Locomotion control in swimming and legged biorobots

Auke Jan Ijspeert

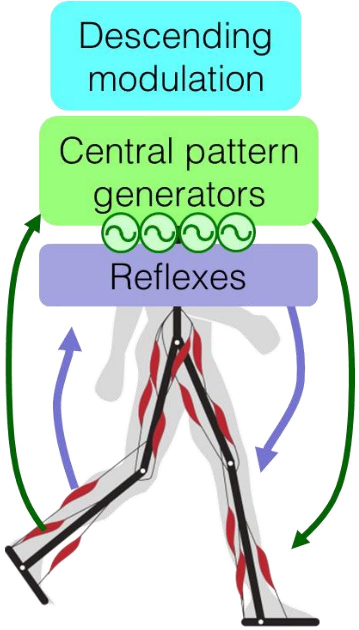
Topics in Autonomous Robotics, April 2025

Content of the talk

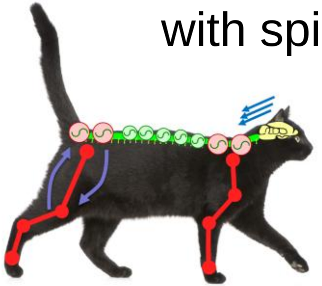
Modeling of spinal circuits in lower vertebrates

Paleontology Robotics

Modeling of spinal circuits in humans

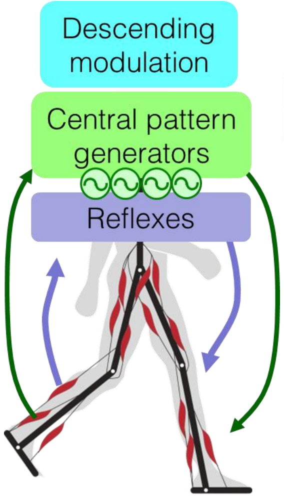


Learning with spinal cords



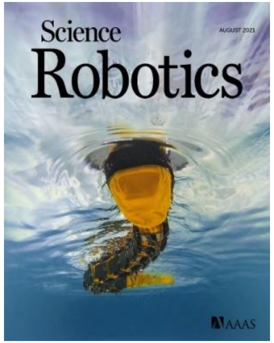
Assistive furniture

Biorobotics Laboratory (Ijspeert)



Robotics

Engineering locomotion



Biology

Healthcare

Understanding locomotion

Assisting locomotion

Biorobotics Laboratory (Ijspeert)

Robotics

Engineering locomotion

Biology

Healthcare

Understanding locomotion

Assisting locomotion


BBC
A PERFECT PLANET
Fish


BBC
Birds


Amphibians
TSI, Swiss Italian Television


Mammals
National Geographics

Big questions in animal motor control

Q1 Principles What are the **key principles** of animal locomotion?

Q2 Evolution How have these changed during **evolution**?

Q3 Learning How do animals perform **learning and planning**?

Robotics can help address these questions!

The beauty of animal locomotion

How is this possible with neurons that are **so slow**?

ANIMAL LOCOMOTION

Science Robotics 2024

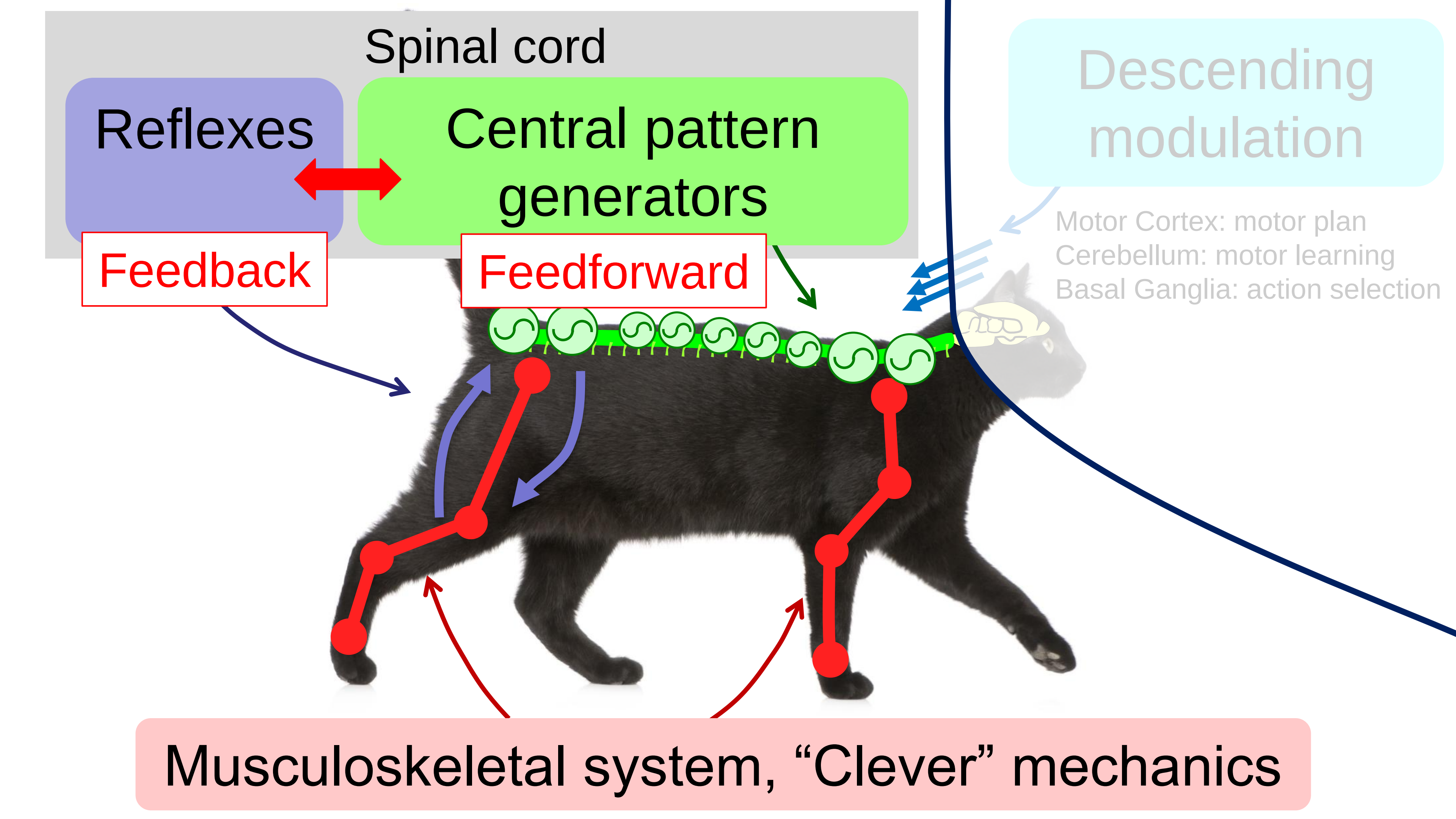
Why animals can outrun robots

Samuel A. Burden[1]*†, Thomas Libby[2]†, Kaushik Jayaram[3], Simon Sponberg[4], J. Maxwell Donelan[5]

Animals are much better at running than robots. The difference in performance arises in the important dimensions of agility, range, and robustness. To understand the underlying causes for this performance gap, we compare natural and artificial technologies in the five subsystems critical for running: power, frame, actuation, sensing, and control. With few exceptions, engineering technologies meet or exceed the performance of their biological counterparts. We conclude that biology's advantage over engineering arises from better integration of subsystems, and we identify four fundamental obstacles that roboticists must overcome. Toward this goal, we highlight promising research directions that have outsized potential to help future running robots achieve animal-level performance.

Control	Myelinated nerve	Network cable
Specific latency	~10^{-3} [s]	~10^{-6} [s]
Specific bandwidth [bits/m^2]	~10^{13} [bits/m^2]	~10^{16} [bits/m^2]

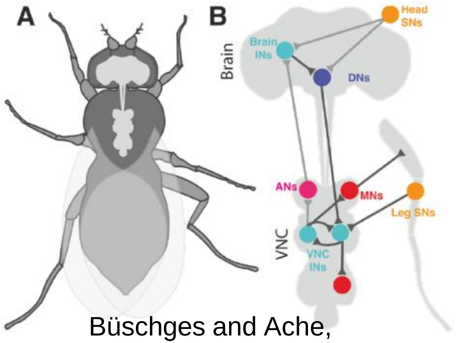
Fig. 3. Subsystem-level performance of animal and robot runners above 1 kg.


Spinal cord
Reflexes
Central pattern generators
Feedback
Feedforward
Descending modulation
Motor Cortex: motor plan
Cerebellum: motor learning
Basal Ganglia: action selection
Musculoskeletal system, “Clever” mechanics

Q2 Evolution

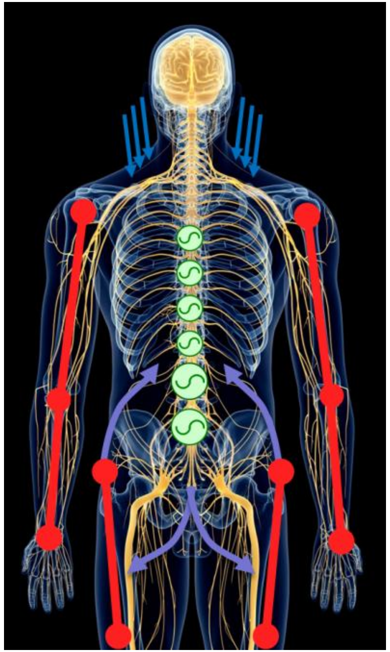
The neural organization is surprisingly conserved

Also in invertebrates (insects)

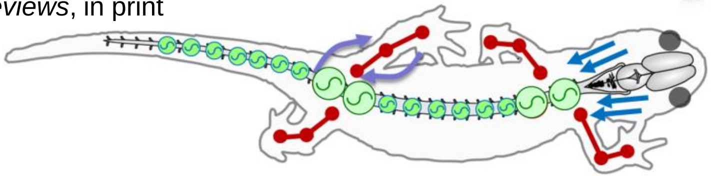


Büschges and Ache, *Physiological Reviews*, in print

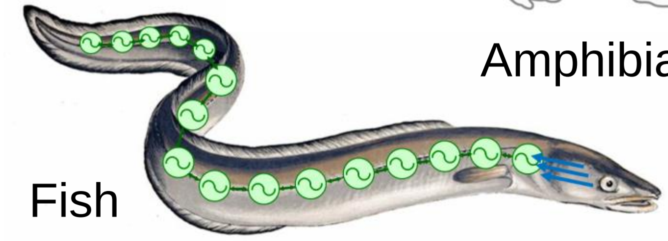
Mammals



Humans



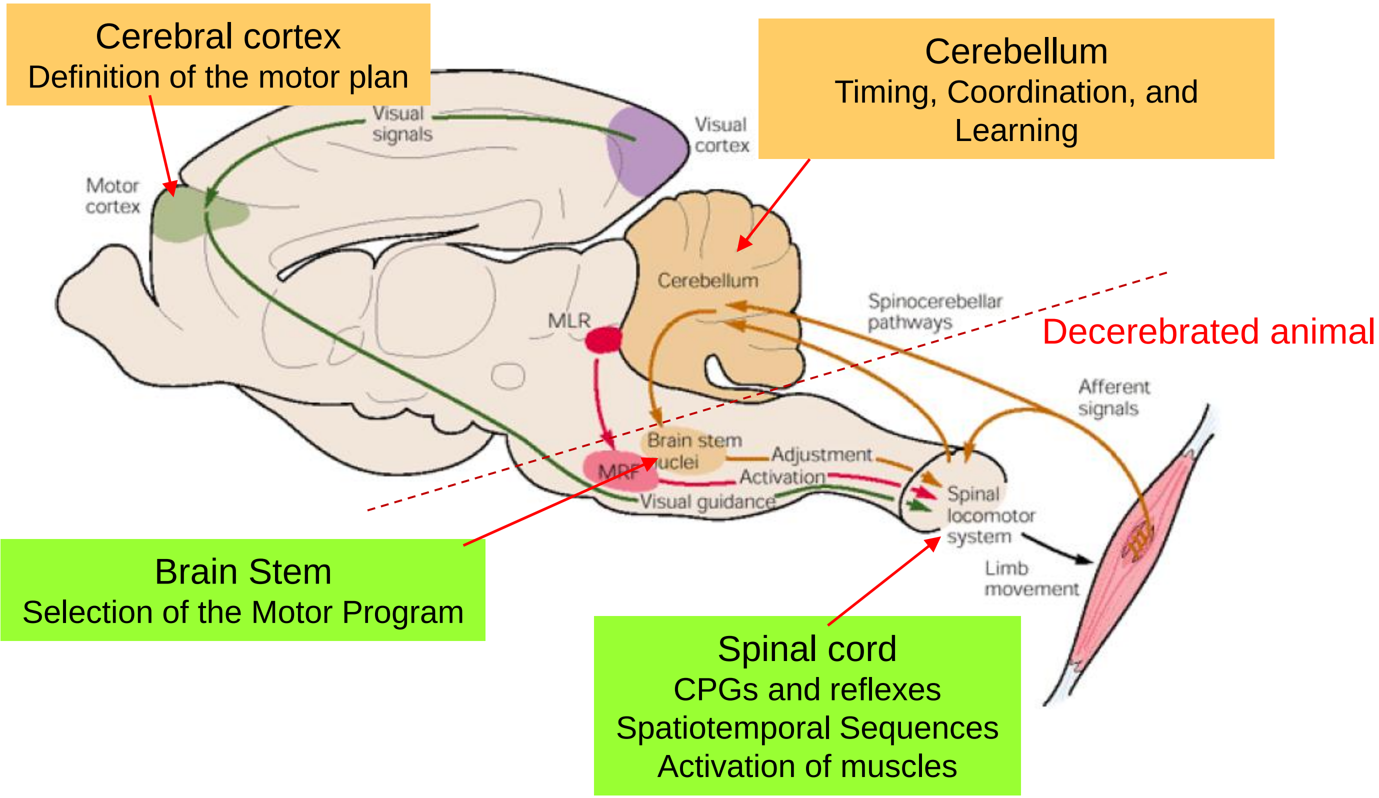
Amphibians/reptiles



Fish

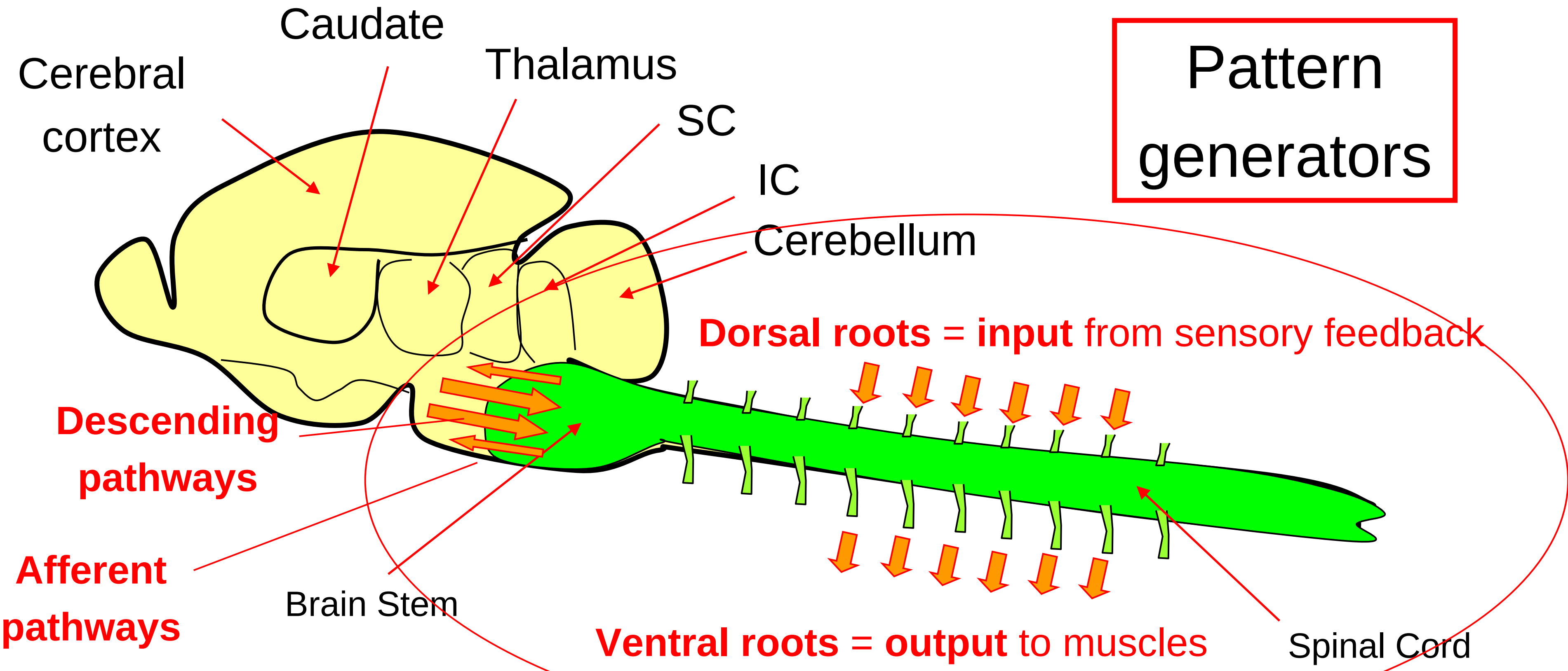
Much more than the morphology

Brain centers involved in vertebrate motor control



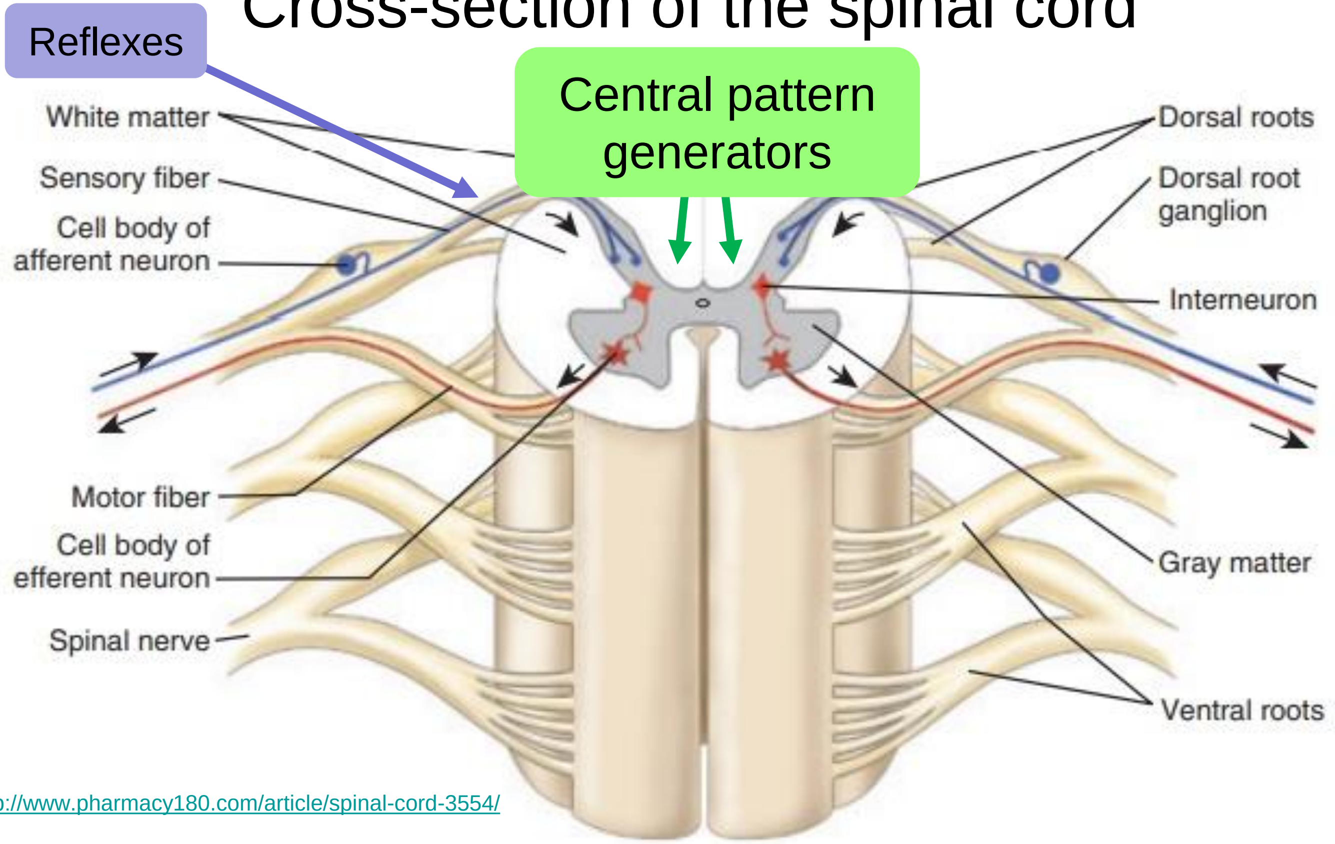
From: *Principles of Neural Science*. 4th edition. Edited by E.R. Kandel, J.H. Schwartz and T.M. Jessell. Appleton & Lange, New York.

Building bricks for motor control: **pattern generators**



Simple inputs ➔ complex outputs. E.g gait transition by electrical stimulation of the brain stem (Shik and Orlosky 1966)

Cross-section of the spinal cord

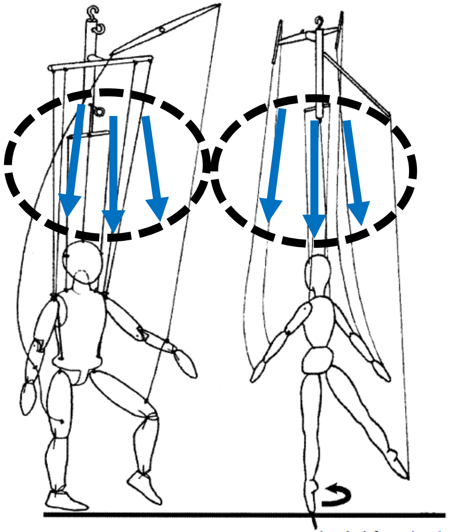


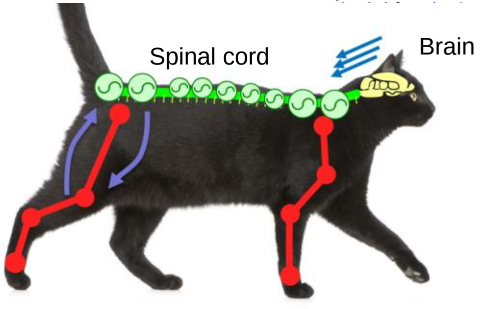
http://www.pharmacy180.com/article/spinal-cord-3554/

Important: the spinal cord is not just a relay station.
It has **multiple sophisticated circuits for motor control**

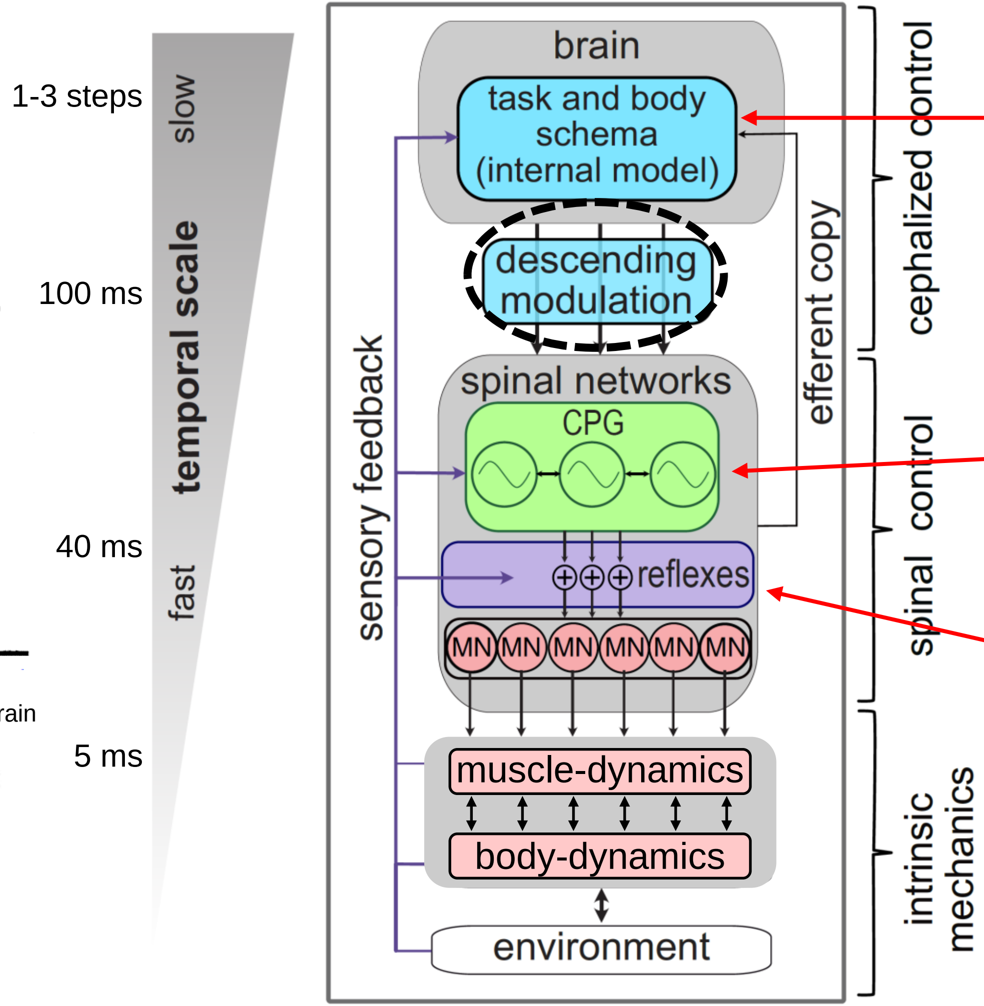
Q1 Principles

Jerry Loeb's Puppet analogy





Musculoskeletal system



Internal models
Feedback and Feedforward

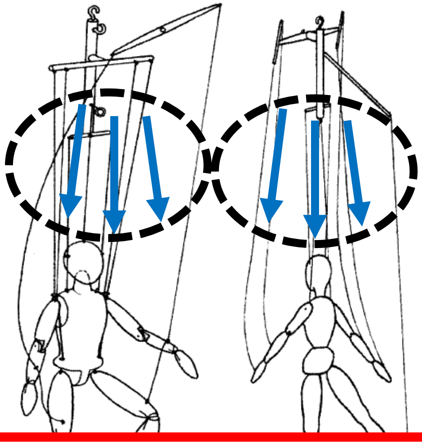
Central pattern generators (CPGs)
Feedforward

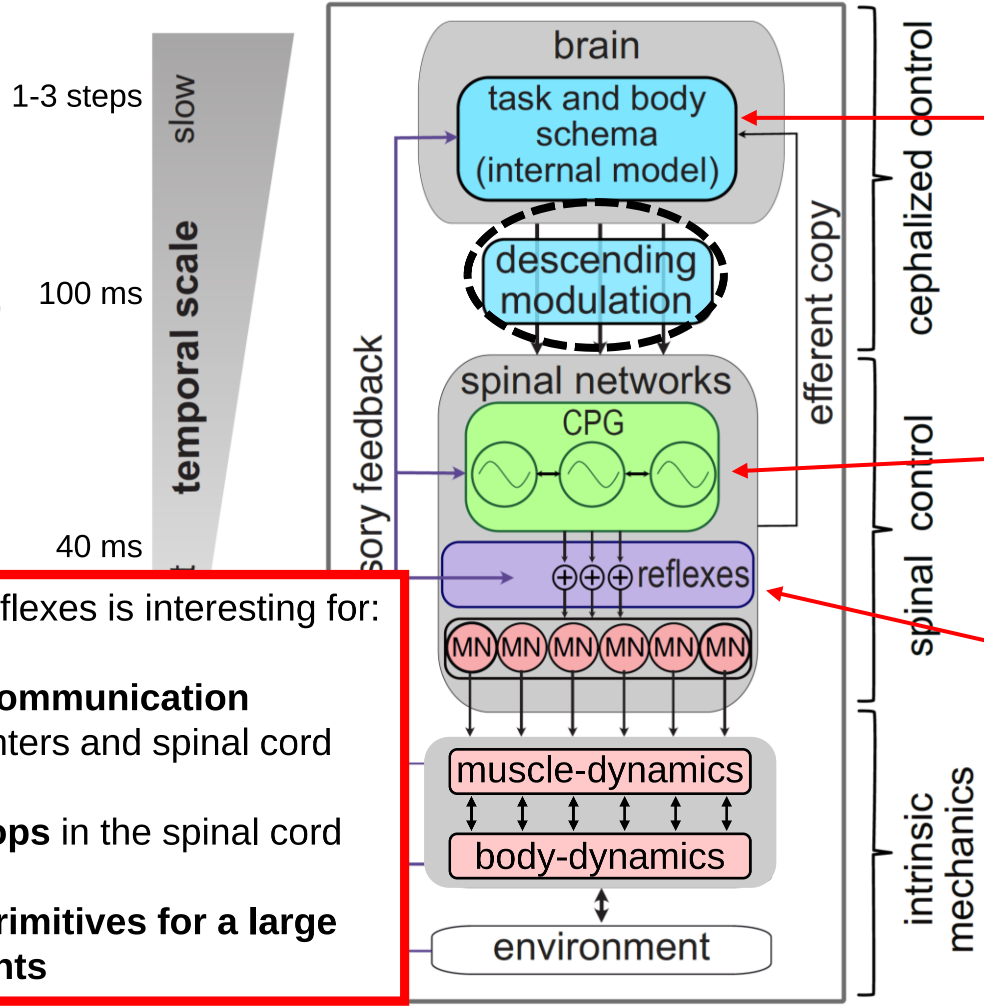
Reflexes
Feedback

Ijspeert and Daley, JEB 2023

Q1 Principles

Jerry Loeb's Puppet analogy





Internal models
Feedback and Feedforward

Central pattern generators (CPGs)
Feedforward

Reflexes
Feedback

The concept of CPG + reflexes is interesting for:

(1) **Low bandwidth communication** between higher centers and spinal cord

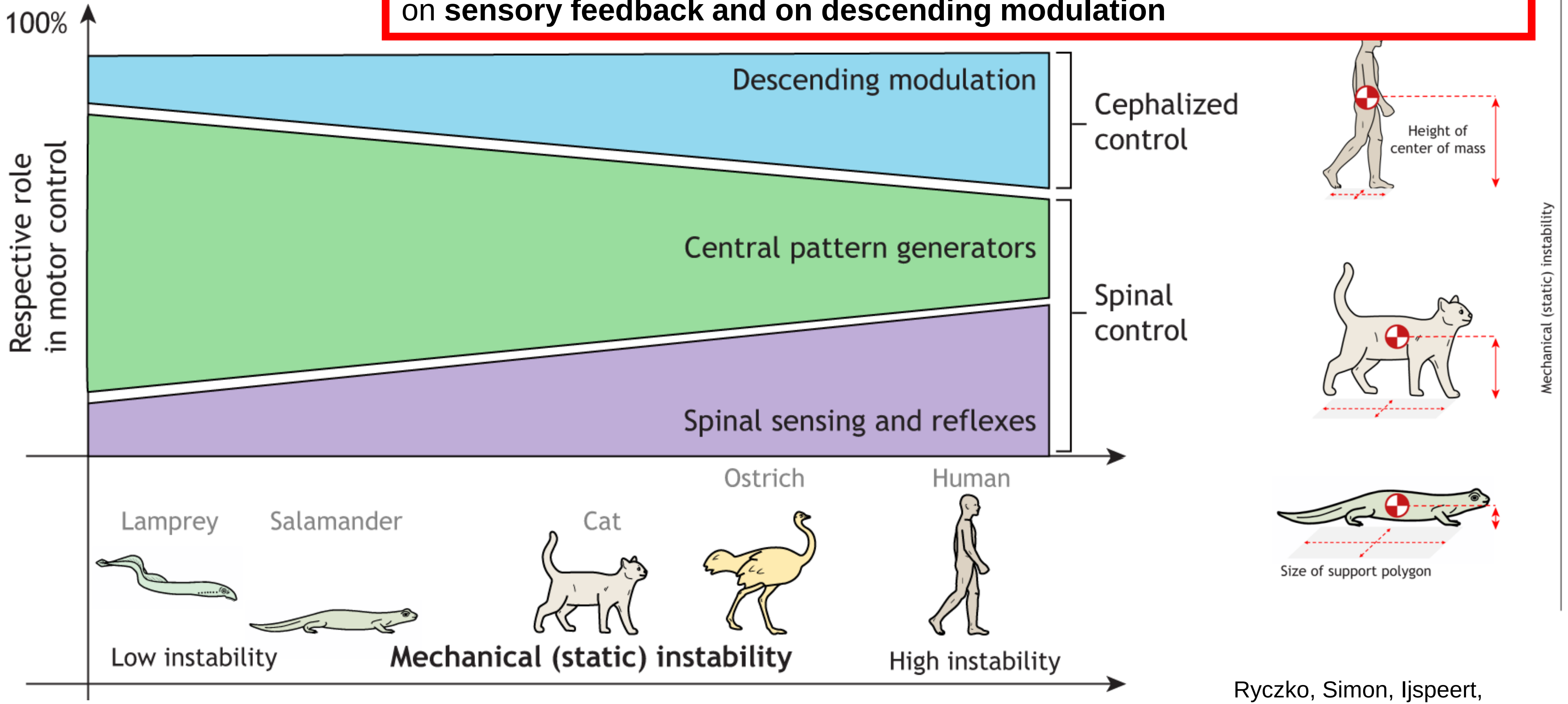
(2) **Fast feedback loops** in the spinal cord

(3) providing **motor primitives for a large range of movements**

Ijspeert and Daley, JEB 2023

Q2 Evolution

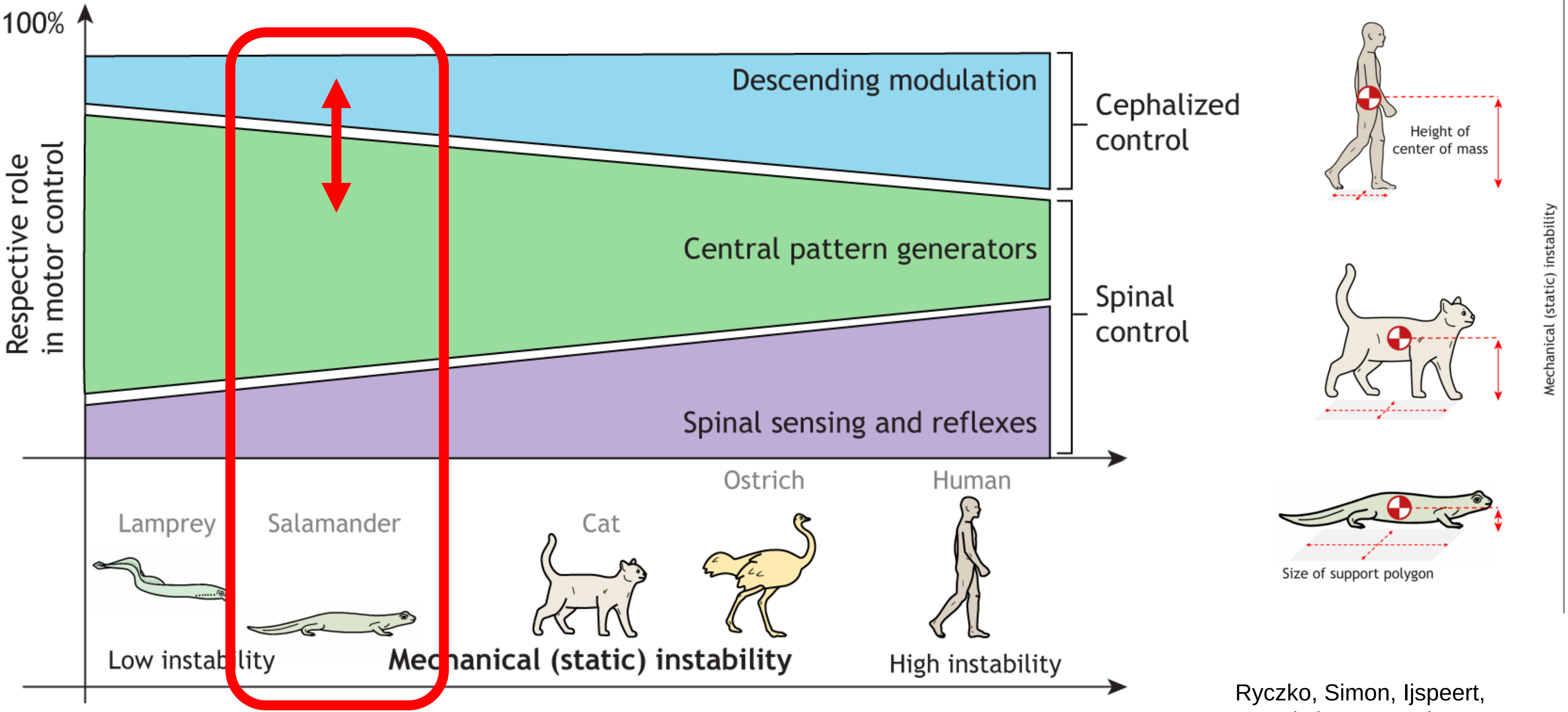
Hypothesis: **lower vertebrates** are relying proportionally more on **CPG circuits. Higher vertebrates (**like mammals) that are **mechanically unstable** rely more on **sensory feedback and on descending modulation**



Ryczko, Simon, Ijspeert, *Trends in Neuroscience,* 2020

Ijspeert and Daley, J. of Exp. Biol., JEB 2023

Q2 Evolution



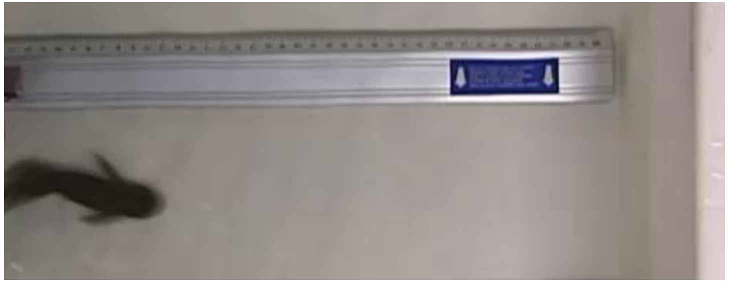
Ryczko, Simon, Ijspeert, *Trends in Neuroscience,* 2020

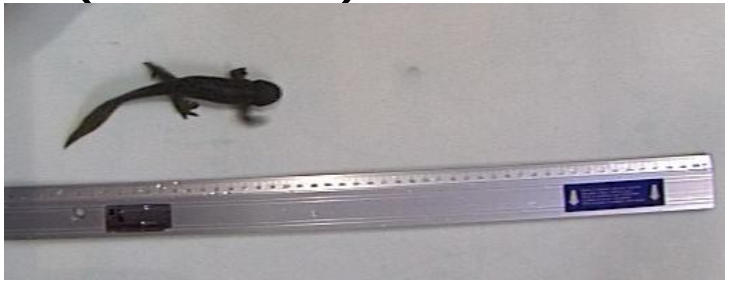
Ijspeert and Daley, J. of Exp. Biol., JEB 2023

