Central pattern generators for locomotion control:

Mathematical models and experiments with lamprey and salamander robots

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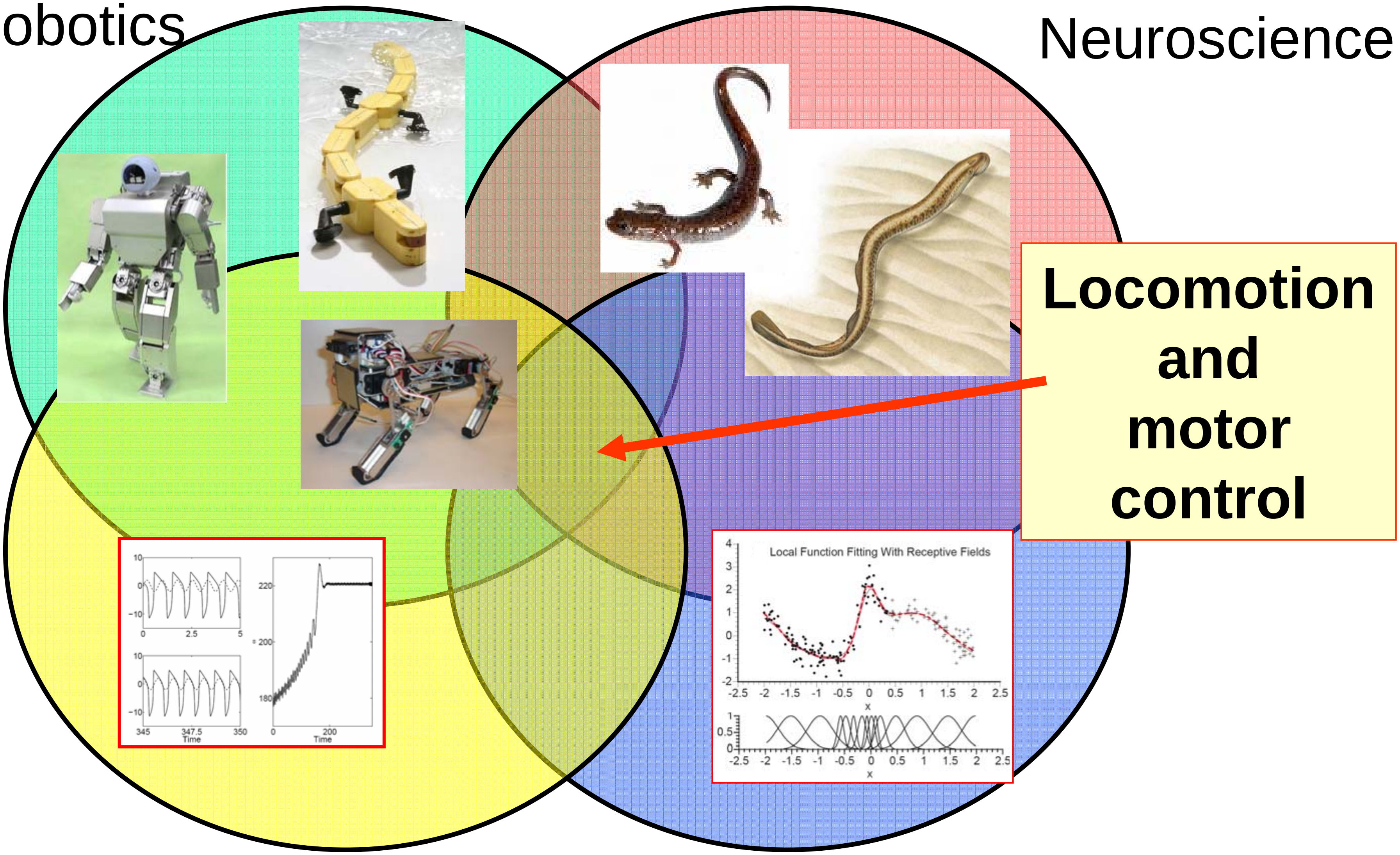
Biologically Inspired Robotics Group (BIRG)

Telluride, July 14 2007

Research interests



Robotics

Neuroscience

Locomotion and motor control

Nonlinear dynamical systems

Applied machine learning

Outline of the talk

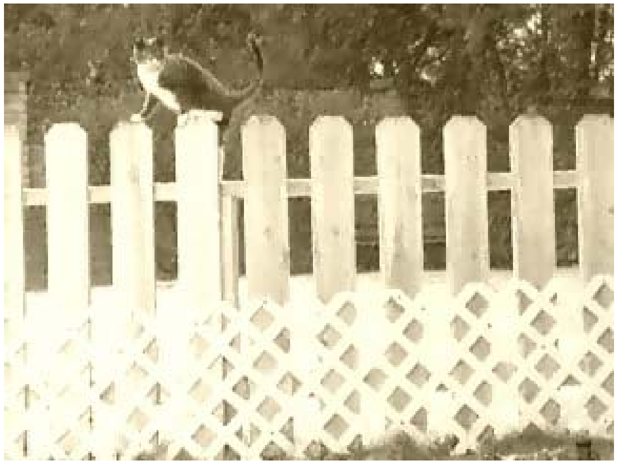
- Central pattern generators (CPGs) in biology
- Modeling the salamander CPG
- Adaptive frequency oscillators
  - Self-tuning CPGs
  - Programmable CPGs
- Online learning in modular robots

What is adaptive movement control?

Coordination of
multiple degrees of freedom

Visuomotor coordination
Switching between motor tasks

Modulation



Learning new skills

Neural control of movement

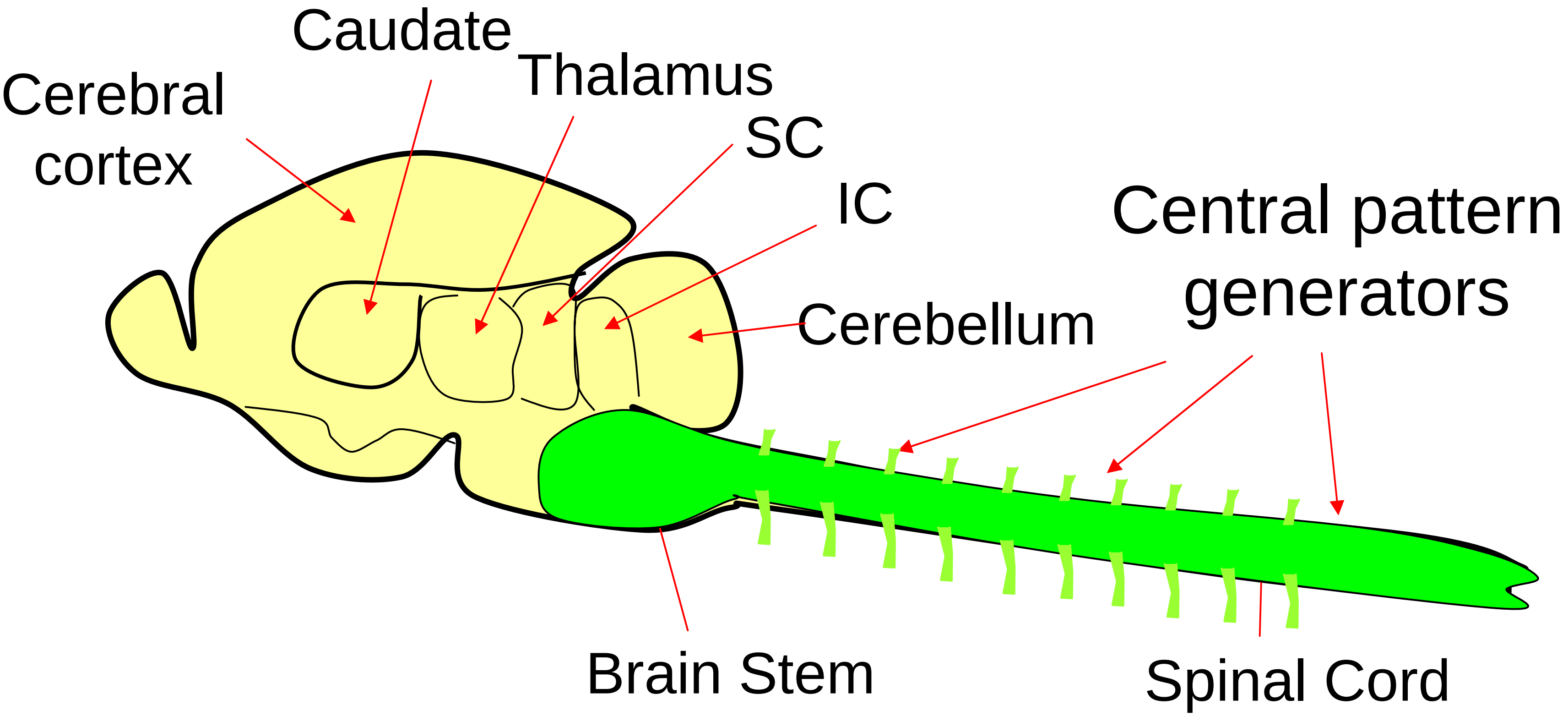
A difficult and « ill-posed » problem:

Requires good coordination (right frequencies, phases, signal shapes,…) of multiple degrees of freedom,

despite the multiple redundancies:

- Many possible end-point trajectories
- Many possible postures for a given end-point
- Many possible muscle activations for a given posture
- Many possible motor unit activations for a given muscle activations

Neural control of movement

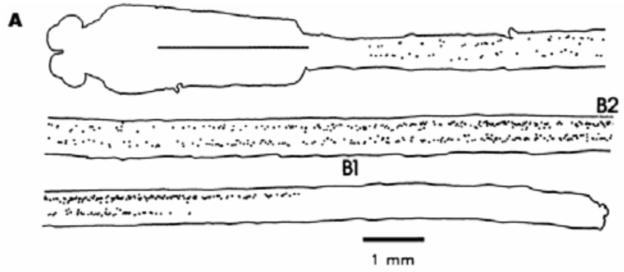


Central pattern generators

- Central pattern generators: neural networks capable of producing oscillatory patterns without oscillatory inputs

- Simple inputs ➔ complex outputs

- Found in many animals: invertebrates and vertebrates (e.g. lamprey)



- Locomotion: CPGs in spinal cord

- Relatively simple control signals from higher control centers to the spinal cord (Shik and Orlosky 1966)
- Distributed system: multiple coupled oscillators, at least one per DOF (Cohen 1980, Grillner 1985)

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Central pattern generators in robotics

BIOLOGICALLY INSPIRED
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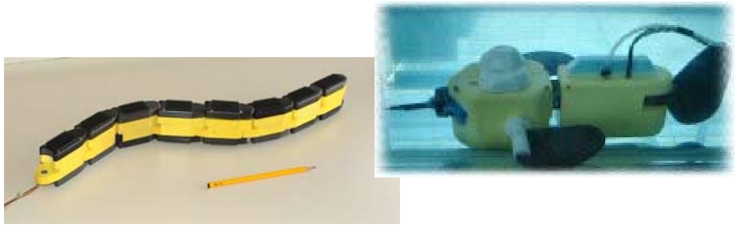
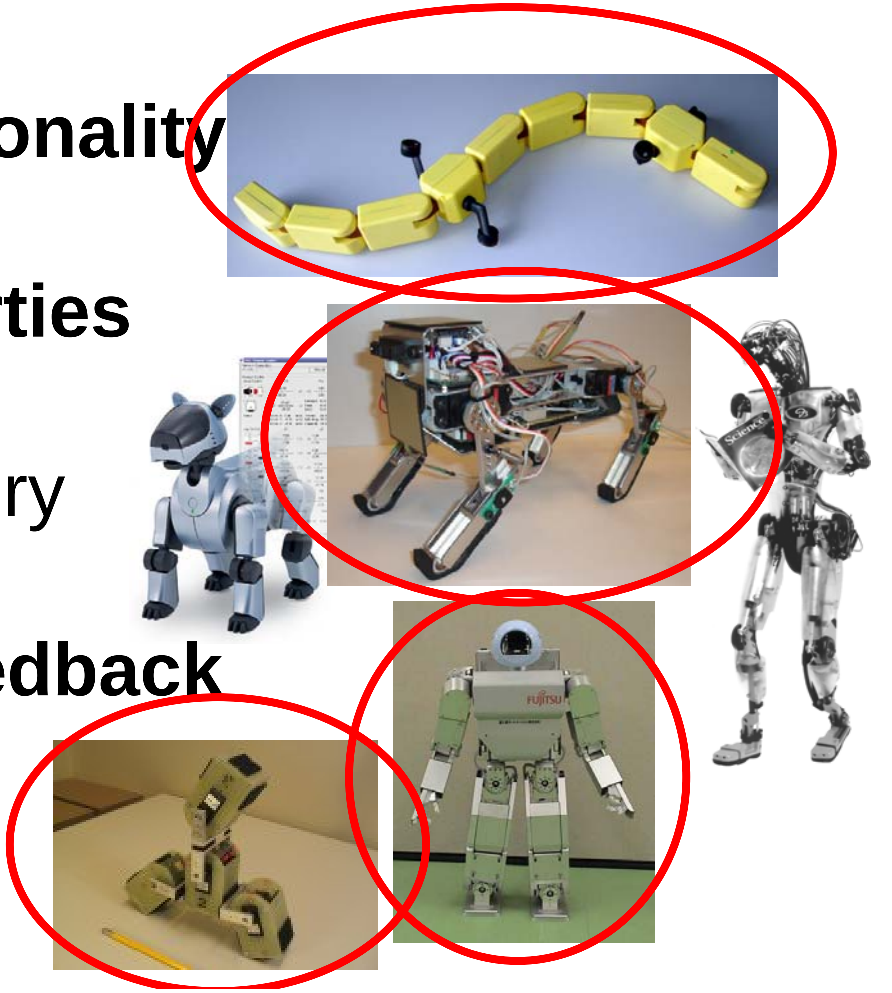
CPG-like controllers can be very useful in robotics:



- **Reduction of the dimensionality** of the control problem
- Interesting **stability properties** (limit cycle behavior)
- **Modulation** (online trajectory generation)
- **Integration of sensory feedback**



Outline of the talk

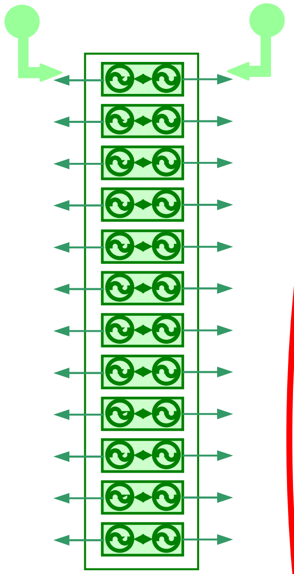
- Central pattern generators (CPGs) in biology
- **Modeling the salamander CPG**
- Adaptive frequency oscillators
  - Self-tuning CPGs
  - Programmable CPGs
- Online learning in modular robots

Work done in collaboration with

- Alessandro Crespi (EPFL)
- Jean-Marie Cabelguen (Univ. Bordeaux I and INSERM)
- Dimitri Ryczko (Univ. Bordeaux II)
- André Guignard (EPFL)
- André Badertscher (EPFL)

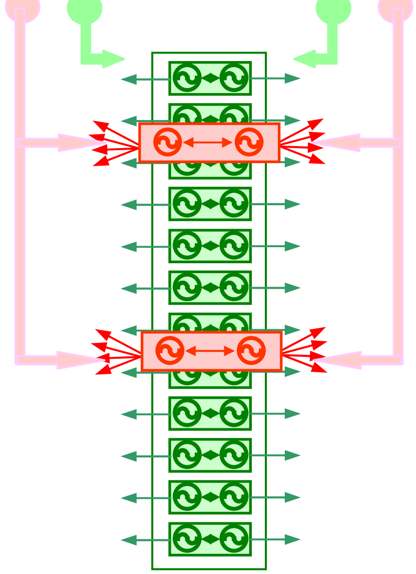
Models of locomotion control

Lamprey



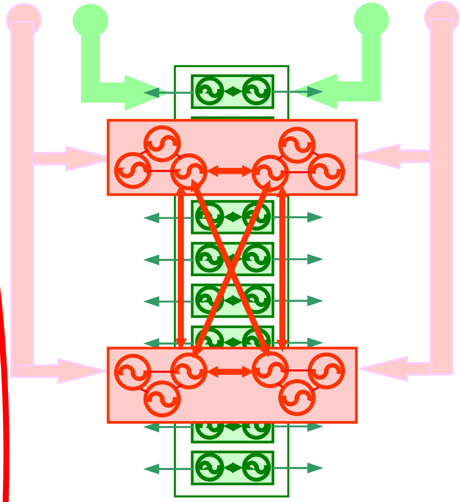
Ijspeert et al,
Adaptive Behavior 1999

Salamander



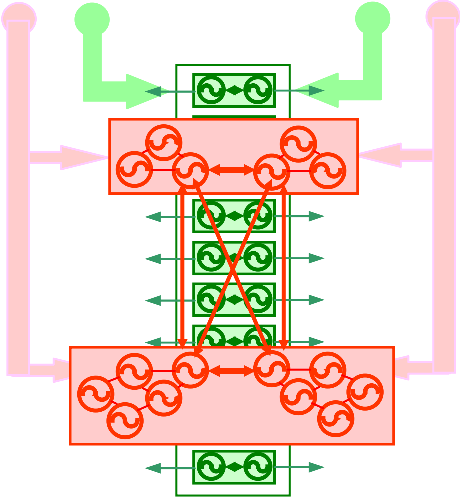
Ijspeert et al,
Science. 2007

Cat



Buchli & Ijspeert,
Proc. BioADIT 2004

Human



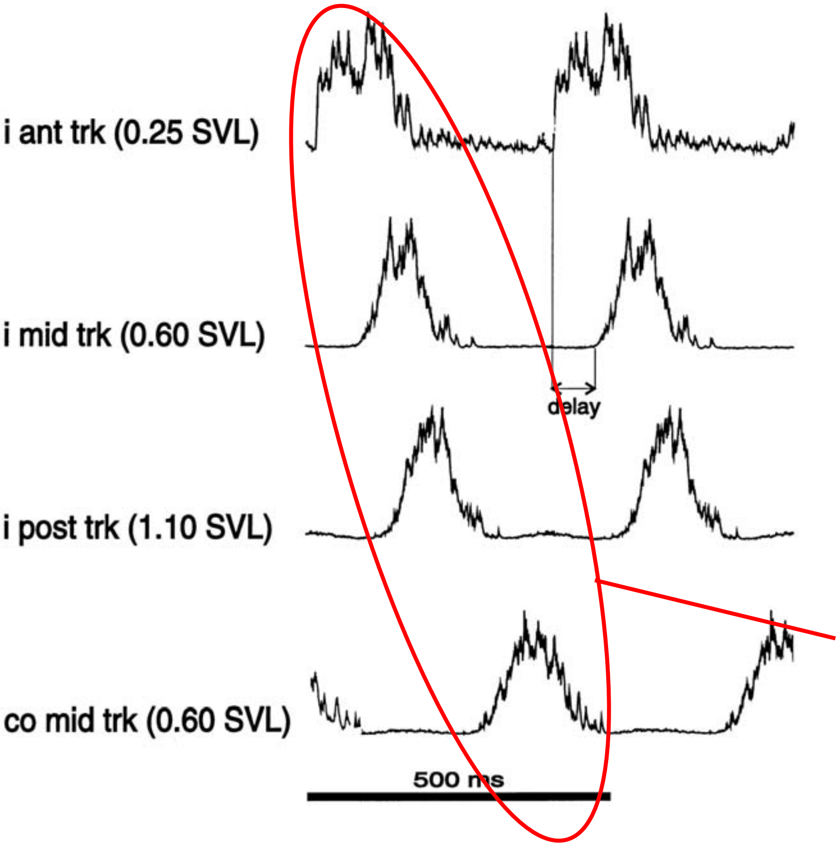
Why modeling/studying salamanders?

1. Interesting bimodal locomotion (swimming + walking)
2. Its body plan has changed little over 150 million years (Gao & Shubin, Nature, 2002). Key animal to study the transition from aquatic to terrestrial locomotion during evolution.
3. Link between research on lamprey and tetrapod locomotion.

Gao & Shubin, 2002

Aquatic locomotion

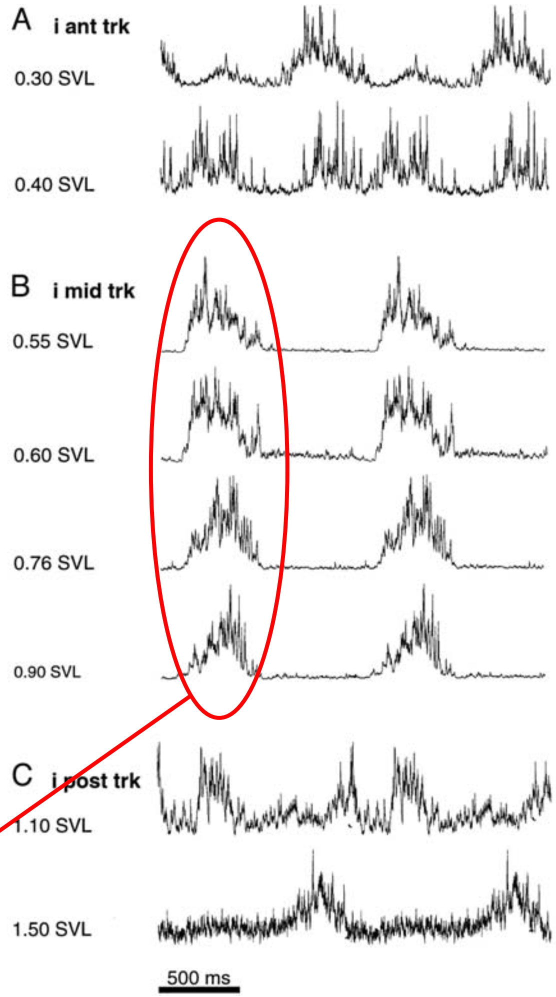
(Frolich 1992, Delvolvé 1997, Ashley-Ross 2004):
Traveling wave during swimming, (anguilliform swimming)



Traveling wave during swimming,
Wavelength = approx one body length

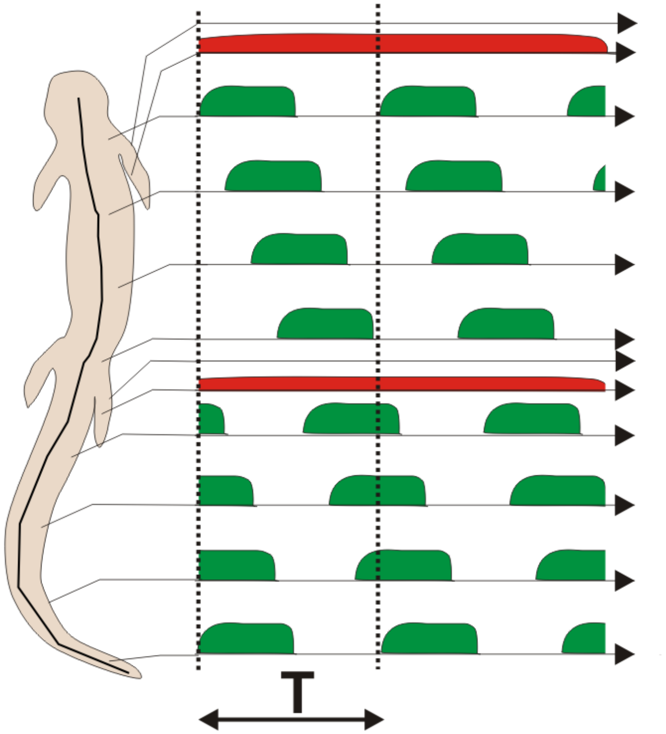
Terrestrial locomotion

Standing wave during trotting



Perfect synchrony in the trunk

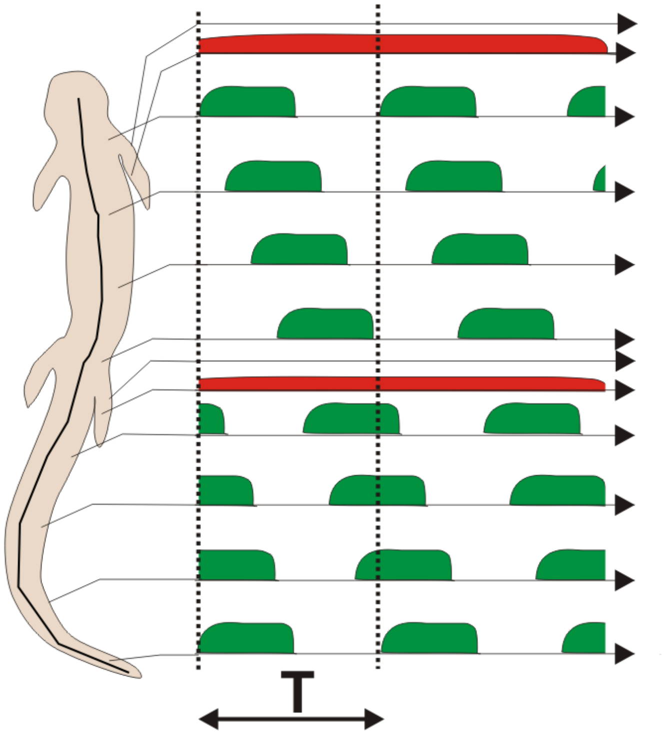
Biomodal locomotion (cartoon)

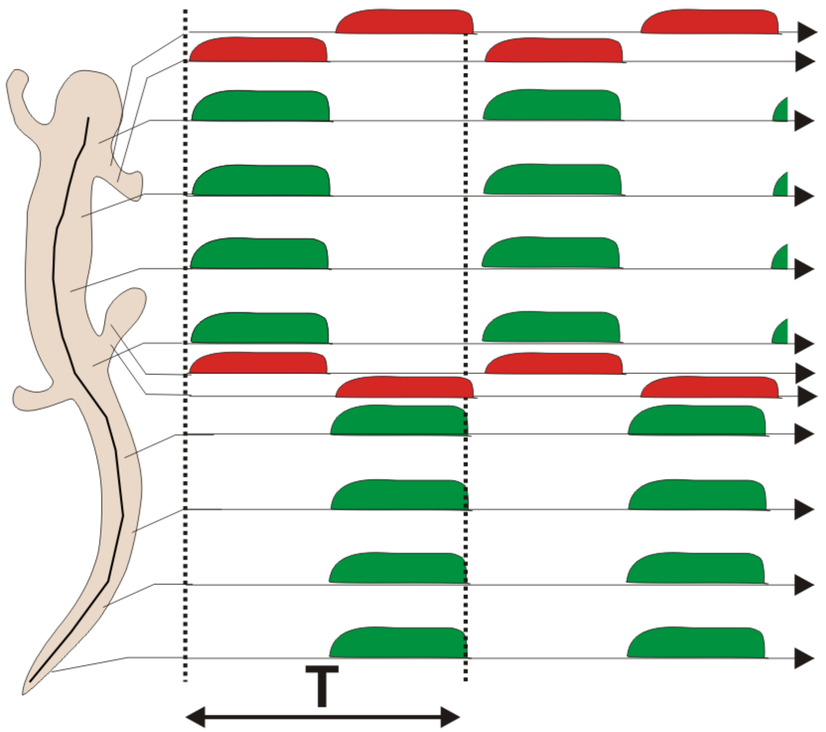


Swimming:

- Traveling wave in axial muscles
- Wavelength = body length
- Limb retractors are tonic
- Short cycle durations

Biomodal locomotion (cartoon)





Swimming:
- Traveling wave in axial muscles
- Wavelength = body length
- Limb retractors are tonic
- Short cycle durations

Walking:
- Standing wave
- Limb retractors/protactors are phasic
- Longer cycle durations

Questions:

1. Which type of neural networks can produce the observed bimodal locomotion, in particular the traveling waves for swimming and standing waves for walking?

2. Can a « lamprey network » be modified to control both swimming and walking?

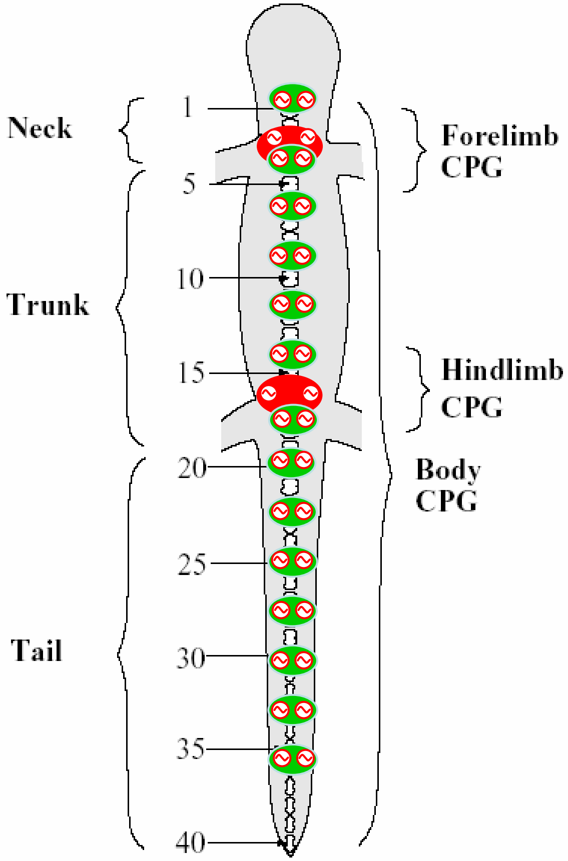
3. What are the mechanisms underlying gait transition? In particular, the automatic transition with MLR stimulation?

4. Why are walking frequencies always lower than swimming frequencies?

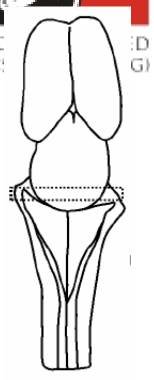
Ijspeert A.J., Crespi A., Ryczko D., Cabelguen J.-M. , *Science*, Vol. 315., pp. 1416-1420, 2007
Ijspeert A.J., Crespi A., Cabelguen J.-M., *Neuroinformatics*, 3:3, pp 171-195, 2005.
Ijspeert A.J., *Biological Cybernetics*, 84:5, pp 331-348, 2001.

Biological data on salamander CPG

- Locomotion controled by a spinal Central Pattern Generator (Delvolvé et al 1999)
- The CPG is distributed along the spinal cord
- Localized limb neural oscillatory centers (Szekely et al 1976), with independent flexor and extensor centers (Cheng et al 1998)
- Locomotion and gait transition can be induced by electrical stimulation of the MLR

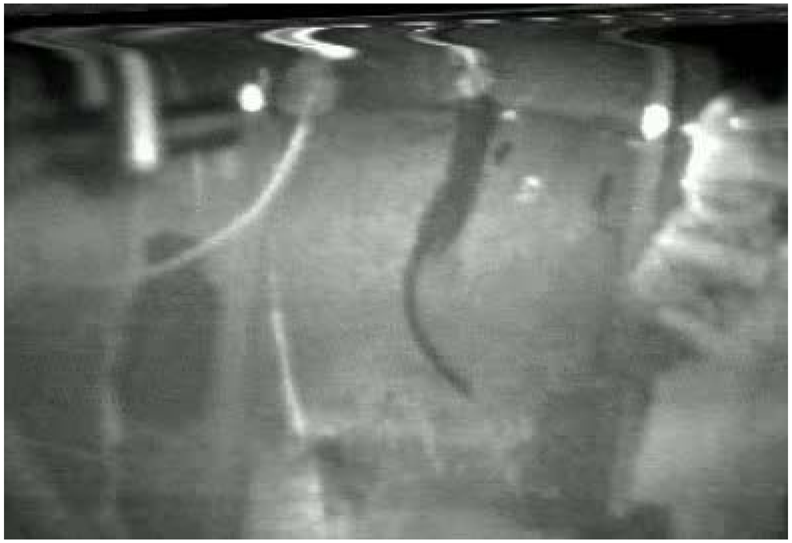


Stimulation of MLR



MLR: Mesencephalic Locomotor Region
Cabelguen et al, Journal of Neuroscience, 23 (6), 2003

Low current stimulation: **(slow) stepping**



Larger current stimulation: **(fast) swimming**

Latest model based on phase oscillators

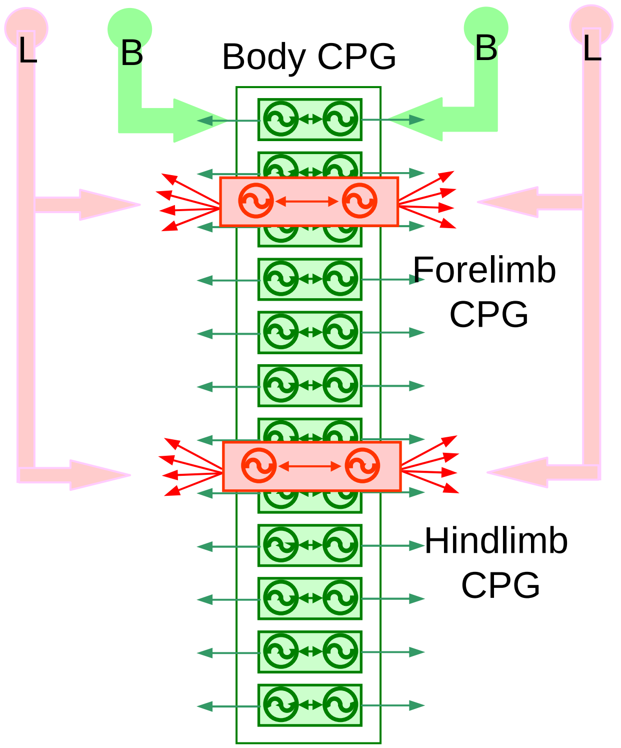
- System of coupled amplitude-controlled phase oscillators
- Suitable both for biological modeling and for a robotic implementation

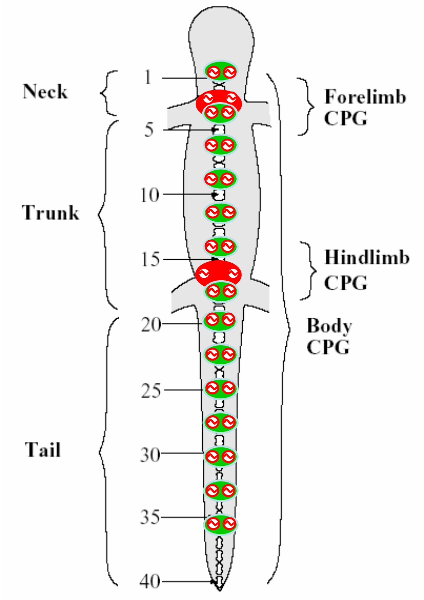
- Explains:
    - Control of speed, direction, and type of gait
    - **Automatic gait transition** from walking to swimming with MLR stimulation
    - **Why swimming frequencies are systematically higher than walking frequencies**

From swimming to walking with a salamander robot driven by a spinal cord model, A. J. Ijspeert, A. Crespi, D. Ryczko, J.-M. Cabelguen, *Science*, Vol. 315. no. 5817, pp. 1416 - 1420, 2007

Hypotheses underlying the latest model

- Hypothesis 1: The isolated **body CPG is lamprey-like** and spontaneously produces traveling waves when activated with a tonic drive. The **limb CPG, when activated, forces the whole CPG into the walking mode**.





