuned is important

Evolved
Obstacle Avoidance Behavior

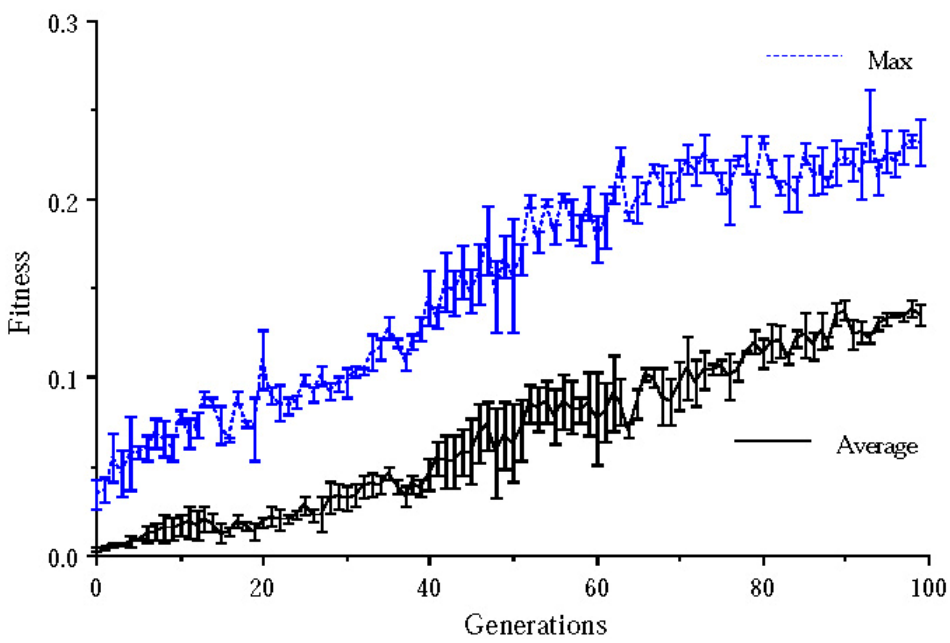
Generation 100, on-line, off-board (PC-hosted) evolution

Note: Direction of motion (forwards vs. backwards) NOT encoded in the fitness function: GA automatically discovers asymmetry in the sensory system configuration (6 proximity sensors in the front and 2 in the back)

Evolving Obstacle Avoidance



Evolved path



Fitness evolution

Expensive Optimization and Noise Resistance

Expensive Optimization Problems

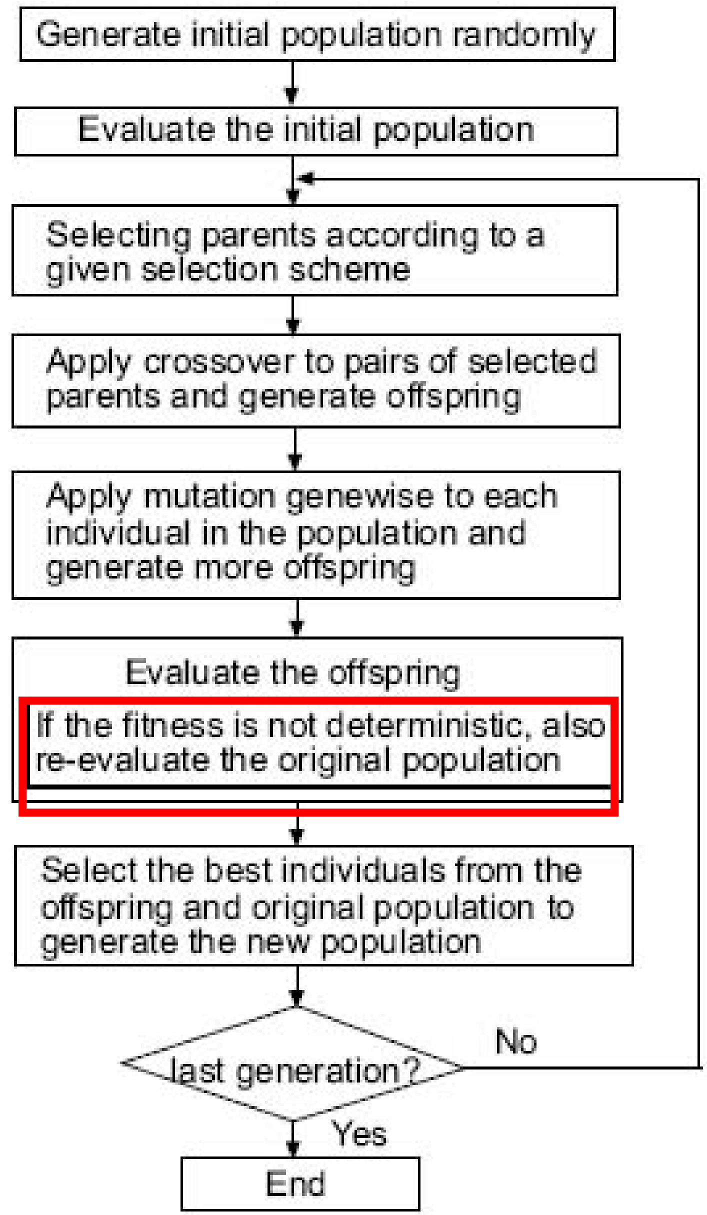
Two fundamental reasons making embedded system design and optimization expensive in terms of time:

1. Time for evaluation of candidate solutions (e.g., tens of seconds) >> time for application of metaheuristic operators (e.g., ms)
2. Noisy performance evaluation disrupts learning process and require multiple evaluations for actual performance
   - Multiple evaluations at the same point in the search space yield different results
   - Noise causes decreased convergence speed and residual error

Algorithmic Principles for Dealing with Expensive Optimization Problems

- Better information about candidate solution can be obtained by combining multiple noisy evaluations
- We could evaluate systematically each candidate solution for a fixed number of times → not efficient from a computational perspective
- We want to dedicate more computational time to evaluate promising solutions and eliminate as quickly as possible the "lucky" ones → each candidate solution might have been evaluated a different number of times when compared
- In GA good and robust candidate solutions survive over generations
- Use dedicated functions for aggregating multiple evaluations: e.g., minimum and average (perhaps combined with a statistical test)

Noise-Resistant GA



Dynamic population management during evaluation/selection: competition between offspring (new candidate solutions) and re-evaluated parents (old candidate solutions)

Testing Noise-Resistant GA on Benchmarks

- Benchmark 1 : generalized Rosenbrock function
  - 30 real parameters
  - Minimize objective function
  - Expensive only because of noise

