Self-creation of autonomous robot behaviour

Ralf Der

Max Planck Institute for Mathematics in the Sciences
Leipzig, Germany

Content of the talk

- Self-organization of robotic forms of life: Find a general principle which gives autonomous embodied agents a life of their own.
- Here: A systematic approach to self-organization by
  - The maximization of predictive information
  - The minimization of the time loop error
- Examples by videos:
  - Humanoids
  - Dogbots, Snakebots,
  - and other strange creatures

Robotic vs. biological forms of life

Biology

- Life developed through evolution.
- Evolution driven by the necessity of survival.
- Incremental development building on established solutions. No „playing around“.

Evolution has no intrinsic drive for innovation

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Example Crossopterygian –

No evolution over billions of years

On the other hand, animals can be trained to performances never observed in nature.

Question: How to find a general drive for development

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Robotic world

- Assume a world with unlimited resources, potential immortality, no externally given goals, ...
- Key question: Without external goals and drives, why should anybody do anything at all.
- An answer would us help to understand internal motivation, creativity, ...

Look for general paradigms for the creation of life like artifacts

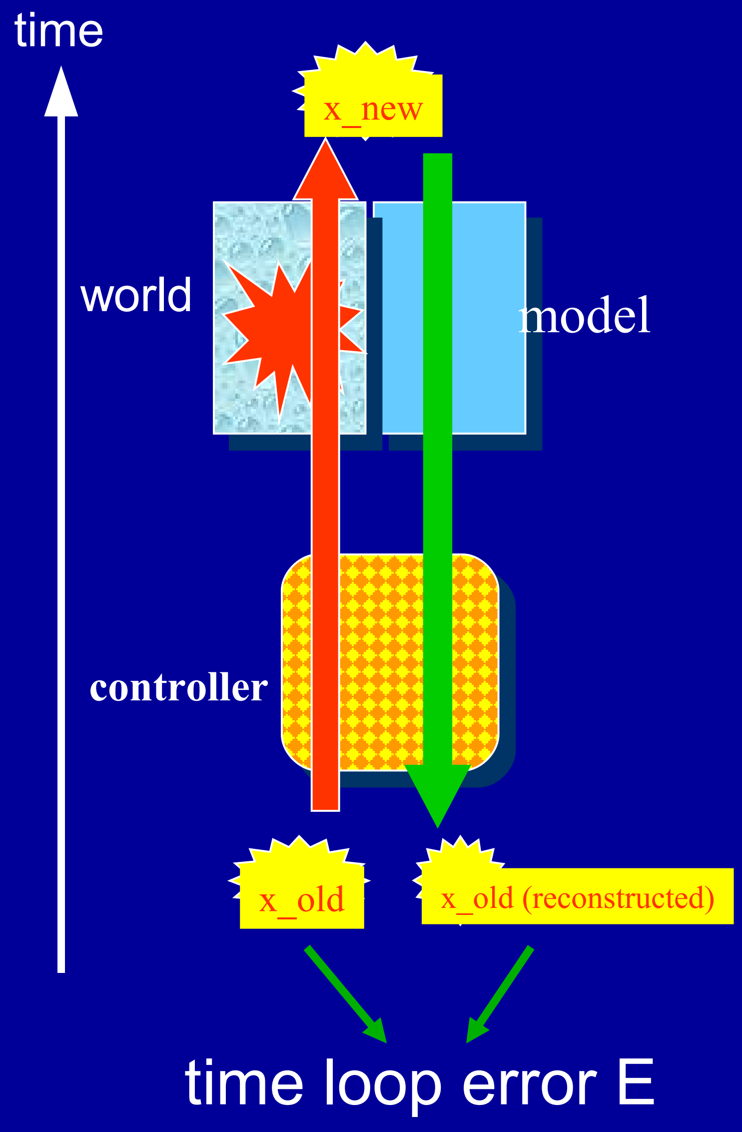
Candidate Paradigms

- Homeostasis (Cannon, Ashby): Life is a phenomenon of self-regulation with the aim of keeping internal parameters at a viable level. Overall *stasis* as aim.
- Autopoiesis - The paradigm of self-creation and self-maintenance. Formulated at the level of living cells (Varela, Marurana).
-
- Here: Self-creation of behavior. Given a robot of fixed morphology. Self-creation of behavior for instance by striving for increasing knowledge of the self and its (dynamical) embedding into the environment.
- Our approach – homeokinesis – one step into that direction.