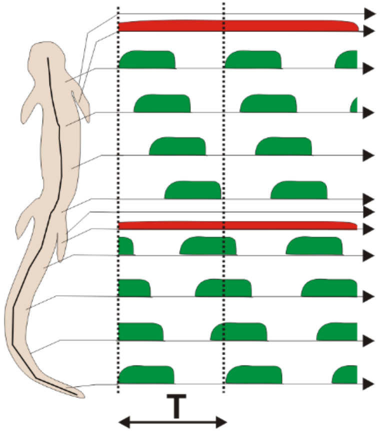
- Relatively simple animal
- Interesting bimodal locomotion
- Its body plan has changed little over 150 million years (Gao & Shubin, Nature, 2002).
- Good link between lamprey and mammal research
- Impressive regeneration abilities

TSI, Swiss Italian Television

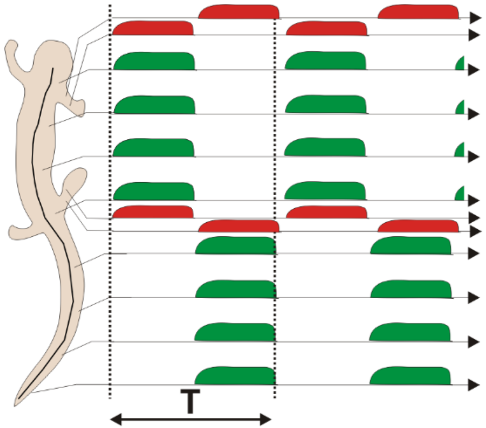
Bimodal locomotion (cartoon)





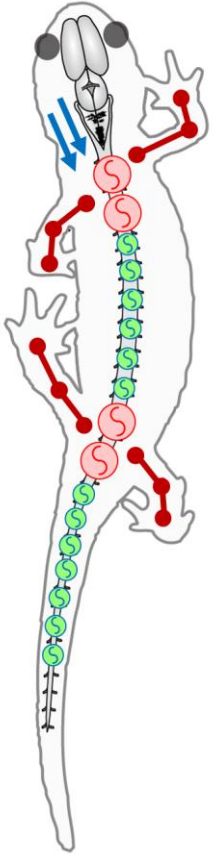


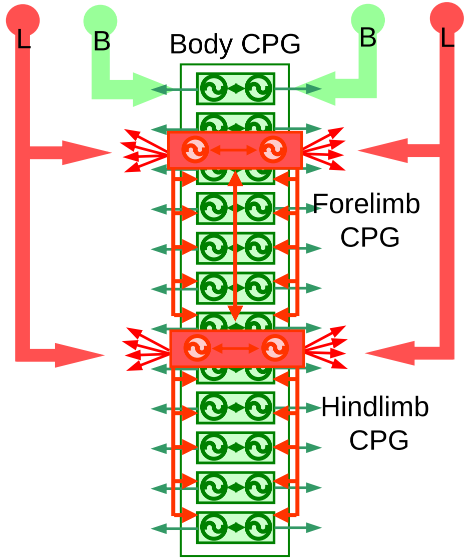
Swimming:
Traveling wave in axial muscles
Wavelength ≈ body length
Limb retractors are tonic
Short cycle durations



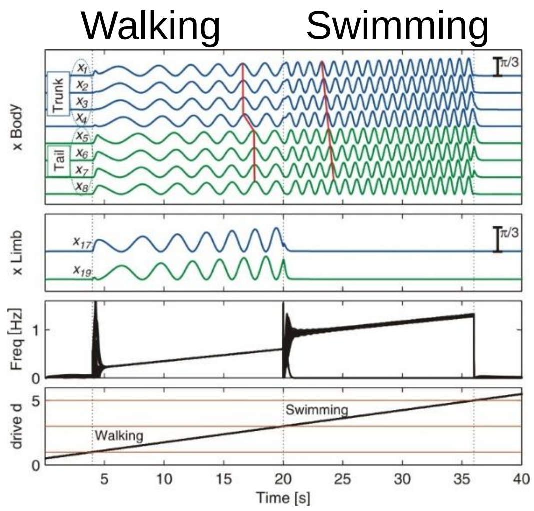
Walking:
Standing wave
Limb retractors/protactors are phasic
Longer cycle durations

A mathematical model to study the transition from swimming to walking





System of coupled oscillators



Gait transition due to an increase of the descending drive

Ijspeert *et al*, *Science*, March 2007

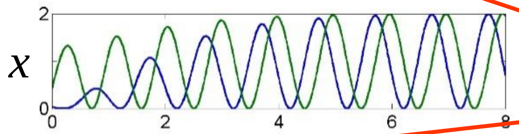
Modeling the CPG with coupled oscillators

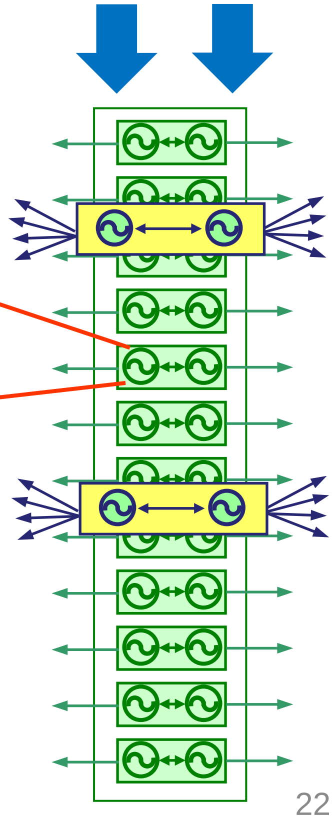
A segmental oscillator is modeled as an amplitude-controlled phase oscillator as used in (Cohen, Holmes and Rand 1982, Kopell, Ermentrout, and Williams 1990) :

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

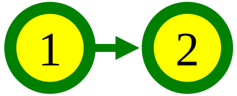


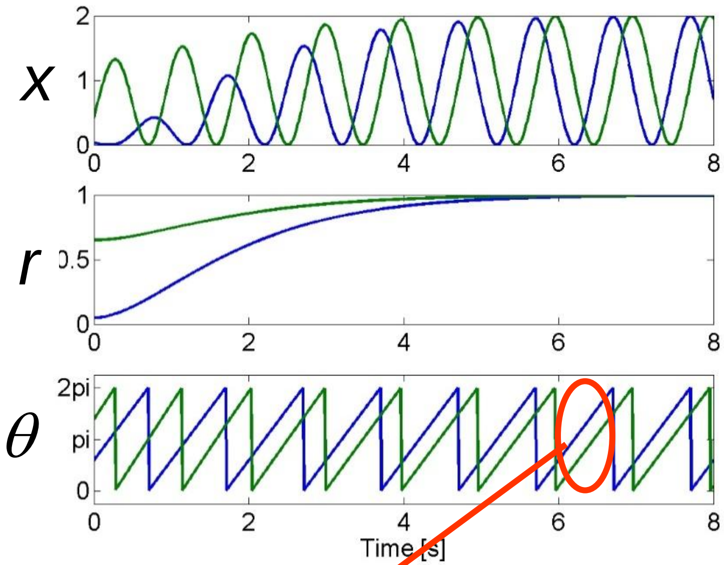


Setpoints: $$\varphi_i = x_i - x_{N+i} \quad \textit{for the axial motors}$$
$$\varphi_i = f(\theta_i) \quad \textit{for the (rotationd) limb motors}$$

Ijspeert *et al*, *Science*, March 2007

Example with two oscillators





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

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

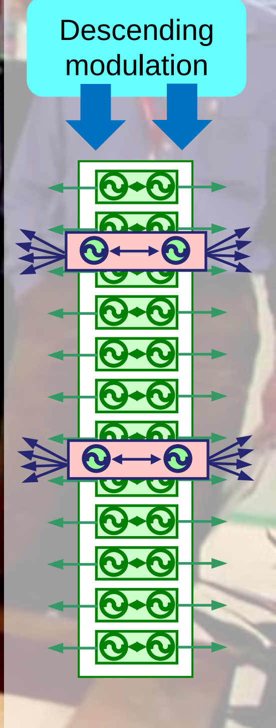
$$x_i = r_i(1 + \cos(\theta_i))$$

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

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

[Ijspeert *et al*, *Science*, March 2007].

CPGs can modulate **speed**, **heading**, and **type of gait** under the modulation of a few drive signals



Ijspeert *et al*, *Science*, 2007, Crespi et al, *IEEE TRO*, 2013.

Distributed control

CPGs can be implemented in a distributed way, with robustness about changing morphology

Knuesel et al. *Frontiers in Neurorobotics*, 2020

Modeling the salamander locomotor circuits: different levels of abstraction

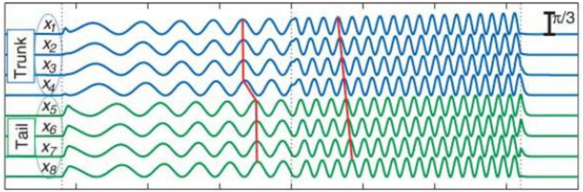
- Coupled oscillators

(Ijspeert et al 2007, Knüsel et al 2020, Suzuki et al 2021)

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

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

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

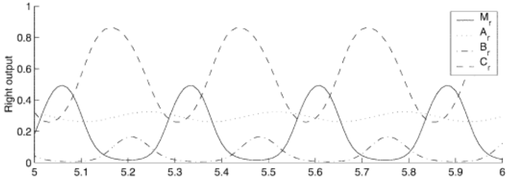


- Leaky-integrator neurons

(Ijspeert 2001)

$$\tau_i \frac{\mathrm{d}m_i}{\mathrm{d}t} = -m_i + \sum_j w_{i,j} x_j$$

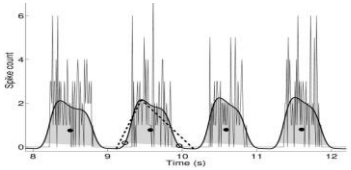
$$x_i = (1 + \mathrm{e}^{(m_i + b_i)})^{-1}$$



- Integrate-and-fire neurons

(Knuesel et al 2013, Pazzaglia et al 2025)

$$\tau\dot{u} = -g(u - E_{rest}) - \alpha_1\omega_1 - \alpha_2\omega_2 + RI + \sum w_{syn} g_{syn}(u - E_{revsyn})$$

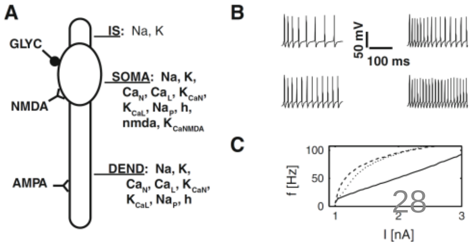


- Hodgkin-Huxley types of neurons

(Bicanski et al 2013)

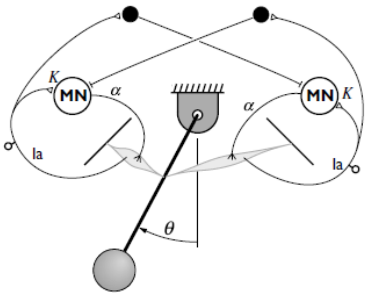
$$C\frac{\mathrm{d}U}{\mathrm{d}t} = \sum_i (U_i - U) g_{\mathrm{core}} + \sum_j I_j + I_{\mathrm{leak}},$$

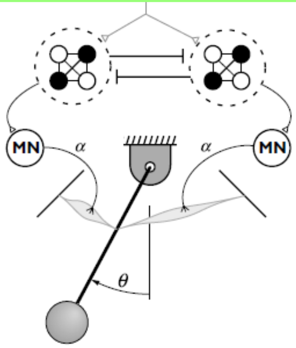
$$I_j = g_j p^a q^b (U_i - E_{\mathrm{rev}})$$



The big question

Sensory feedback vs CPGs

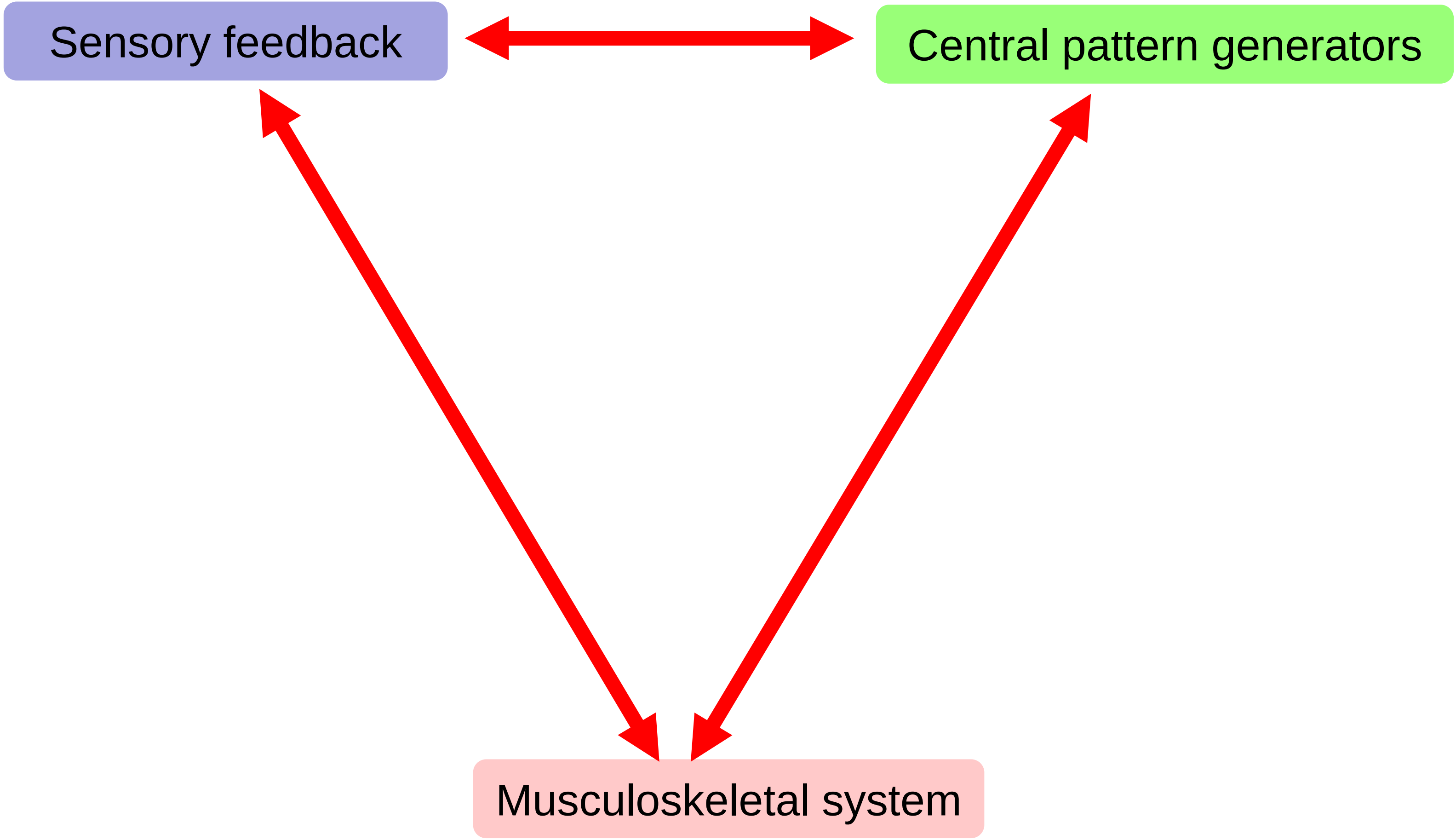




Kuo 2002,
Motor Control

Chain of reflexes	Sherrington	↔	Graham Brown	Half centers
	Peripheral control	↔	Central control	
	Feedback control	↔	Feedforward control	

The bridge: body dynamics



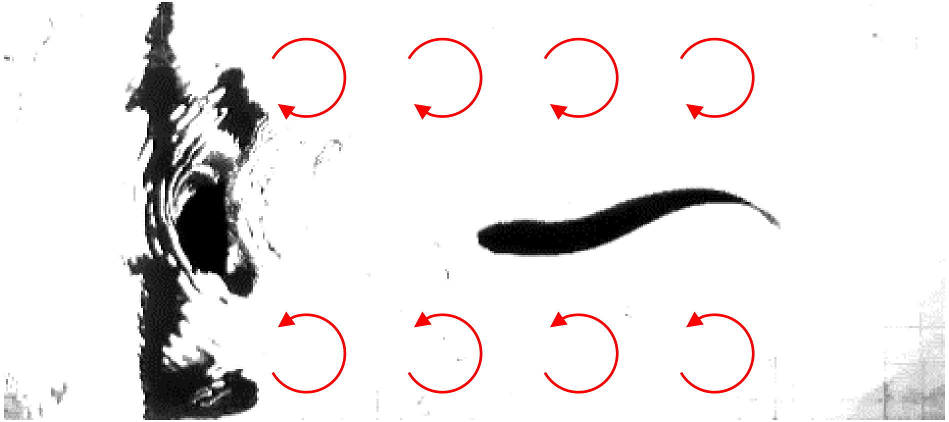
The bridge: body dynamics

Sensory feedback ⟷ Central pattern generators

Passive walker

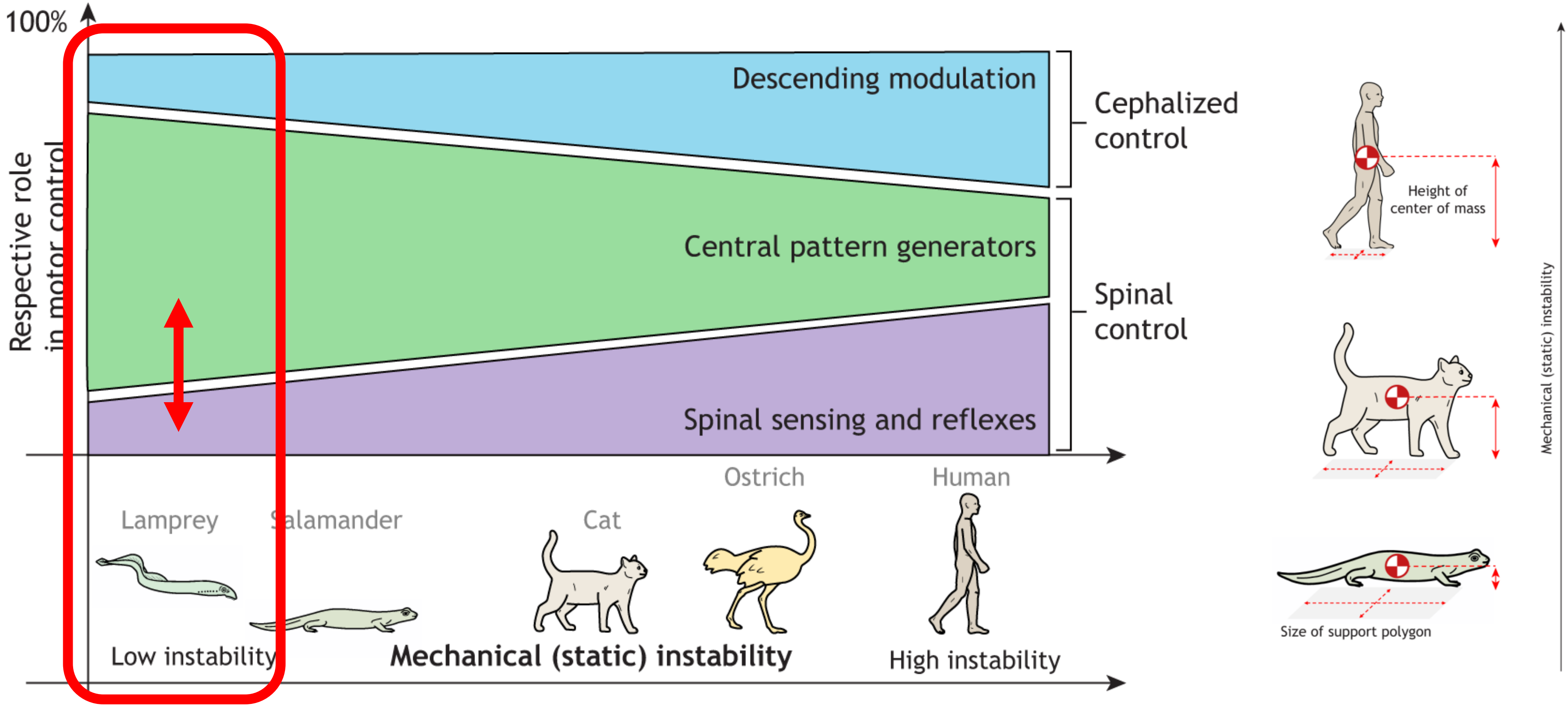
Collins, S. H., Wisse, M., Ruina, A. (2001)
International Journal of Robotics Research,
Vol. 20, No. 2, Pages 607-615

Dead ! trout swimming



Liao, J. C. (2004).
Journal of Experimental Biology,
Vol. *207*(20), 3495-3506.
MIT tow tank, Lauder Lab Harvard
http://web.mit.edu/towtank/www/

Musculoskeletal system

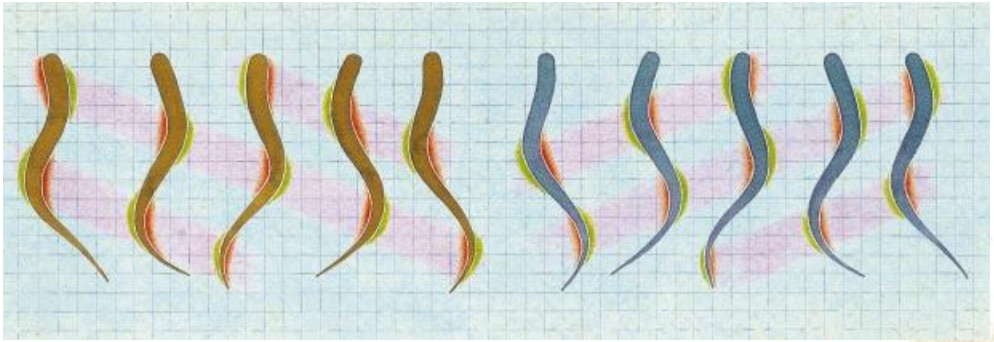


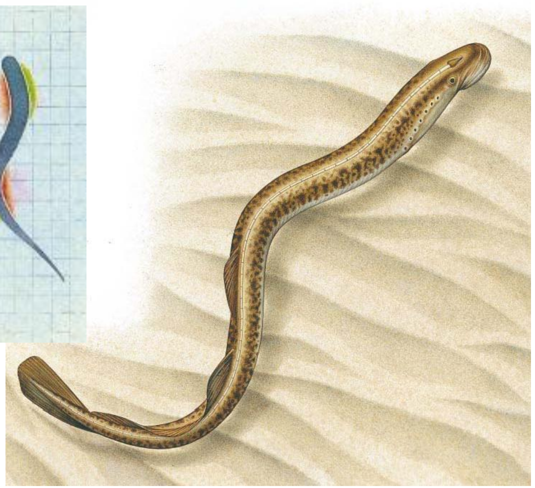
Ijspeert and Daley, J. of Exp. Biol., JEB 2023

The lamprey

- Lamprey: one of the most primitive vertebrate
- Anguilliform swimming
- Believed to be very similar to the ancestor of all vertebrates
- Has been studied in detail by neurobiologists
- Very nice example of fruitful interaction between neurobiology and computational neuroscience (i.e. modeling)

Movie by J.T. Buchanan





Numerical models of lamprey circuit

Williams, T. L., Sigvardt, K. A., Kopell, N., Ermentrout, G. B., & Rempler, M. P. (1990). Forcing of coupled nonlinear oscillators: Studies of intersegmental coordination in the lamprey locomotor central pattern generator. J. of Neurophysiology, 64, 862–871.

Cohen, A. H., Bard Ermentrout, G., Kiemel, T., Kopell, N., Sigvardt, K. A., & Williams, T. L. (1992). Modelling of intersegmental coordination in the lamprey central pattern generator for locomotion. *Trends in Neurosciences*, *15*(11), 434–438. https://doi.org/10.1016/0166-2236(92)90006-T

Ekeberg, Ö. (1993). A combined neuronal and mechanical model of fish swimming. *Biological Cybernetics*, *69*, 363–374.

Grillner, S., Degliana, T., Ekeberg, Ö., El Marina, A., Lansner, A., Orlovsky, G. N., & Wallén, P. (1995). Neural networks that co-ordinate locomotion and body orientation in lamprey. *Trends in Neuroscience*, *18*(6), 270–279.

Wadden, T., Hellgren, J., Lansner, A., & Grillner, S. (1997). Intersegmental coordination in the lamprey: Simulations using a network model without segmental boundaries. *Biological Cybernetics*, *76*, 1–9.

Hamlet, C., Fauci, L., Morgan, J. R., & Tytell, E. D. (2023). Proprioceptive feedback amplification restores effective locomotion in a neuromechanical model of lampreys with spinal injuries. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(11), e2213302120. https://doi.org/10.1073/pnas.2213302120

Eels are amazingly robust

Coordinated swimming despite one or two **full spinal cord transections**

Likely explanation: important role for **stretch and pressure feedback**

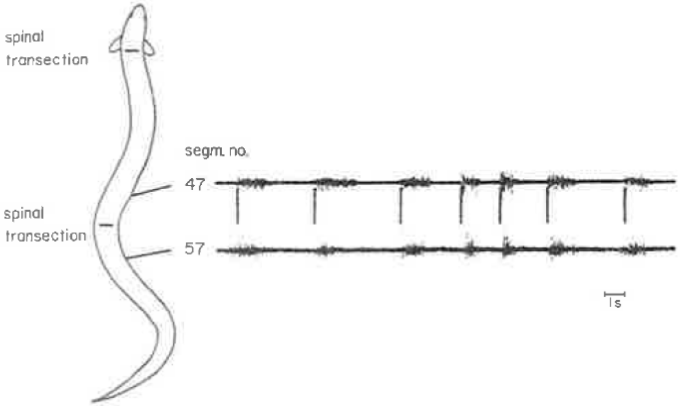
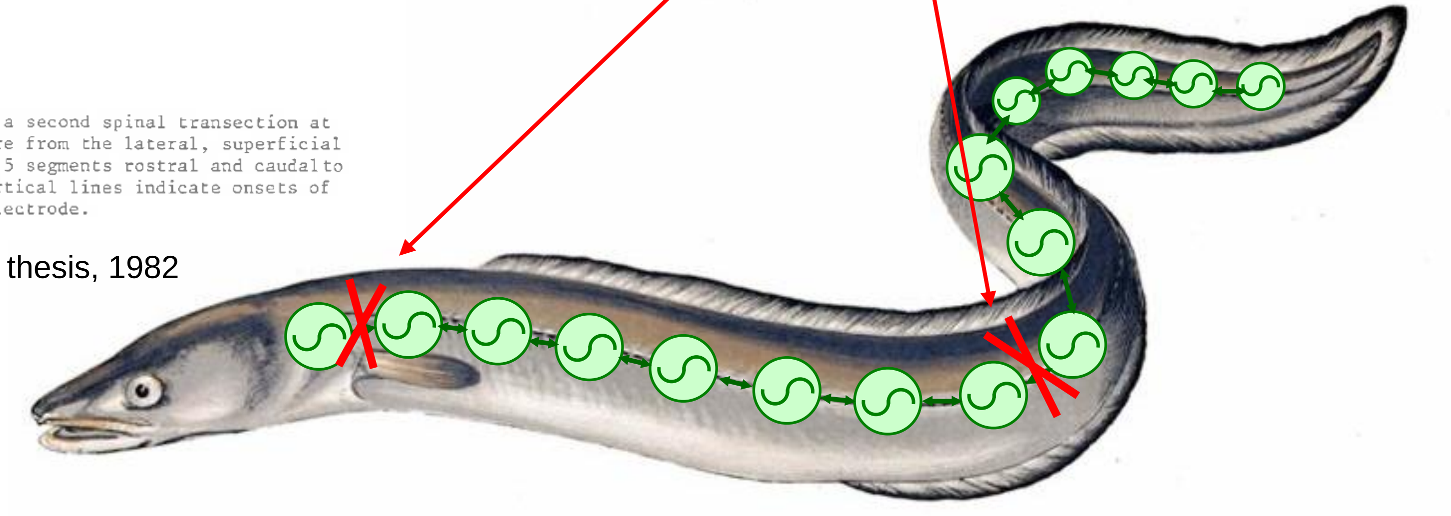


Fig. 3. Swimming spinal eel, with a second spinal transection at mid-body level. Electromyograms are from the lateral, superficial musculature at segments indicated, 5 segments rostral and caudal to the transection, respectively. Vertical lines indicate onsets of burst discharges at the rostral electrode.

Peter Wallen, PhD thesis, 1982

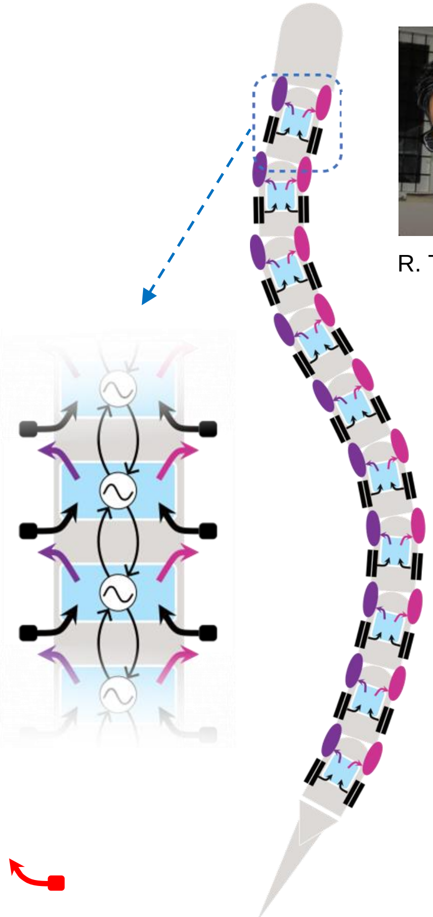


https://www.ttbook.org/interview/weird-world-eels

Synchronization through local pressure feedback

- CPG: Distributed phase oscillators
- **Local sensory <u>pressure</u> feedback**
- Sensors: dorsal cells (mechano-receptors)

R. Thandiackal



Phase oscillator dynamics:

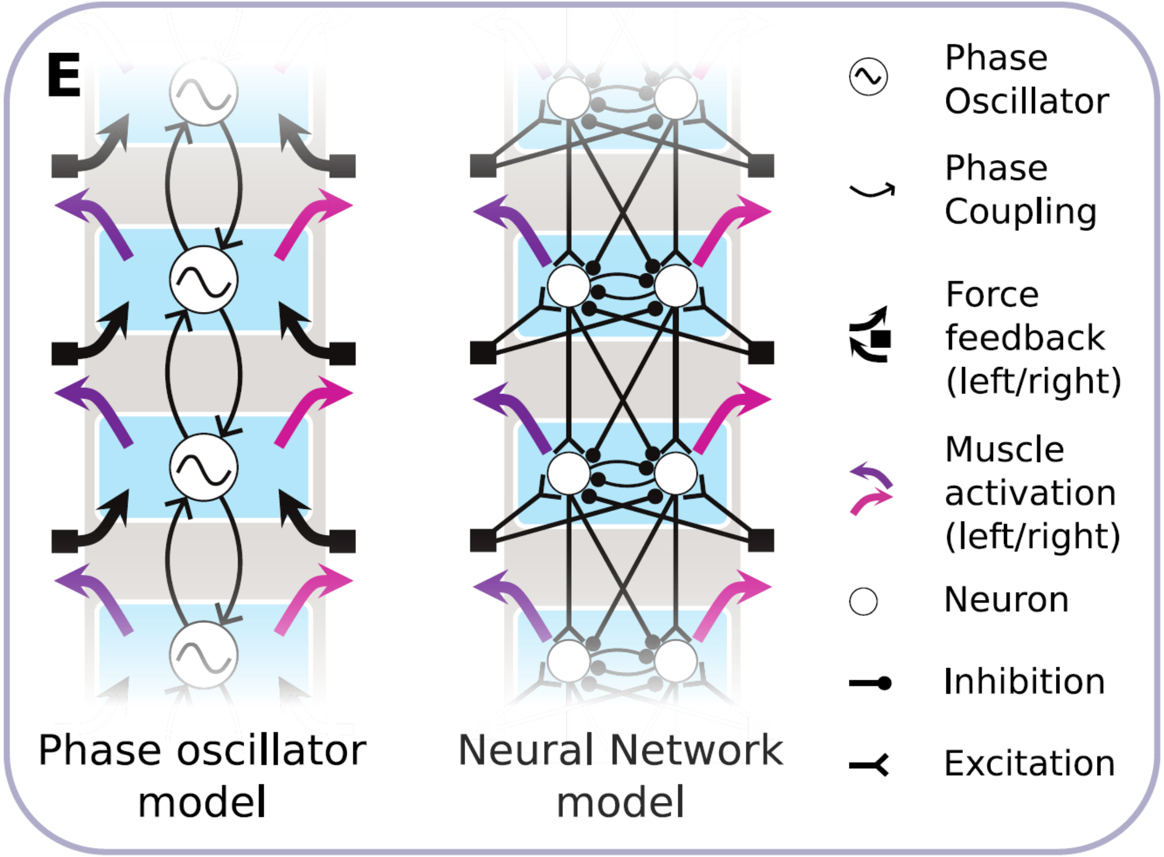
$$u_i = \cos(\phi_i)$$

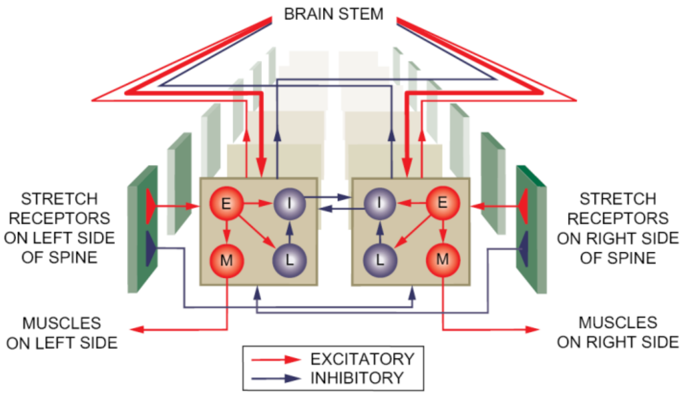
Muscle contraction signal

$$\dot{\phi}_i = \underbrace{\omega}_{\text{CPG oscillator}} + \underbrace{\sum_{j=1}^{N} w_{ij}\ \sin\left(\phi_i - \phi_j - \psi_{ij}\right)}_{\text{CPG coupling}} + \underbrace{b\ F_i \cos(\phi_i)}_{\text{Local feedback}}$$

Thandiackal *et al*, *Science Robotics*, 2021

Oscillator and neural network implementations



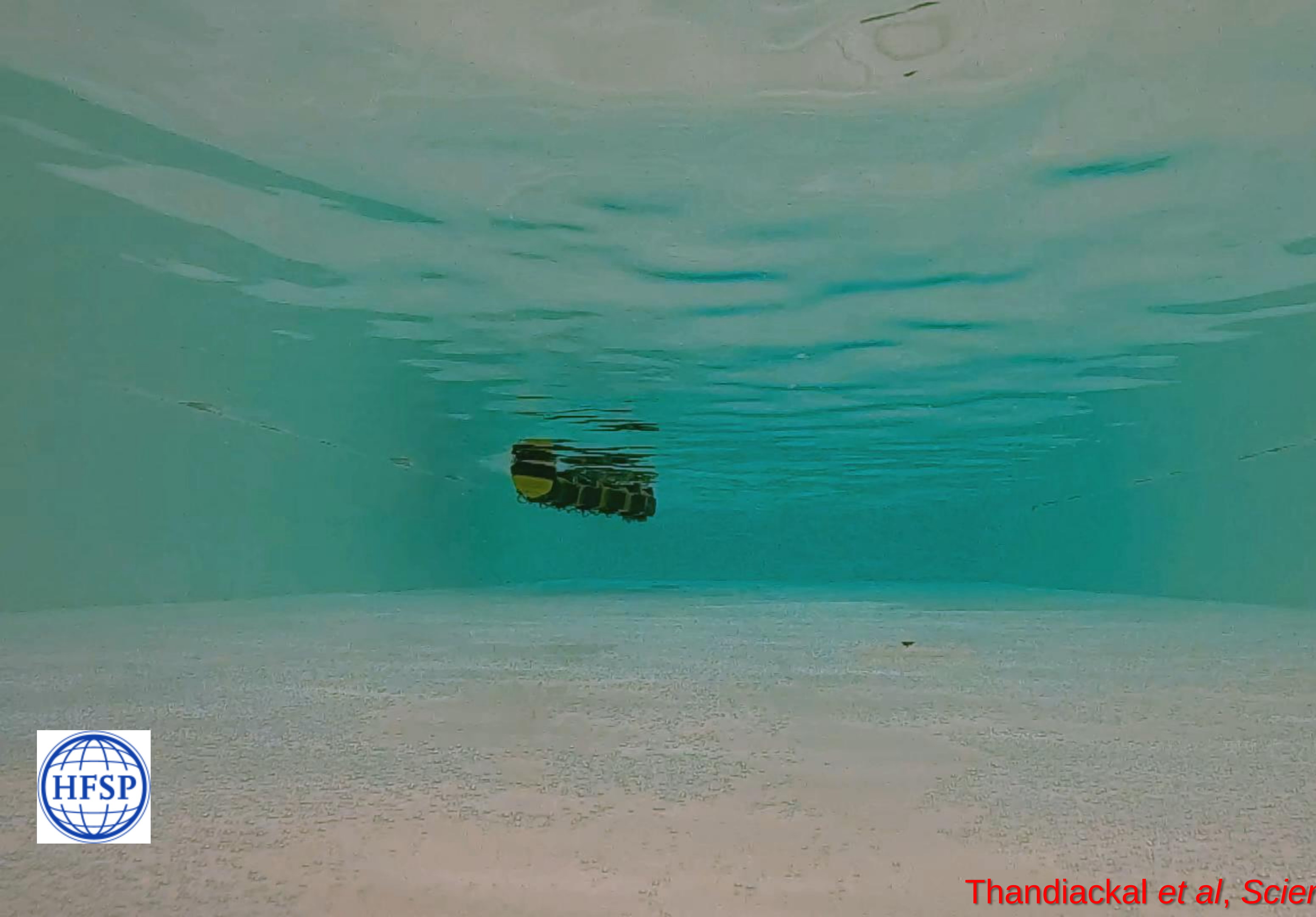


Grillner, Sci. Am. 1996

$u_i = \cos(\phi_i)$ Muscle contraction signal

$$\dot{\phi}_i = \underbrace{\omega}_{\text{CPG oscillator}} + \underbrace{\sum_{j=1}^{N} w_{ij} \sin(\phi_i - \phi_j - \psi_{ij})}_{\text{CPG coupling}} + \underbrace{b\, F_i \cos(\phi_i)}_{\text{Local feedback}}$$

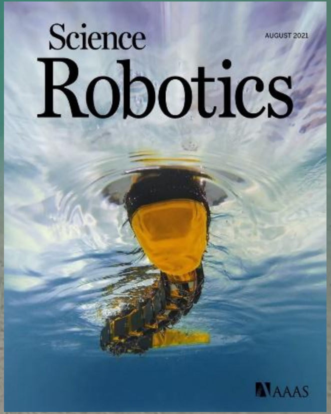
Thandiackal *et al*, *Science Robotics*, 2021