Hypotheses (continued)

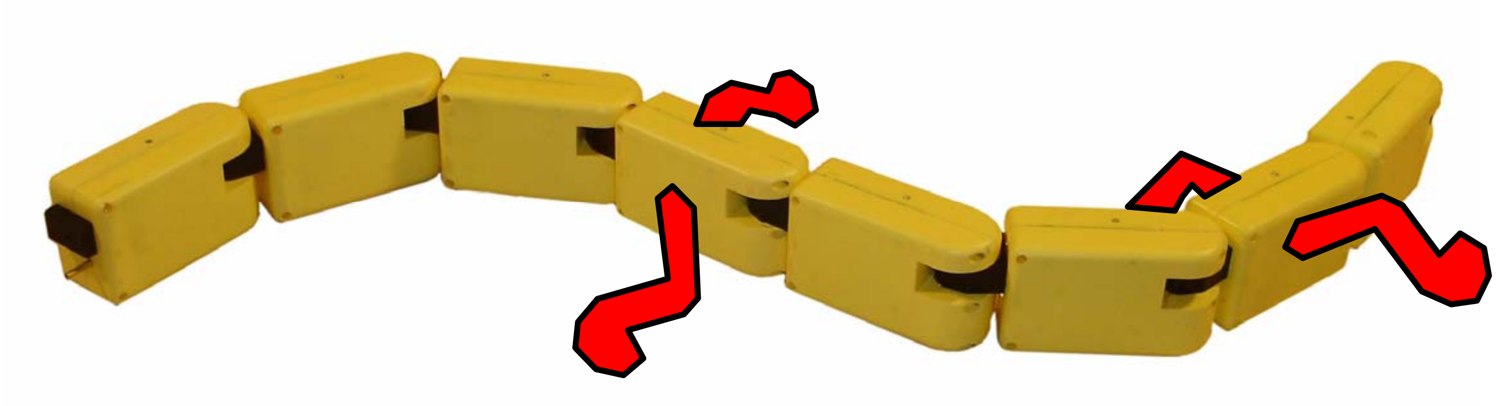
- Hypothesis 2: the strengths of the **couplings from limb to body oscillators are stronger** than those from body to body oscillators and from body to limb oscillators.

- Hypothesis 3: **Limb oscillators can not oscillate at high frequencies**, that is, they saturate and stop oscillating at high levels of tonic drive.

- ~~Hypothesis 4: For the same tonic drive, **limb oscillators have lower intrinsic frequencies** than the body oscillators.~~

Observation

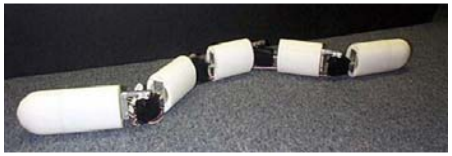
From a lamprey robot to a salamander robot



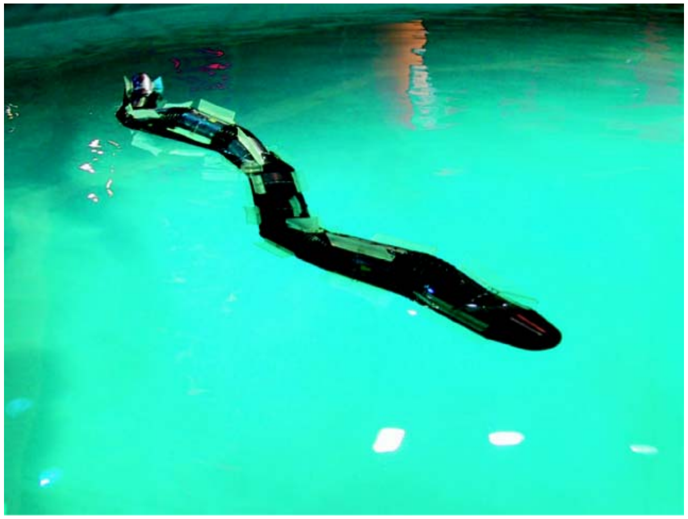
Snake robots: related work

Polychaete-like robot
(Sfakiotakis et al.)

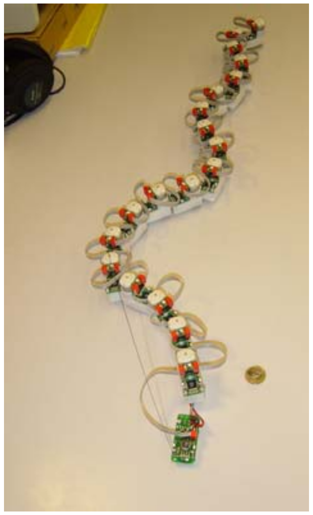
Lamprey robot
(Ayers et al.)



REEL II
(McIsaac and Ostrowski)



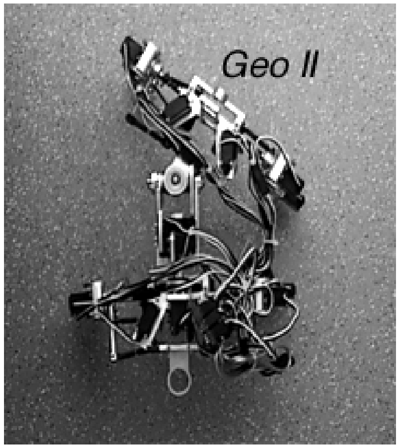
Helix-I + ACM-R5
(Hirose et al.)



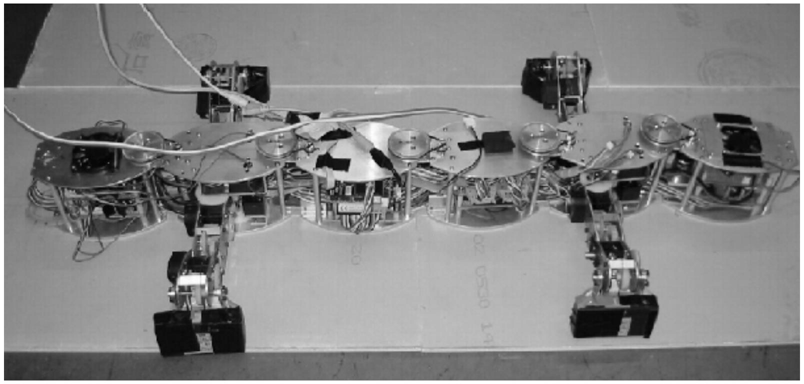
WormBot
(Conradt and
Varshavskaya)

Lamprey robot
(Arena et al.)

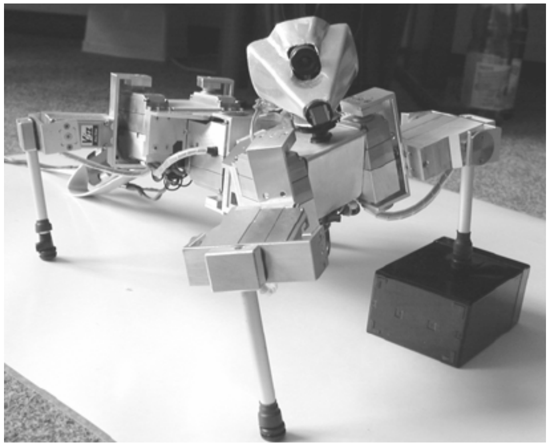
Salamander robots: related work



Geo, Tony Lewis

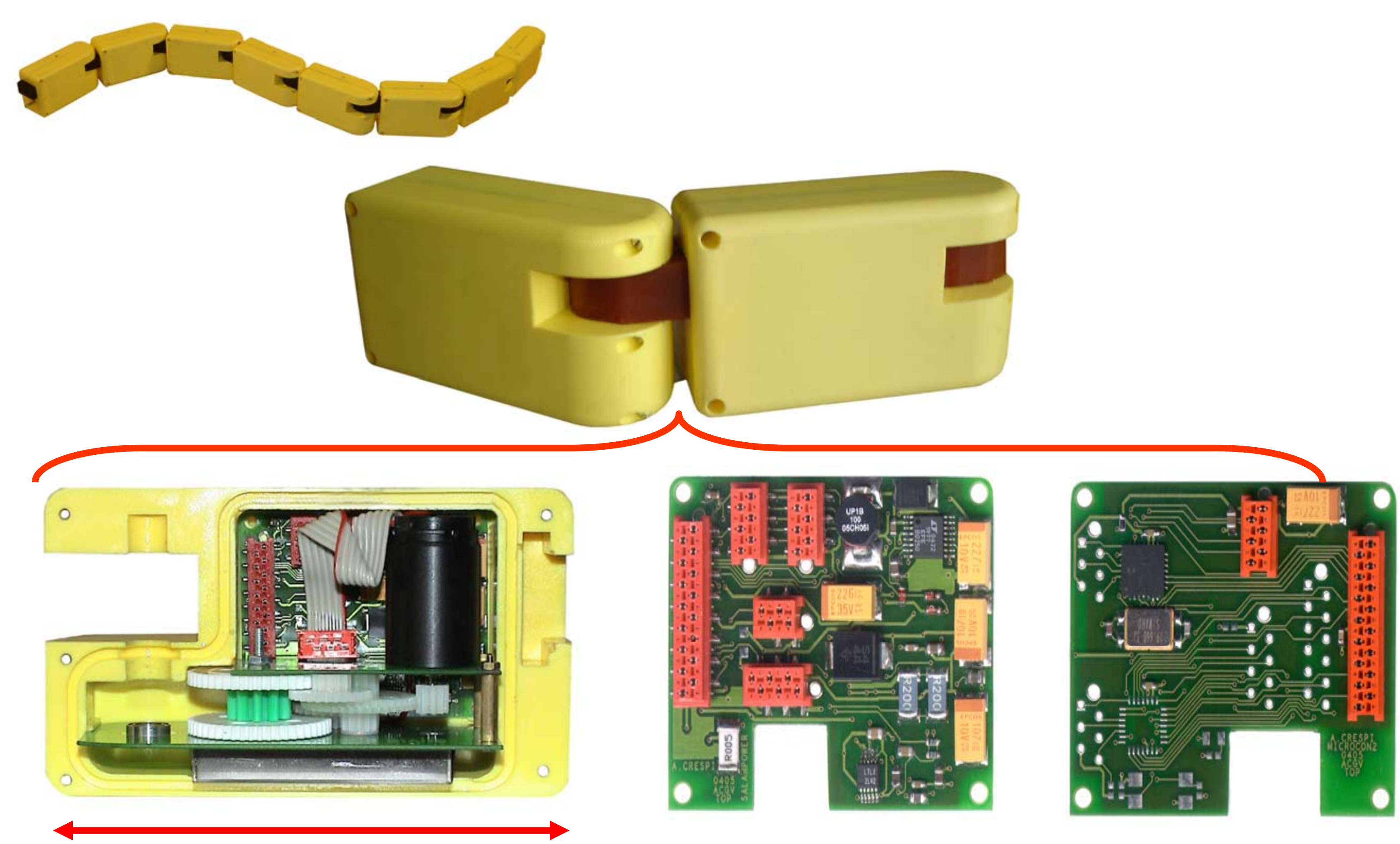


Salamander robot, Hiraoka and Kimura



Robo-salamander, Breithaupt

Amphibot II



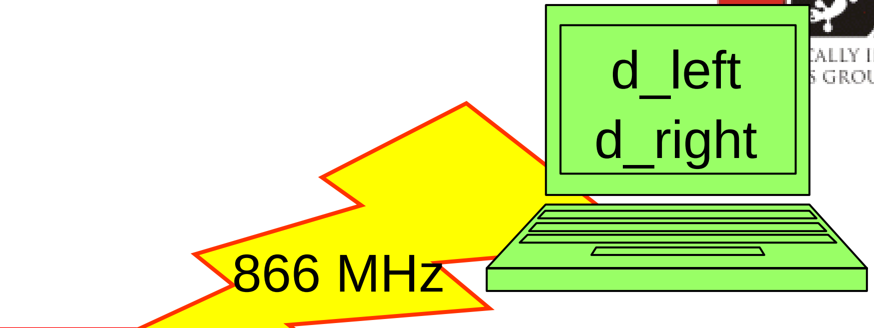
Crespi A. *et al*, Robotics and Autonomous Systems, 2004.
Crespi A. *et al*, ICRA2005, Ijspeert and Crespi, ICRA 2007

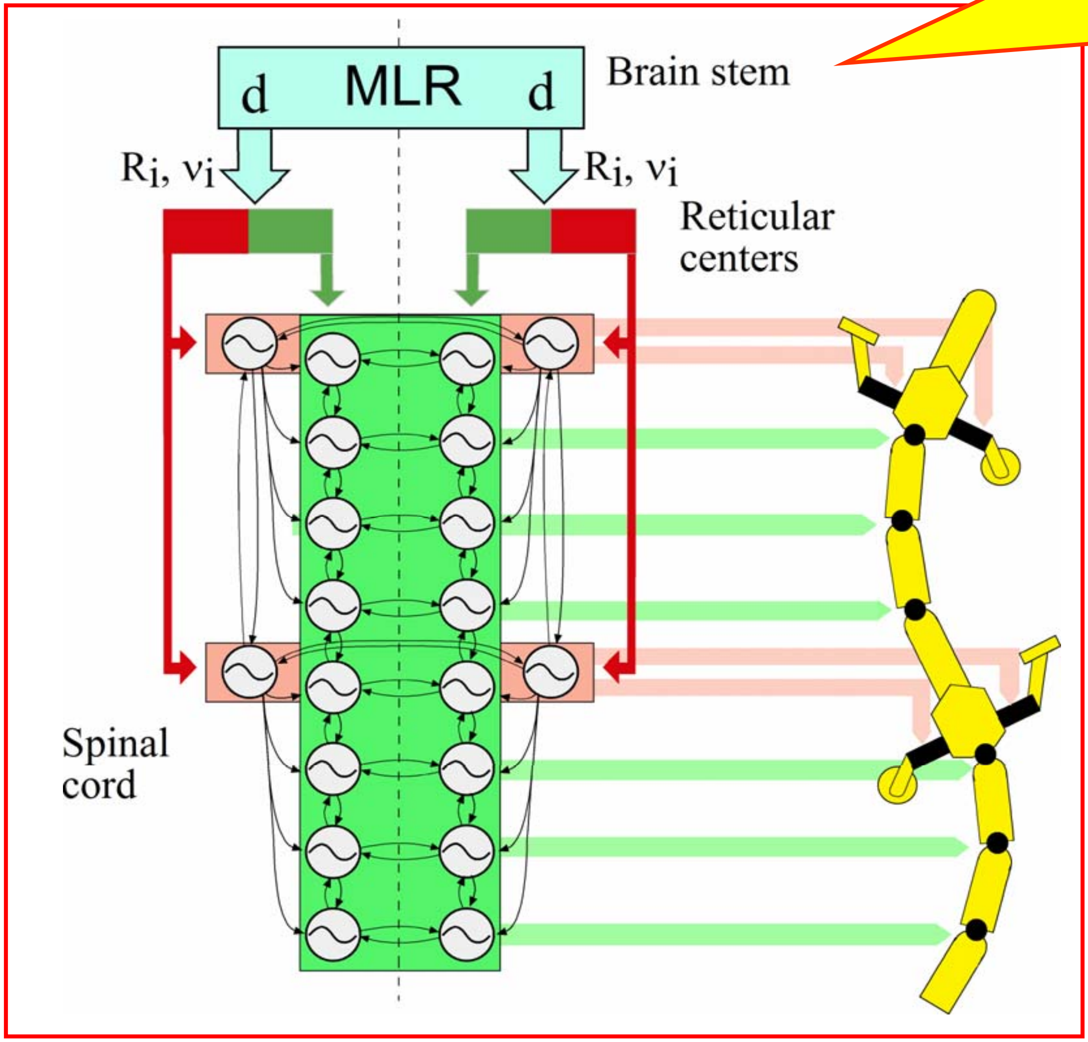
Example

From
serpentine locomotion
to
anguilliform swimming

Ijspeert and Crespi, ICRA 2007

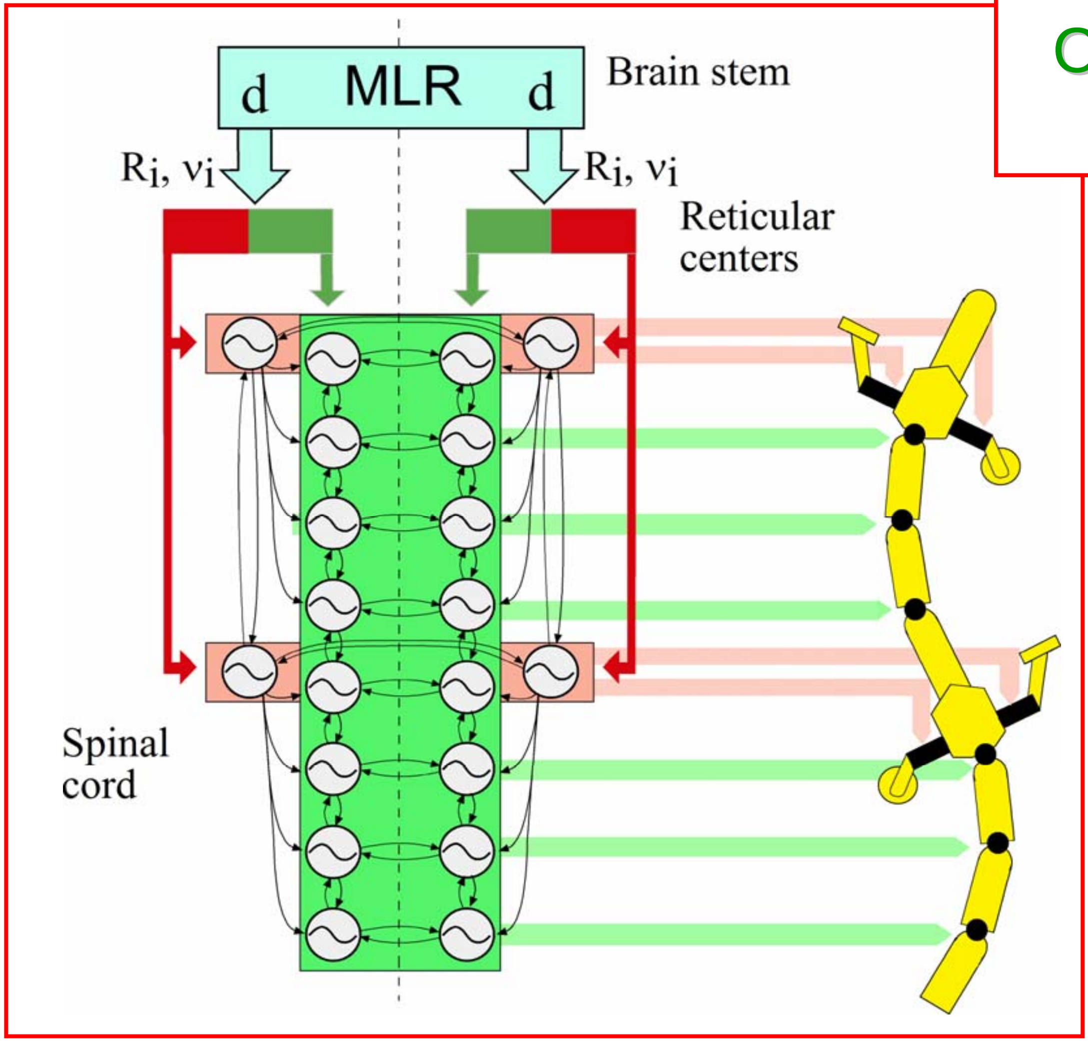
CPG and robot

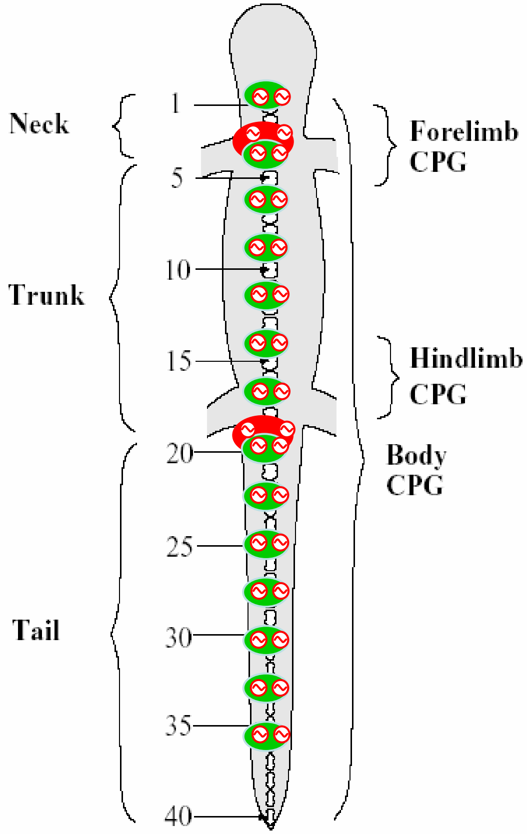




New model: CPG configuration

Hyp. 1: Lamprey-like body CPG extended with a limb CPG





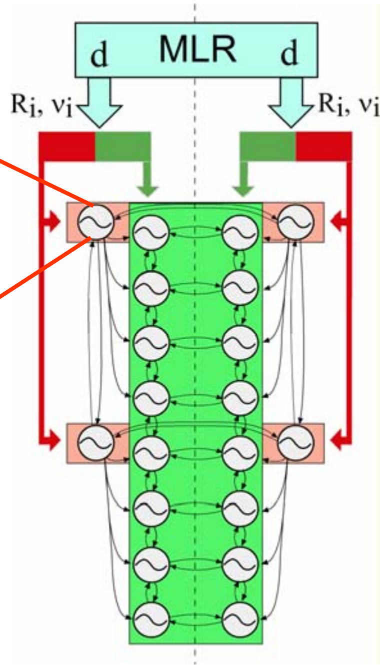
Oscillator model

- A segmental oscillator is modeled as an amplitude-controlled phase (Kuramoto-like) oscillator (e.g. Cohen et al 1982):

Phase: $$\dot{\theta}_i = 2\pi \nu_i + \sum_j r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})$$

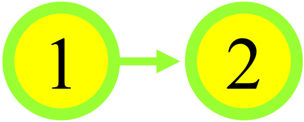
Amplitude: $$\ddot{r}_i = a_i \left(\frac{a_i}{4}(R_i - r_i) - \dot{r}_i \right)$$

Output: $$x_i = r_i(1 + \cos(\theta_i))$$



Setpoints: $$\varphi_i = x_i - x_{N+i}$$

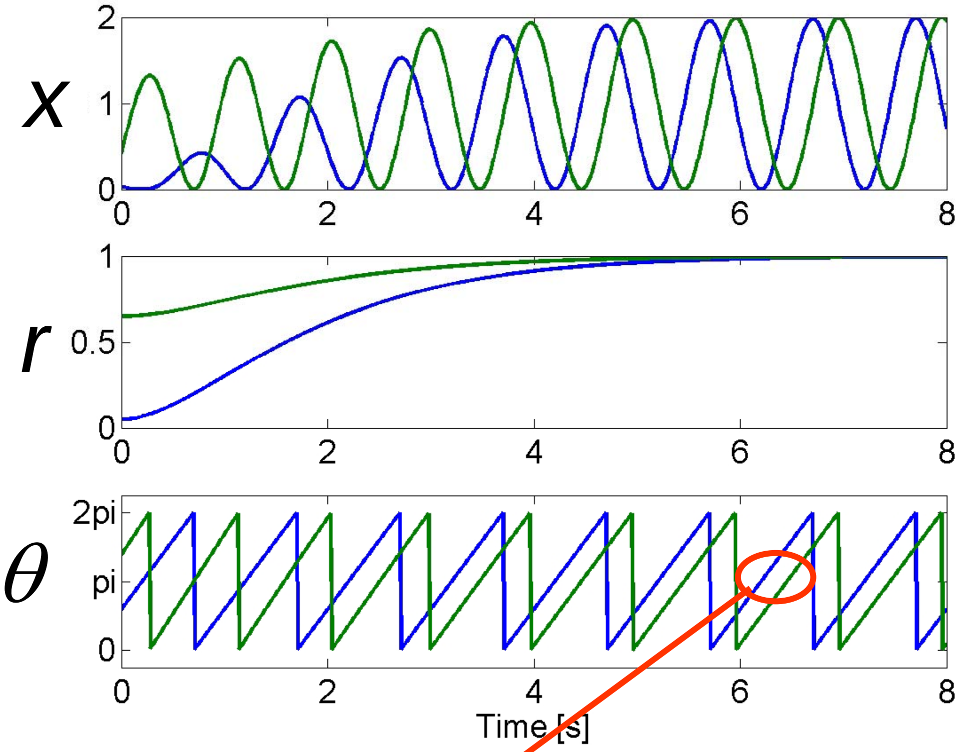
Example with two oscillators



$$\dot{\theta}_i = 2\pi\nu_i + \sum_j \left(r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij}) \right)$$

$$\ddot{r}_i = a_i \left(\frac{a_i}{4}(R_i - r_i) - \dot{r}_i \right)$$

$$x_i = r_i(1 + \cos(\theta_i))$$



The phase difference $\phi = \theta_1 - \theta_2$ between two oscillators converges to

$$\phi_\infty = \arcsin\left(\frac{2\pi(\nu_1 - \nu_2)}{R_1 w_{21}}\right) - \phi_{21}$$

Oscillator model: saturation function

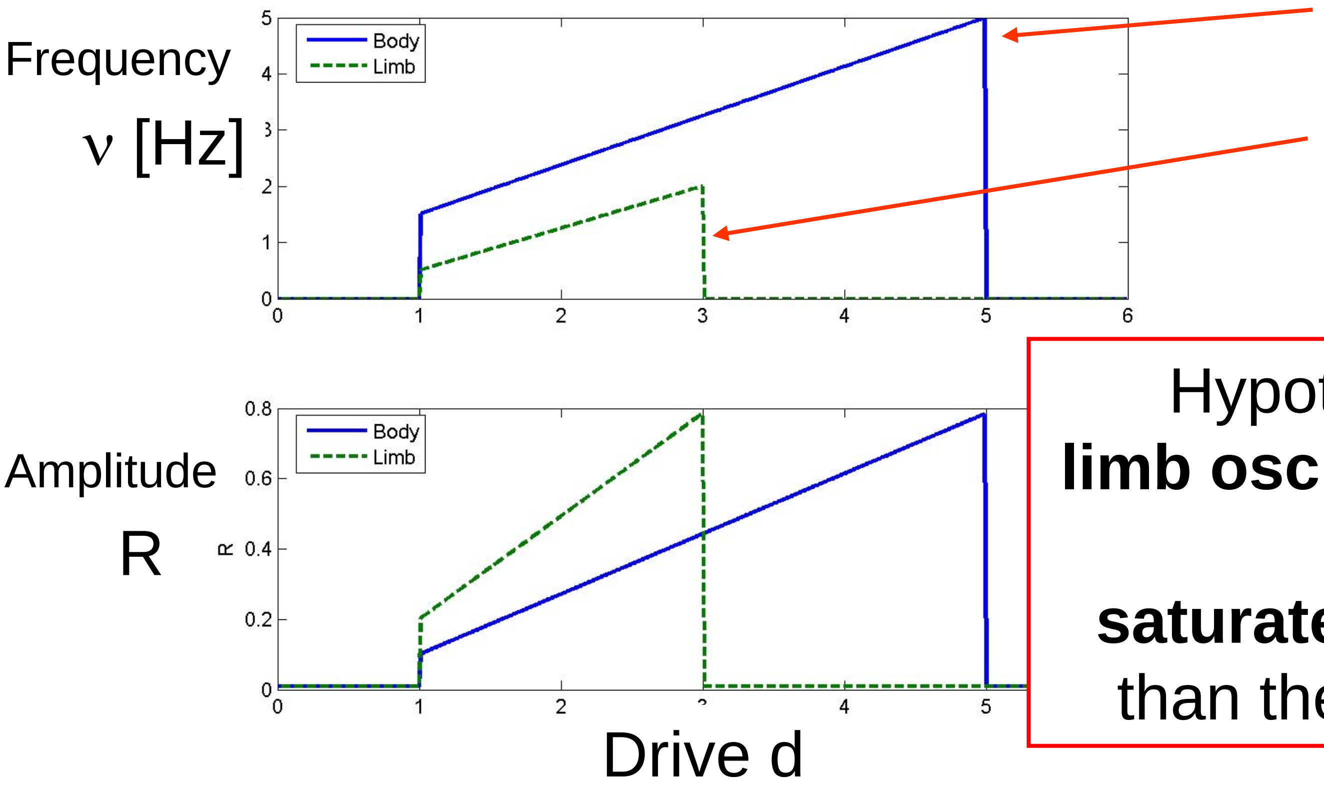
- This simple model has independent (and explicit) parameters for the intrinsic frequency ν_i and the amplitude of oscillators R_i of each oscillatory center *i*

- *But **real oscillatory centers** produce oscillatory bursts in which **frequency and amplitude are correlated**, and which are **limited to specific frequency ranges***

- ➔ we introduce a *saturation function*

Oscillator model: saturation function

- The oscillators are controlled by a **tonic drive *d*.** Both the frequency and the amplitude of the oscillations linearly increase with *d* between a lower and upper threshold:

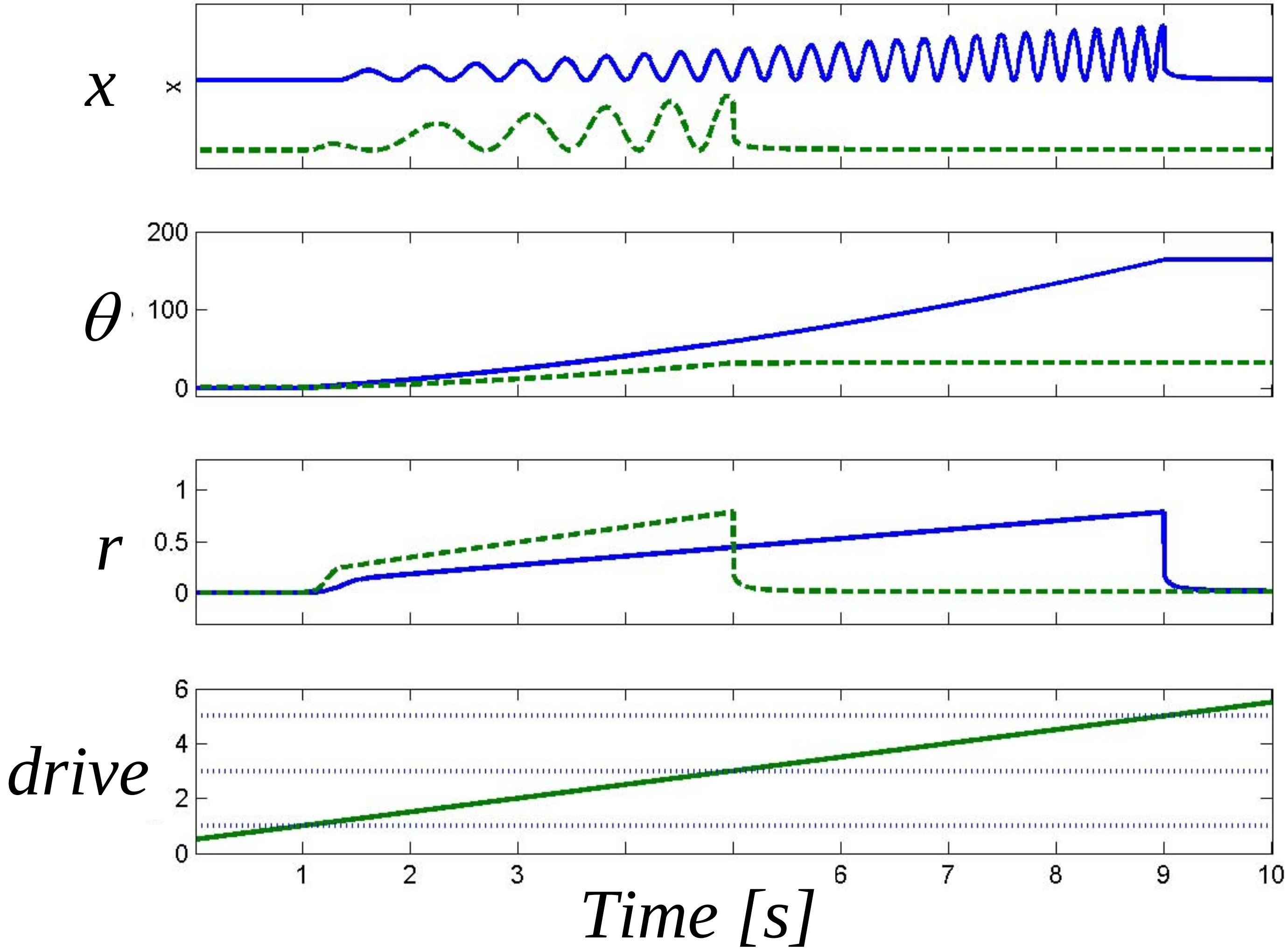


Body oscillator

Limb oscillator

Hypotheses 3 and 4:
limb oscillators are slower
and
saturate at a lower drive
than the body oscillators

Sweep of the drive signal

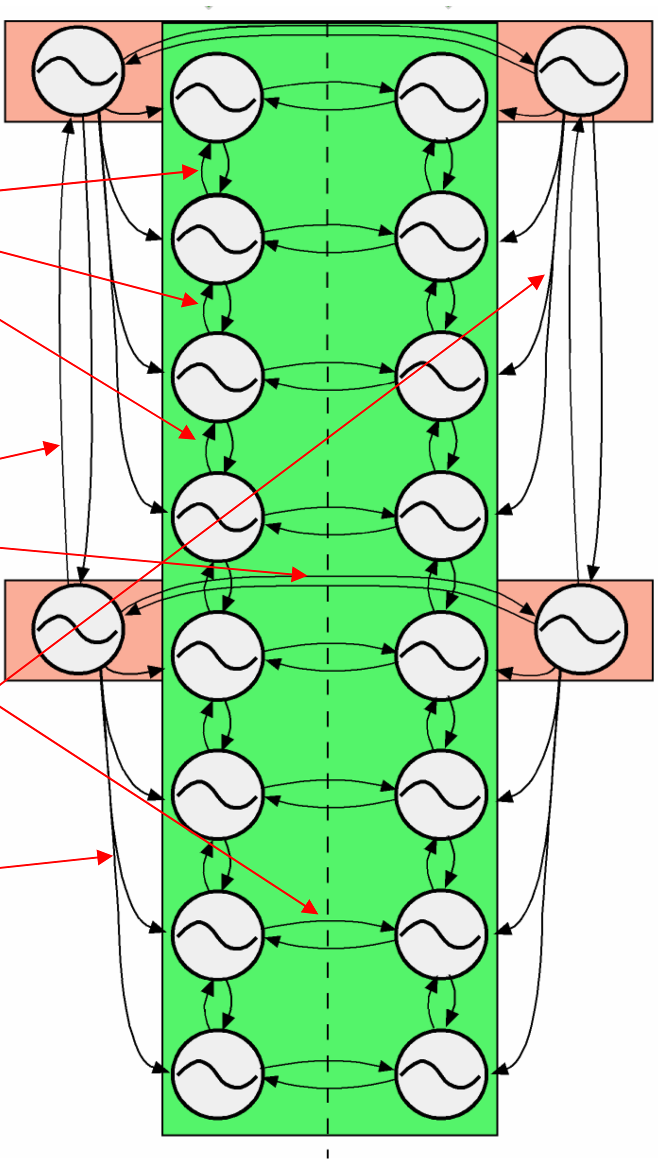


Body oscil.
0.5 - 1.3 Hz

Limb oscil.
0.2 - 0.6Hz

CPG couplings

The couplings are defined as follows:



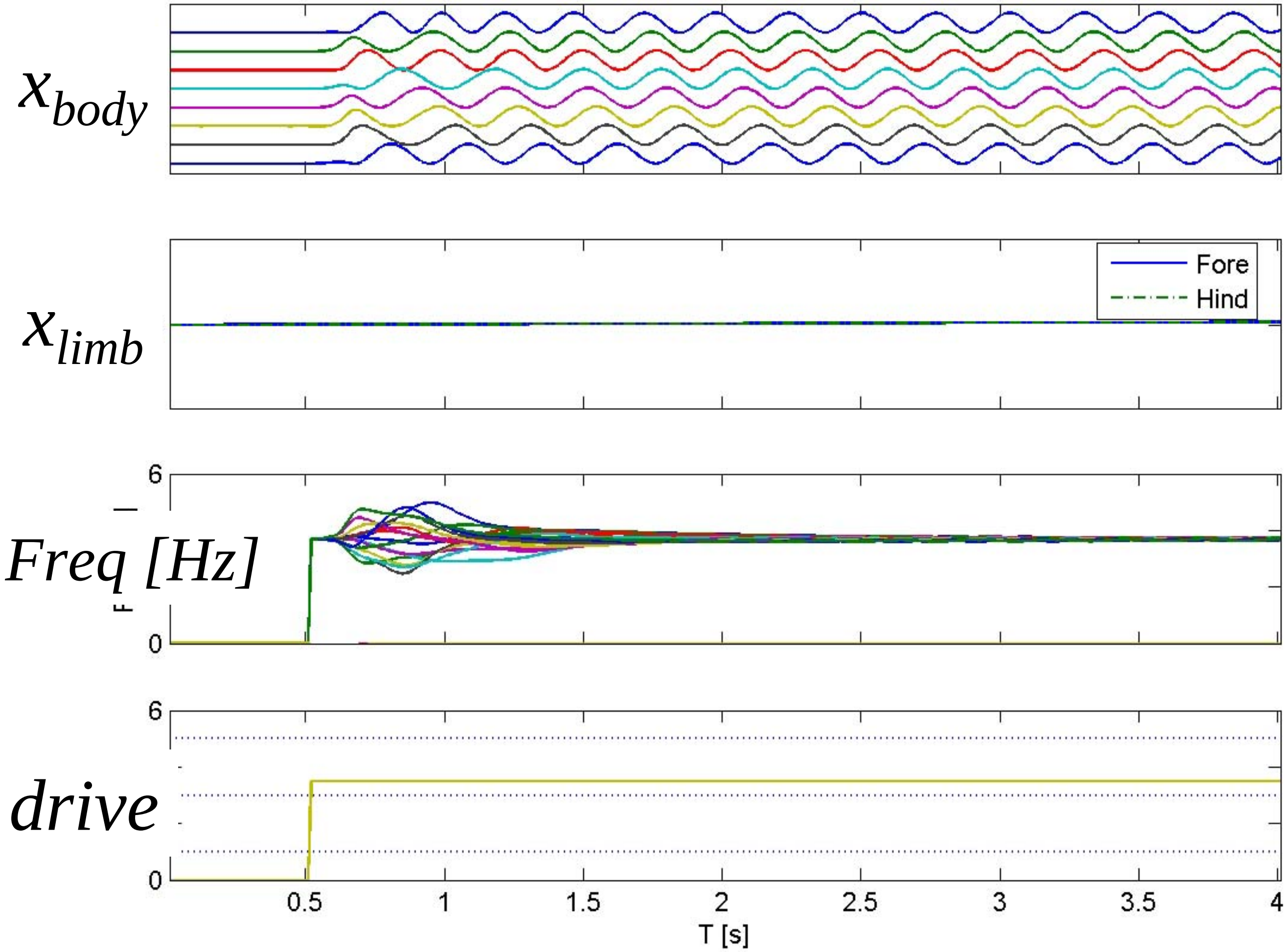
Traveling wave $$\phi_{ij} = \pm\frac{2\pi}{8}, w_{ij} = 10$$

Antiphase $$\phi_{ij} = \pi, w_{ij} = 10$$

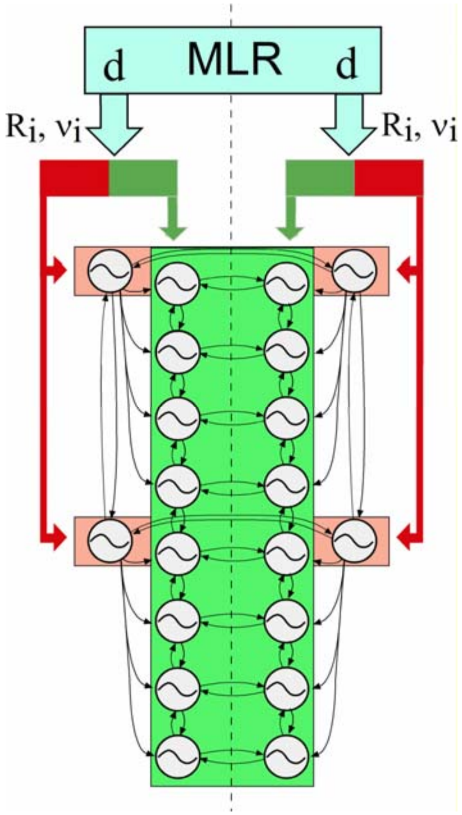
In phase $$\phi_{ij} = 0, w_{ij} = 30$$

Hyp. 2: strong limb to body couplings

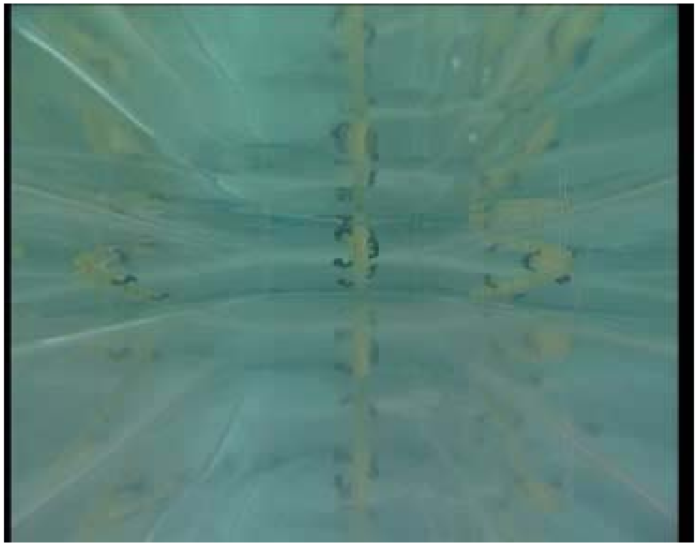
Swimming



High drive

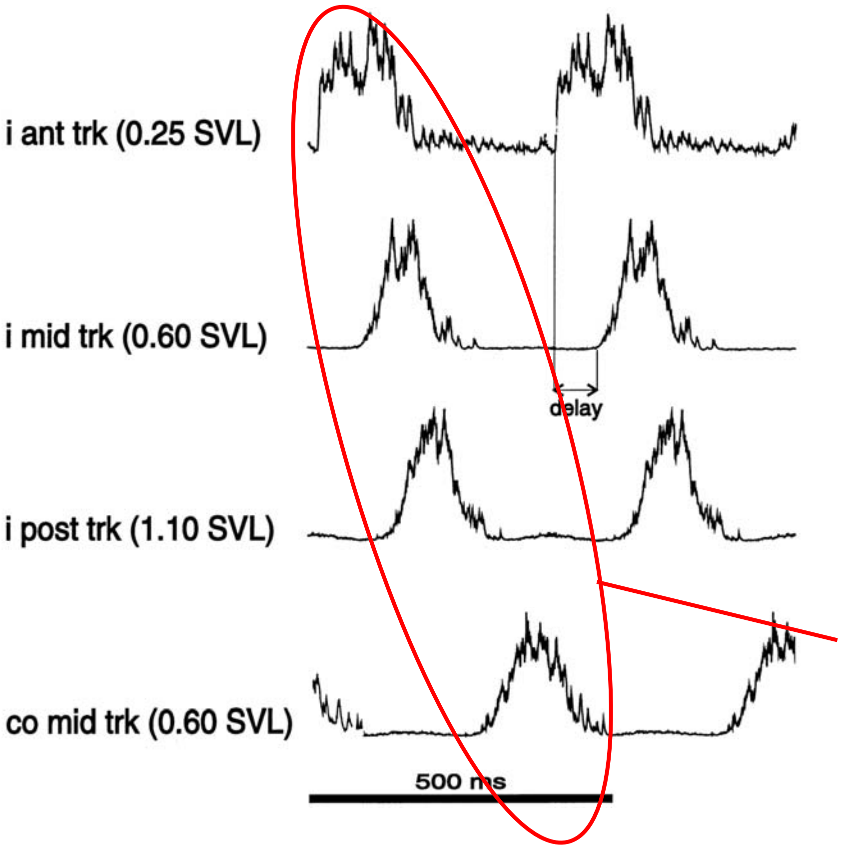


Swimming



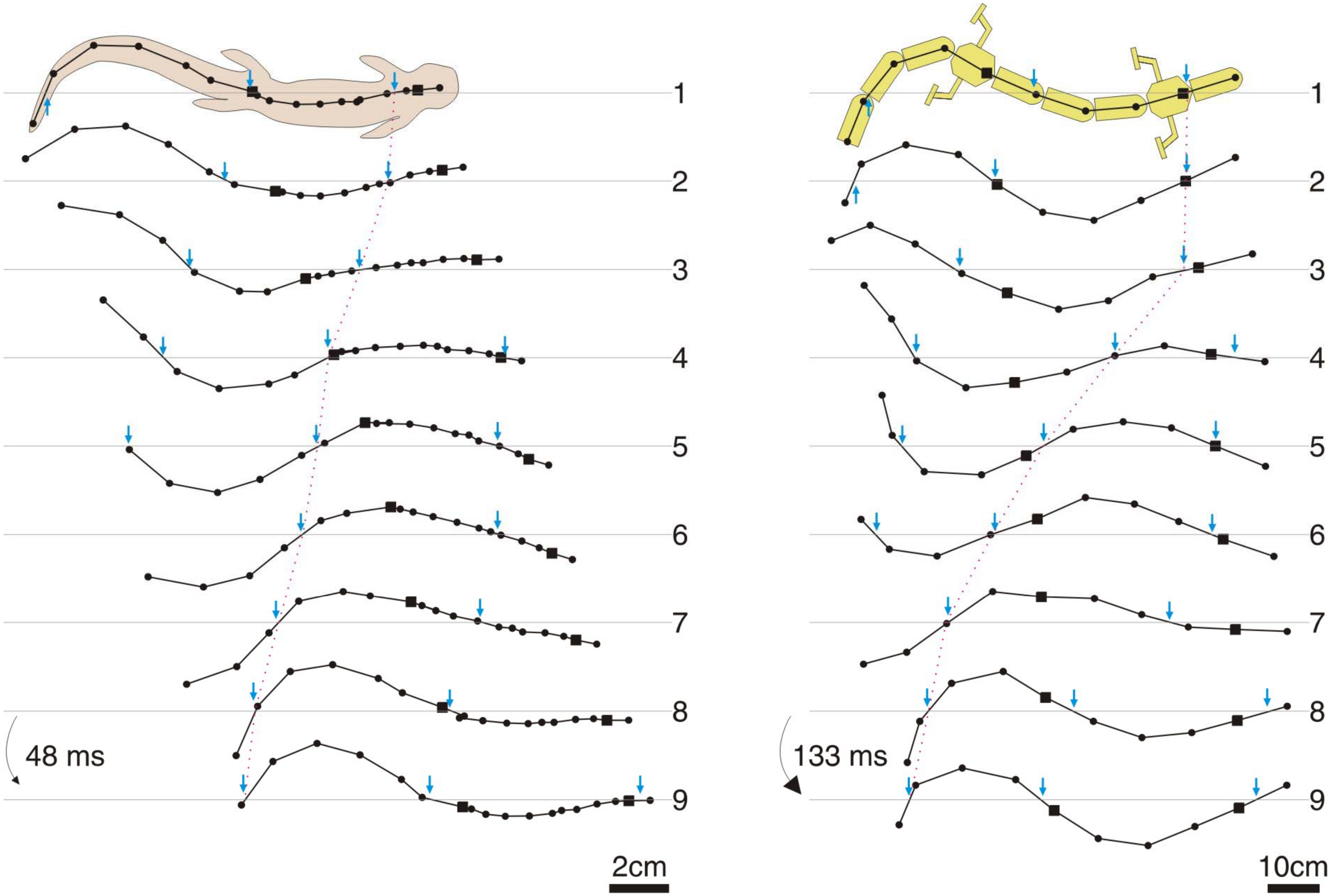
Aquatic locomotion

(Frolich 1992, Delvolvé 1997, Ashley-Ross 2004):
Traveling wave during swimming, (anguilliform swimming)