Homeokinesis

- Aim is not overall *stasis* but a common kinetic regime of brain, body, and environment.
- How to achieve this? Steps:
- Generalize homeostasis: Give the agent a general drive for activity and stabilize behaviors that can be modeled well by an adaptive internal model.
- Homeokinesis is HS in a time inverted world.
- Arrow of time can be inverted in the model dynamics.
- This general idea can be condensed into a concrete objective function the so called time loop error.

The time loop error



- The time loop error is minimized by an agent behavior which is qualified by being both **sensitive** (creative) and predictable.
- Gradient descent on E drives both controller and model on-line.
- The „**plug-and-play brain**“

Realization

- Take a neural network ("brain") realizing the controller

$$y_t = K(x_t;c)$$

x_t: vector of sensor values y_t: vector of motor values

c: controller parameters (synaptic strengths)

- and a neural network realizing the (adaptive!) self model

$$x_{t+1} = F(x_t, y_t) + \text{modeling error}$$

The challenge, as we understand it, ctd.

- Find an objective function E depending only on
  - sensor values x,
  - controller output y,
  - and self model F
  - Define the dynamics of the controller parameters c as

$$\Delta c = -\varepsilon \frac{\partial E}{\partial c}$$

- Connect the brain to an arbitrary body (real or simulated)
- Put the creature into an unknown, unstructured, dynamical environment.
- Brain body and environement form a self-referential dynamical system.

Paradigms for the objective function E

- Homeostasis (Ashby, ... , di Paolo): Keep certain **intrinsic** variables within survivable limits. **E measures the distance to the target values.**
- Perceptual control theory (Powell): **Behavior as the control of Perception.** **E measures the lack of control over the perceptions.**
- Information theoretic measures: (Lungarella, Sporns, Polani, Prokopenko, Ay et. al.): *Life as an information creating process* **E = convenient information measure**
- Dynamical complexity measures of trajectories in sensor space. **E measures the dynamical complexity .**

- Problems:
  - 1. and 2. not constructive
  - 3. to 4. need (extensive) sampling
  - but **behaviors are contingent**.

Our approaches

- The paradigm: A controler is optimal if it
  1. Amplifies sensorimotor variations but such that
  2. Future sensor values stay predictable

- Two approaches exemplified so far
  1. Predictive information = past-future mutual information in sensor space (most recent).
  2. Time loop error

Paradigm I: Predictive information I

- Consider the time series of sensor values

$$x_t \in R^n \quad mit \quad t = 0, 1, 2, \ldots$$

- Separate at a given time t the series into past and future.
- Predictive information is the information we can have about the future from knowing the past.
- PI essentially is the mutual information between past and future.

