

# Computational motor control

## Lecture 1

Auke Jan Ijspeert

# Content of today's lecture

- Explanation of the **objectives and organization** of the course
- Overview of the **numerical modeling approach**
- **Overview of the content** of all lectures

# The beauty of animal locomotion



<https://www.youtube.com/watch?v=CoL8GtvxfI0>

# The beauty of animal locomotion



Crufts

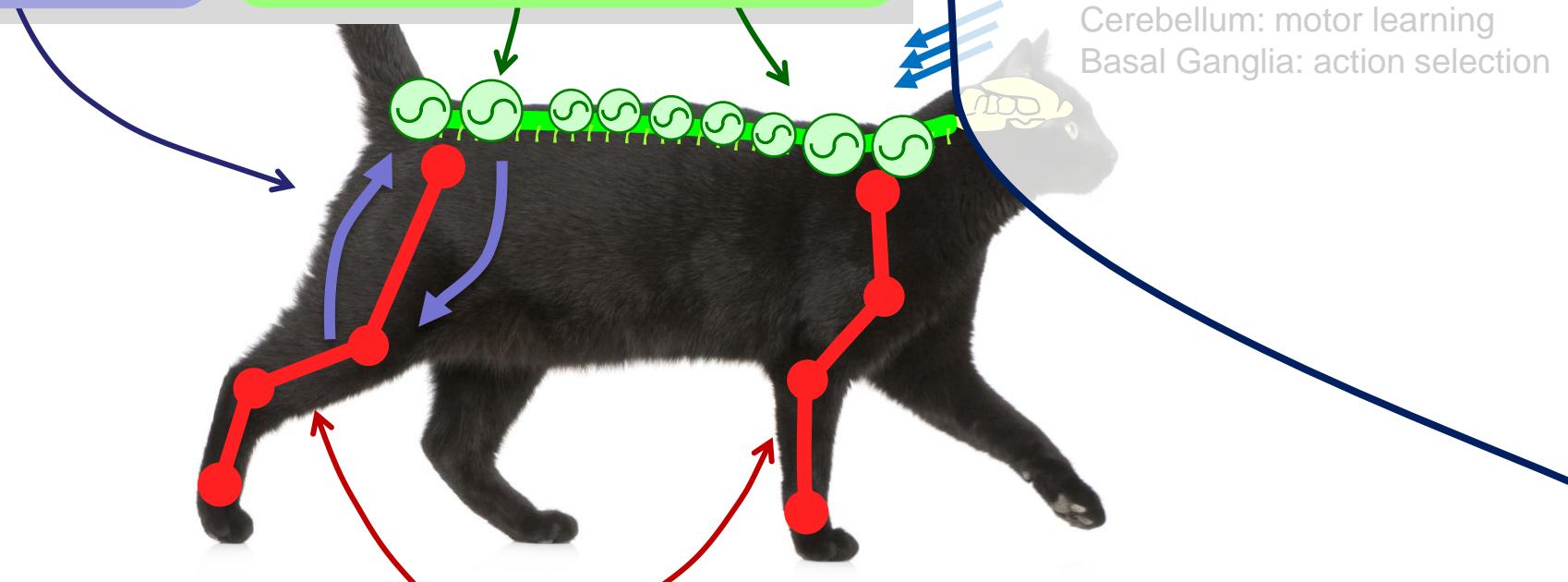
AG CH NEDLO DETOX SPROGLETT  
Greg Derrett

Spinal cord

Reflexes

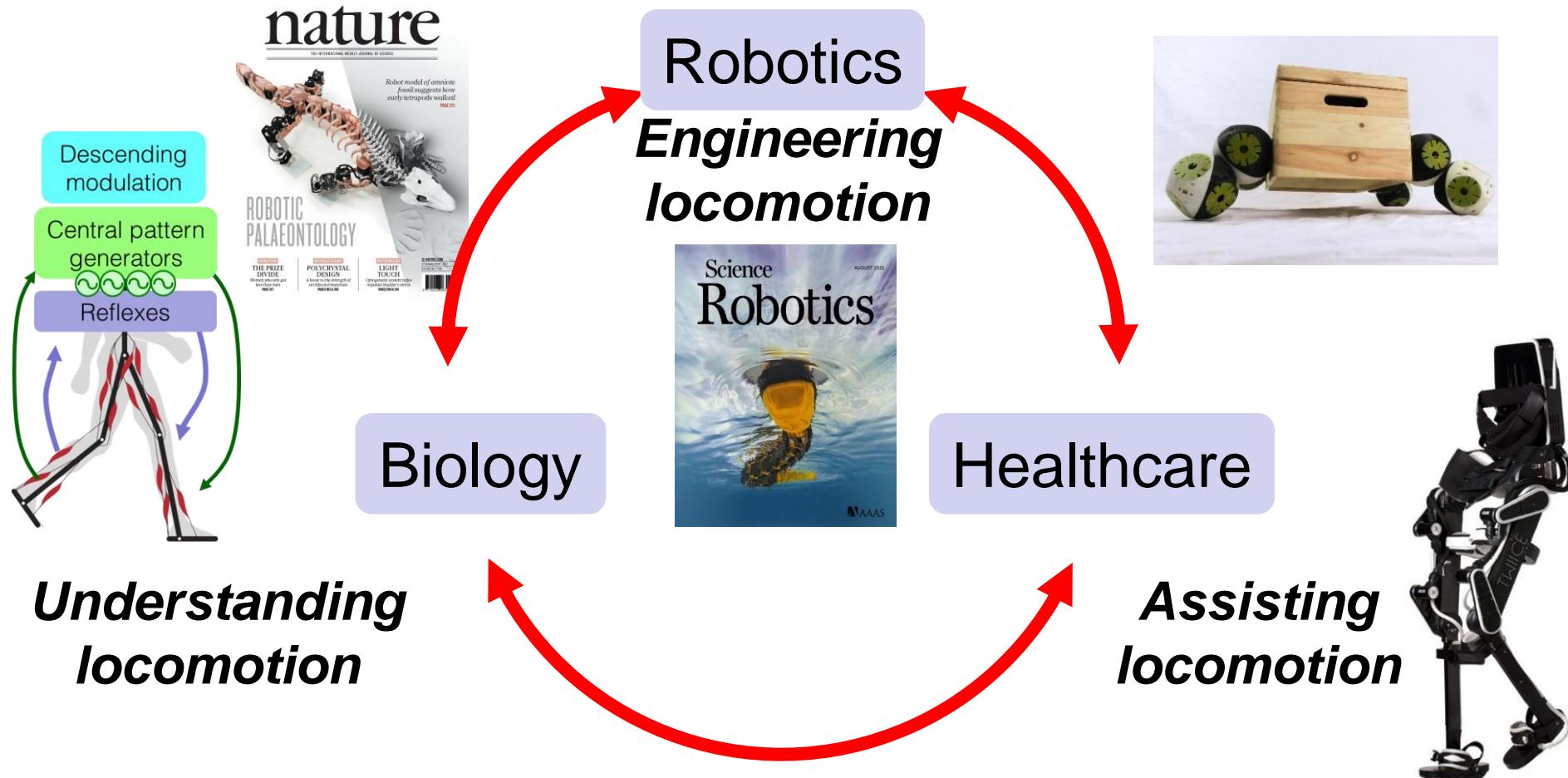
Central pattern generators

Descending modulation



Musculoskeletal system, “Clever” mechanics

# Biorobotics Laboratory (Ijspeert)



# Goals of the course

- To explore how **numerical simulations can be used to explain *motor control* in biology** (note: *motor control* = control of movements in neuroscience)
- To learn **how to design good numerical models**, and **how to evaluate them**
- To present how inspiration from biology can bring useful contributions to the **new design and control principles for robotics**
- To apply concepts from the lectures to (1) **design and test simple models in Python**, and (2) **develop sensory-motor models applied to a simulated zebrafish**

# Implementation

- Lectures every week: Thursday 10:15-12:00 **AAC 231**
- Support for modeling projects: 13:15-15:00, **INF 2**
- Video recordings will be made available as much as possible (but try to attend lectures)
- Handouts: copies of slides before each course + additional articles/documents
- Use of Moodle for all course materials, cf  
<http://moodle.epfl.ch>

# Implementation (continued)

- Practical work:
  - (1) Series of **modeling exercises in Python**
  - (2) Sensory-motor models of a **zebrafish**
- Teams of three students
- One written report, with different subparts (exploration of swimming gaits, exploration of muscle properties, implementing a controller based on phase oscillators, exploring the role of sensory feedback).
- Final mark: **40% written exam, 60% reports**
- **Written exam** at the end of the semester, **on May 15 (TBC)**

# Prerequisites

- Good background in mathematics (differential equations)
- At ease with programming (for the practical)
- Python (installation and tutorial today)
- Interest in
  - understanding biology,
  - using mathematical and numerical tools to do science (computational science),
  - using inspiration from biology to develop new algorithms and new robot controllers
- Be proactive, curious, willing to explore new territories

# FARMS

## Framework for animal and robot modeling and simulation



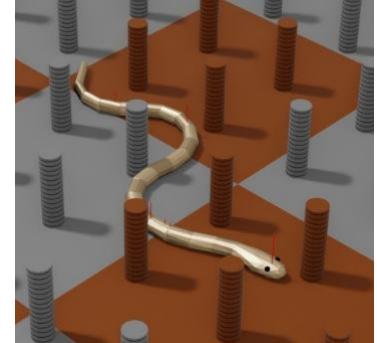
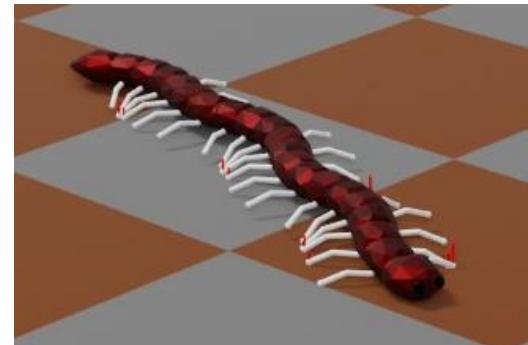
Jonathan Arreguit O'Neil Shravan Ramalingasetty



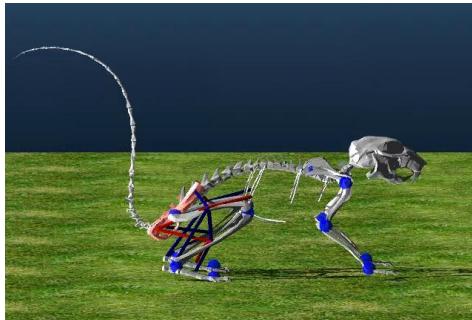
Pavan Ramdya



Lobato-Rios et al, Nature methods 2022



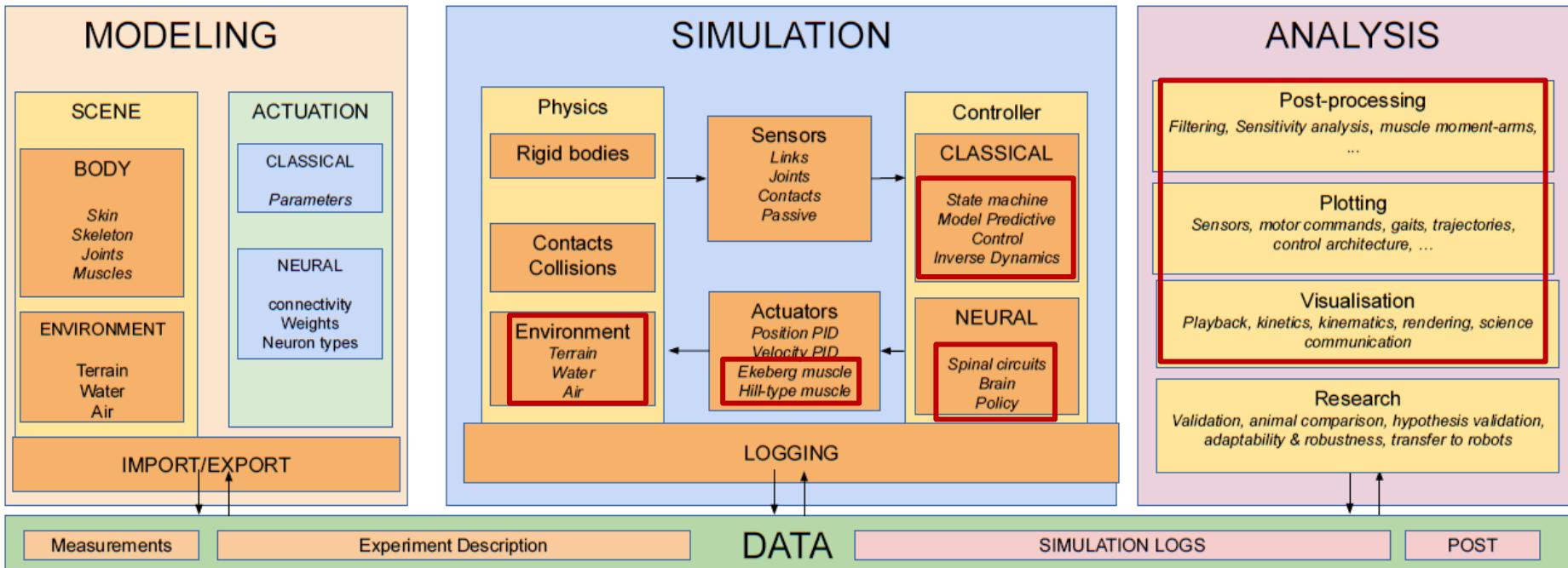
Simon Danner



Tata Ramalingasetty et al, IEEE Access 2021

Arreguit, Tata Ramalingasetty, Ijspeert, BioRxiv, 2023

# FARMS



OPTIMIZATION  
REINFORCEMENT LEARNING

# Model for the practicals

## Neuromechanical model of the Zebrafish



<https://powersscientific.com/effects-of-lighting-on-zebrafish/>

Why the zebrafish?

- **Key model animal** in biology and in neuroscience
- Many **transgenic lines**
- **Transparent** at the larval stage
- Ideal for **optogenetic experiments**
- Increasing number of papers studying its locomotion

# Model for the practicals

## Neuromechanical model of the Zebrafish



Slower than real time

- Exploration of **swimming gaits**,
- Exploration of **muscle properties**,
- Implementation of a **central pattern generator model made of phase oscillators**,
- Exploring the **role of sensory feedback**
- Open-ended question

# Reports

- What is important: **good reports with a careful scientific evaluation of the model and the results**
- To get a good mark:
  - **Good scientific graphs**
  - Careful and **critical analysis of the results**
  - Relate the results to **biological observations**
  - Suggestions of **additional experiments**
  - Possibly: **make predictions**
- Note: this is research, i.e. solutions might not be known yet and there will be less guidance than usual lab projects
- **Warning: no plagiarism!! (also between teams)**
- **Tell us asap if work is not properly shared among team members.**

# Content of today's lecture

- Explanation of the objectives and organization of the course
- **Overview of the numerical modeling approach**
- Overview of the content of all lectures

# What do we mean by model?

- A **mathematical description** or a **numerical simulation** of a biological system (i.e. systems of equations or algorithms)
- Should be **based on well-specified (explicit) assumptions and idealizations**
- Should **answer a clear question**
- Should **allow experimenting**, i.e. exploration of how changes of parameters affect the behavior of the model
- Should be **carefully evaluated and validated** against biological data
- Should **make predictions** and **suggest new biological experiments** for future validation

# What are assumptions and idealizations?

- **Assumptions** are statements or premises that are taken as given within a particular scientific framework. They may or may not be strictly true, but they are accepted to enable the development of a theory or model.
- **Idealizations**, on the other hand, are **deliberate distortions or simplifications** of reality that are introduced to make problems more tractable or to highlight key mechanisms. Unlike assumptions, idealizations are knowingly false but useful approximations.

	<u>Assumptions</u>	<u>Idealizations</u>
<b>Truth value</b>	May be true or false	Explicitly false
<b>Purpose</b>	Provide foundational premises	Simplify reality for modeling
<b>Role in models</b>	Set boundaries or define a system	Distort reality to highlight key mechanisms
<b>Example</b>	"The speed of light is constant" (empirical assumption)	"A pendulum swings without air resistance" (idealization)

**Note:** In this course, we will often treat them as having the same meaning

# Why make numerical models?

## Scientific Value:

- They force us to **conceptualize all the relevant components of a system and the mechanisms of interaction between them**
- They help **understanding the mechanisms of complex dynamical regimes**
- They allow us to **test hypotheses and validate them against biological data**
- They allow **recording and monitoring multiple quantities** (many of which might not be able to be recorded in animal experiments)
- They allow us **to make predictions, and suggest new experiments**

# Why make numerical models?

## Ethical value:

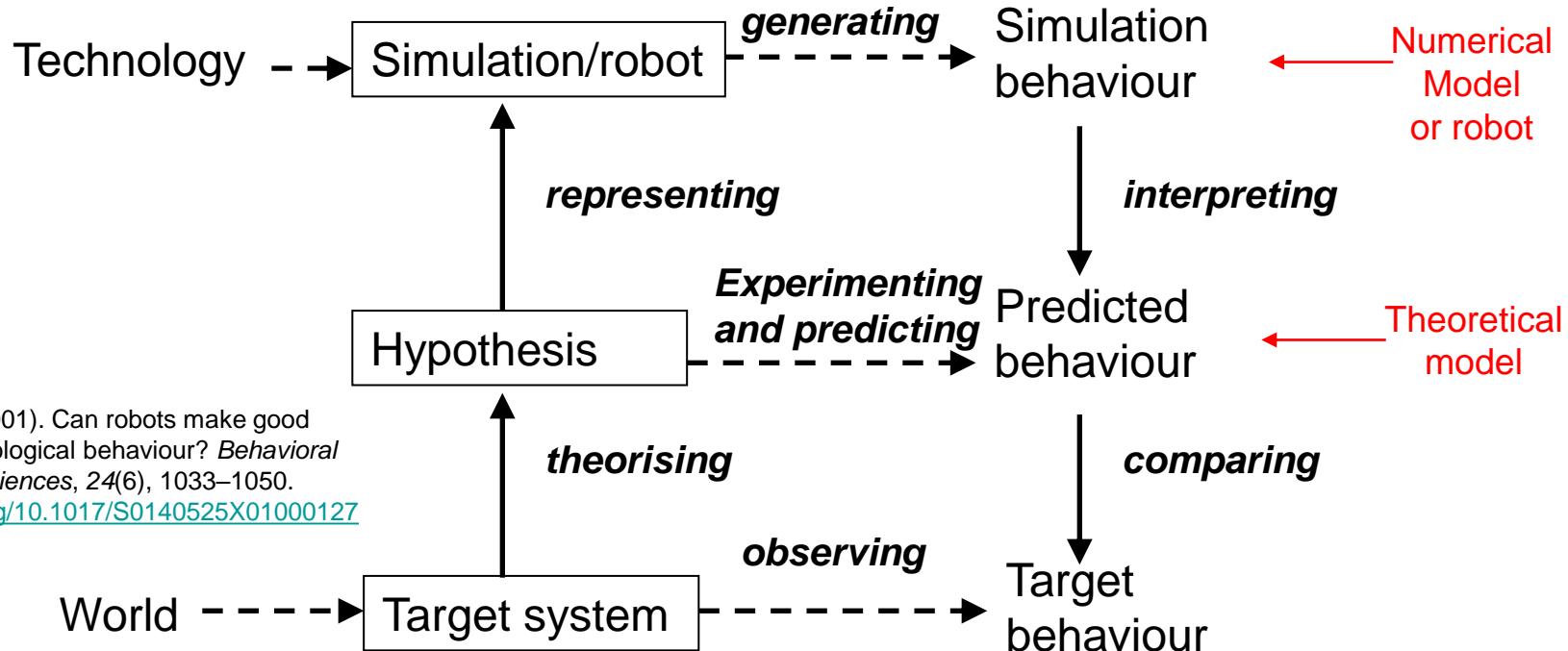
- Using numerical models can **reduce the number of animal experiments**

## Economical value:

- Numerical experiments are **much cheaper to run than real animal experiments** (e.g. in terms of recording equipment + animal costs)
- Modeling can **serve as inspiration for new algorithms, devices or robots**
- Numerical models can be used for **optimization** (e.g. designing an optimal prosthesis, improving athletes, ...)