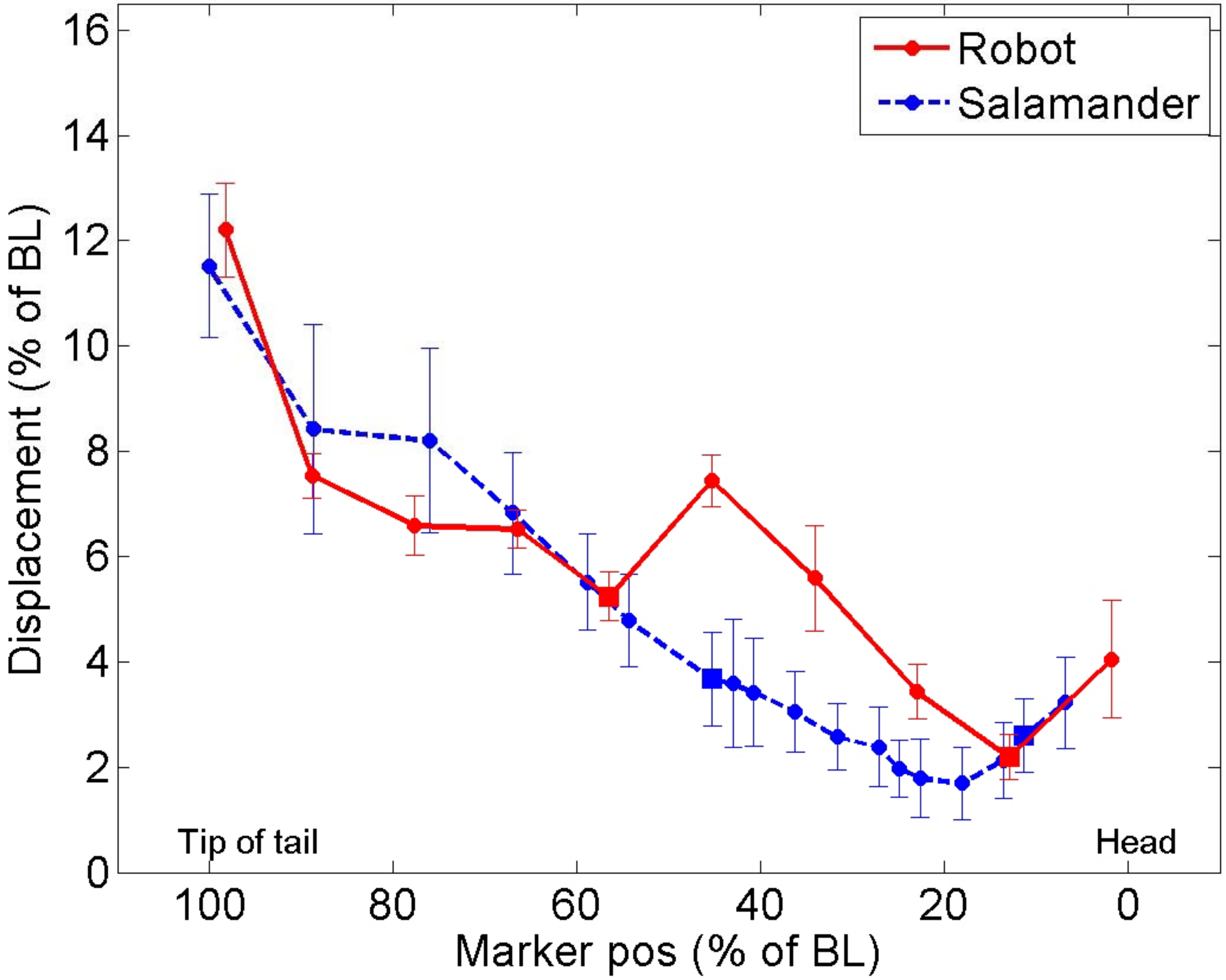


Traveling wave during swimming,
Wavelength = approx one body length

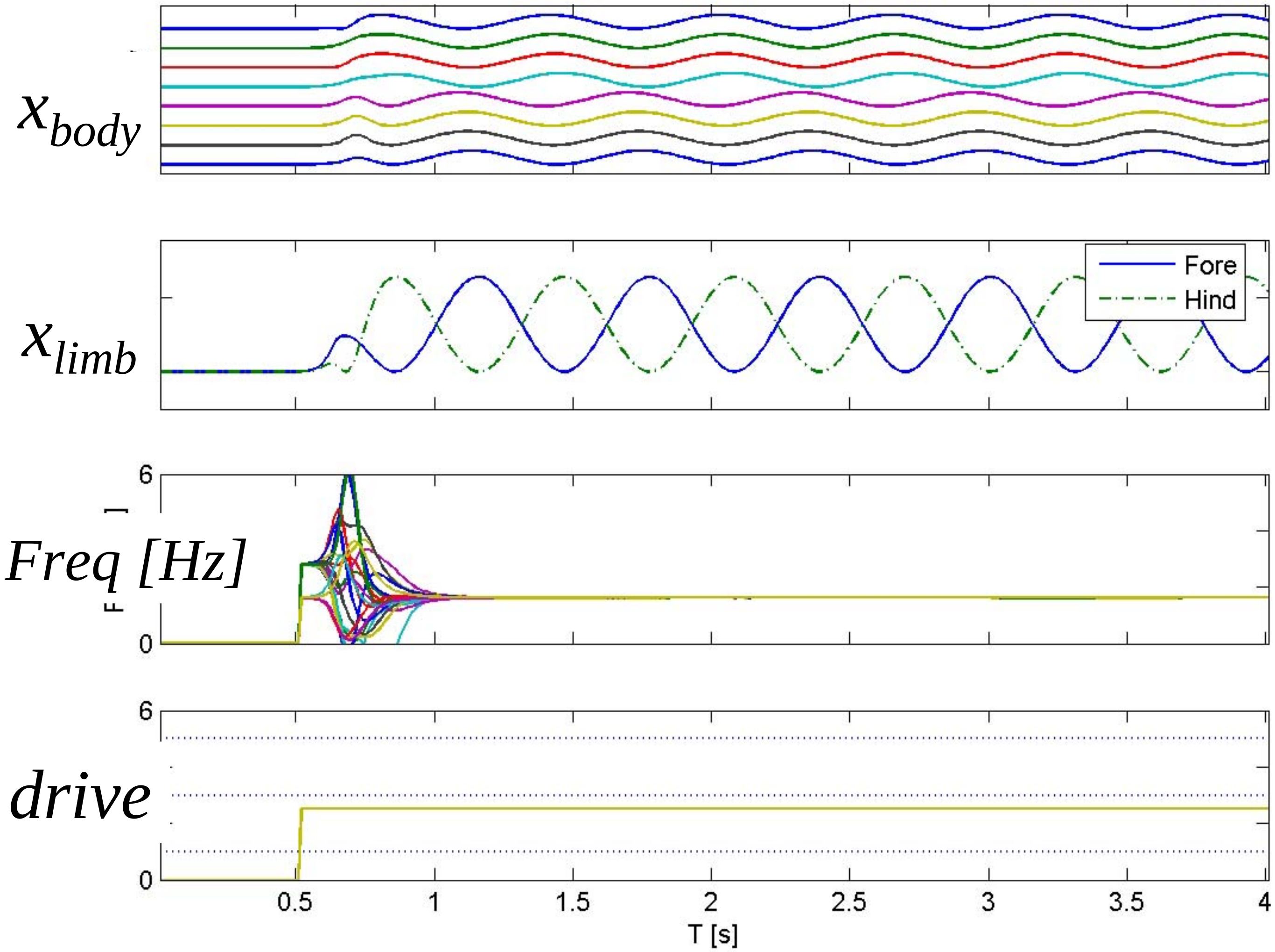
Swimming kinematics



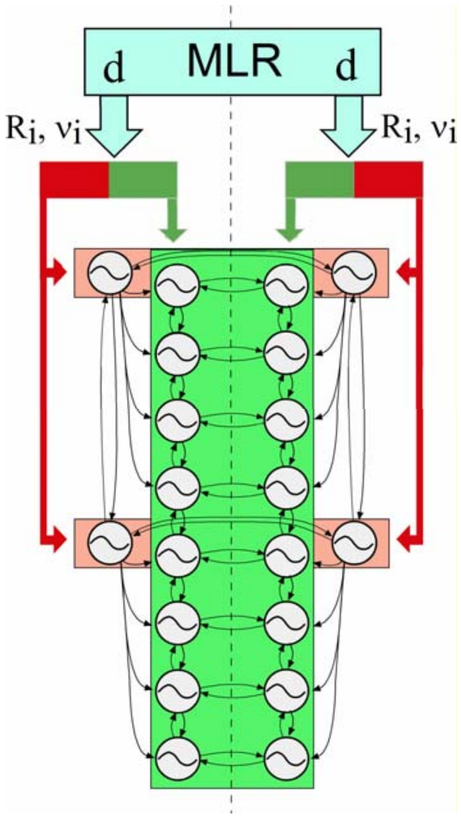
Swimming kinematics



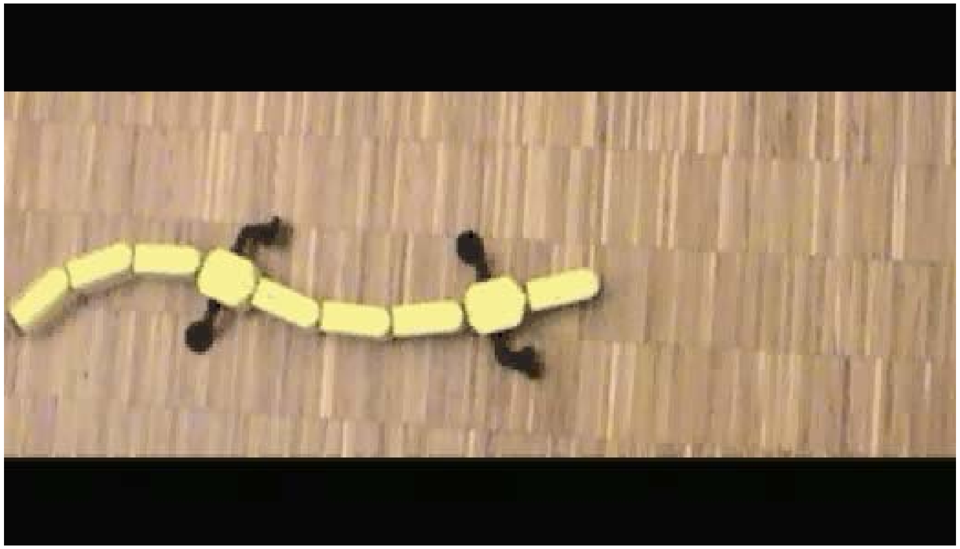
Walking



Low drive

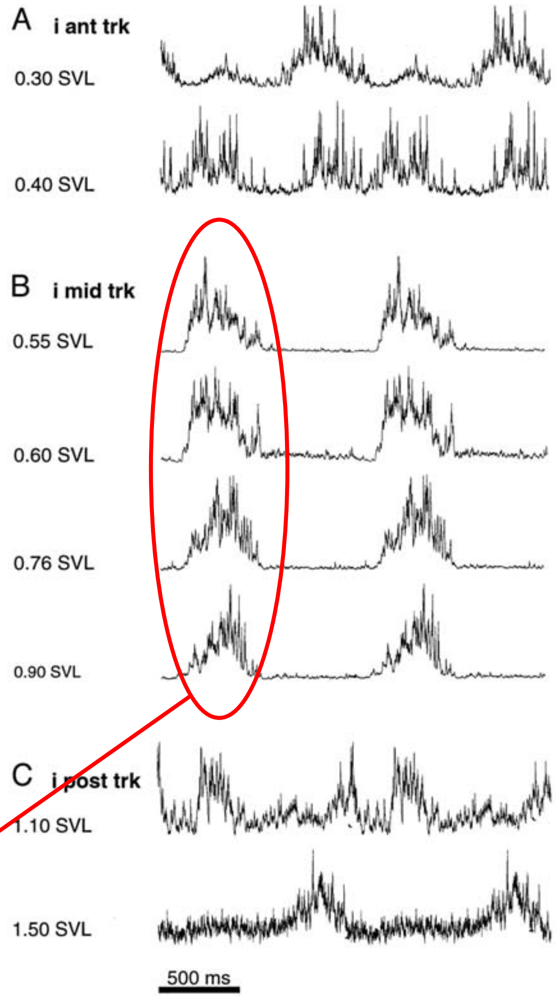


Walking



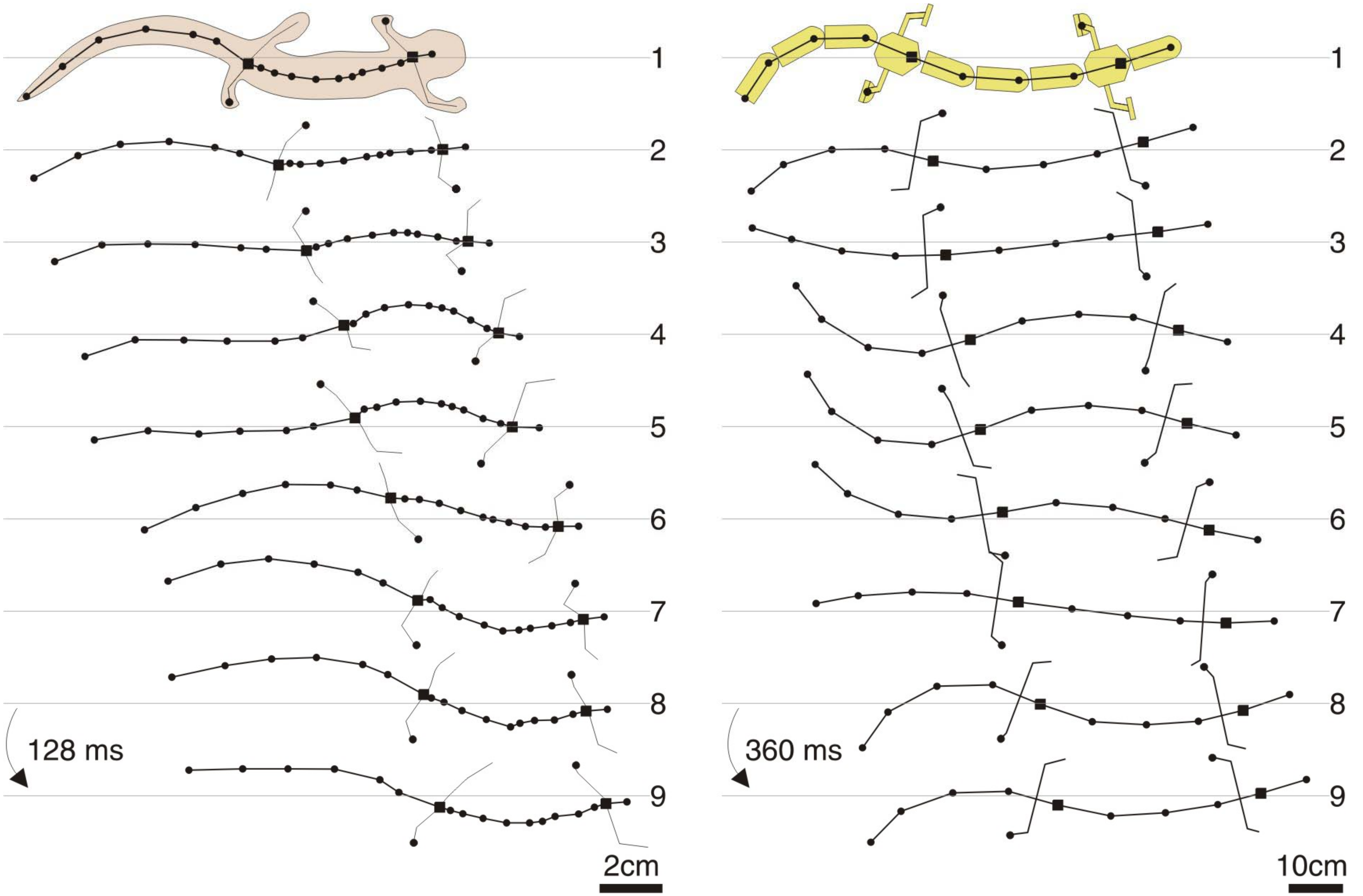
Terrestrial locomotion

Standing wave during trotting

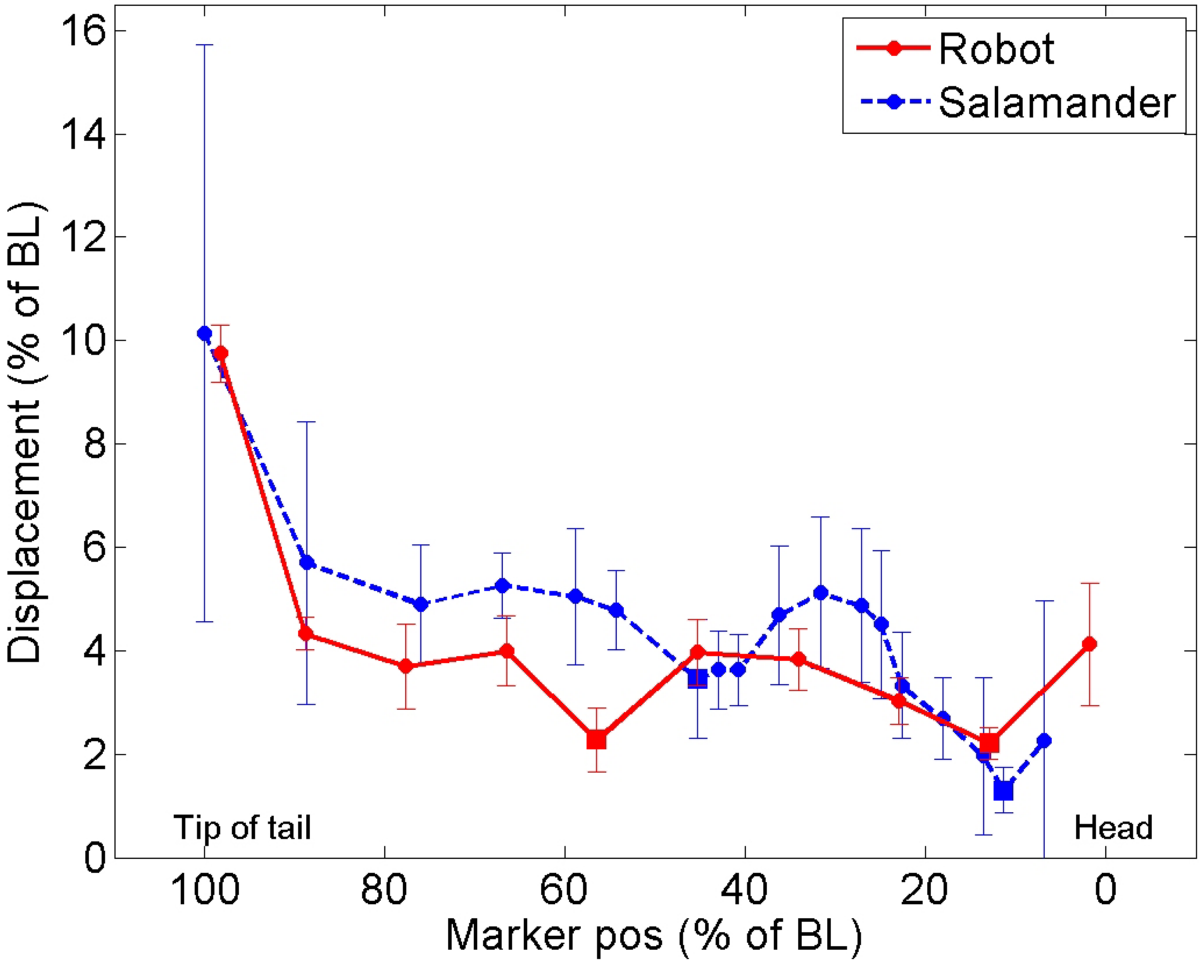


Perfect synchrony in the trunk

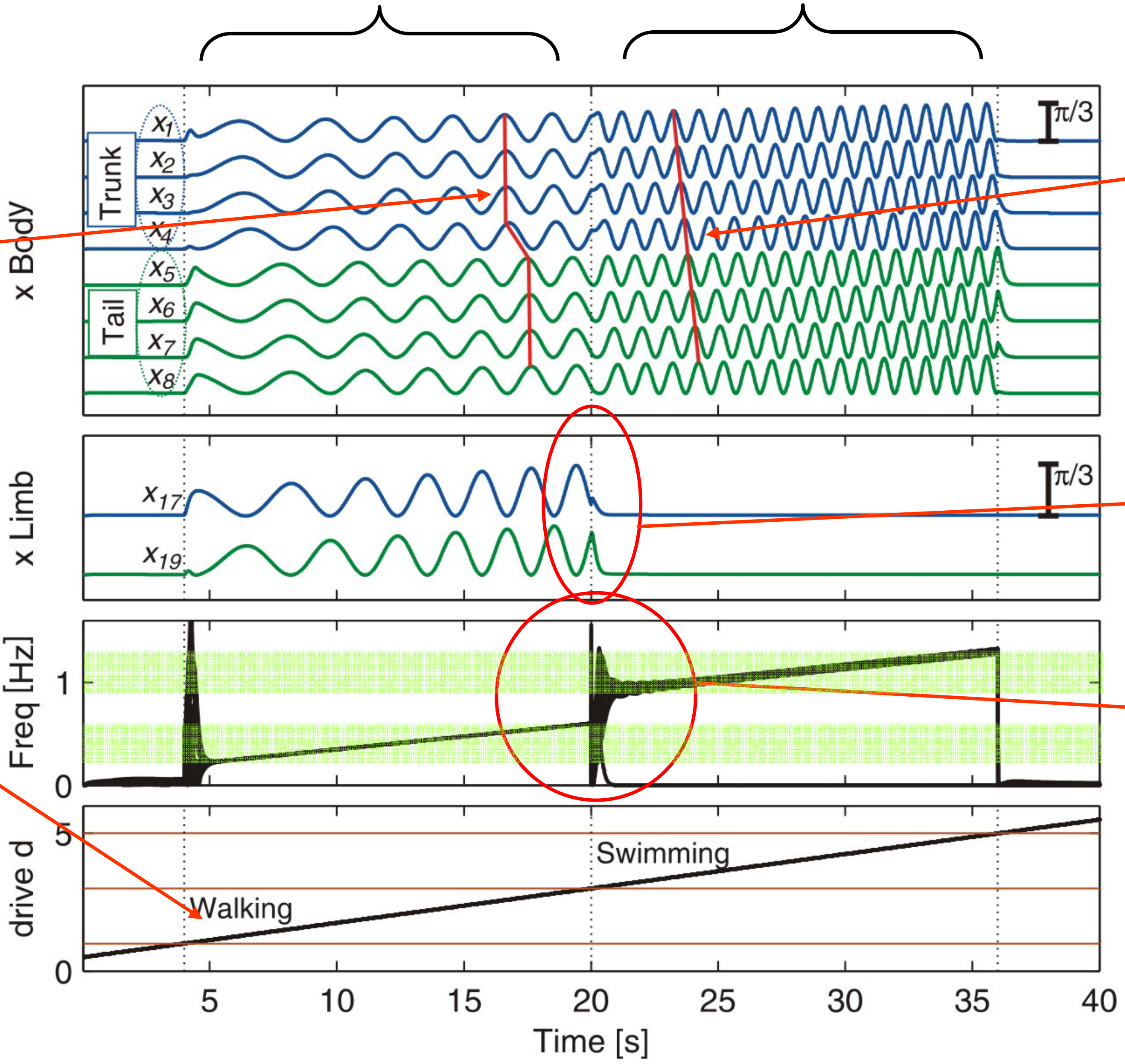
Walking kinematics



Walking kinematics



From walking to swimming



Standing wave

Traveling wave

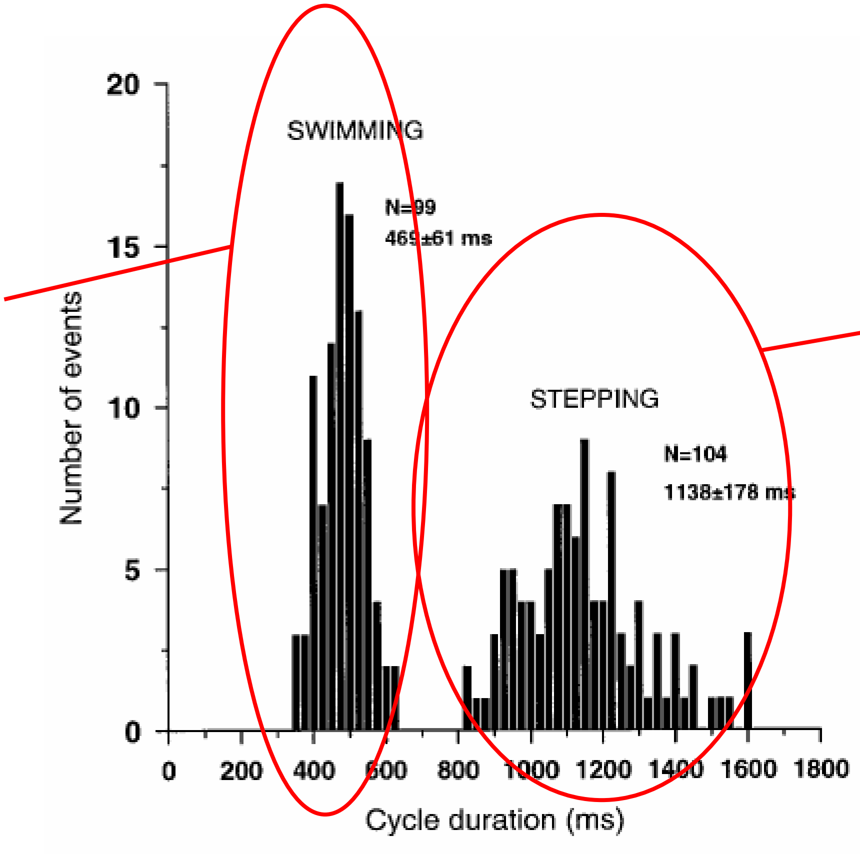
Limb oscil. saturate

Linear increase of the drive

Rapid frequency increase and frequency gap

Kinematic and EMG studies

The frequencies of swimming are systematically higher than those of stepping in freely behaving animals



Swimming:
1.6-3.0 Hz

Stepping:
0.6-1.2 Hz

New experiment:
measuring frequencies of limb and body CPGs

Fictive rhythms

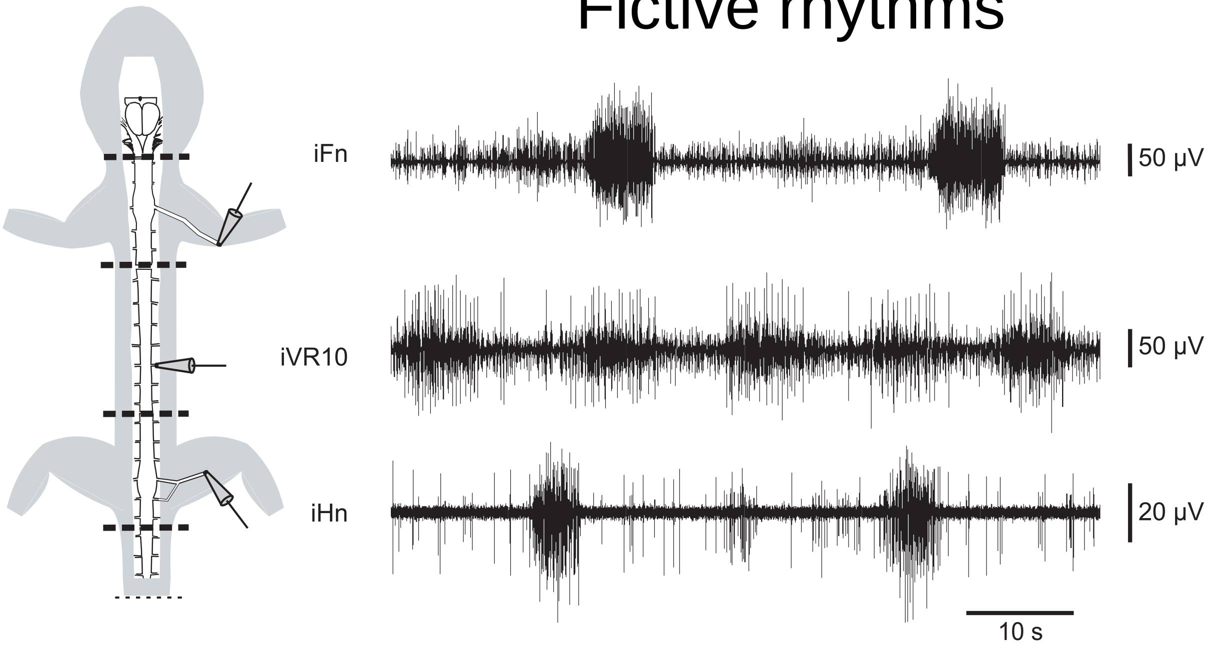
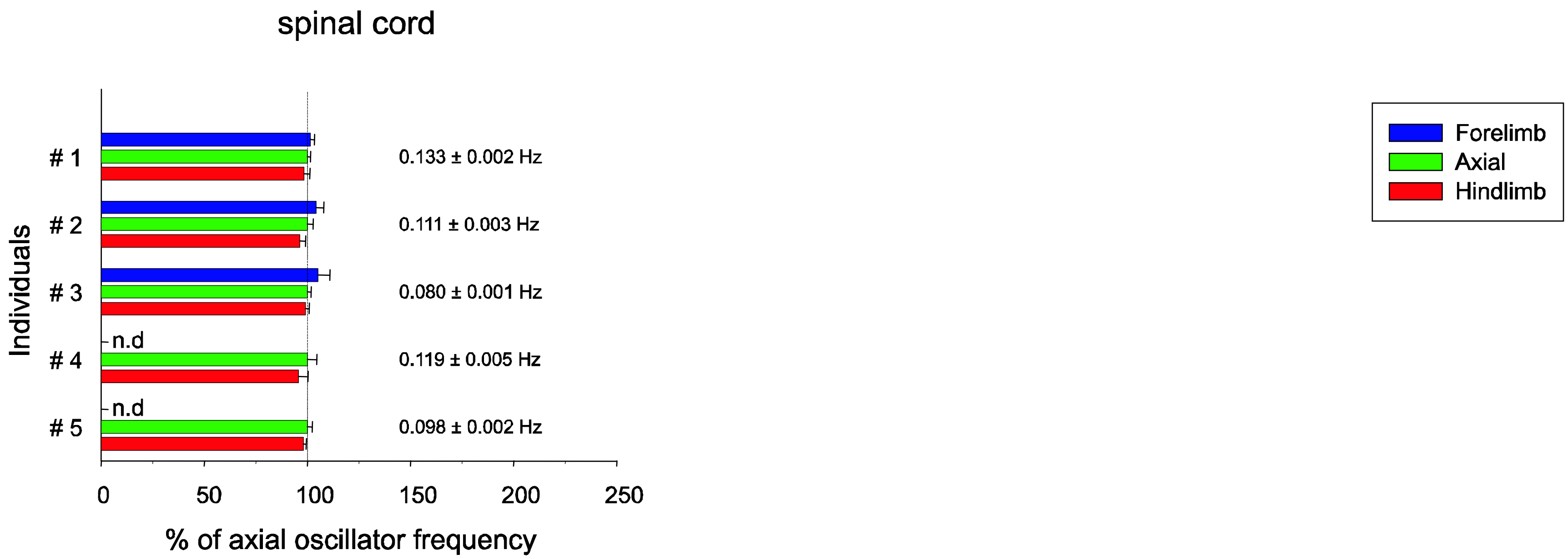


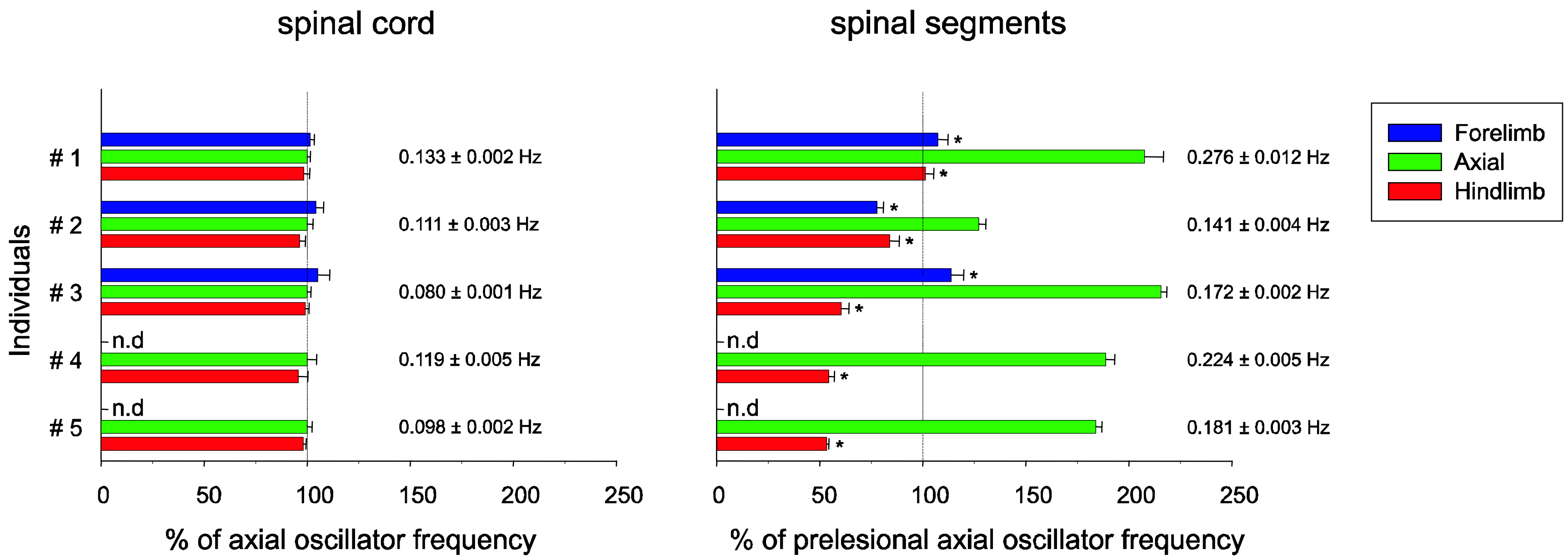
Fig. S6. Example of rhythmic motor activities induced in 3 isolated portions of salamander spinal cord by bath co-application of *N*-methyl-D-aspartate (20 µM) and D-serine (10 µM). Efferent activities (right panel) were recorded from a forelimb muscle nerve (iFn), the 10th ventral root (iVR10), and from a hindlimb muscle nerve (iHn) on the same side of the spinal cord. The dashed lines in the drawing of the preparation (left panel) indicate the levels of the spinal cord transections.

Limb oscillators are slower!



Before transection

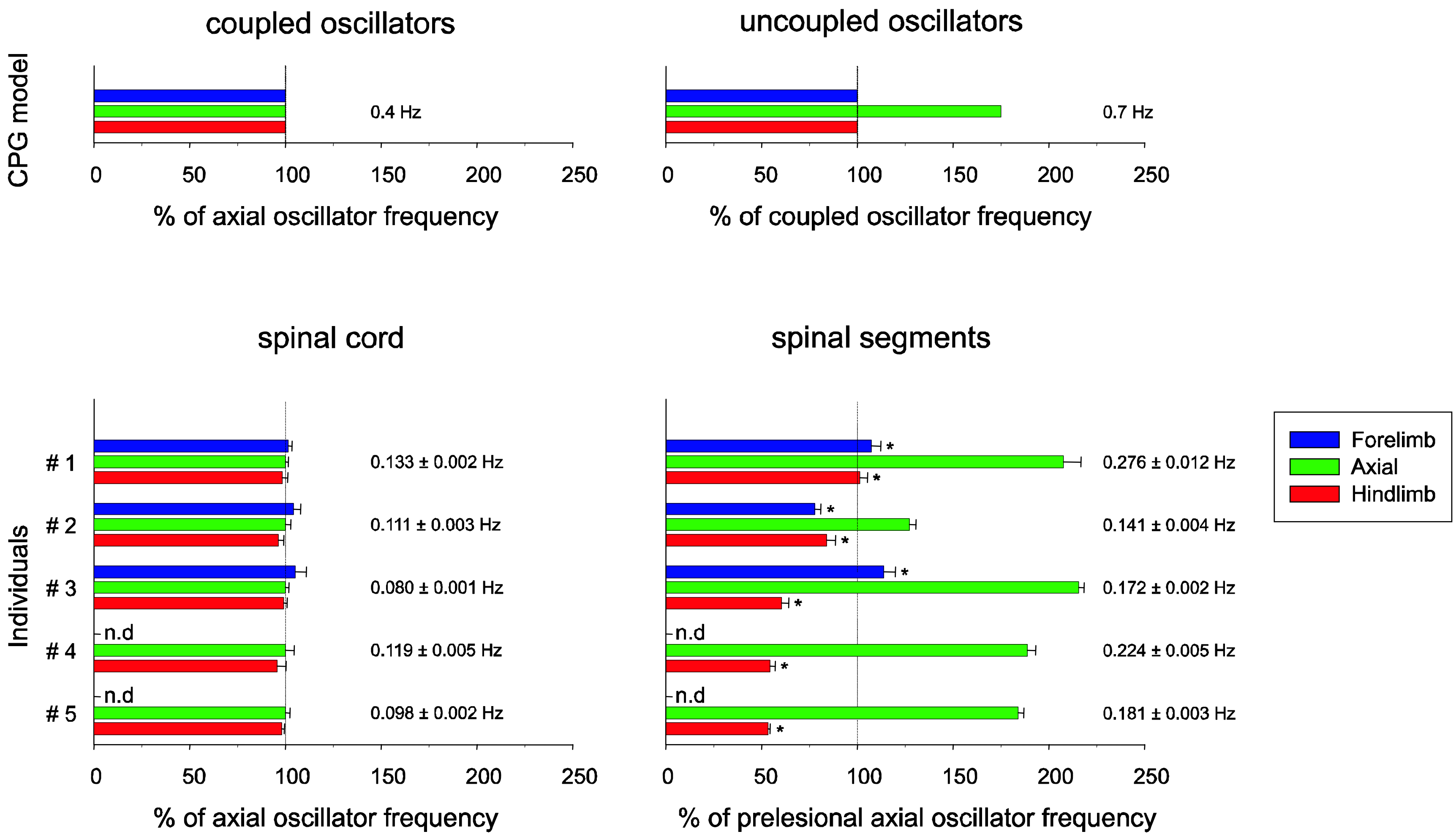
Limb oscillators are slower!



Before transection

After transection

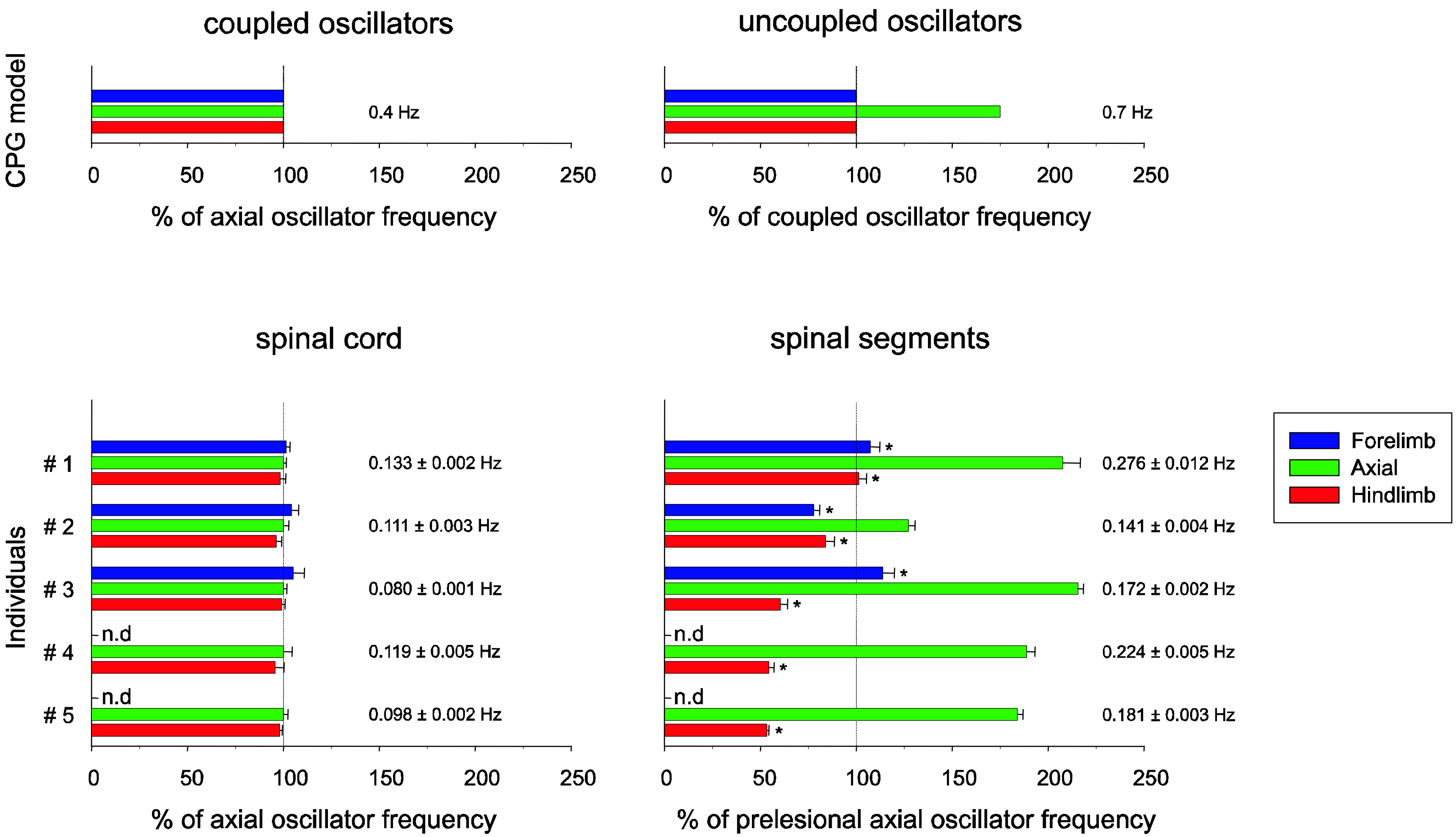
Limb oscillators are slower!



Before transection

After transection

Limb oscillators are slower!



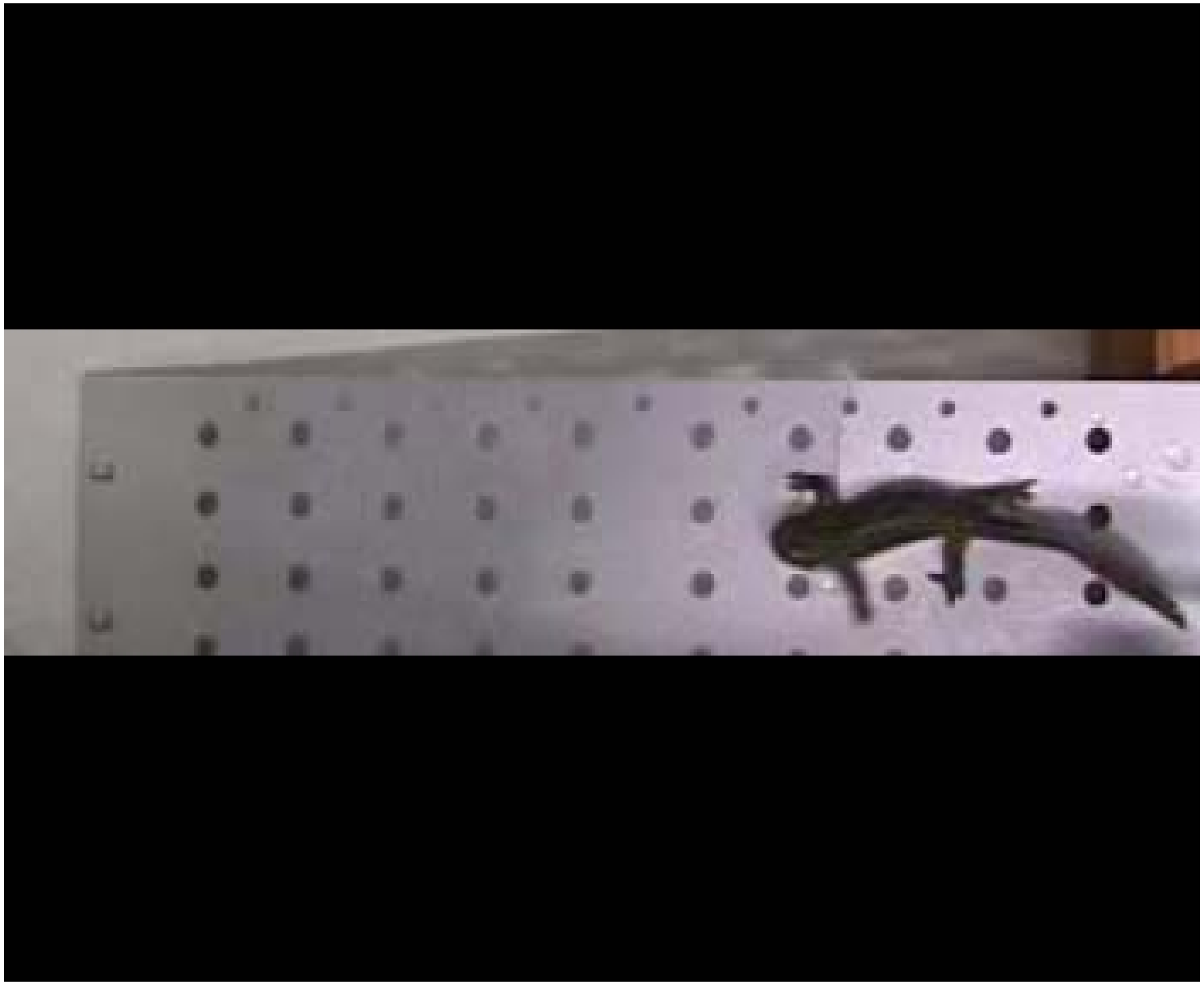
Hypothesis 4 is confirmed

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

BIOLOGICALLY INSPIRED
ROBOTICS GROUP (BIRG)

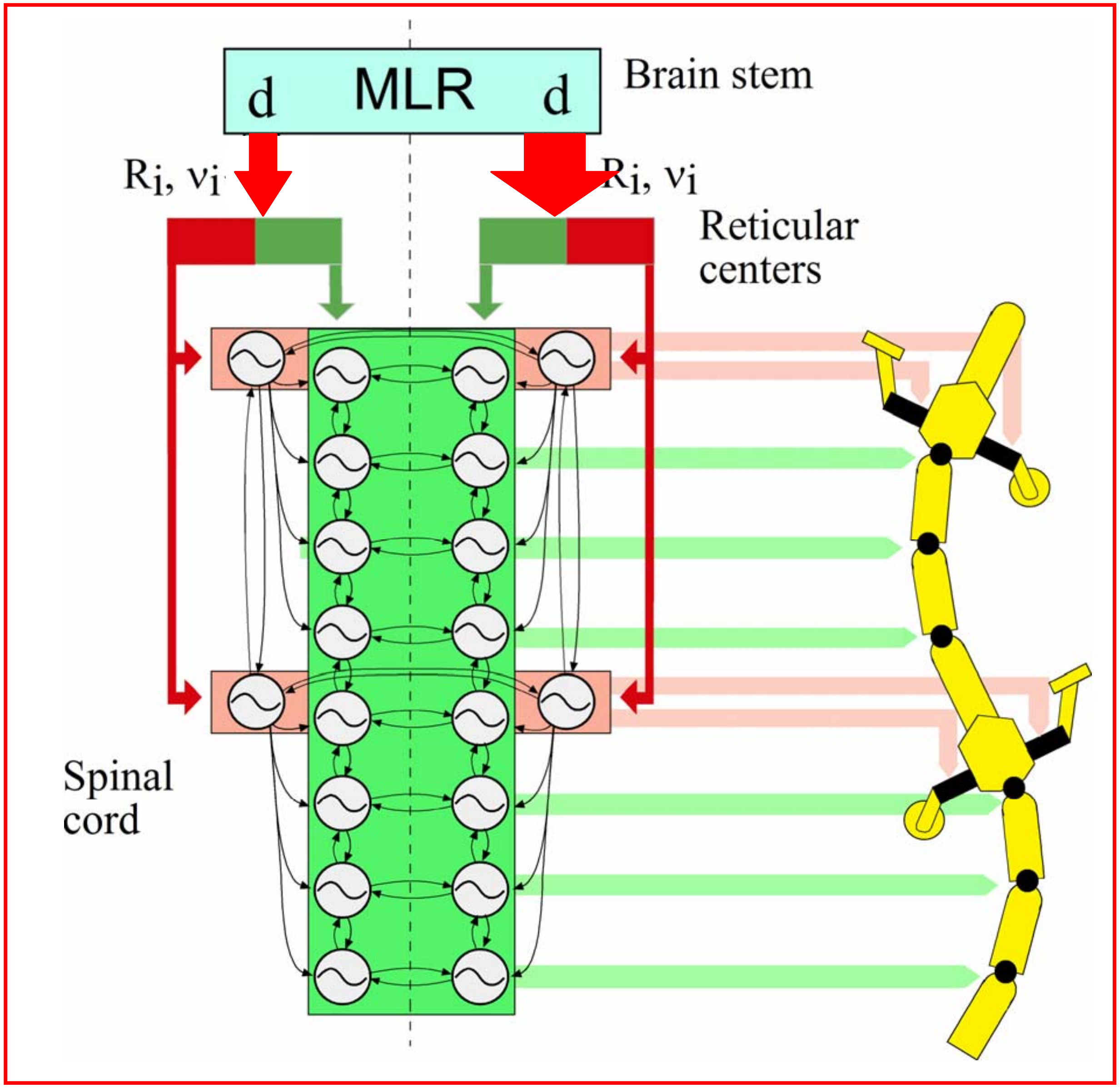
Transitions between walking and swimming

Real salamander: from walking to swimming

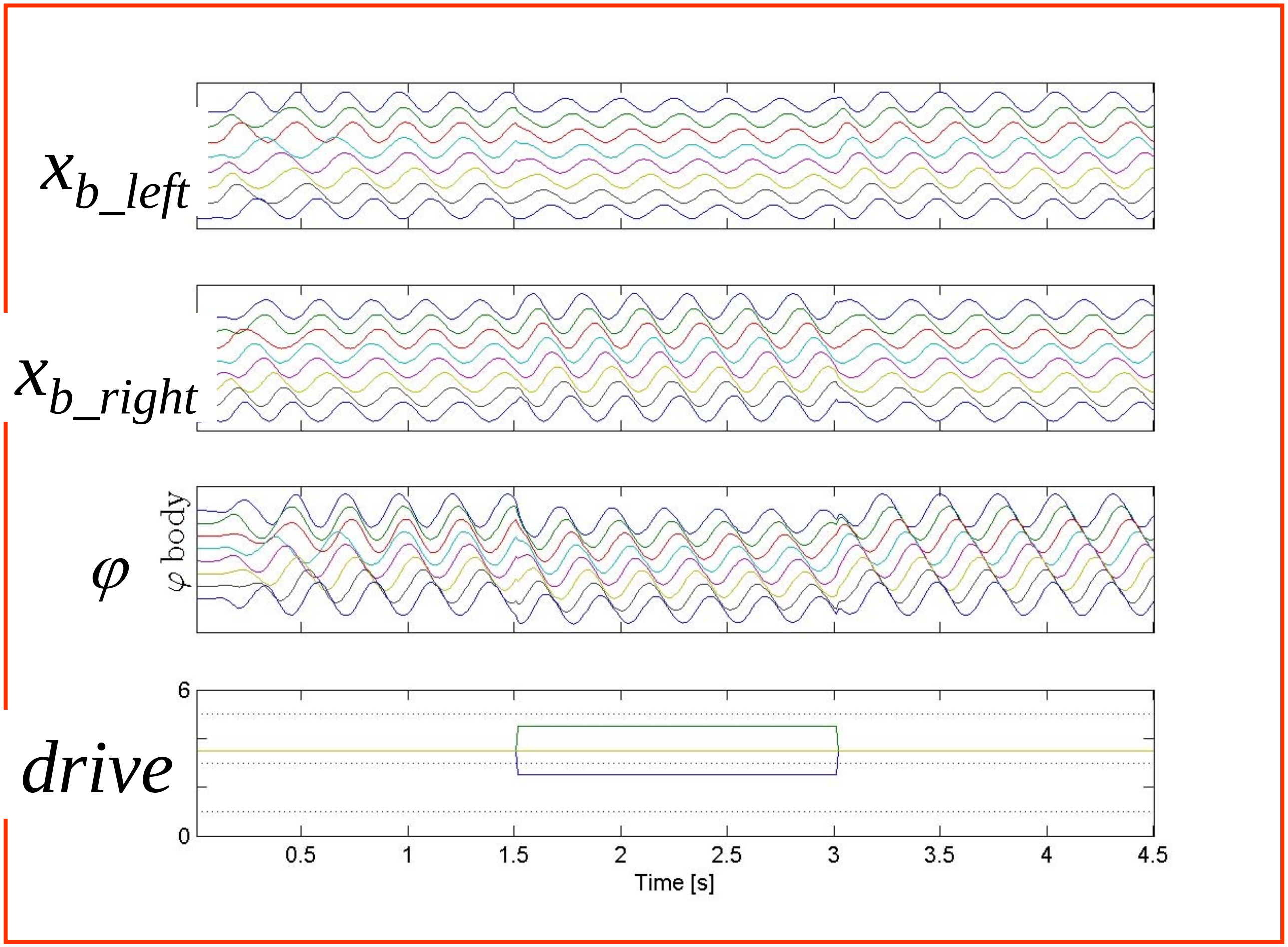


Real salamander: from swimming to walking

Turning with asymmetric left/right drive

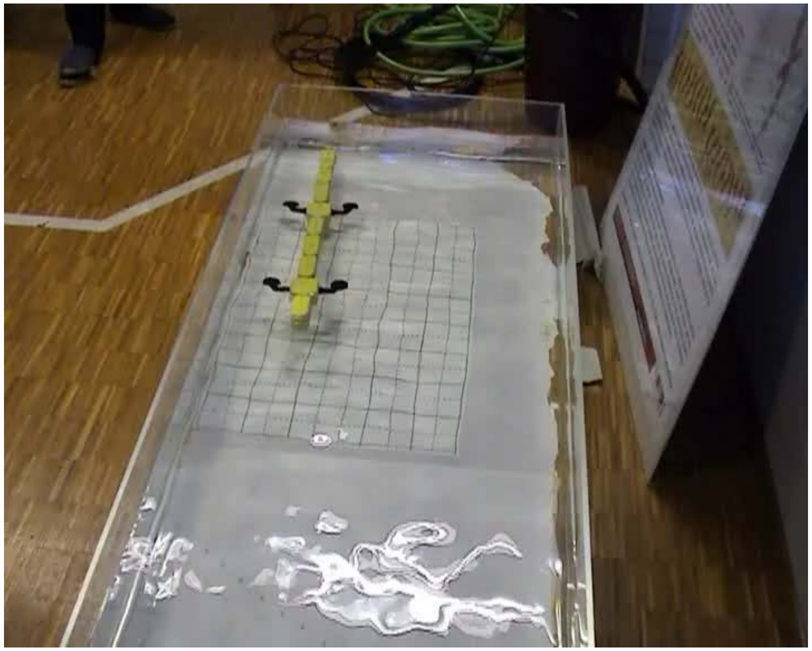


Turning

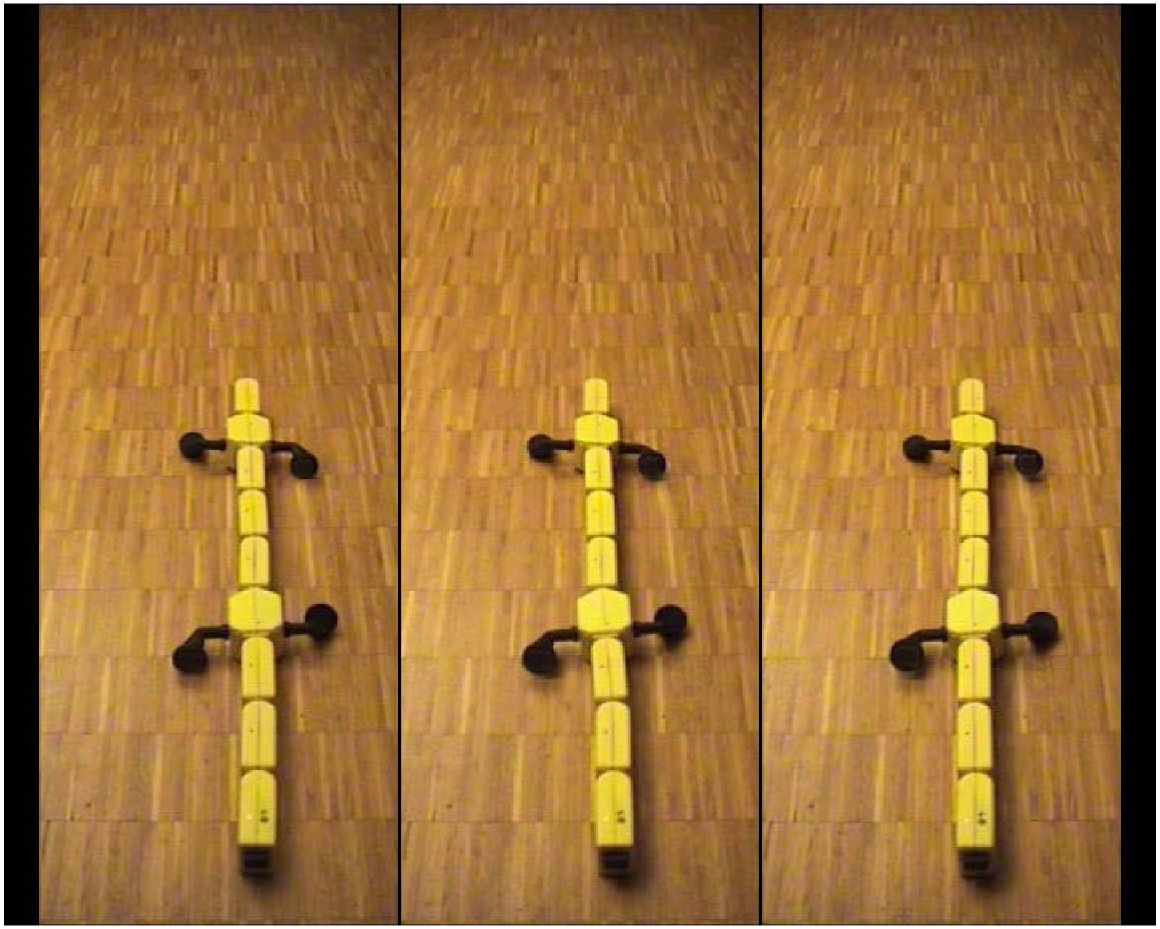


Asymmetric drive: Oscillators remain synchronized and only amplitudes change

Control of direction



The body limb coordination optimizes speed



Conclusion

The new CPG model provides an explanation for:

- The **automatic transition** from walking to swimming by simple electrical stimulation,
- The **rapid increase of frequency** at the gait transition
- The **lack of overlap between walking and swimming frequencies**
- the **control of speed and direction** by the modulation of a simple tonic drive.