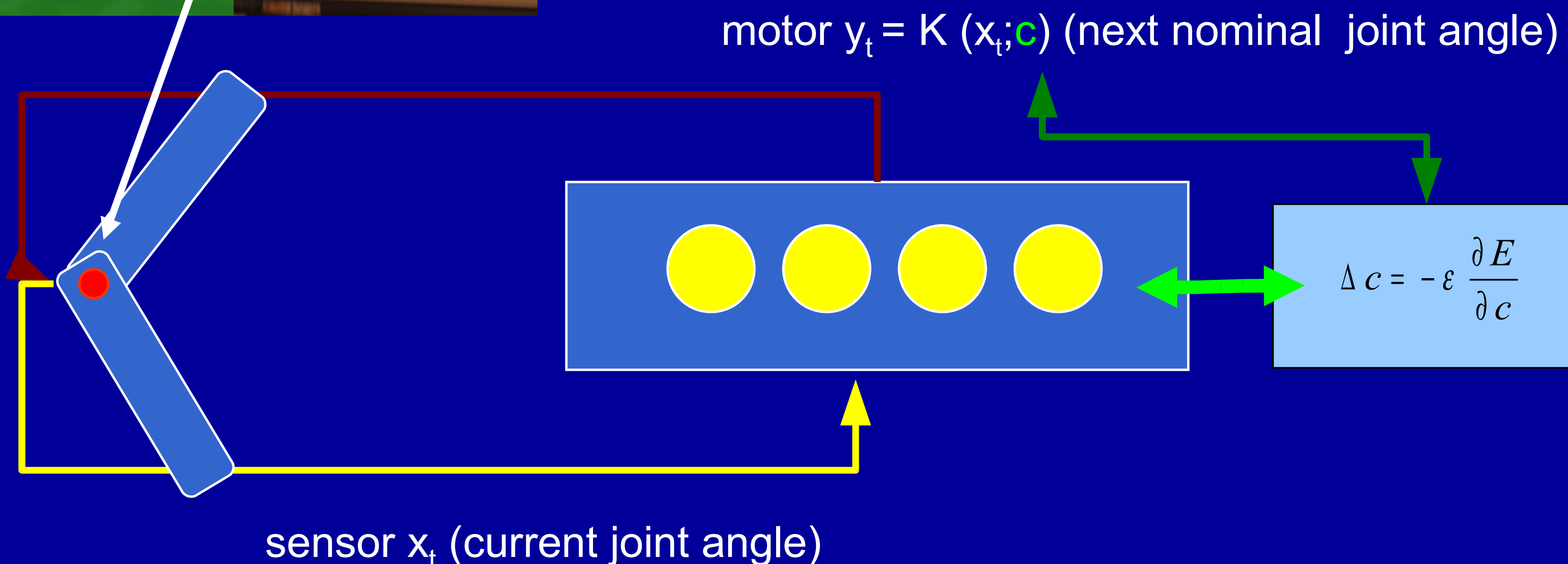
$$PI = \left\langle \log\left(\frac{P(X_{future}, X_{past})}{P(X_{future})\,P(X_{past})}\right)\right\rangle$$

Predictive information II

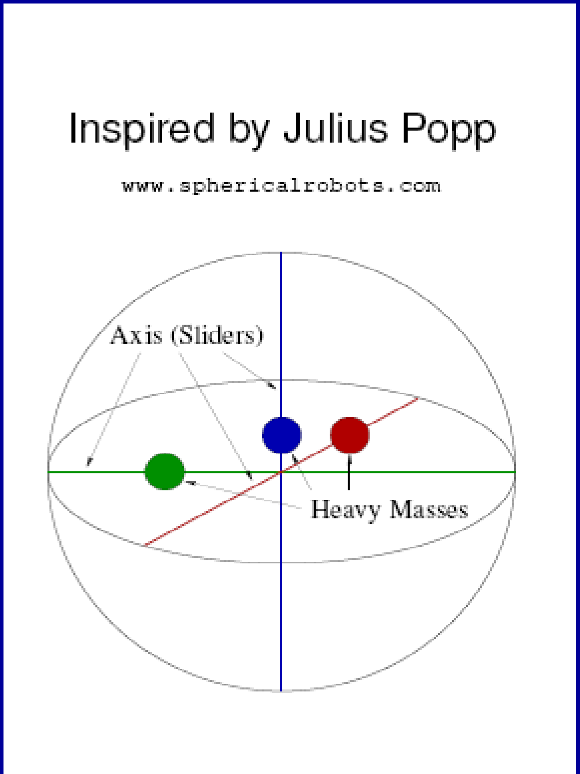
- Cases:
  - Ordered behavior: PI is low.
  - Random behavior: PI = 0.
  - PI is maximal if the behavior is rich but still „under control“, meaning predictable.
  - This is what we need for the explorative robot.