# Scientific methodology (from B.Webb 2001)

Models, and especially numerical simulations, are now an essential element of a scientific approach:



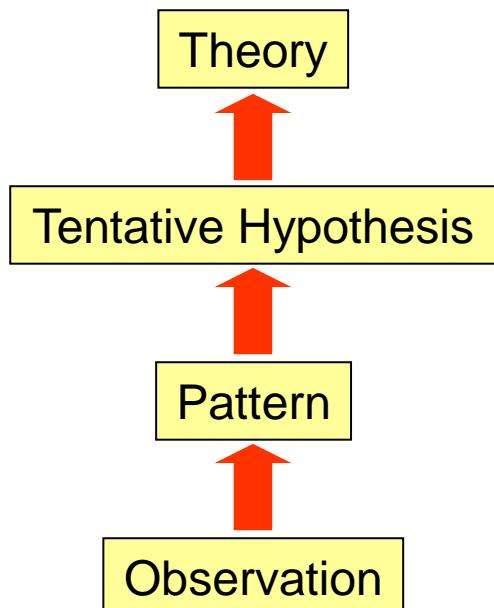
Webb, B. (2001). Can robots make good models of biological behaviour? *Behavioral and Brain Sciences*, 24(6), 1033–1050.

<https://doi.org/10.1017/S0140525X01000127>

# Inductive vs deductive research

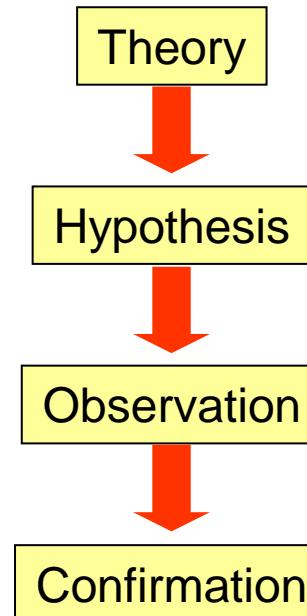
## Inductive reasoning:

From the specific observations  
to generalization



## Deductive reasoning:

From the general to the specific



# Modeling and numerical simulation

Some additional thoughts:

A model should be **as simple as possible**, but not more (Einstein?) (i.e. not much can be learned from a model that is as complex as the real thing)

A model should have **explanatory power** (i.e. not only descriptive, e.g. as a blackbox).

Like any scientific theory, you should be **ready to throw away models** when they do not correspond to new evidence from experiments.

But models that can not explain some biological data are still useful to indicate that more thinking is needed.

*All models are wrong, some are useful...* (George Box, statistician)

# Interesting example of the modeling approach: the lamprey swimming network

Neural networks that co-ordinate locomotion and body orientation in lamprey, S. Grillner et al, Trends in Neuroscience, 18, pp 270-279, 1995

Neural networks for vertebrate locomotion. S. Grillner. Scientific American, 274(1), pp 64-69, 1996

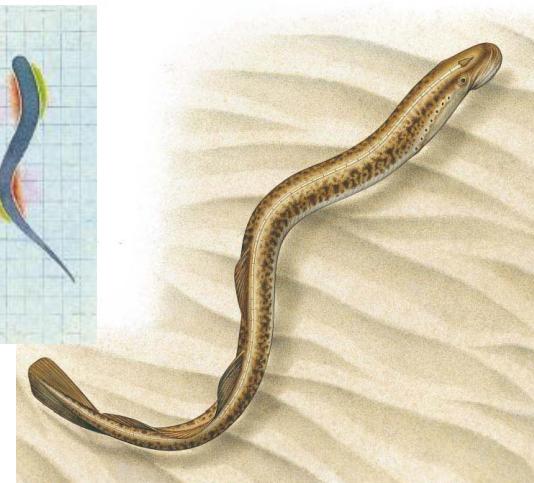
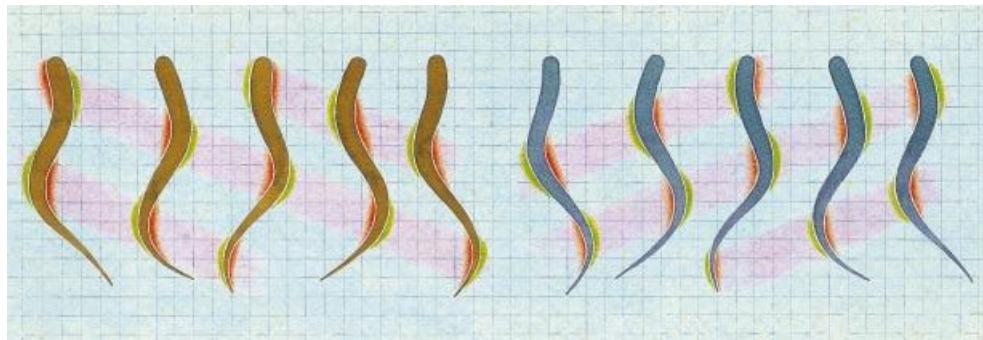
A combined neuronal and mechanical model of fish swimming.  
Ö. Ekeberg. Biological Cybernetics, 69:363-374, 1993.

# 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



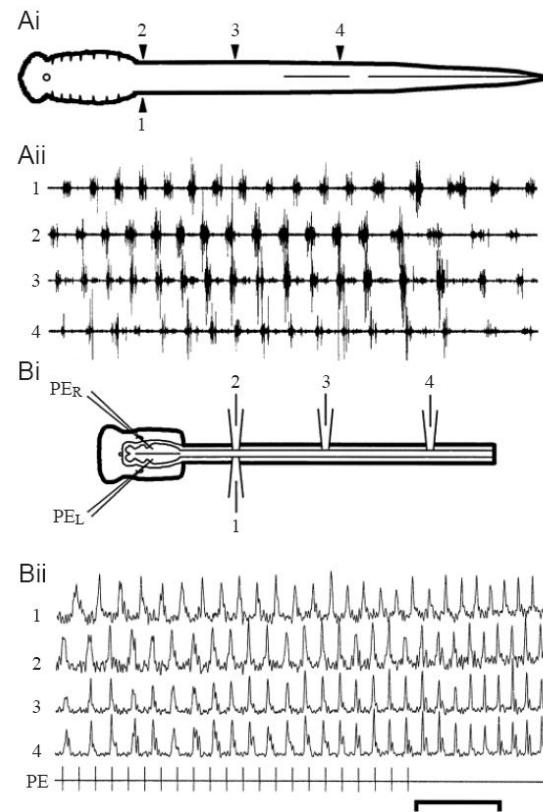
# The lamprey

Example of recordings  
(Boyd and McClelland 2002)

Electromyographs (EMGs)

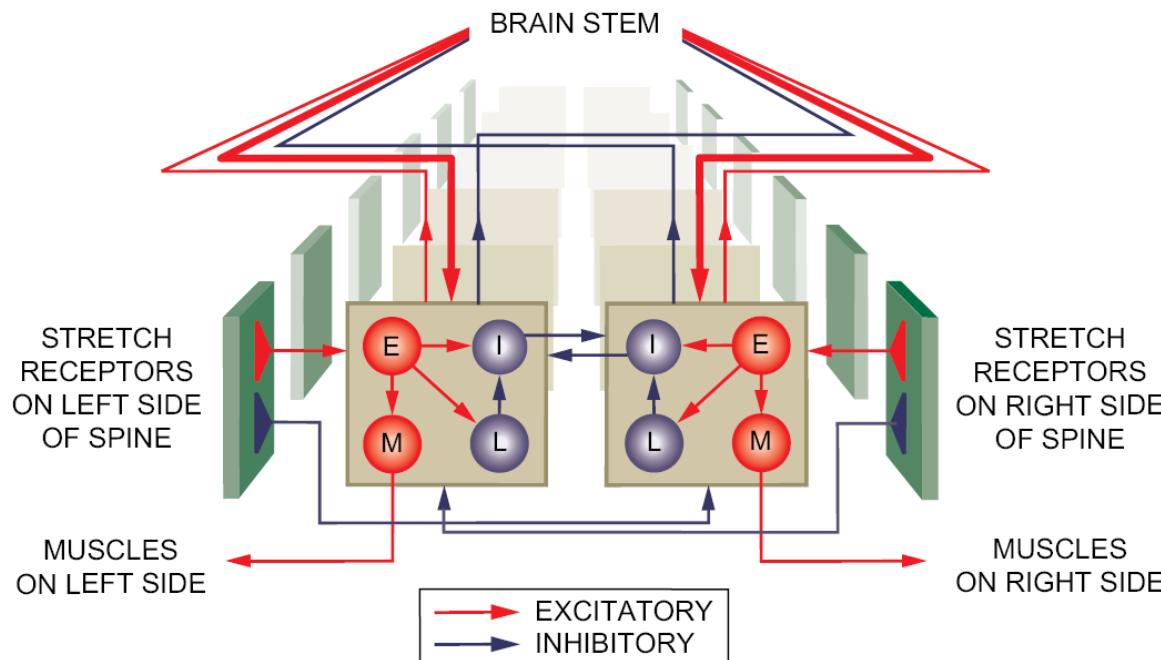
***Fictive locomotion:***  
the spinal cord can produce  
rhythmic patterns in a petri dish!  
No muscles, no sensory feedback

Ventral root recordings  
of an isolated spinal cord



# The lamprey swimming network

Conceptual model (Grillner, Sci. Am. 1996)



# Methodology of modeling

Important steps:

1. Identify the **questions to be addressed**,
2. Identify **important quantities** in the biological data,
3. Choose the **level of abstraction**,
4. Specify the **assumptions (idealizations)**,
5. Extensively **test the model**
6. **Validate the results** against biological data
7. **Suggest new biological experiments**

# Lamprey models: four levels of abstraction

Analytical models of oscillators

Numerical models of nonlinear oscillators

Connectionist neural network models

Biophysical neural network models

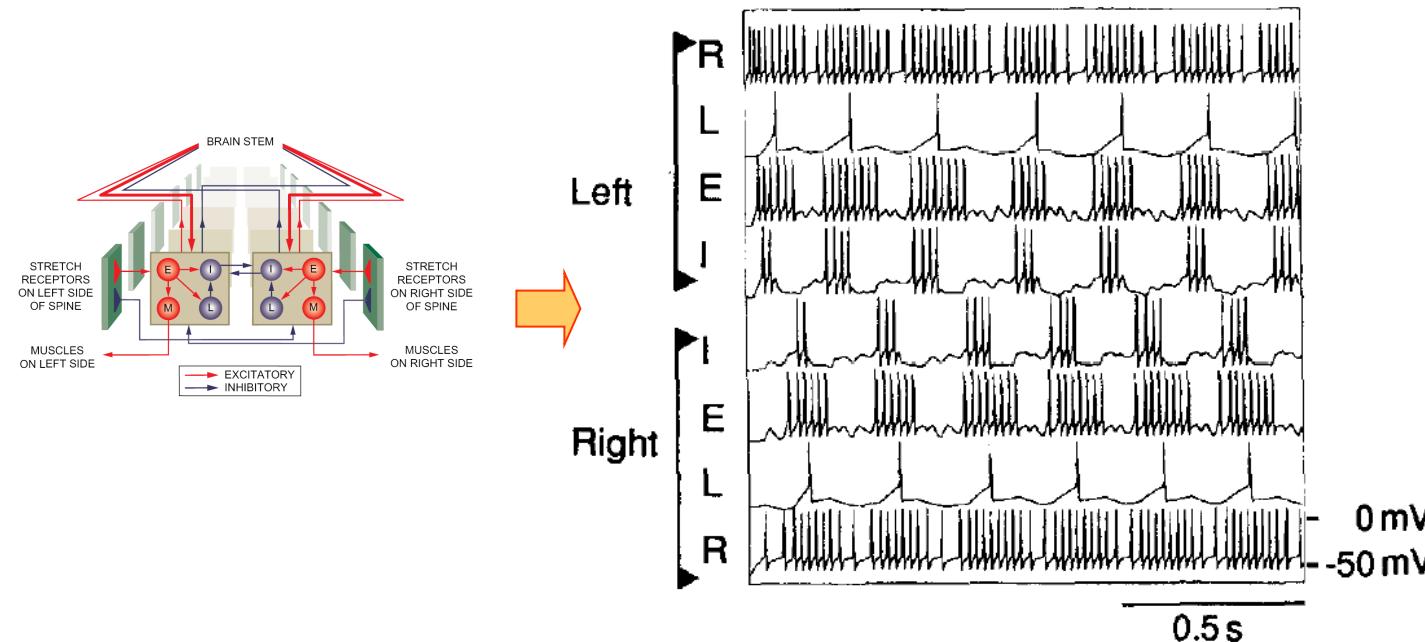
abstract



detailed

# The lamprey: biophysical models

Biophysical models have helped **understanding the oscillating properties of the segmental network**



(Grillner et al 1995)

# Biophysical models: steps

## 1. Questions to be addressed:

How are oscillations generated in a segmental network?

## 2. Important quantities:

Intracellular voltages, ion concentrations,...

## 3. Level of abstraction:

Biophysical model: Hodgkin-Huxley like neuron model

## 4. Assumptions:

Single cell represents a whole population of neurons,...

## 5. Test the model:

See (Grillner et al 1995)

## 6. Validation

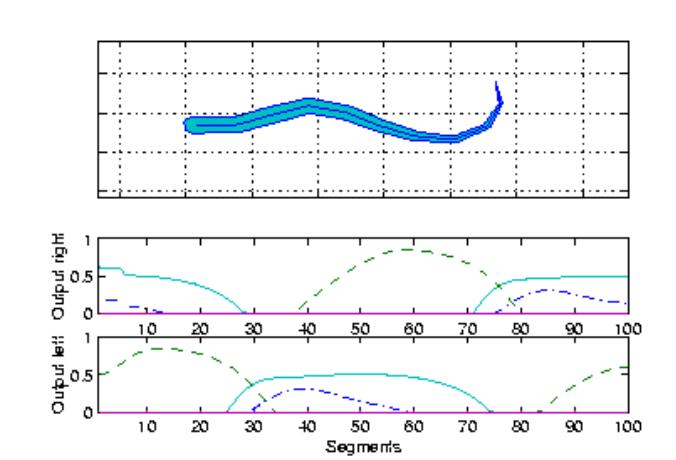
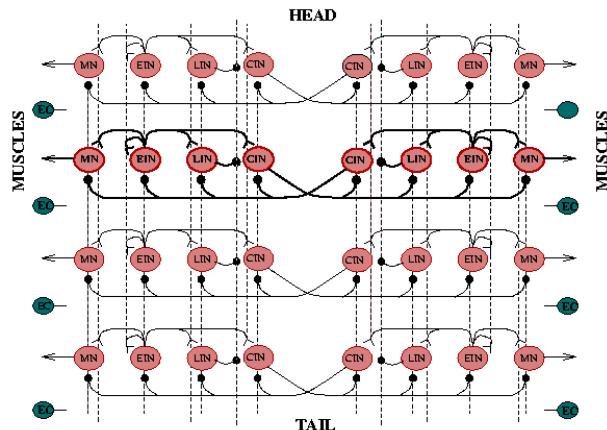
Several mechanisms act together to produce oscillations. Production of oscillations over a large frequency range. See (Grillner et al 1995)

## 7. Suggestion of new biological experiments:

Pharmacological manipulations, ...

# The lamprey: connectionist models

Leaky-integrator models have helped understanding the intersegmental coupling mechanisms that generate traveling waves



(Ekeberg 1993)

# Connectionist models: steps

## 1. Questions to be addressed:

How are traveling waves generate in the spinal cord?

How is a wavelength of one body length maintained?

## 2. Important quantities:

Average firing frequency, phase lags between segments,...

## 3. Level of abstraction:

Connectionist model: leaky-integrator neuron model

## 4. Assumptions:

Symmetries (left-right, along the spinal cord), ...

