Evolutionary swarm robotics

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$\Rightarrow$ *Although each robot is autonomous, the swarm can solve problems that a single robot can't.*

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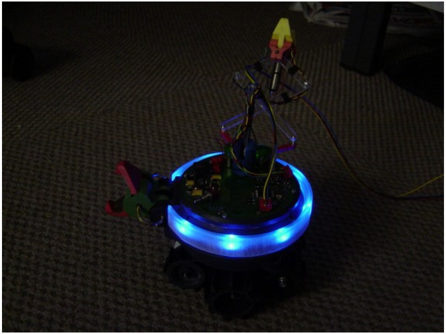

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- Aggregation

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- Coordinated motion

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- Positive and negative feedback interact, keeping the system in a stable state.

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- Given a global behavior, it is difficult to decompose individual behaviors.

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- relies on the evaluation of the system as a whole
- can deal with the richness/complexity of the dynamic system, involving not only a multiple-agent scenario but also a possible physical link between the agents
- is easy to implement

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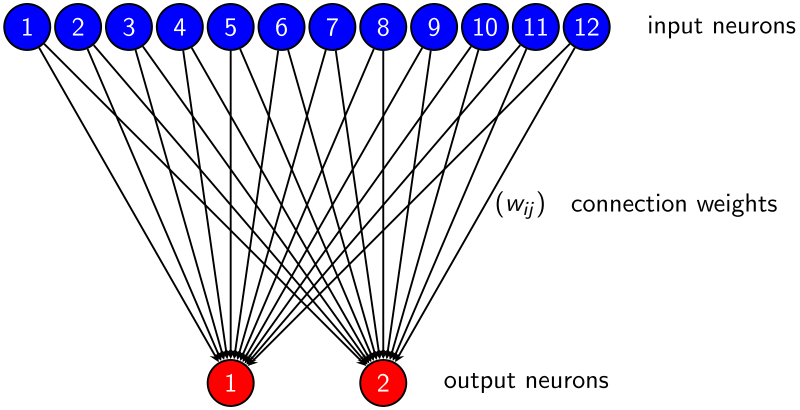
- connect sensory input and motor output through an artificial neural network
- determine the details of this network using artificial evolution

Single Layer Perceptron



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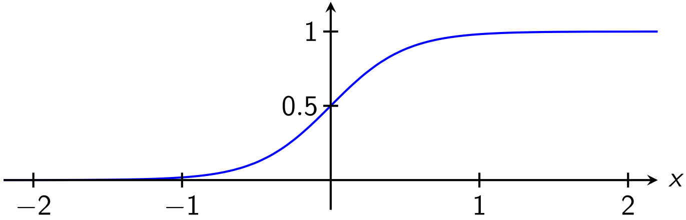
Used activation function (sigmoid function):

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



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In the following experiment, S-Bot controllers only differ in (2).

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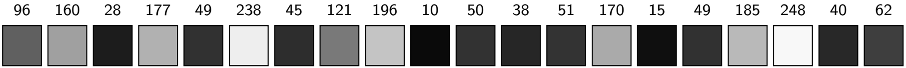
  5. repeat 2-4

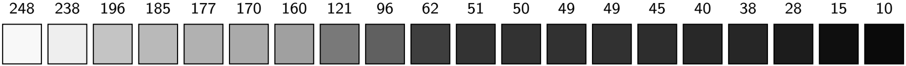
Example

Initialization



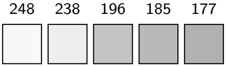
Example

Ordered by fitness



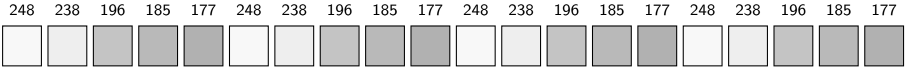
Example

Selection



Example

Reproduction



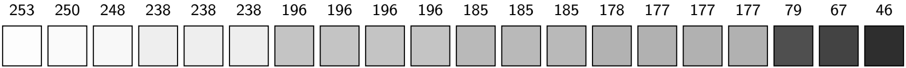
Example

Mutation

248	238	196	185	177	250	67	196	185	79	178	238	196	185	177	46	238	196	253	177

Example

Ordered by fitness again



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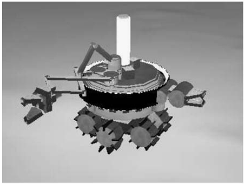
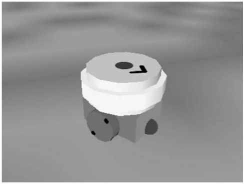


(b)



(c)

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Here: only 1-3.