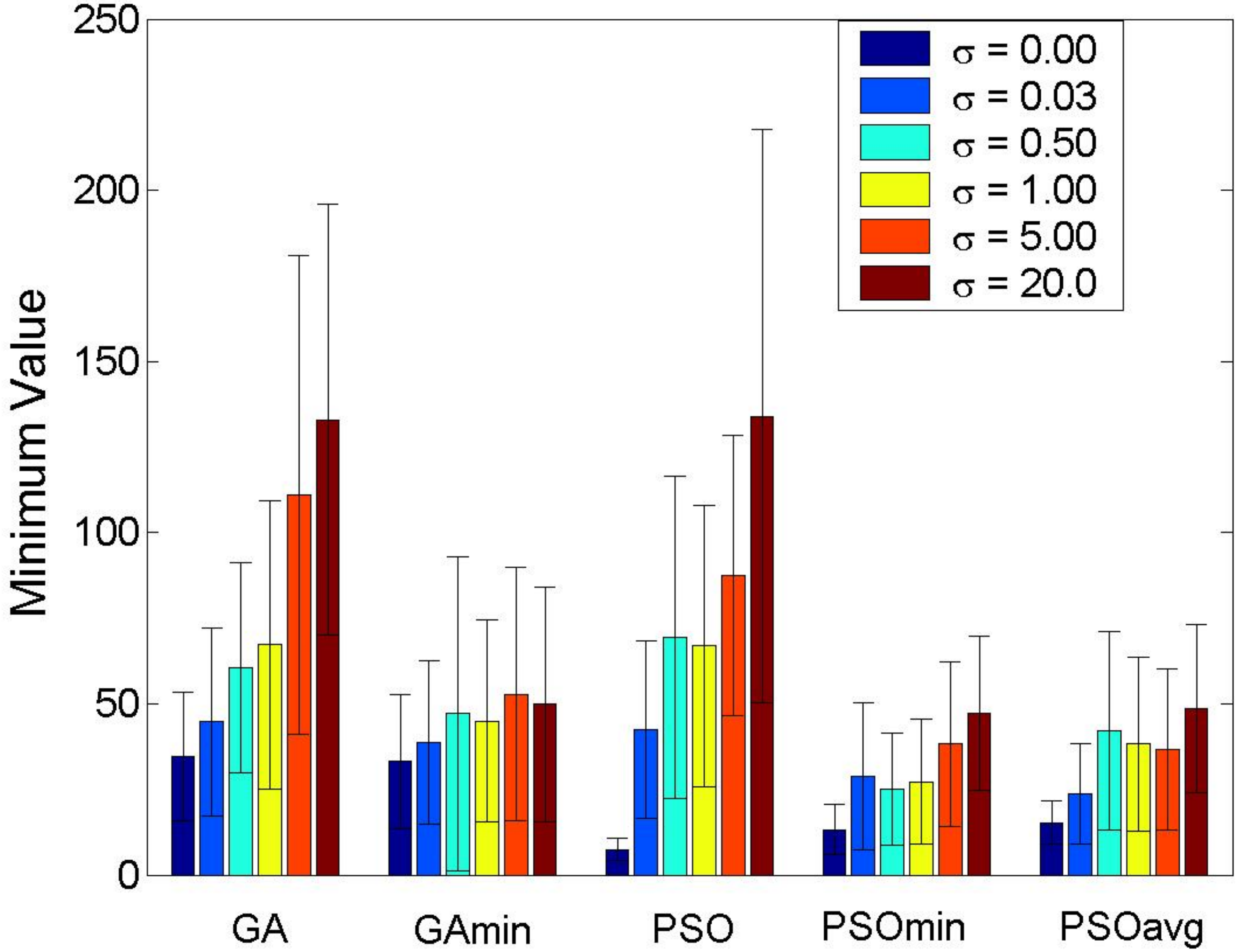
- Benchmark 2: obstacle avoidance on a robot
  - 22 real parameters
  - Maximize objective function
  - Expensive because of noise and evaluation time

Benchmark 1: Gaussian Additive Noise on Generalized Rosenbrock

$$f'_j(\bar{x}) = \mathcal{N}(0, \sigma^2) + f_j(\bar{x})$$

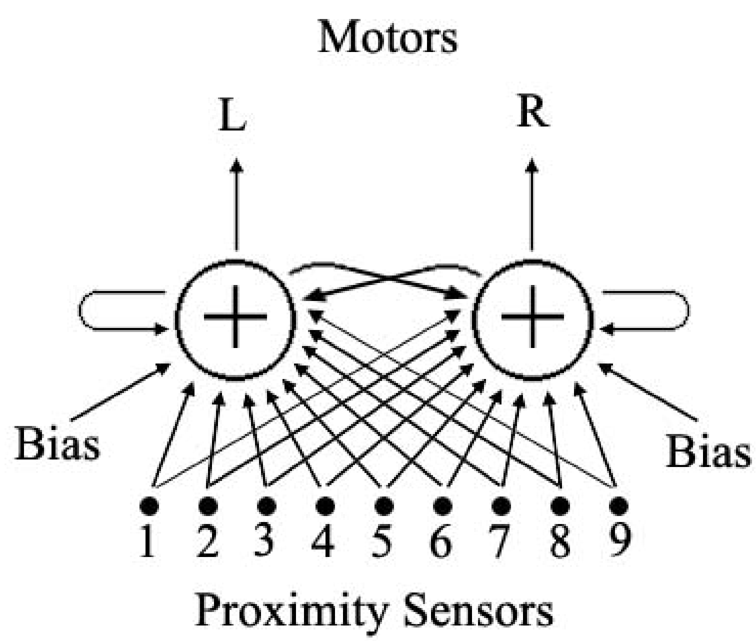
Fair test: **same** number of evaluations candidate solutions for all algorithms

(i.e. n generations/ iterations of standard versions compared with n/2 of the noise-resistant ones)



Benchmark 2: Obstacle Avoidance on a Mobile Robot

- Discrete-time, single-layer, artificial neural network controller
- Learning: neural weights and biases (22 real parameters)
- Fitness function (Floreano and Mondada 1996) rewards speed, straight movement, avoiding obstacles:

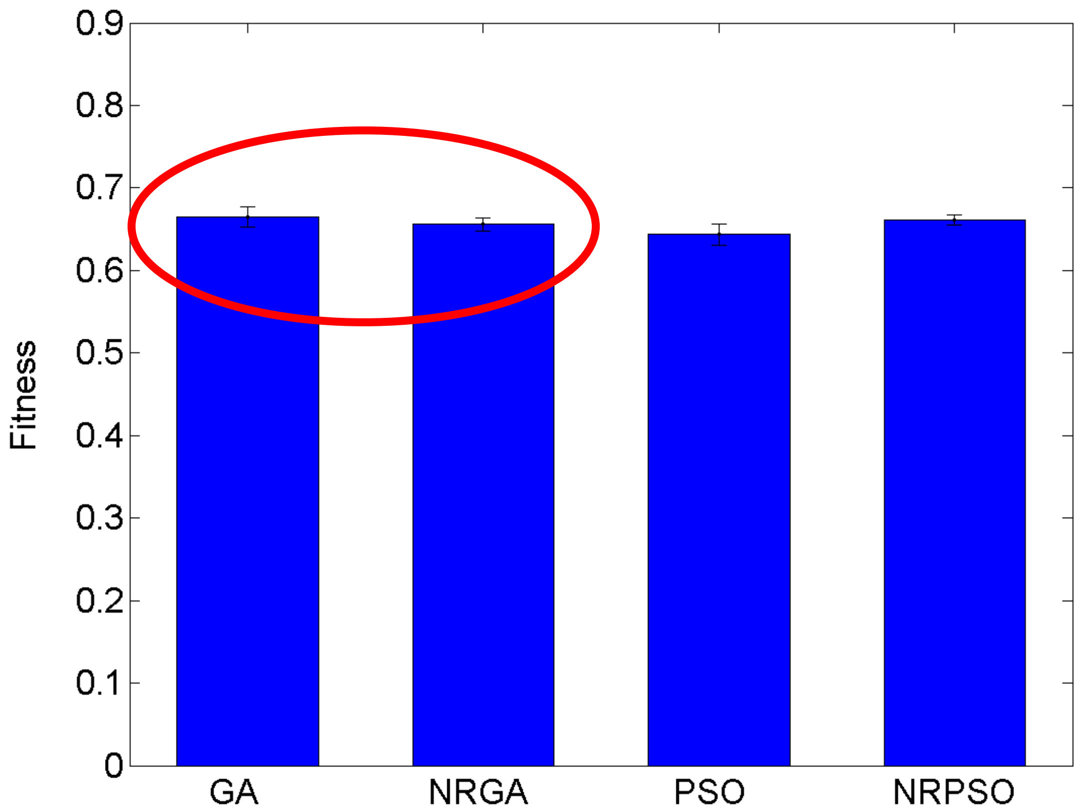


$$F = V \cdot (1 - \sqrt{\Delta v}) \cdot (1 - i)$$

$$0 \leq V \leq 1,\ \ 0 \leq \Delta v \leq 1,\ \ 0 \leq i \leq 1$$

- V = average wheel speed, Δv = difference between wheel speeds, i = value of most active proximity sensor

Extended-Time Robotic Learning



- Compare GA and Noise-Resistant GA (PSO solution not considered in this course)
- Population size 100, 100 iterations, evaluation span 300 seconds → 34.7 days
- Similar performance for all algorithms
- Module-based simulation (Webots)