## 5. Test the model: see (Ekeberg 1993)

## 6. Validation: Constant wavelength at different frequencies, see (Ekeberg 1993)

## 7. Suggestion of new biological experiments:

Mechanical manip., changing the sensory feedback, ...

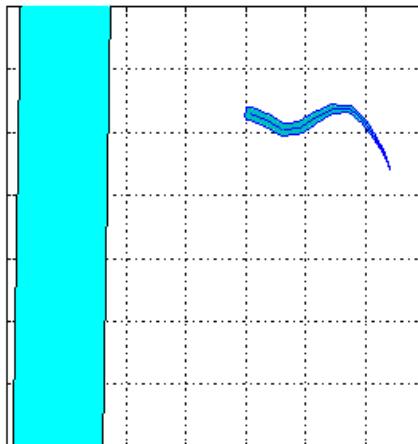
# Neuromechanical models

Neuromechanical models = models of neural circuits + of the biomechanics

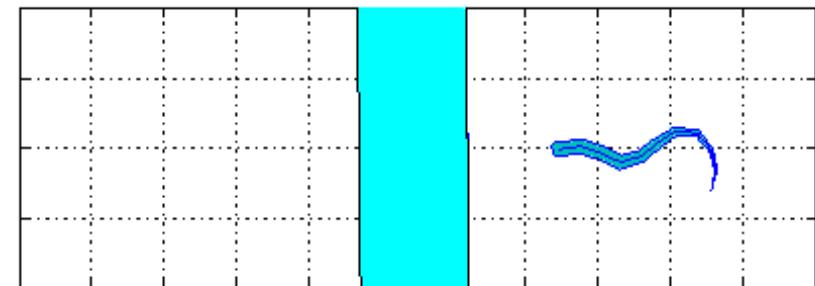
They have helped understanding:

- **the role of sensory feedback** from stretch receptor cells in **burst termination**.

Swimming through a speed barrier  
**without** sensory feedback



Swimming through a speed barrier  
**with** sensory feedback



(Ekeberg et al 1995, Ijspeert et al 1999)

For more details about  
the usefulness of modeling see:

Webb, B. (2001). Can robots make good models of biological behaviour? *Behavioral and Brain Sciences*, 24(6), 1033–1050.  
<https://doi.org/10.1017/S0140525X01000127>

Neural networks that co-ordinate locomotion and body orientation in lamprey, S. Grillner et al, Trends in Neuroscience, 18, pp 270-279, 1995

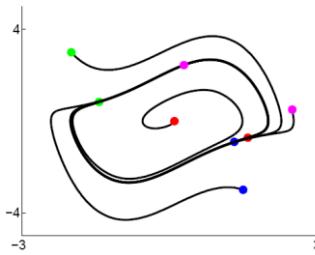
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Cf Moodle folder

# Overview of the content of the course

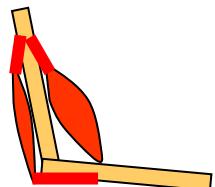
# Contents of lectures



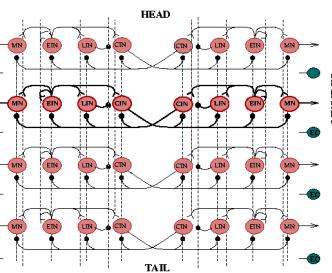
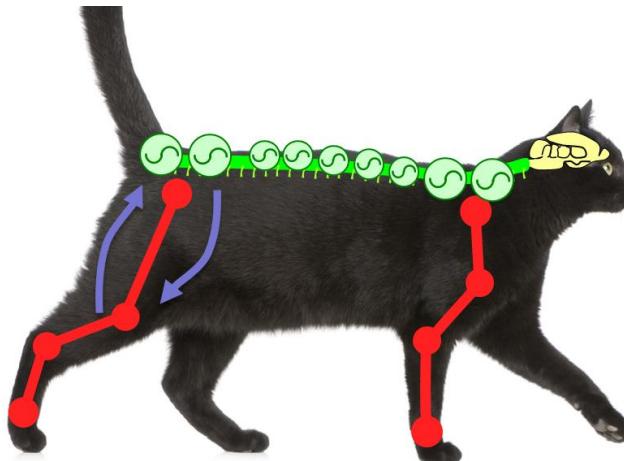
Dynamical systems



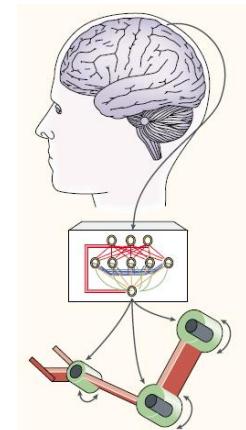
Neuron models



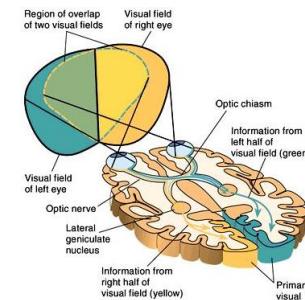
Muscle and  
Biomech. models



Motor system  
models



Neuroprosthetics



Visual system  
models

# Introduction to nonlinear dynamical systems

Topics:

- Ordinary differential equations (ODEs)
- Methods for solving (ODEs)
- Geometrical interpretation, phase portrait
- Differences between linear and nonlinear systems
- Linear stability analysis

# Introduction to nonlinear dynamical systems

Topics:

- Oscillators and limit cycles
- Different oscillator models
- Chains of oscillators
- Bifurcations and chaos

# Ordinary differential equations

Most models presented in the course will be based on ordinary differential equations (ODEs):

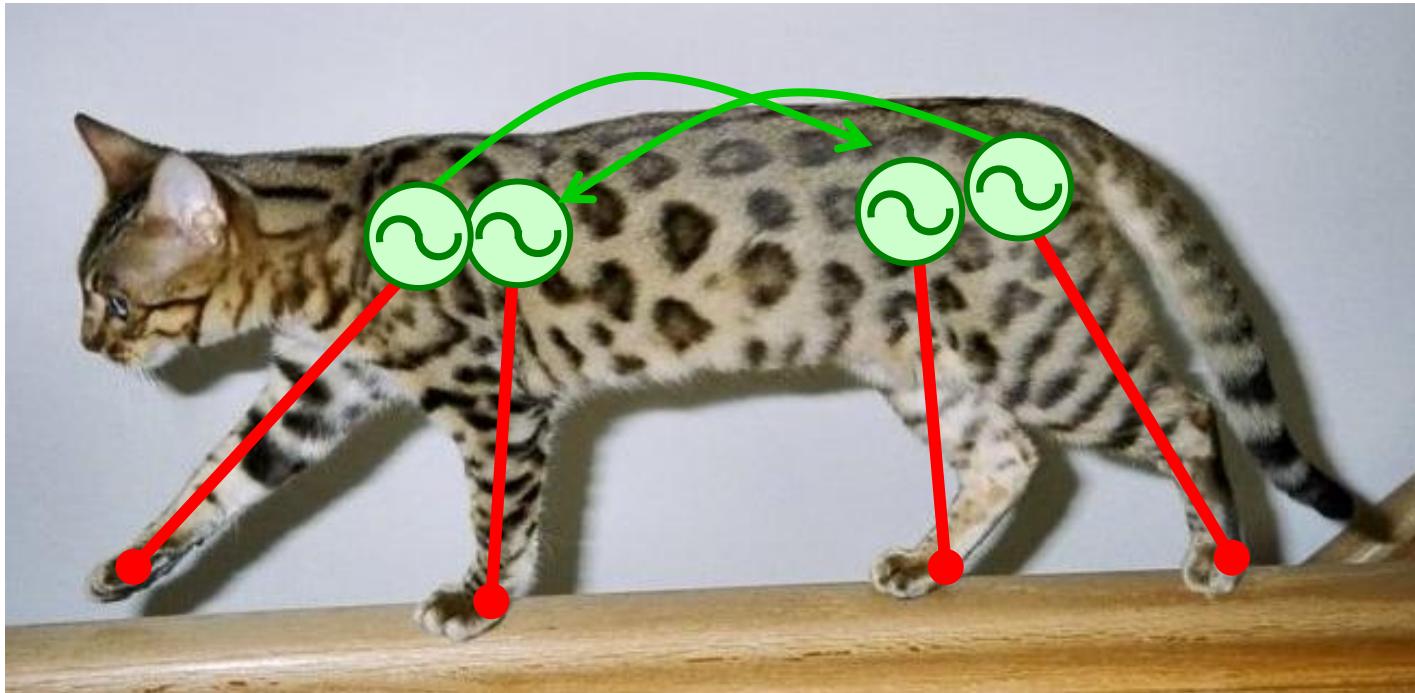
$$\frac{d}{dt} \vec{x} = f(\vec{x}, \vec{\alpha}, t)$$

These types of equations are used in many types of numerical models. They determine how the *state variables*  $\vec{x}$  vary over time. The time derivative of the state variables  $\vec{x}$  are described as a (usually nonlinear) function of the state variables, some *parameters*  $\vec{\alpha}$  and (possibly) the time  $t$ .

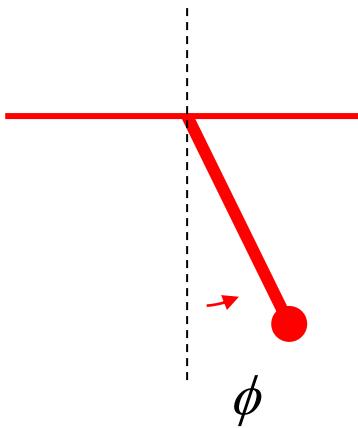
*Autonomous ODEs:*  $\frac{d}{dt} \vec{x} = f(\vec{x}, \vec{\alpha})$  no explicit dependence on time

*Non-autonomous ODEs:*  $\frac{d}{dt} \vec{x} = f(\vec{x}, \vec{\alpha}, t)$  explicit time dependence, much harder to deal with

# Numerical simulation of systems of coupled oscillators



# A limb $\cong$ a damped pendulum



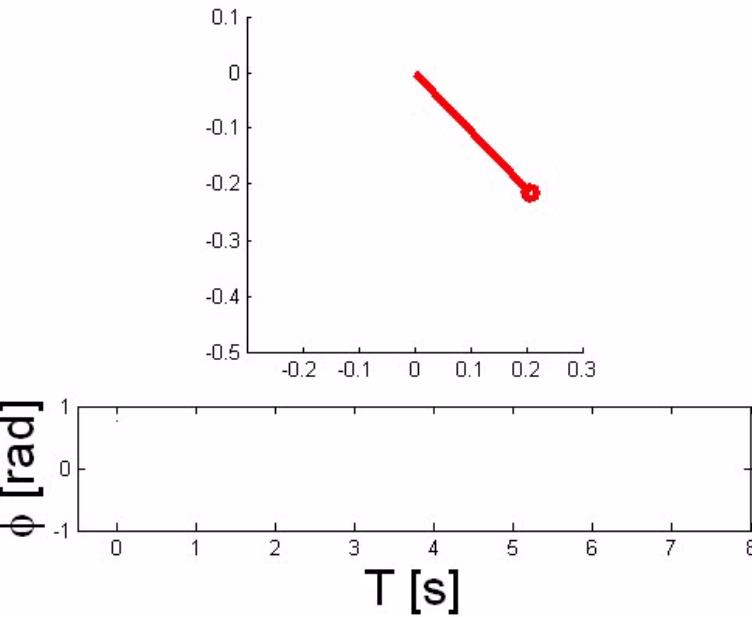
$$\ddot{\phi} = -d \dot{\phi} - \sin(\phi) \cdot \frac{g}{L}$$

$\phi$ : angle

$d$ : damping

$g$ : gravity

$L$ : length



$$\text{Frequency of oscillation: } \omega = \sqrt{\frac{g}{L}} = \sqrt{\frac{9.81}{0.3}} = 2\pi \cdot 0.9 \text{ [Hz]}$$

# A Hopf oscillator to model a neural oscillatory center



$$\dot{x} = \alpha(\mu - \sqrt{x^2 + y^2}) x - \nu y$$

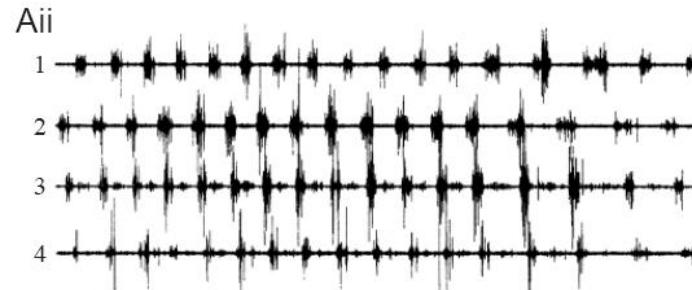
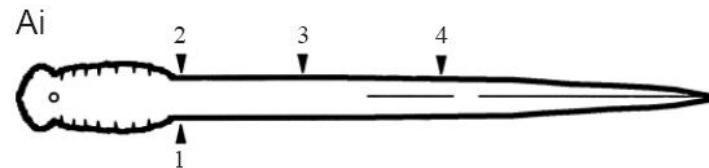
$$\dot{y} = \alpha(\mu - \sqrt{x^2 + y^2}) y + \nu x$$

$\mu$ : amplitude

$\alpha$ : positive parameter

$\nu$ : intrinsic frequency

$w_i$ : couplings



Boyd and McClellan, the Journal of Experimental Biology 2002

Frequency of oscillation:  $\nu$

# A Hopf oscillator to model a neural oscillatory center

Stable limit cycle:



$$\dot{x} = \alpha(\mu - \sqrt{x^2 + y^2}) x - \nu y$$

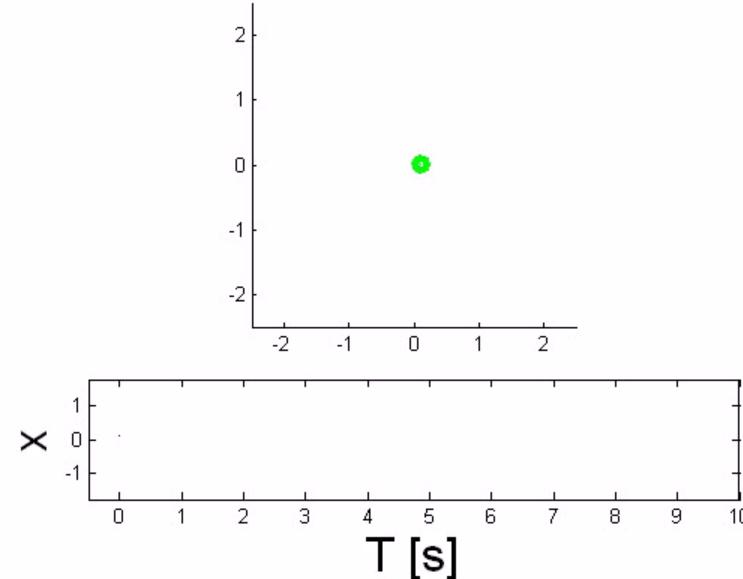
$$\dot{y} = \alpha(\mu - \sqrt{x^2 + y^2}) y + \nu x$$

$\mu$ : amplitude

$\alpha$ : positive parameter

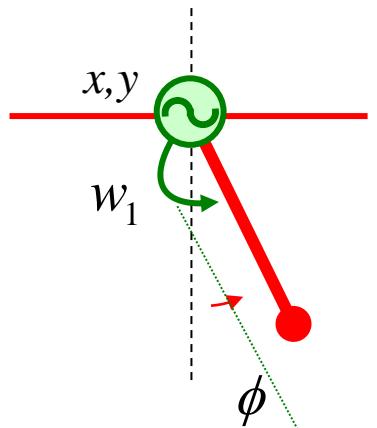
$\nu$ : intrinsic frequency

$w_i$ : couplings



Frequency of oscillation:  $\nu$

# A pendulum coupled to an oscillator



$$\ddot{\phi} = -d \dot{\phi} - \sin(\phi) \cdot \frac{g}{L} + w_1 x$$

$$\dot{x} = (\mu - \sqrt{x^2 + y^2}) x - \nu y$$

$$\dot{y} = (\mu - \sqrt{x^2 + y^2}) y + \nu x$$

$\phi$ : angle

$d$ : damping

$g$ : gravity

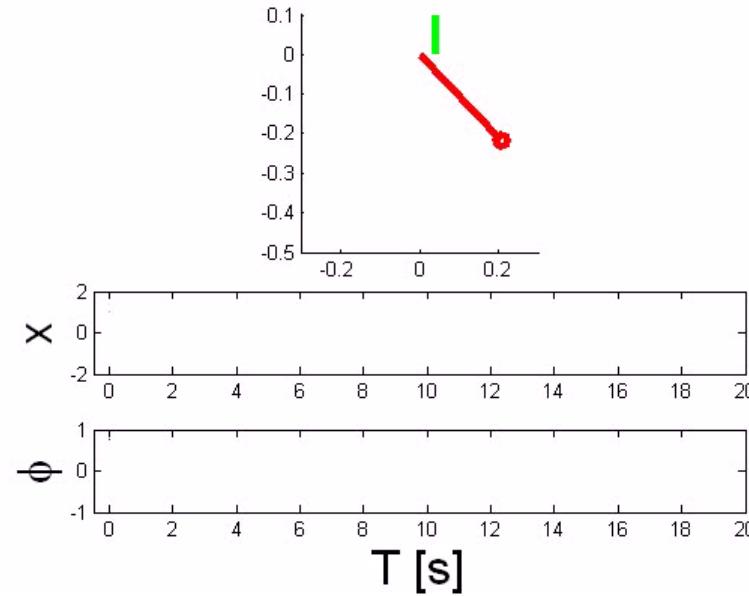
$L$ : length

$\mu$ : amplitude

$\nu$ : intrinsic frequency

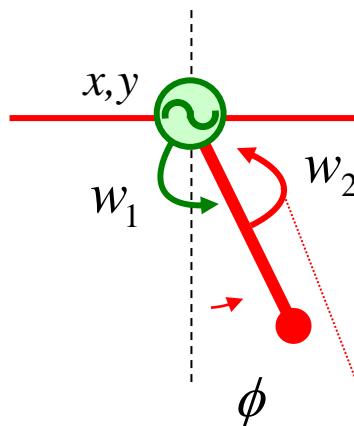
$w_i$ : couplings

Forced pendulum: complex dynamics



Raibert: “**the central nervous system does not control the body; it can only make suggestions**”.