R. Thiandiackal

K. Melo

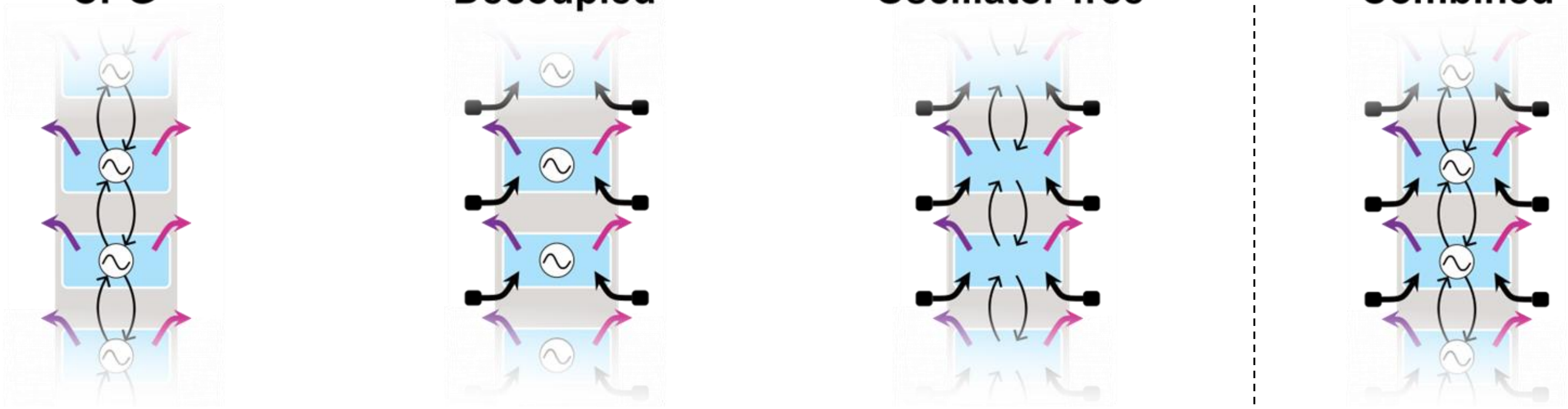
L. Paez



Thandiackal *et al*, *Science Robotics*, 2021

Test of different configurations

CPG	Decoupled	Oscillator-free	Combined



Central | Mainly peripheral | Combined

Muscle contraction signal $u_i = \cos(\phi_i)$

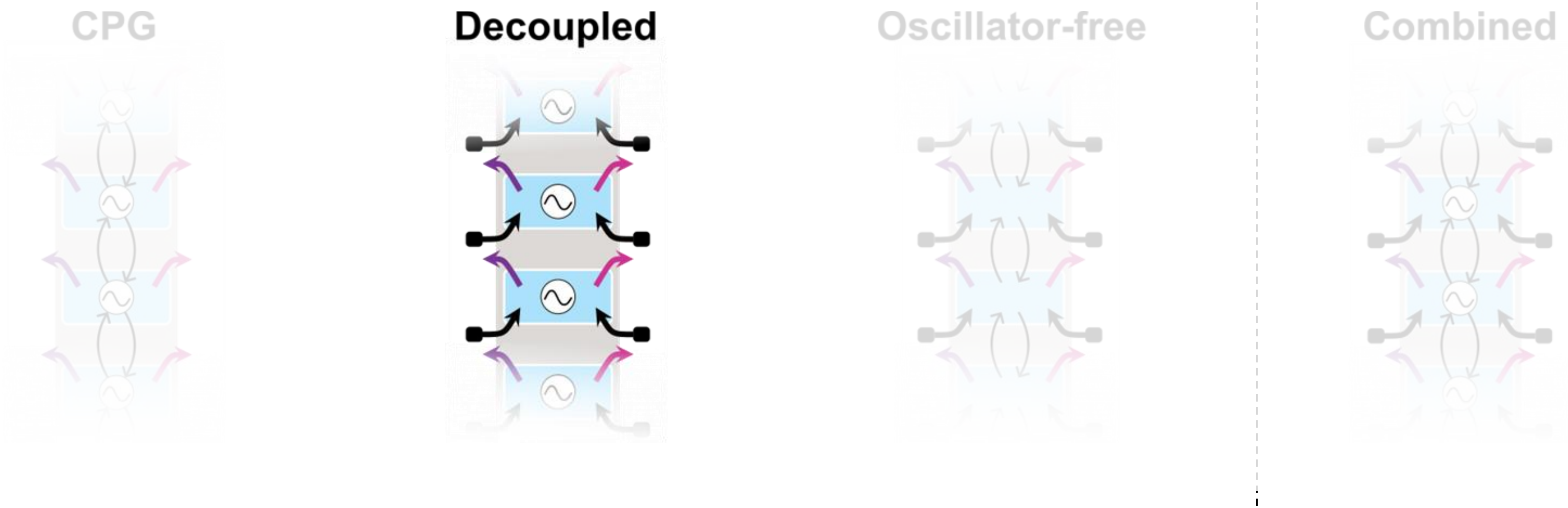
$$\dot{\phi}_i = \omega + \underbrace{\sum_{j=1}^{N} w_{ij} \sin(\phi_i - \phi_j - \psi_{ij})}_{\text{CPG coupling}} + \underbrace{b\, F_i \cos(\phi_i)}_{\text{Local feedback}}$$

CPG

CPG coupling

Local feedback

Test of different configurations



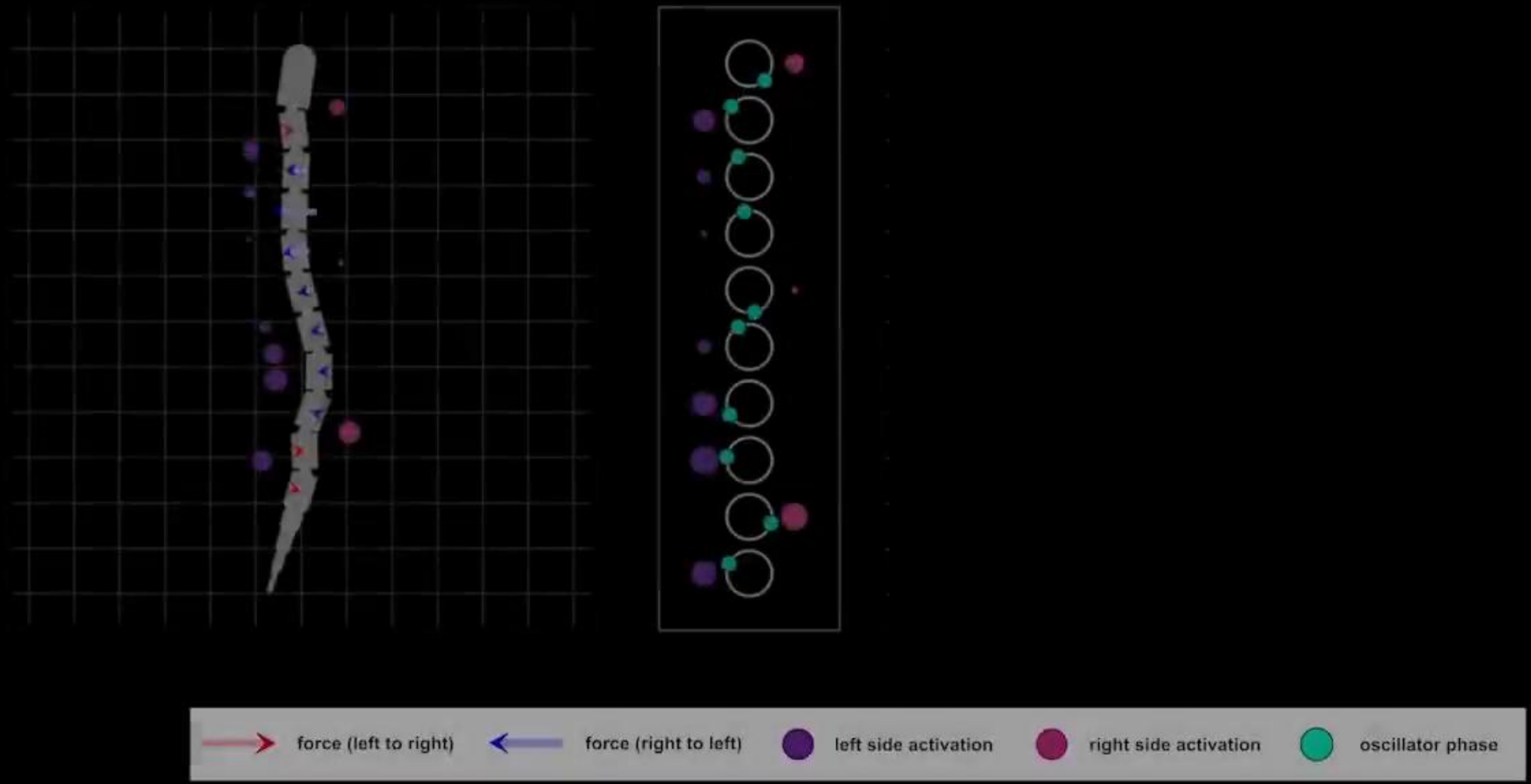
Muscle contraction signal

$$u_i = \cos(\phi_i)$$

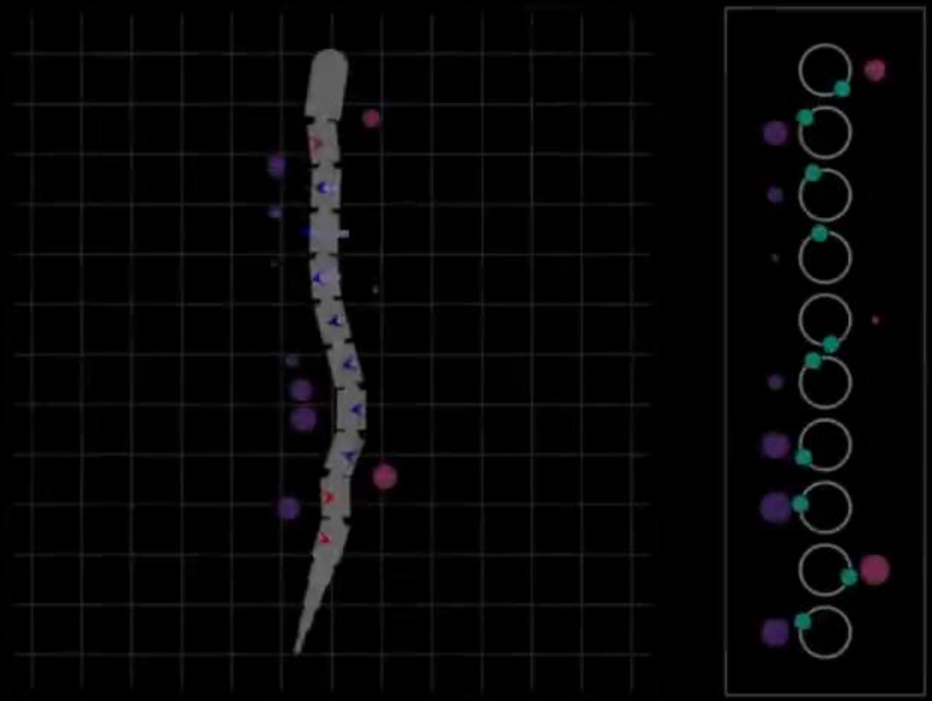
$$\dot{\phi}_i = \omega + \underbrace{\cancel{\sum_{j=1}^{N} w_{ij}\ \sin(\phi_i - \phi_j - \psi_{ij})}}_{\text{CPG coupling}} + \underbrace{b\ F_i \cos(\phi_i)}_{\text{Local feedback}}$$

CPG

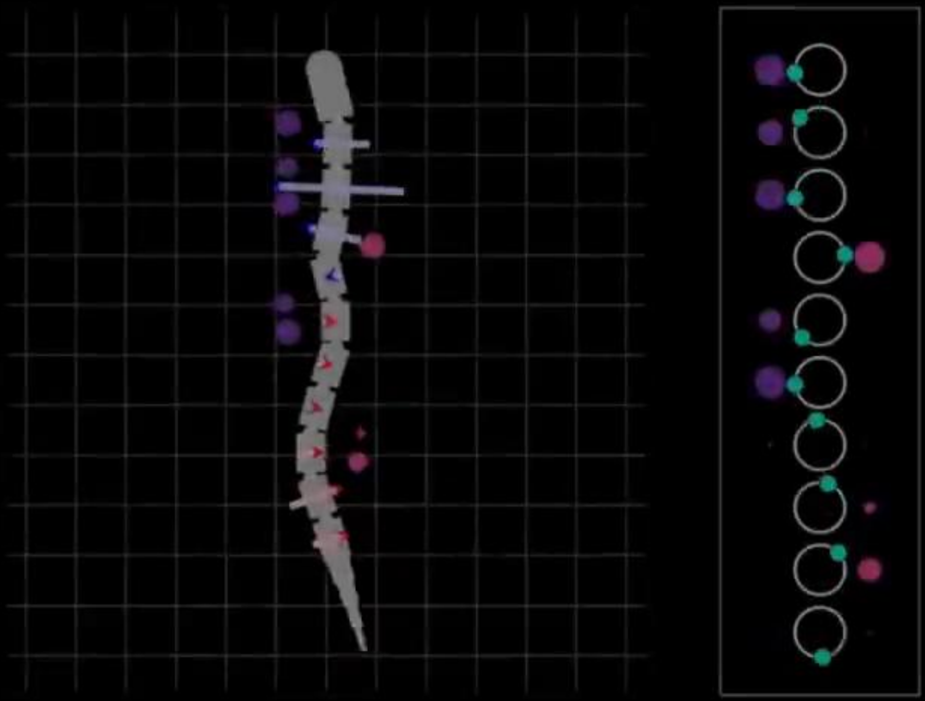
Decoupled Configuration Without Feedback



Decoupled Configuration Without Feedback

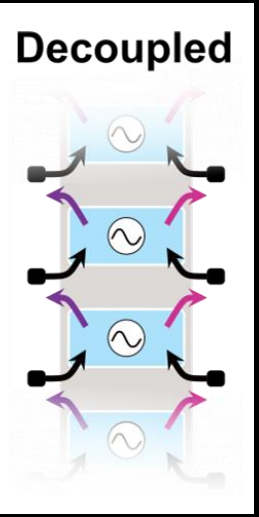


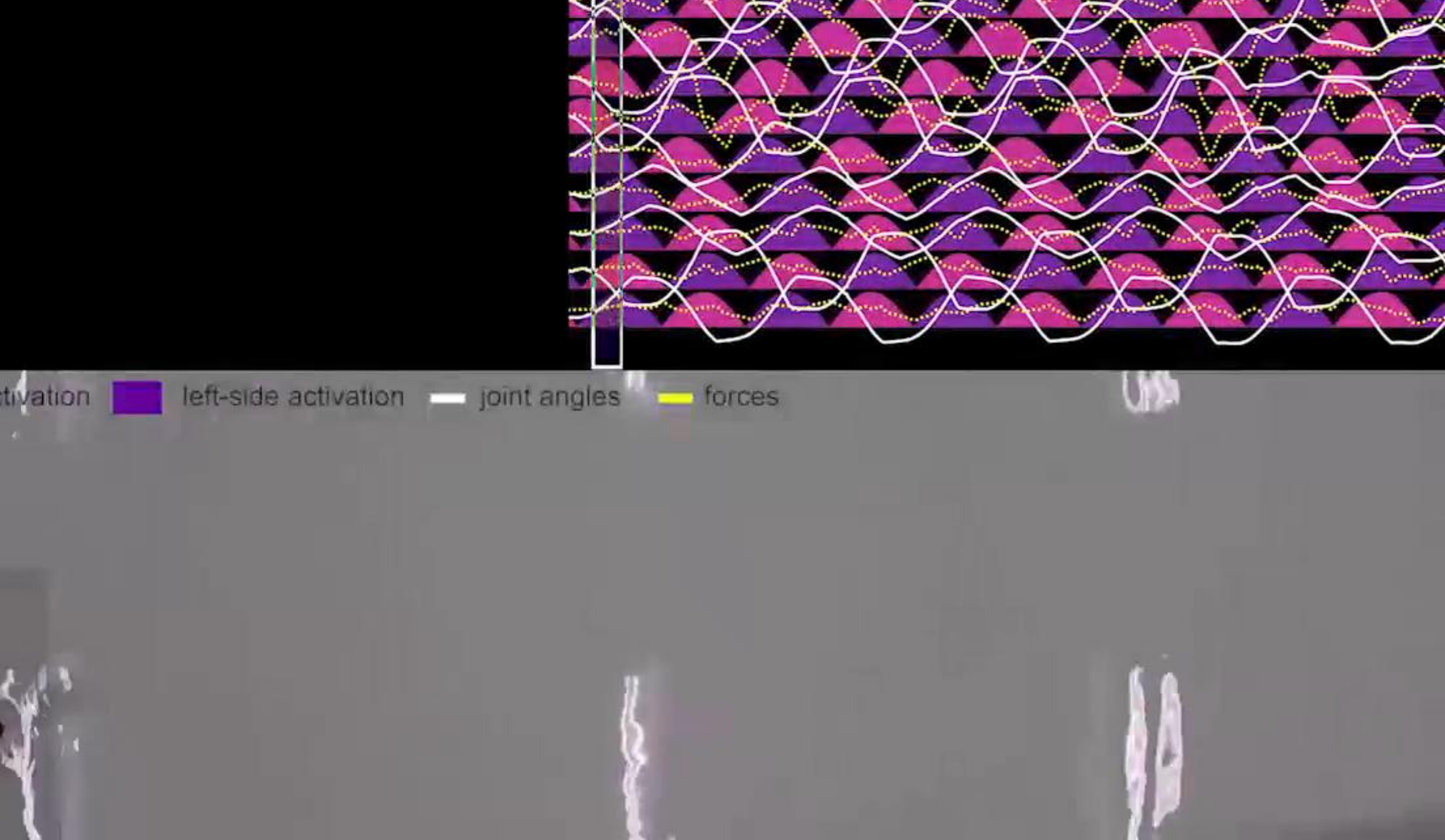
Decoupled Configuration With Feedback



Sensory feedback can **synchronize decoupled oscillators**

Sensory feedback can synchronize decoupled oscillators





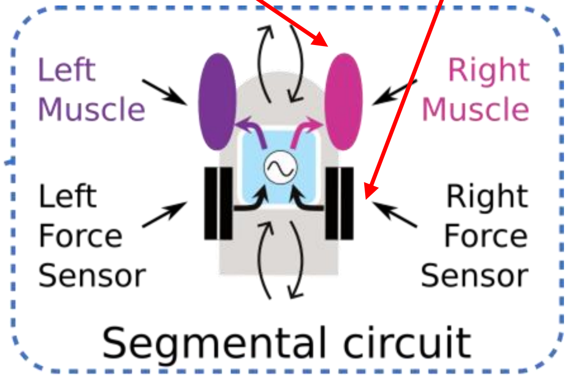
Why a caudo-rostal traveling wave?

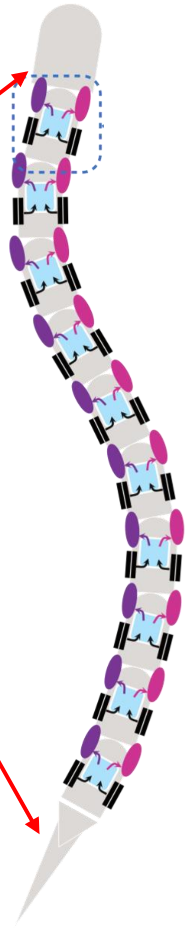
Why does the traveling wave travel from head to tail?

1. Asymmetry of the body (tail and head)

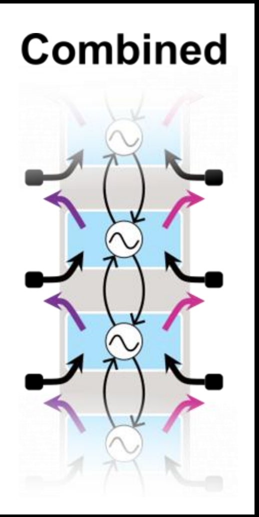
2. Spatial shift between actuation and perception

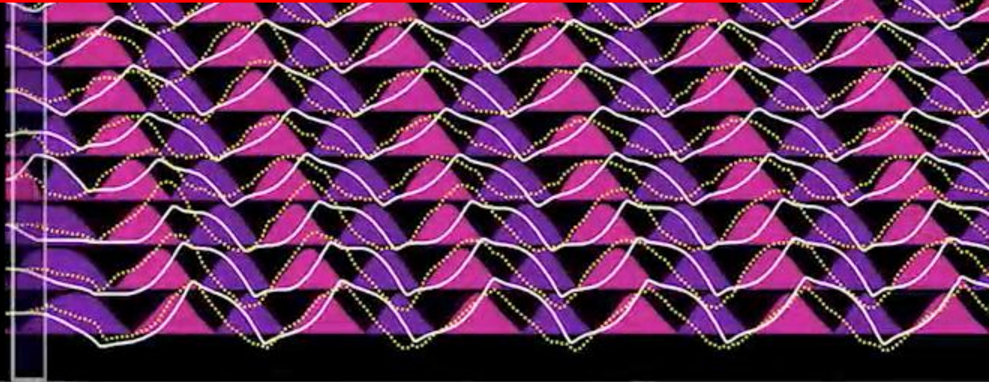
Pressure-sensitive dorsal cells in the lamprey tend to have receptive fields that are caudal (i.e. closer to the tail) to their position in the spinal cord

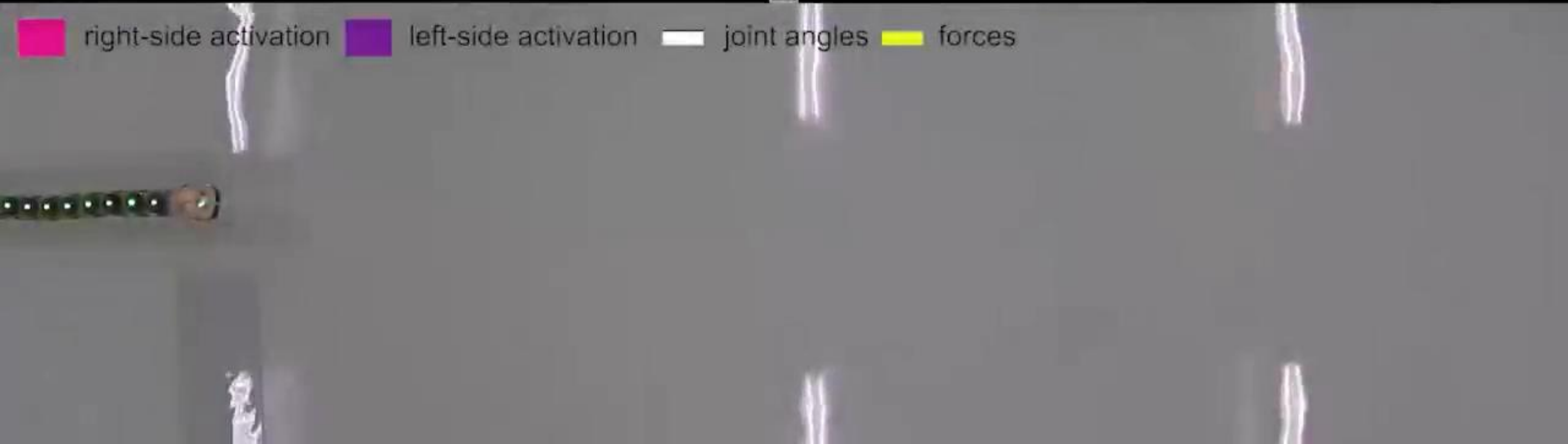




Shorter transients and most robust swimming with the **combined** configuration

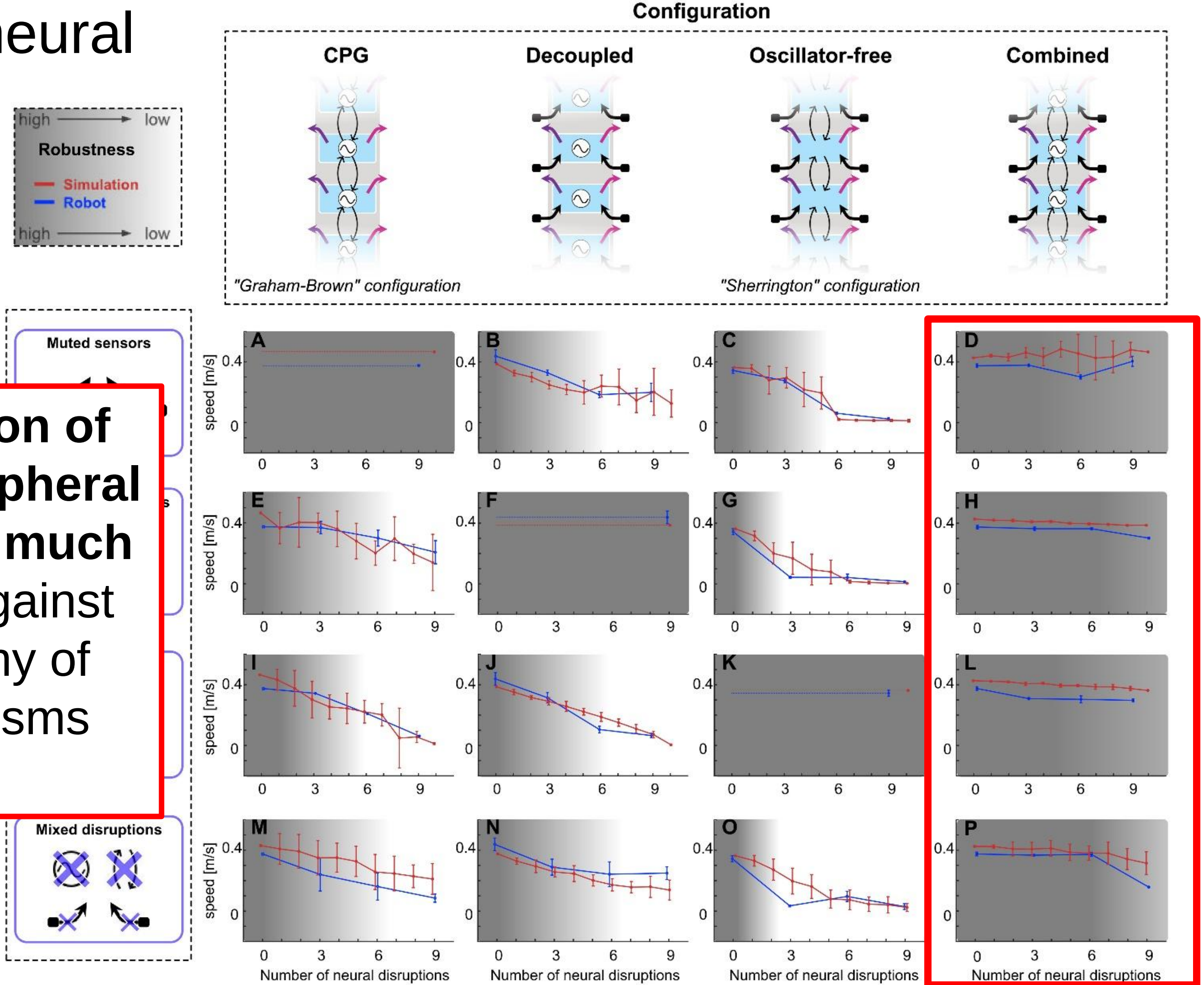






Robustness to neural disruptions

The **combination of central and peripheral mechanisms is much more robust** against lesions than any of these mechanisms alone



Lamprey and salamander summary

CPG circuits can generate and modulate various locomotion patterns (central mechanism)

- Probably **weaker inter-oscillator couplings** than we thought

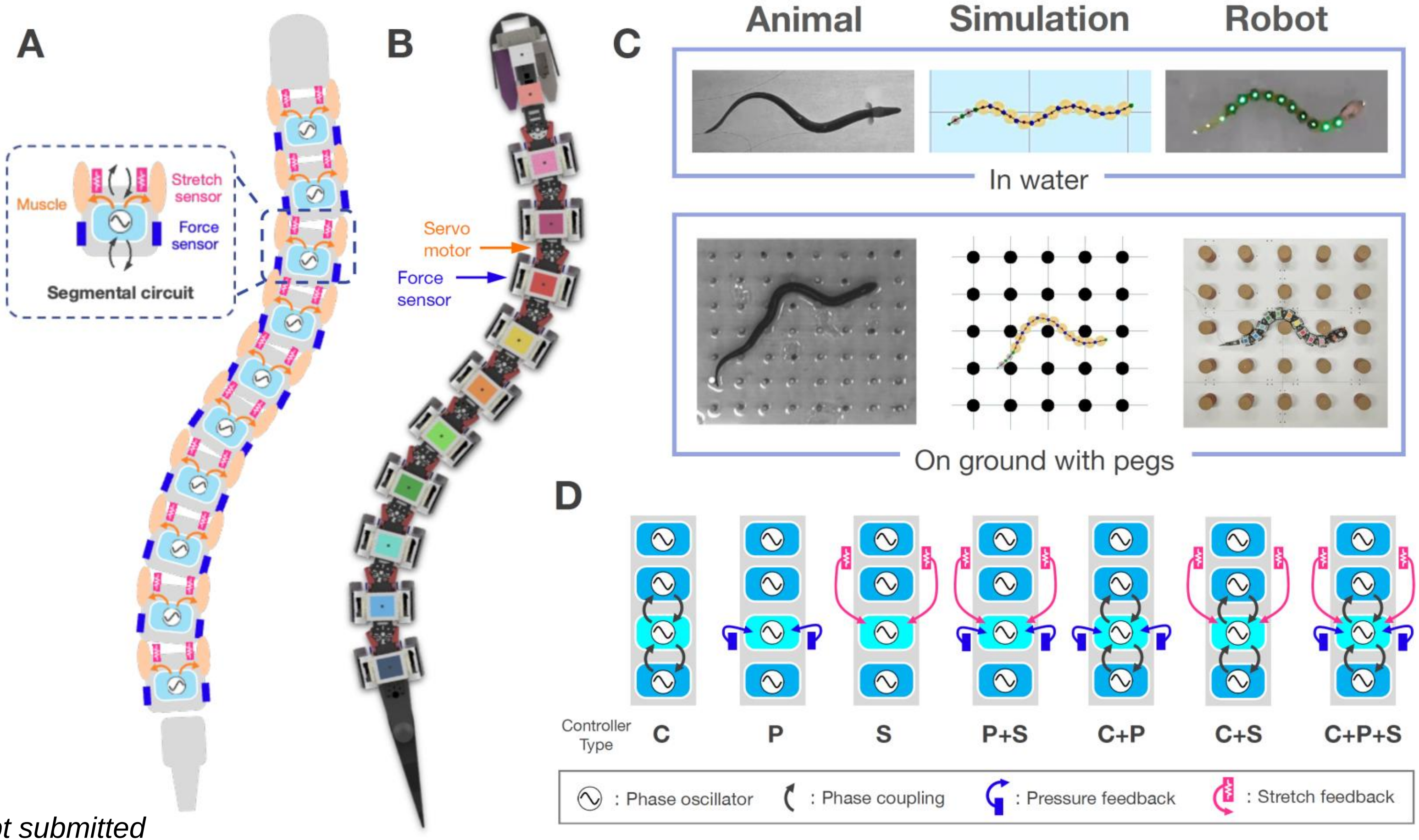
Local sensory feedback (peripheral mechanism):

- helps **handle perturbations**
- Can also contribute to
    - **synchronize oscillators** (i.e. replace intersegmental coupling)
    - **generate rhythms** (i.e. replace oscillators)

- **High flexibility** and **self-organized locomotion** (multiple mechanisms are contributing)
- **Strong robustness and redundancy:** many aspects of locomotion can be generated both by **central <u>and</u> peripheral mechanisms**

- Work in progress: adding **stretch feedback** improves robustness as well

New: exploring stretch and pressure feedback

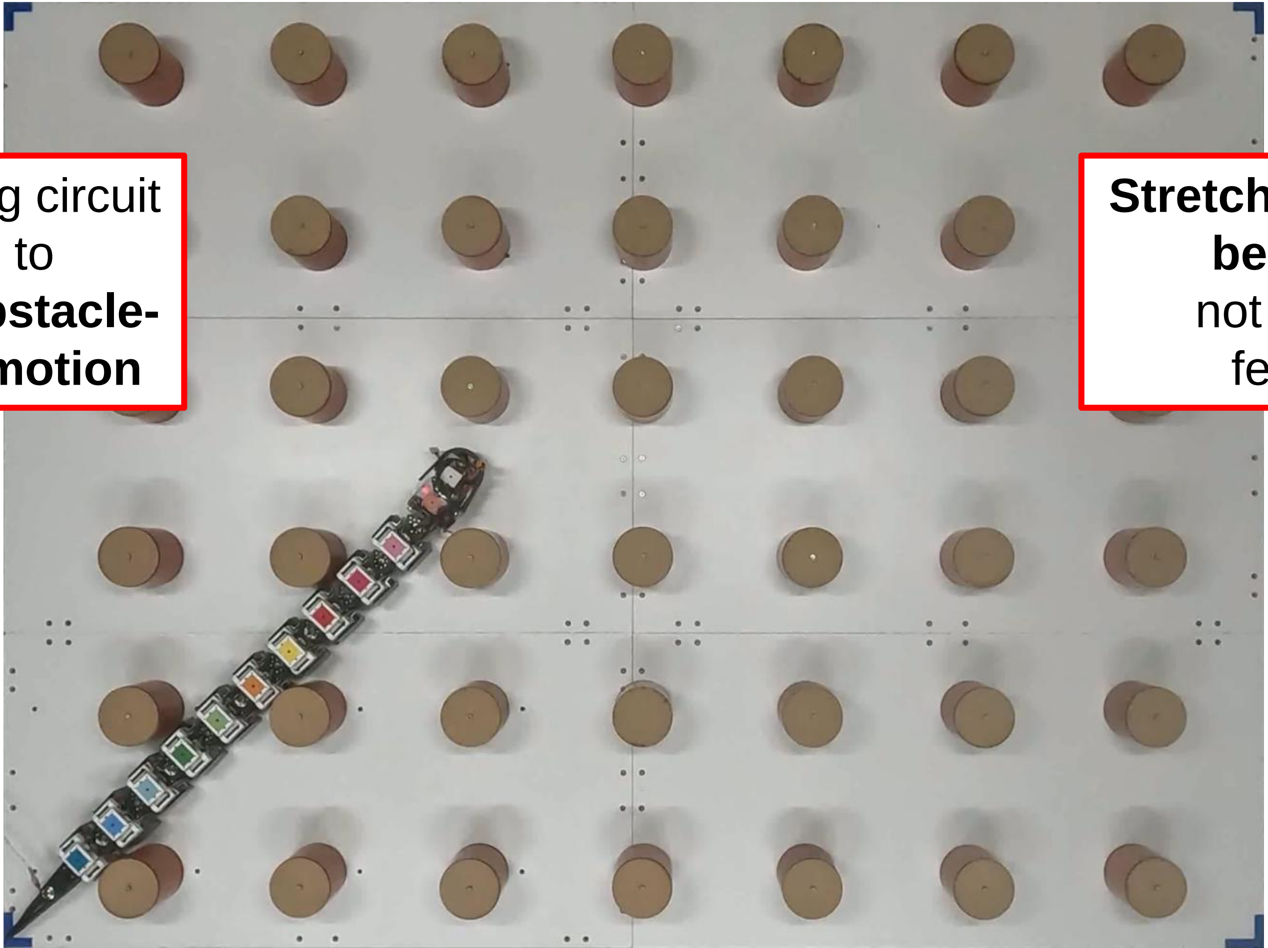


Manuscript submitted

Stretch and local pressure feedback on ground

P+S

The swimming circuit can lead to **terrestrial obstacle-based locomotion**



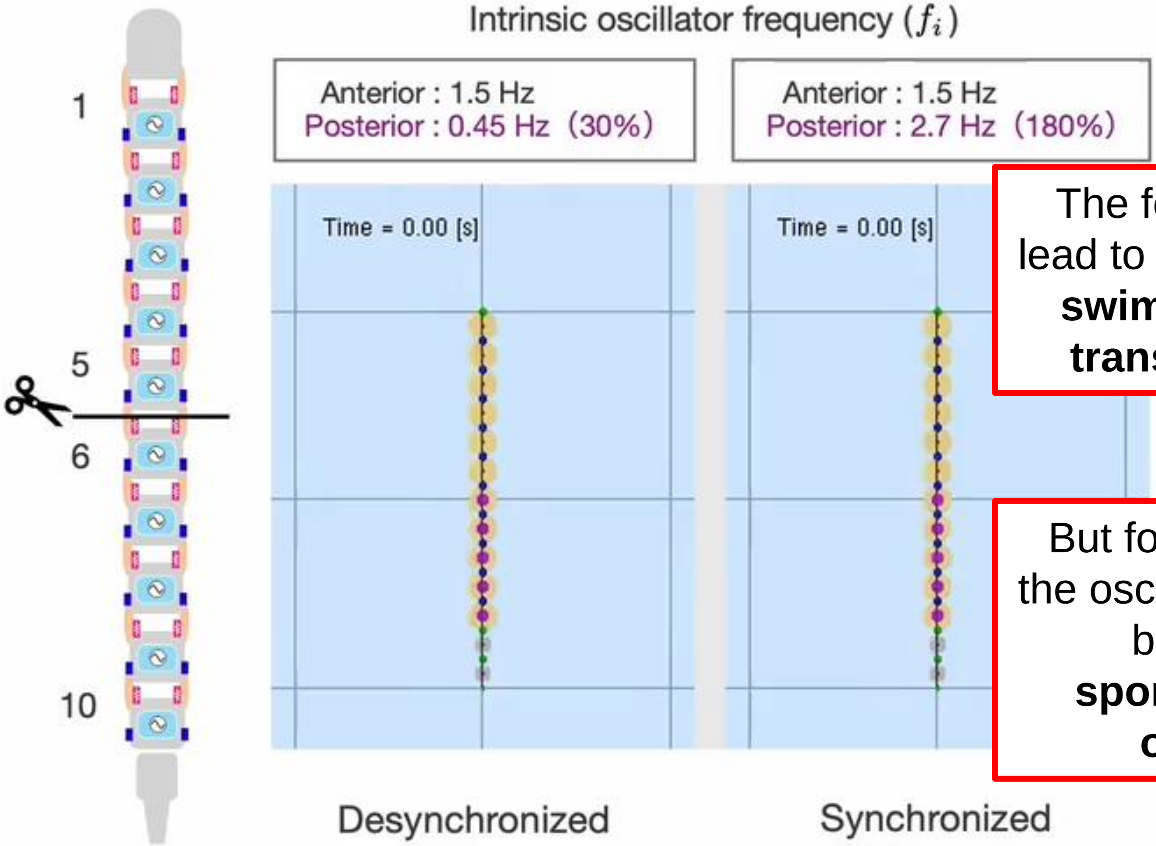
Stretch feedback is beneficial, not pressure feedback

Manuscript submitted

Transected eel

Controller : C+P+S (Spinal transected)

Spinal cord transected at 50% body length



The feedback can lead to **synchronized swimming** like in **transected eels**

But for this to work the oscillators need to be able to **spontaneously oscillate**