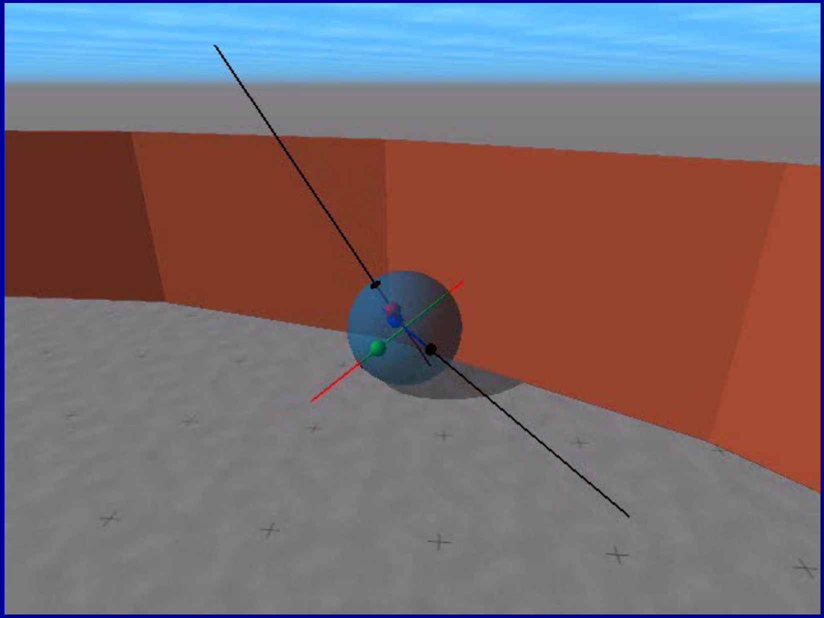
Using the The time loop error

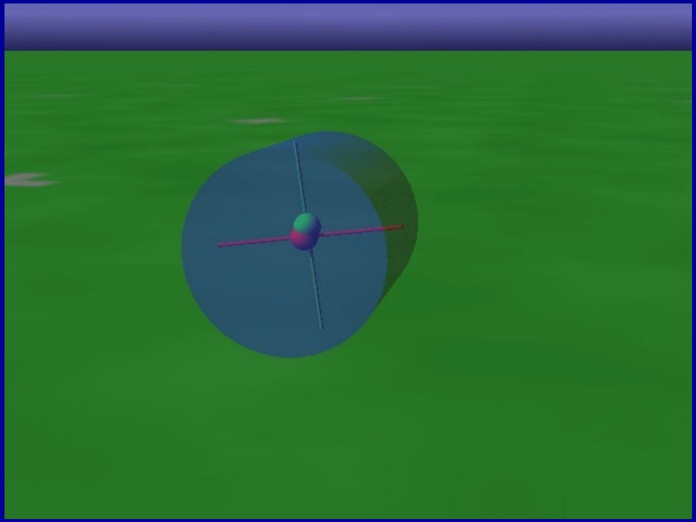
Brain, body and environment form a self-referential dynamical system.