# A pendulum coupled to an oscillator

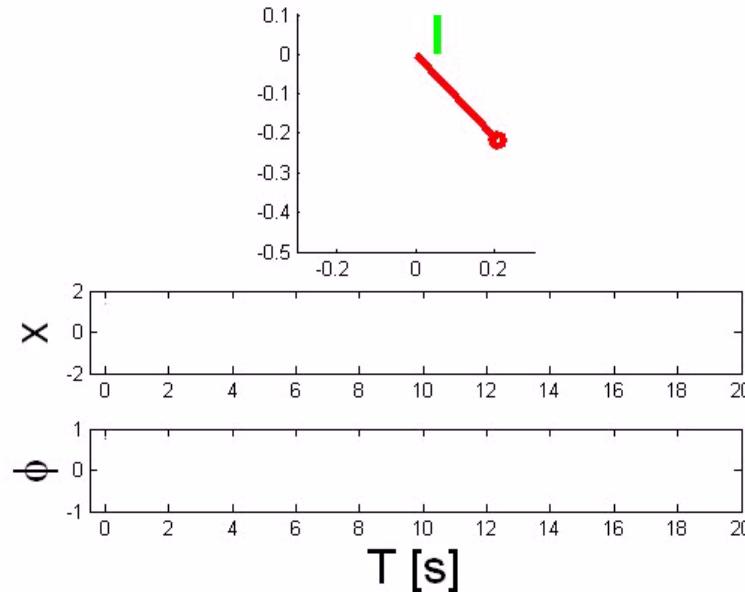


Bidirectional coupling:  
**Entrainment!!**  
(different systems reaching a same resulting frequency)

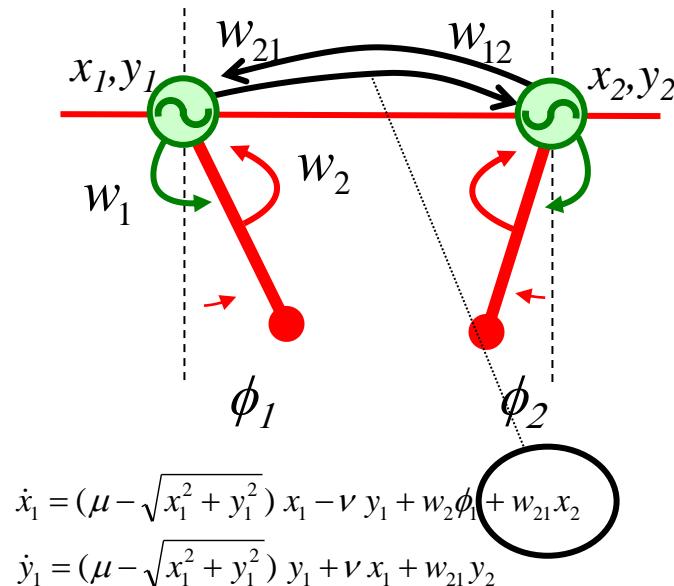
$$\ddot{\phi} = -d \dot{\phi} - \sin(\phi) \cdot \frac{g}{L} + w_1 x$$
$$\dot{x} = (\mu - \sqrt{x^2 + y^2}) x - \nu y + w_2 \phi$$
$$\dot{y} = (\mu - \sqrt{x^2 + y^2}) y + \nu x$$

$\phi$ : angle  
 $d$ : damping  
 $g$ : gravity  
 $L$ : length

$\mu$ : amplitude  
 $\nu$ : intrinsic frequency  
 $w_i$ : couplings



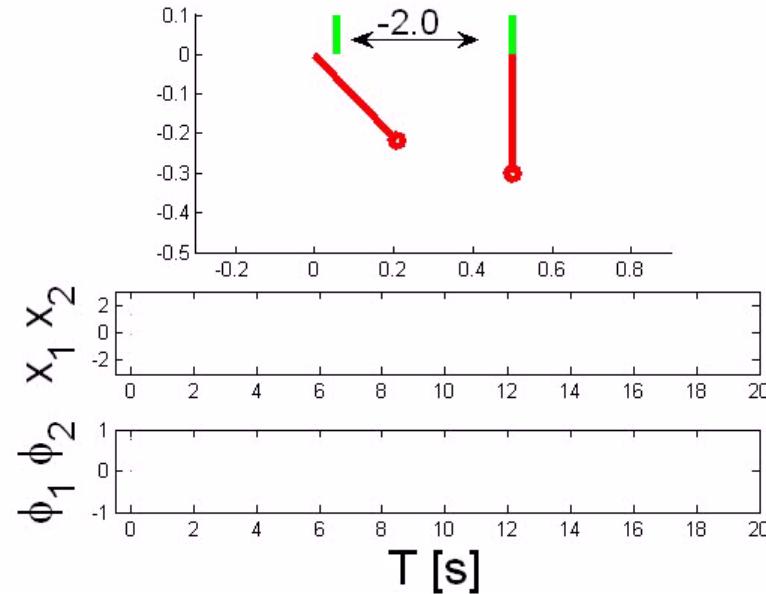
# More legs !



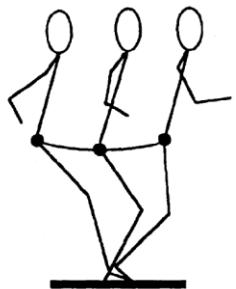
$\phi$ : angle  
 $d$ : damping  
 $g$ : gravity  
 $L$ : length

$\mu$ : amplitude  
 $\nu$ : intrinsic frequency  
 $w_i$ : couplings

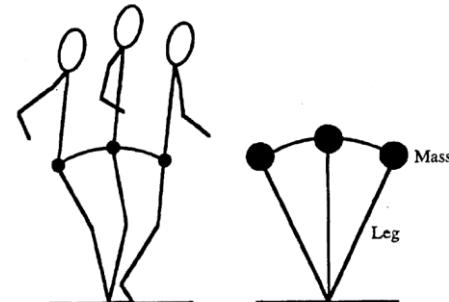
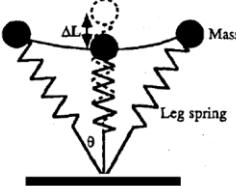
Interlimb coordination  
and gait transition !!



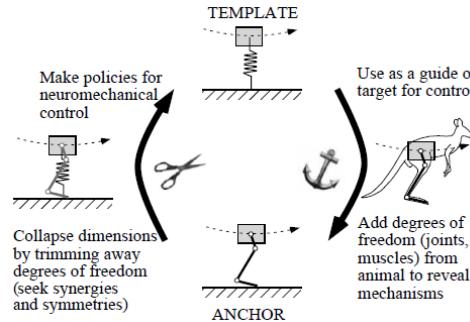
# Mathematical models are very useful to study locomotion



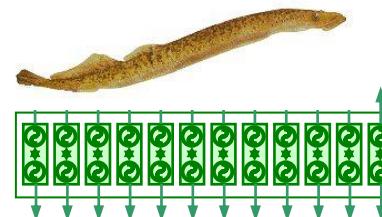
Spring-loaded inverted pendulum (SLIP) (Blickhan,



Inverted pendulums

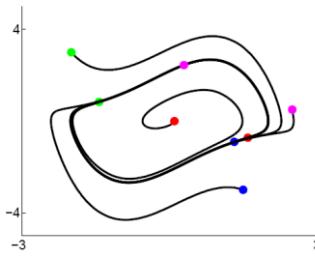


Templates and anchors  
(Koditchev and Full 1999)

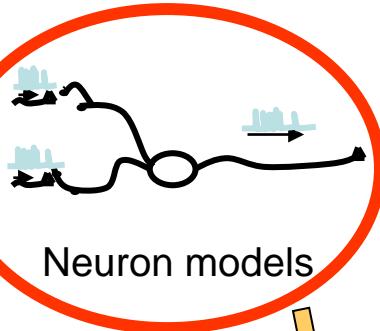
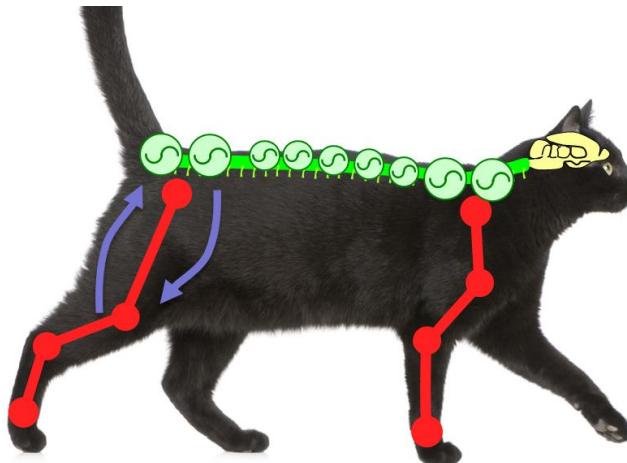


Systems of coupled oscillators,  
Kopell, Ermentrout, ...

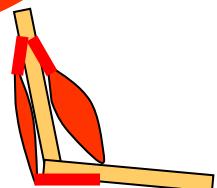
# Contents of lectures



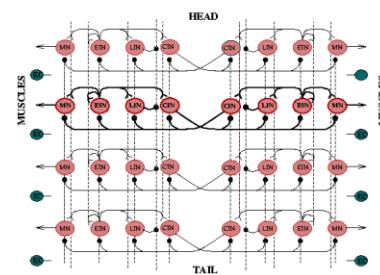
Dynamical systems



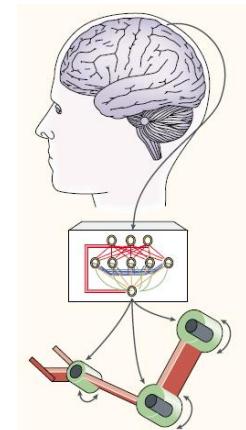
Neuron models



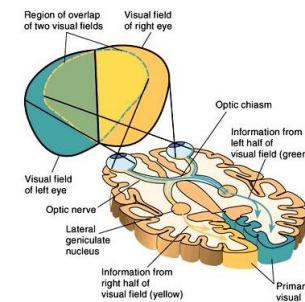
Muscle and  
Biomech. models



Motor system  
models

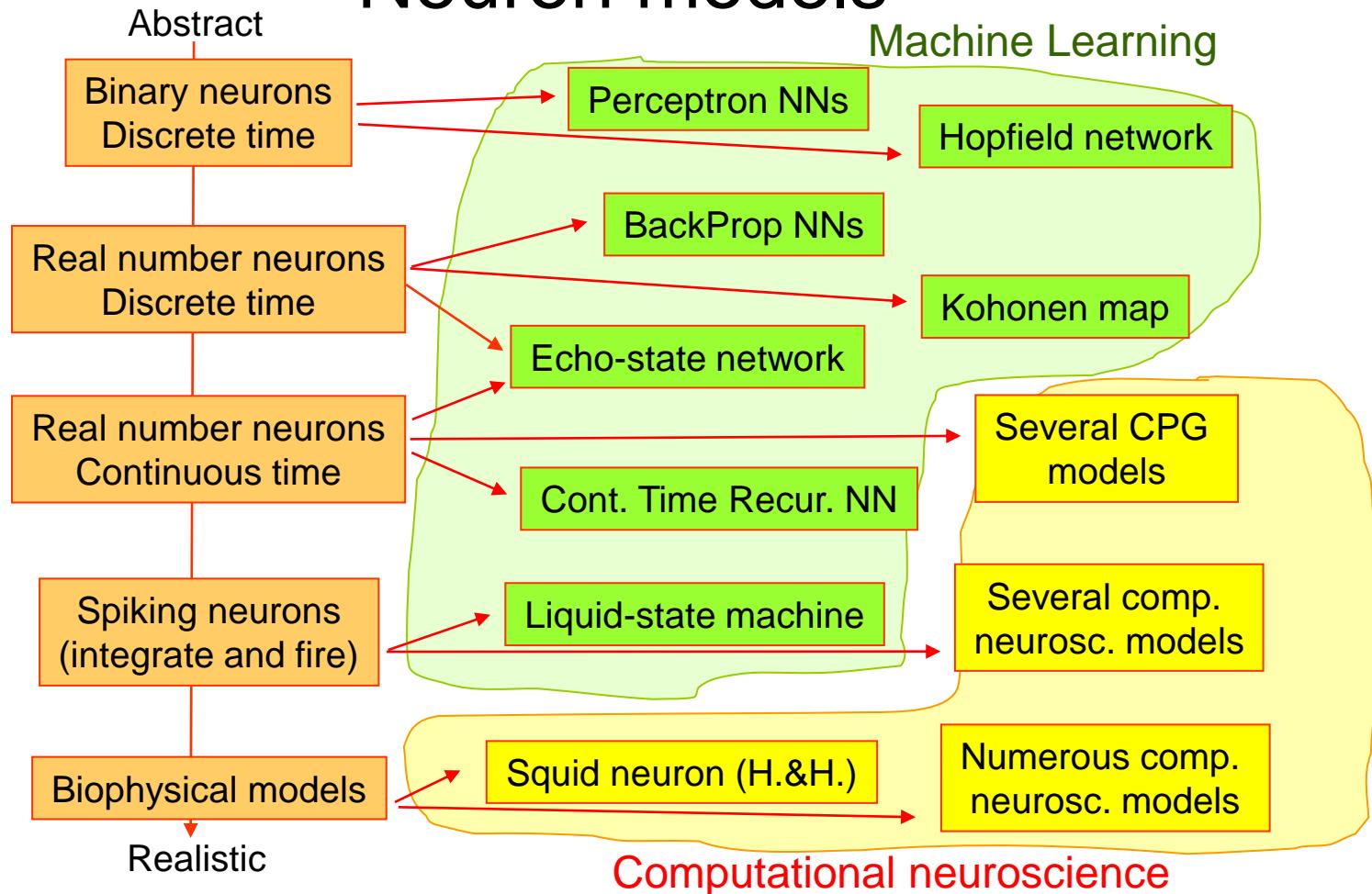


Neuroprosthetics

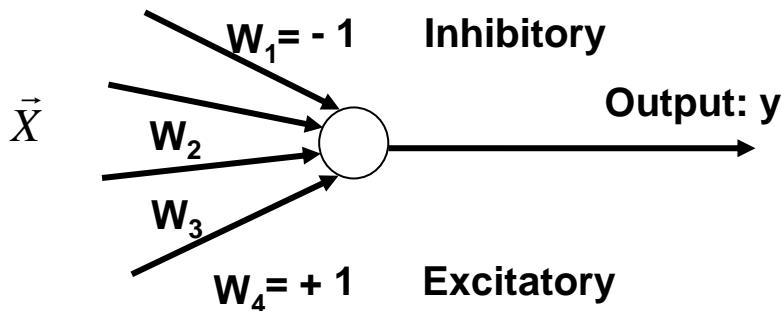


Visual system  
models

# Neuron models



# McCulloch-Pitts neuron



$X$ : *Input vector* from all other neurons

$w_i$ : the *strength/weight* of each synapse

$y$ : *neuron output*

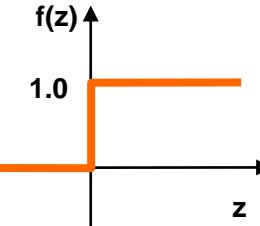
$f(x)$ : *transfer function*

$$y = f\left(\sum_i w_i \cdot x_i\right)$$

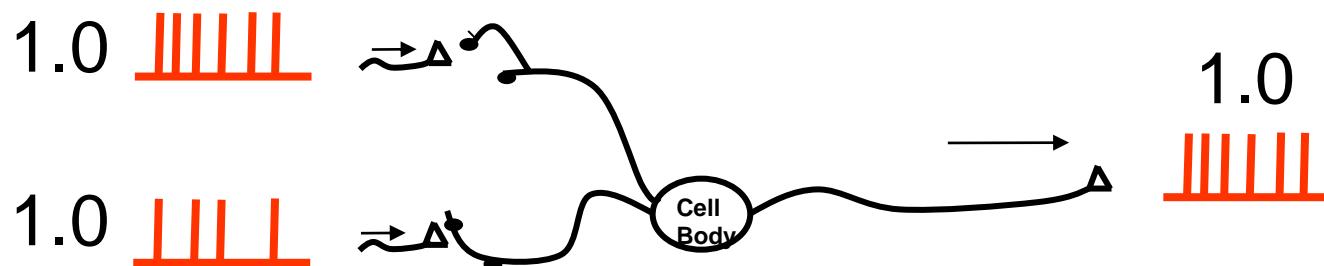
# McCulloch-Pitts neuron (1943)

Transfer function = threshold function :

$$f(z) = \theta(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{if } z < 0 \end{cases} \quad \Rightarrow \quad y = \theta\left(\sum_i w_i \cdot x_i\right)$$



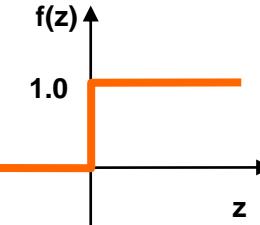
- This type of transfer function depends on **firing rates**, not individual spikes
- Binary neuron: a neuron is either in a high firing rate 1, or a low firing rate 0



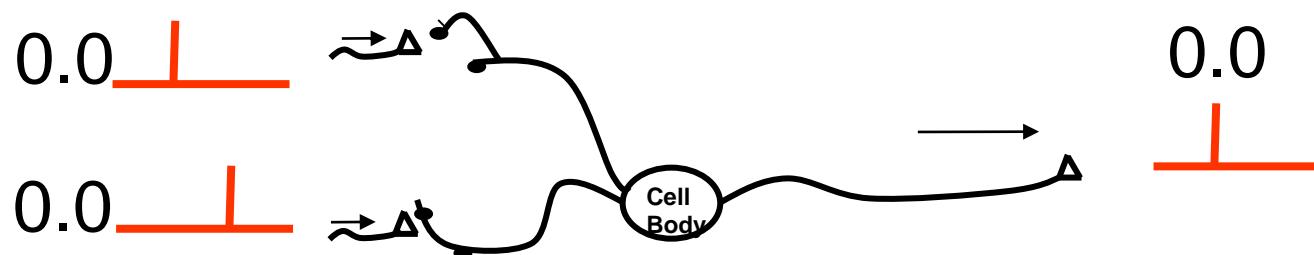
# McCulloch-Pitts neuron (1943)