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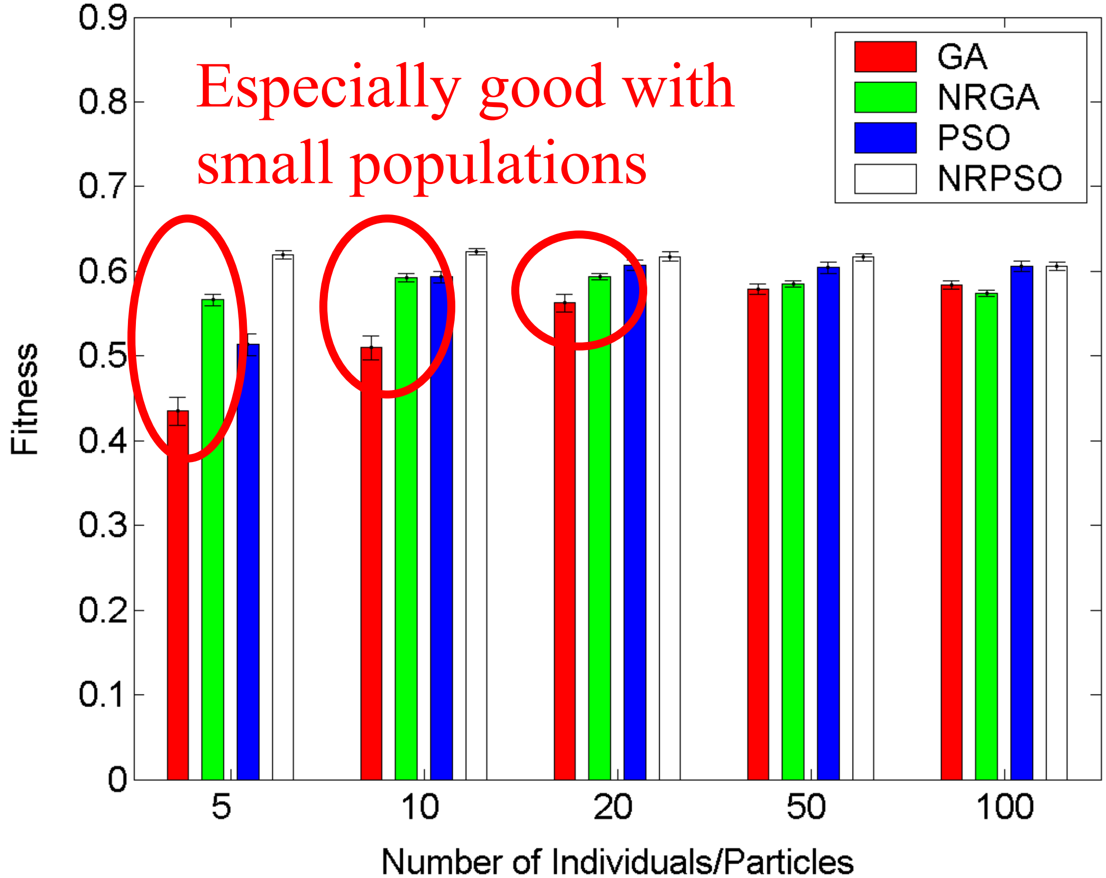
Limited-Time Learning Trade-Offs

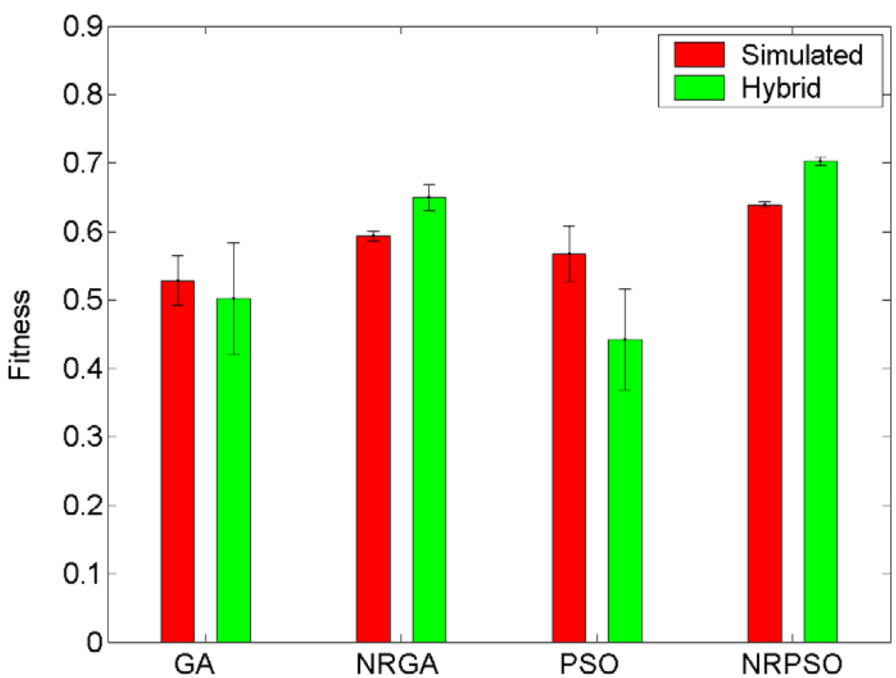


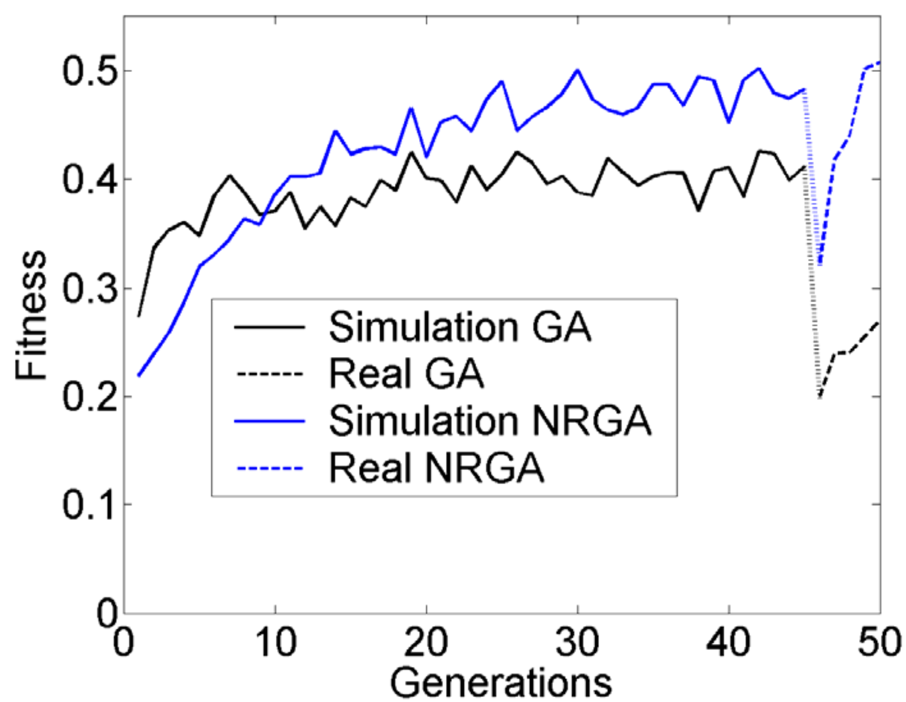
Varying population size vs. number of iterations

- Total learning time = 8.3 hours (1/100 of previous learning time)
- Trade-offs: population size, number of iterations, evaluation span
- Module-based simulation (Webots)

Hybrid Learning with Real Robots

- Move from simulation (module-based, Webots) to real robots after 90% learning (even faster evolution)
- Compromise between time and accuracy
- Noise-resistance helps manage transition

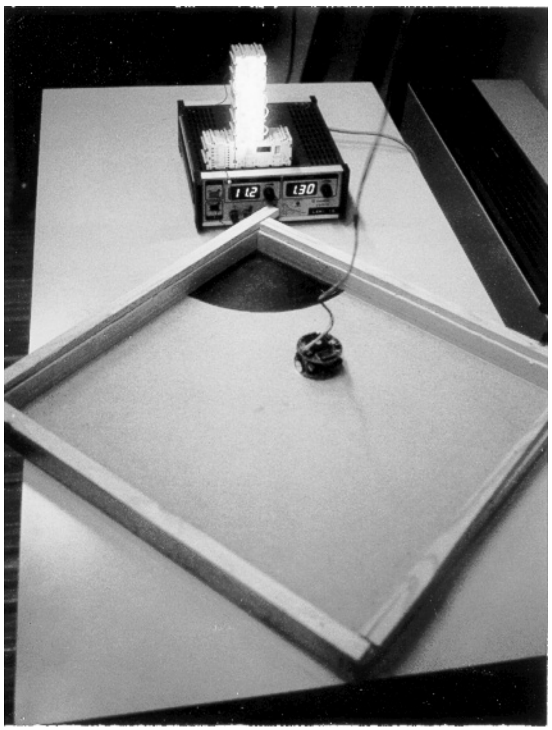




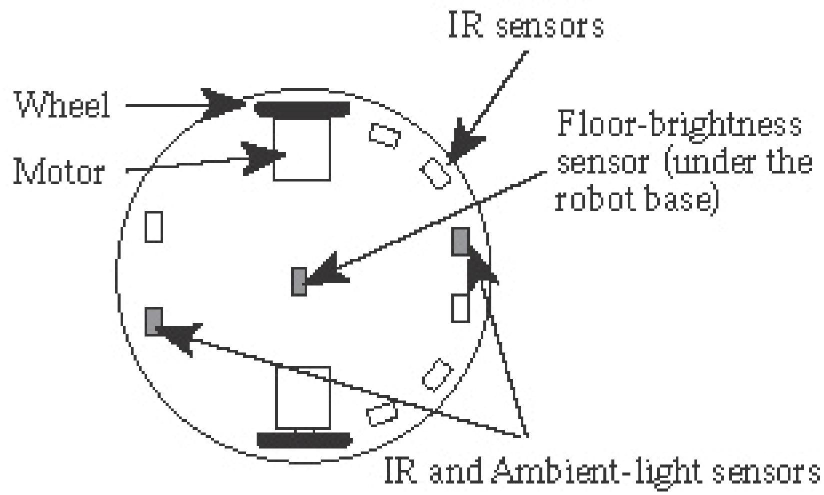
Not only Obstacle Avoidance: Evolving More Complex Behaviors