Manuscript submitted

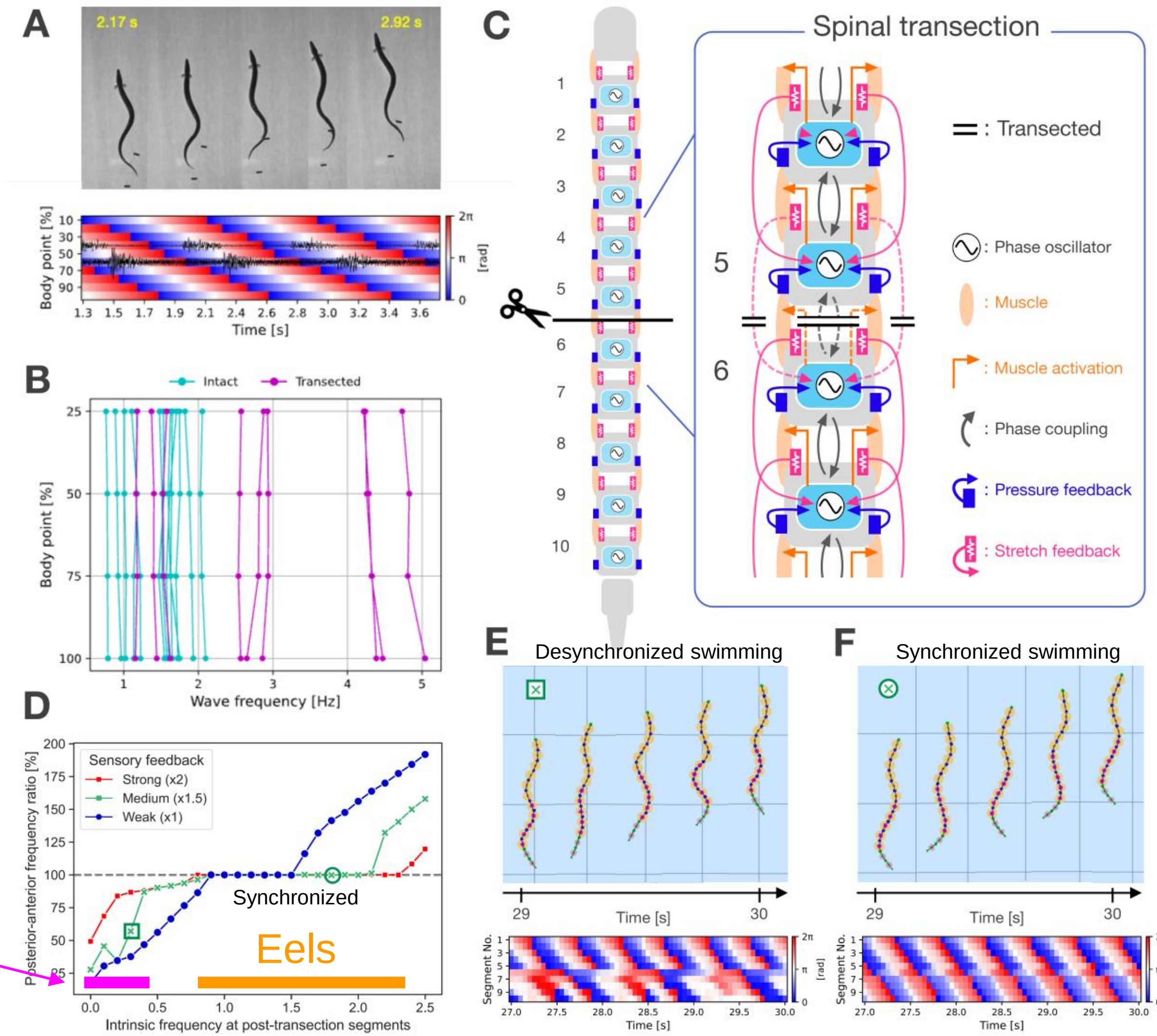
Two conditions for synchronized swimming:

(1) the **feedback should be strong enough**

(2) The oscillators below transection should be capable of **spontaneous oscillations**

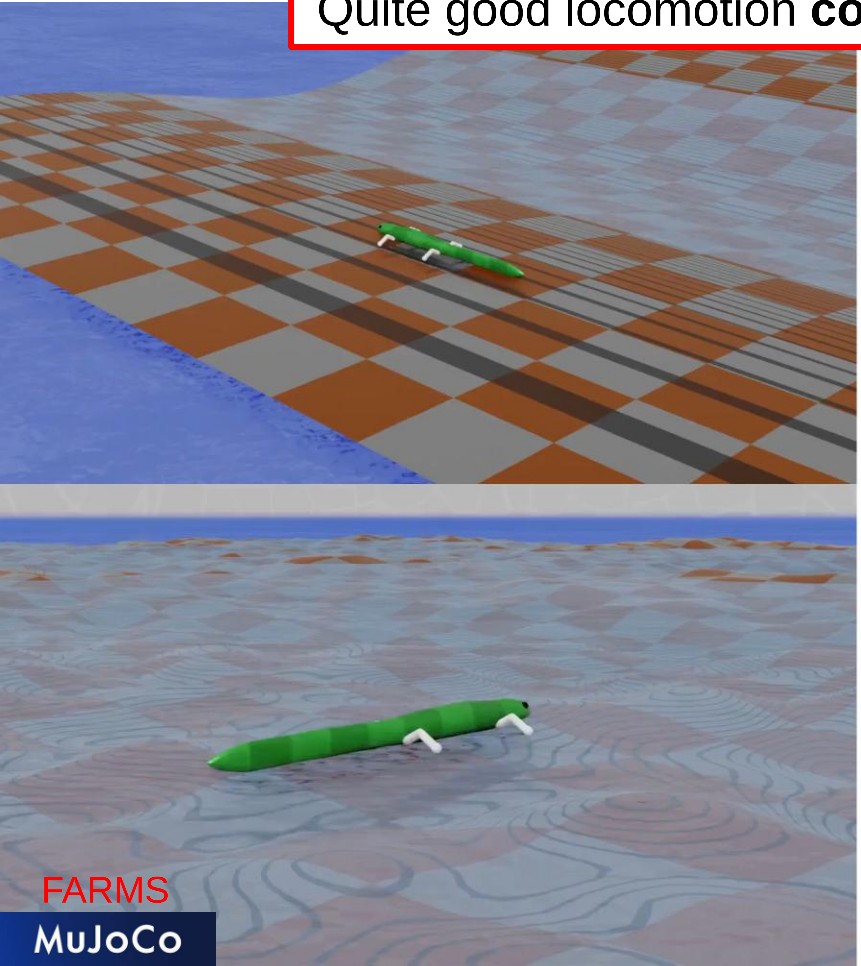
This could explain why **eels** can swim directly after transection and **not salamanders**

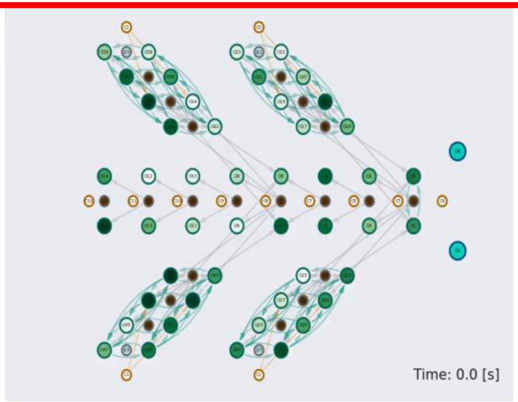
Salamanders

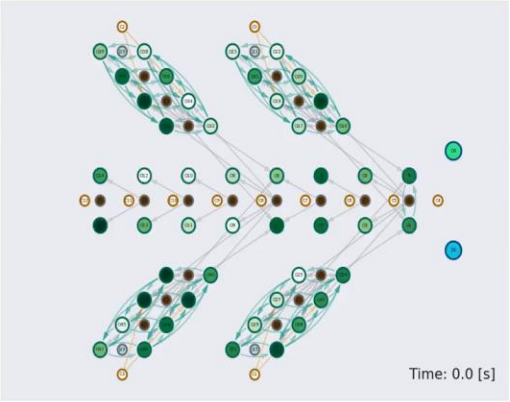


Swimming and walking coordinated through sensory feedback

Quite good locomotion **coordinated by sensory feedback**







Jonathan Arreguit O'Neil

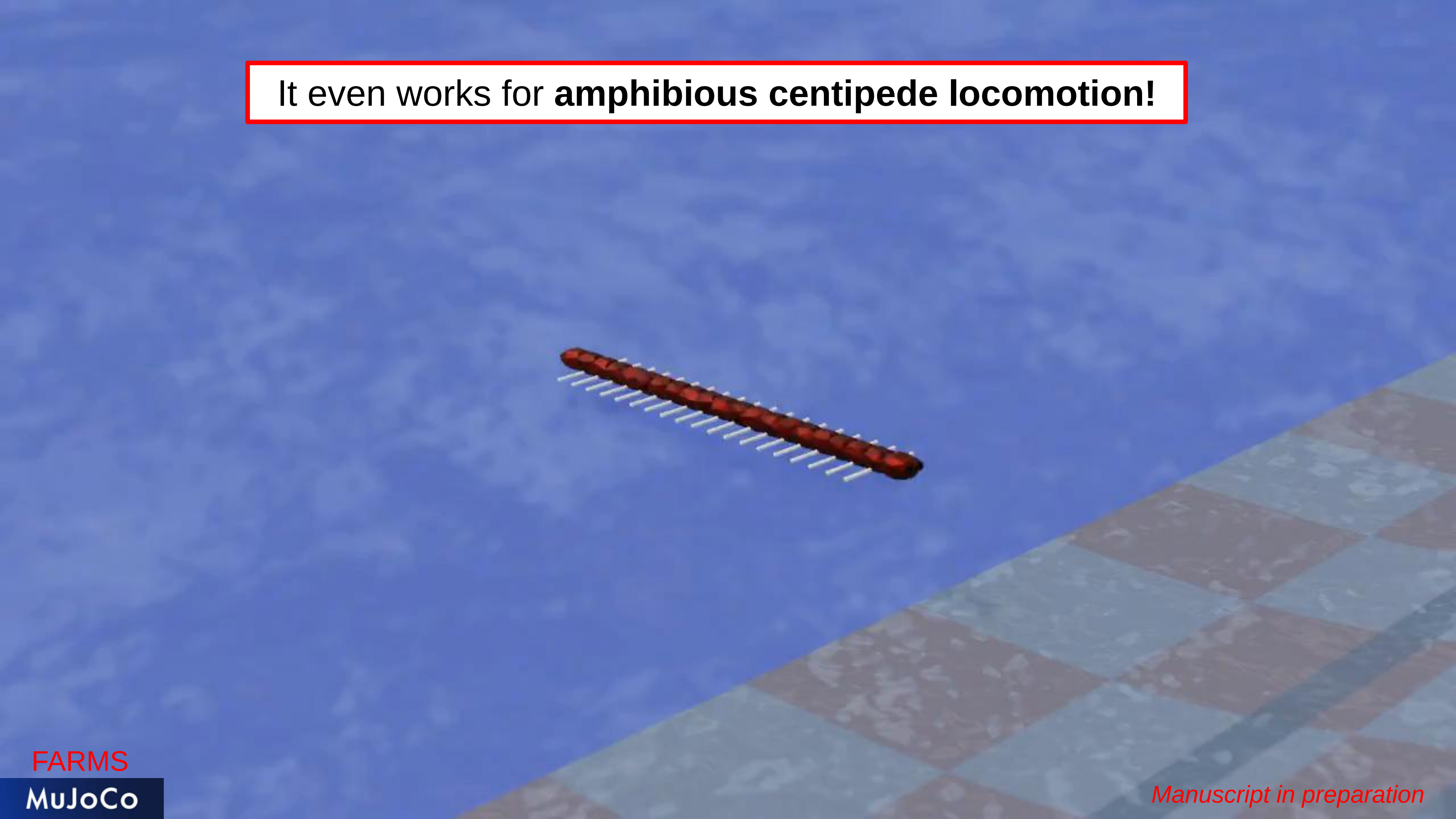
No axial coupling
No interlimb coupling
(but intralimb coupling)

Three types of feedback:

- Limb force
- Muscle stretch
- Muscle stretch velocity

Manuscript in preparation

It even works for **amphibious centipede locomotion!**



FARMS

MuJoCo

Manuscript in preparation

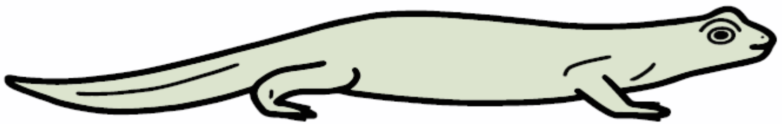
Q2 Evolution

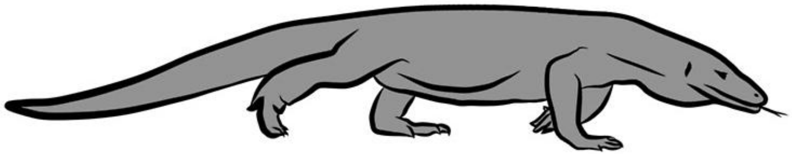
From **amphibians**

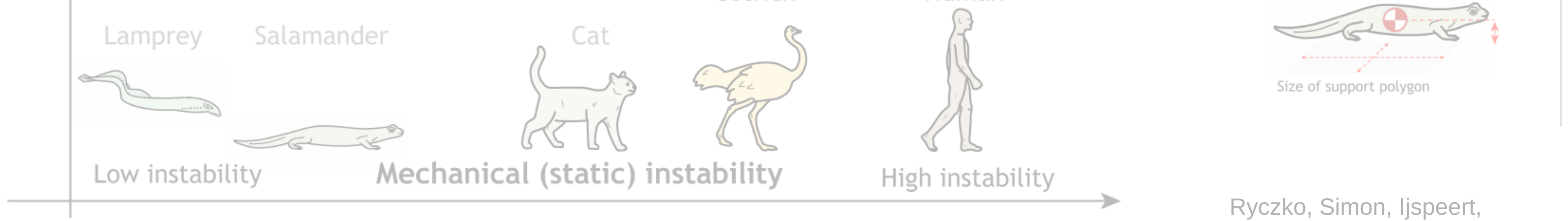
- Low to the ground
- Slow
- Anamniotes (eggs in water)

to **reptiles**

- More erect
- Faster, more agile
- Amniotes (eggs in a shell)


Salamander


Komodo dragon



Ryczko, Simon, Ijspeert, *Trends in Neuroscience*, 2020

Ijspeert and Daley, J. of Exp. Biol., JEB 2023

Robotic Paleontology: reverse engineering the locomotion of Orobates, an early tetrapod

John A. Nyakatura, Kamilo Melo, Tomislav Horvat, Kostas Karakasiliotis, Vivian R. Allen, Amir Andikfar, Emanuel Andrada, Patrick Arnold, Jonas Lauströer, John R. Hutchinson, Martin S. Fischer & Auke J. Ijspeert

Nature 565, 351–355 (2019)

K. Melo

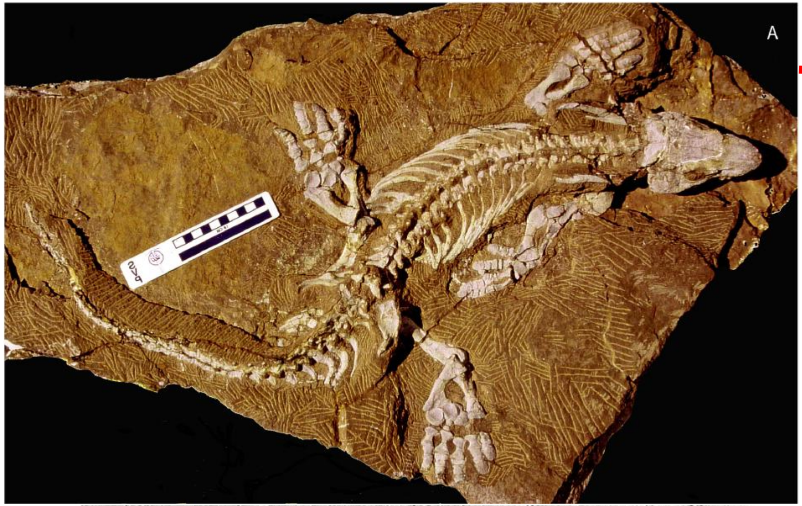
T. Horvat

K. Karakasiliotis

John A. Nyakatura

John R. Hutchinson

Robotic Paleontology: reverse engineering the locomotion of Orobates, an early tetrapod



Well-preserved fossil

What was the **most likely gait**?

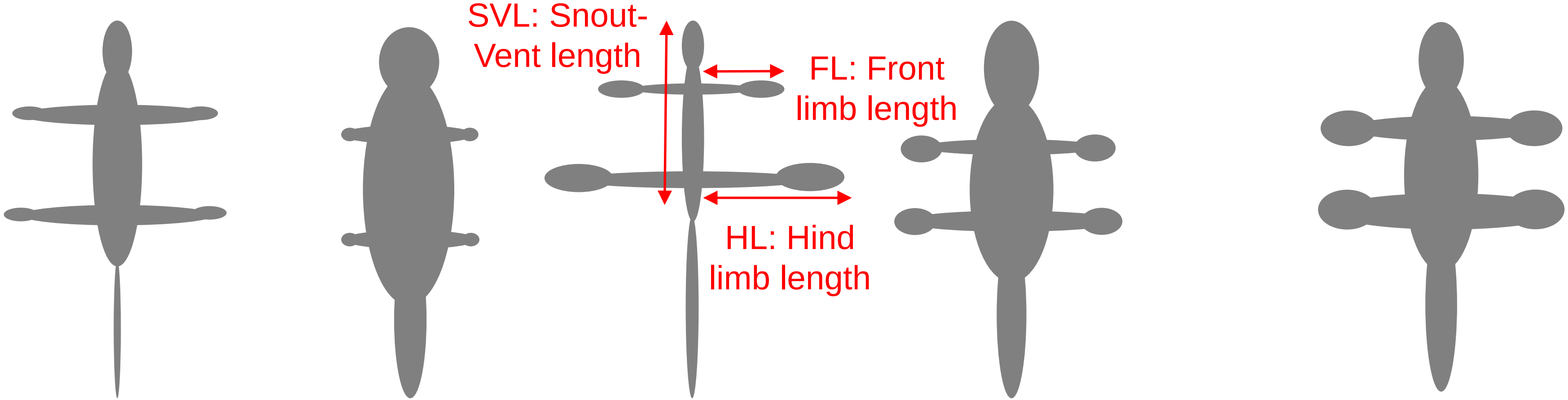
Foot track for the same species

Sprawling locomotion in extant tetrapods

Salamander | Skink | Iguana | Caiman







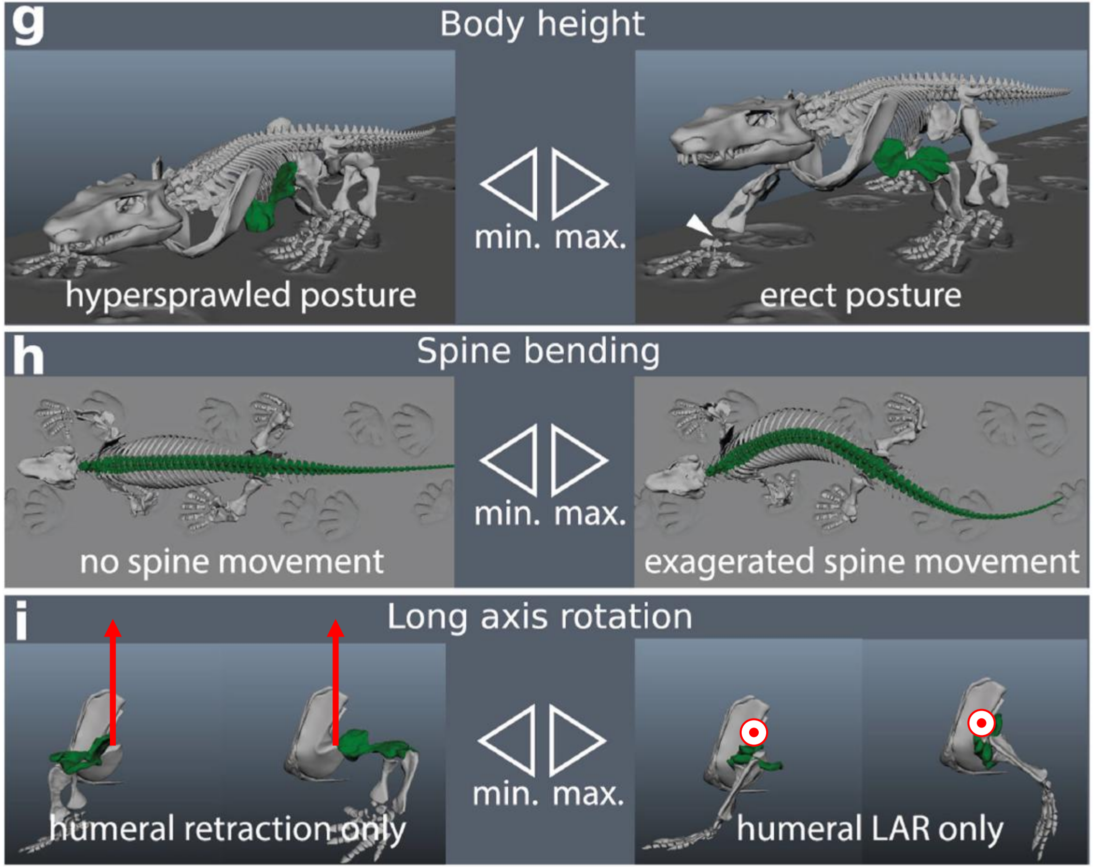
HL/SVL	0.3	0.17	0.55	0.39	0.41
FL/HL	0.85	1.0	0.67	0.75	0.93

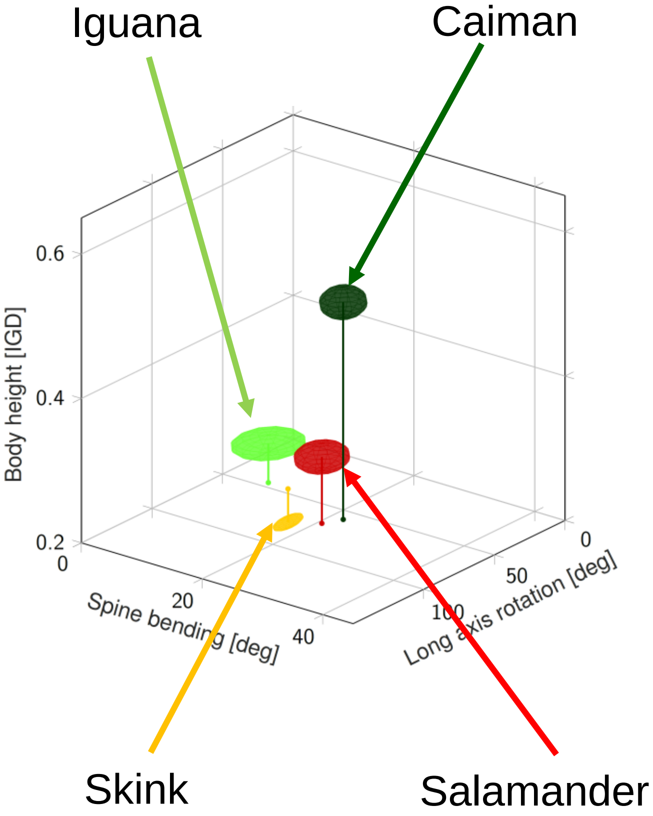
Slide from J. Nyakatura

X-ray motion analysis & measurement of ground reaction forces

Slide from J. Nyakatura

Defining a sprawling gaits space



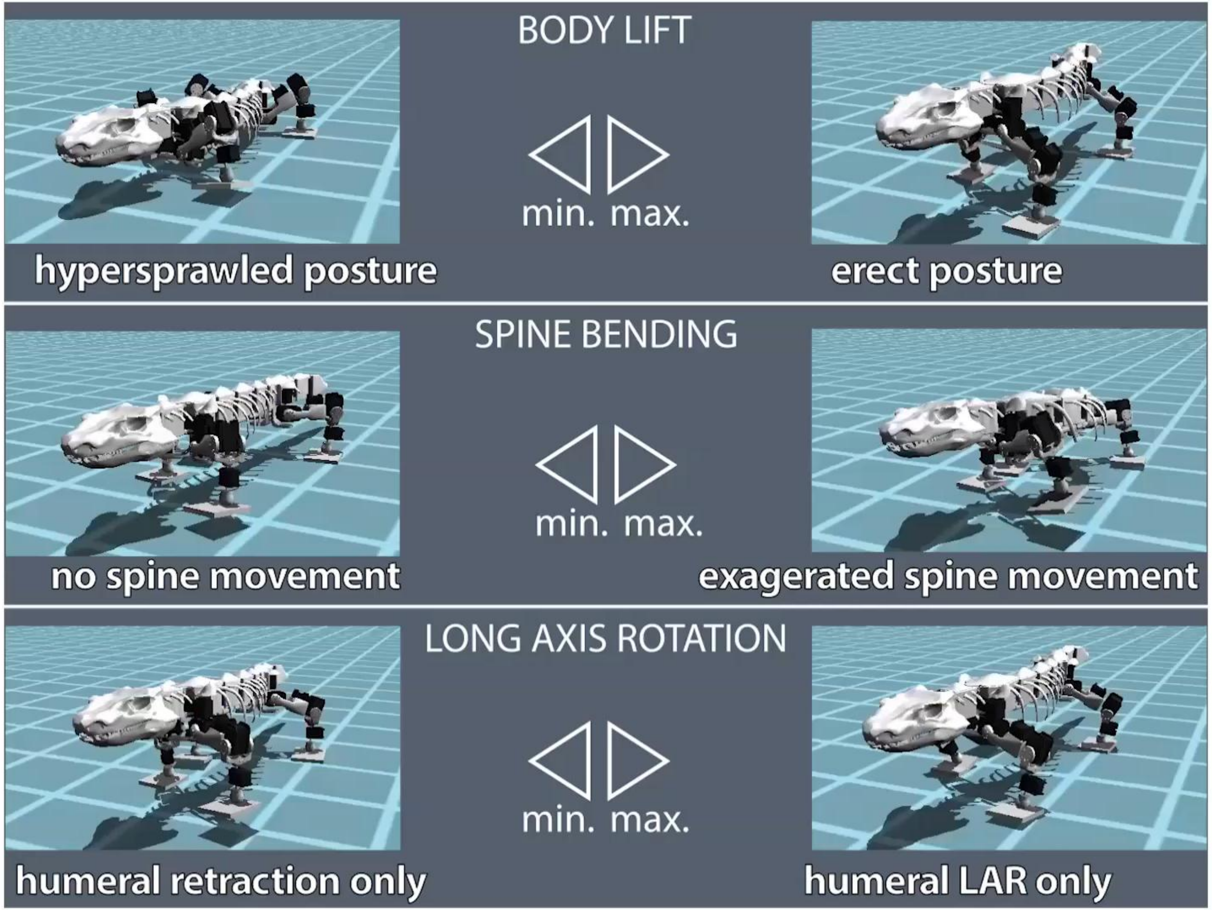


Nyakatura *et al*, *Nature*, 2019

Gait parameters – dynamic simulation

Inverse-kinematic controllers are used to generate gaits that:

- **Step in the footprints**
- Allow **modulation of quantities defining the SGS** (sprawling gait space)



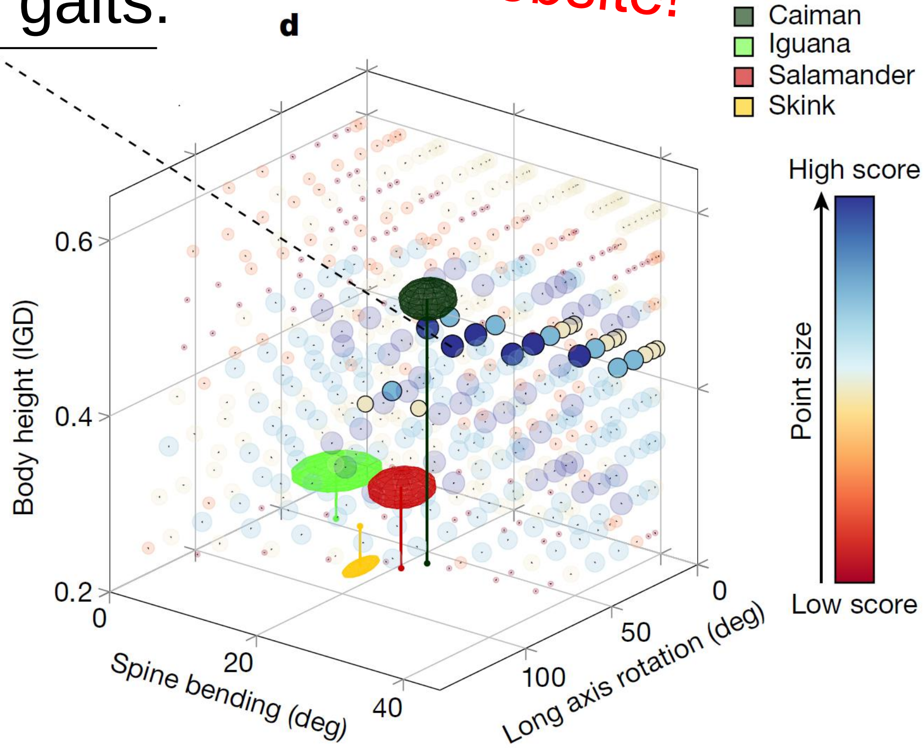
Most likely gaits

Check out the interactive website!

Metrics for finding the most likely gaits:

- Bone collisions
- Power expenditure
- Balance
- Precision
- GRF Ground reaction forces

Exclusion-based approach: filtering out unlikely gaits (lowest 50% percentile for each metric)



https://biorob2.epfl.ch/pages/Orobates_interactive/
https://cyberbotics2.cyberbotics.com/orobot/simulation.php

Most likely gaits

Check out the interactive website!

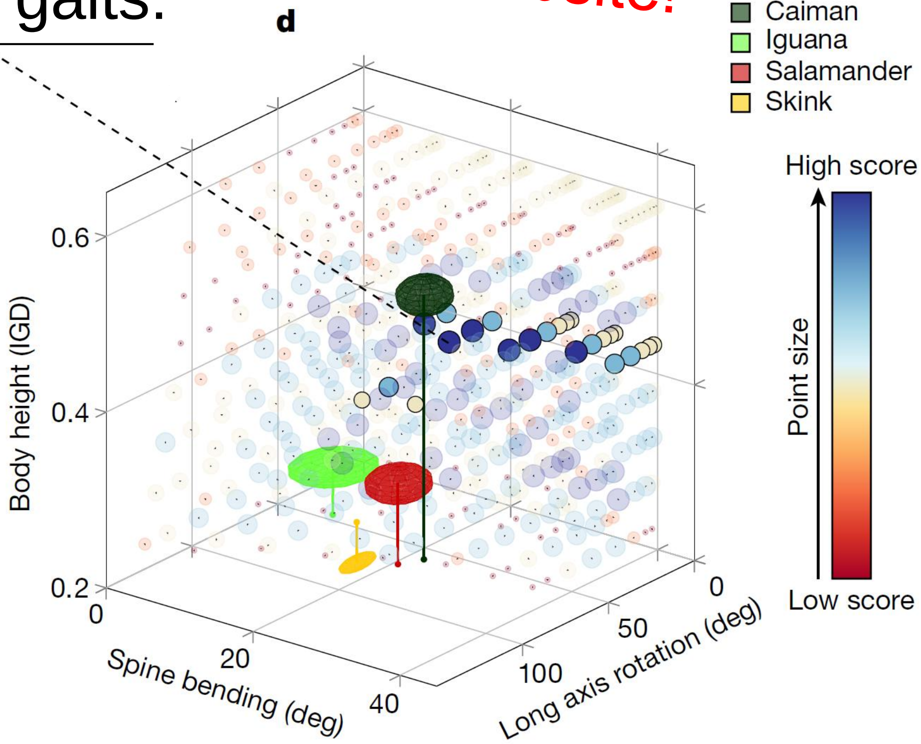
Metrics for finding the most likely gaits:

Orabates could have used many different types of gaits

-
-
-
- Precision
- GRF Ground reaction forces

The most likely one is close to the Caiman's

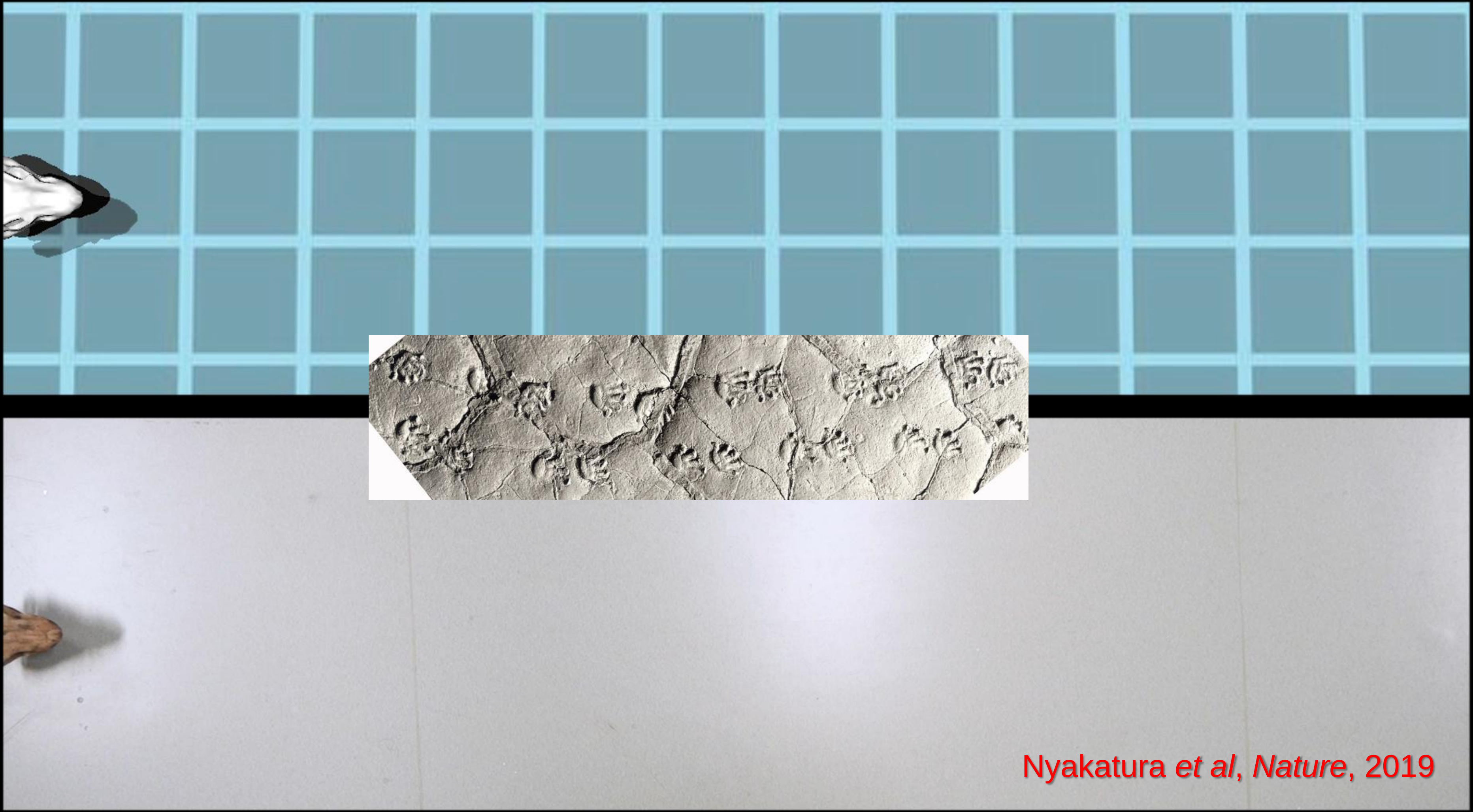
Ex... filtering out unlikely gaits (lowest 50% percentile for each metric)