Evolution: **addition of oscillatory centers with different intrinsic frequencies and saturation frequencies** to a lamprey CPG

In addition, the CPG model offers an interesting way to do **online locomotion control for robots** with multiple d.o.f.s.

Outline of the talk

- Central pattern generators (CPGs) in biology
- Modeling the salamander CPG
- **Adaptive frequency oscillators**
  - **Self-tuning CPGs**
  - **Programmable CPGs**
- Online learning in modular robots

Central pattern generators for robotics

- Problem: not yet a clear methodology for designing CPGs
- Most approaches use either hand-coding or off-line optimization algorithms

- Alternatives that we are currently testing:

1) A system based on **adaptive frequency oscillators** for learning rhythmic trajectories as limit cycles

2) Online optimization (later)

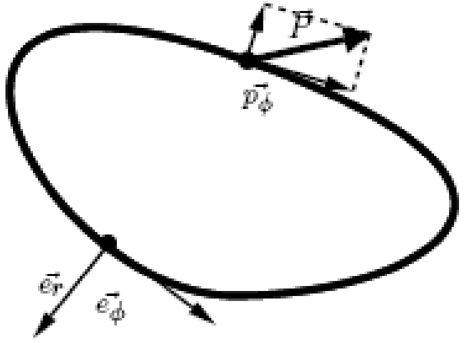
Adaptive frequency oscillators

- Designed jointly by Jonas Buchli and Ludovic Righetti
- Example: an adaptive frequency Hopf oscillator receiving a periodic input *F(t).*

Teaching signal

$$\begin{aligned}\dot{x} &= \gamma(\mu - (x^2 + y^2))x - \omega y + \epsilon F(t)\\ \dot{y} &= \gamma(\mu - (x^2 + y^2))y + \omega x\\ \dot{\omega} &= -\epsilon F(t)\frac{y}{\sqrt{x^2 + y^2}}\end{aligned}$$

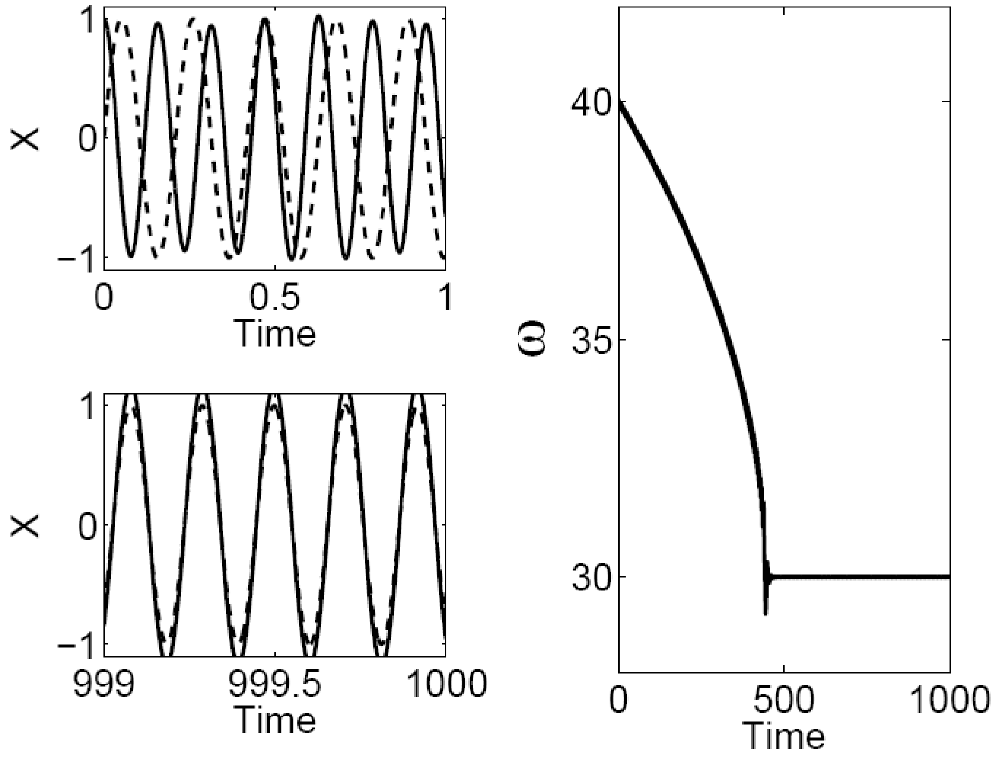
Tuning of the intrinsic frequency



Righetti, Buchli and Ijspeert, Physica D, 2006,

Adaptive Hopf oscillators

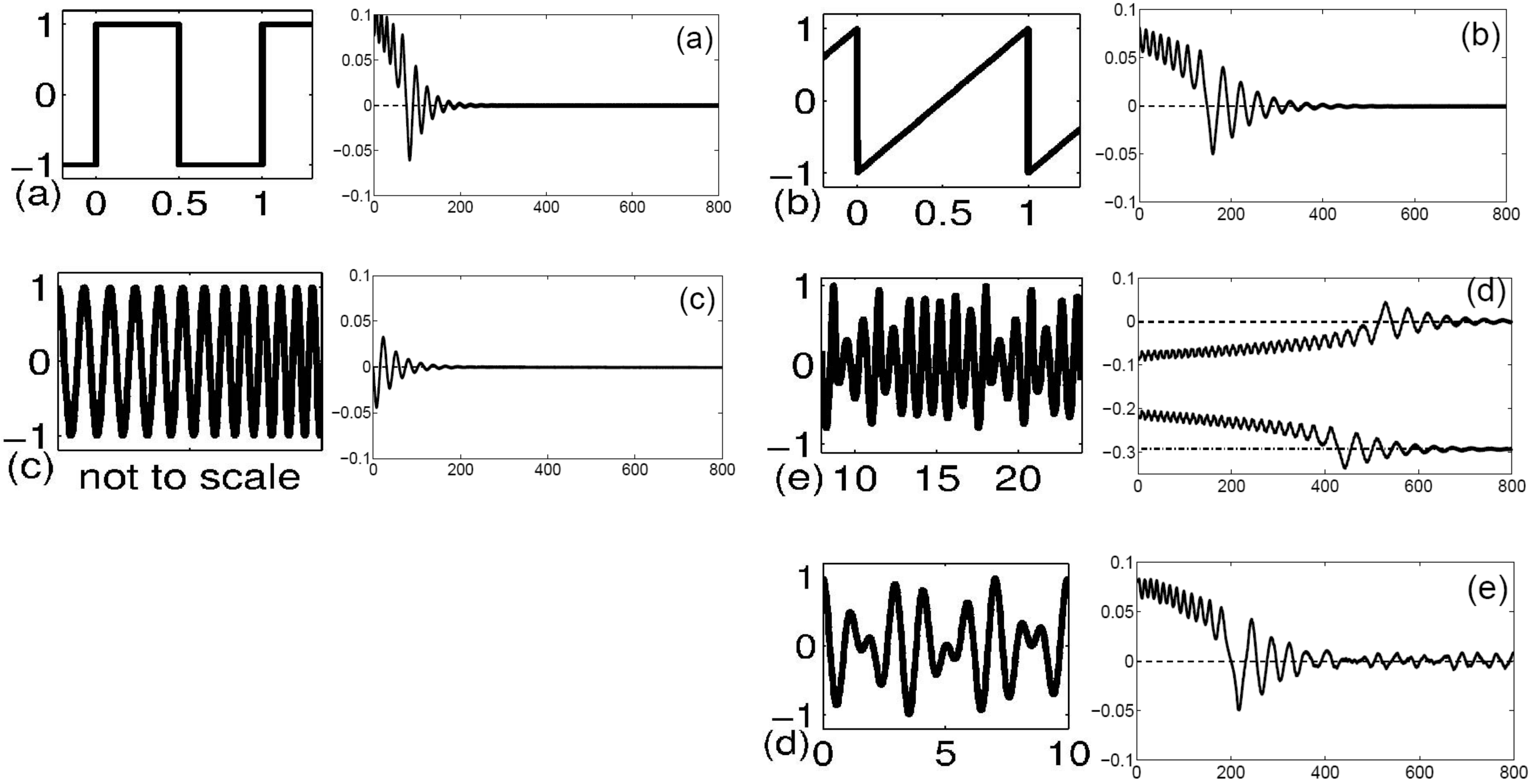
$$\begin{aligned}
\dot{x} &= \gamma(\mu - (x^2 + y^2))x - \omega y + \epsilon F(t) \\
\dot{y} &= \gamma(\mu - (x^2 + y^2))y + \omega x \\
\dot{\omega} &= -\epsilon F(t) \frac{y}{\sqrt{x^2 + y^2}}
\end{aligned}$$



Righetti, Buchli and Ijspeert, Physica D, 2006

Adaptive Hopf oscillators

Input signal Error Input signal Error



Righetti, Buchli and Ijspeert, Physica D, 2006

Applications

Adaptive frequency oscillators

Self-tuning CPGs

Unsupervised learning

Automatic tuning to resonant frequencies of compliant robots

Jonas Buchli

Programmable CPGs

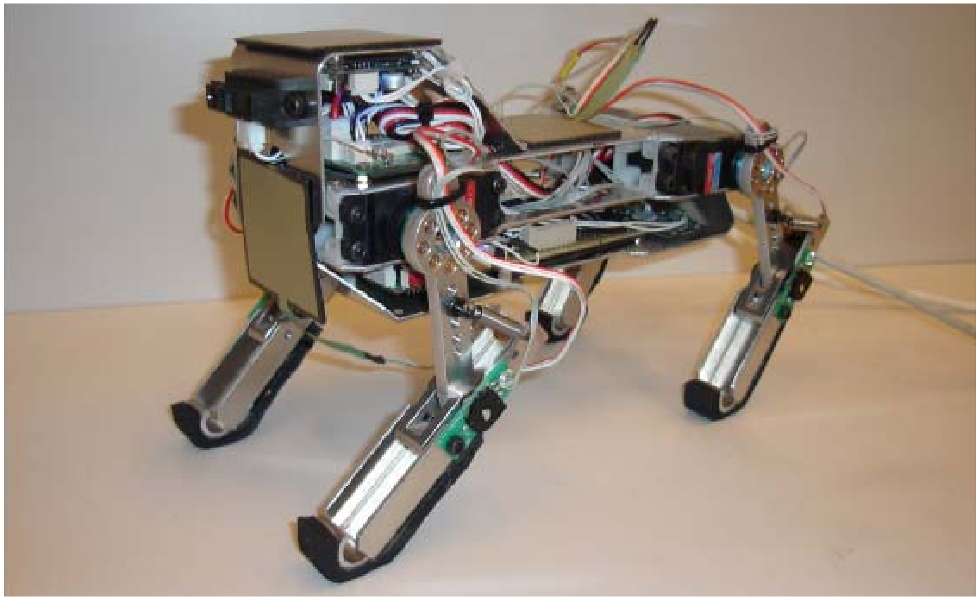
Supervised learning

Transforming periodic signals into limit cycles

Ludovic Righetti

Self-tuning CPGs

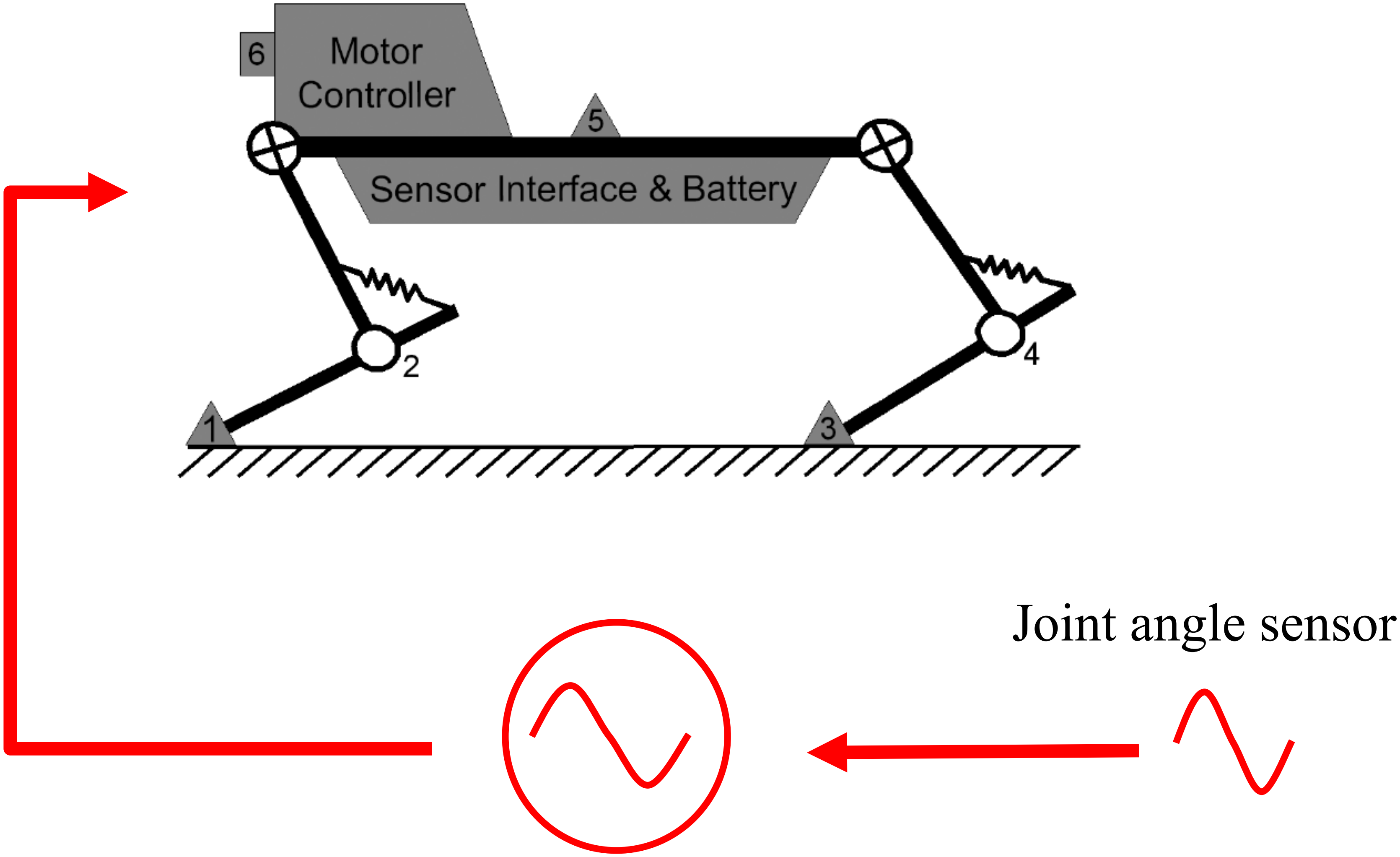
- Idea: use the adaptive frequency oscillators to tune themselves to resonant frequencies of a compliant robot



Work done in collaboration with Fumiya Iida and Rolf Pfeifer at the University of Zurich (also part of RobotCub)

Buchli et al, IROS 2006

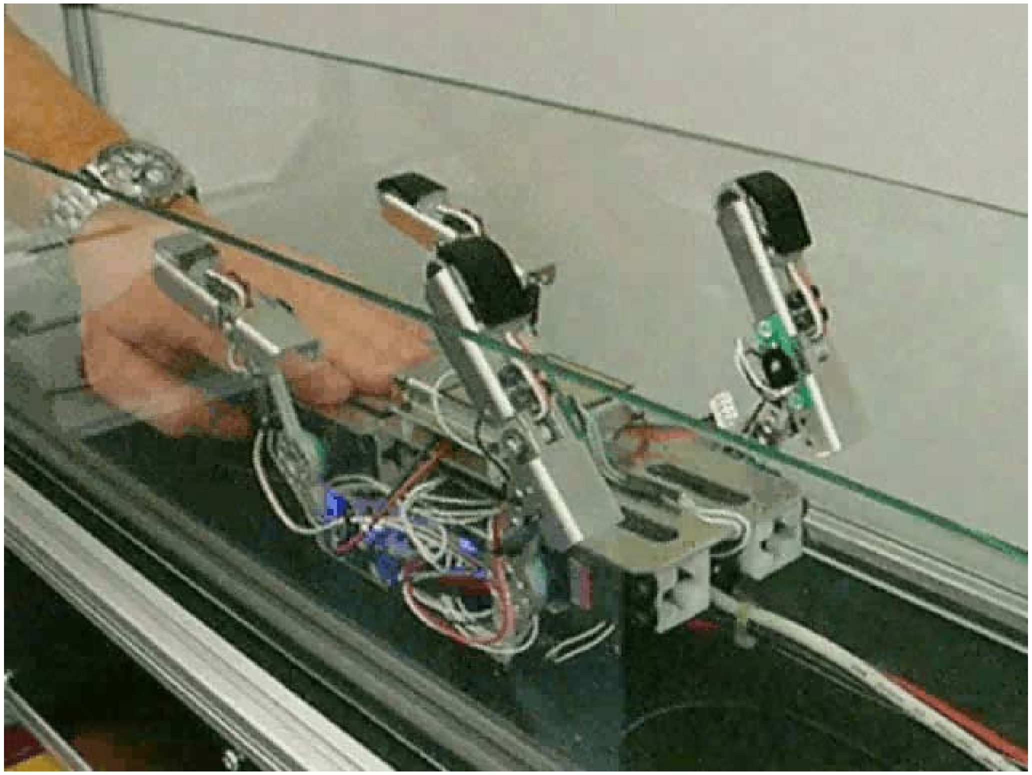
Self-tuning CPGs



Joint angle sensor

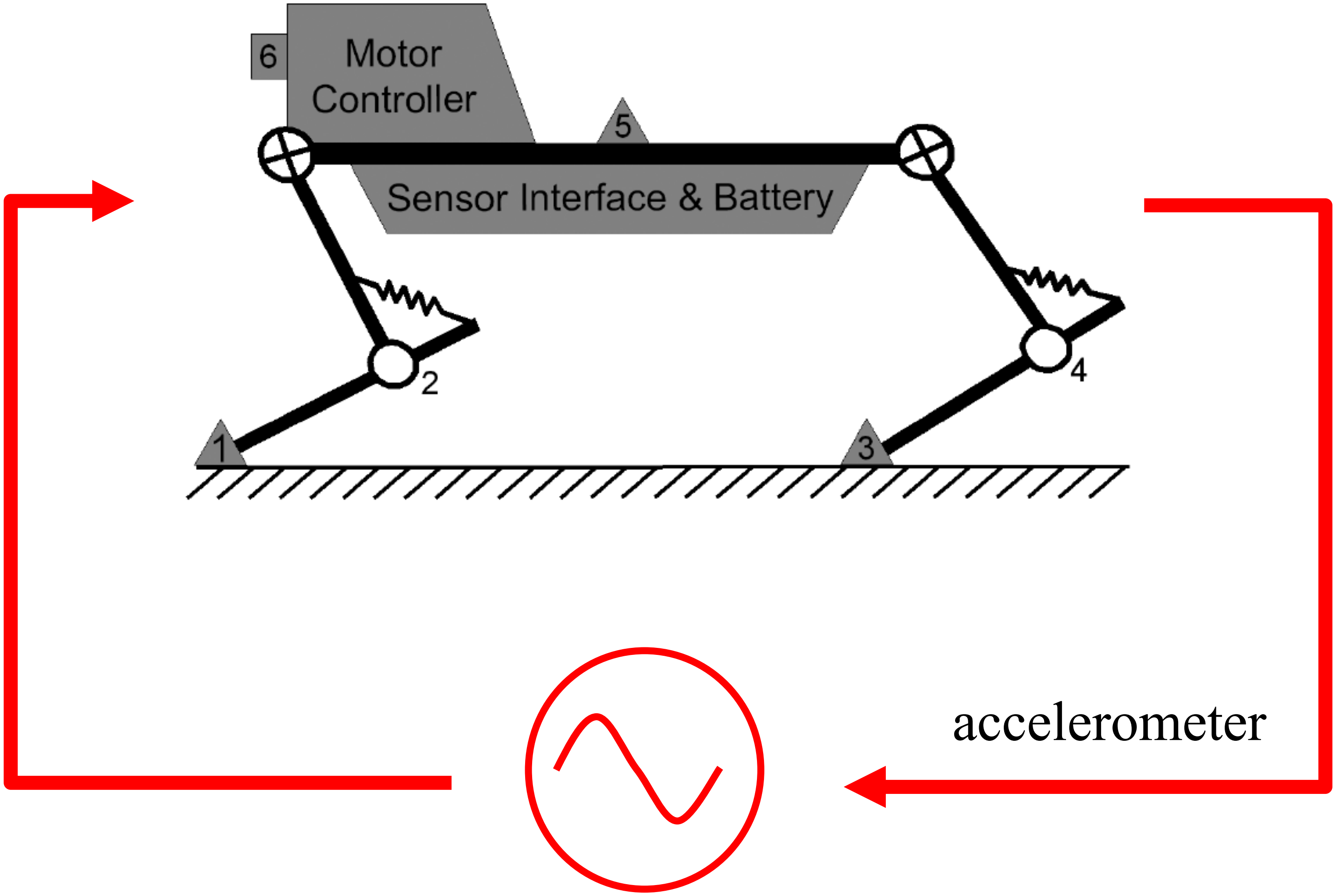
Buchli et al, IROS 2006

Results: tuning of the frequency



Buchli et al, IROS 2006

Self-tuning CPGs



Buchli et al, IROS 2006

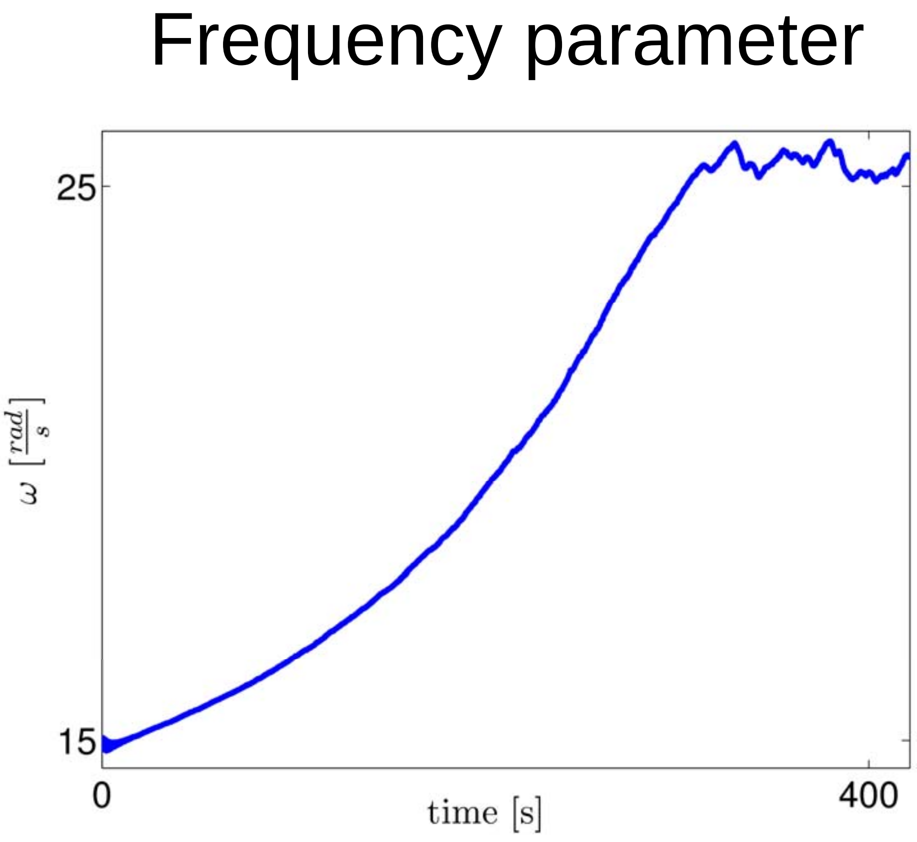
Results: tuning of the frequency

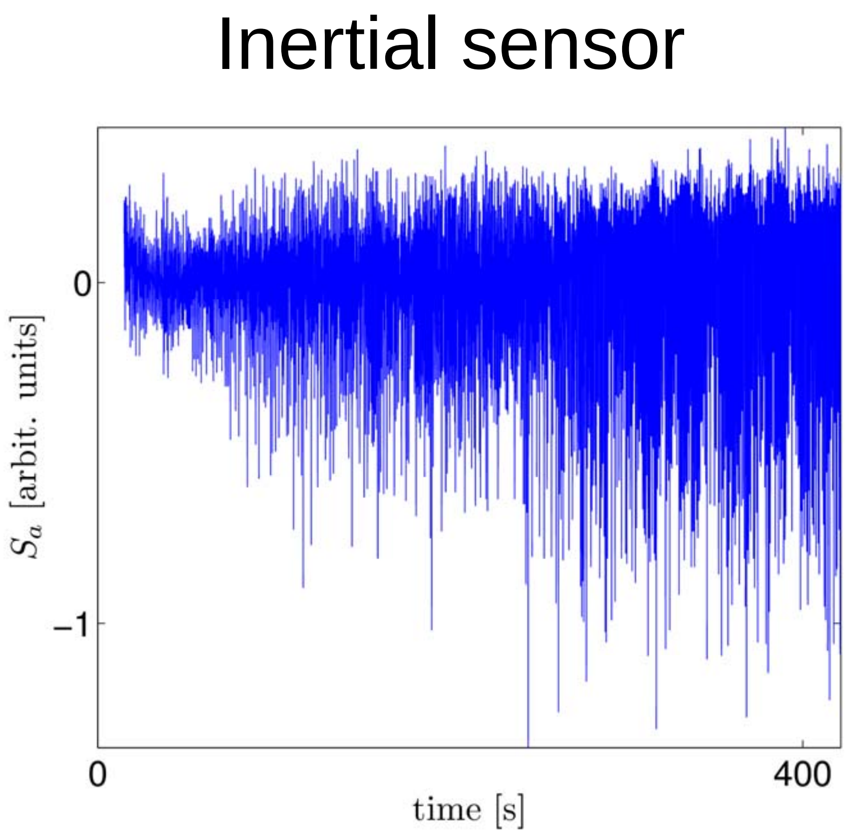
Movie

Movie slowed down

Buchli et al, IROS 2006

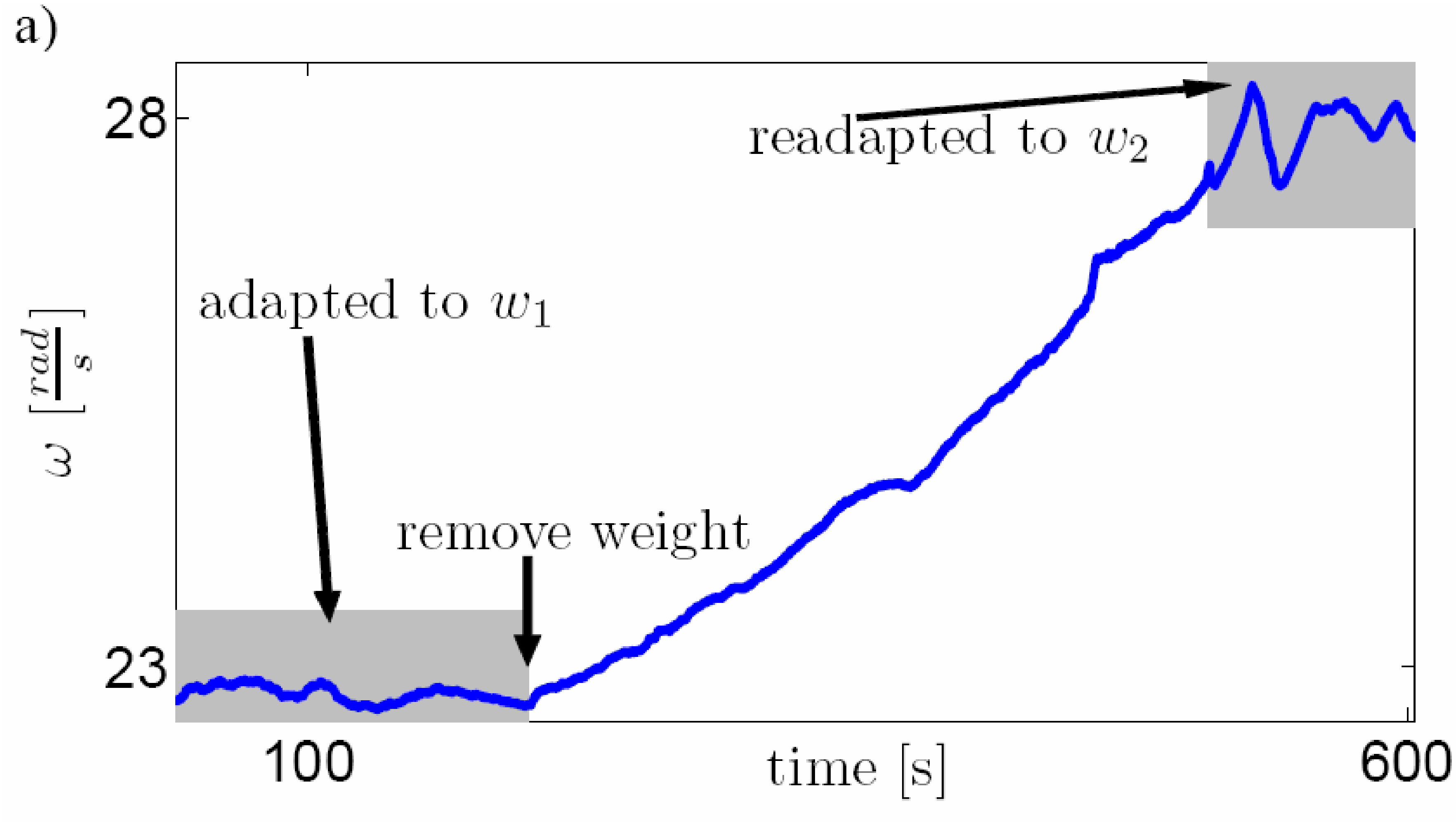
Results: tuning of the frequency





Buchli et al, IROS 2006

Results: adjusting to a change of weight



Buchli et al, IROS 2006

Results: locomotion

Buchli et al, IROS 2006

Applications

Adaptive frequency oscillators

Self-tuning CPGs

Unsupervised learning

Automatic tuning to resonant frequencies of compliant robots

Programmable CPGs

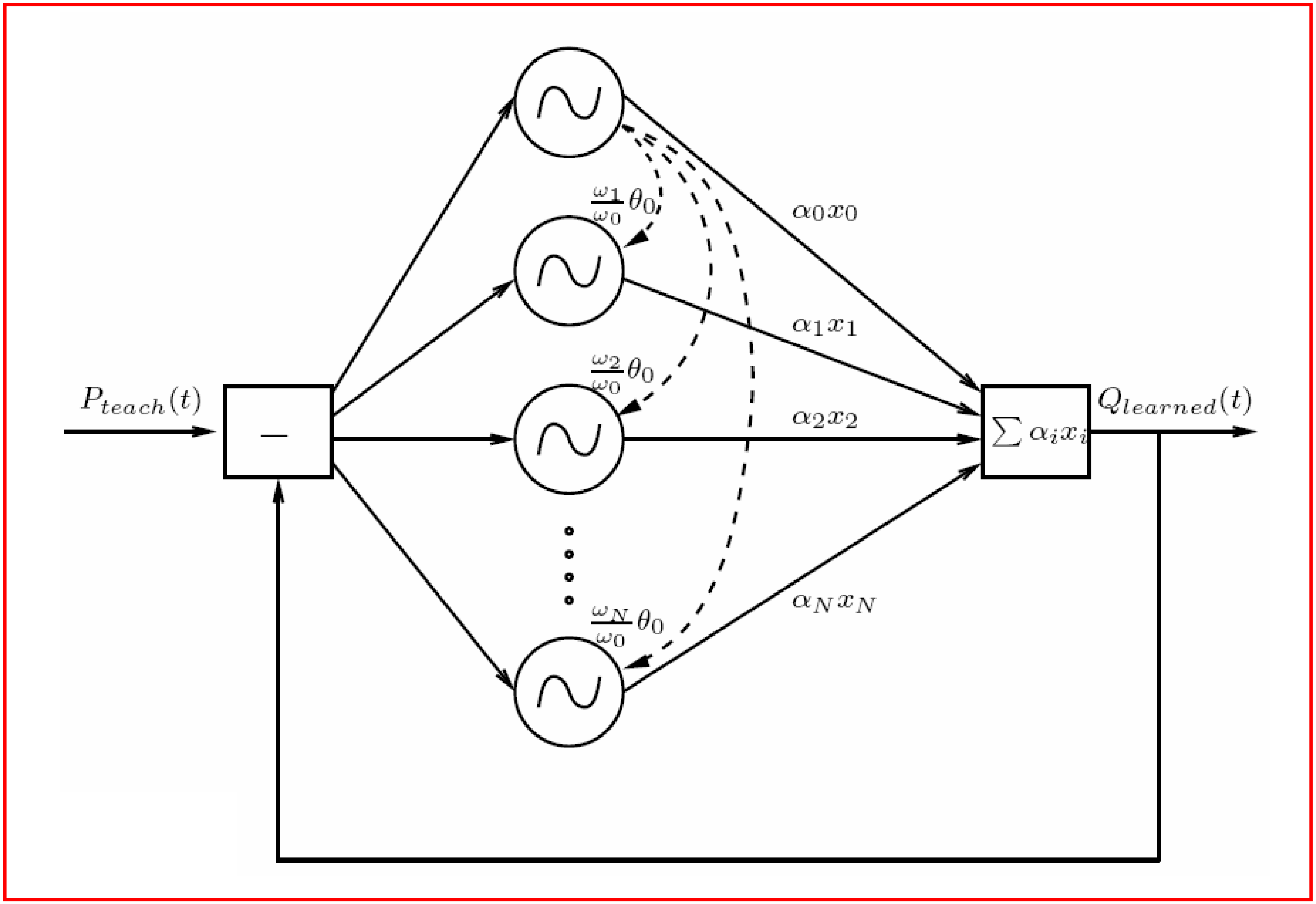
Supervised learning

Transforming periodic signals into limit cycles

Jonas Buchli

Ludovic Righetti

Programmable CPGs



Righetti et al, AMAM2005, ICRA 2006

Programmable CPGs: equations

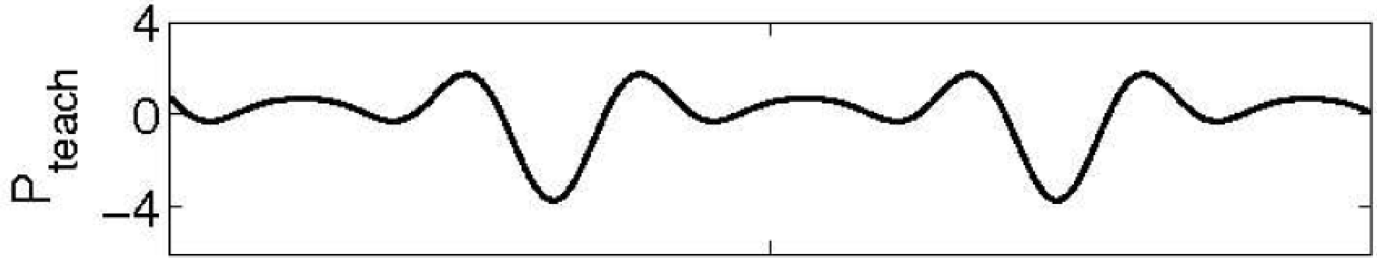
$$
\begin{aligned}
\dot{x}_i &= \gamma(\mu - r_i^2)x_i - \omega_i y_i + \epsilon F(t) + \tau \sin(\theta_i - \phi_i) \\
\dot{y}_i &= \gamma(\mu - r_i^2)y_i + \omega_i x_i \\
\dot{\omega}_i &= -\epsilon F(t) \frac{y_i}{r_i} \\
\dot{\alpha}_i &= \eta x_i F(t) \\
\dot{\phi}_i &= \sin\left(\frac{\omega_i}{\omega_0}\theta_0 - \theta_i - \phi_i\right)
\end{aligned}
$$