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- This type of transfer function depends on **firing rates**, not individual spikes
- Binary neuron: a neuron is either in a high firing rate 1, or a low firing rate 0



# Leaky integrator neuron model

Idea: add a state variable  $m_j$  (membrane potential) that is controlled by a differential equation

$$\tau_j \frac{dm_j}{dt} = -m_j + S$$
$$x_j = \frac{1}{1 + e^{-D \cdot (m_j + b)}}$$

$m_j$  : membrane potential

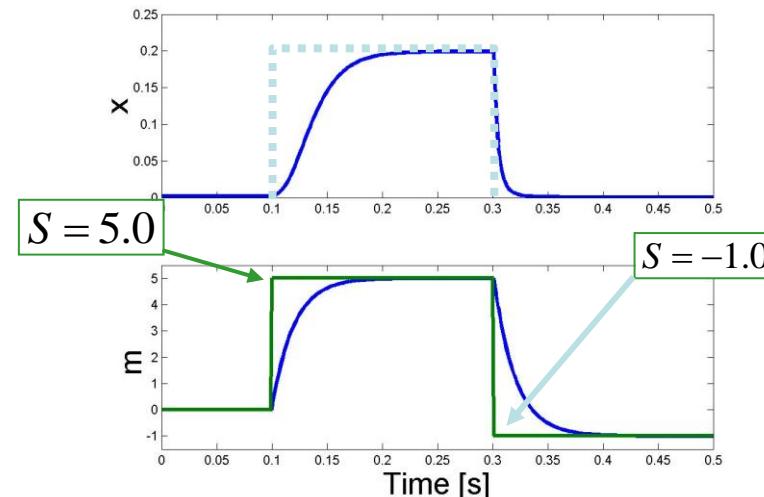
$x_j$  : firing rate

$\tau_j$  : time constant

$b$  : bias

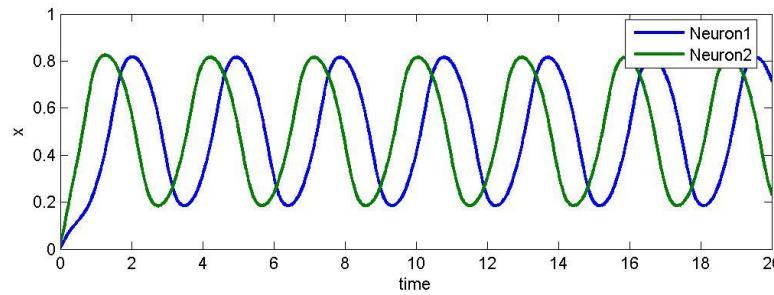
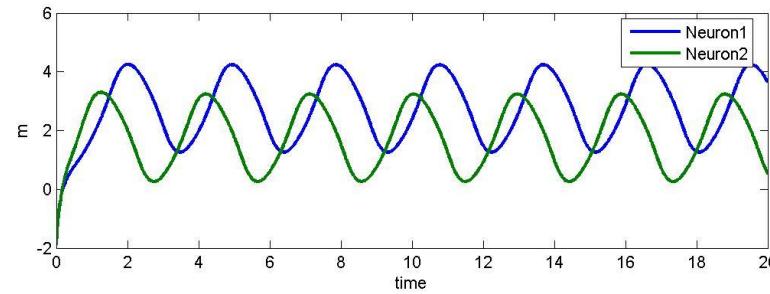
$S$  : input (dendritic sum)

$$S = \sum_i w_{ij} \cdot x_i$$



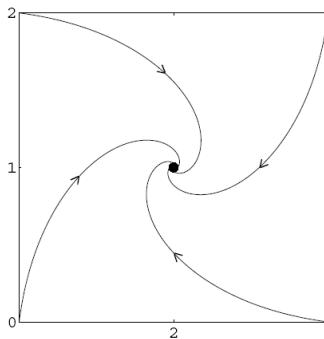
$m_j$  converges to  $S$  with a speed that depends on  $\tau_j$

# Two-neuron oscillator



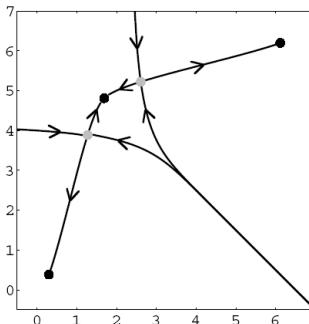
# Two-neuron network: other possible behaviors

One stable point

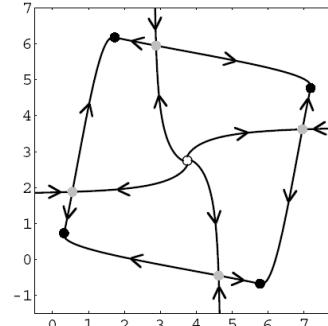


One stable point  
One unstable  
One saddle  
One limit cycle

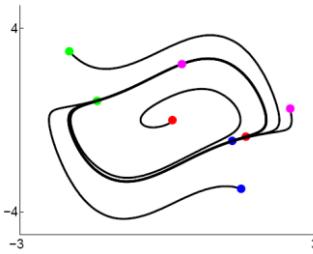
Three stable points  
Two saddles



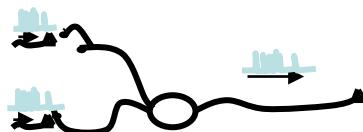
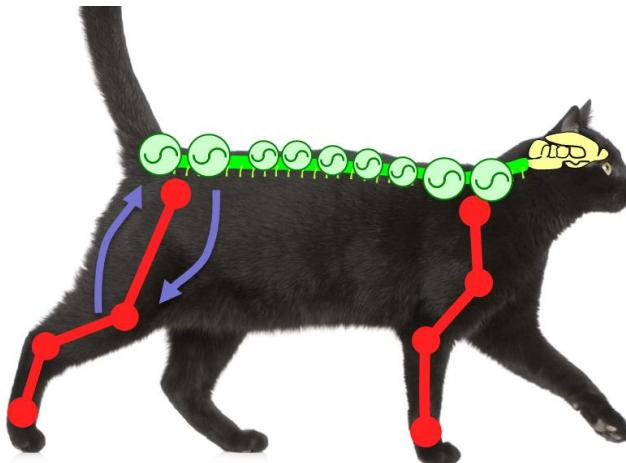
Four stable points  
One unstable  
Four saddles



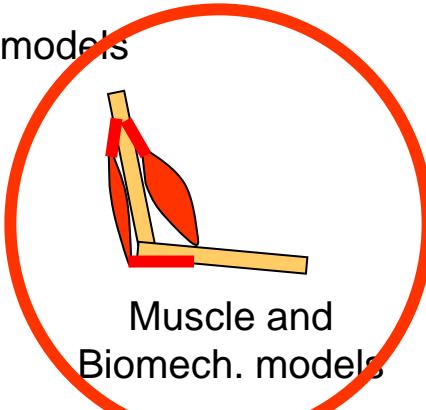
# Contents of lectures



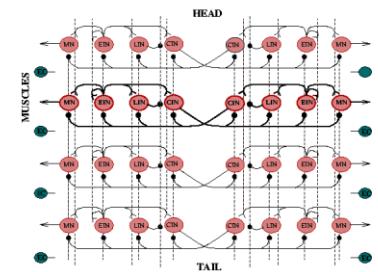
Dynamical systems



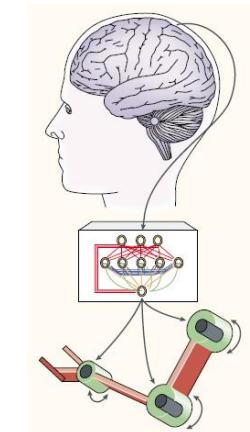
Neuron models



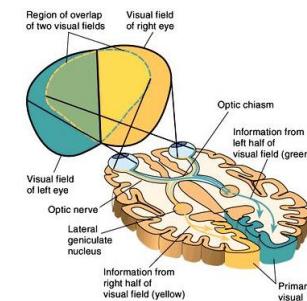
Muscle and  
Biomech. models



Motor system  
models



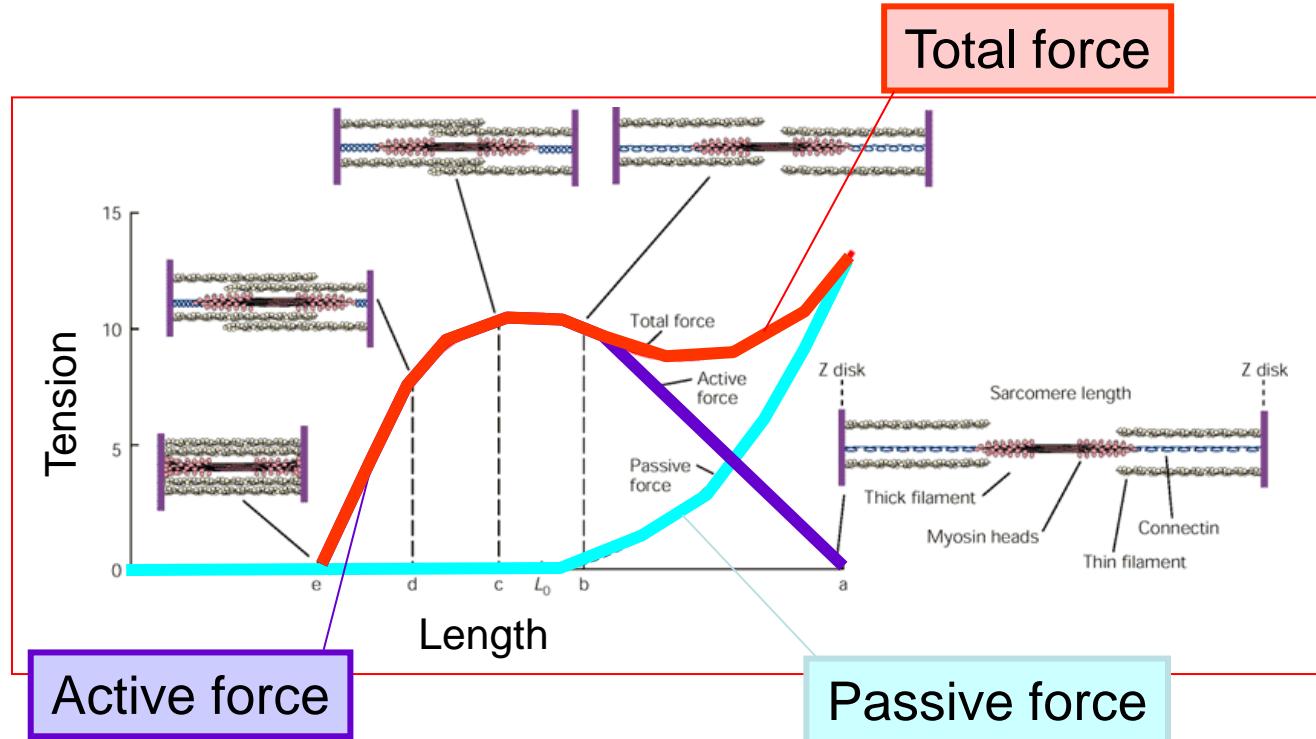
Neuroprosthetics



Visual system  
models

# Muscle models

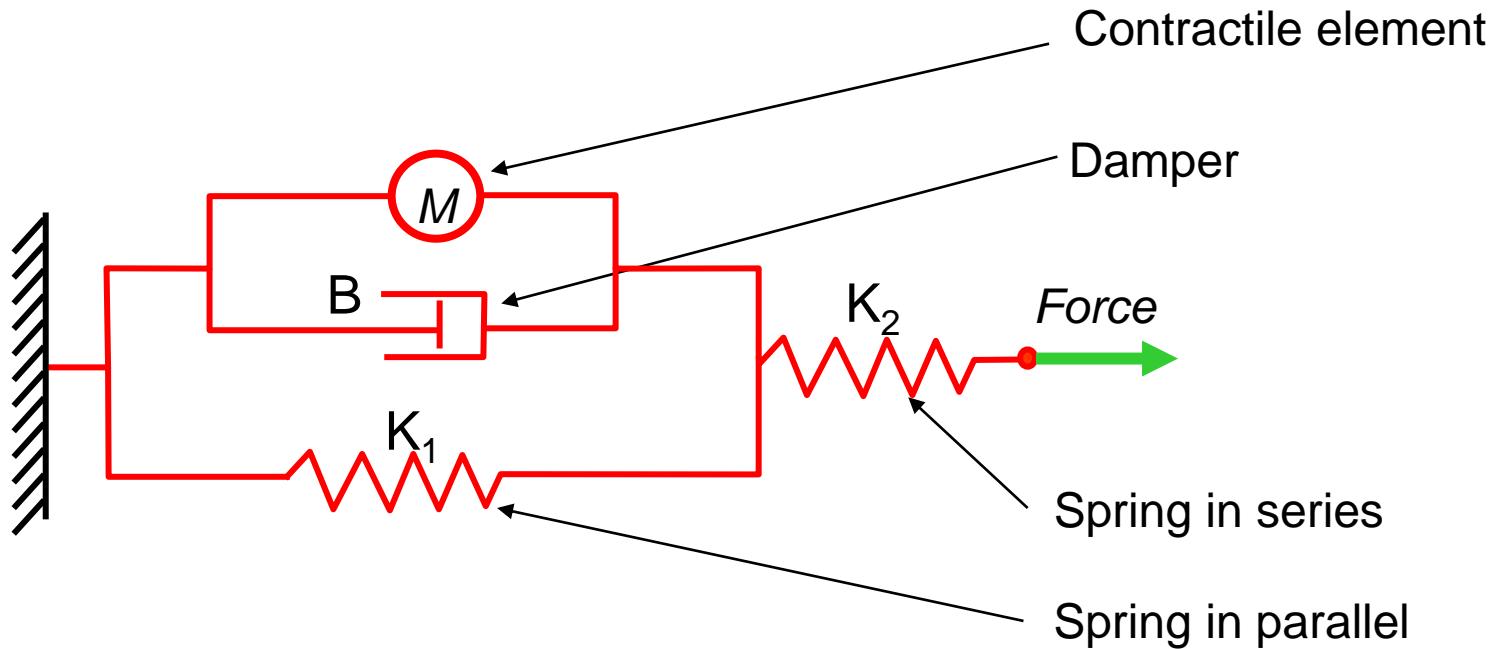
The amount of active contractile force developed during contraction depends on the degree of overlap of thick and thin filaments



# Hill Muscle model

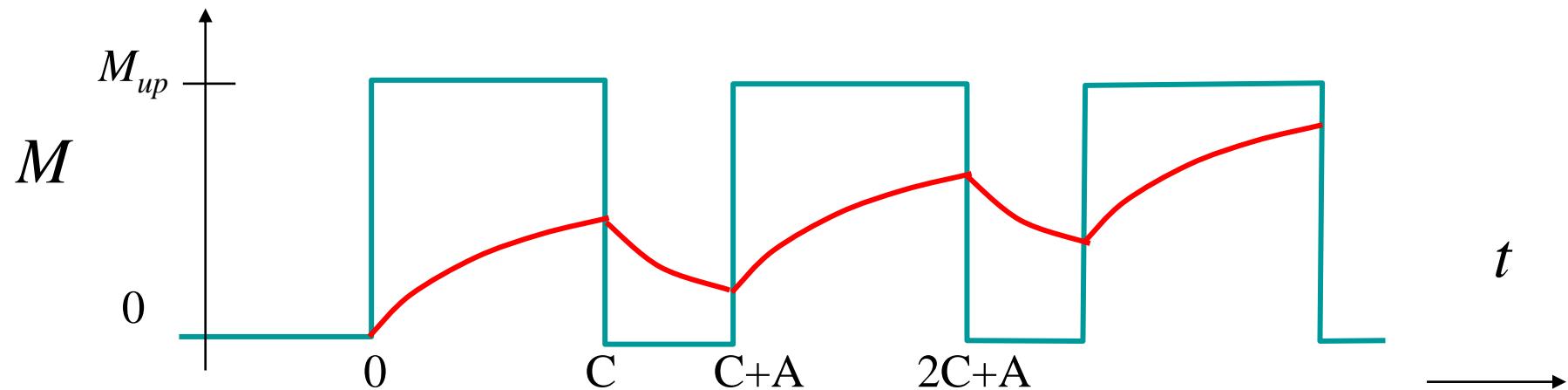
Very influential model made in the 1930's, most modern models are variations of it.