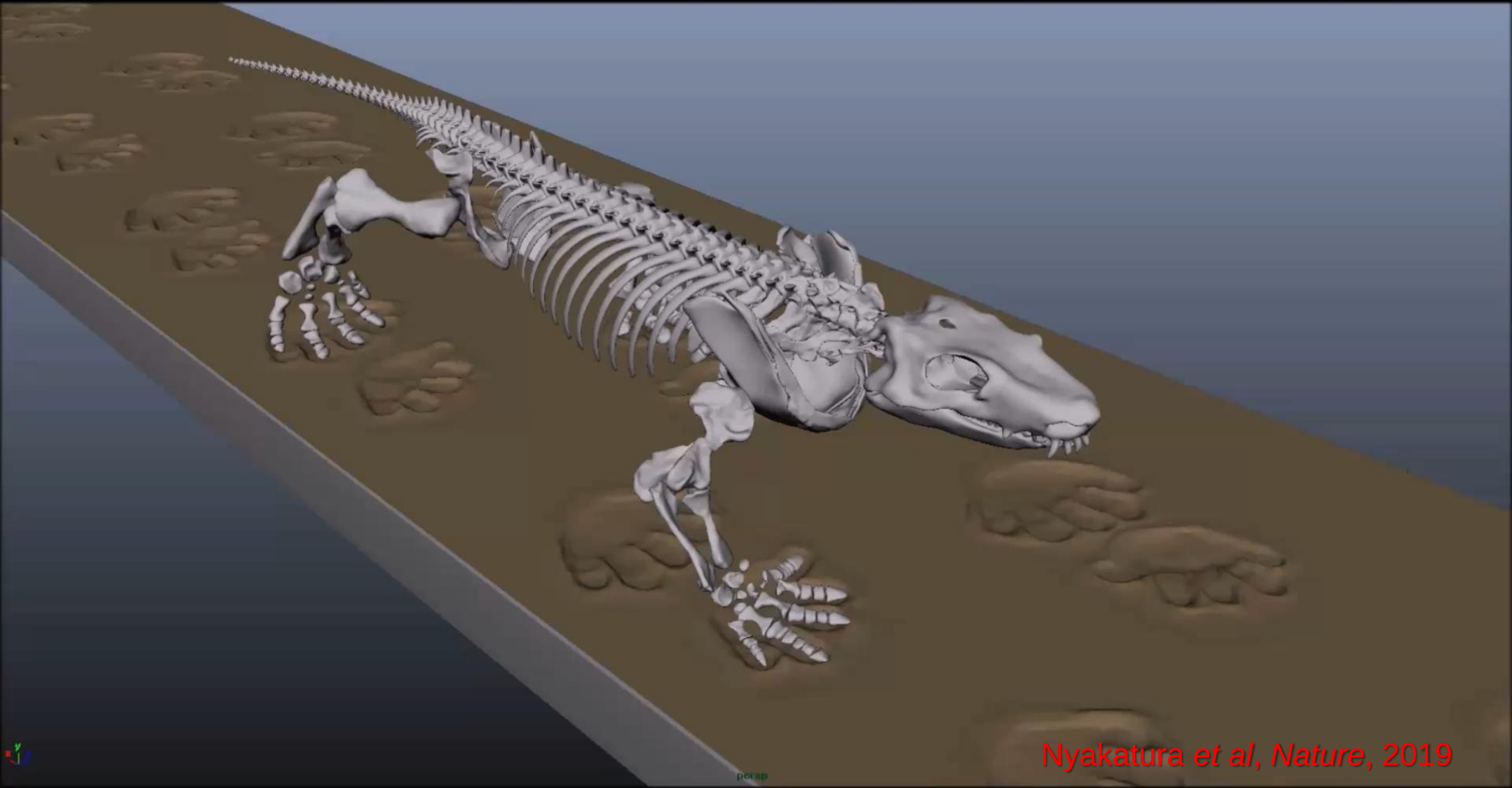
https://biorob2.epfl.ch/pages/Orobates_interactive/

https://cyberbotics2.cyberbotics.com/orobot/simulation.php

Nyakatura *et al*, *Nature*, 2019



Nyakatura *et al*, *Nature*, 2019

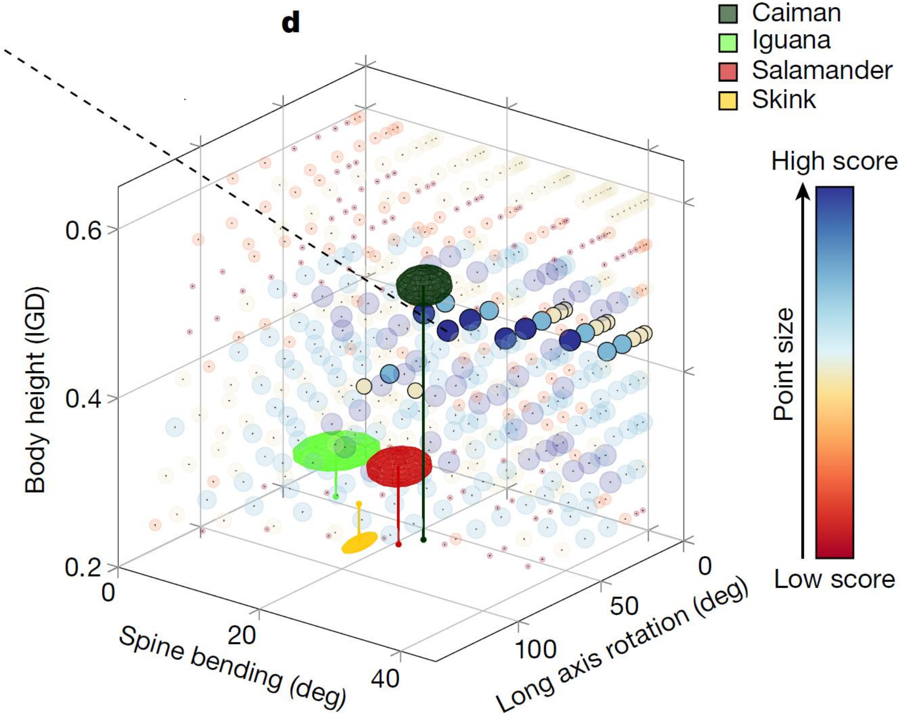


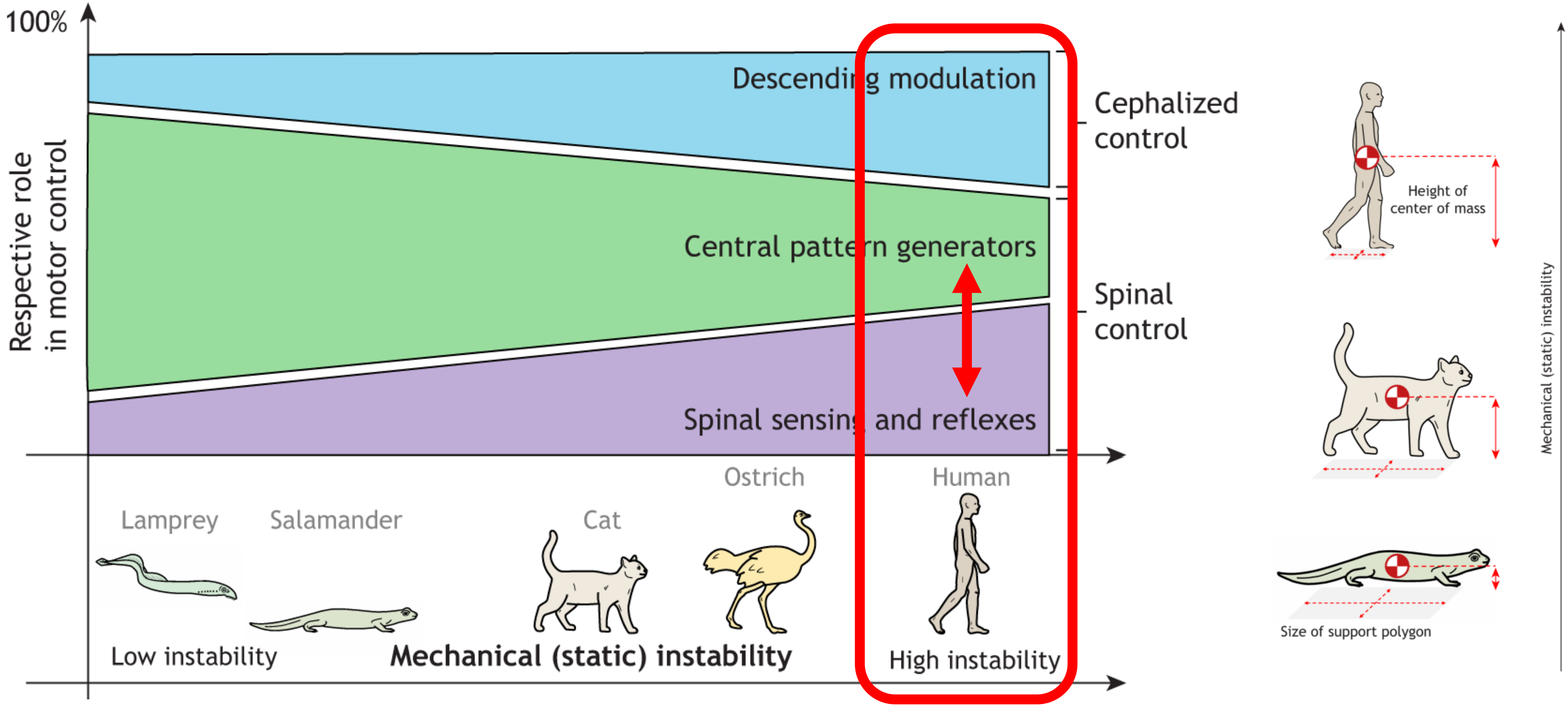
Nyakatura *et al*, *Nature*, 2019

Paleontology: take-home messages

- Orobates could in principle have used a **large diversity of gaits**
- Most likely: a **quite erect and athletic gait**
- More **similar to Caiman** than to salamander
- **More advanced than initially thought** for this stem amniote

- New **quantitative methodology for paleontology**





Indirect evidence of CPGs in human: Minassian et al, *Neuroscientist,* 2017

Ijspeert and Daley, J. of Exp. Biol., JEB 2023

Great progress in humanoid robots

Wabian, Waseda U.

Asimo, Honda

HRP2

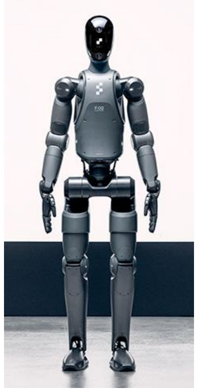


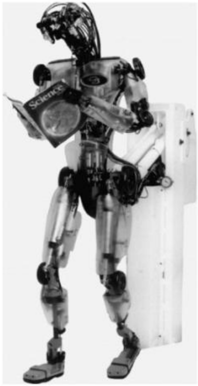
Figure AI

G1, Unitree

Optimus, Tesla

Digit, Agility R.

Qrio, SONY



DB, Sarcos

Atlas, Boston Dynamics

New Atlas

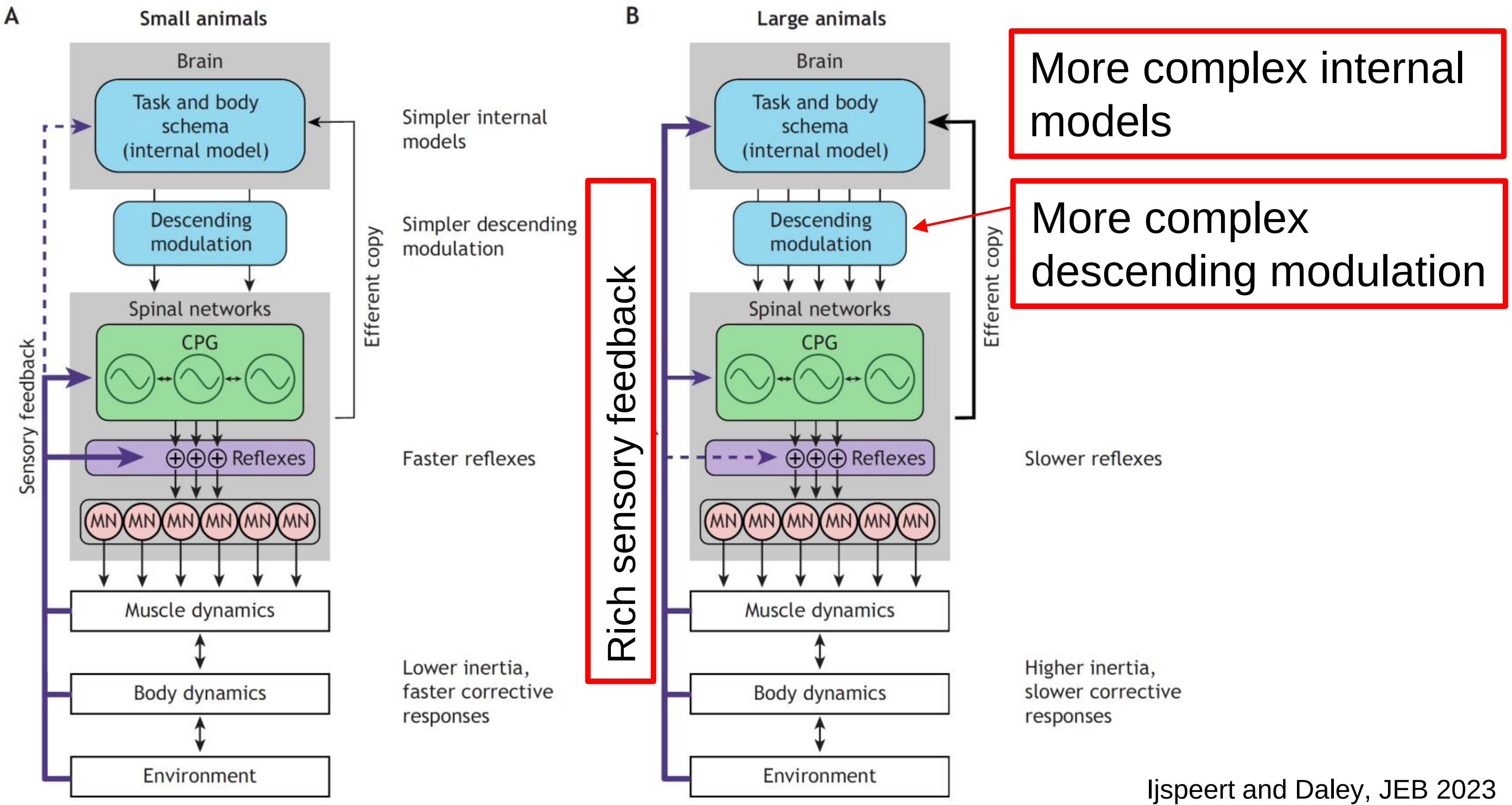
Nao, Aldebaran

Apollo Apptronic

A2, Agibot

https://www.youtube.com/watch?v=6XR7cr3QIV8

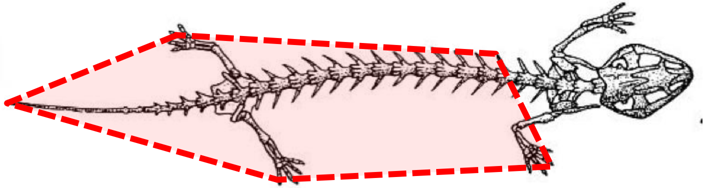
Human motor control relies more on **sensory signals** and **higher-brain centers** (supra-spinal control)



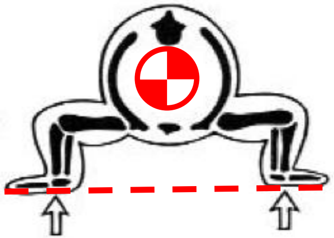
Ijspeert and Daley, JEB 2023

Key transition from amphibians to mammals

Sprawling posture



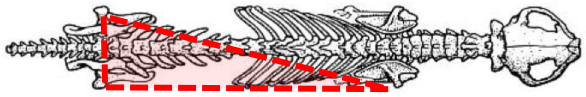
Salamander



Low center of mass

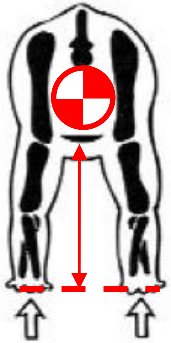
Large support polygon

Upright posture



studyblue.com

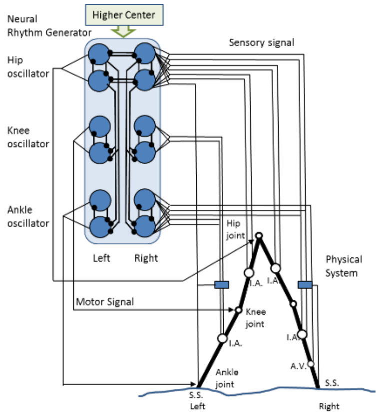
Mammal



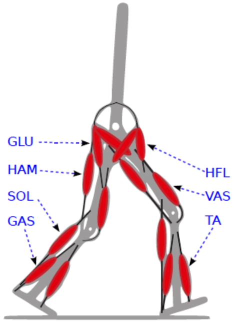
High center of mass

Small support polygon

Neuromechanical models of human locomotion

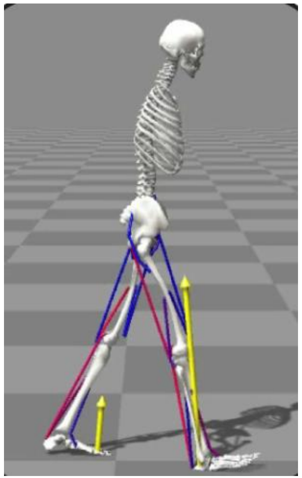


Taga 1995, 1998



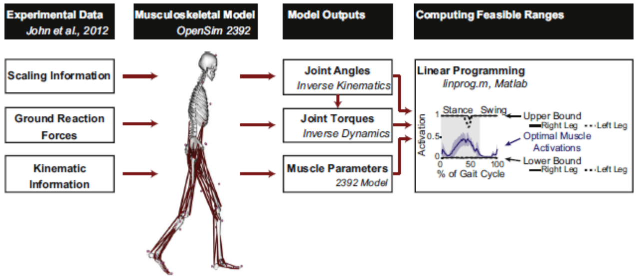
Geyer and Herr, 2010.
Song and Geyer 2015

Lee et al 2019e

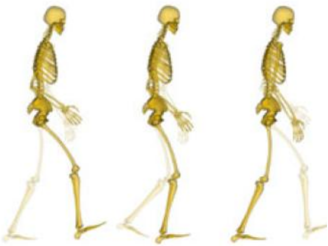


Ong et al 2019

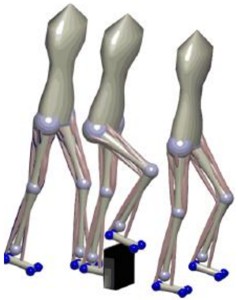
Nakamura lab
(Sreenivasa et al 2012)



Ting lab (Simpson et al 2016)



Falisse et al 2019



Ramadan et al 2022

Geyer and Herr's sensory-driven model

Sensory-driven model

+

7 muscles per leg

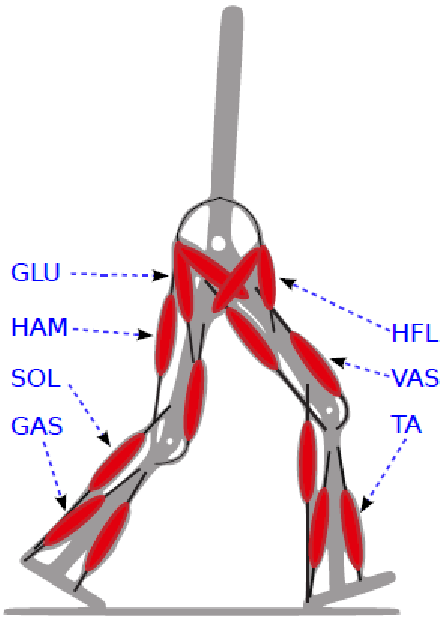
+

Different reflexes

(positive and negative force feedback, limits of overextension, …)

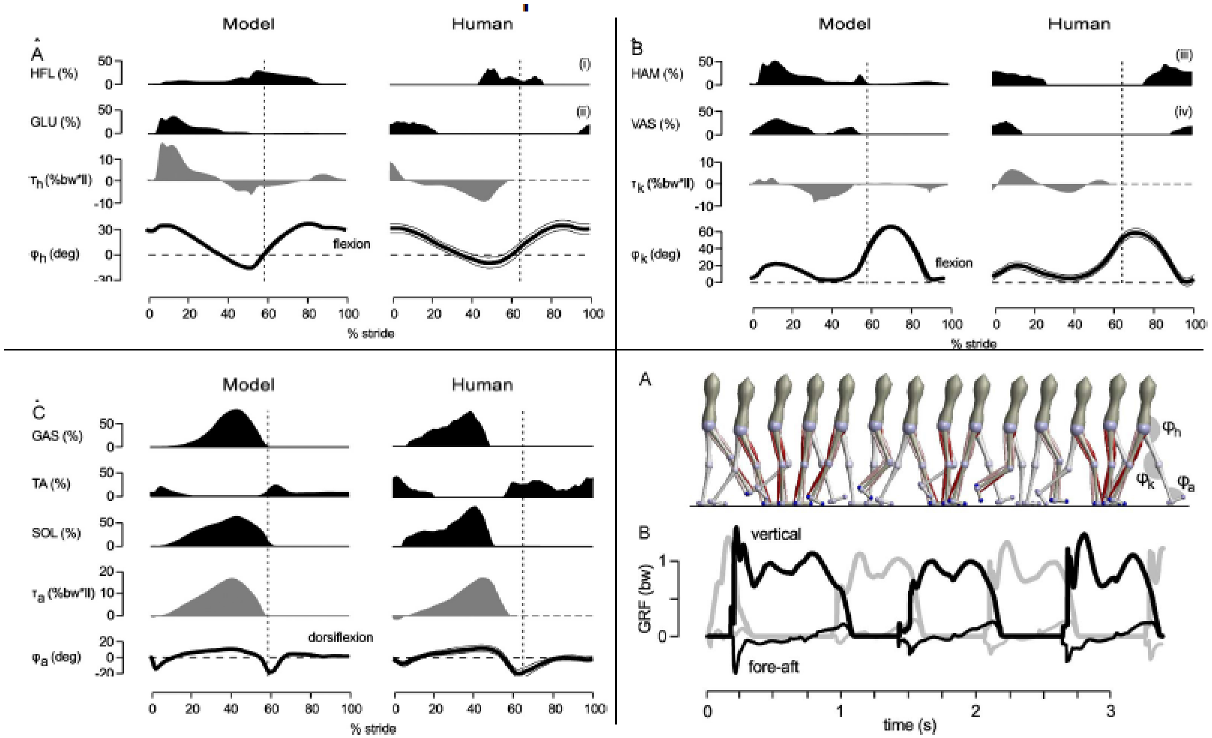
+

Posture control (torso angle)



H Geyer, HM Herr. A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities. **IEEE Trans Neural Syst Rehabil Eng** 18(3): 263-273, 2010.

Good match to human data



H Geyer, HM Herr. A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities. **IEEE Trans Neural Syst Rehabil Eng** 18(3): 263-273, 2010.

Benefits of a CPG?

- Is it worth adding a CPG to the sensory-driven network?
- Yes, we think so!

Florin Dzeladini

N. van der Noot

A. Wu

Hypotheses: adding a CPG to the feedback-driven controller can
1) Improve the **control of speed**
2) Improve **robustness against sensory noise**
3) Improve **robustness against sensory failure**
4) Reduce **transient times.**

This can be seen as adding a feedforward controller to a feedback controller

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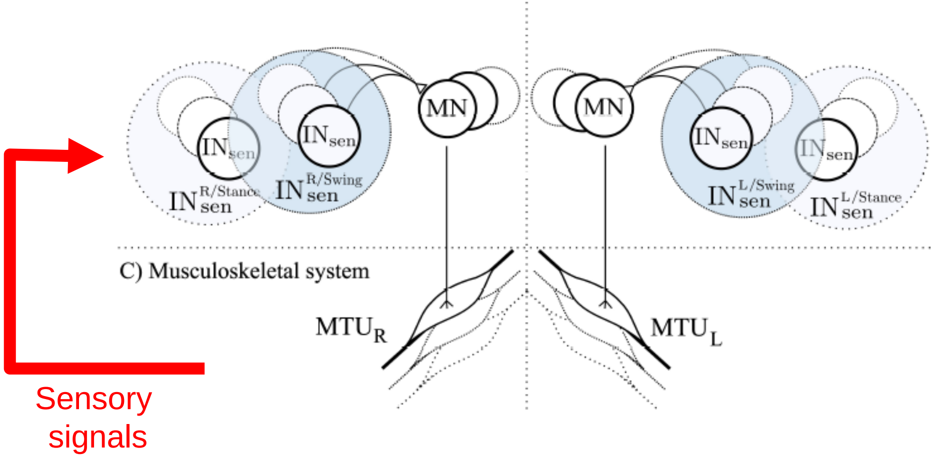
Florin Dzeladini


N. van der Noot


A. Wu

CPG construction

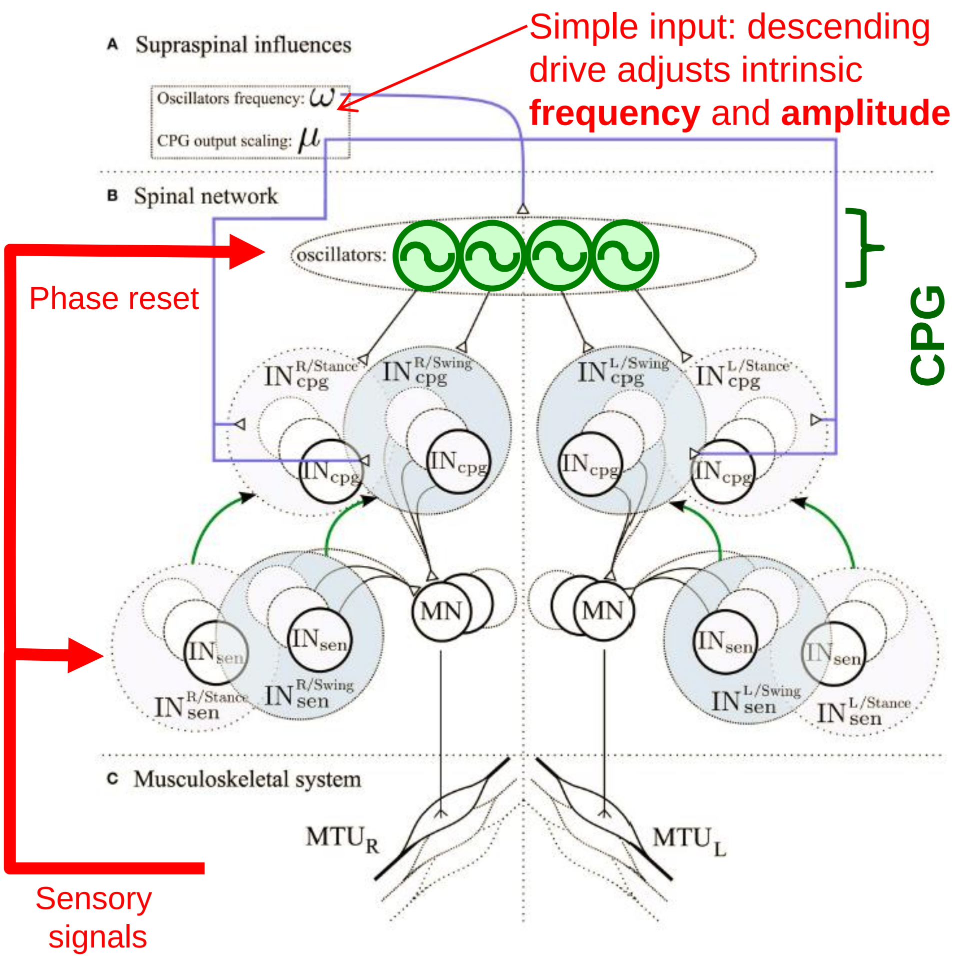
We start with the sensory-driven model:



Dzeladini et al 2014, *Frontiers in Human Neuroscience*

CPG construction

… and add a **CPG that replicates the control signals produced during steady-state**



Dzeladini et al 2014, *Frontiers in Human Neuroscience*

CPG construction

Feedback & CPG network

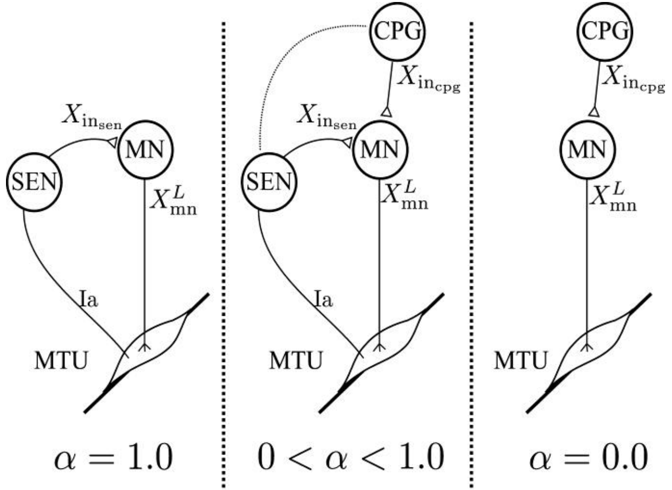
$$X_{\mathrm{mn}} = f\left(X_{\mathrm{in}_{\mathrm{sen}}}, X_{\mathrm{in}_{\mathrm{cpg}}}\right) + X^{0}_{\mathrm{mn}}$$

$$f(x_{\mathrm{fb}}, x_{\mathrm{ff}}) = G^{s}\Big(x_{\mathrm{ff}} + \alpha\big(x_{\mathrm{fb}} - x_{\mathrm{ff}}\big)\Big)$$

$\alpha = 0$ $\rightarrow$ pure feedforward

$\alpha = 1$ $\rightarrow$ pure feedback

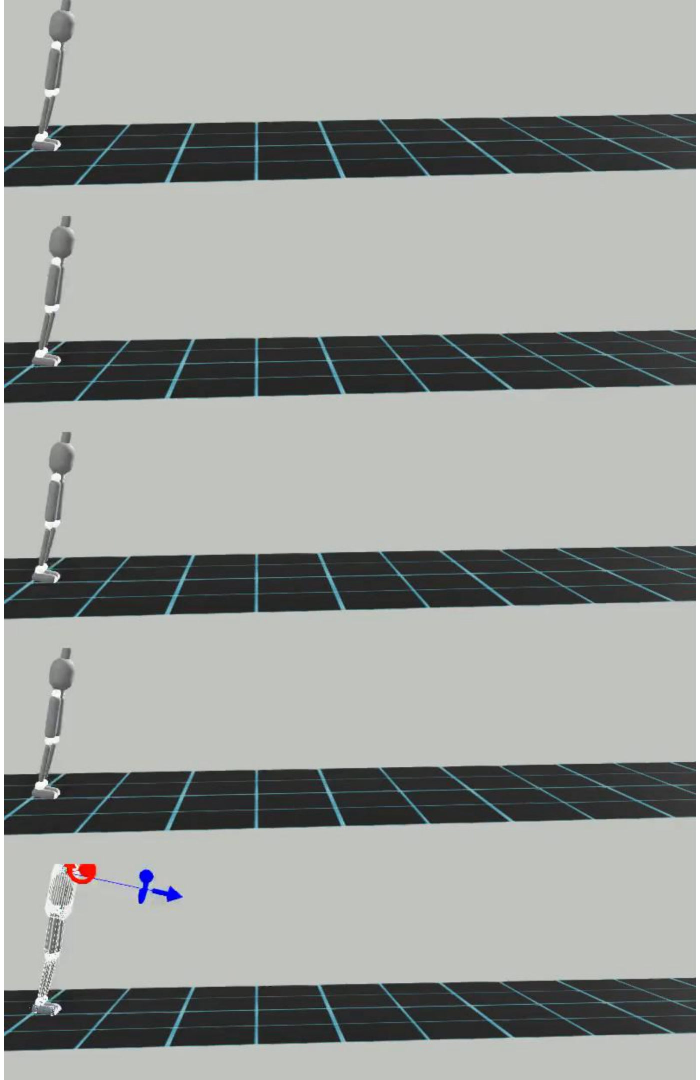
Similarly to Kuo 2002, Motor Control



pure feedback

pure feedforward

Dzeladini et al 2014, *Frontiers in Human Neuroscience*

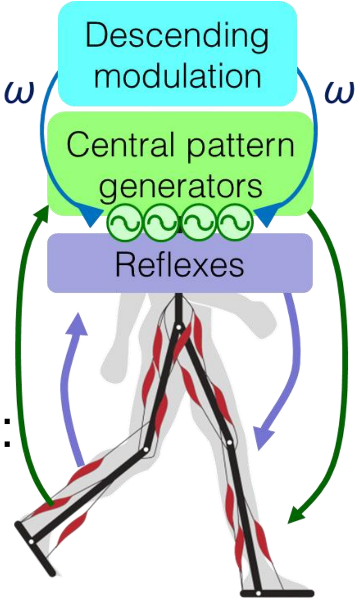


Optimization of parameters

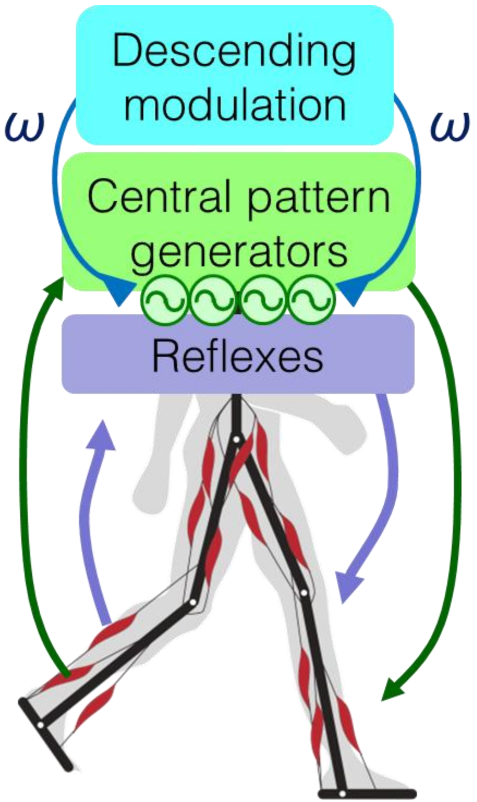
Optimizer:
Particle Swarm optimization

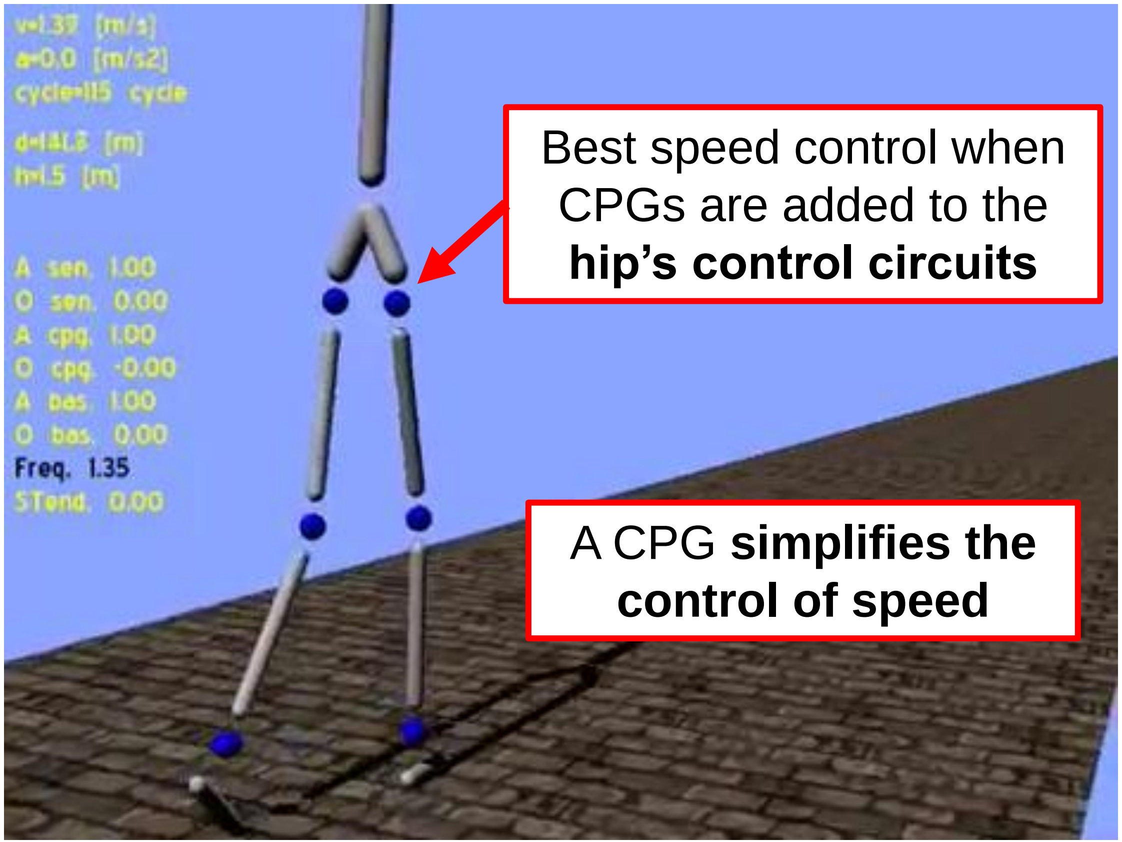
Open parameters (25):
Reflex gains and thresholds

Fitness function (staged evol.):
1) Reach a minimum distance
2) Reach a **desired speed**
3) Limit knee over extension
4) **Minimize energy**



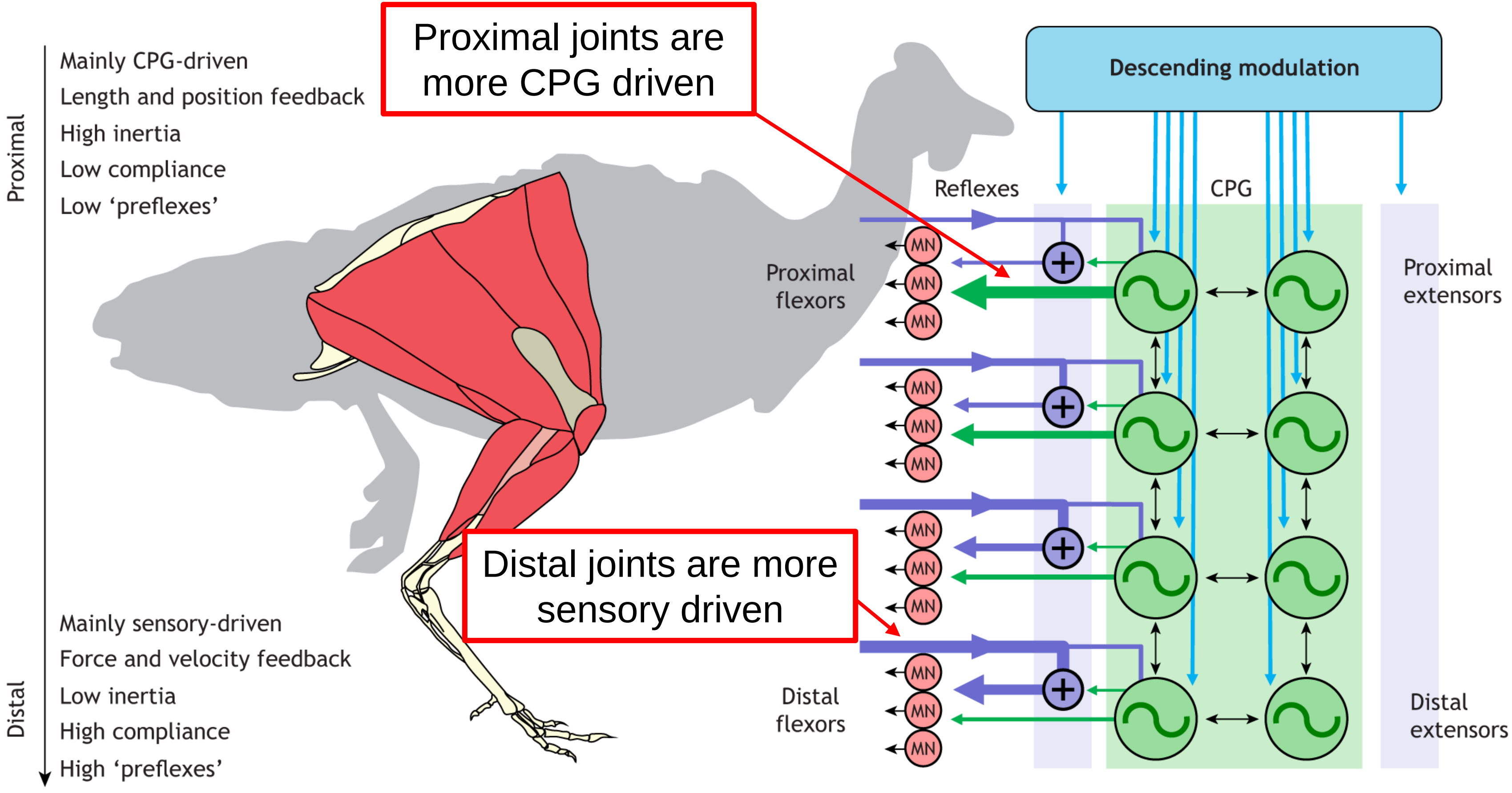
Neuromechanical model





Dzeladini et al, The contribution of a central pattern generator in a reflex-based neuromuscular model, ***Frontiers in Human Neuroscience***, Vol 8, 371, 2014

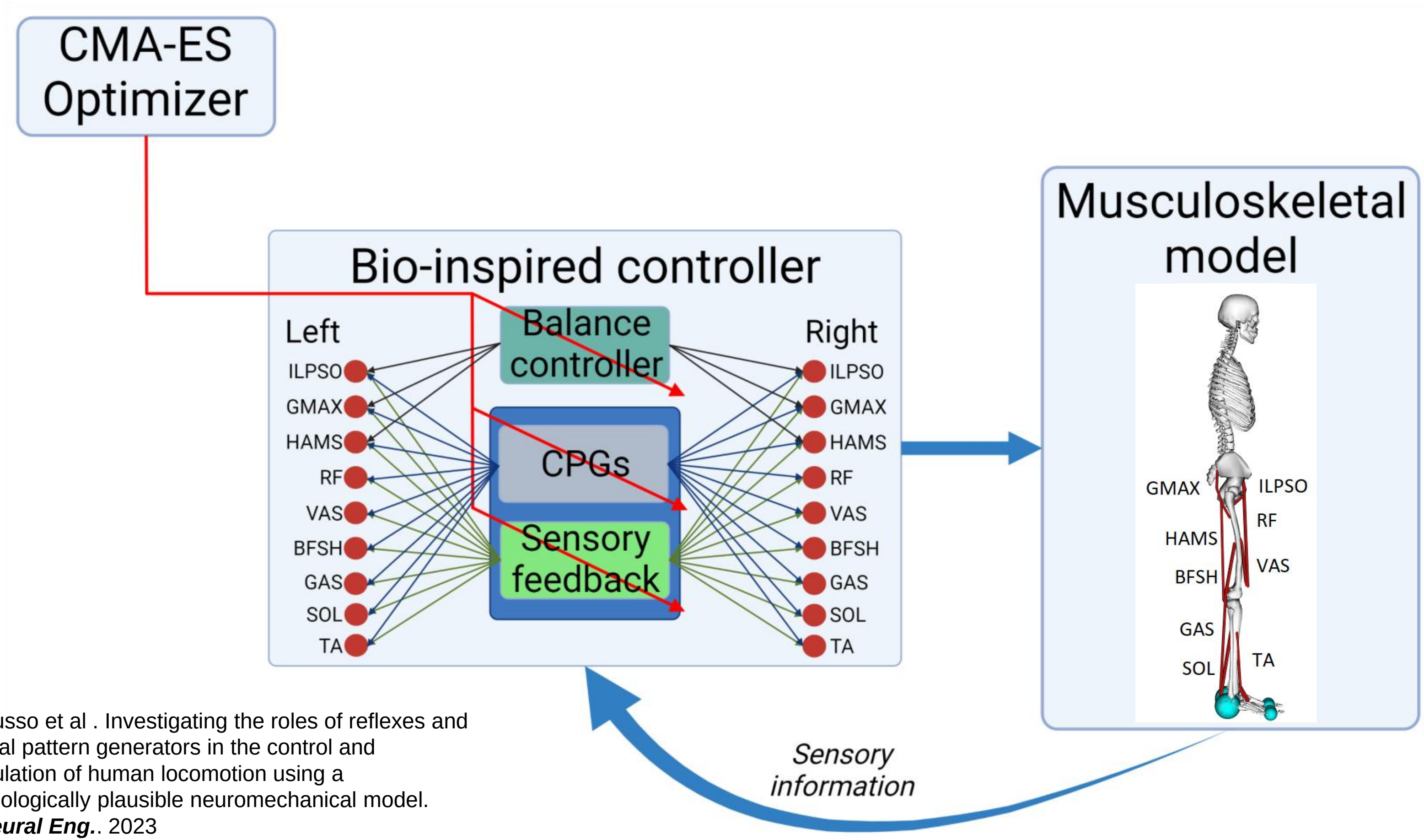
A proximal-distal gradient?