Evolving Homing Behavior

(Floreano and Mondada 1996)



Set-up



Robot's sensors

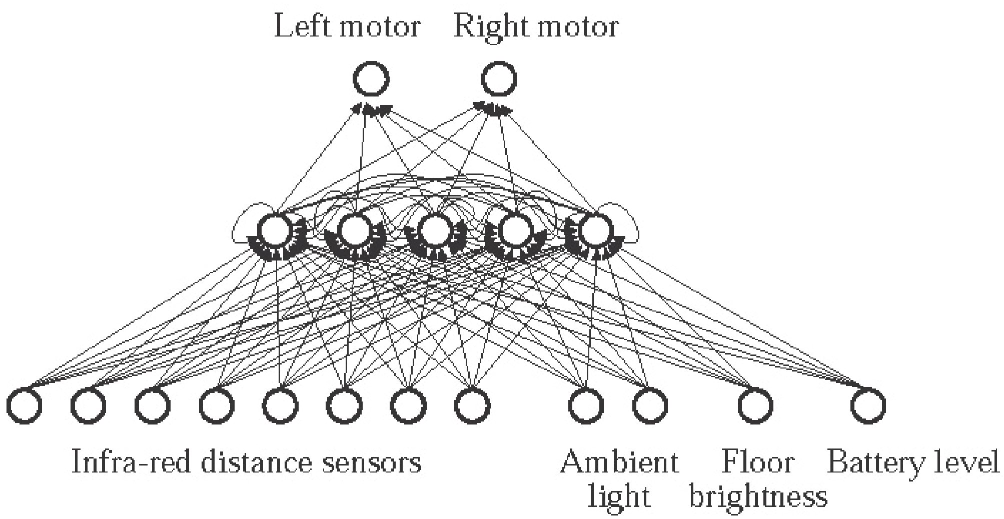
Evolving Homing Behavior

- **Fitness function:**

$$\Phi = V(1 - i)$$

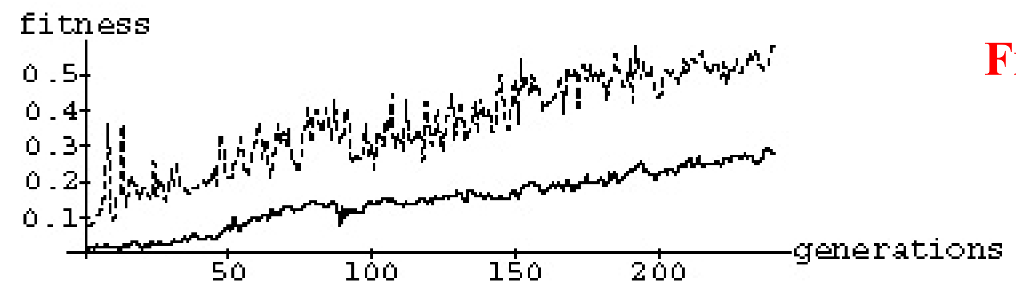
- **V** = mean speed of wheels, $0 \leq V \leq 1$
- **i** = activation value of the sensor with the highest activity, $0 \leq i \leq 1$

Controller

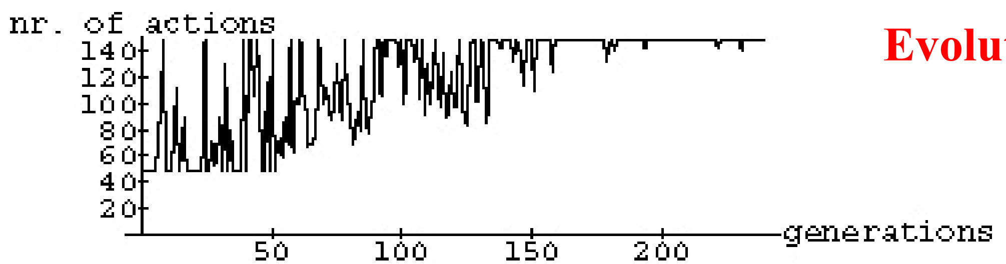


- Fitness accumulated during life span, normalized over maximal number (150) of control loops (actions).
- No explicit expression of battery level/duration in the fitness function (implicit).
- Chromosome length: 102 parameters (real-to-real encoding).
- Generations: 240, 10 days embedded evolution on Khepera.