with

$$
\begin{aligned}
\theta_i &= \operatorname{sgn}(x_i)\cos^{-1}\left(-\frac{y_i}{r_i}\right) \\
F(t) &= P_{\text{teach}}(t) - Q_{\text{learned}}(t) \\
Q_{\text{learned}}(t) &= \sum_{i=0}^{N} \alpha_i x_i
\end{aligned}
$$

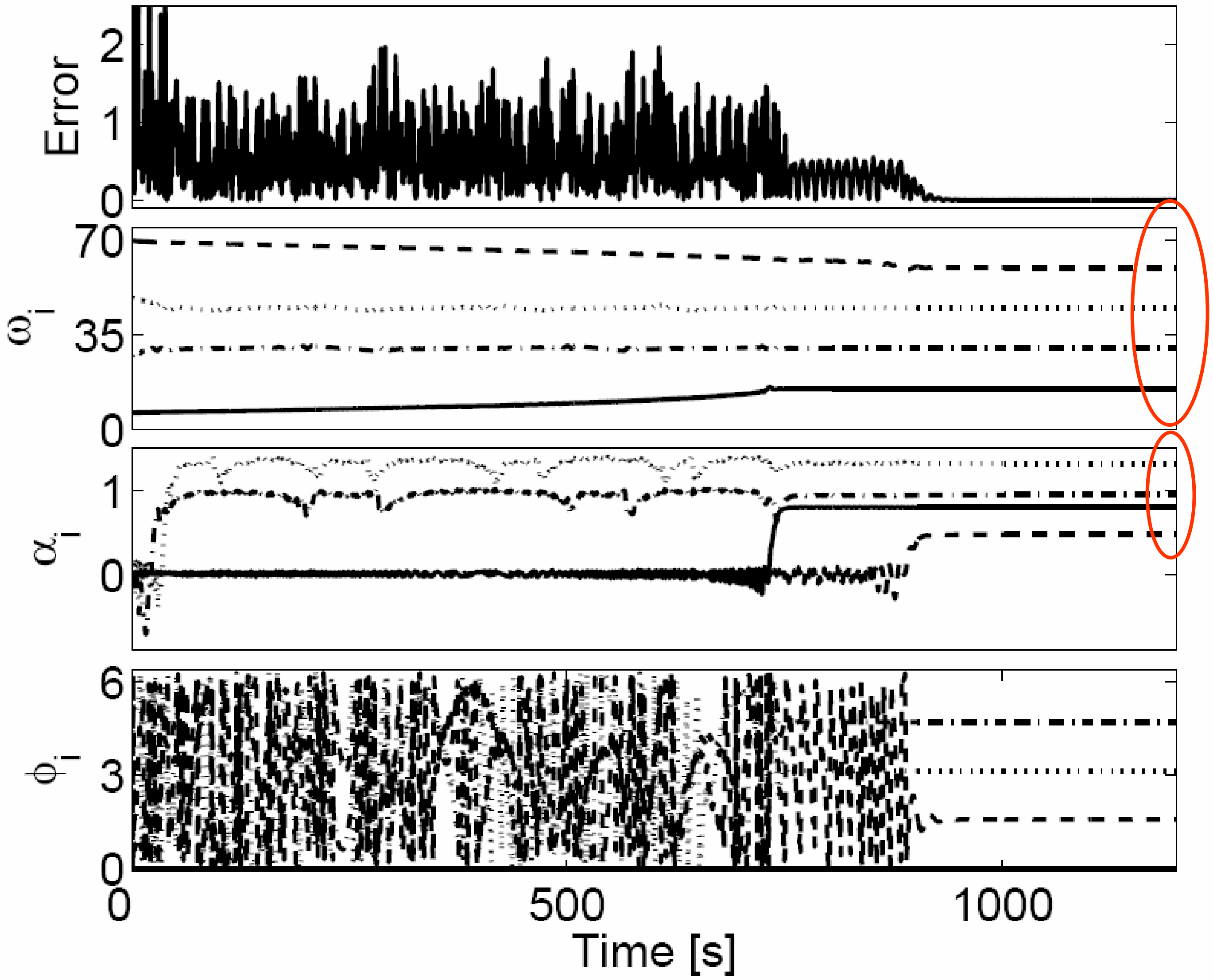
Righetti et al, AMAM2005, ICRA 2006

Example of learning



$$P_{\text{teach}} = 0.8\sin(15t) + \cos(30t) - 1.4\sin(45t) - 0.5\cos(60t)$$

Example of learning

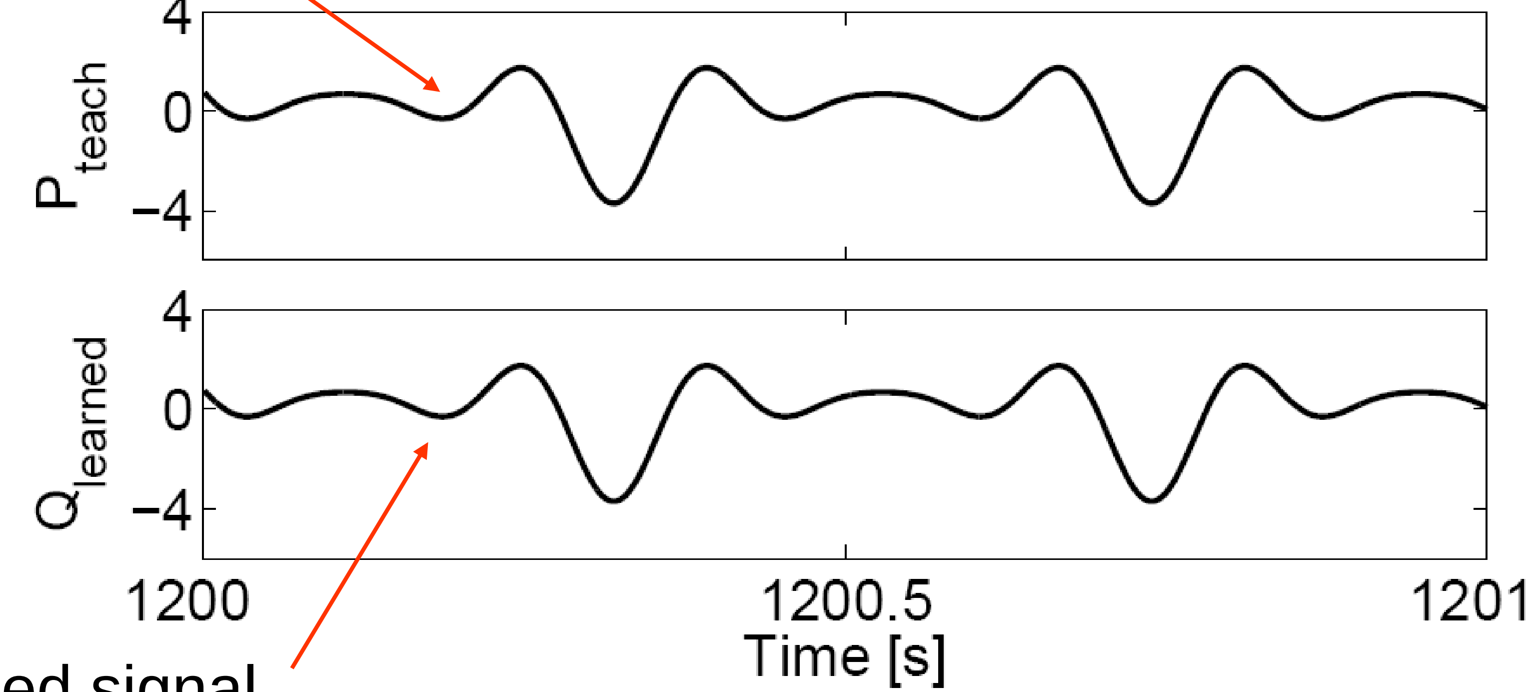


Correct frequencies

Correct amplitudes

Example of learning

Teacher signal

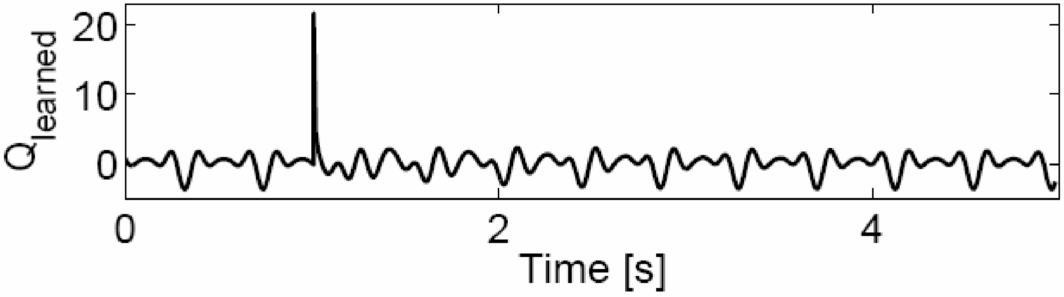


Learned signal

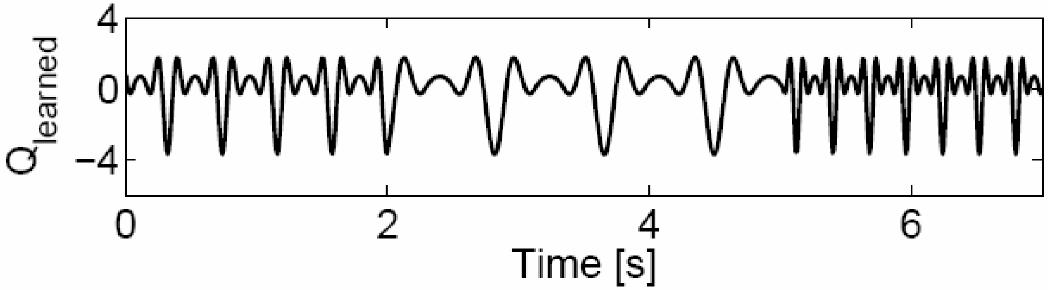
$$P_{\text{teach}} = 0.8\sin(15t) + \cos(30t) - 1.4\sin(45t) - 0.5\cos(60t)$$

Righetti et al, AMAM2005, ICRA 2006

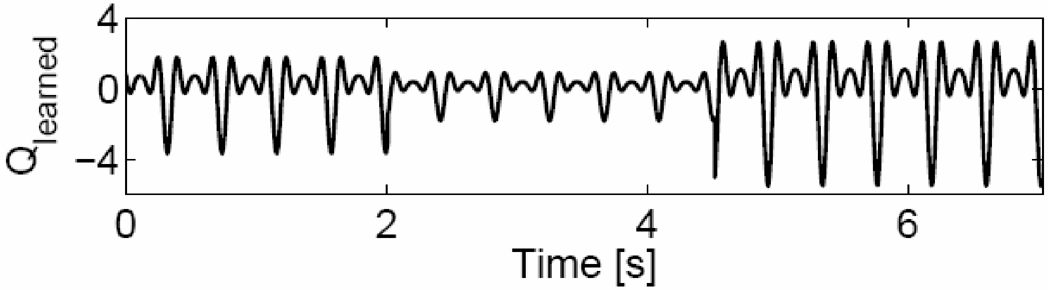
Interesting properties



Stability against perturbations



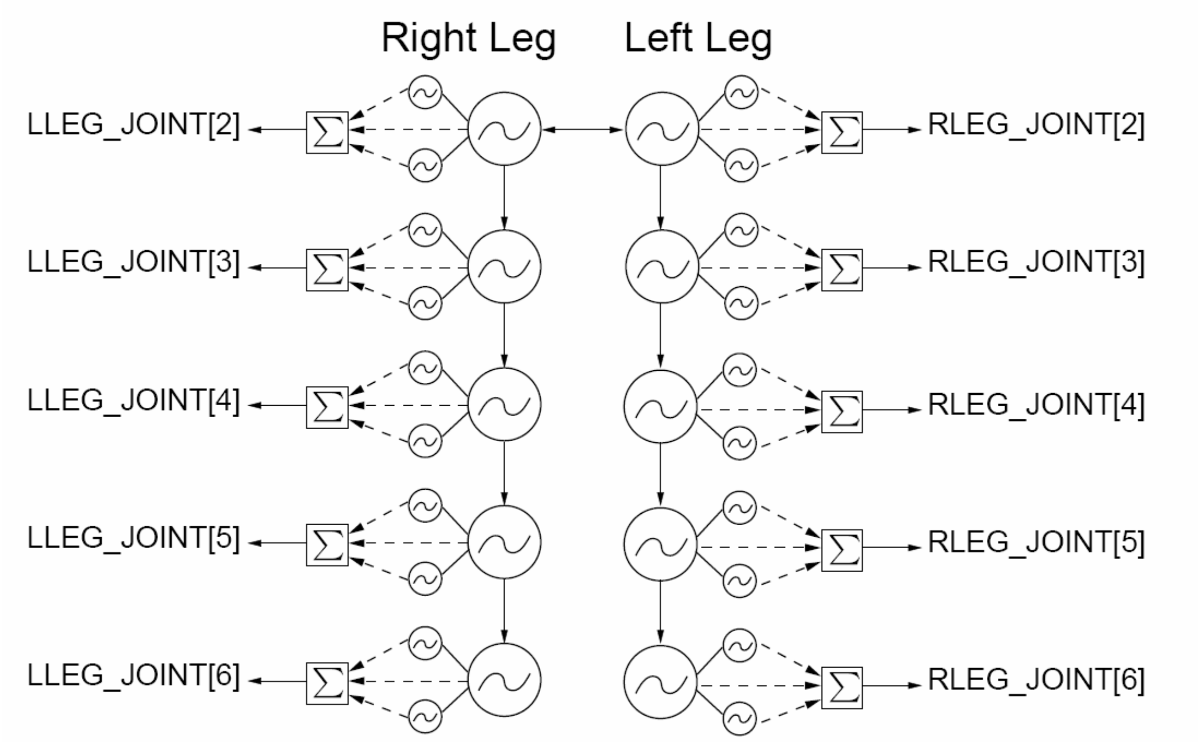
Frequency Modulation



Amplitude Modulation

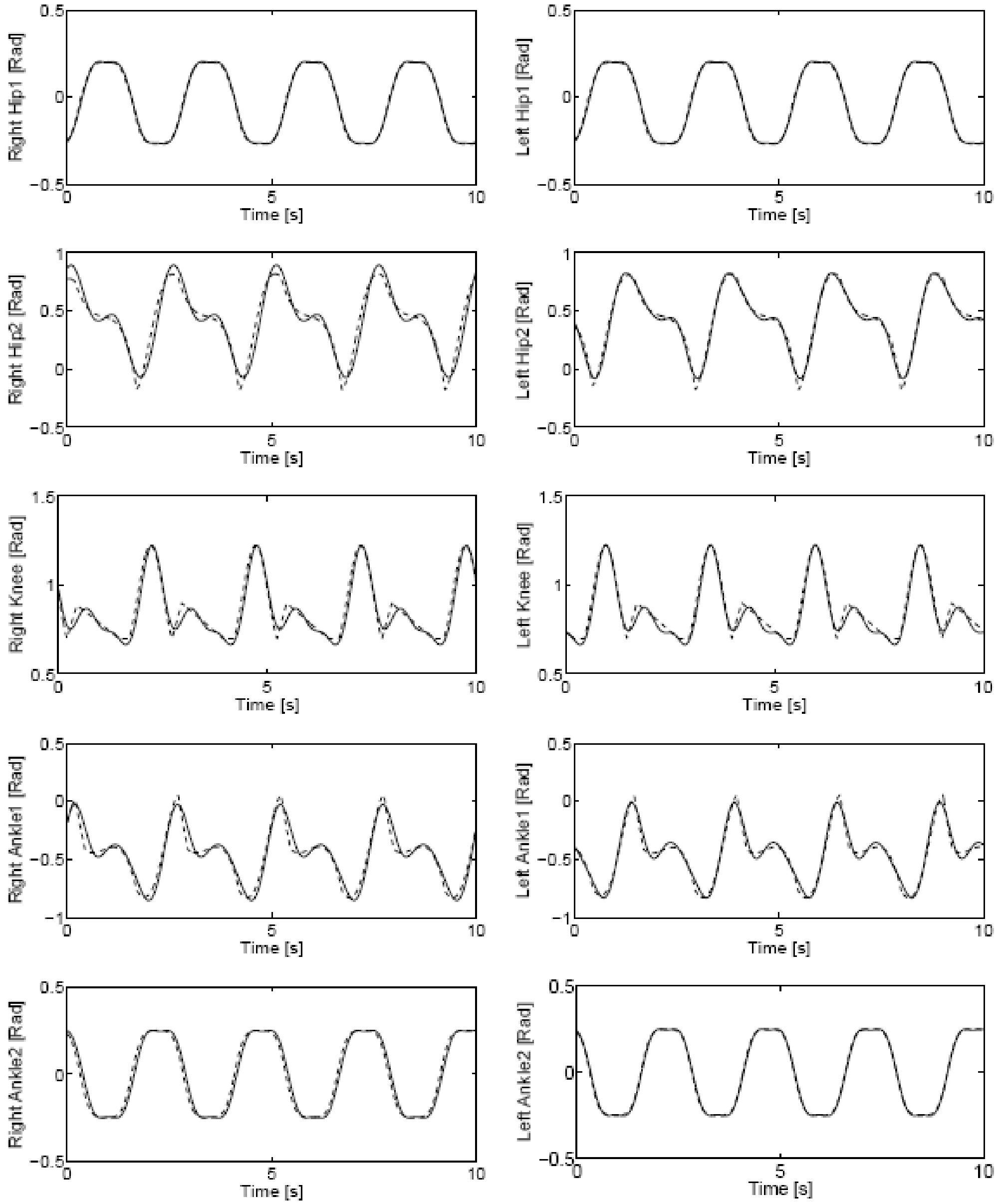
Application to locomotion control

Three oscillators per dof

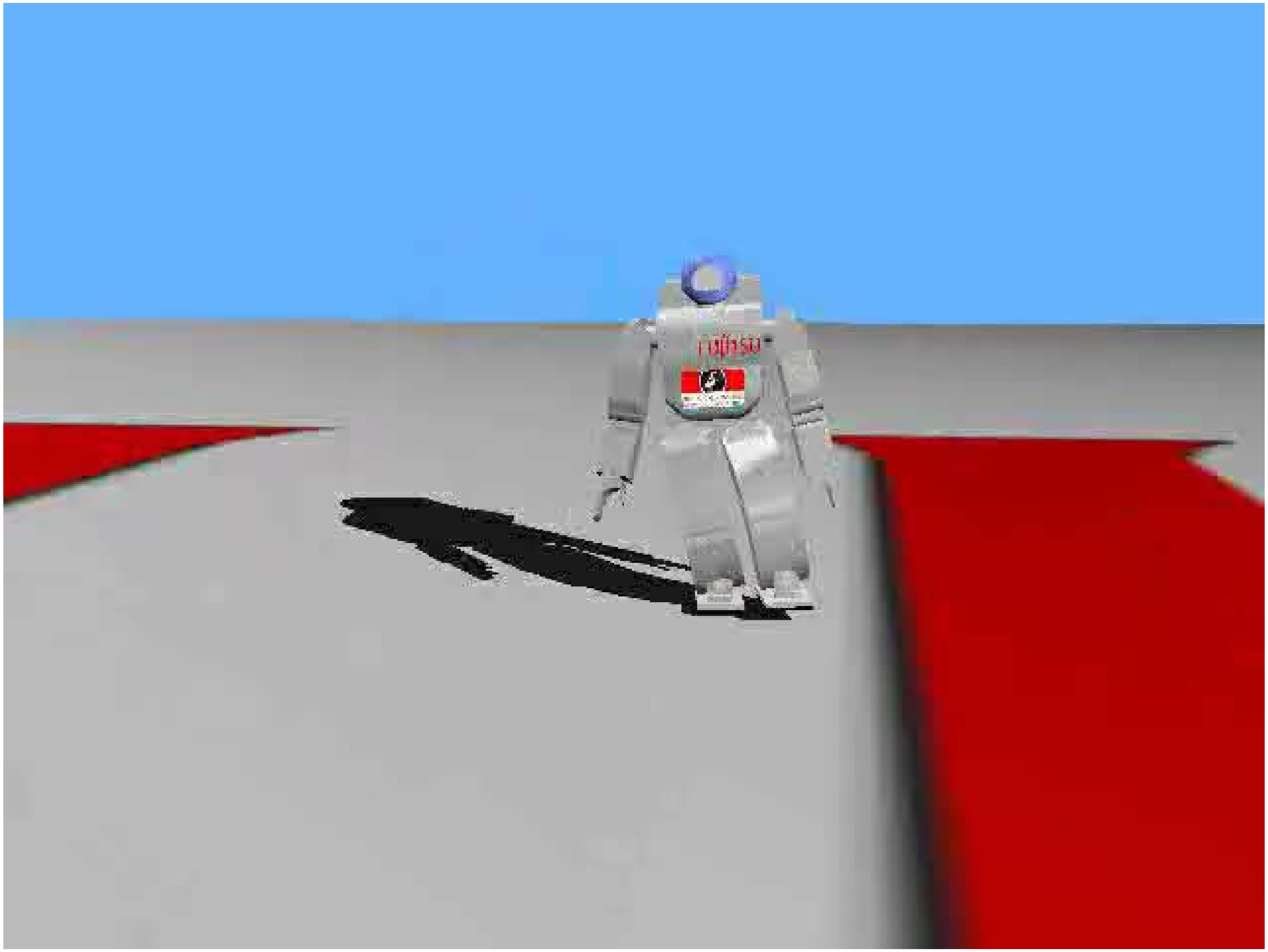


Righetti et al, ICRA 2006

Application to locomotion control



Application to locomotion control



Righetti et al, ICRA 2006

Simple feedback terms

Preventing leaning too much forward or backward:

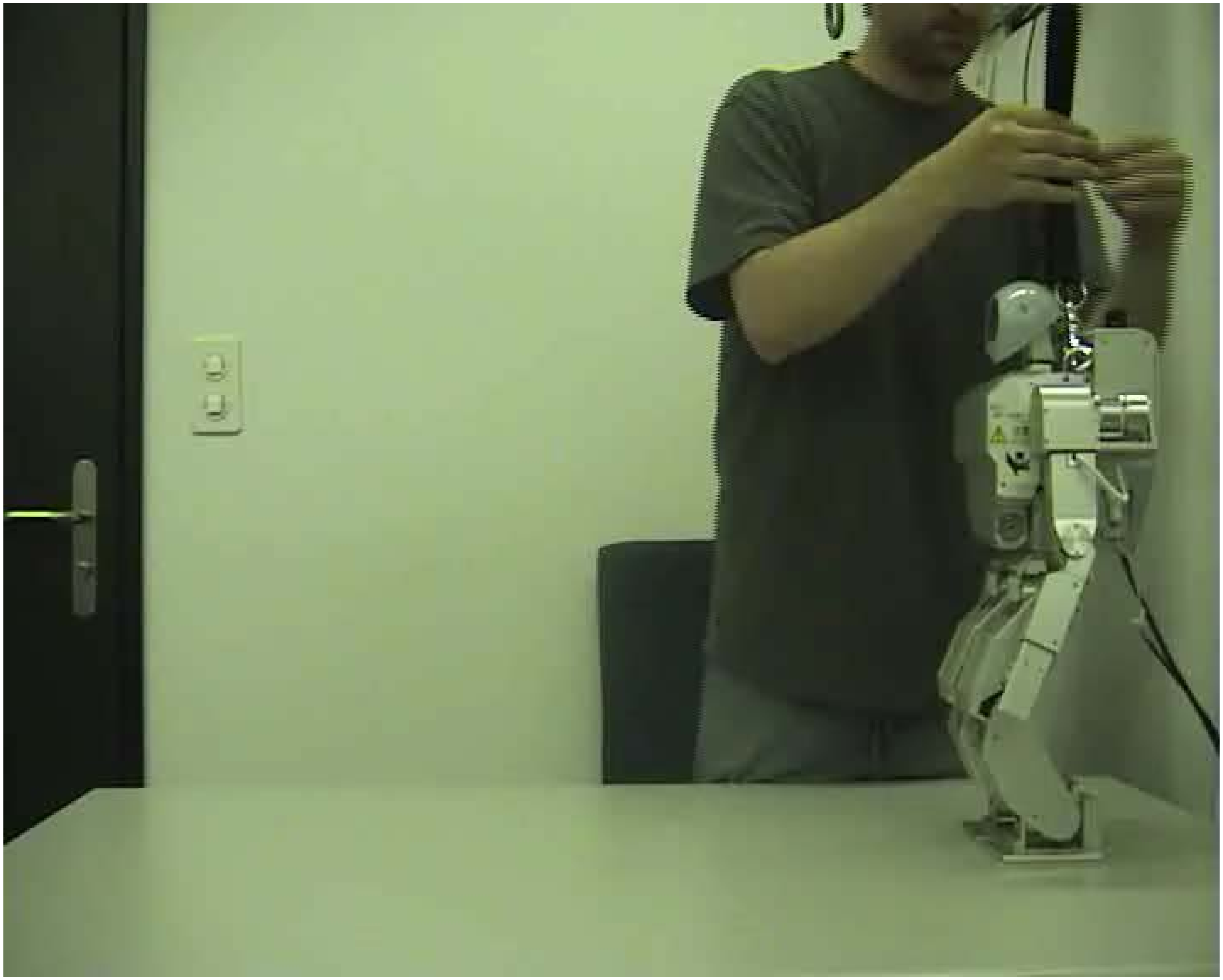
Ψ: *forward leaning angle (from gyroscope)*

Ψ_0: *reference angle*

$$\dot{x} = \gamma(\mu - r^2)x - \omega y + \boxed{\frac{x}{r}K(\psi - \psi_0)}$$

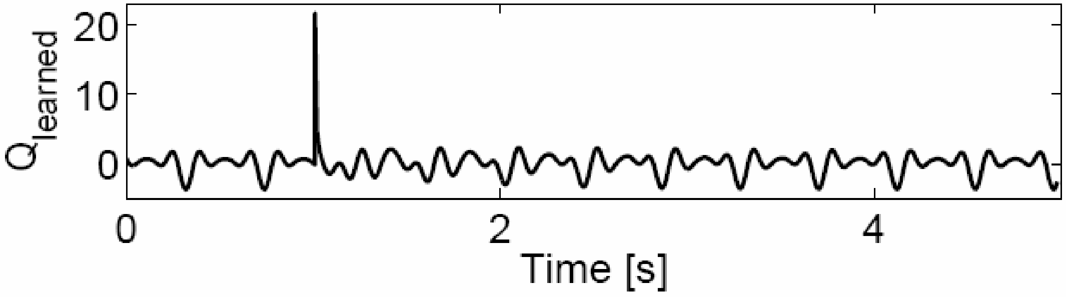
$$\dot{y} = \gamma(\mu - r^2)y + \omega x + \boxed{\frac{y}{r}K(\psi - \psi_0)}$$

Application to locomotion control

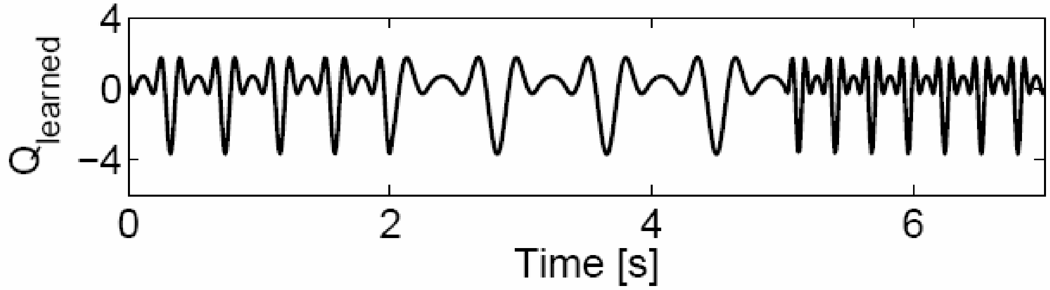


Righetti et al, ICRA 2006

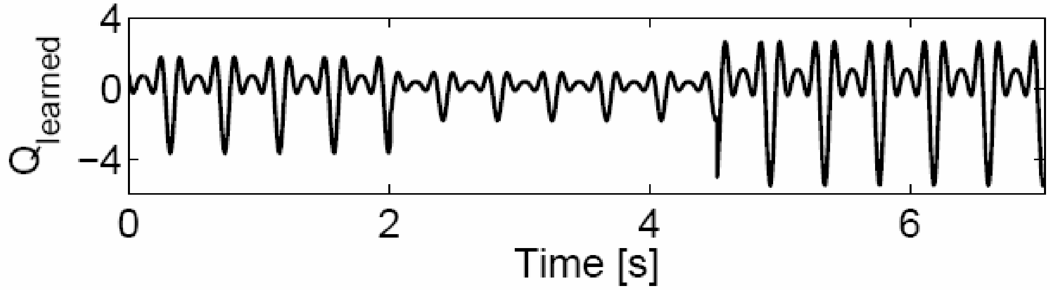
Interesting properties



Stability against perturbations



Frequency Modulation



Amplitude Modulation

Adaptive frequency oscillators: summary

Interesting properties:

- Frequency adaptation with **any initial frequency** (not mere synchronization)
- Works with **arbitrary input waveforms**
- Works for several nonlinear oscillators
- **Convergence proven** for the adaptive frequency **Hopf** oscillators
- No external optimization algorithm (learning is part of the dynamical system)
- Can implement a kind of **dynamic Fourier transform**

Outline of the talk

- Central pattern generators (CPGs) in biology
- Modeling the salamander CPG
- Adaptive frequency oscillators
  - Self-tuning CPGs
  - Programmable CPGs
- **Online learning in modular robots**