Ijspeert and Daley, J. of Exp. Biol., JEB 2023

A

Modeling the human spinal cord



A. Di Russo

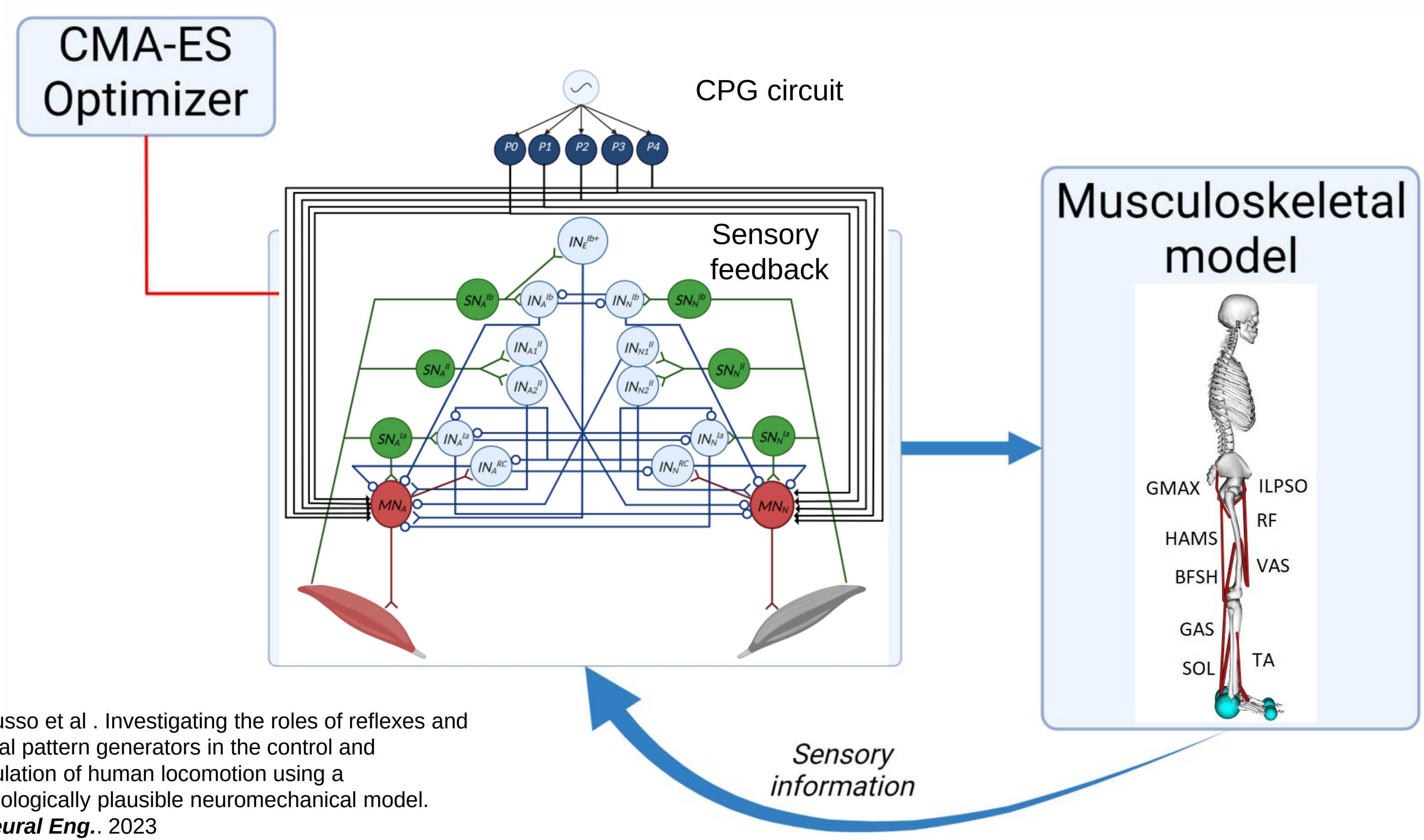
A. Bruel

Simon Danner

Di Russo et al . Investigating the roles of reflexes and central pattern generators in the control and modulation of human locomotion using a physiologically plausible neuromechanical model. ***J. Neural Eng.***. 2023

A

Modeling the human spinal cord



A. Di Russo

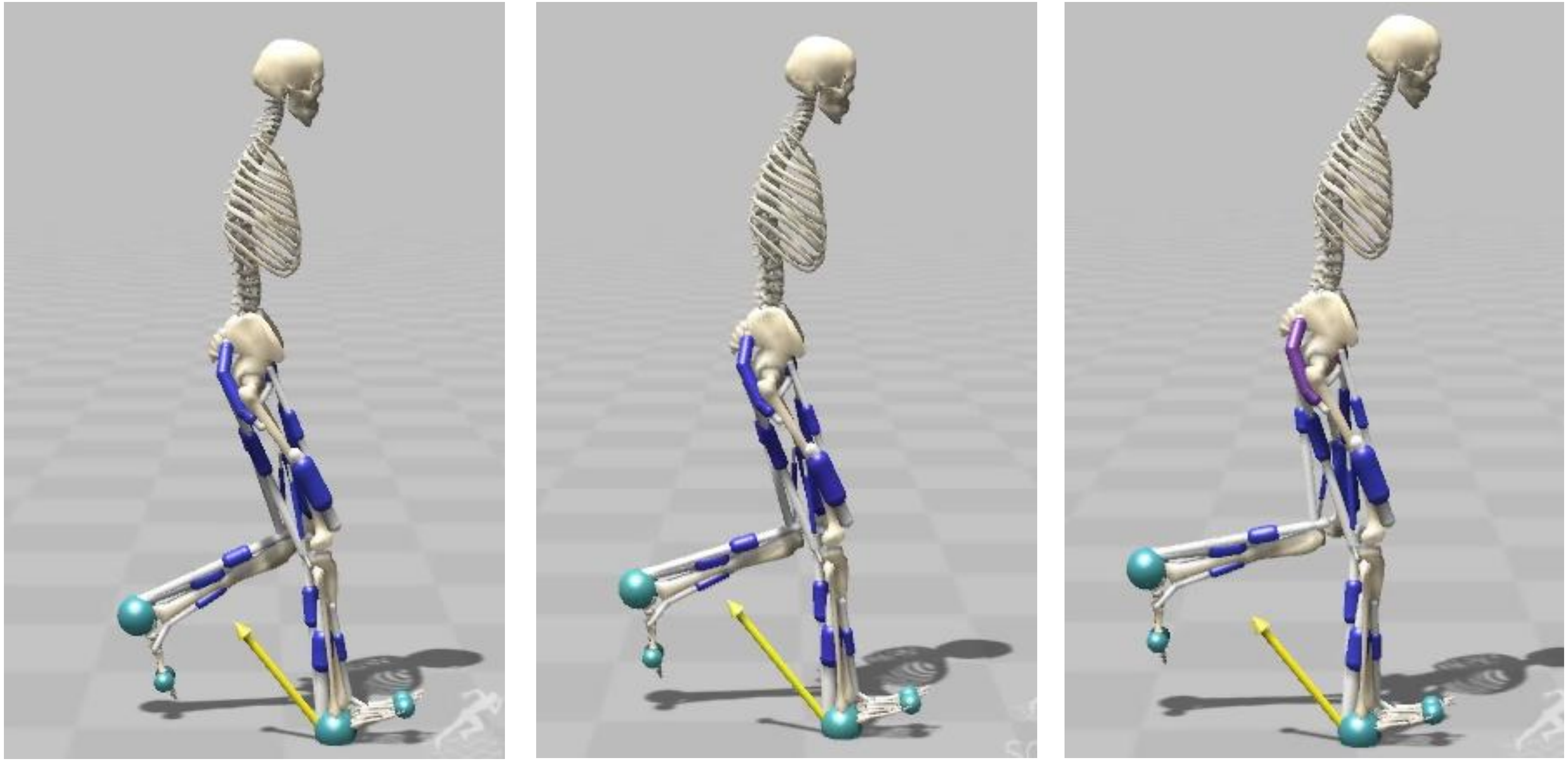
A. Bruel

Simon
Danner

Di Russo et al . Investigating the roles of reflexes and central pattern generators in the control and modulation of human locomotion using a physiologically plausible neuromechanical model. ***J. Neural Eng.***. 2023

Control of speed

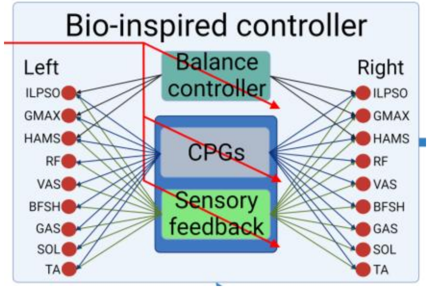
0.55 m/s, 0.92 m, 1.67 s | **1.17 m/s**, 1.57 m, 1.34 s | **1.86 m/s**, 1.98 m, 1.06 s



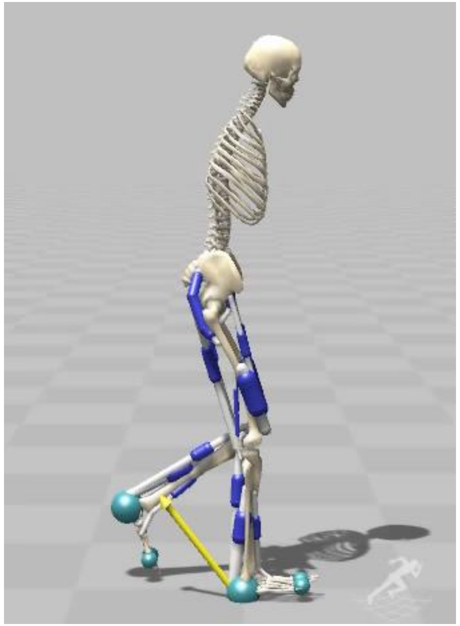
Di Russo et al. ***J. Neural Eng.***. 2023

SCONE

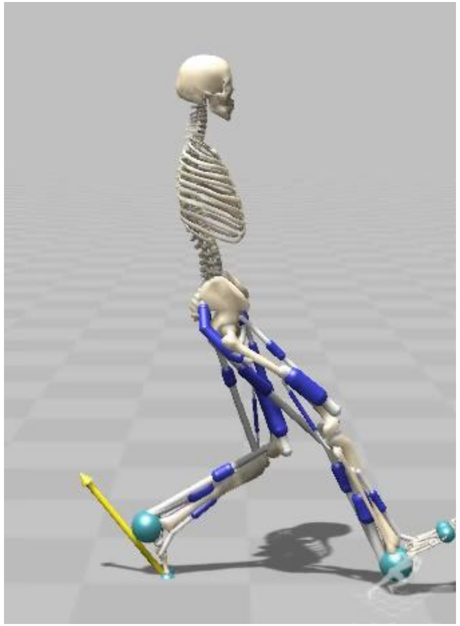
Effects of controller's missing components



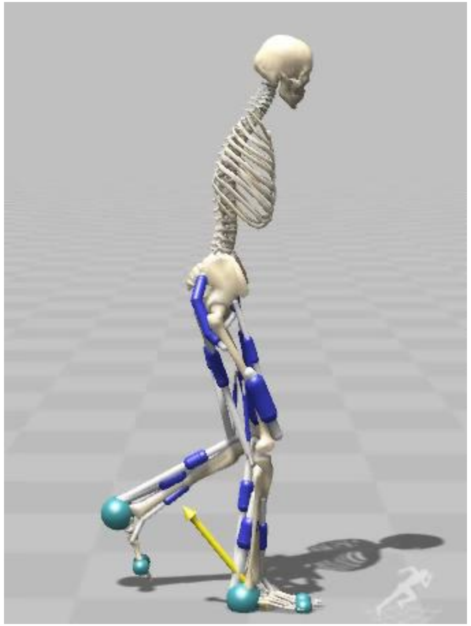
Missing balance control



Missing CPGs and feedforward signals



Missing reflexes



SCONE

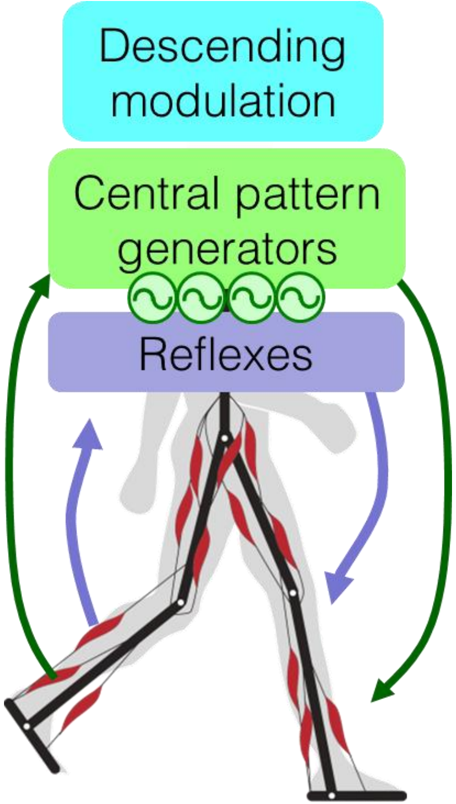
Di Russo et al. ***J. Neural Eng.***. 2023

Using a similar model as a robot controller

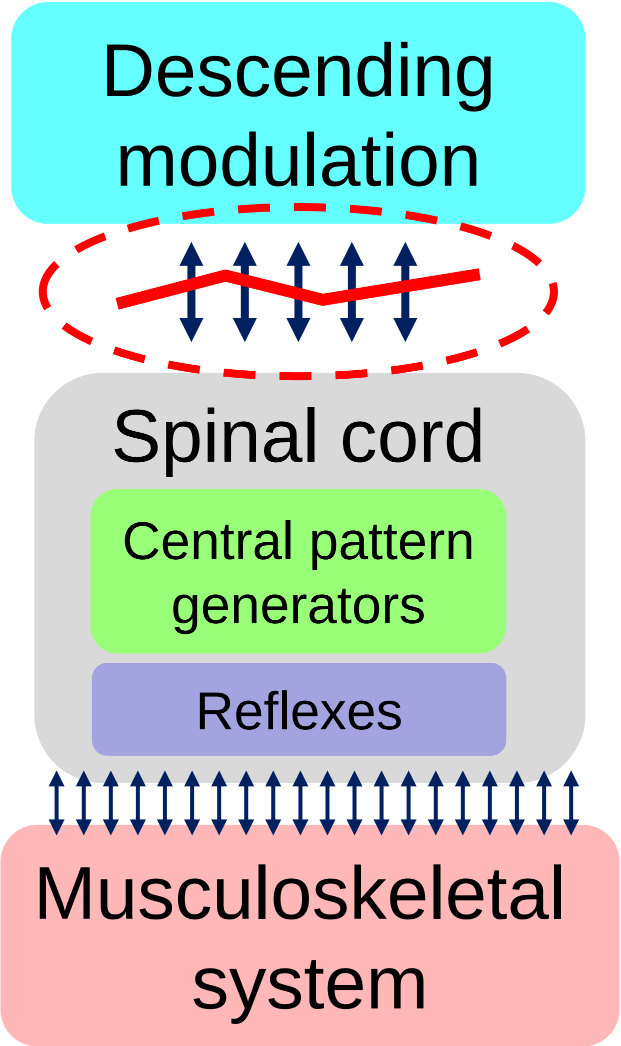
Nicolas Van der Noot

Renaud Ronsse

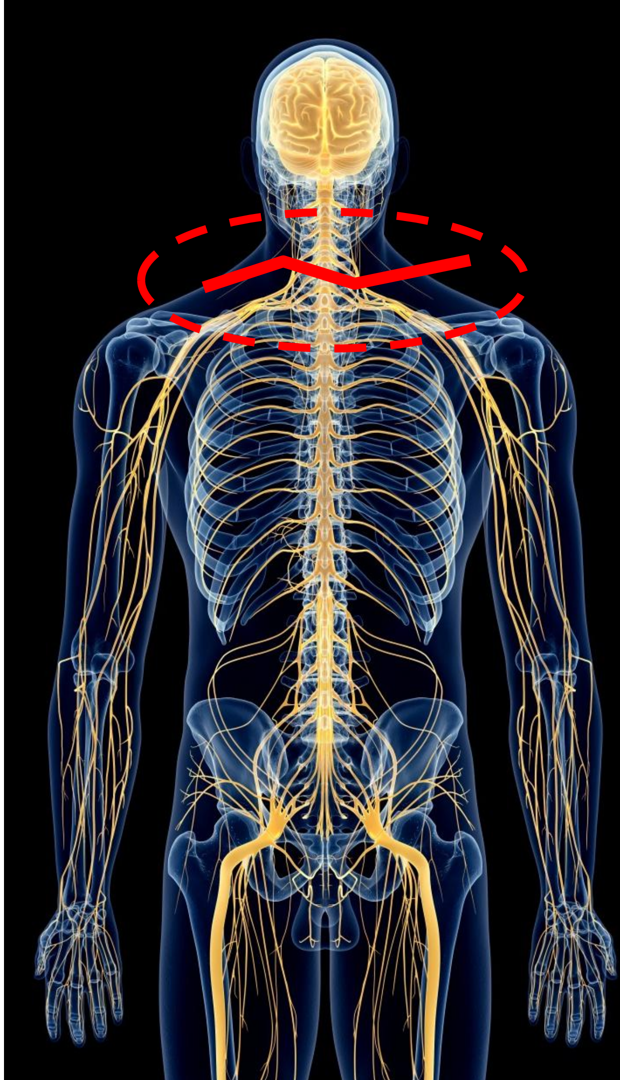
Van Der Noot et al, *The International Journal of Robotics Research*, 2018



Descending modulation
Central pattern generators
Reflexes

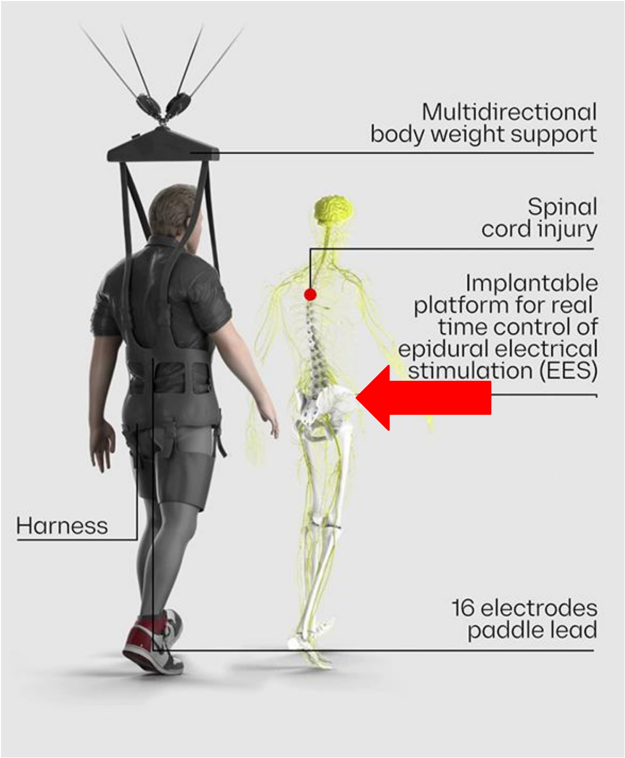


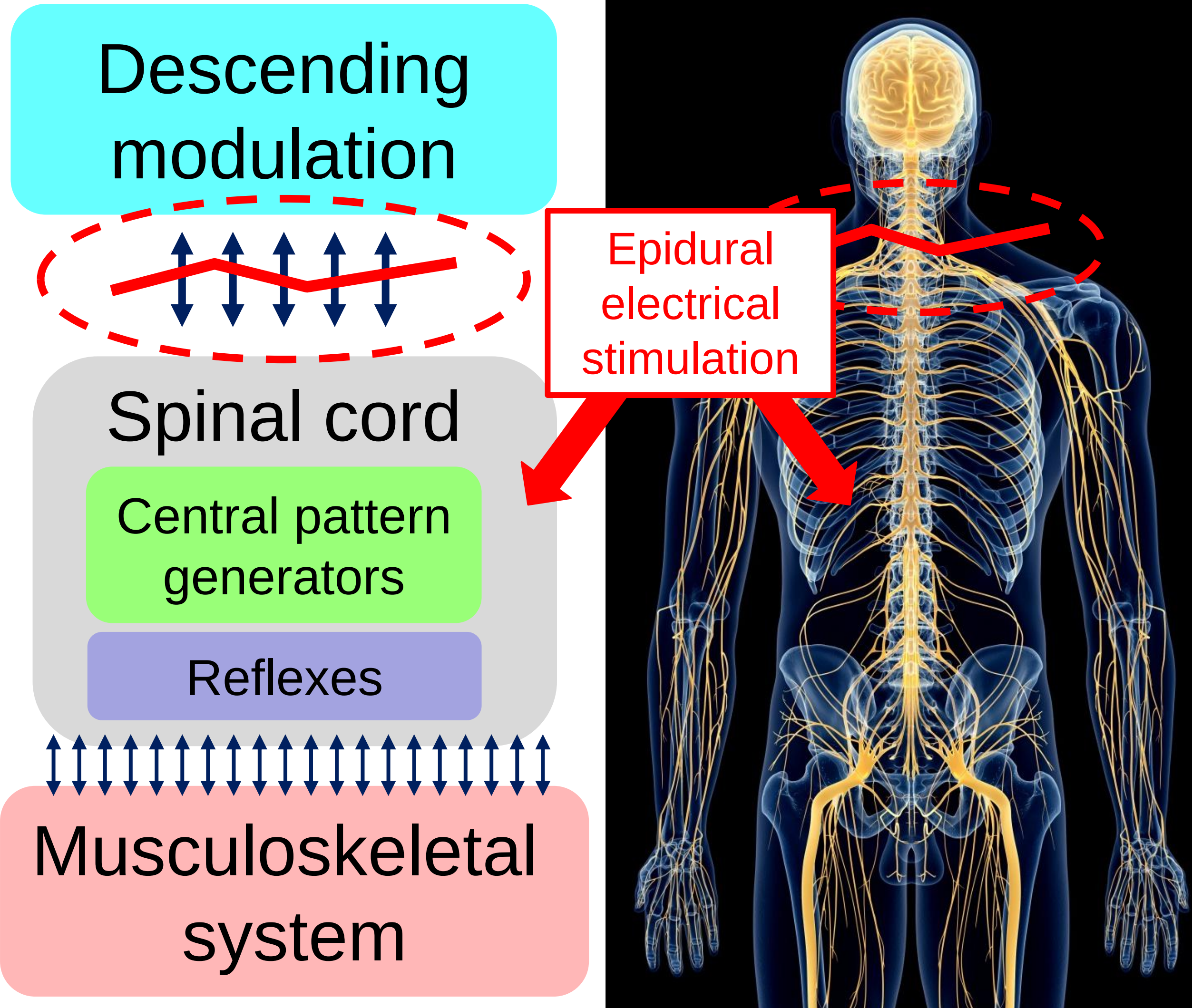
Descending modulation
Spinal cord
Central pattern generators
Reflexes
Musculoskeletal system

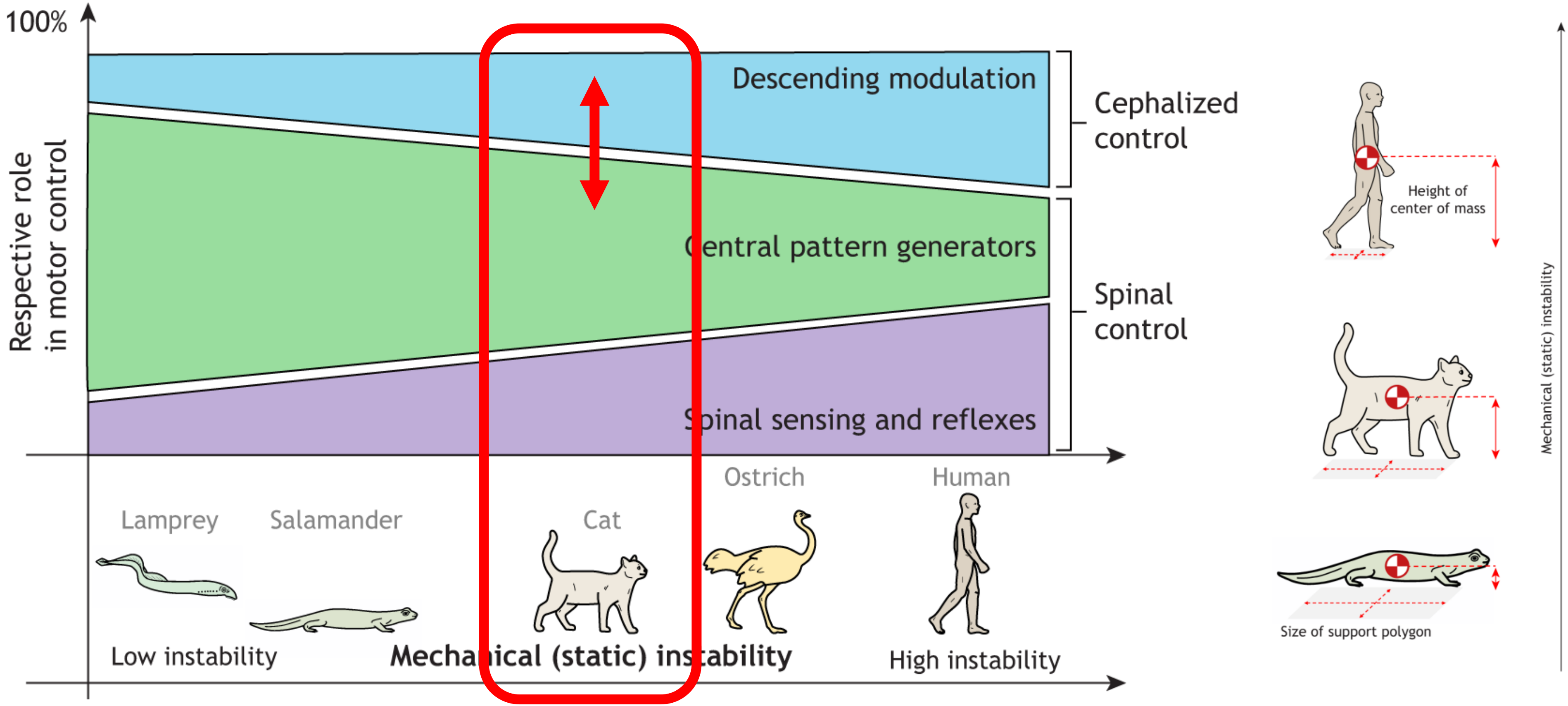


Jocelyne Bloch (UNIL)

Grégoire Courtine (EPFL)







Ijspeert and Daley, J. of Exp. Biol., JEB 2023

Incredible progress in legged robotics

Sangbae Kim

Open source MIT Mini Cheetah

Unitree, China

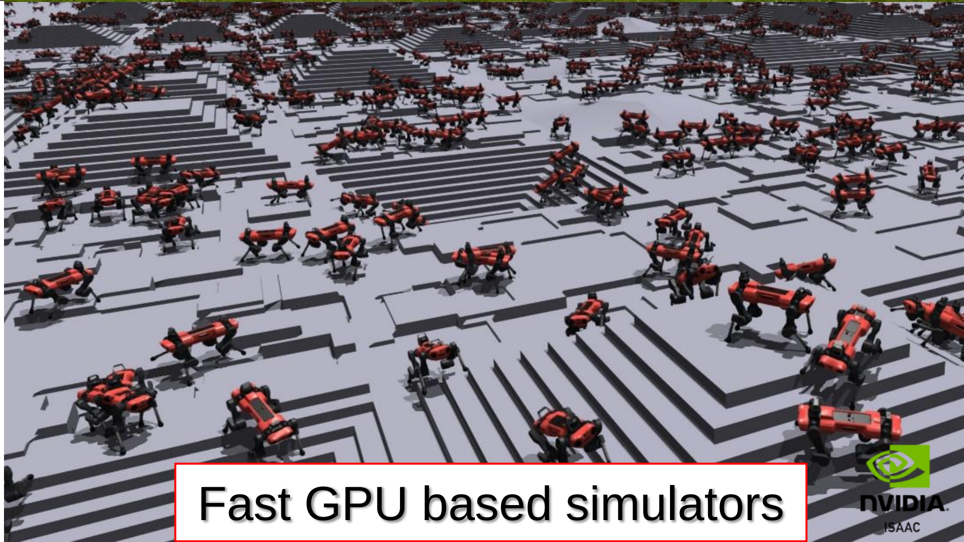
Boston Dynamics, USA

Affordable commercial platforms

Open source MIT Mini Cheetah

Good use of deep reinforcement learning

Affordable commercial platforms



Fast GPU based simulators

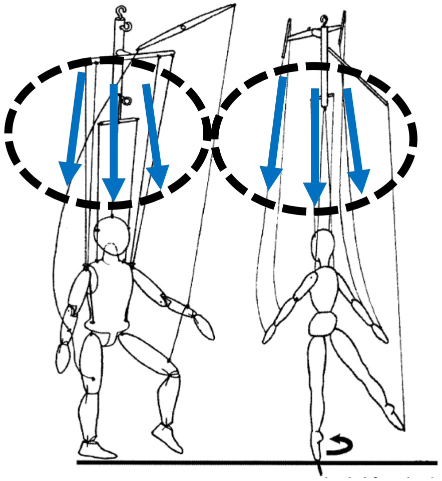
How to **learn and plan movements** taking into account spinal cord dynamics?

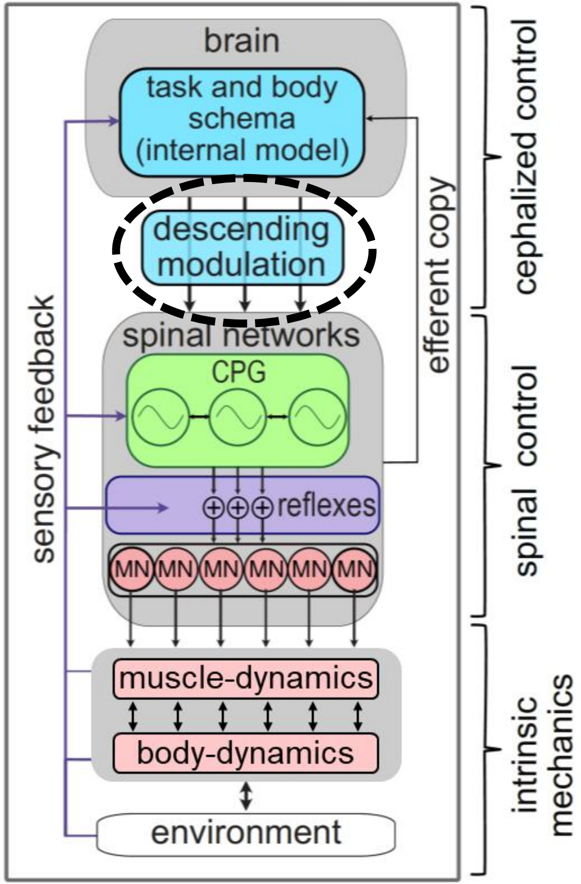
G. Bellegarda

M. Shafiee

How to **learn and plan movements** taking into account spinal cord dynamics?

Jerry Loeb's Puppet analogy

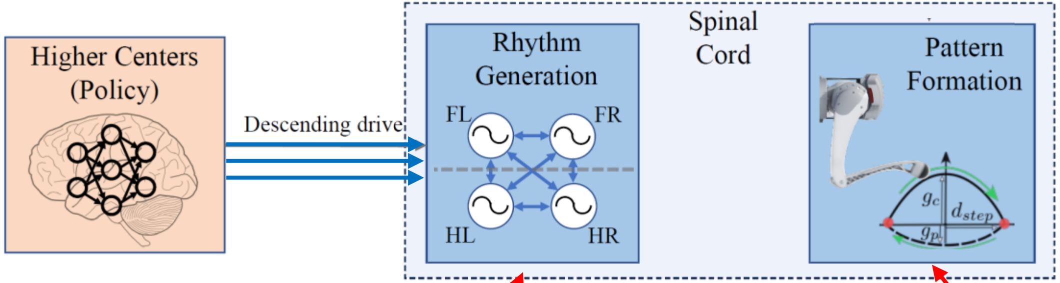




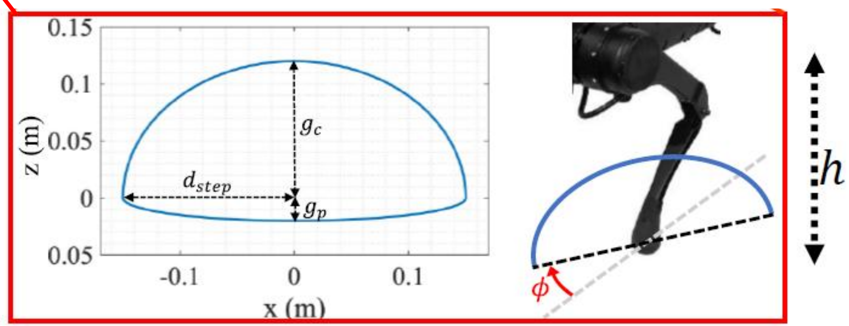
G. Bellegarda

M. Shafiee

CPG-RL: Learning Central Pattern Generators for Locomotion



$$\ddot{r}_i = a\left(\frac{a}{4}(\mu_i - r_i) - \dot{r}_i\right)$$
$$\dot{\theta}_i = \omega_i$$
$$\dot{\phi}_i = \psi_i$$



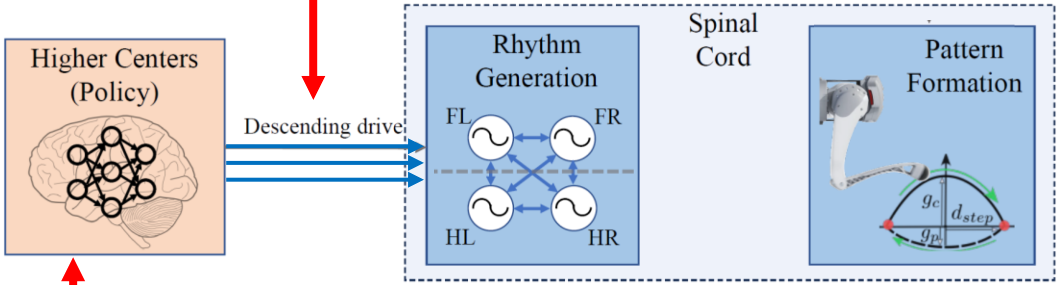
G. Bellegarda

M. Shafiee

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

CPG-RL: Learning Central Pattern Generators for Locomotion

Modulation of **frequencies and amplitudes** of the CPG, as well as the **limb orientation** (yaw movement)



G. Bellegarda

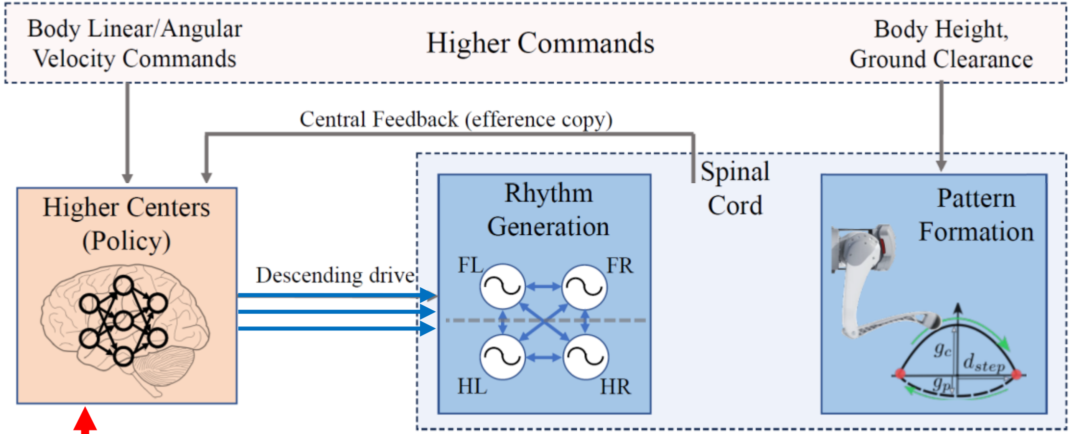
M. Shafiee

Neural network, 3 hidden layers [512, 256,128]
PPO, Proximal Policy Optimization

Proximal policy optimization (PPO) is a model-free, online, on-policy, **reinforcement learning** method.