Evolving Homing Behavior

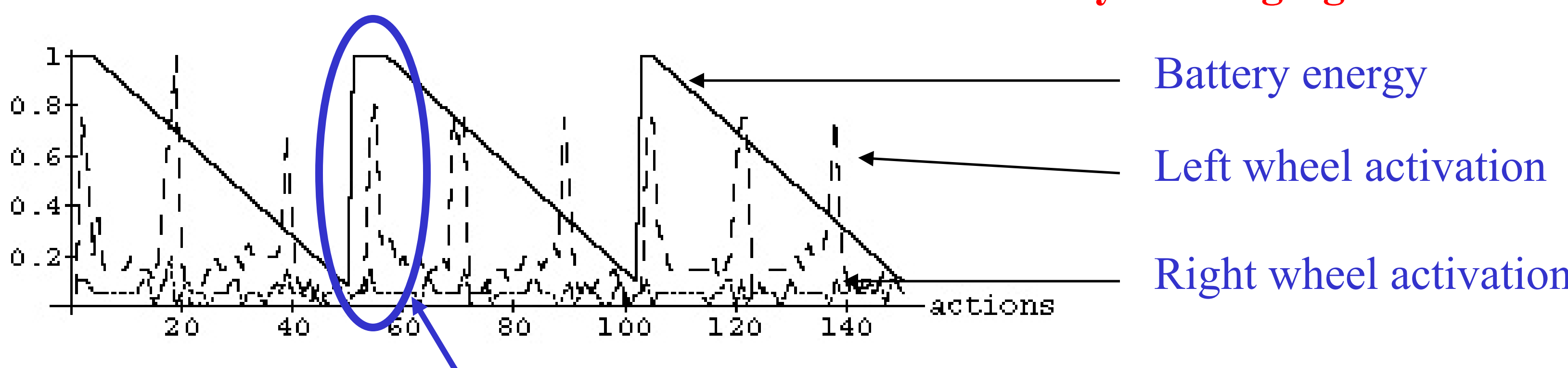


Fitness evolution



Evolution of # control loops per evaluation span

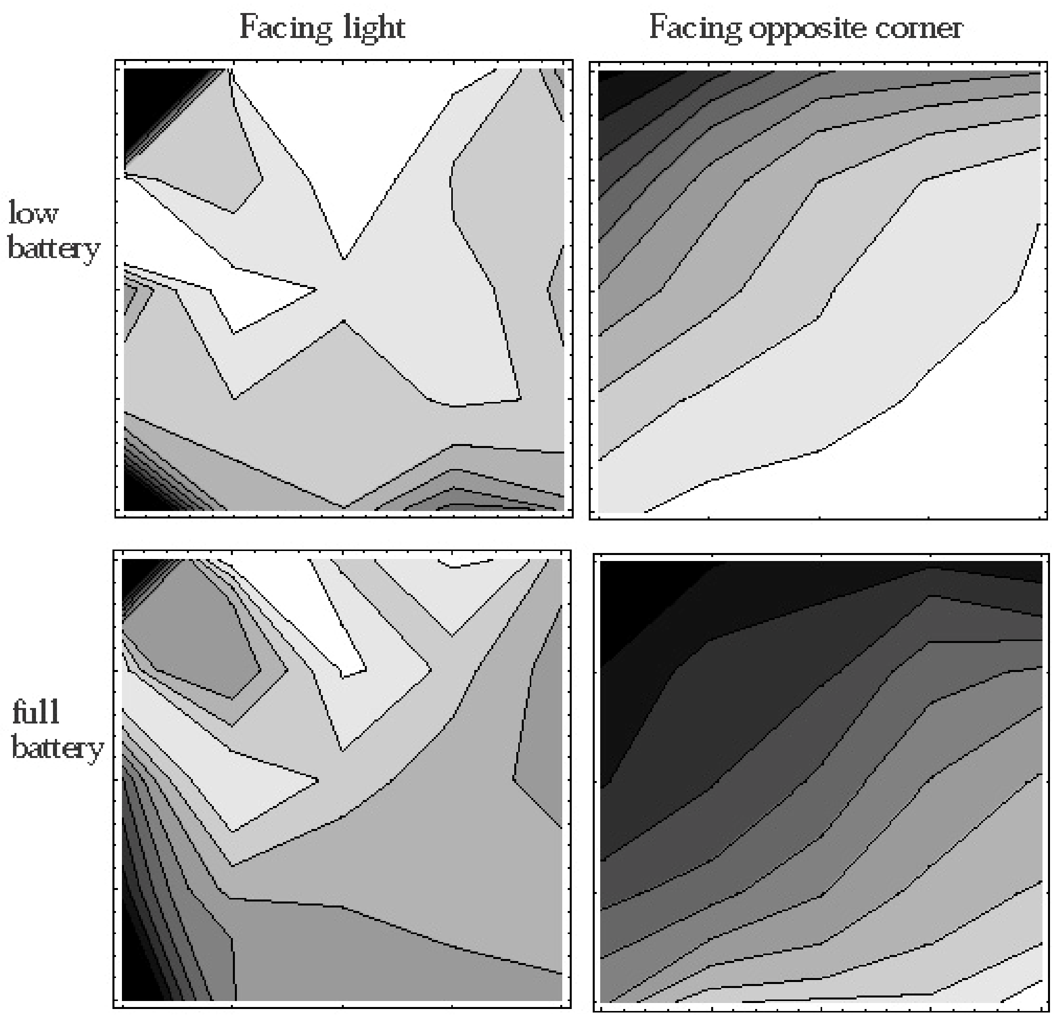
Battery recharging vs. motion patterns



Reach the nest -> battery recharging -> turn on spot -> out of the nest

Evolved Homing Behavior

Evolving Homing Behavior



Activation of the fourth neuron in the hidden layer

Firing is a function of:

- battery level
- orientation (in comparison to light source)
- position in the arena (distance form light source)

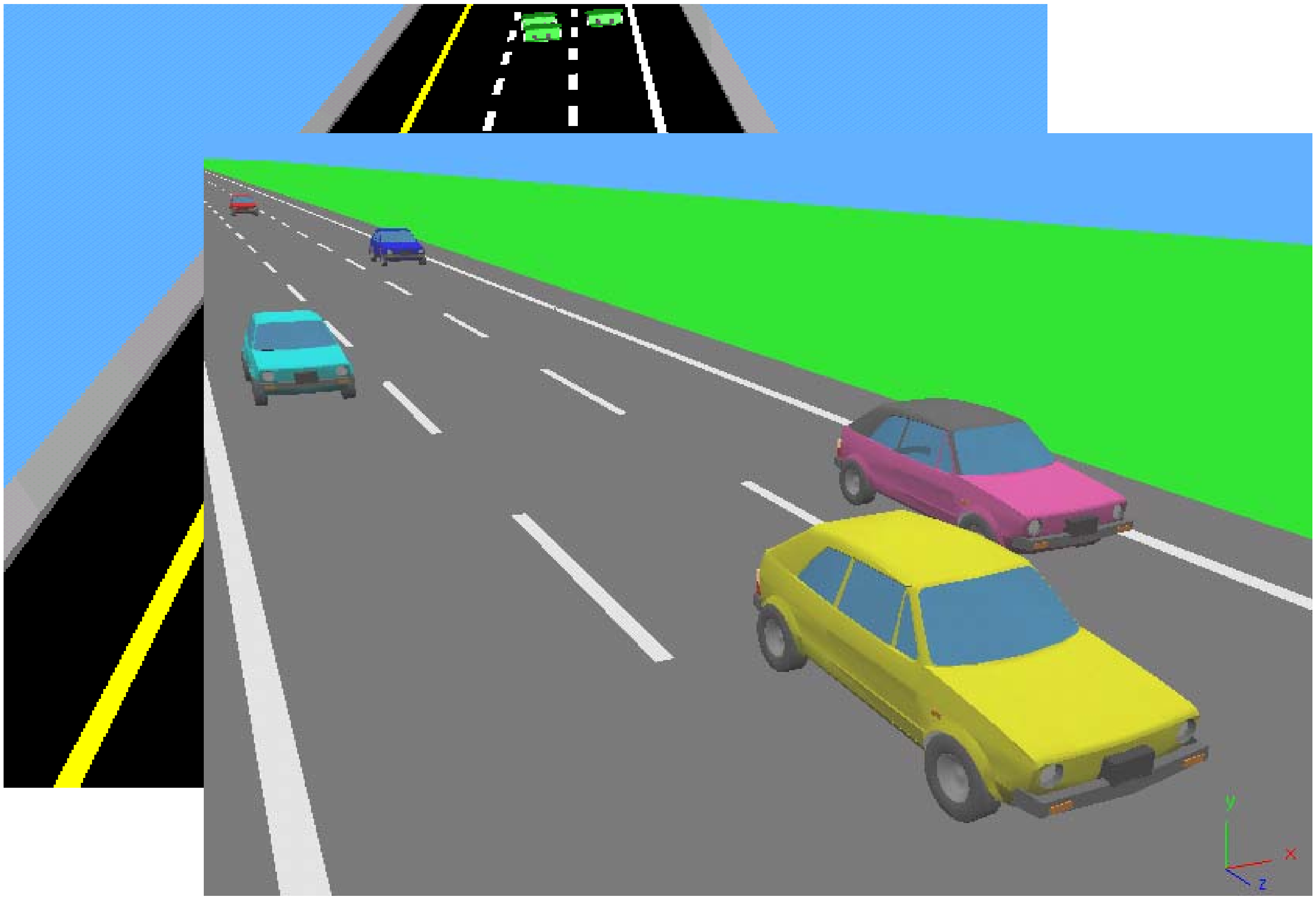
Not only Control Shaping: Off-line Automatic Hardware-Software Co-Design and Optimization

Moving Beyond Controller-Only Evolution

- Evidence: Nature evolve HW and SW at the same time …
- Faithful realistic simulators enable to explore design solution which encompasses evolution of HW features (body shape, number of sensors, placement of sensors, etc.) or co-evolution of both control and HW features
- GA are powerful enough for this job and the methodology remain the same; only the problem formulation changes