Work done in collaboration with

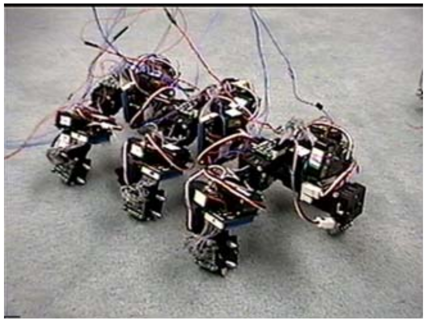
- Alexander Sproewitz
- Rico Moeckel, Daniel Marbarch, Michel Yerli

Modular robotics: characteristics

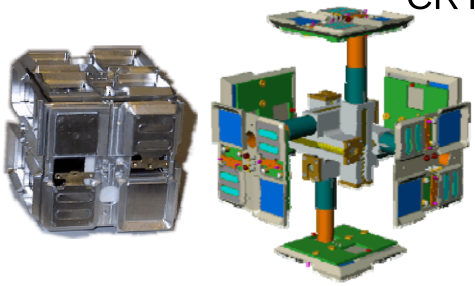
- Robots made of multiple units
- Possiblity of self reconfiguration
- Versatility, robustness against lesions
- Two types of locomotion:
  - «flow-like», locomotion through continuous reconfiguration
  - «actuated joints», locomotion through the actuation of joints

MTRAN

CRYSTALLINE ROBOT



CONRO



TELECUBE

POLYBOT

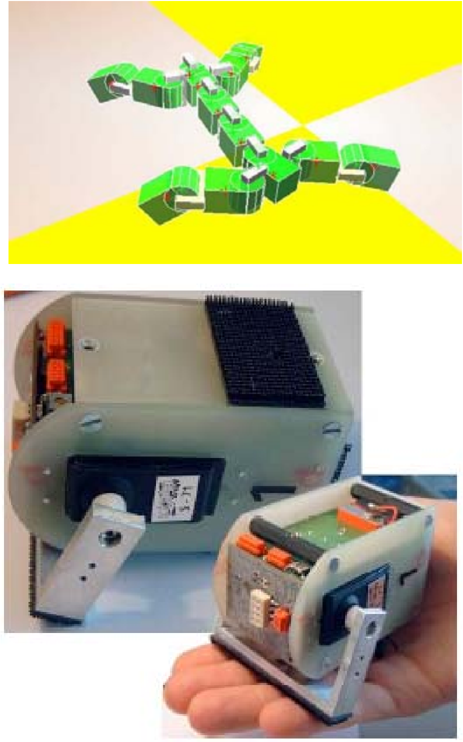
Modular robotics: challenges

- Efficient locomotion despite unknown configurations
- Configurations that change over time
- Distributed control

- Traditional model-based control is not well suited
- Interesting domain for adaptive locomotion

- Sofar few approaches use *online* learning, i.e. learning while moving without requiring a simulator

Our approach



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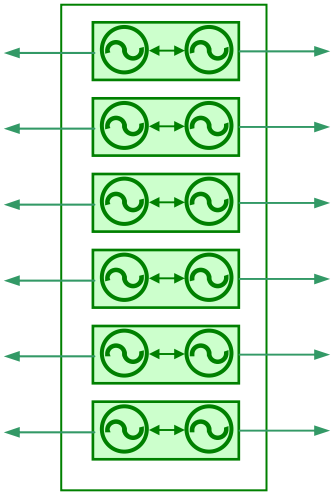

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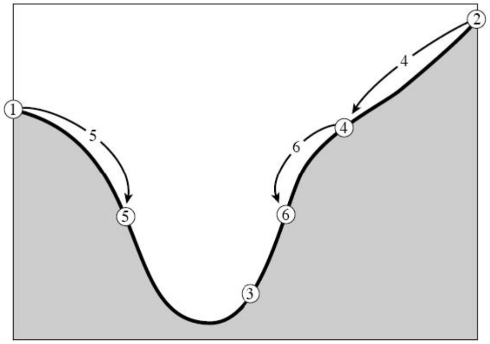


YAMOR units

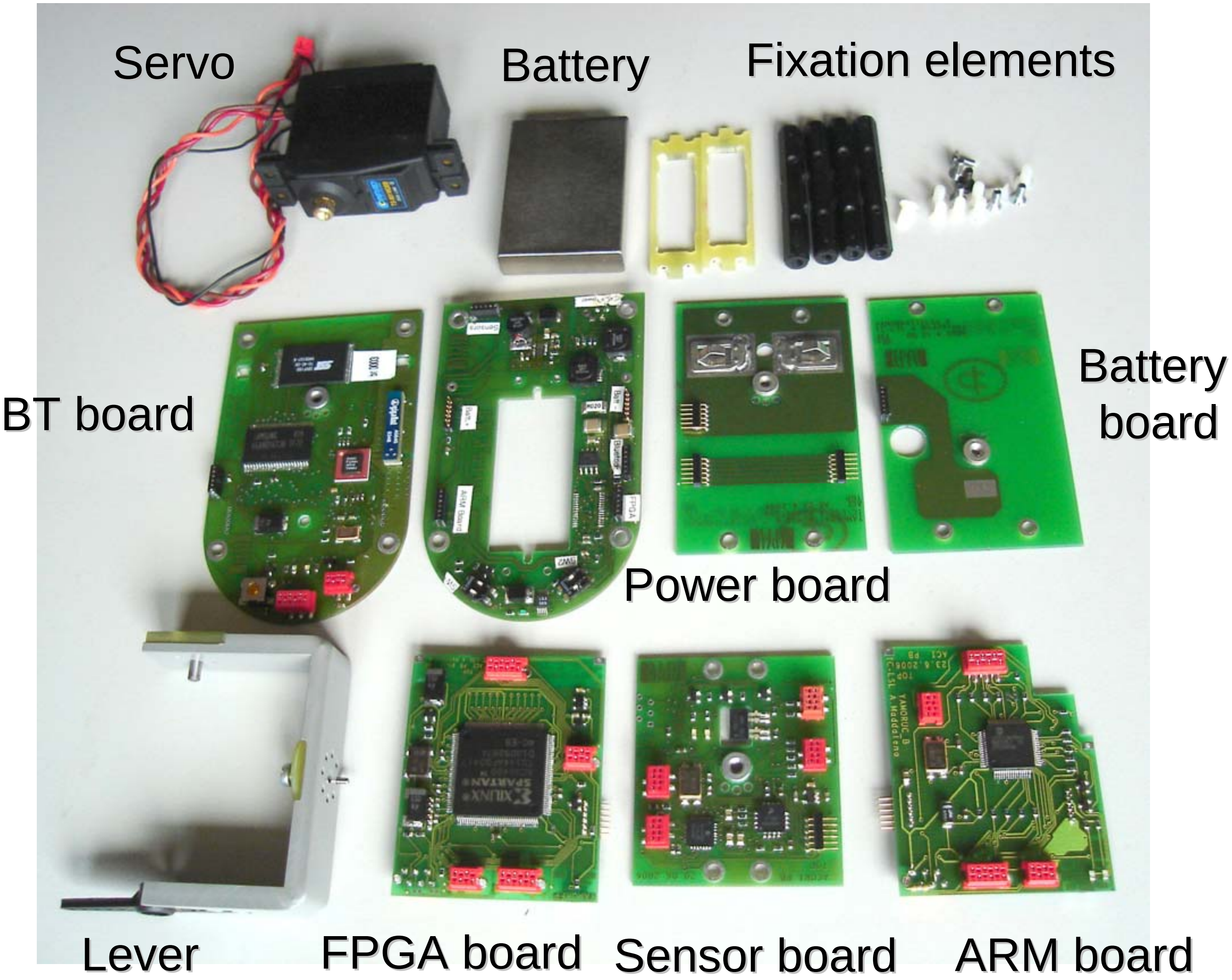
CPGs

Online optimization

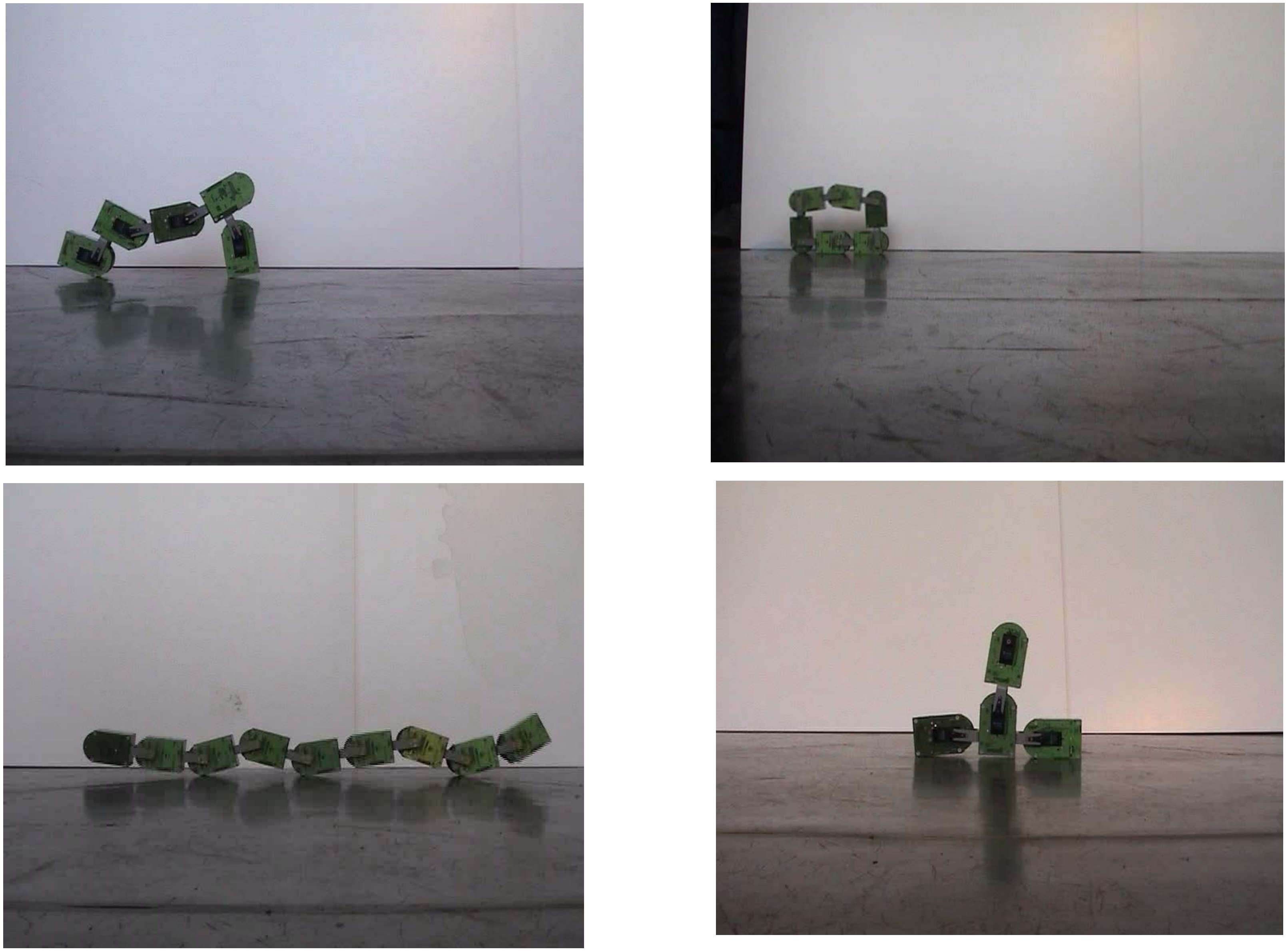
Yamor: key characteristics

- One-DOF
- Autonomous: each unit has its own battery and microprocessor (micro controller and FPGA)
- **Wireless bluetooth communication**
- Connections: strong velcro or screws and bolts

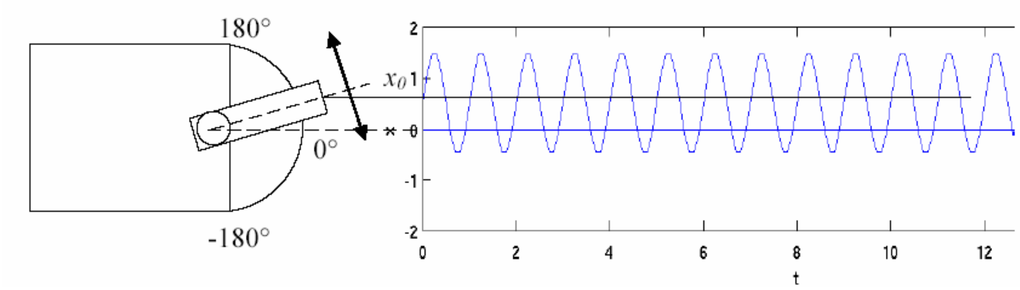
Yamor: content



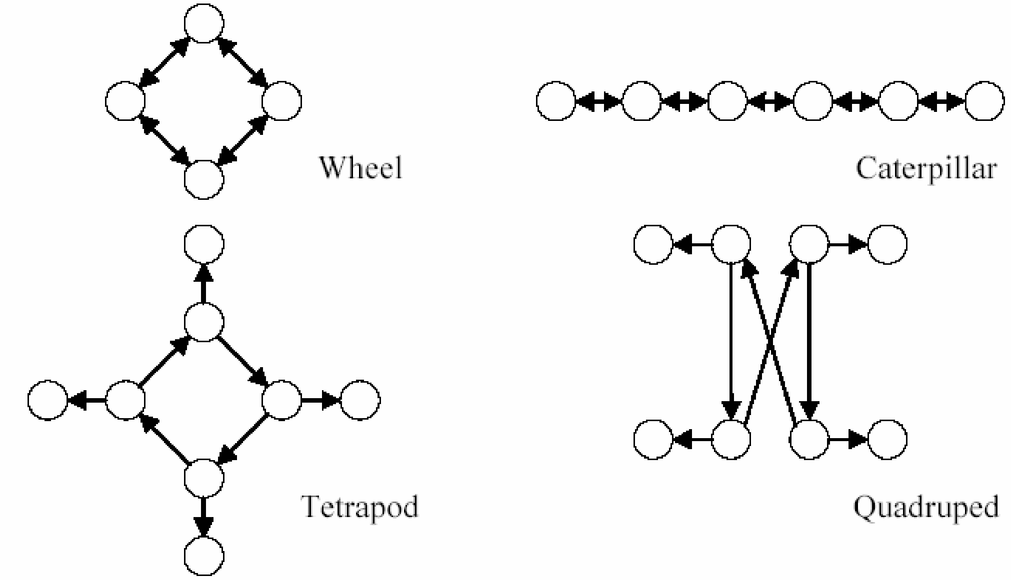
YAMOR Examples

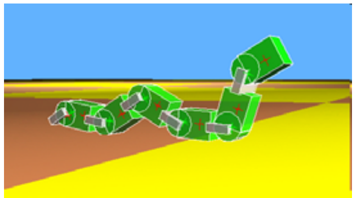


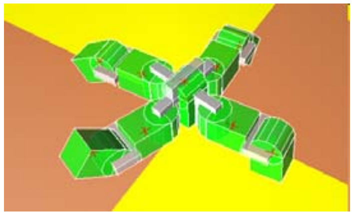
Designing CPGs for the YaMoR modules



Typically, the CPG connectivity matches the mechanical connections:

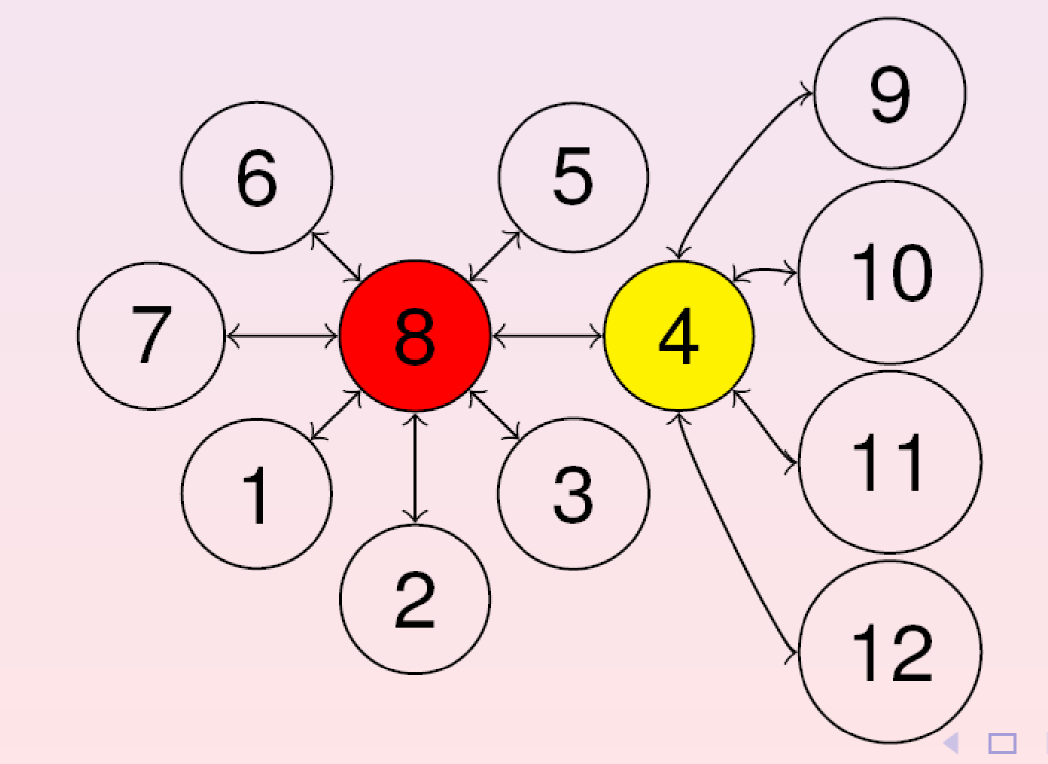






Bluetooth communication protocol

- Scatternet protocol,
- Transparent communication between modules
- Oscillators coupled in the CPG network communicate states



Rico Moeckel

Oscillator model

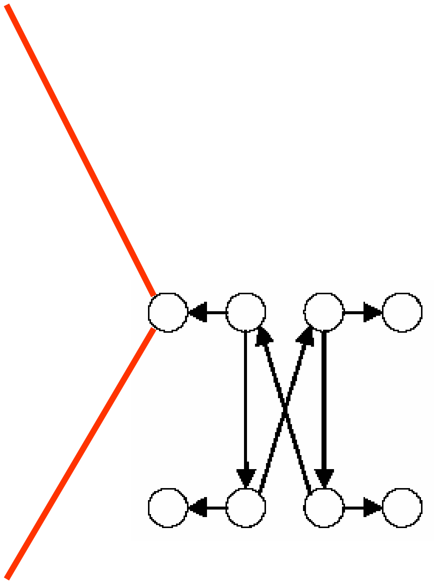
Amplitude controlled phase oscillator (Kuramoto-like):

Phase
$$\dot{\phi}_i = \omega_i + \sum_j \left(w_{ij} r_j \sin(\phi_j - \phi_i - \varphi_{ij}) \right)$$

Amplitude
$$\ddot{r}_i = a_i \left(\frac{a_i}{4}(R_i - r_i) - \dot{r}_i \right)$$

Offset
$$\ddot{x}_i = a_i \left(\frac{a_i}{4}(X_i - x_i) - \dot{x}_i \right)$$

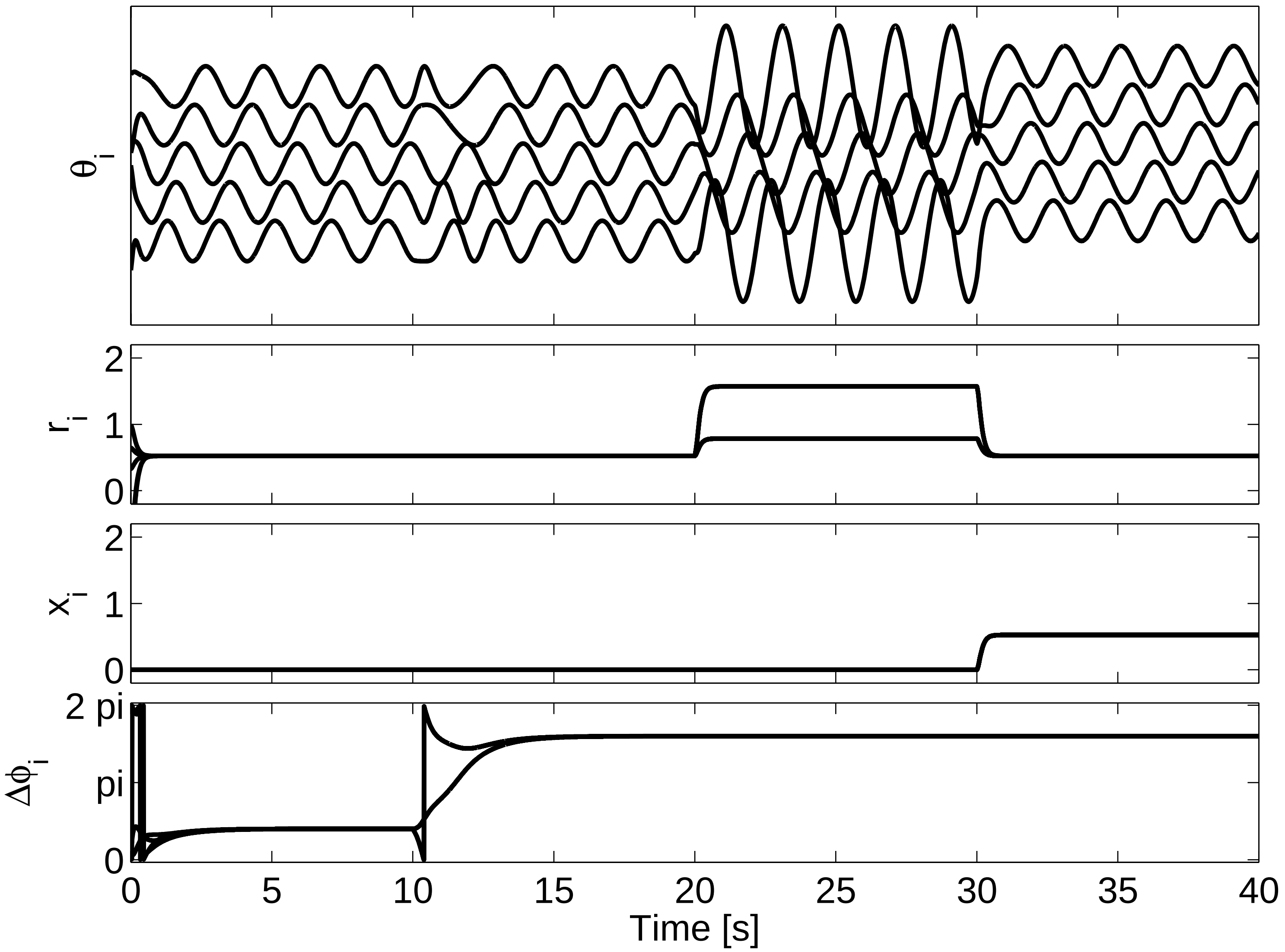
Output
$$\theta_i = x_i + r_i \cos(\phi_i)$$



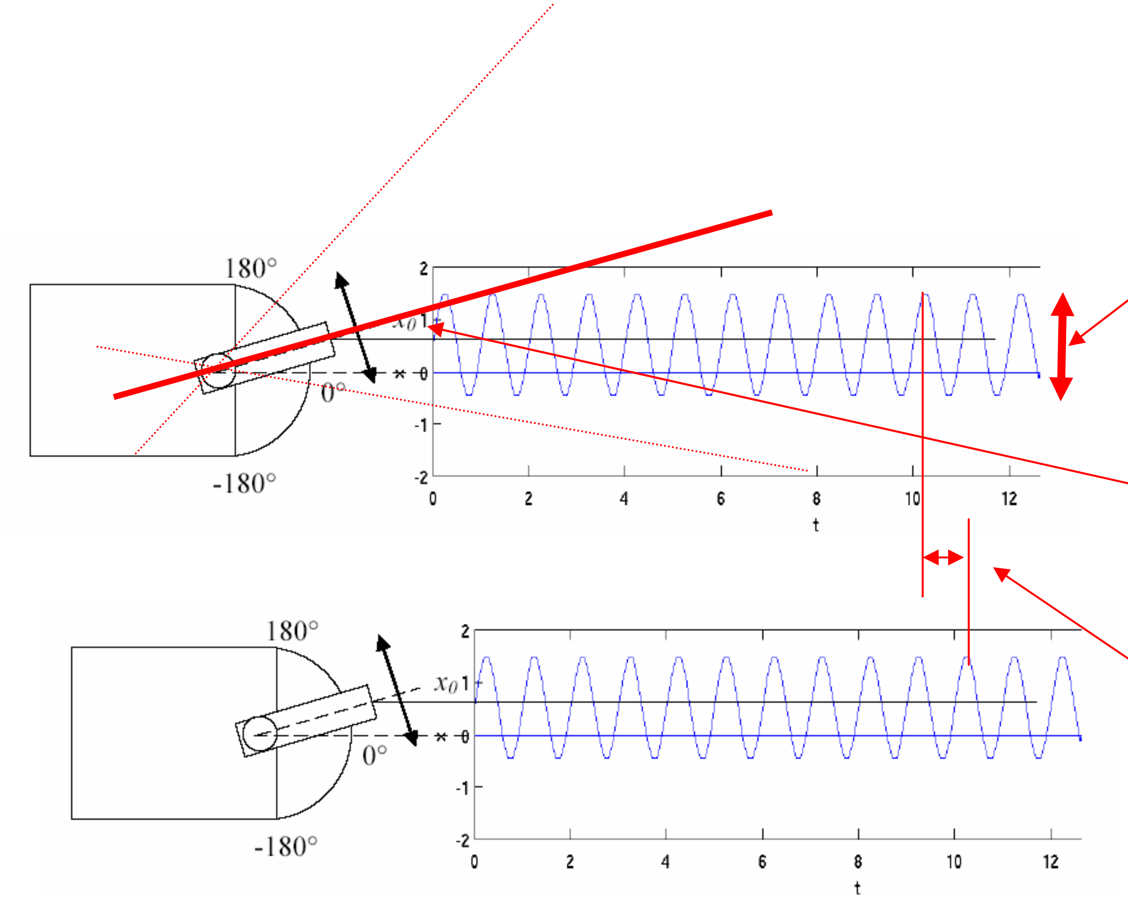
An isolated oscillator converges to the following limit cycle:

$$\theta_i^\infty(t) = X_i + R_i \cos(\omega_i t + \varphi_{ij} + cst)$$

Example of CPG output modulation



To be optimized for each oscillator:



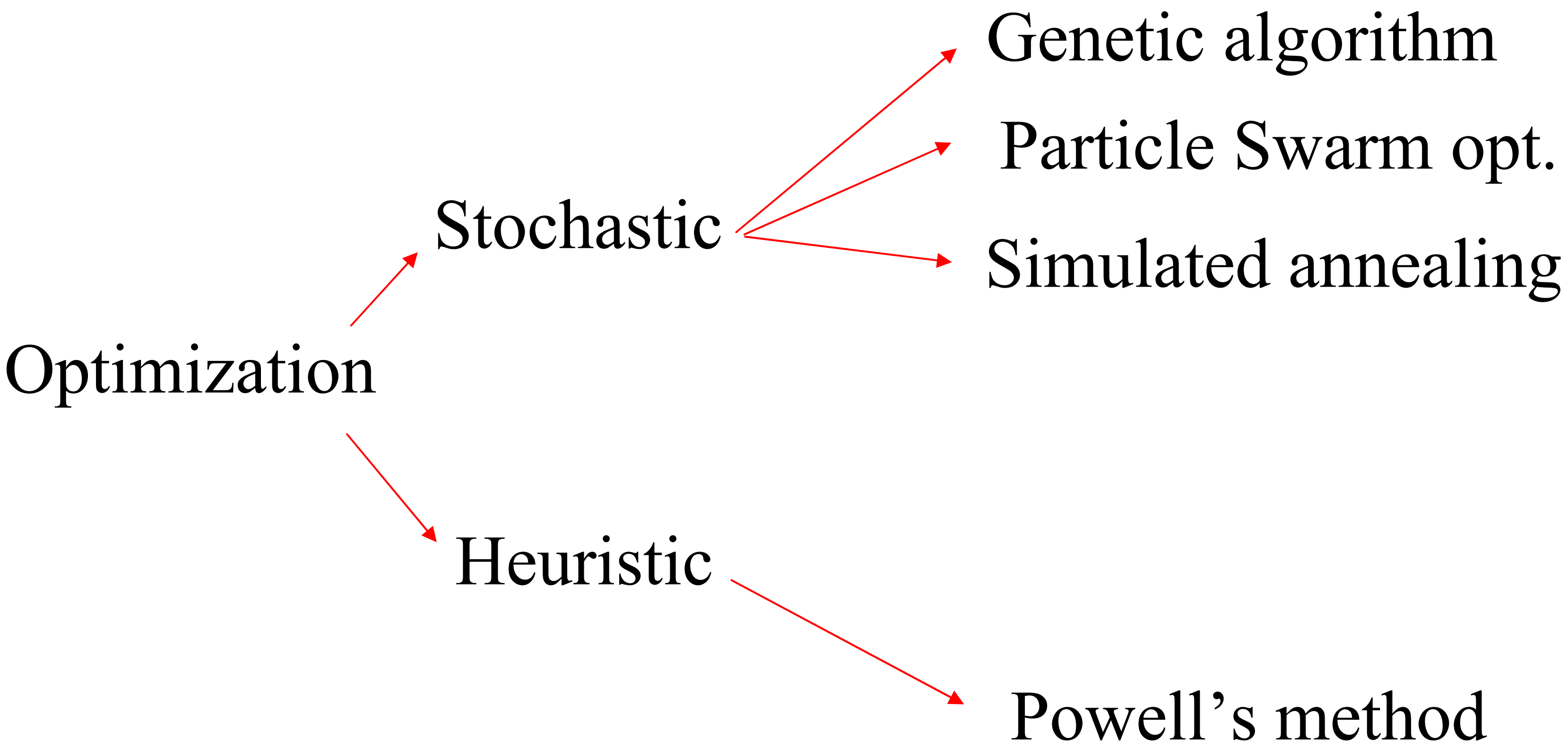
The amplitude *R*

The offset *X*

The relative phase lag $\Delta\phi$ (the coupling parameters ω and φ)

= 4 (or more) parameters per module

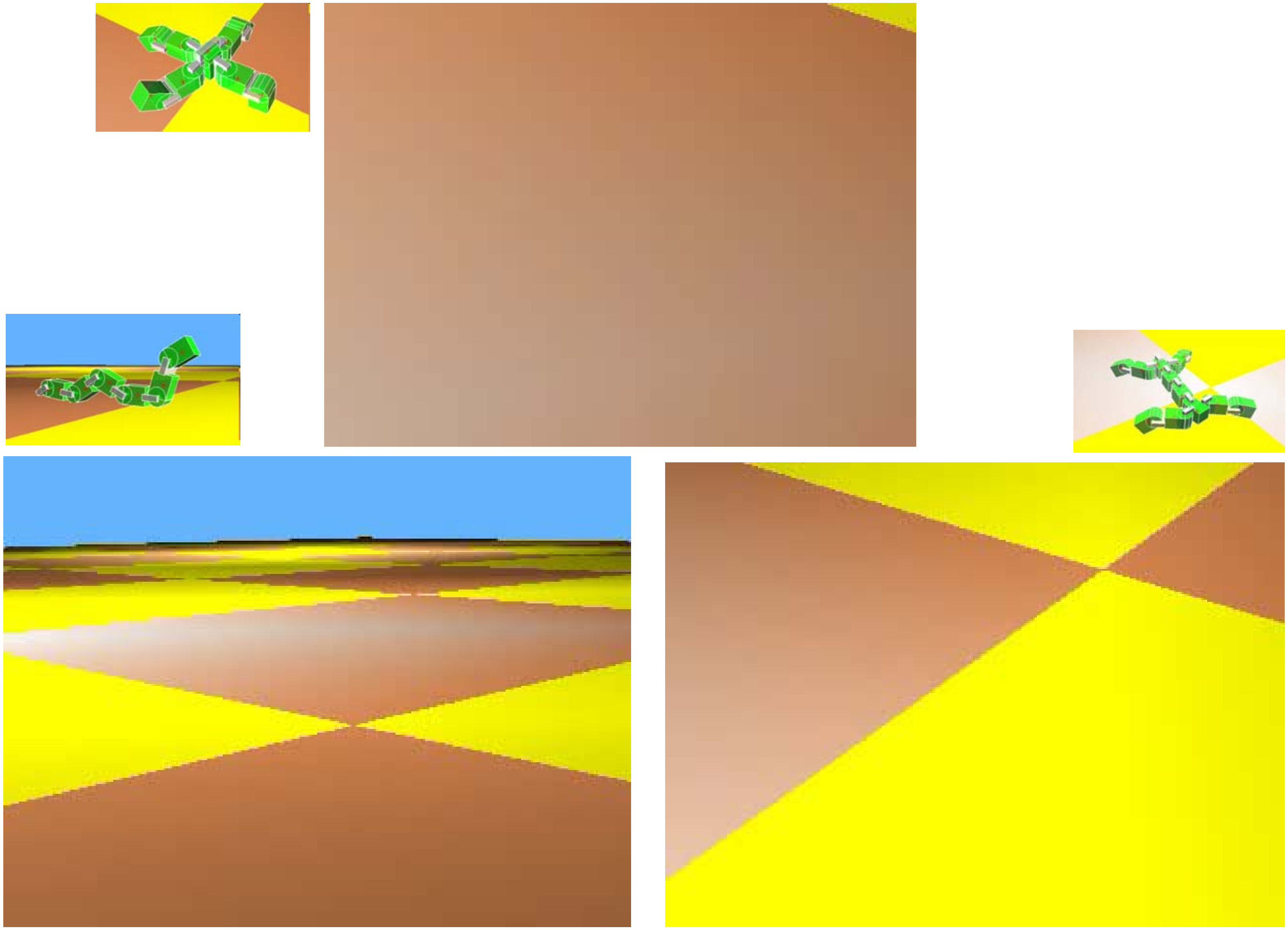
Different algorithms tested



- Optimization
  - Stochastic
    - Genetic algorithm
    - Particle Swarm opt.
    - Simulated annealing
  - Heuristic
    - Powell’s method

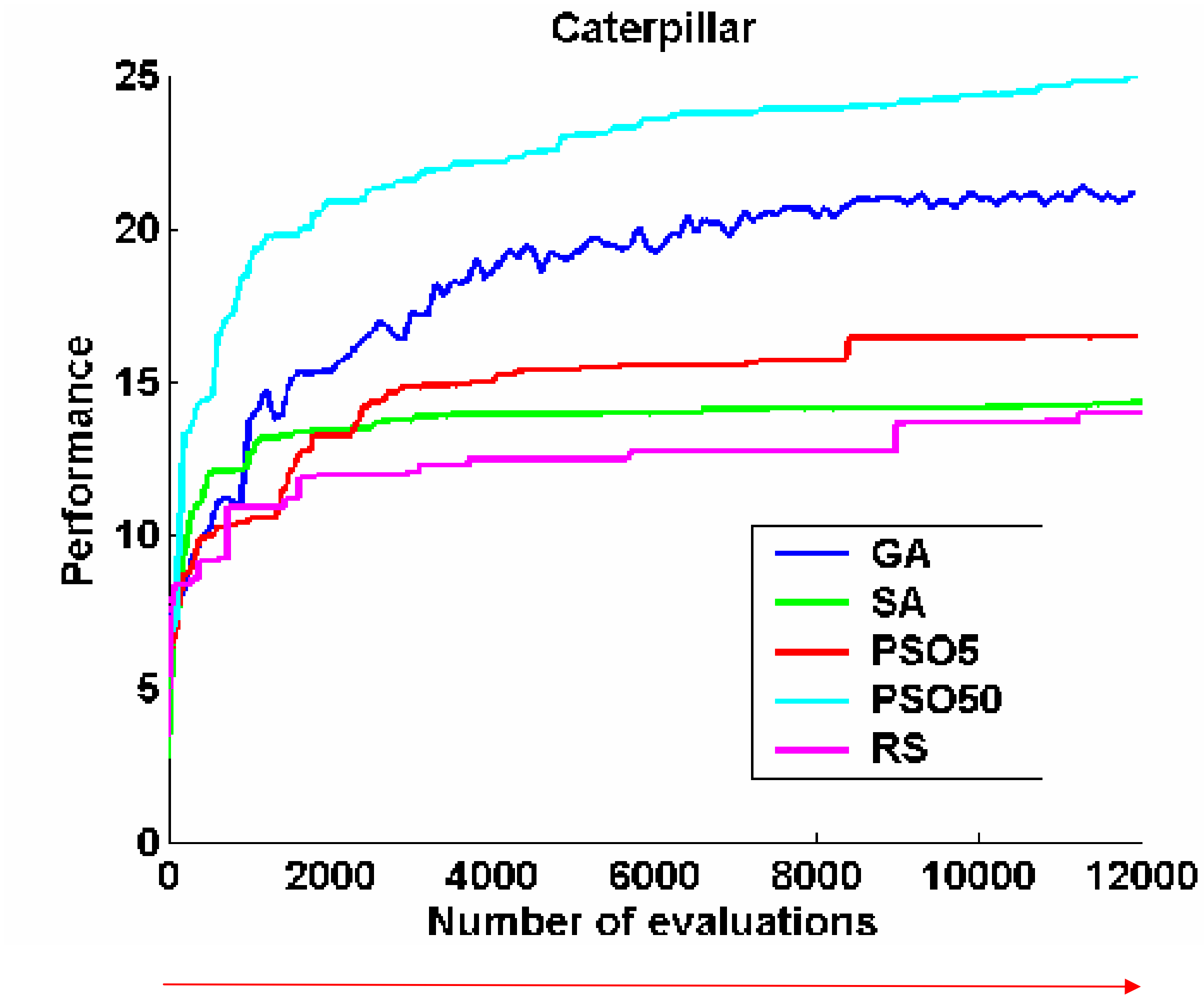
Fitness function: distance covered

Stochastic optimization



Yvan Bourquin

Stochastic optimization: results



Approx. 100 hours: too slow!