It is made of 4 elements:



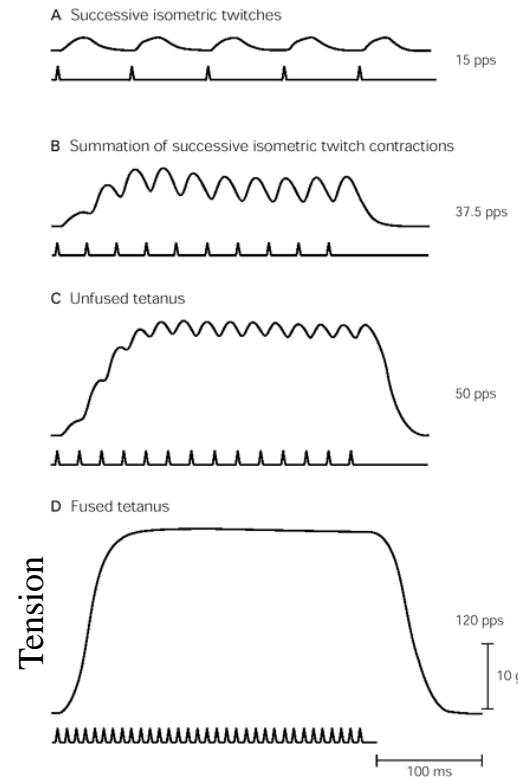
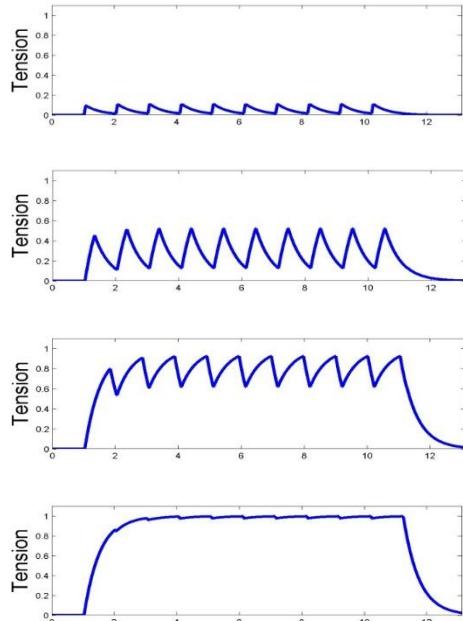
# Hill model: isometric case with pulse stimulation

$$T(t) = (T_0 - M) e^{-\frac{K}{B}(t-t_0)} + M \quad \text{where} \quad M = \begin{cases} 0 \\ M_{up} \end{cases} \text{ depending on } t_0$$



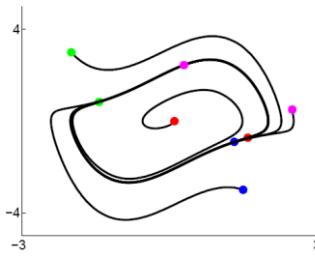
# Hill model: isometric case with pulse stimulation

This is a good approximation of how tension builds up in a muscle



Elect. stimulation

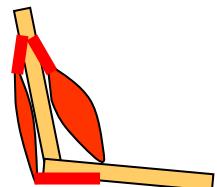
# Contents of lectures



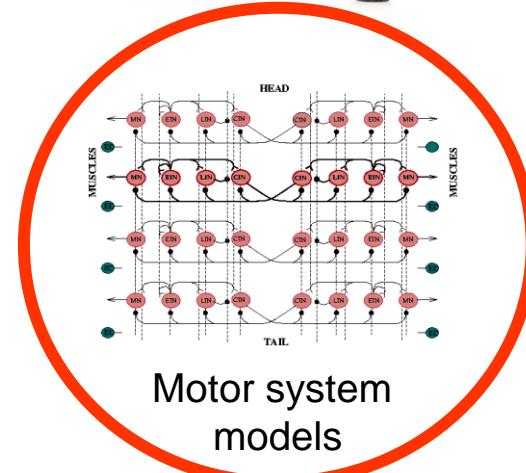
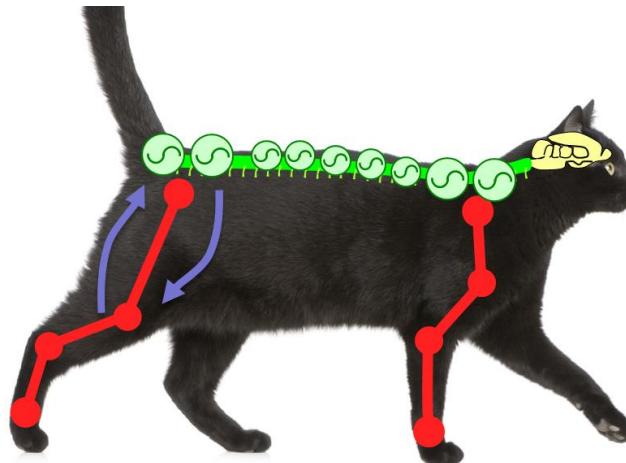
Dynamical systems



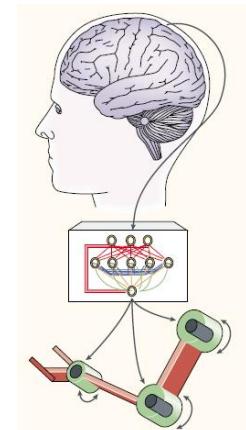
Neuron models



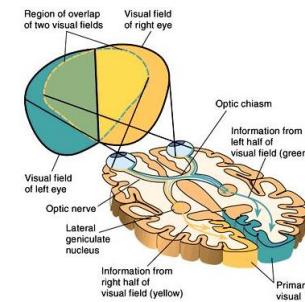
Muscle and  
Biomech. models



Motor system  
models



Neuroprosthetics



Visual system  
models

# Models of locomotion control

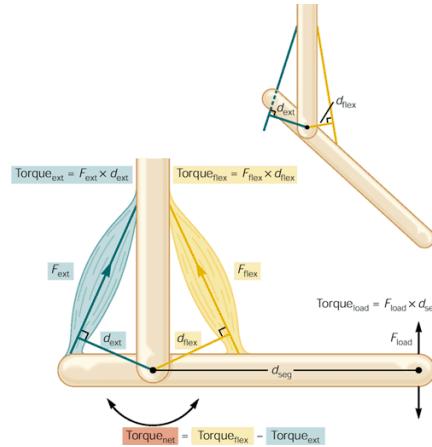
Topics:

- Locomotion control in animals
- Locomotion of the lamprey
- Different models of the lamprey locomotor system
- Neuromechanical simulation of the salamander
- Applications to robotics

# Biomechanics of animal Locomotion

General principles:

1. To **rhythmically apply forces** to the environment,
2. Use of **antagonist muscles** → creation of torques + modification of the stiffness of a joint
3. **Storage of mechanical energy** (spring properties of muscles and tendons)
4. **Multiple degrees of freedom**

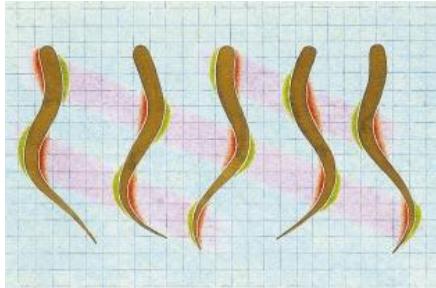


G.E. Loeb, C. Ghez (2000) The Motor Unit and Muscle Action. In: *Principles of Neural Science*. 4th edition. Edited by E.R. Kandel, J.H. Schwartz and T.M. Jessell. Appleton & Lange, New York. pp. 675-694.

# Animal Locomotion (ct'd)

Generation of forces:

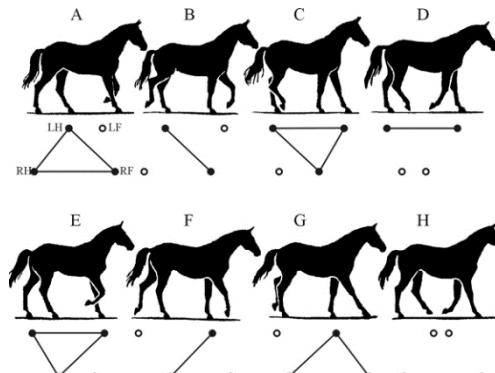
- Animals use the **principles of action-reaction**
- Key feature: **creation of asymmetries in the external forces due to the environment** (little resistance in the direction of locomotion compared to the other directions)
- Examples: elongated form of the body, scales on snake skin, legs (transition between swing and stance)



Asymmetric drag



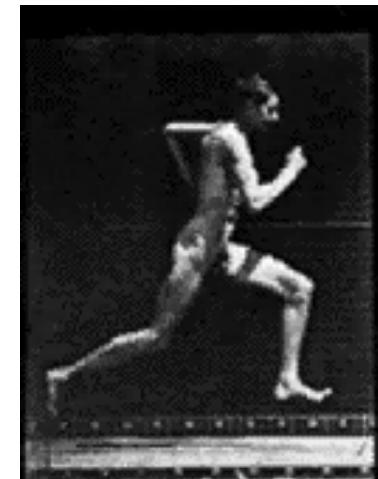
Scales:  
Asymmetric friction



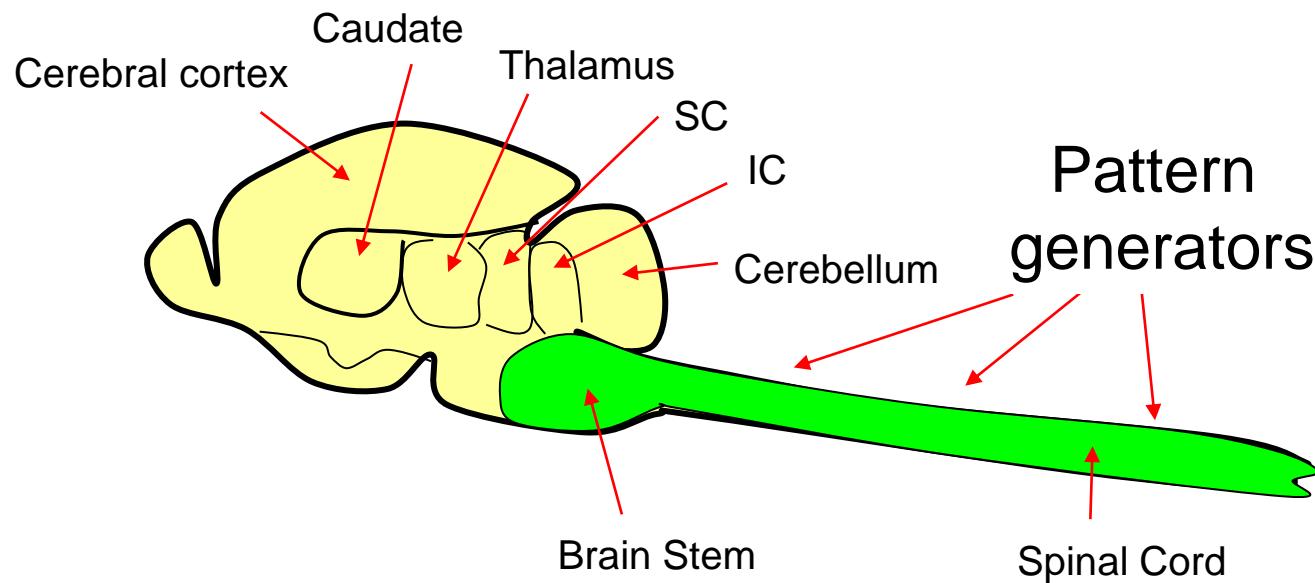
Swing-stance alternation

# Animal locomotion

Large diversity of different types of locomotion: swimming, crawling, walking, hoping, burrowing, flying,...  
but **all use the same principles.**

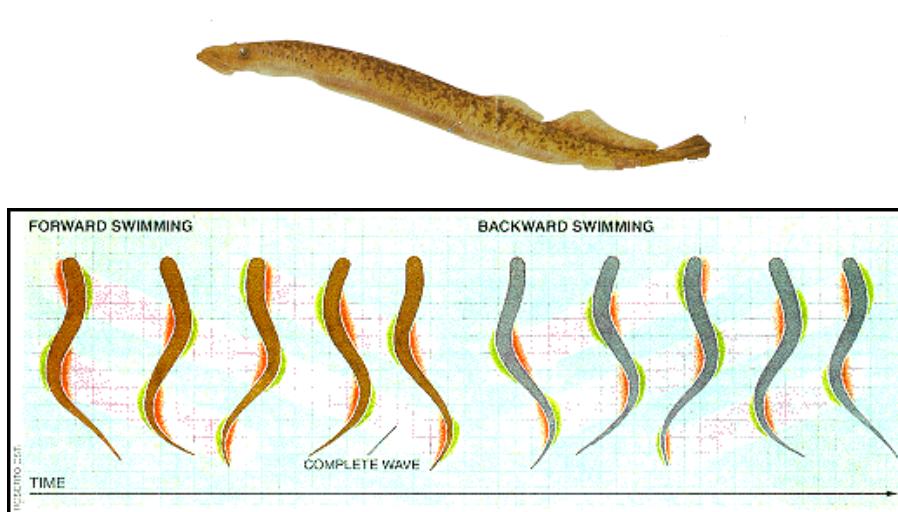


# Neural control of movement



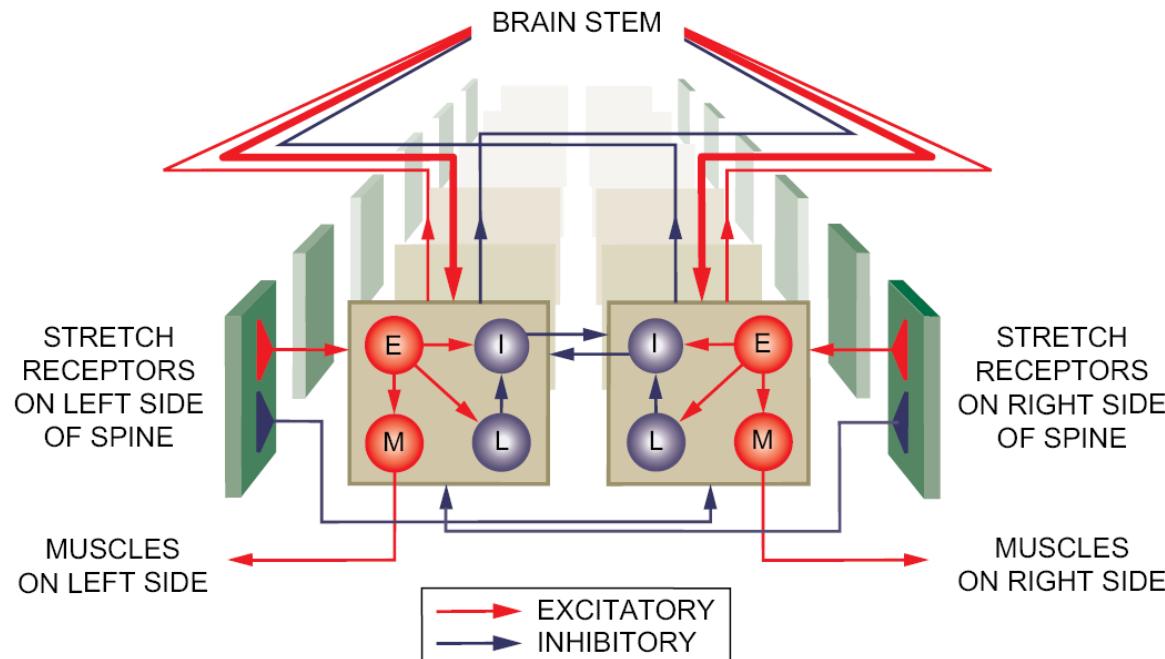
# Locomotion of the lamprey

- Lamprey: one of the most primitive vertebrate
- Anguilliform swimming
- Has been studied in detail by neurobiologists
- Believed to be very similar to the ancestor of all vertebrates



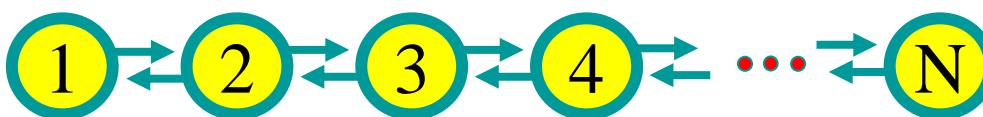
# The lamprey swimming network

Conceptual model by Sten Grillner (Grillner et al, Sci. Am. 1996)



# Lamprey: Analytical analysis of chain of oscillators

Lamprey CPG modeled as a chain of oscillators with nearest neighbor coupling:



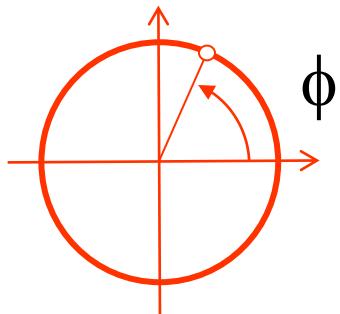
$$\frac{d\phi_i}{dt} = \omega_i + h(\phi_{i-1}, \phi_i, \phi_{i+1})$$

$\phi_i$  : Phase of oscillator

$\omega_i$  : Intrinsic frequency of oscillator

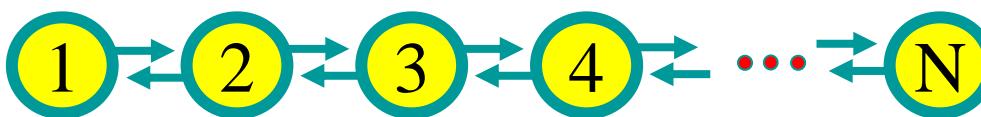
$h(\phi_{i-1}, \phi_i, \phi_{i+1})$  : Coupling function

$x_i = A_i \cos(\phi_i)$  : Oscillating output



# Lamprey: Analytical analysis of chain of oscillators

Lamprey CPG modeled as a chain of oscillators with nearest neighbor coupling:



Assumptions: nearest neighbor coupling, same coupling constants  $a$ , symmetric coupling

$$\frac{d\phi_1}{dt} = \omega_1 + a \sin(\phi_2 - \phi_1)$$

$$\frac{d\phi_i}{dt} = \omega_i + a \sin(\phi_{i+1} - \phi_i) + a \sin(\phi_{i-1} - \phi_i)$$

$$\frac{d\phi_N}{dt} = \omega_N + a \sin(\phi_{N-1} - \phi_N)$$

# Lamprey: Analytical analysis of chain of oscillators

Introducing the phase differences  $\varphi_i = \phi_i - \phi_{i+1}$

This can be expressed in matrix form:

$$\frac{d\vec{\varphi}}{dt} = \vec{\Omega} + \mathbf{A} \vec{S}$$

$$\vec{\varphi} = \begin{bmatrix} \varphi_1 \\ \dots \\ \varphi_{N-1} \end{bmatrix}, \quad \vec{S} = \begin{bmatrix} \sin \varphi_1 \\ \dots \\ \sin \varphi_{N-1} \end{bmatrix}, \quad \vec{\Omega} = \begin{bmatrix} \omega_1 - \omega_2 \\ \dots \\ \omega_{N-1} - \omega_N \end{bmatrix}, \quad \mathbf{A} = \begin{bmatrix} -2 & 1 & & & \\ 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & 1 & -2 & 1 \\ & & & 1 & -2 \end{bmatrix}$$

# Lamprey: Analytical analysis of chain of oscillators

Does the chain phase-lock? We look at

$$\frac{d\vec{\phi}}{dt} = \vec{\Omega} + \mathbf{A}\vec{S} = 0$$

Solution:

$$\vec{\tilde{\phi}} \quad \text{such that} \quad \vec{S} = -\mathbf{A}^{-1}\vec{\Omega}$$

No solution exists if any of the component of  $\mathbf{A}^{-1}\vec{\Omega}$  are larger than unity in absolute value (i.e. the system would drift).