Emergence of sensorimotor coordination in gravity driven machines



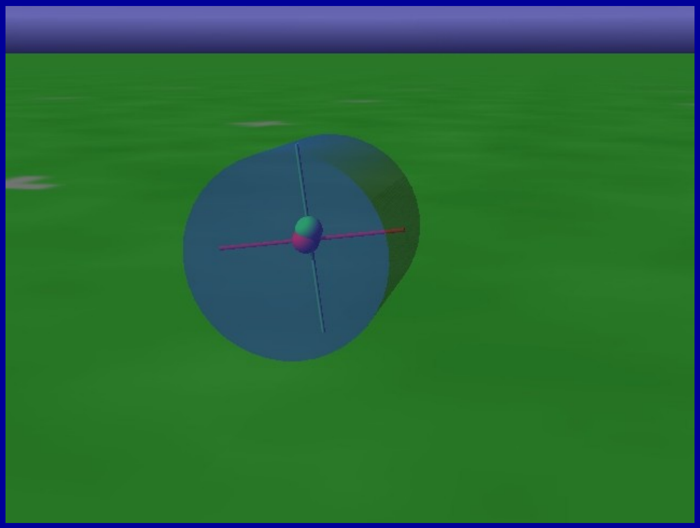


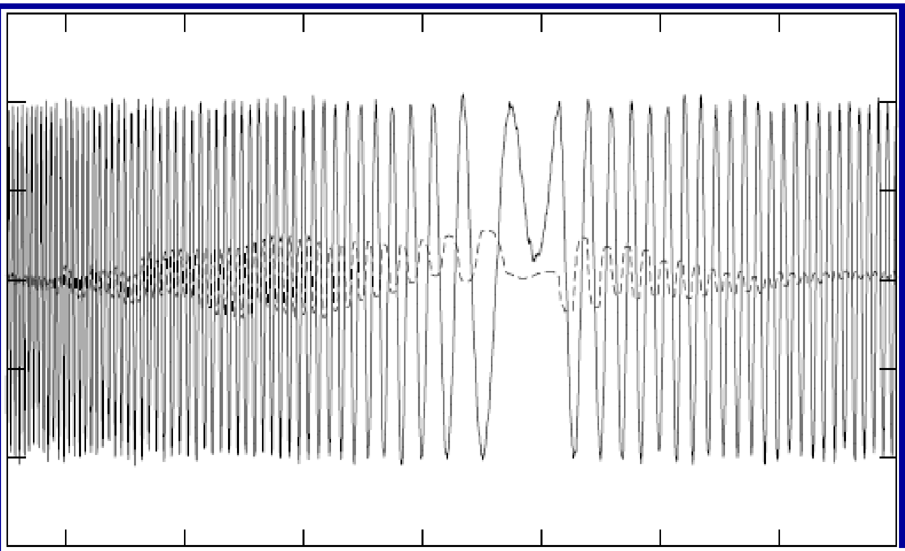


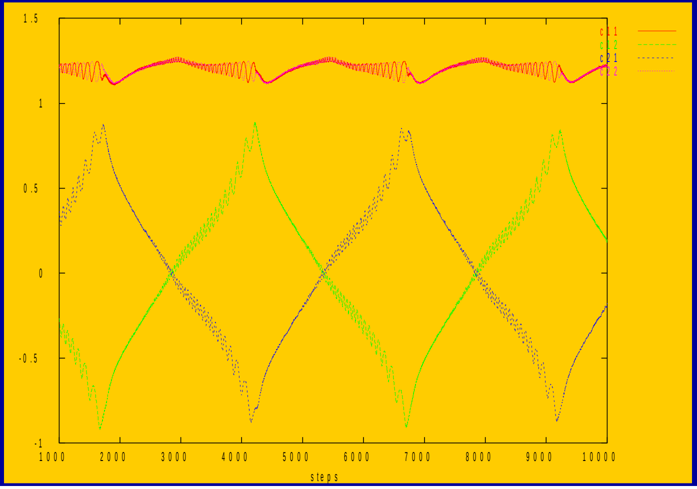
Sensors:

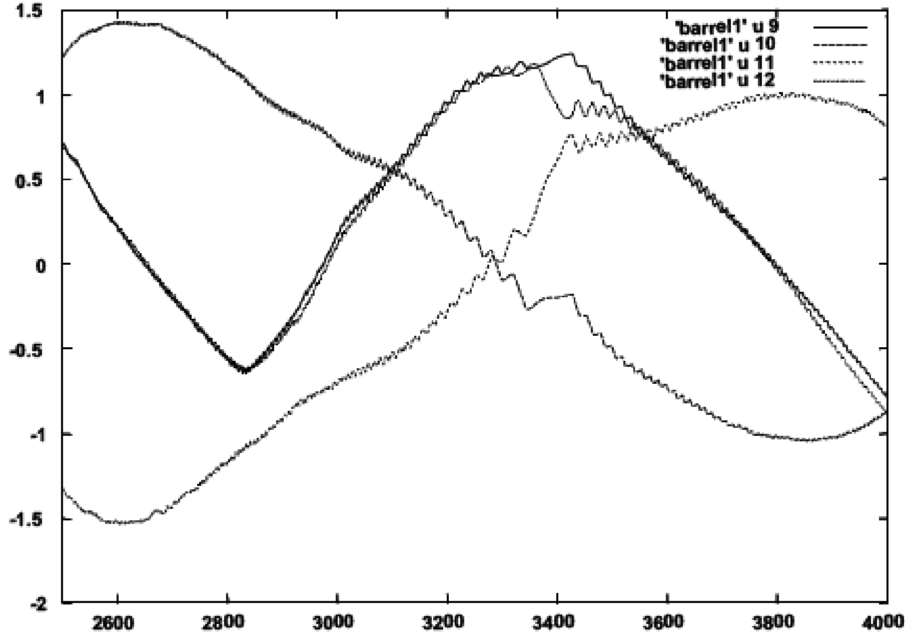
2. Infrared (above)
3. Gyroscope

Embodiment - The barrel bot









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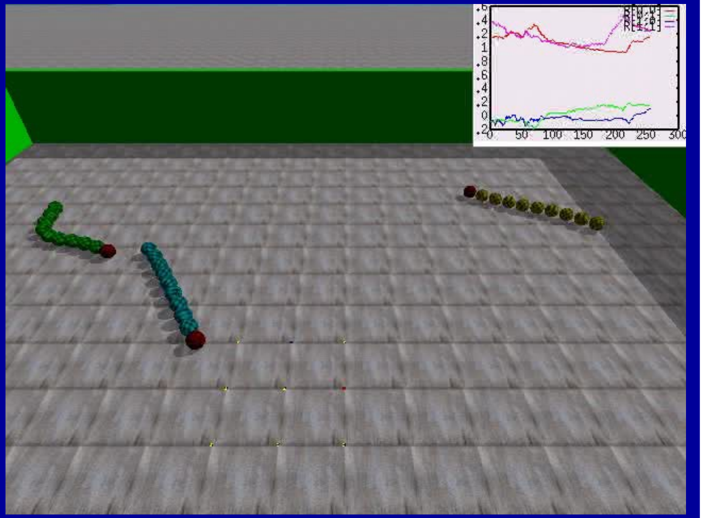
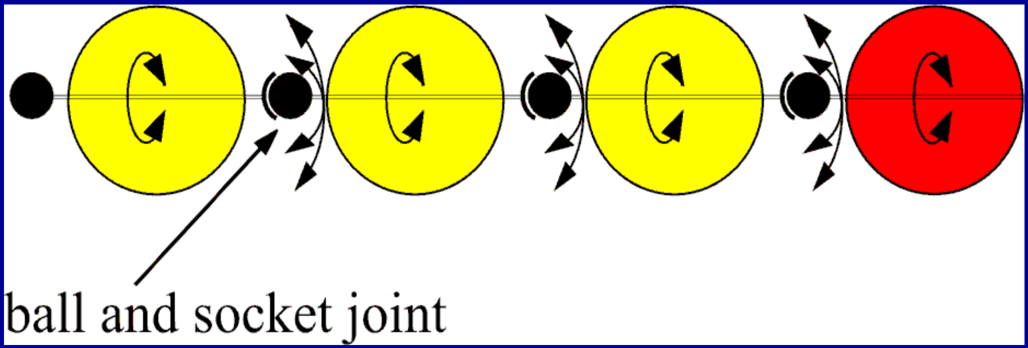
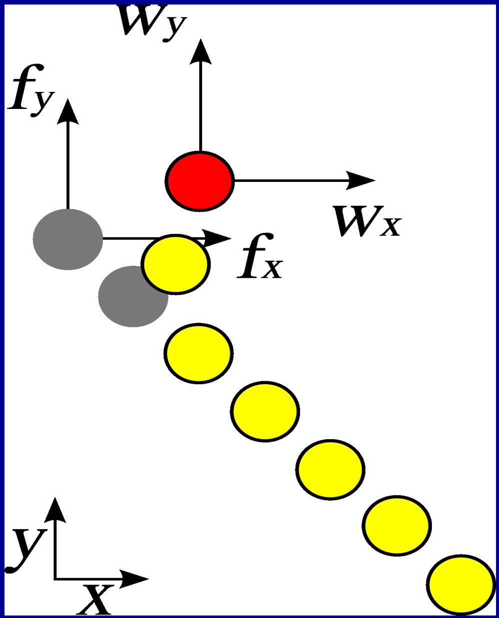
Example – Snake bot I