Yvan Bourquin

Online optimization using Powell's method

- Multidimensional optimization method which does not require gradient computation
- **Fast enough to be used *online***

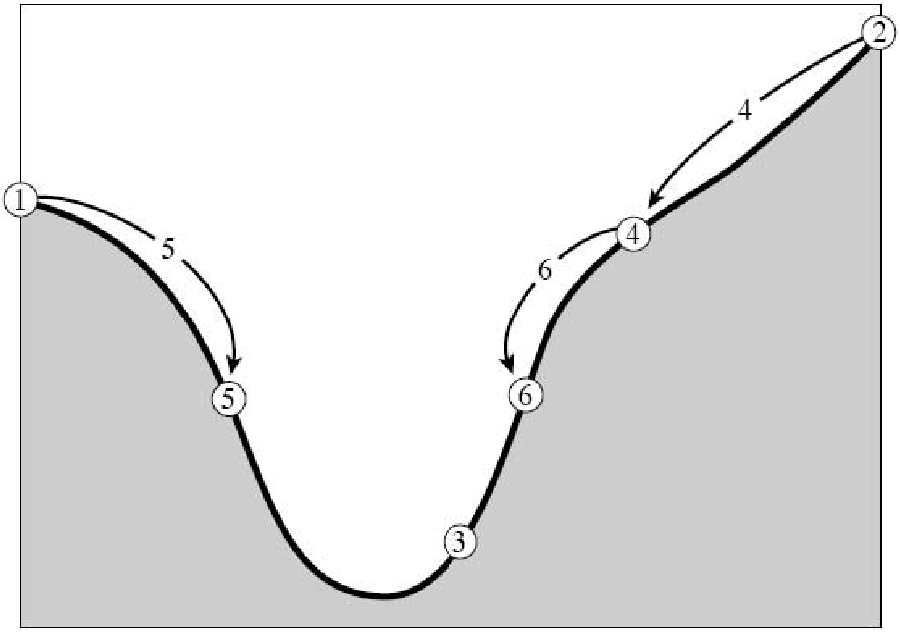
- Idea:
    - use Brent's method for unidimensional optimization
    - Carefully choose direction sets for multidimensional optimization

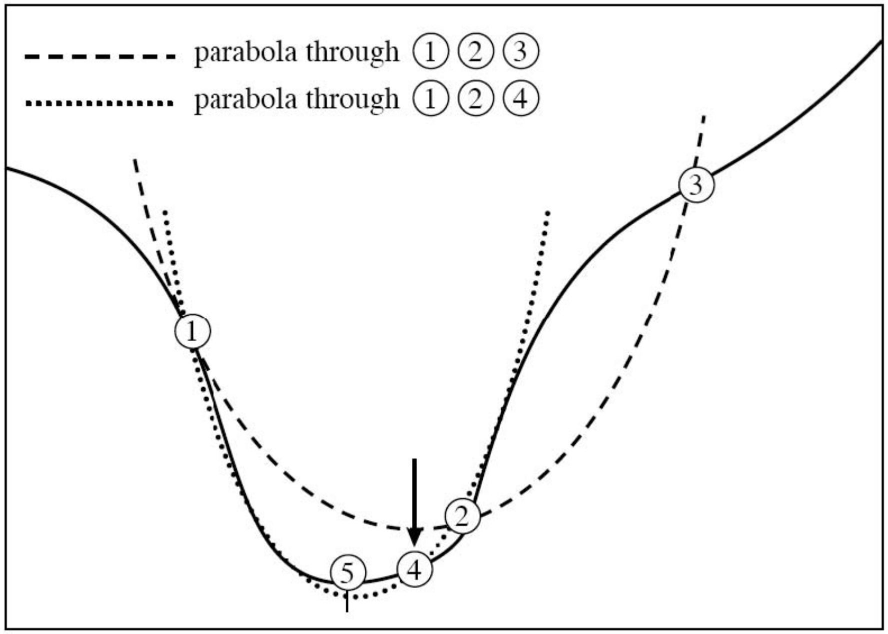
- Numerical Recipes in C, W.H. Press, S.A. Teukolsky

Unidimensional optimization : Brent’s method

Combination of

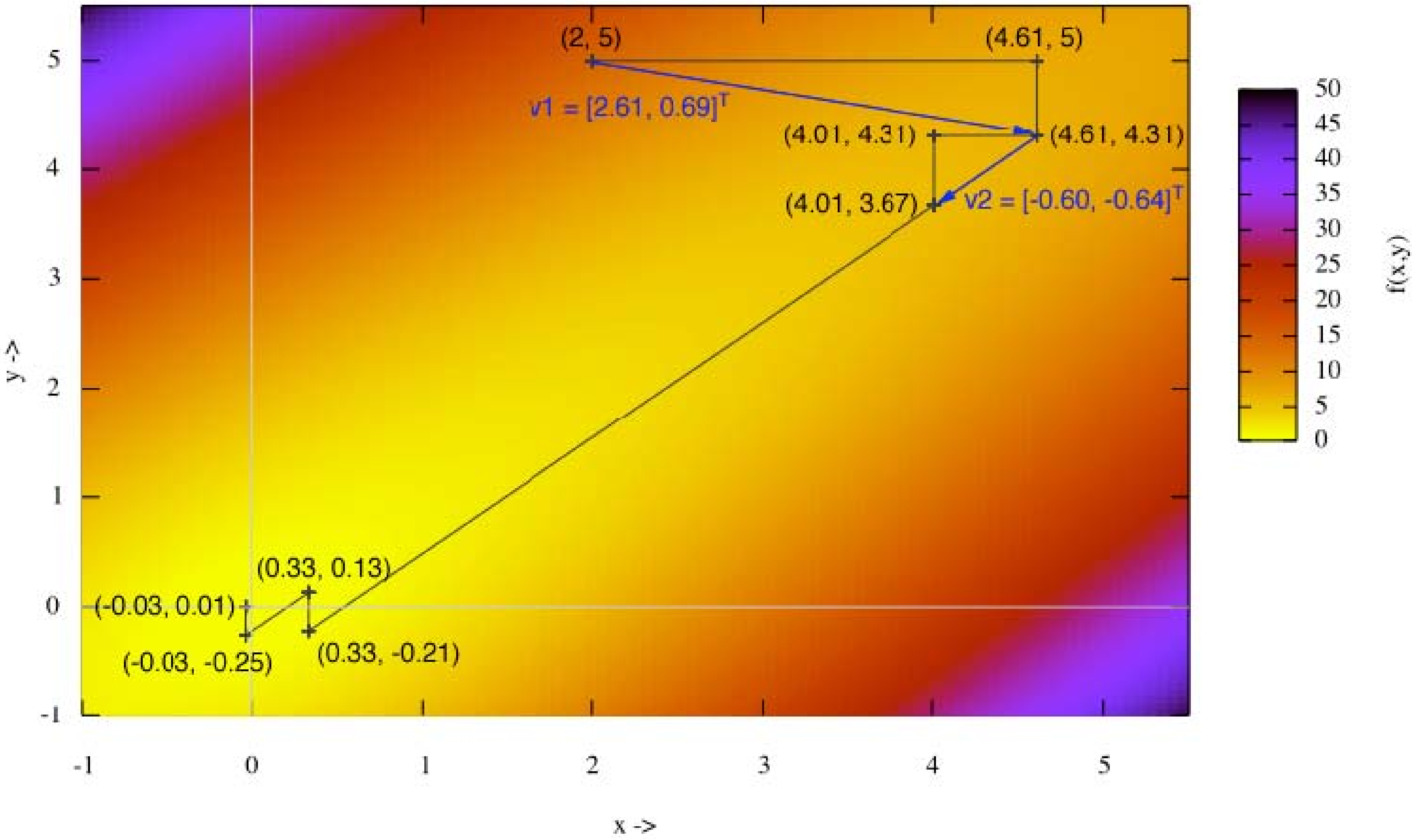
Successive bracketing and parabolic interpolation



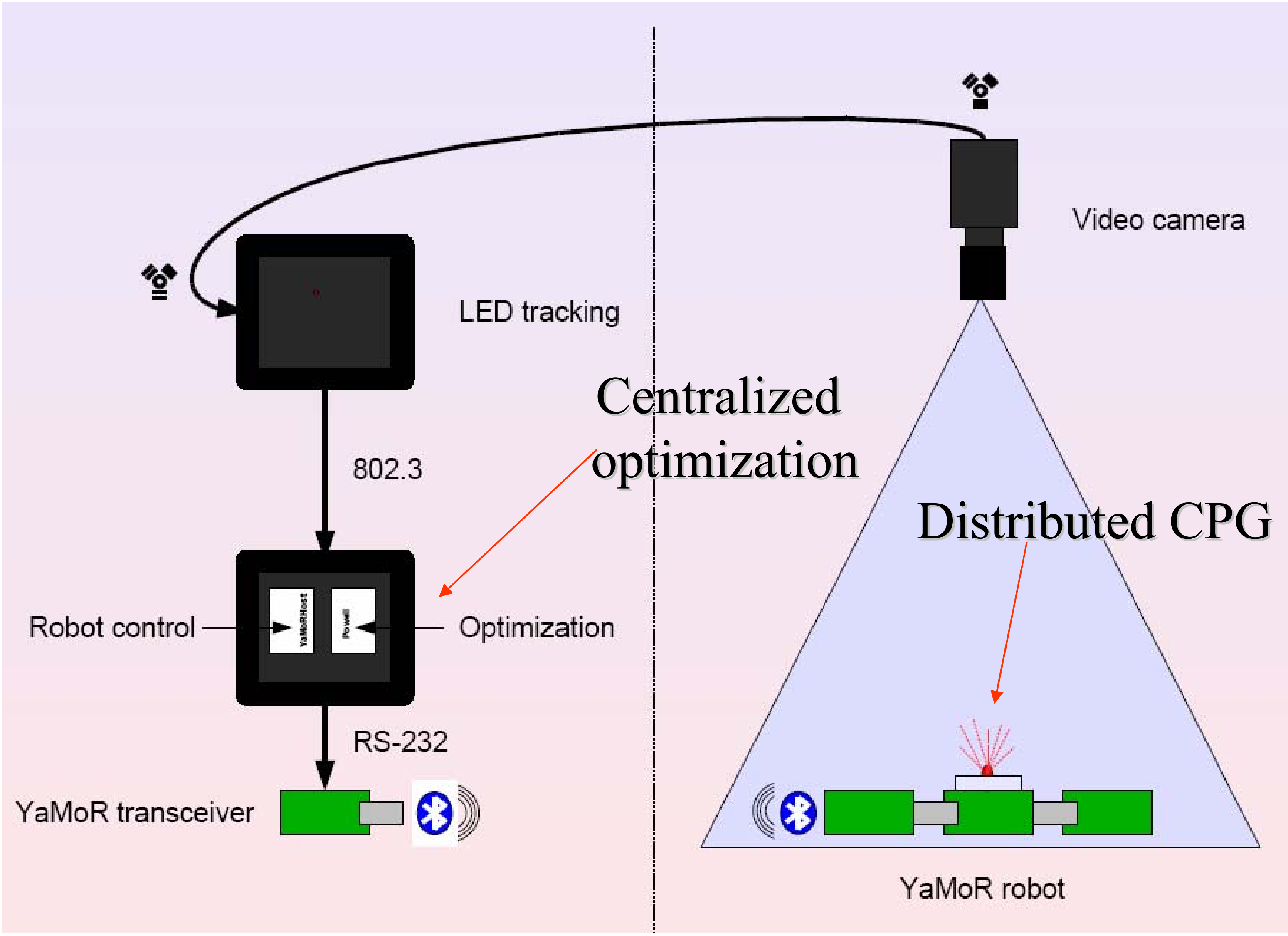


Powell's optimization method

Method for choosing directions for one-dimensional opt.



Experimental setup



Video camera

LED tracking

802.3

Robot control

Optimization

RS-232

YaMoR transceiver

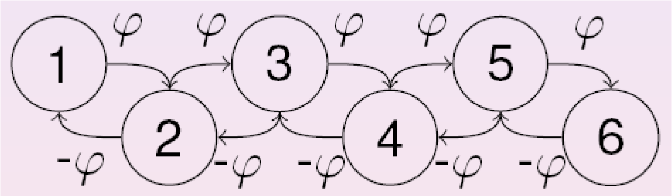
Centralized optimization

Distributed CPG

YaMoR robot

Example of results

Simple test with two open parameters: amplitude and phase lag



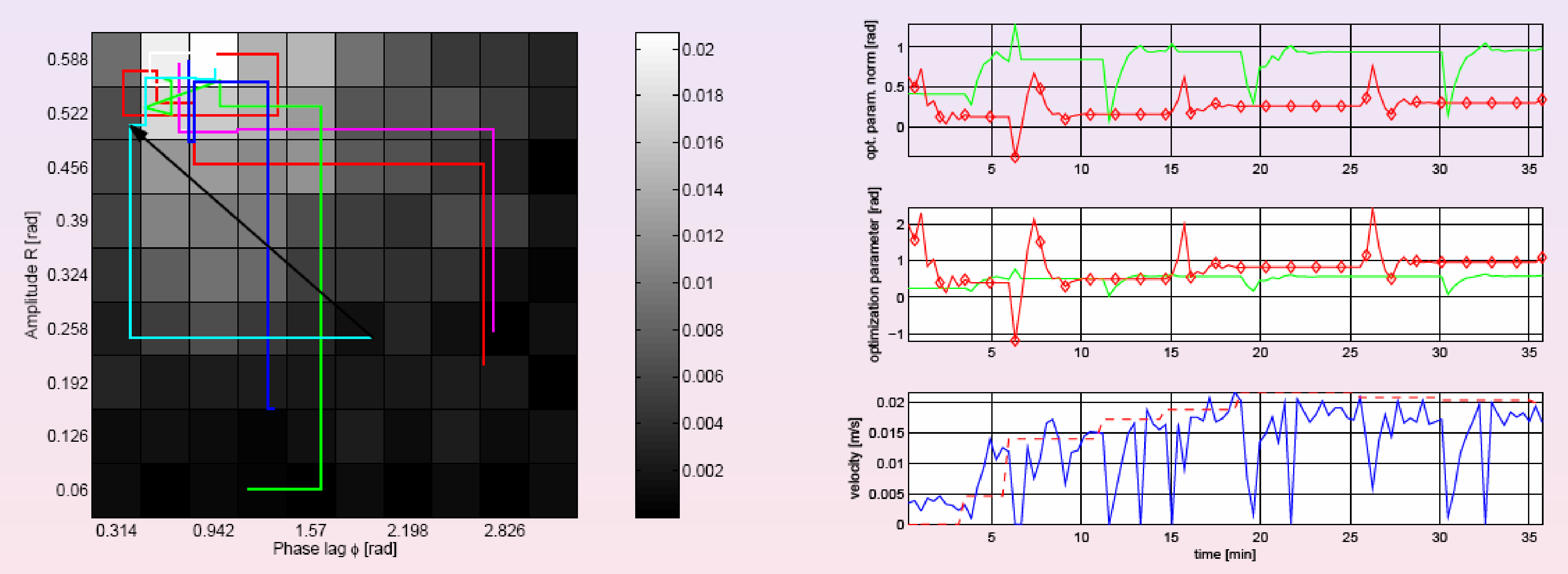
Before

20 minutes

After

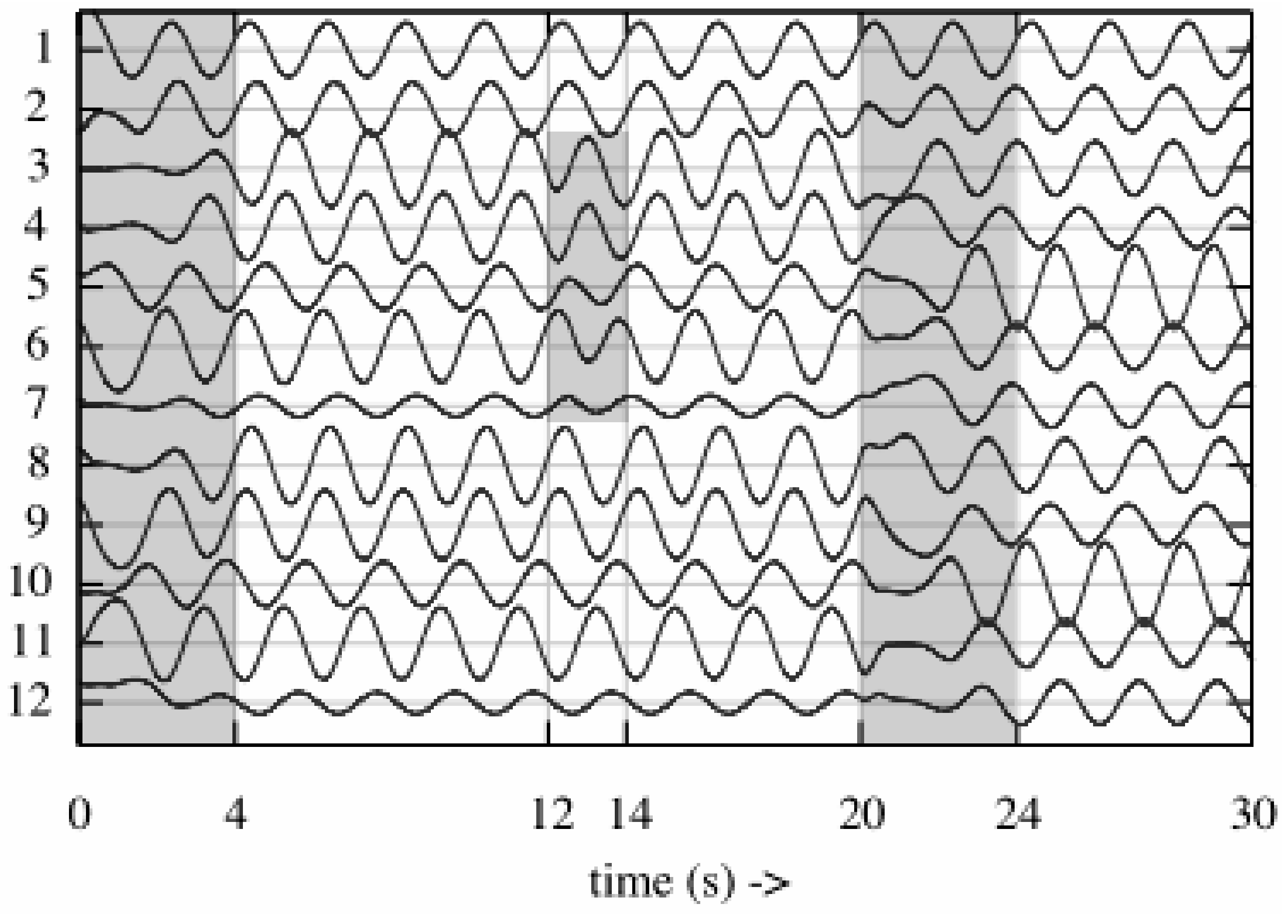
Example of results

- Convergence to the same gait
- Same solution as found by a systematic search (in much less time)



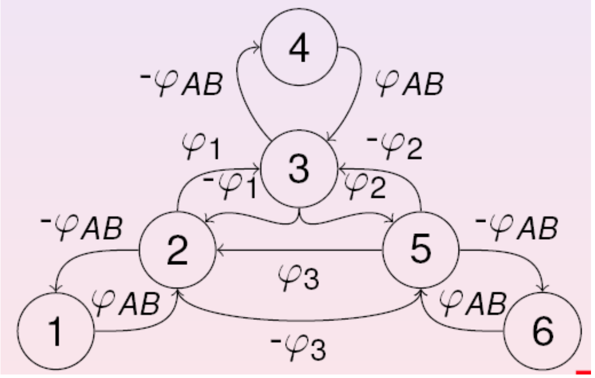
Optimization can run in parallel with CPG

Modifications of parameters without stopping/resetting the robot



Example of results

Six open parameters



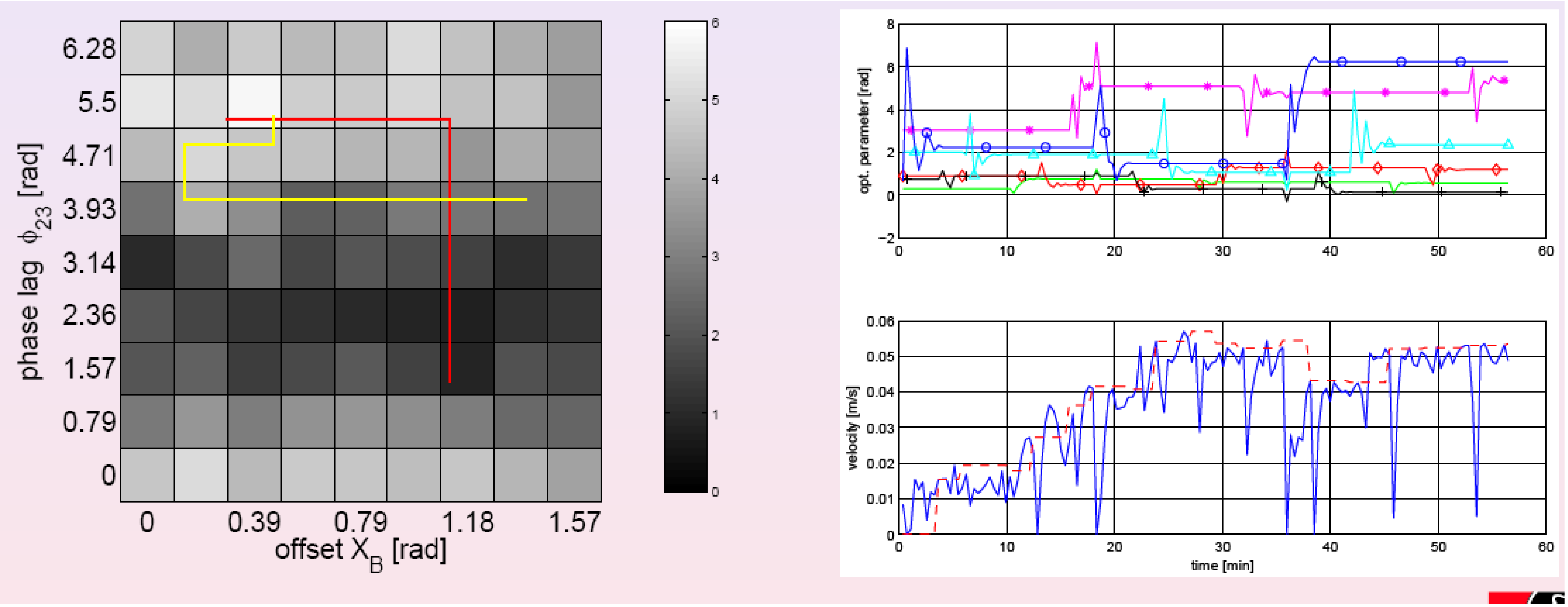
Before

40 minutes

After

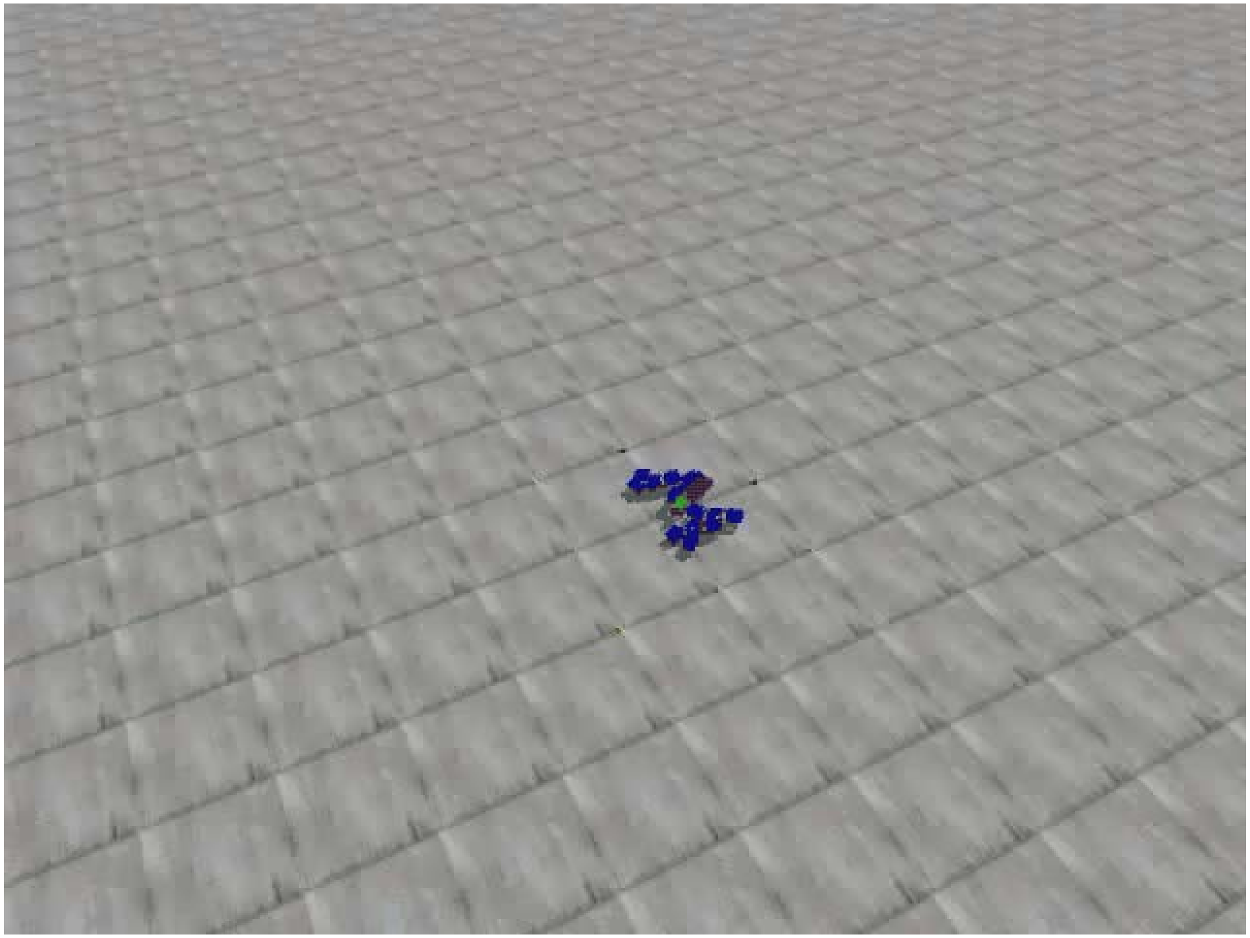
Example of results

- Convergence to interesting gaits
- Larger variety of gaits



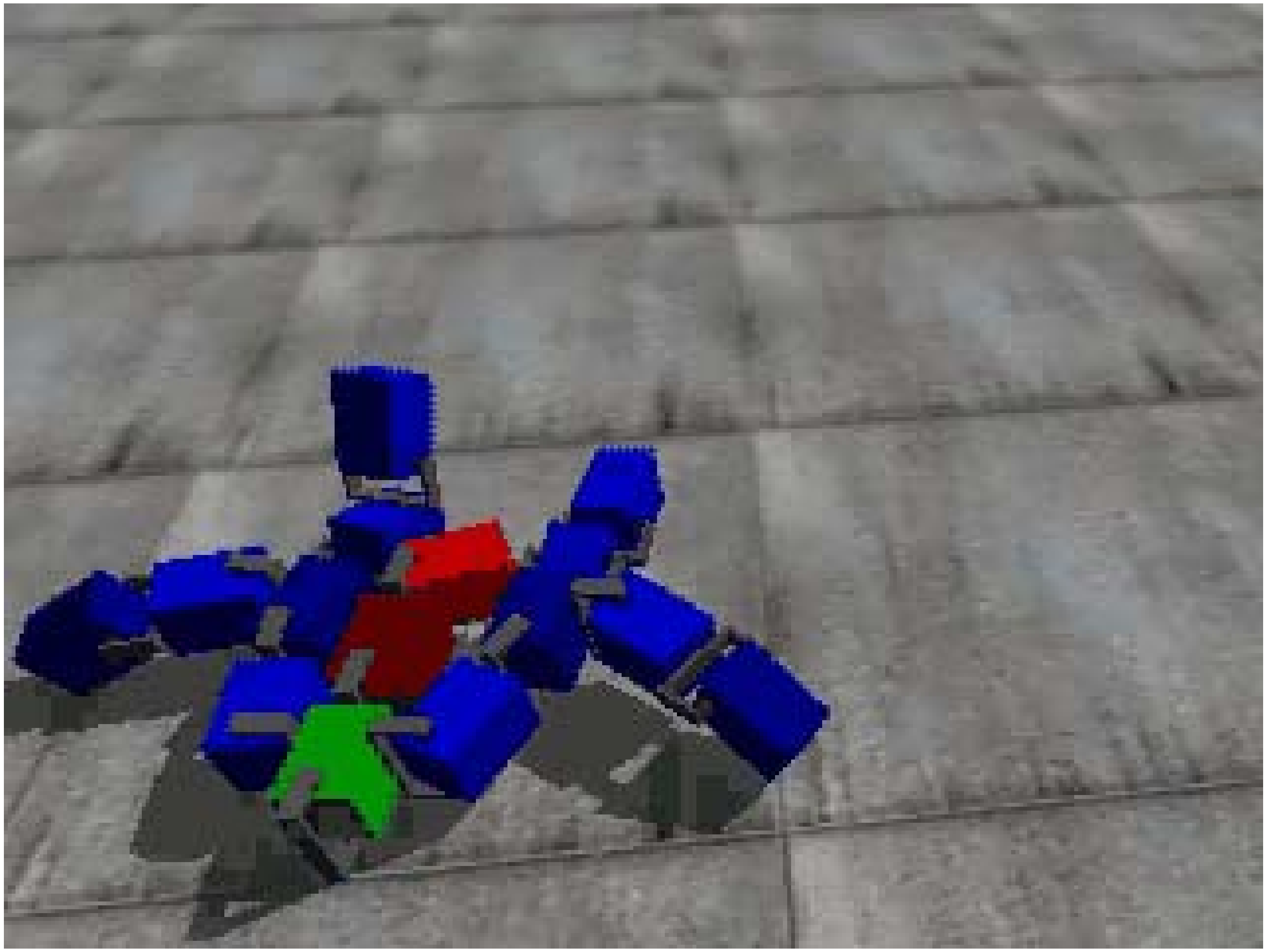
More modules in simulation

Time = 0.0, starting from random initialization



More modules in simulation

Resulting gait after 30 minutes



Summary of results

CPG models are well suited for modular robots:

- Distributed implementation
- Natural synchronization properties
- Robust against time delays and lost packets
- Production of smooth trajectories, despite abrupt parameter changes
- Allows one to run an optimization algorithm in parallel to locomotion control

Future work

- Adapting to lesions and/or body reconfigurations
- Control of speed and direction
- *Distributed* (local) learning algorithm

Take home message 1

CPGs are **sophisticated control circuits that can produce and modulate complex locomotion patterns**

Modulation of speed, direction, and type of gait

Take home message 2

CPG-like controllers offer an interesting solution for the control of robot locomotion:

CPGs are **useful for reducing the dimensionality of the control problem**

Interesting properties:
Smooth **online trajectory generation**,
Possibility to **integrate sensory feedback**
Possibility to **modulate locomotion**

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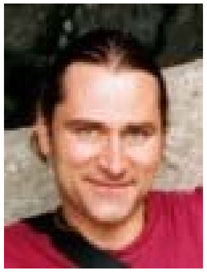
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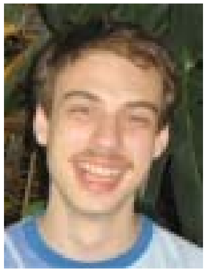
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