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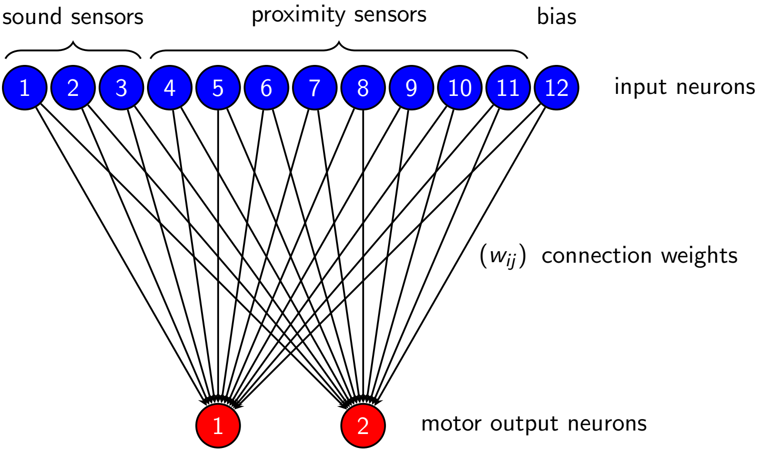
- global area is 3×3 meters, bigger than the perceptual range of the S-Bots

Network structure



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- tested for 20 evolutionary runs

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  - do the wheels of the sbot turn in the same direction?

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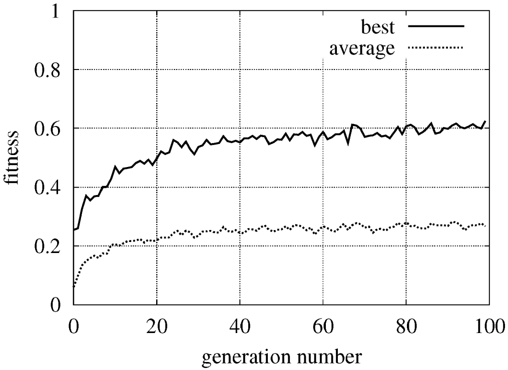
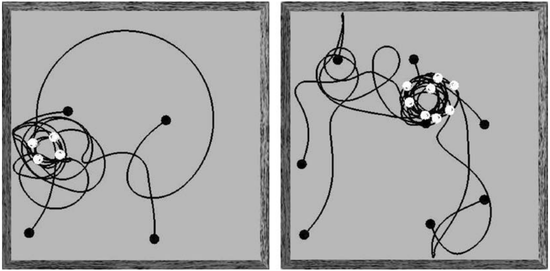


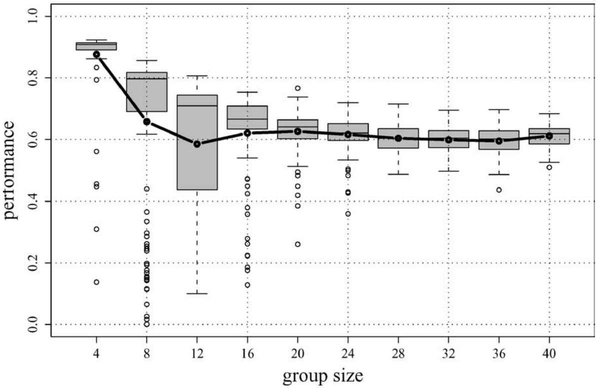
- Aggregation perfomance averaged over 20 evolutionary runs

Observations



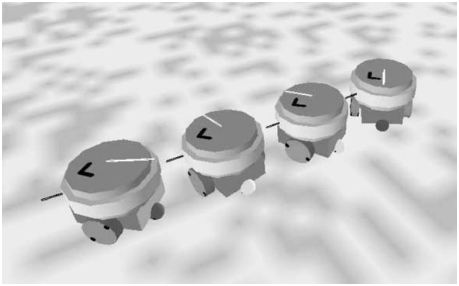
- Aggregation behavior.
  Following behavior of small groups emerges, if the group size gets larger, chaos increases.

Scalability



- Best genotype of each run tested against increasing group sizes.