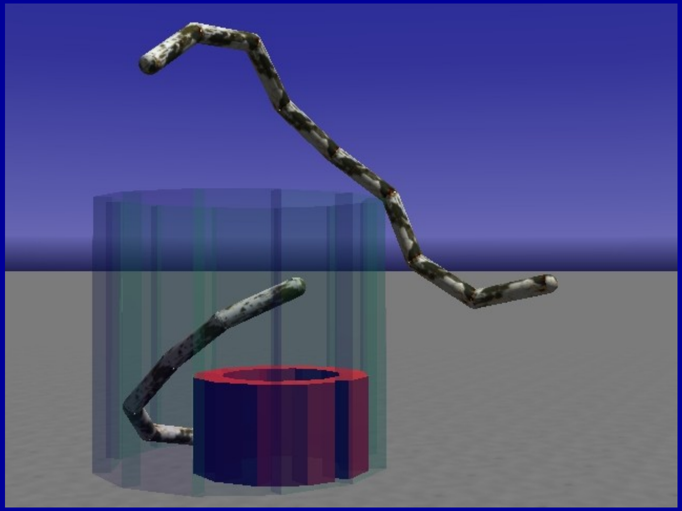


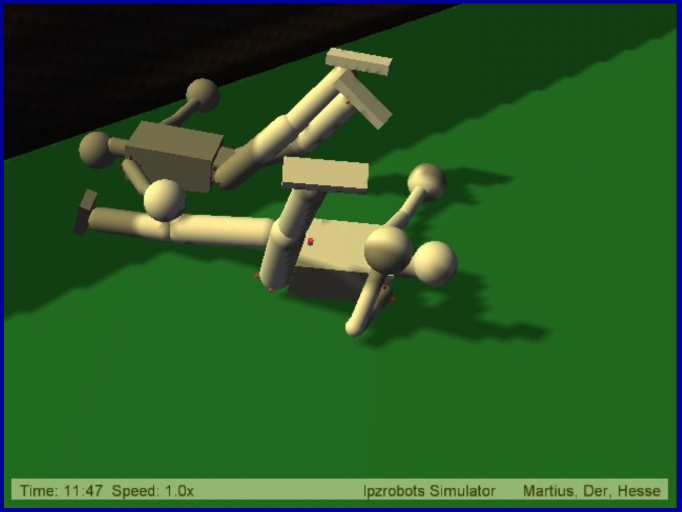
A string of beads with an activated head – a system with two active and many passive degrees of freedom and very complicated physics