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

CPG-RL: Learning Central Pattern Generators for Locomotion



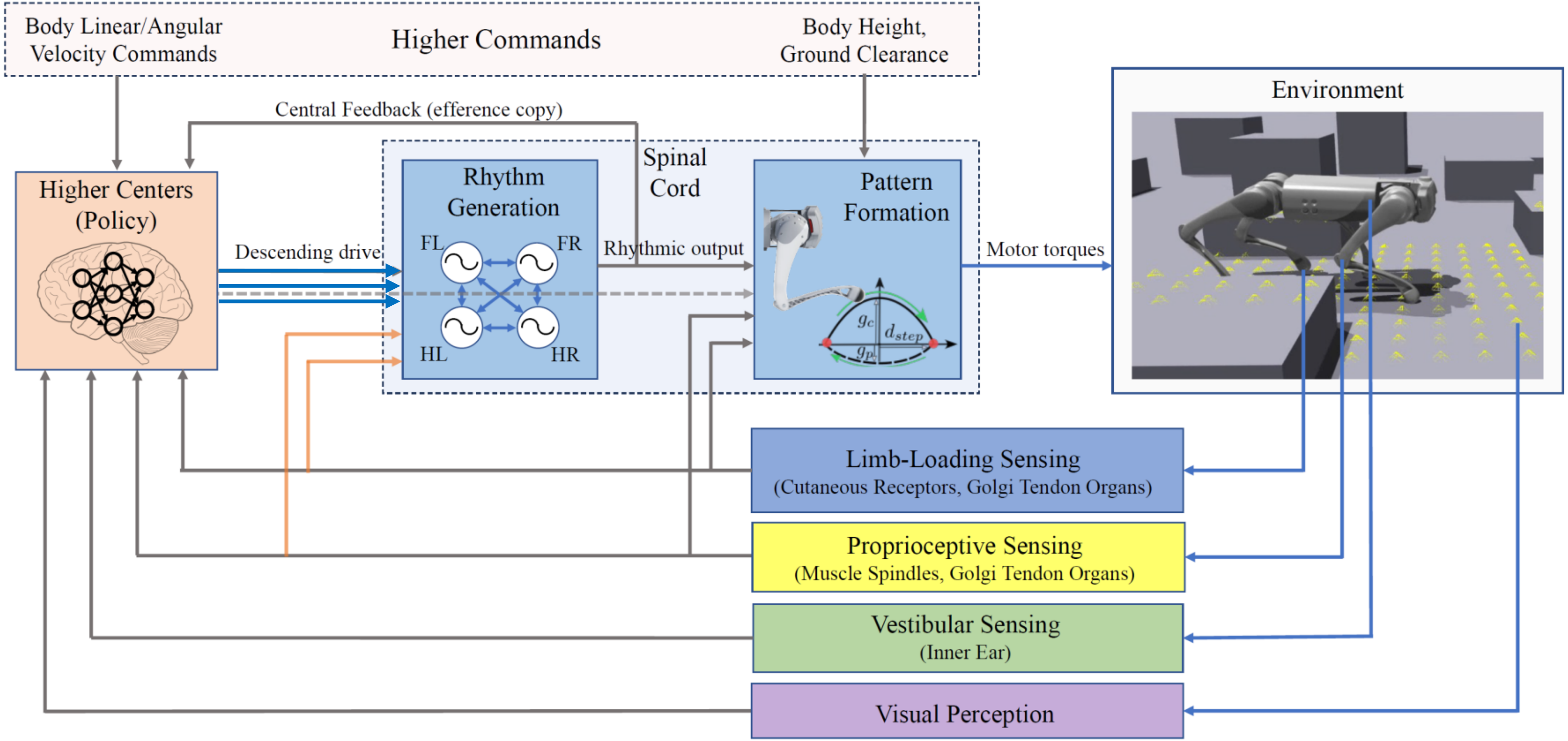
G. Bellegarda

M. Shafiee

Neural network,
3 hidden layers
[512, 256,128]
PPO, Proximal
Policy Optimization

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL),* 2022

CPG-RL: Learning Central Pattern Generators for Locomotion



G. Bellegarda

M. Shafiee

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

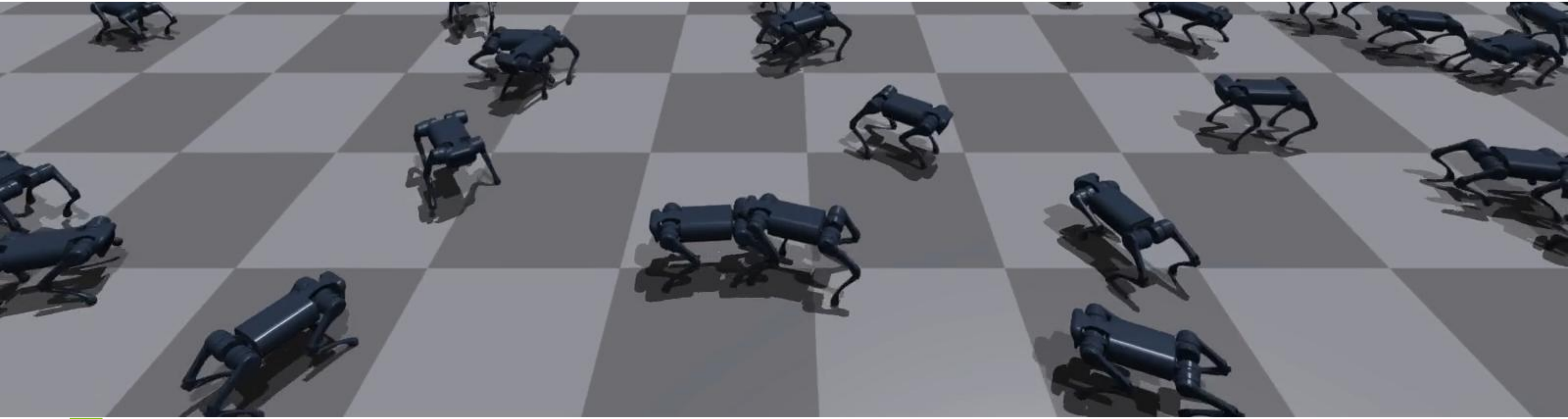
A **simple reward** is sufficient to learn **omnidirectional control**

Reward function for the PPO:

- \+ Track base **velocity commands** (v_x, v_y, ω_z)
- \- Penalize other base velocities $(v_z, \omega_x, \omega_y)$
- \- **Penalize energy**

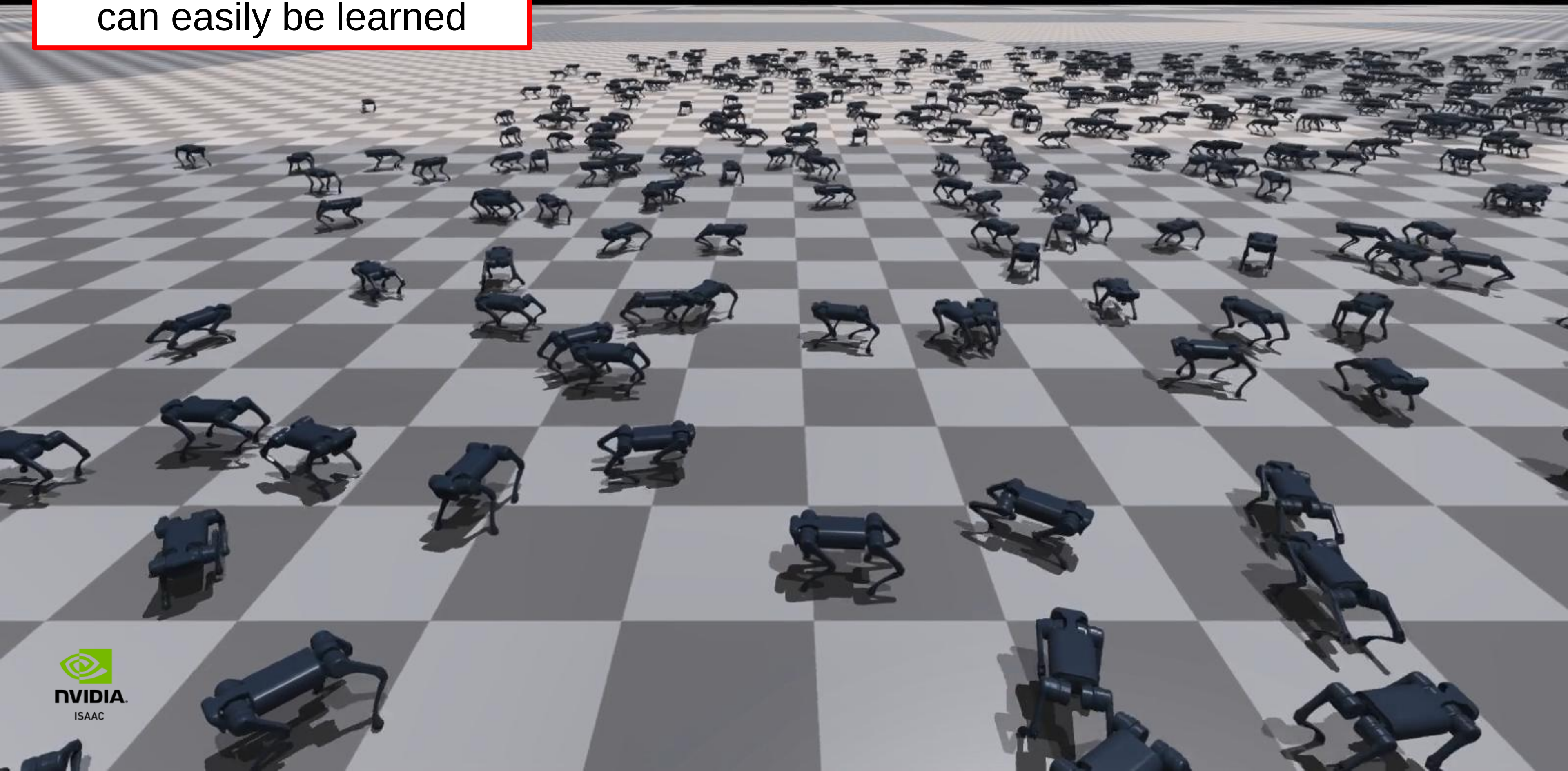
During training: modulation of **velocity commands**, **height**, and **ground clearance**.

- **ground coefficient of friction** varied in [0.3, 1]
- **limb mass** varied within 20% of nominal values
- **added base mass** up to 5 kg
- **external push** of up to 0.5 m/s applied in a random direction to the base every 15 seconds



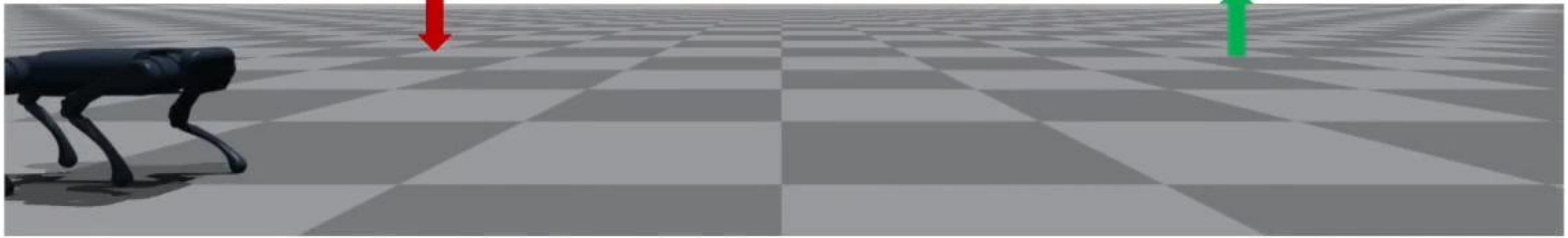
Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

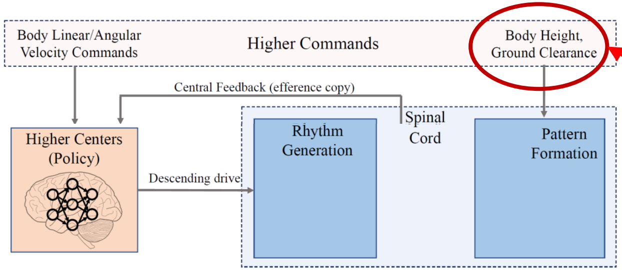
Omnidirectional control
can easily be learned



Body Height and Swing Foot Height can be adjusted on the fly

Body Height: 0.3 (m) 0.19 (m) 0.3 (m)





Modulation of **height** and **ground clearance**


Robustness against perturbations
Unitree

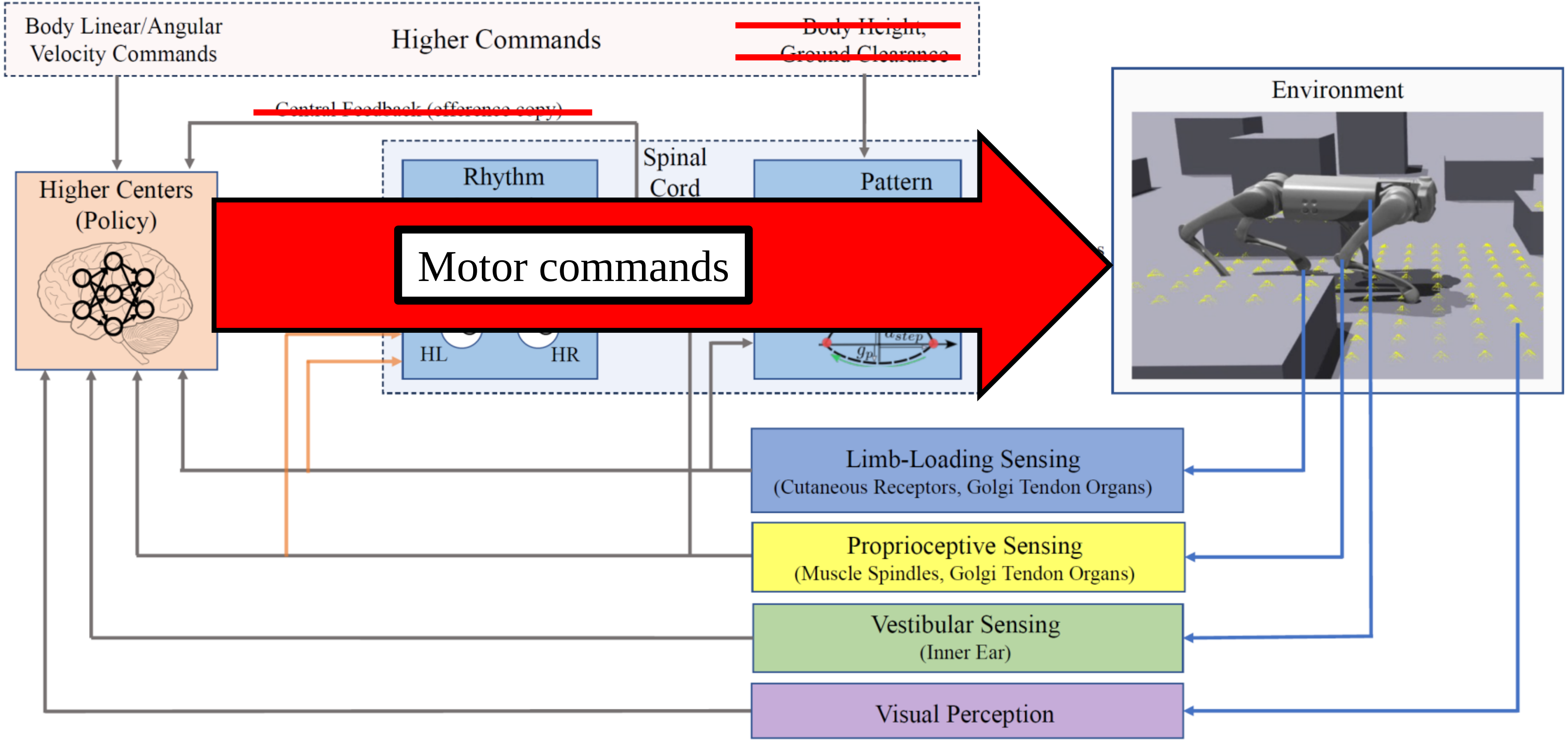
Is learning **faster** with a CPG than in joint angle space?

No!

Is it **“easier”?**

Yes, (much) simpler to design reward functions

Compare with **learning directly in joint motor commands**



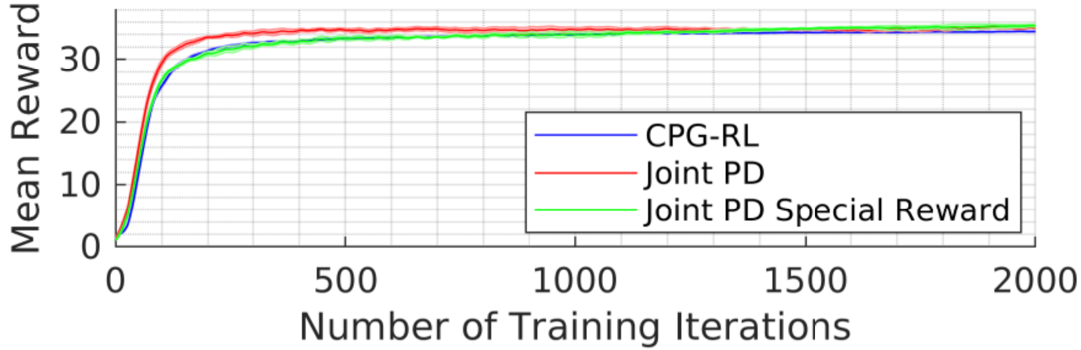
G. Bellegarda

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

Learning **without the CPG** tends to **generate pathological gaits**

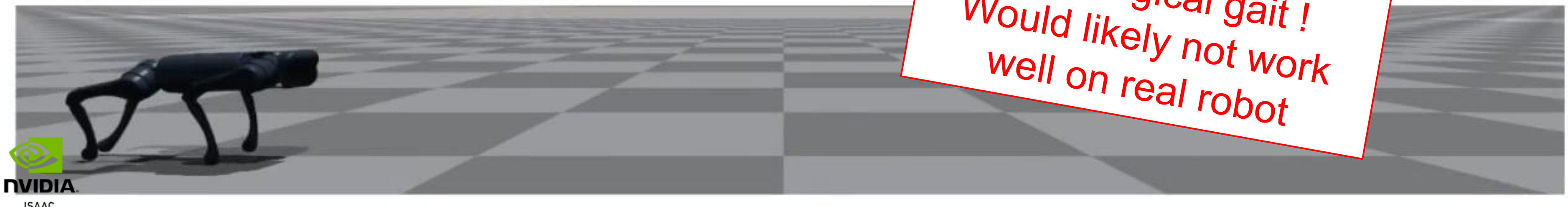
Same reward function:

- \+ Track base **velocity command** (v_x, v_y, ω_z)
- \- Penalize other base velocities $(v_z, \omega_x, \omega_y)$
- \- **Penalize energy**



Training is not faster with CPG-RL

But the same (simple) reward function leads to **more natural-looking gaits**

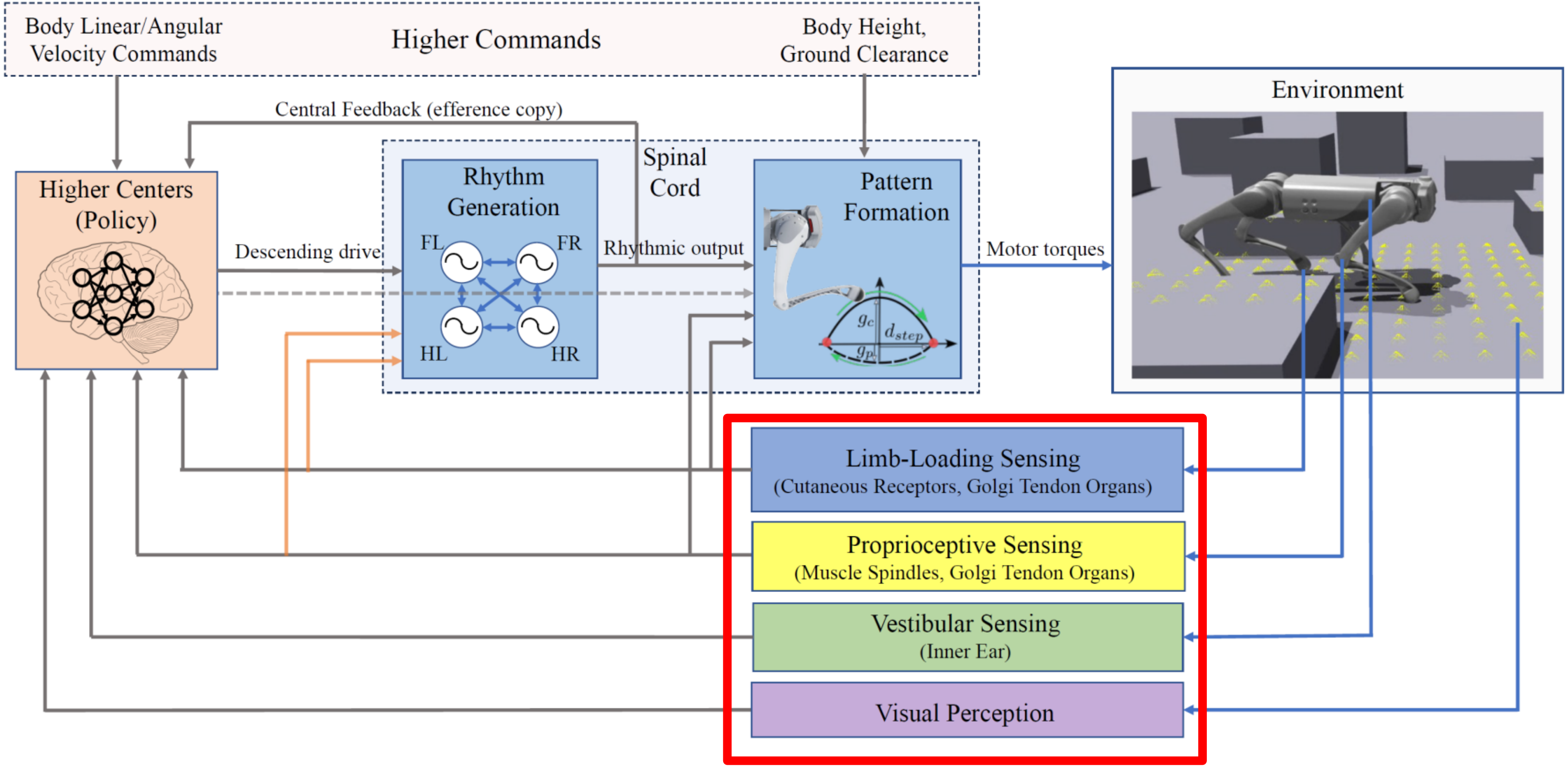


Pathological gait !
Would likely not work well on real robot

Which sensory information is important?

Limb contact seems to be necessary and sufficient

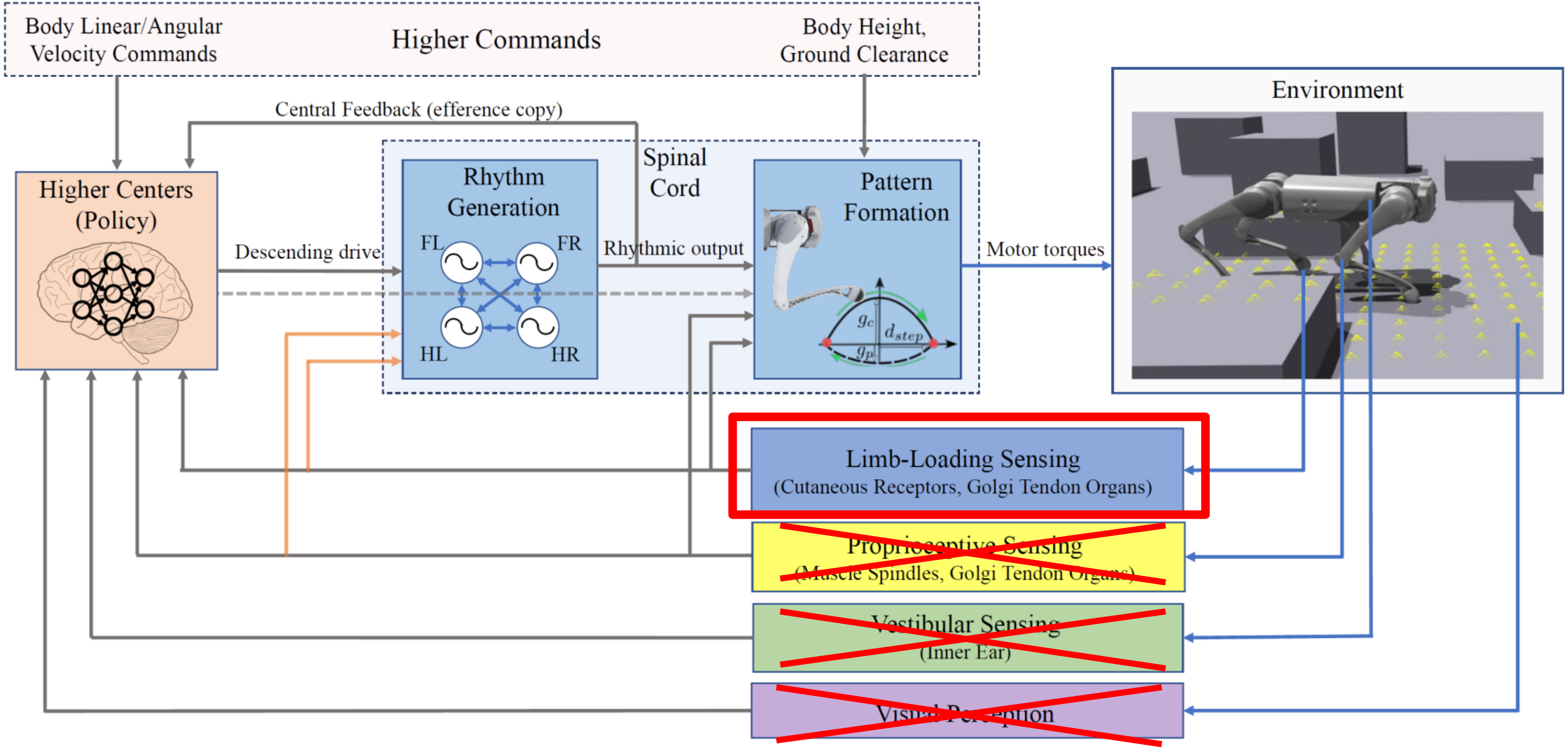
Which sensory information is important?



G. Bellegarda

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

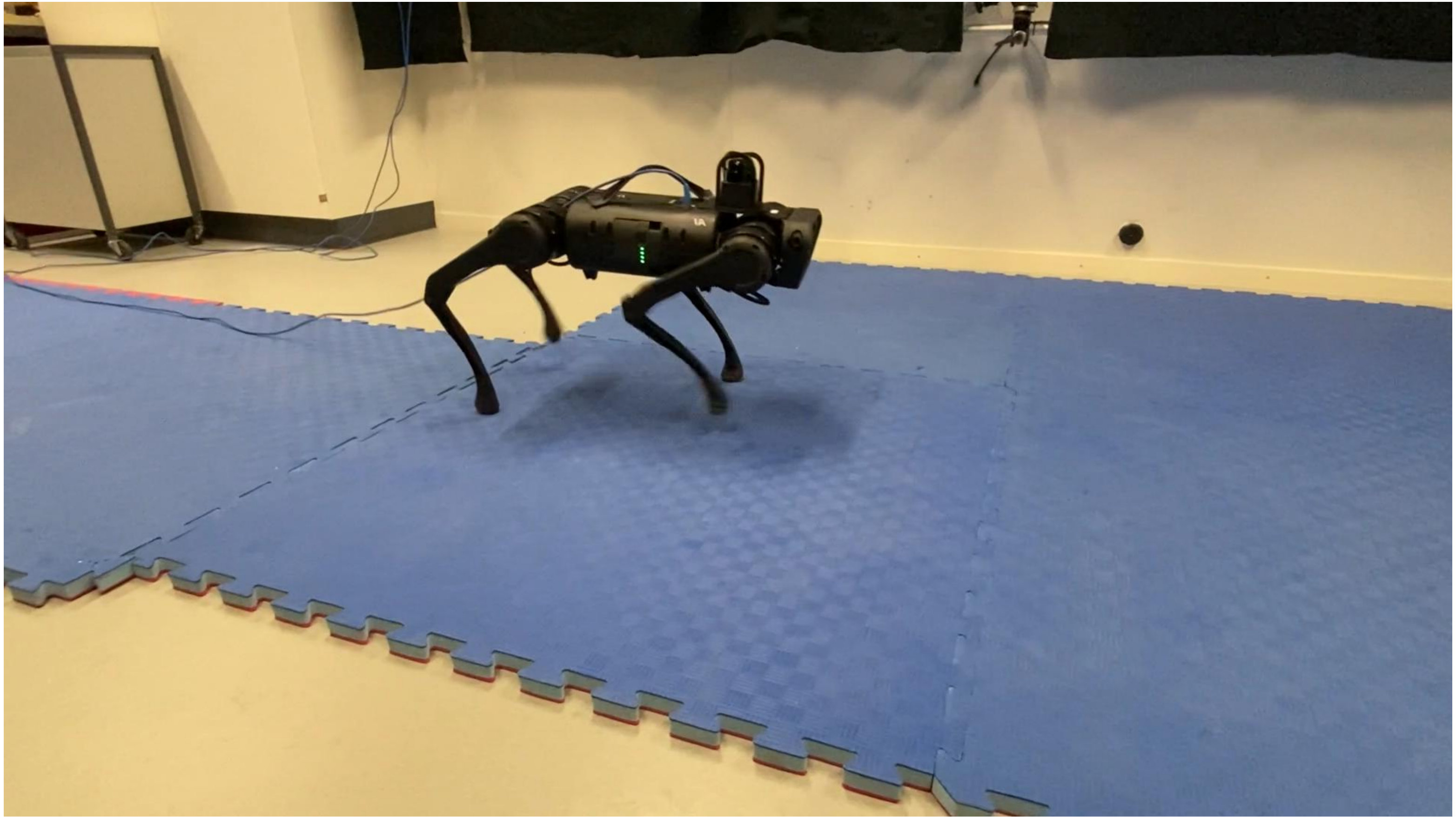
Which sensory information is important?



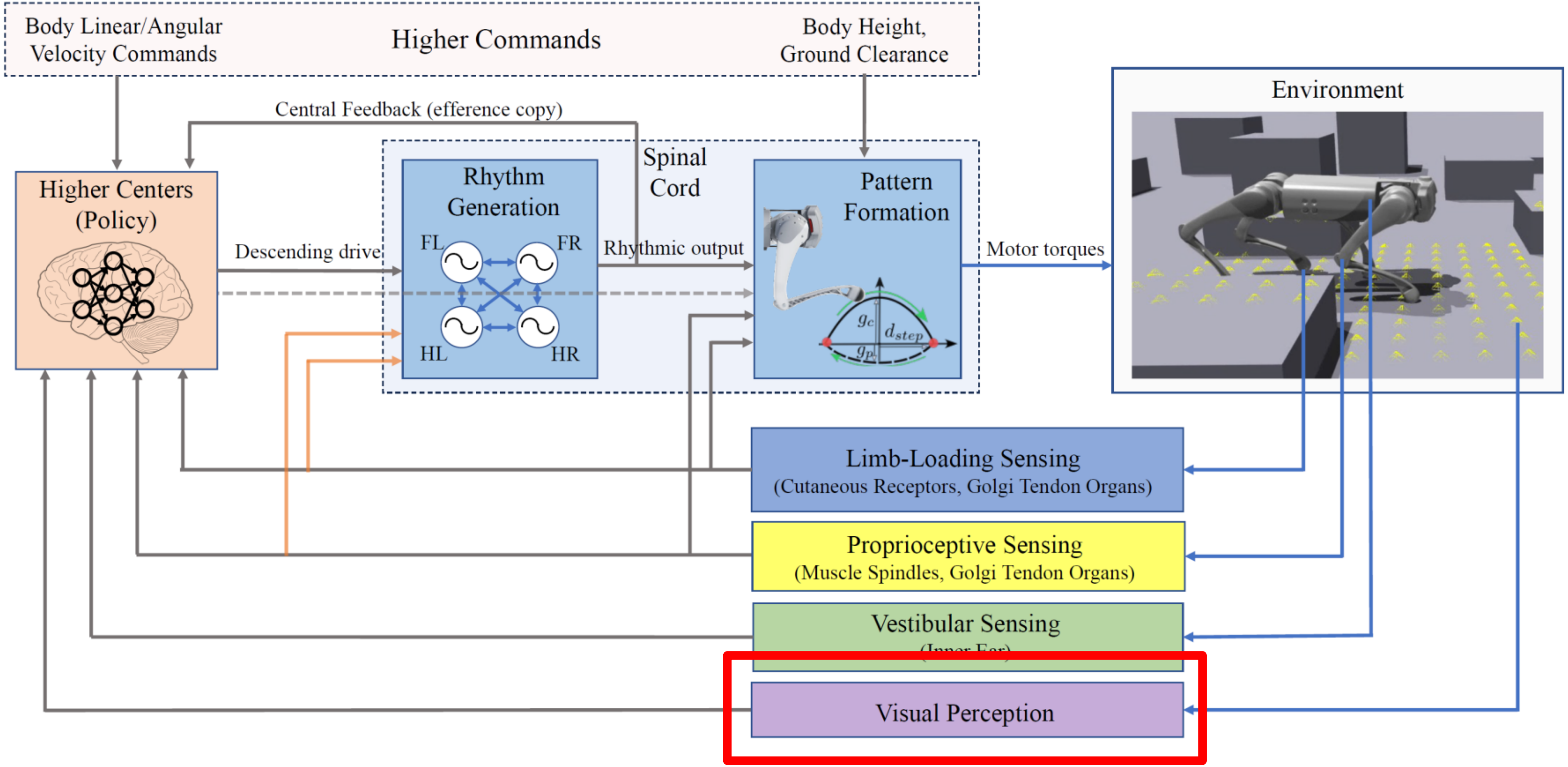
G. Bellegarda

Bellegarda and Ijspeert, *Robotics and Automation Letters (RAL)*, 2022

Limb contact seems to be **necessary and sufficient** sensory feedback



Adding exteroception, study of gait transitions



M. Shafiee

G. Bellegarda

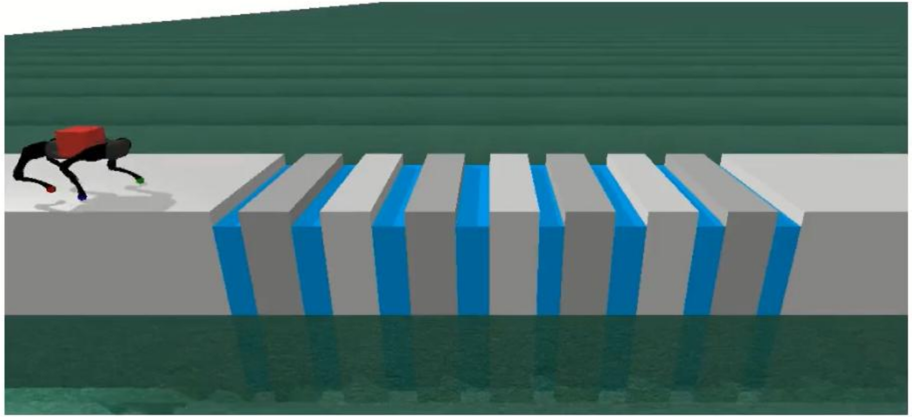
Shafiee et al, *Nature Communications*, 2024

Gait transitions based on exteroception

Adding vision allows for **anticipatory behaviors**

Testing different possible criteria for gait transitions: maximizing **energy efficiency**, minimizing **peak forces**, and maximizing **viability** (i.e. avoiding falls).