Multi-Vehicle Scenario

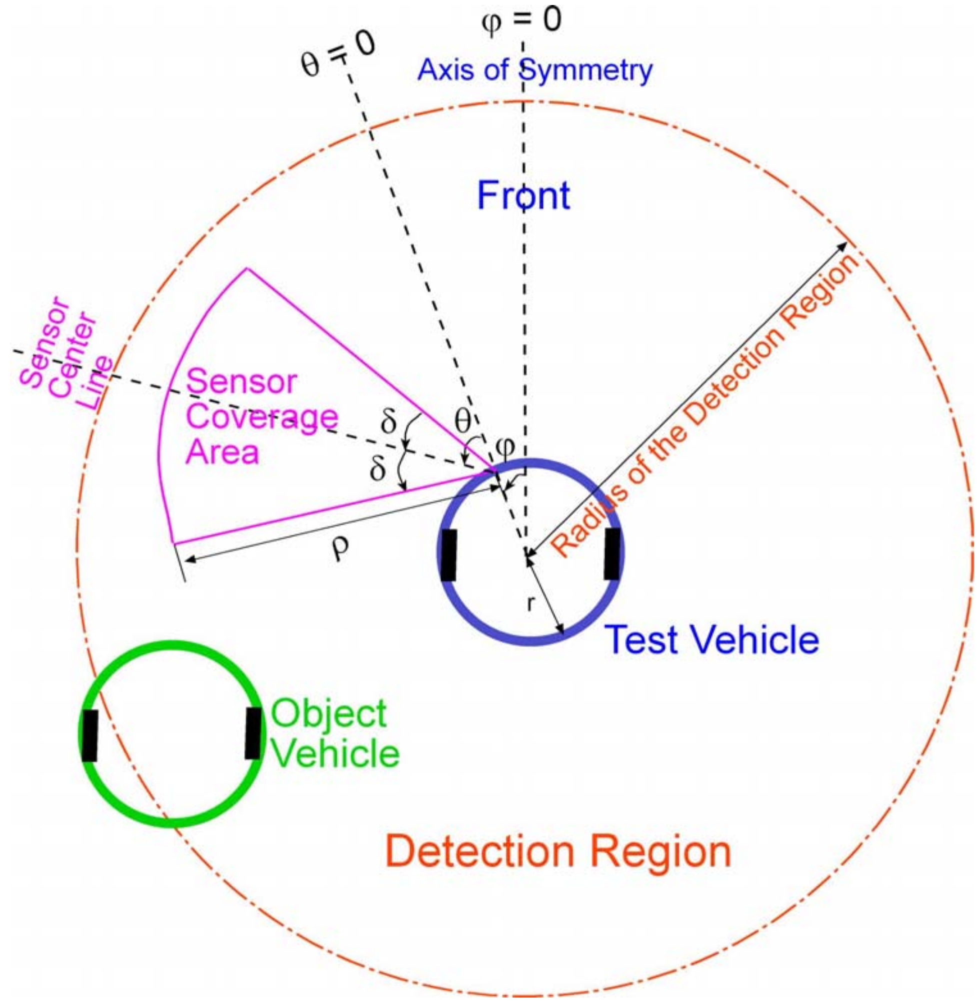
Webots 2004



Webots 2009

Evolving Sensory Configuration

- Number n (variable chromosome length!)
- Type
  - Range ρ
  - Cone of view δ
  - Cost $f(\rho, \delta)$
- Placement
  - Position φ
  - Orientation θ



[Zhang et al., *RED* 2008]

Fitness Function

$$Fitness(\omega, s) = \left(\frac{\mu_{cost}^{s} + \omega \cdot \mu_{coverage}^{s}}{1+\omega} \right)^{\frac{1}{s}}$$

$$\omega = \frac{\omega_{coverage}}{\omega_{cost}}$$

$$Coverage = \sum_{i=1}^{V} k_i \,\mathrm{PDF}(\alpha_i, r_i)$$

$$Cost = \sum_{i=1}^{n} cost_i$$

$$cost_i = f(\rho_i, \delta_i)$$

μ_{xx}: fuzzy preference on factor xx (0: totally unacceptable; 1: completely acceptable)

ω_{xx}: weight on factor xx

s: degree of compensation

V: actual number of vehicles been in the detection region during an evaluation span

k_i: 1 if the i^{th} car at distance r_i and approaching angle α_i detected; 0 if not detected