Coordinated motion



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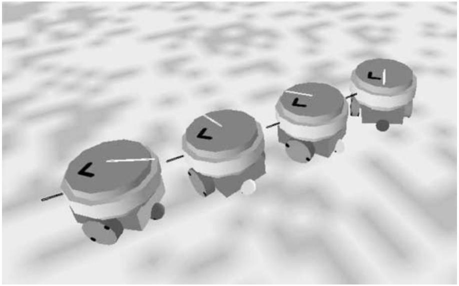

- problem: S-Bot start with different orientations
- try to solve this problem and to evolve coordinated movement using only local information

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  - a traction sensor indicating the angle between its turret and the chassis and the force of the traction

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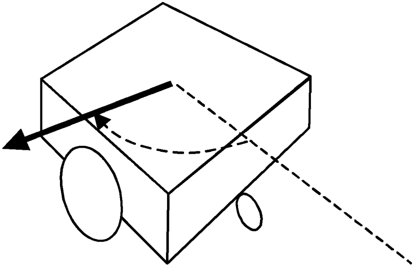

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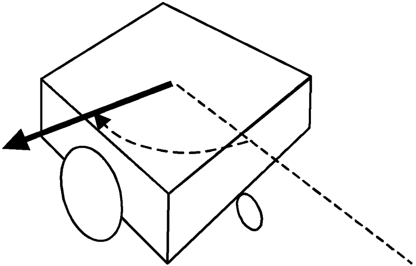

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- measure the mismatch between the group's direction and the S-Bot's chassis direction

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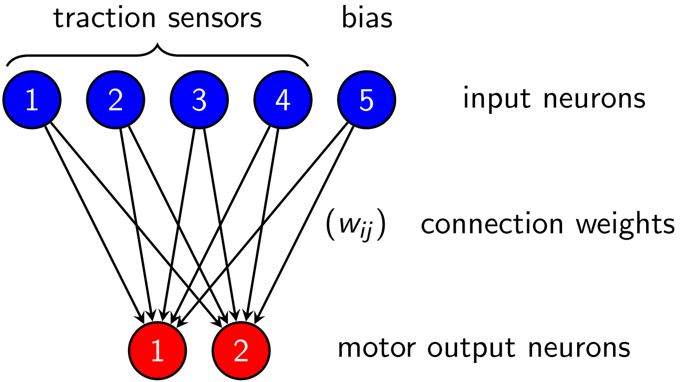

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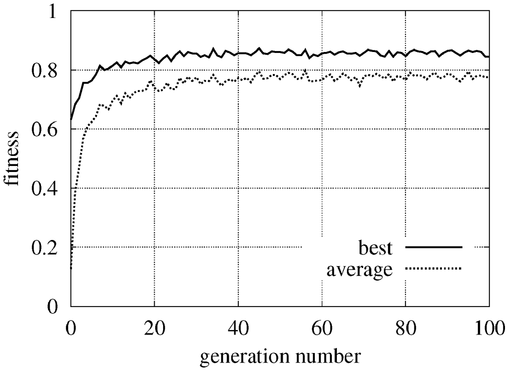

- Coordinated movement performance for 20 runs à 100 generations.

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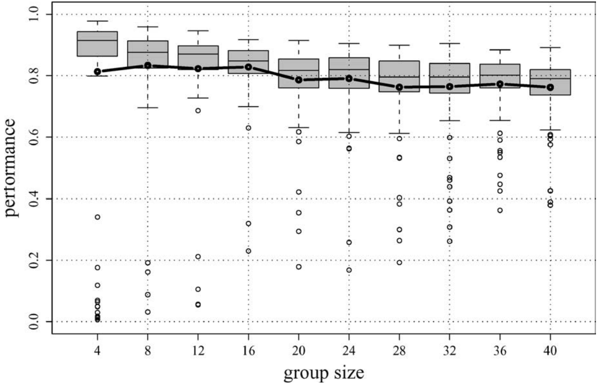
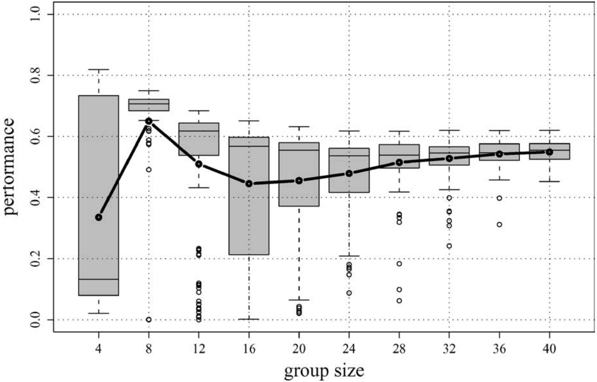
- side effects: object avoidance and object pulling

Scalability



- Coordinated movement performance for increasing group sizes.

Detailed Model



- Aggregation performance for increasing group sizes (detailed model)

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- Drawbacks:
  - the evaluation functions used in this simulation used global information (position of each S-Bot etc.)
  - to evolve these controllers on real hardware evaluation needs to be performed using only local available information
  - could be bypassed by using a camera in a real setup to obtain positions