M. Shafiee



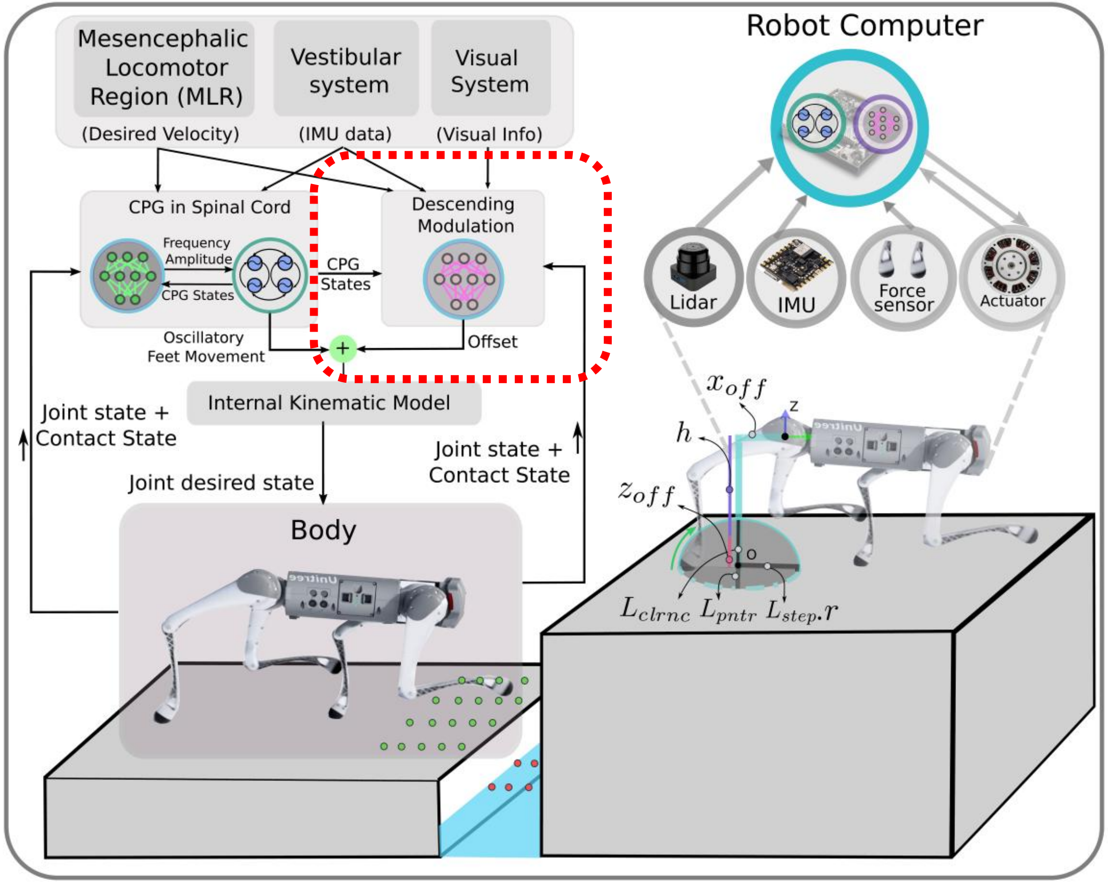
BULLET PHYSICS LIBRARY

Maximizing **viability** can explain gait transitions both on flat terrains and on terrains with gaps

G. Bellegarda

Shafiee et al, *Nature Communications*, 2024

Adding more sophisticated descending modulation



G. Bellegarda

M. Shafiee

G. Sartoretti (NUS)

Sun GE (NUS)

Ge et al, *IROS2024*

The descending policy can learn locomotion over **complex terrain**

A robotics approach can be useful for neuroscience

G. Bellegarda

M. Shafiee

G. Sartoretti (NUS)

Sun GE (NUS)

Surprisingly **robust against time delays** (50ms)

Ge et al, *IROS2024*

Extension to many morphologies

M. Shafiee

G. Bellegarda

Shafiee et al, *ICRA 2024*, Manuscript in preparation

CPG and reinforcement learning (RL): Conclusion

- A policy trained with RL can learn to use the CPGs for **agile locomotion**:
  - **Online modulation** of **speed, heading, body height, and swing foot height**
- Compared to learning in joint angle space: learning with CPGs is not faster, but **simplifies the design of the reward functions**
- Surprisingly **robust locomotion and sim-to-real transfer**
- The multi-layered control **can handle (big) time delays**
- Framework allows to **address scientific questions about descending pathways** and which **sensory modalities** are important

Take-home messages

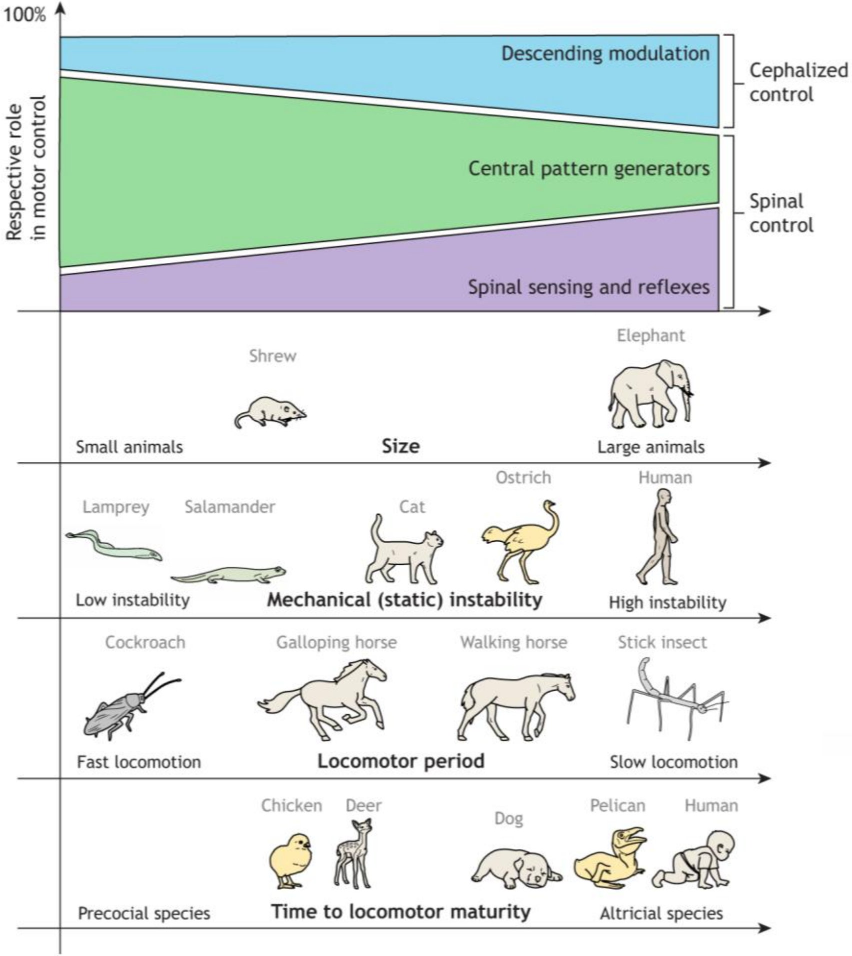
The nervous system combines **feedback and feedforward control in multi layers**

Their respective roles **have probably changed during evolution**

Roles depend on **mechanical stability (**but also on **size, locomotor period** and **time to locomotor maturity)**

There might be **proximal-distal gradients** of feedforward-feedback control in mammal limbs

The spinal cord offers a **good substrate for learning and planning**



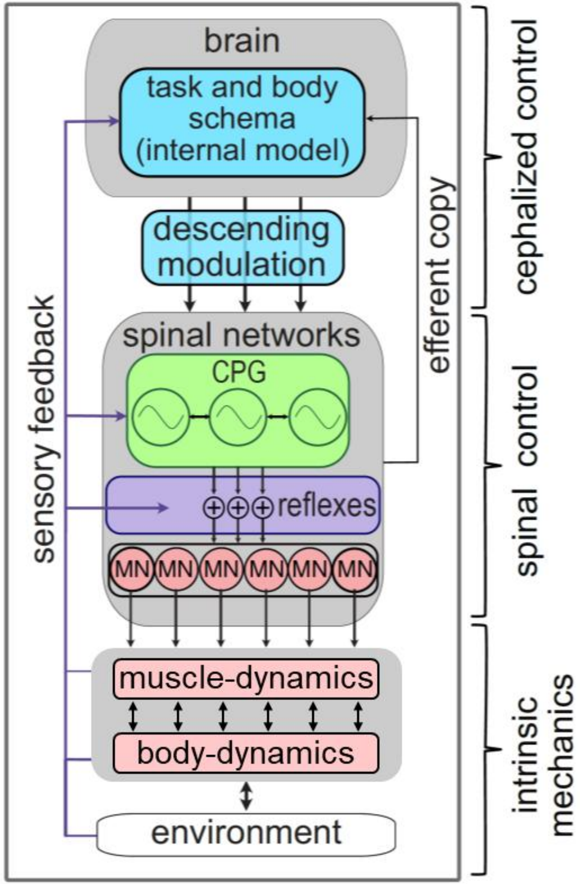
Ijspeert and Daley, J. of Exp. Biol., JEB 2023

Science ➔ Benefits for robotics

Q1 Principles

Q2 Evolution

Q3 Learning



Energy efficiency

Multi-functionality

Agility

Fast learning

Computationally light-weight

Fault-tolerance

Distributed control

Robustness against noise and time delays

Biorobotics Laboratory (Ijspeert)

Robotics

Engineering locomotion

Biology

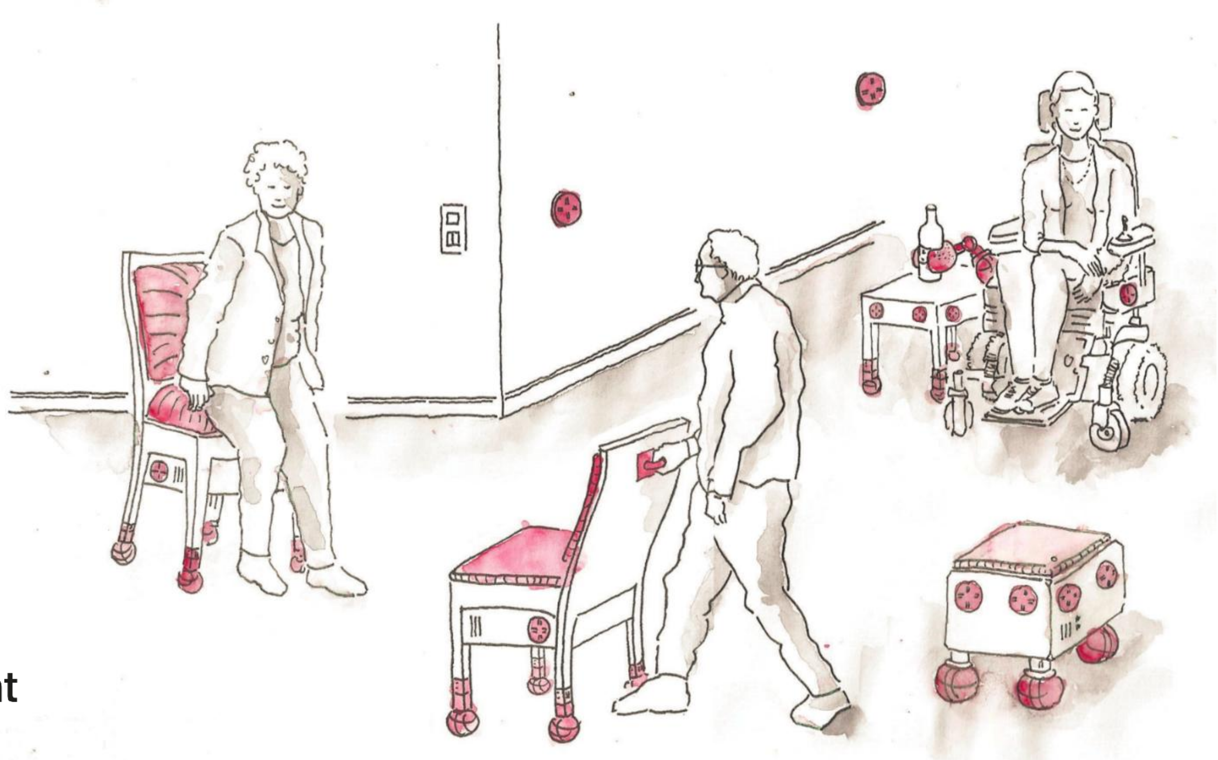
Healthcare

Understanding locomotion

Assisting locomotion

Roombots as assistive furniture

Smart assistive environment for persons with limited mobility



Jamie Paik

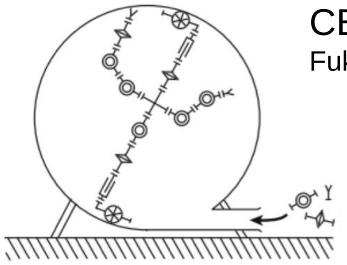
Aude Billard

Alexandre Alahi

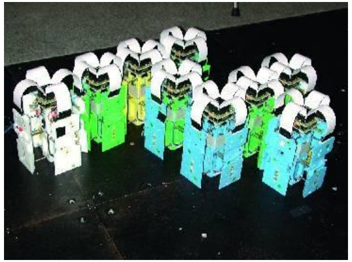
- CIS
  Center for Intelligent Systems
  Collaboration Grant

Also contributions from **Diego Paez-Granados** and **Emmanuel Senft**

Self-Reconfigurable Modular Robots

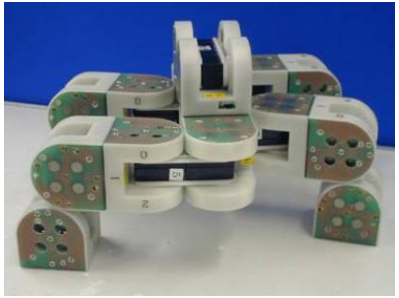


CEBOT
Fukuda et al. 1988

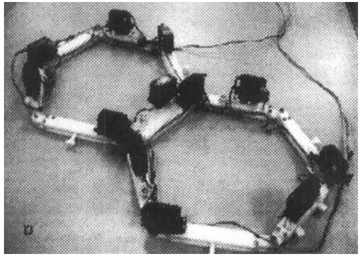


Crystalline
Rus et al. 2000

M-TRAN
Murata et al. 2000

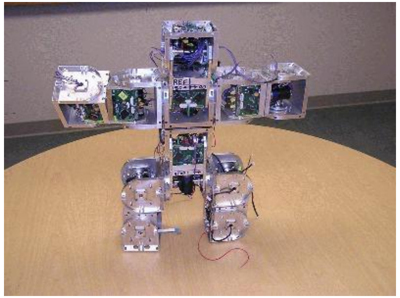


Metamorphic Robot
Chirikjian et al1995



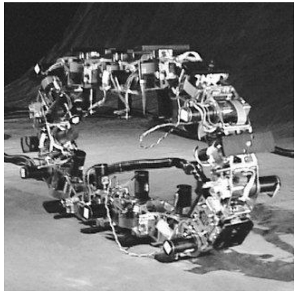
MOLECUBES
Zykov et al 2007

ATRON
Jorgensen et al 2004



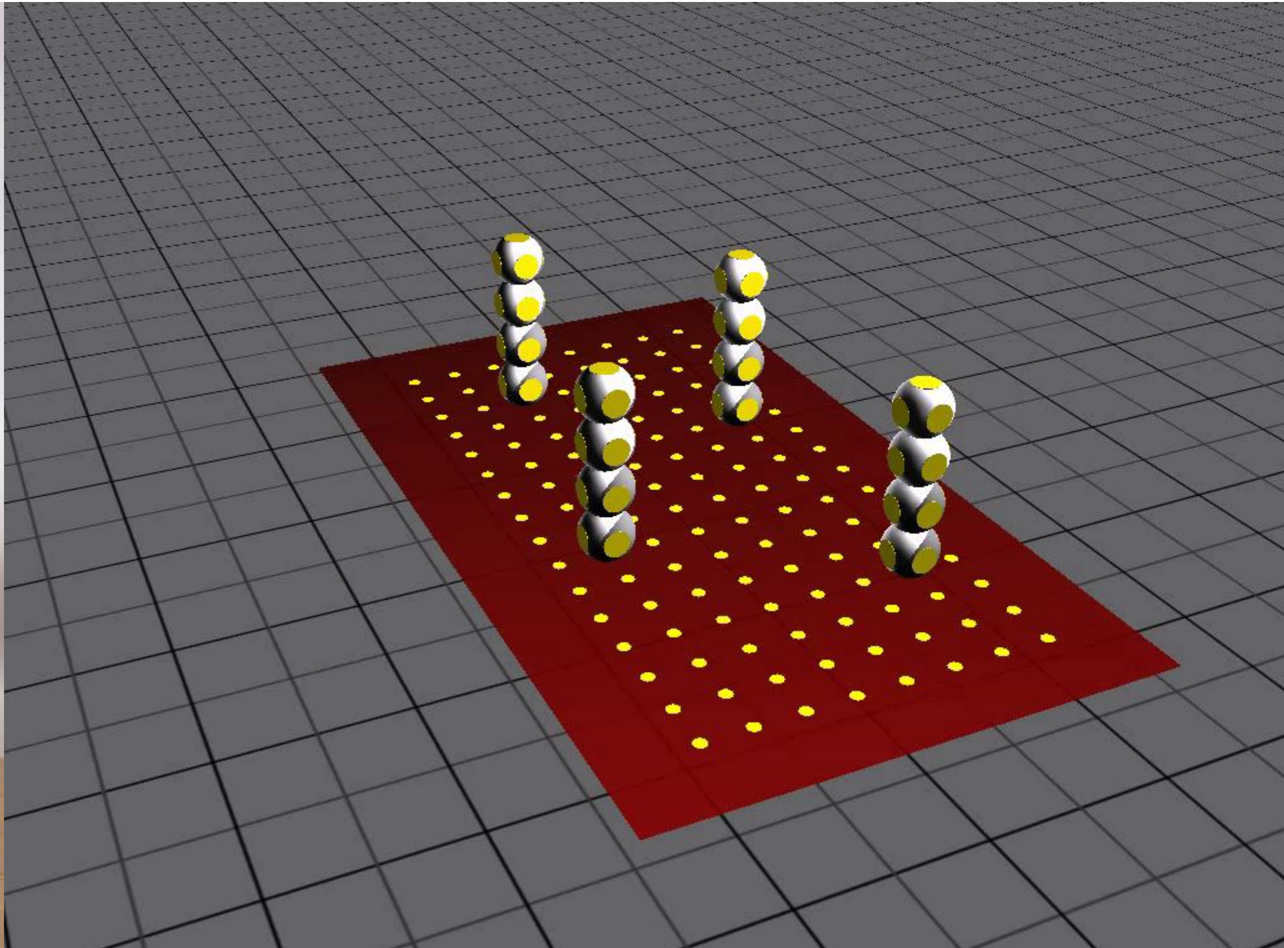
SuperBot
Salemi et al. 2006

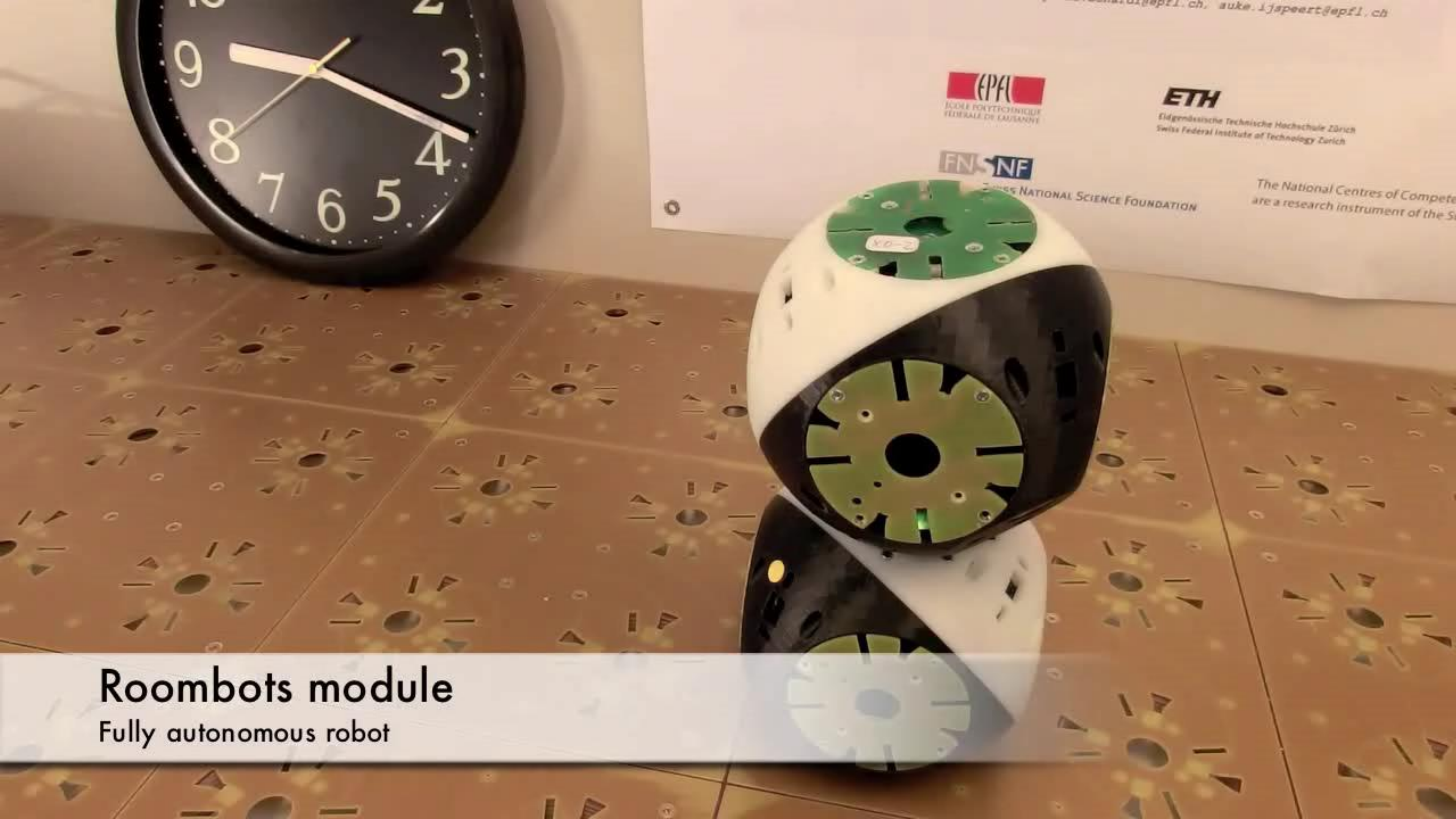
Polybots
Yim et al. 2000



Soldercubes
Neubert et al. 2015

Roombots: Robots for assistive environments





Roombots module

Fully autonomous robot

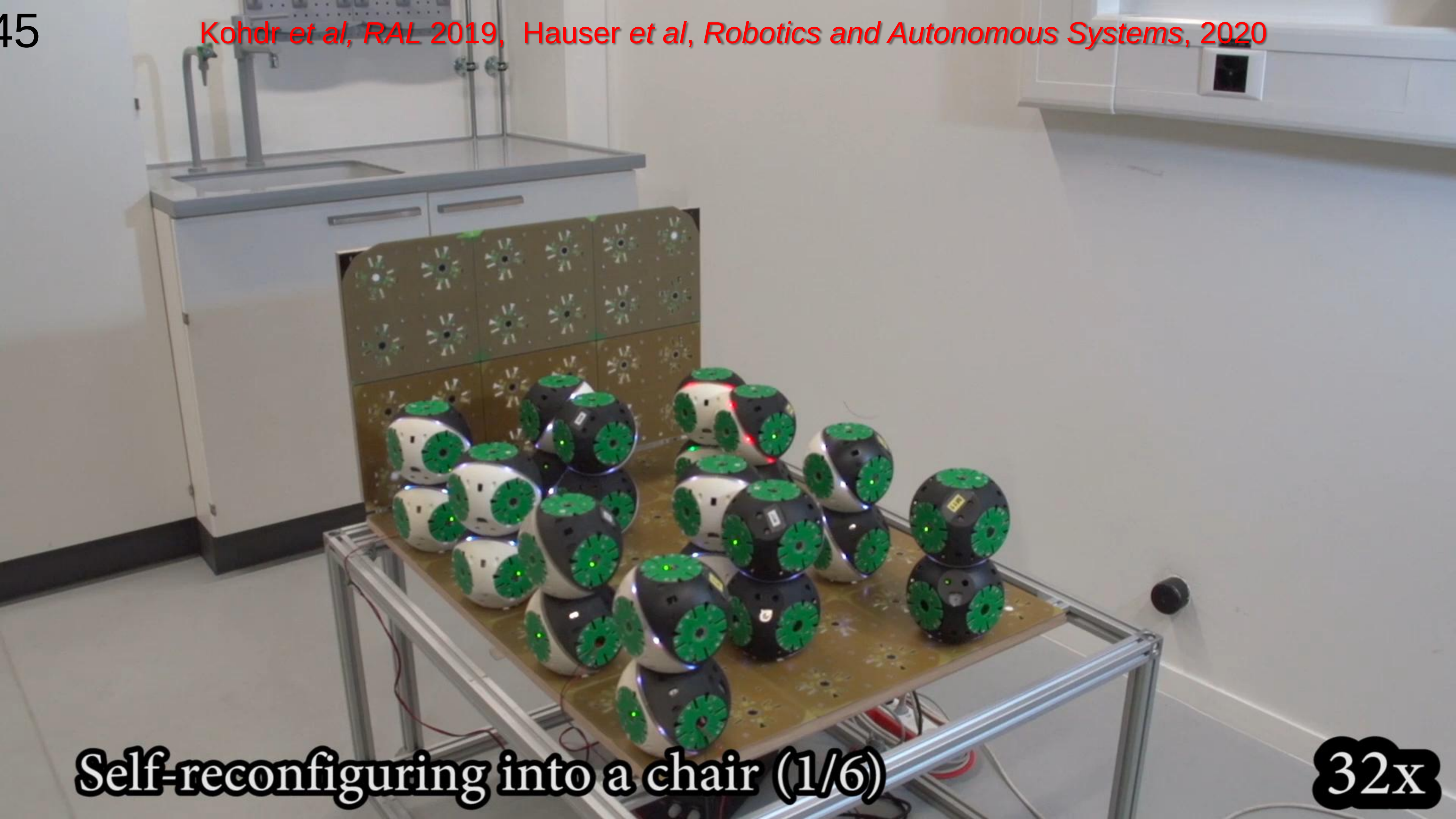
S. Hauser

M. Mutlu

Accelerated 8 times

Hauser *et al*, *Robotics and Autonomous Systems*, 2020

Kohdr *et al*, *RAL* 2019, Hauser *et al*, *Robotics and Autonomous Systems*, 2020



Furniture with **omnidirectional drive**

Anastasia Bolotnikova

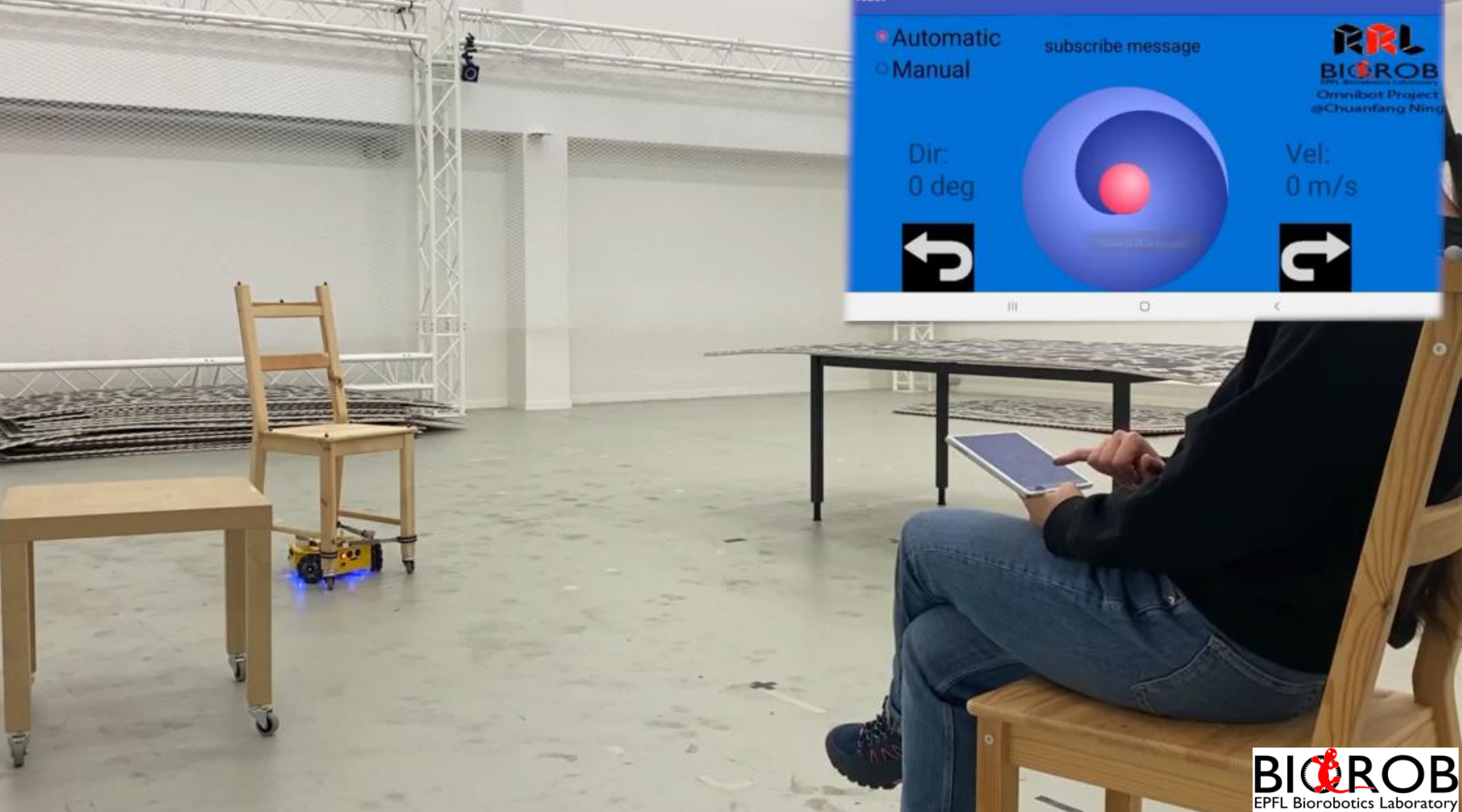
Chuanfang Ning

BIOROB
EPFL Biorobotics Laboratory

Furniture with omnidirectional drive

Anastasia Bolotnikova

Chuanfang Ning



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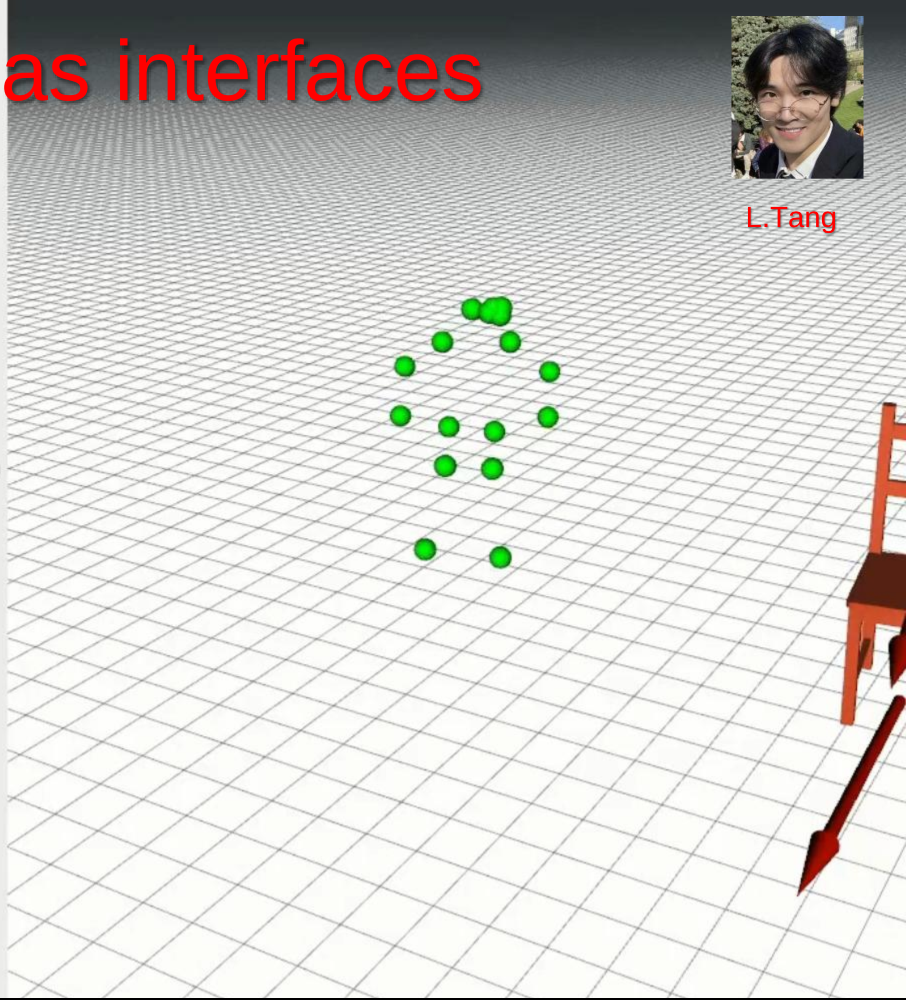
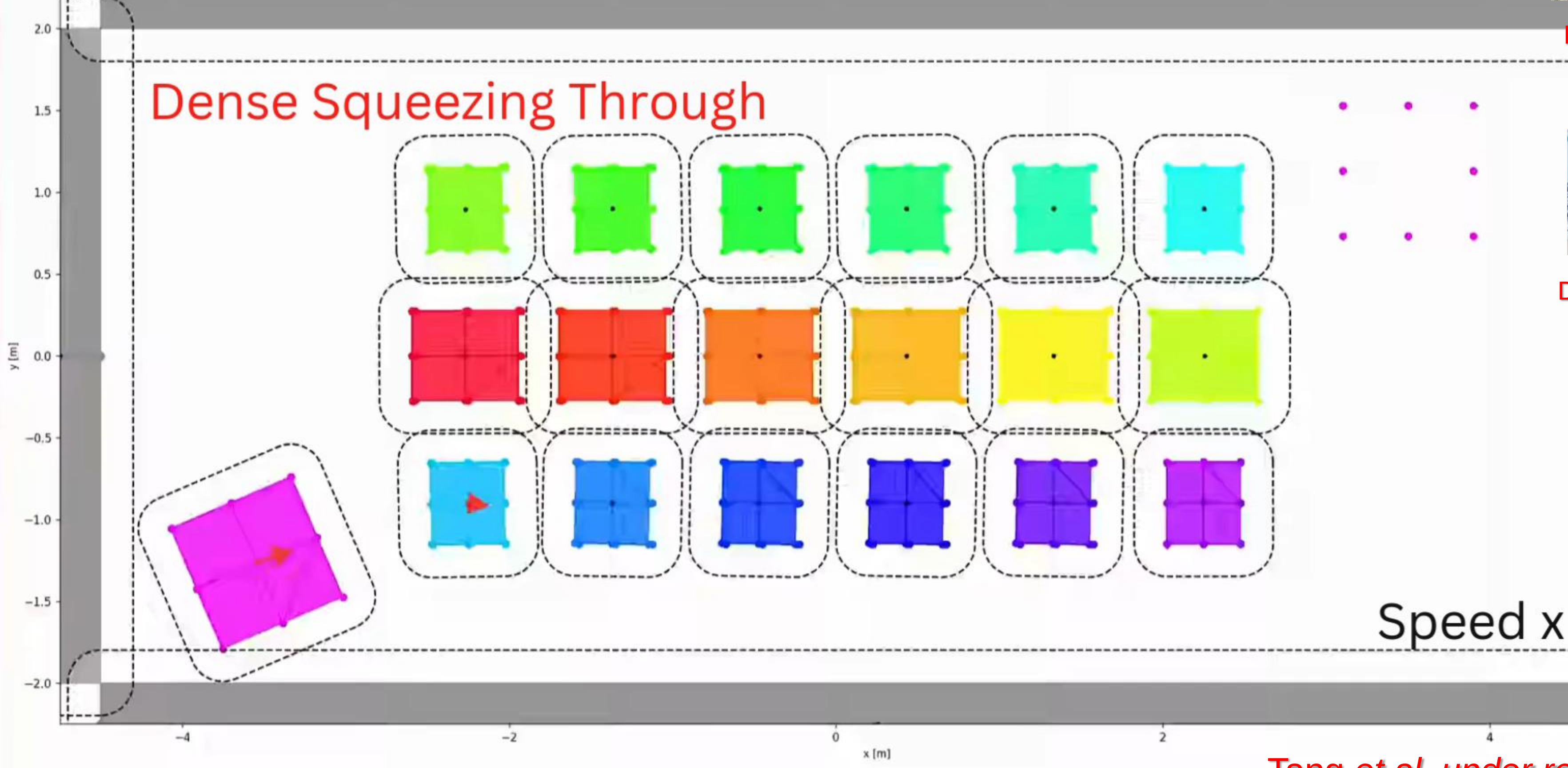
Using gestures as interfaces



L.Tang

Tang *et al*, *RAL 2023*

Reorganization of furniture



L.Tang

D. Ruegg

Tang et al, under review

Reorganization of furniture

L.Tang

D. Ruegg

Tang *et al*, *under review*

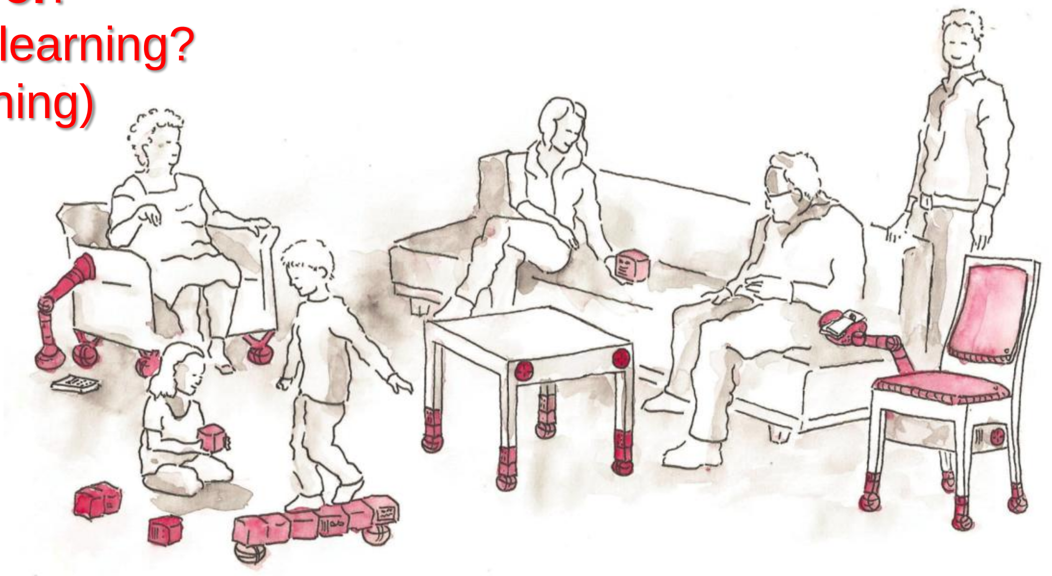
Roombots as assistive furniture

Smart assistive environment for persons with limited mobility

Roombots as assistive furniture

Multiple applications as well as interesting **research questions for AI and robotics**:

- How to make robotic furniture **useful and multifunctional**?
- Which **user interfaces and interactions**?
- How to achieve **robust collective navigation**?
- How to add **object manipulation**?
- **Decentralized vs centralized control**?
- How much **learning**? Which type of learning? (e.g. imitation and reinforcement learning)



https://gitlab.com/farmsim

FARMS

Framework for animal and robot modeling and simulation

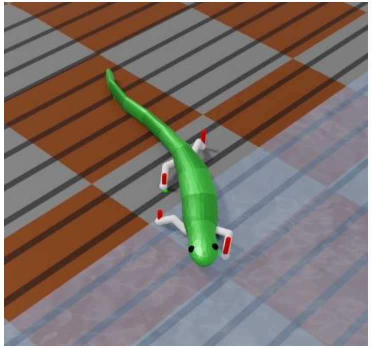
Please use and contribute!!

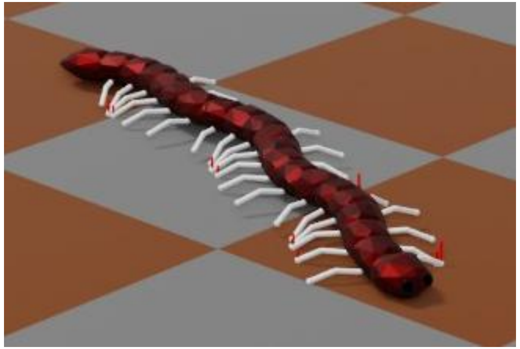
Jonathan Arreguit O'Neil

Shravan Ramalingasetty

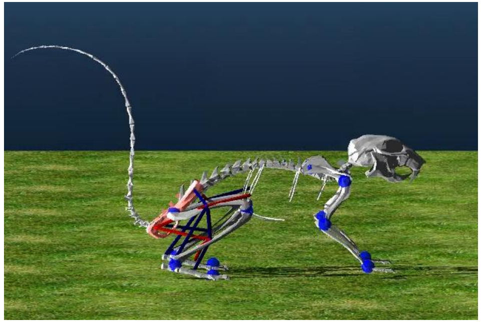
Pavan Ramdya

Lobato-Rios et al, Nature methods 2022

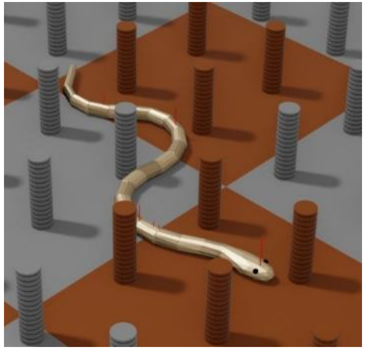




Simon Danner



Tata Ramalingasetty et al, IEEE Access 2021



Arreguit, Tata Ramalingasetty, Ijspeert, BioRxiv, 2023

Possible projects

See:
https://biorob.epfl.ch/students/projects/

And contact the project supervisor
+ auke.ijspeert@epfl.ch in cc

People at BIOROB, EPFL

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ALUMNI

O. Michel, M. Asadpour, J. Buchli, L. Righetti, Y. Bourquin, P.A. Mudry, M. Taric, S. Dégallier, M. Porez, , R.Ronsse , A. Gams, R. Moeckel, K. Karakasiliotis, S. Pouya, A. Sproewitz, J. Knuesel, A. Bicanski, Y. Morel, J.v.d. Kieboom, D. Renjewski, T. Petric, L. Colasanto, S.Bonardi, M. Ajallooeian, M. Vespignani, N. van der Noot, A. Tuleu. P. Müllhaupt, R. Thandiackal, A. Wu, H. Razavi, P. Eckert, S. Faraji, B. Bayat, A Koelewijn, T. Horvat, J. Lanini, S. Hauser, M. Mutlu. F. Dzeladini, R. Baud, M. Estrada, D. Stanev, S. Lipfert, L. Randazzo, I Froybu, M. Caban, M. Falahi, A. Morel, A. Di Russo, S. Ramalingasetty, L. Paez, K. Melo, A. Bolotnikova, X. Liu, R. Zufferey,

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SEVENTH FRAMEWORK PROGRAMME

HFSP

FNSNF