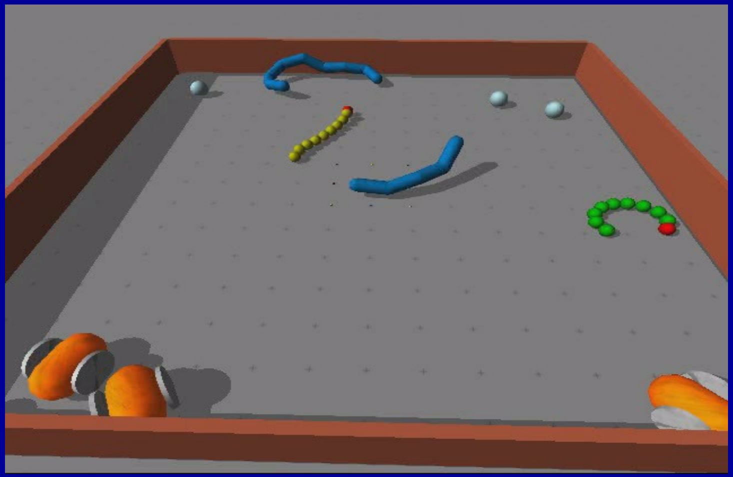


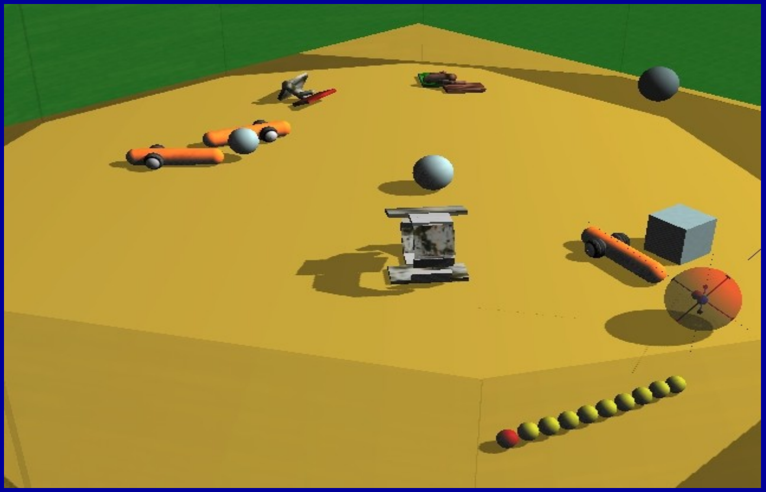
High dimensional robots: Snakes &Co.

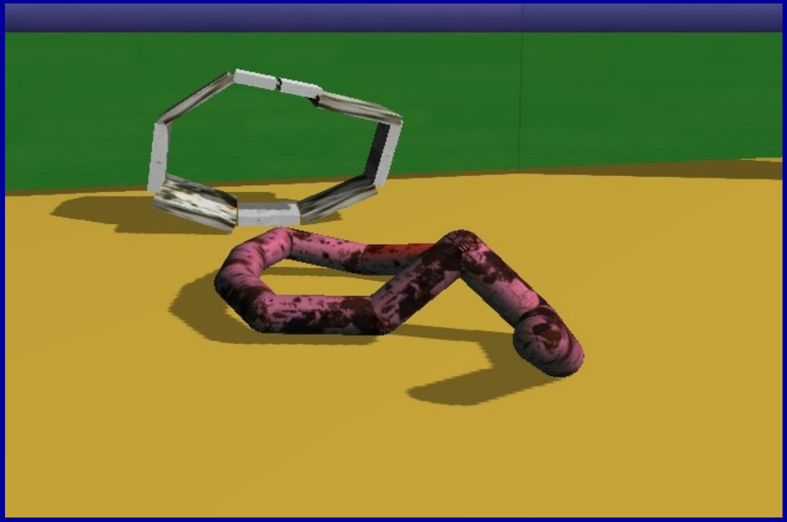




Example – Terra autonomica







All robotic objects are controlled by our „plug-and-play brain" differing only in the number of sensors and motor neurons.

Application –The self-rescue scenario

- Our robots manage to free themselves from various impasse situation.

Take our “brain” as a rescue controller
if a conventional controller
has ridden the robot into an impasse.

Future work: Guided self-organization

- So far the behaviors are without goal, just emerging.
- Self-organisation by the principle of homeokinesis guided by external cues.
- First results: Pirouette mode of the spherical robot, ...
- Enhanced probability for “getting up” of the humanoid robot.

Conclusions

- Starting from scratch, our system bootstraps behavioral self-creation of widely arbitrary robotic systems in unknown, unstructured, and highly dynamic environments.
- A first step in the self-creation of artificial life by self-organization.

- Useful:
  – Developmental robotics → Playful exploration of the bodily affordances of very high-dimensional robotic systems of complicated, widely unknown physics.
  – Self-organization creates a reservoir of potentially useful behaviors in unforeseen situations (self-rescue)

- Further work: Open ended development in a completely autonomous robotic world.

Acknowledgements

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  - [2]Bernstein Center for Computational Neuroscience, Göttingen
  - [1]University Leipzig
  - [3]University of Edinburgh

- Software, videos, and further information on http://robot.informatik.uni-leipzig.de