n: number of sensors used

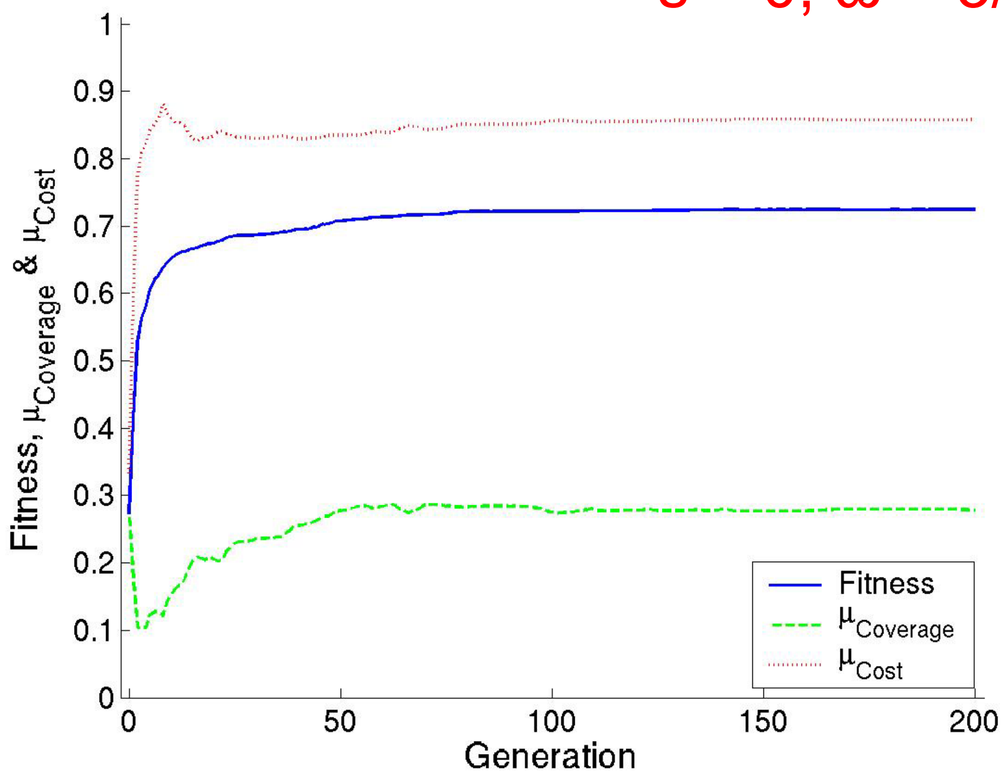
ρ_i: i^{th} sensor's range

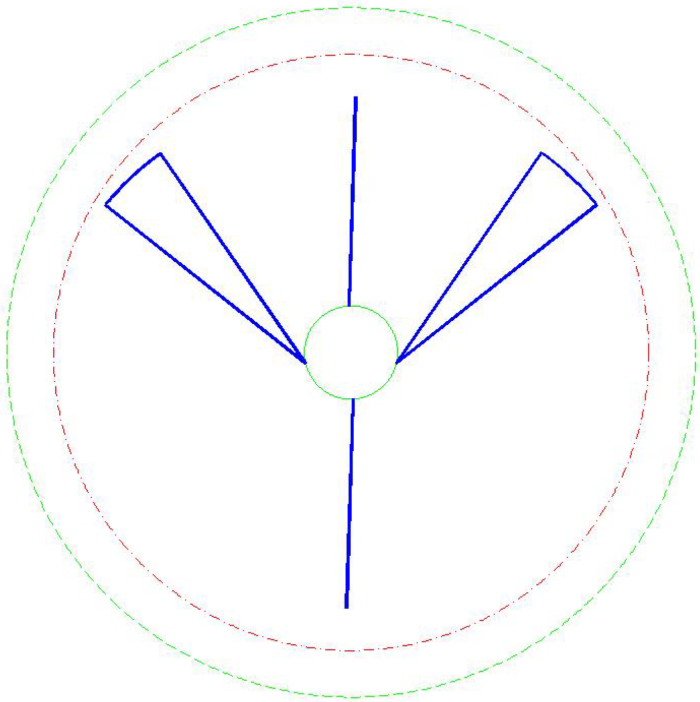
δ_i: i^{th} sensor's cone of view

Sample Results

- Fitness evolution process and the final best design

s = 0, ω = 3/17



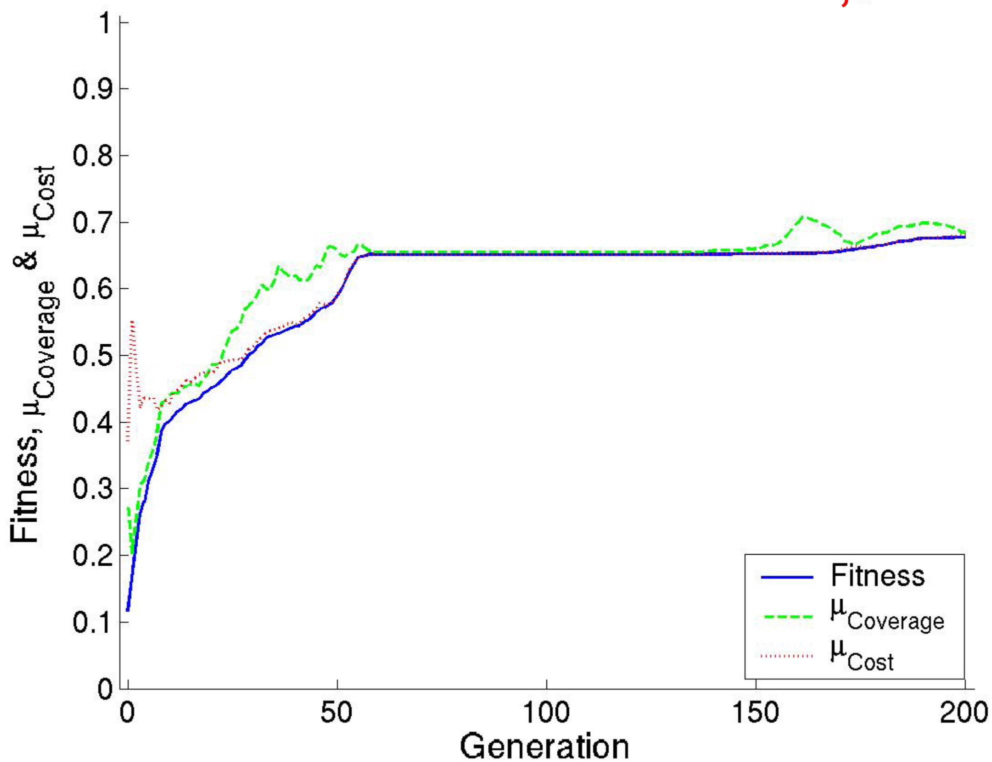


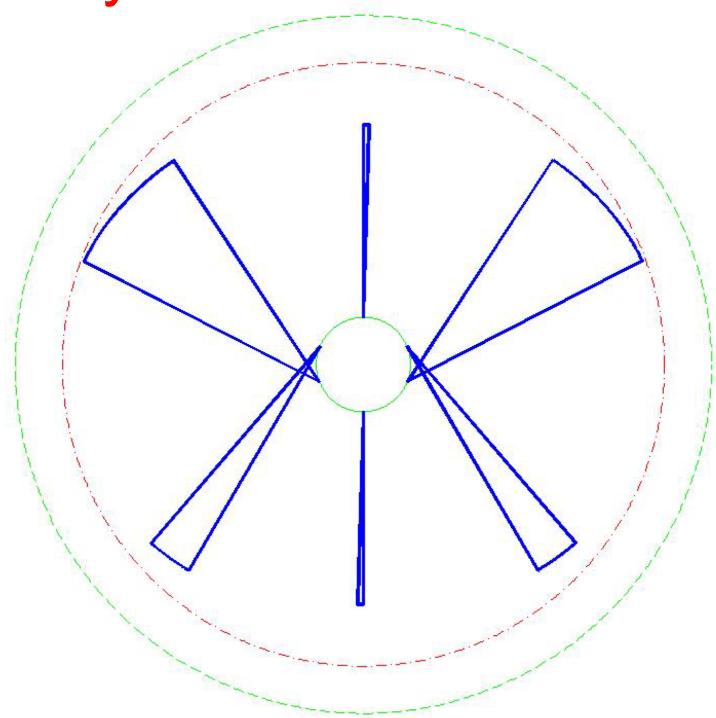
Coverage = 53%, *Total_cost* = 4.6

Sample Results

- Fitness evolution process and the final best design

s = -∞, ω arbitrary



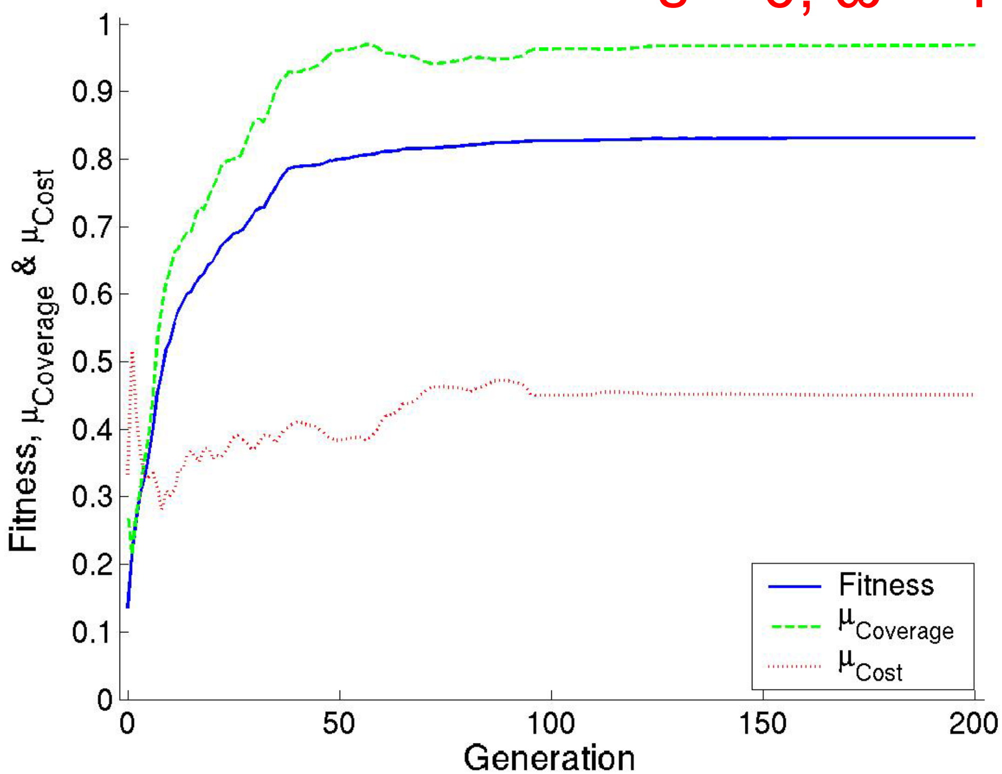


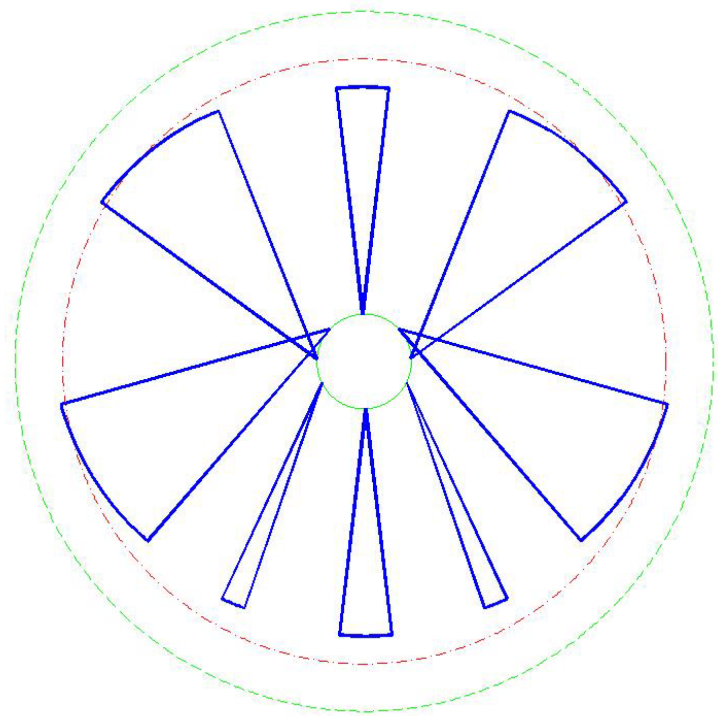
Coverage = 82%, *Total_cost* = 7.7

Sample Results

- Fitness evolution process and the final best design

$s = 0, \omega = 4$

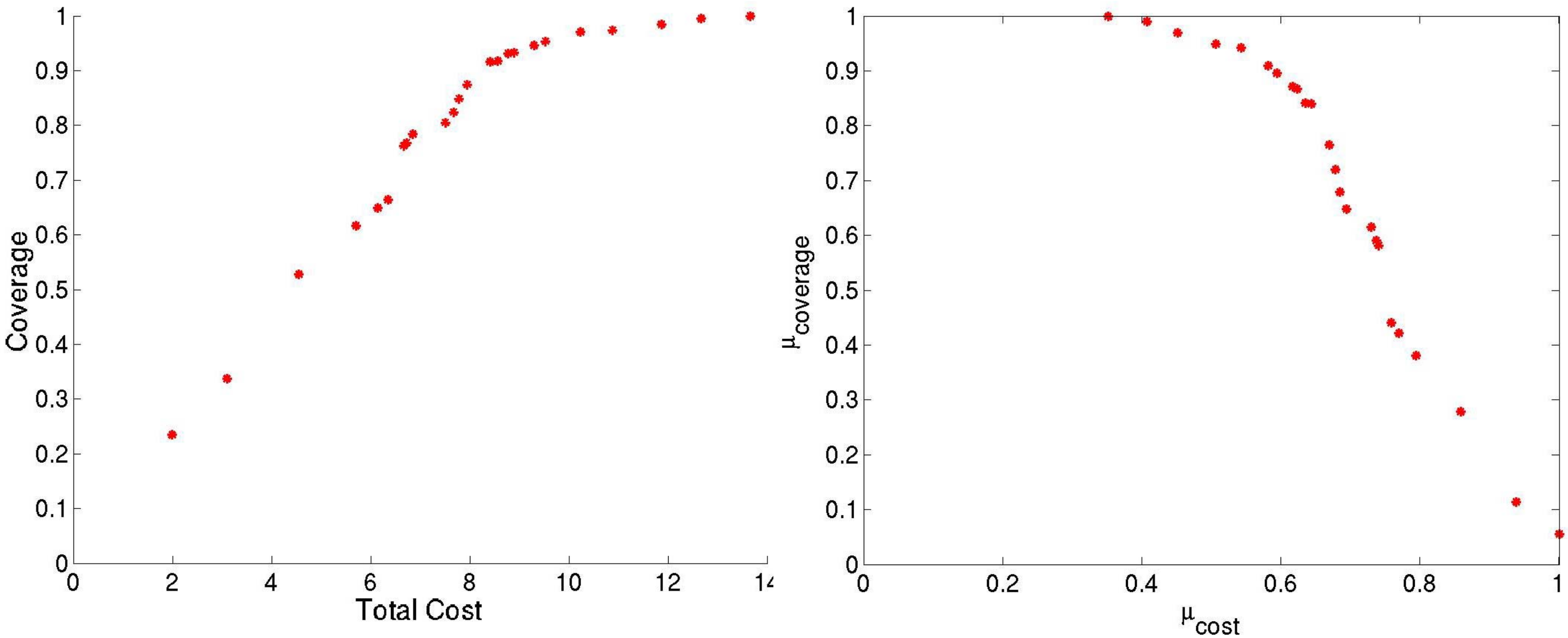




Coverage = 98%, *Total_cost* = 11.9

Sample Results

- Evolved approximate Pareto frontier for the design trade-offs present in the case study

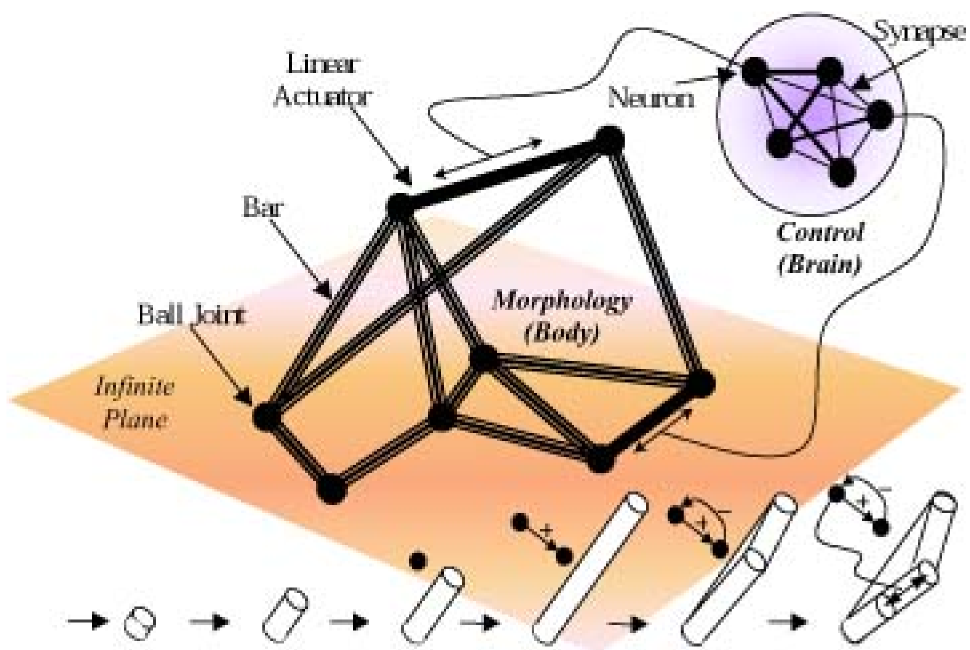


[Zhang et al., *RED* 2008]

Evolving Control and Robot Morphology
(Lipson and Pollack, 2000)

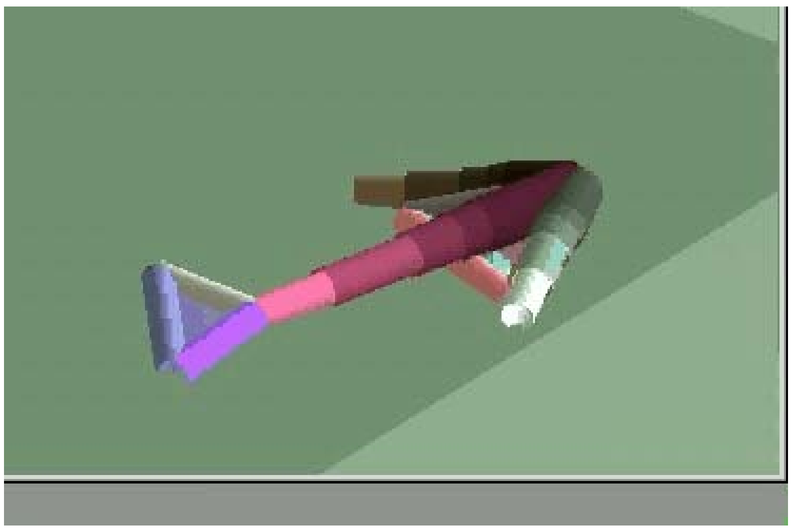
http://www.mae.cornell.edu/ccsl/research/golem/index.html

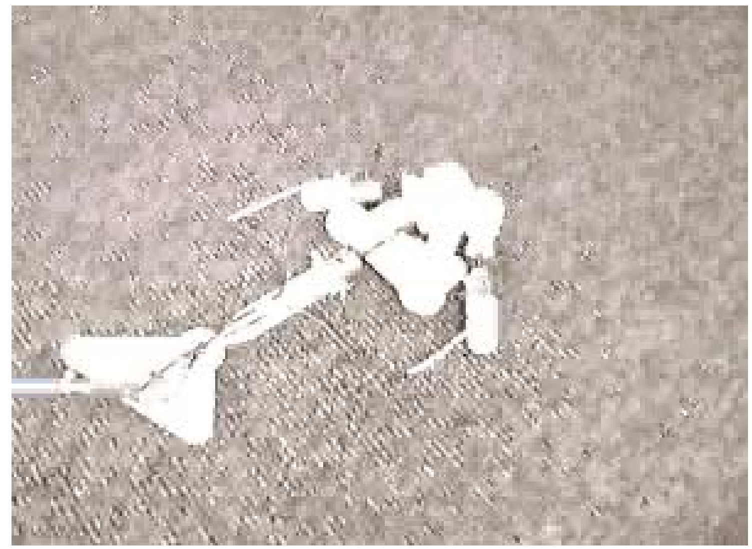
- Arbitrary recurrent ANN
- Passive and active (linear actuators) links
- Fitness function: net distance traveled by the centre of mass in a fixed duration



Example of evolutionary sequence:

Examples of Evolved Machines





Problem: simulator not enough realistic (performance higher in simulation because of not good enough simulated friction; e.g., for the arrow configuration 59.6 cm vs. 22.5 cm)

Conclusion

Take Home Messages

- Key classification in machine-learning is supervised, unsupervised, and reinforcement (evaluative) learning
- Reinforcement/evaluative techniques are key for on-line robotic learning
- A robust multi-agent metaheuristic is GA and can be successfully combined with ANN
- GA can be used to shape the behavior by tuning ANN synaptic weights
- Computationally efficient, noise-resistant algorithms can be obtained with a simple aggregation criterion in the main evolutionary loop

Additional Literature – Week 11

Books

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- Nolfi S. and Floreano D., "Evolutionary Robotics: The Biology, Intelligence, and Technology of Self-Organizing Machines". MIT Press, 2004

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- Pugh J., "Synthesis, Modeling, and Experimental Validation of Distributed Robotic Search"; December 2008, EPFL PhD Nr. 4256.

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