Good news: the matrix  $\mathbf{A}$  can be inverted in close form.

# Lamprey: Analytical analysis of chain of oscillators

Example with 6 oscillators, and constant frequency difference,

$$\omega_1 - \omega_2 = \omega_2 - \omega_3 = \dots = e :$$

$$A^{-1} = -\frac{1}{6a} \begin{bmatrix} 5 & 4 & 3 & 2 & 1 \\ 4 & 8 & 6 & 4 & 2 \\ 3 & 6 & 9 & 6 & 3 \\ 2 & 4 & 6 & 8 & 4 \\ 1 & 2 & 3 & 4 & 5 \end{bmatrix} \quad \vec{\Omega} = \begin{bmatrix} e \\ \dots \\ e \end{bmatrix}$$

Therefore:

$$\begin{bmatrix} \sin \varphi_1 \\ \sin \varphi_2 \\ \sin \varphi_3 \\ \sin \varphi_4 \\ \sin \varphi_5 \end{bmatrix} = \frac{e}{2a} \begin{bmatrix} 5 \\ 8 \\ 9 \\ 8 \\ 5 \end{bmatrix}$$

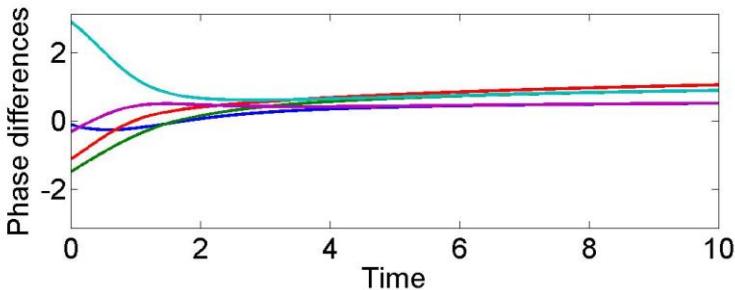
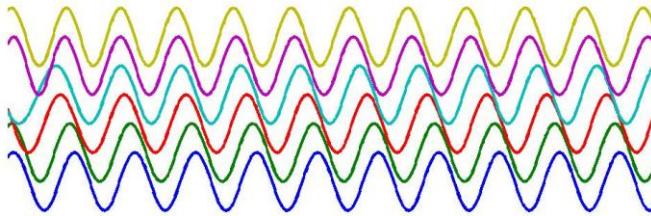
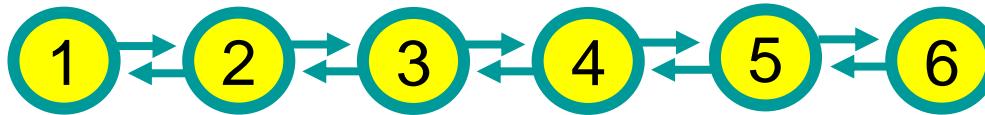
This system will phase lock if:

$$\left| \frac{e}{a} \right| \leq \frac{2}{9} \quad \left| \frac{e}{a} \right| \leq \frac{8}{N^2} \quad N \text{ even}$$

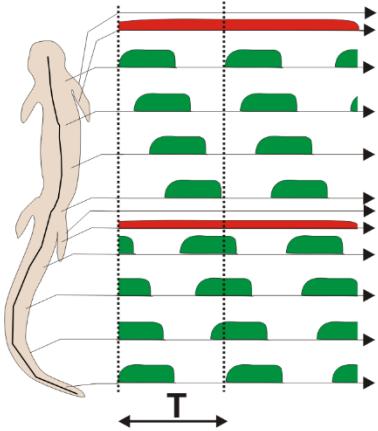
$$\left| \frac{e}{a} \right| \leq \frac{8}{N^2 - 1} \quad N \text{ odd}$$

# Lamprey: Analytical analysis of chain of oscillators

Example with 6 oscillators

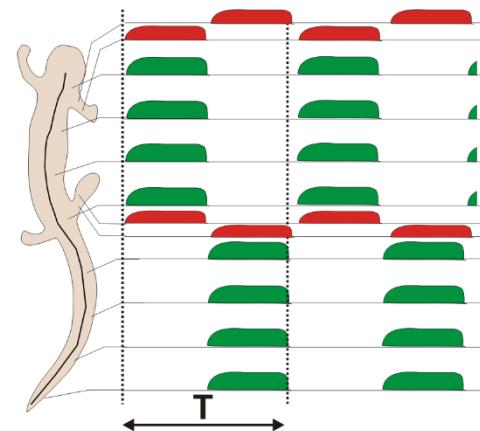


# Bimodal locomotion of salamander (cartoon)



## Swimming:

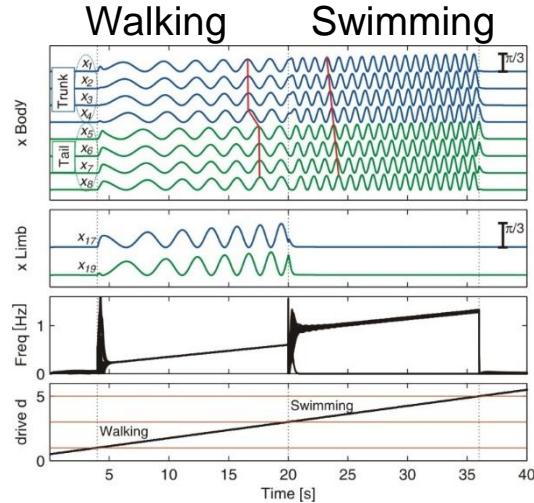
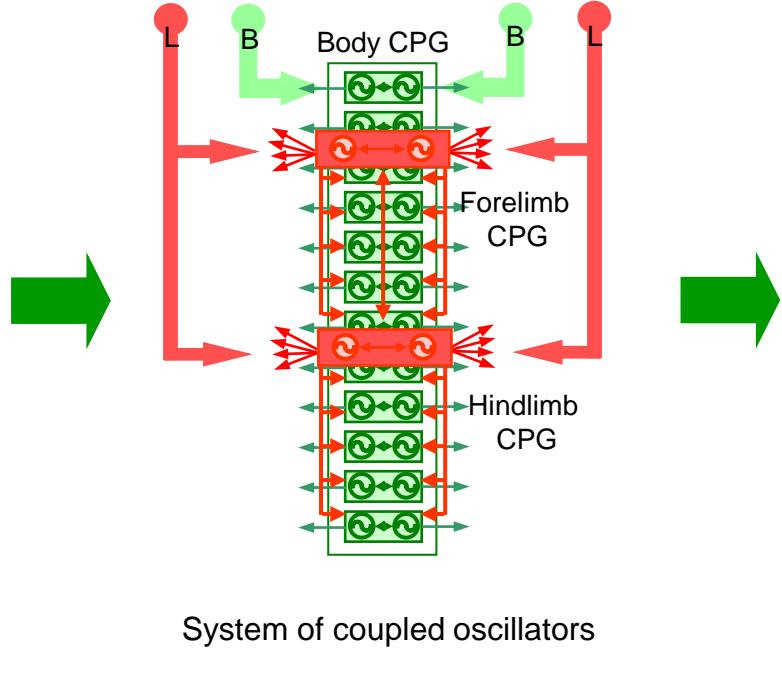
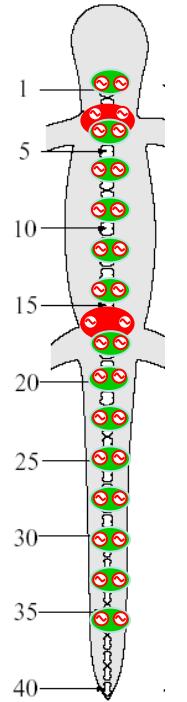
Traveling wave in axial muscles  
Wavelength  $\approx$  body length  
Limb retractor/protactor are tonic  
Short cycle durations



## Walking:

Standing wave  
Limb retractor/protactor are phasic  
Longer cycle durations

# A mathematical model to study the transition from swimming to walking



**Gait transition** due to an increase of the descending drive

# 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:

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

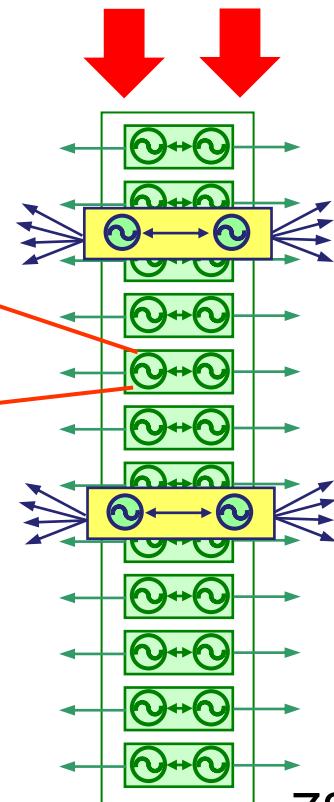
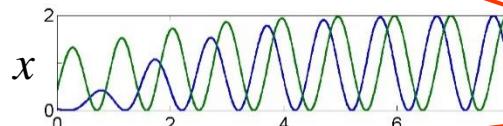
Output:

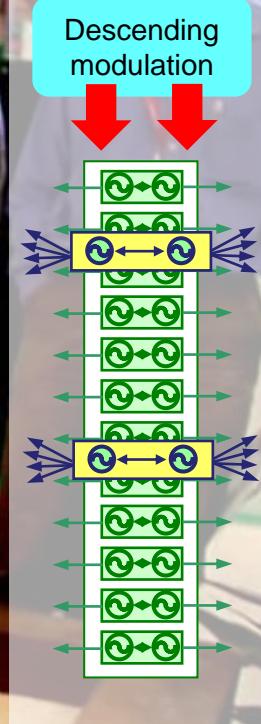
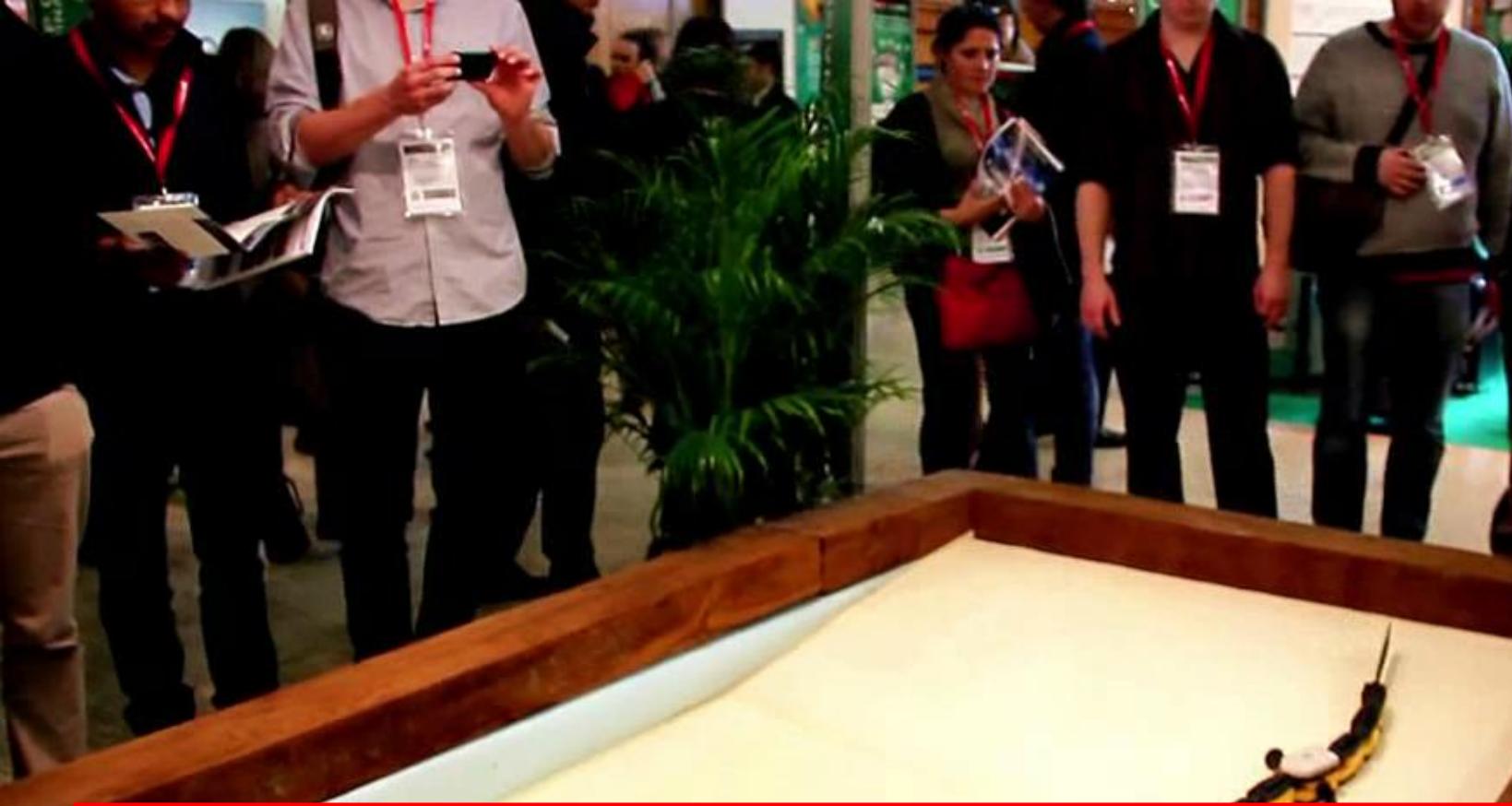
$$x_i = r_i (1 + \cos(\theta_i))$$

Setpoints:

$$\varphi_i = x_i - x_{N+i} \quad \text{for the axial motors}$$

$$\varphi_i = f(\theta_i) \quad \text{for the (rotation and) limb motors}$$





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

# Senses that affect locomotion

All sensing modalities affect locomotion:

- Tactile
- Proprioception
- Vestibular system (inner ear)
- Vision
- Audition
- Smell
- ...

As we will see next, many of these interactions take place in the spinal cord, others involve higher parts of the brain.

Tight integration: **CPG and reflex pathways often share the same interneurons.** This explains why **reflexes are phase-dependent.**

# Sensory information influencing locomotion in mammals

- **Muscle spindles**: provide information about **length**, and changes of lengths of muscles
- **Golgi tendon organs**: provide information about (internal) **force** (i.e. tension) in muscle
- **Cutaneous receptors**: provide information about **contact forces**

- **Vestibular system**: provides the sense of balance, rotational and linear **accelerations**
- **Visual system**: very rich information about visual scene, **optical flow**, colors, edges, patterns, etc.

Spinal

Supraspinal

# Examples of sensory responses

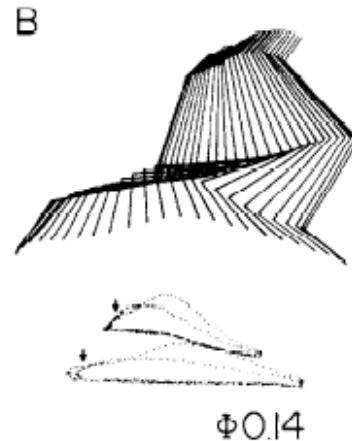
We will see next that these types of sensory information are used to implement multiple **sensory responses**, for instance:

- Stumbling correction reflex
- Leg extension reflex
- Withdrawal reflex (cross extensor reflex)
- Vestibular oculo reflex
- Posture control
- ...

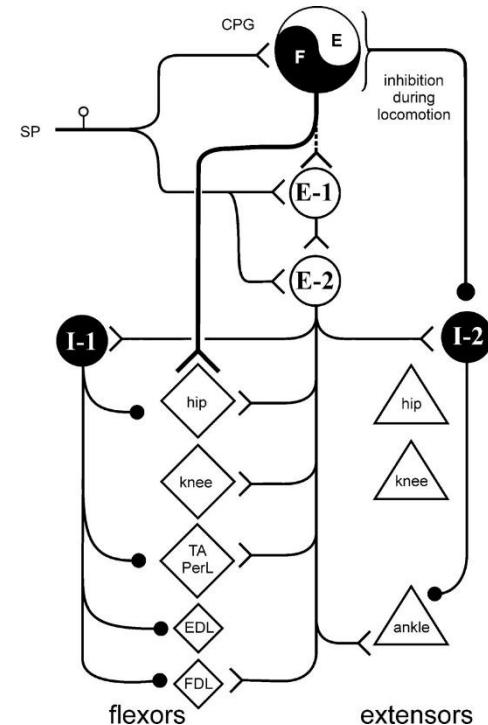
# Stumbling correction reflex

Stumbling correction reflex:

- **Rapid lifting of leg when hitting something during swing**
- Useful to **avoid stumbling and falling**
- **Phase-dependent:** active only during swing, not during stance
- Note: many (most?) reflexes are phase-dependent. Reflexes share interneurons with CPG circuits. CPG activity can therefore gate/modulate reflexes

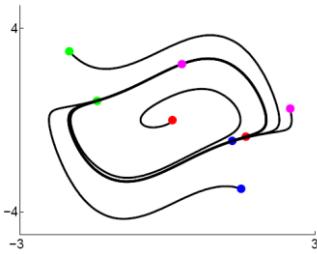


Stumbling corrective reaction: a phase-dependent compensatory reaction during locomotion. H. Forssberg. Journal of Neurophysiology Jul 1979, 42 (4) 936-953;



Jorge Quevedo et al. J Neurophysiol 2005;94:2053-2062

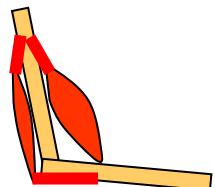
# Contents of lectures



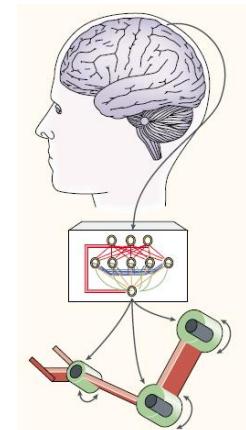
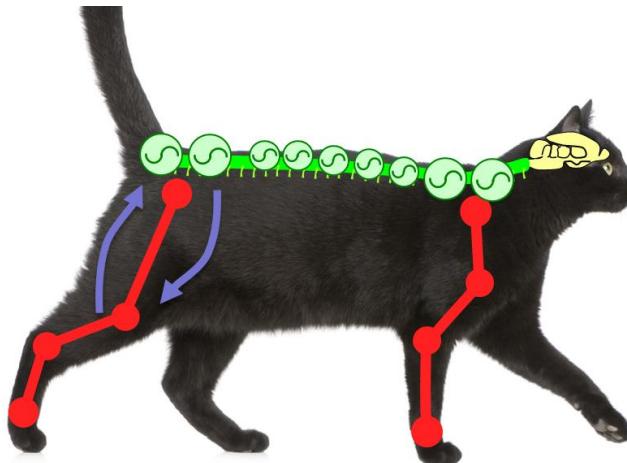
Dynamical systems



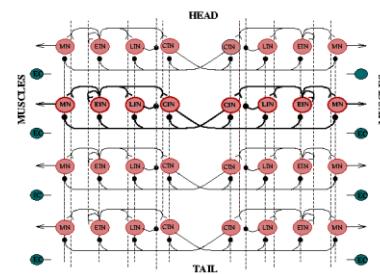
Neuron models



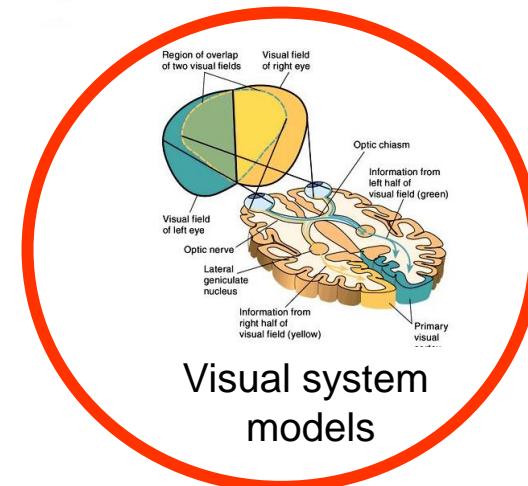
Muscle and  
Biomech. models



Neuroprosthetics



Motor system  
models

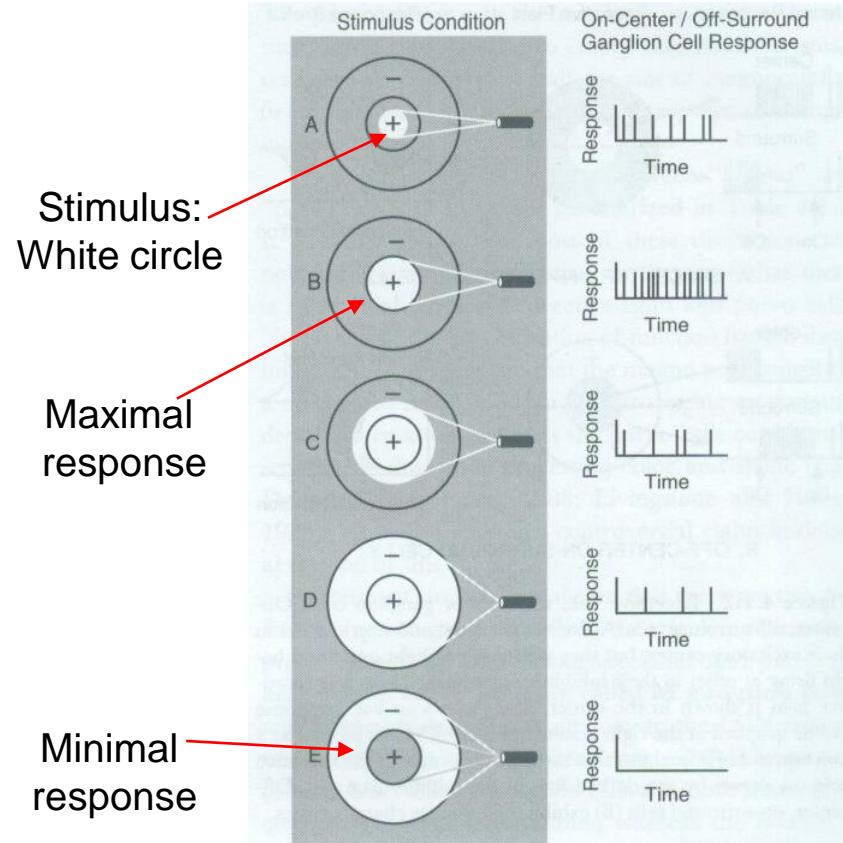


Visual system  
models

# Feature detection in the retina: Center-Surround response

In addition to their receptive fields, neurons are often **sensitive to special features**. E.g. the **center-surround response in retinal ganglion cells**

There are two types of ganglion cells:  
**On-center**: maximally active with light on the center and dark on the surround  
**Off-center**: opposite response



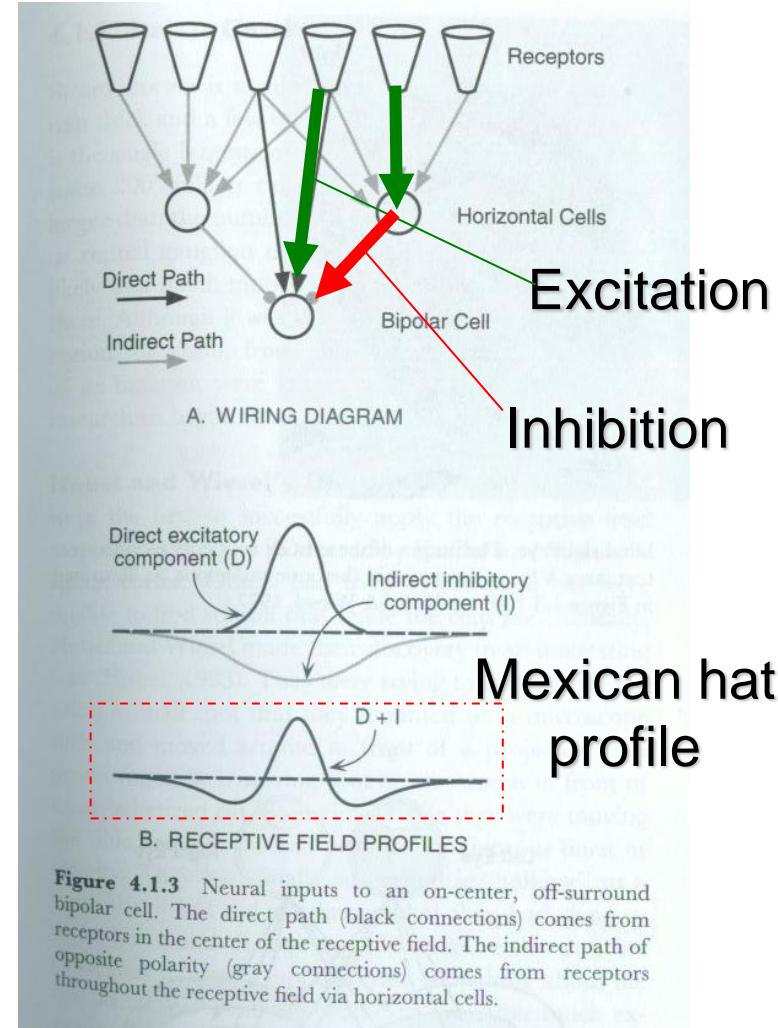
**Figure 4.1.1** Responses of on-center, off-surround ganglion cells. As the size of a spot of light increases, the response of an on-center, off-surround ganglion cell first increases (A), reaching a maximum when it covers just the excitatory center (B), and then decreases as the spot falls on the inhibitory surround (C and D). Minimum response (E) occurs when light falls only on the inhibitory surround.

# Center-surround

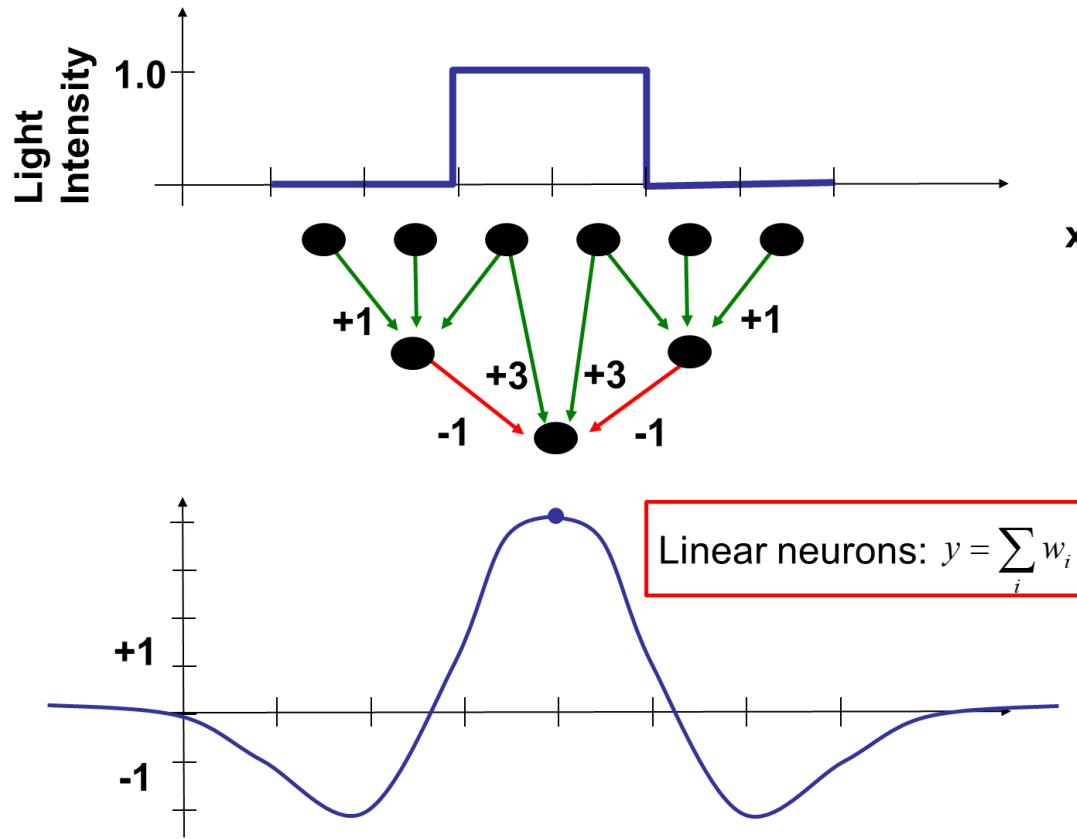
The center-surround response is generated within the retina by excitatory and inhibitory neurons.

This generates a response that corresponds to a ***mexican-hat*** profile, with **excitation in the center and inhibition on the surround**

The underlying network is a **feedforward network**

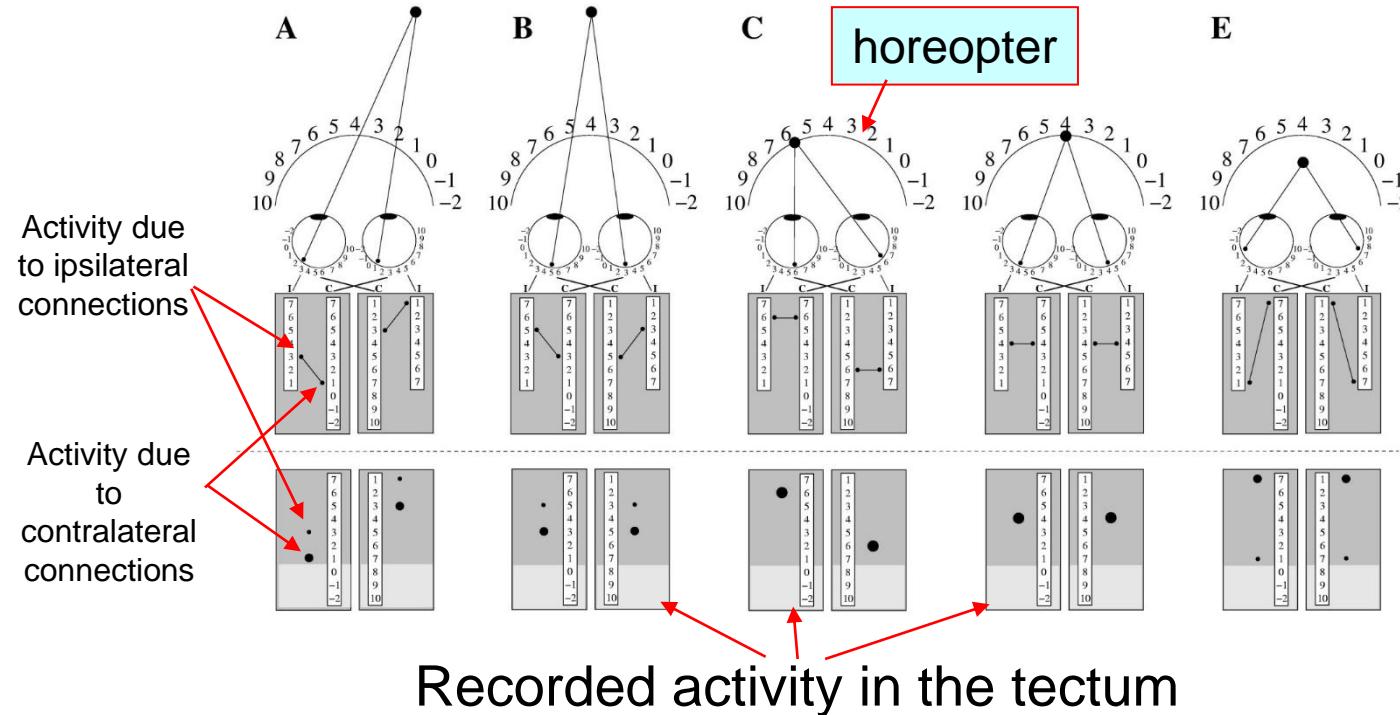


# Models of the center-surround response

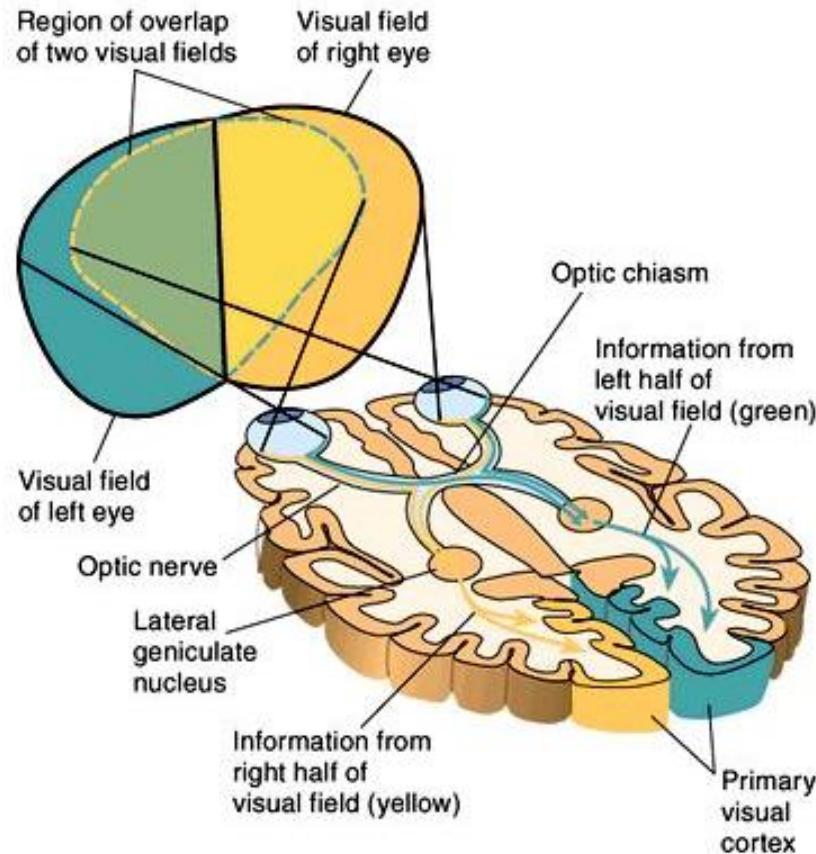


# Models of salamander optic tectum

Comparisons between left and right maps in the tectum can be used to compute a target's **angular position and distance**:



# Primary Visual Pathway in primates

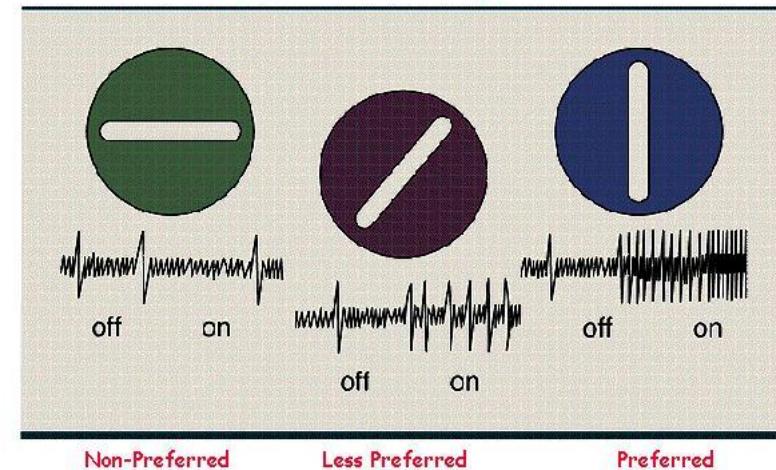


# Visual cortex: Neuronal Tuning

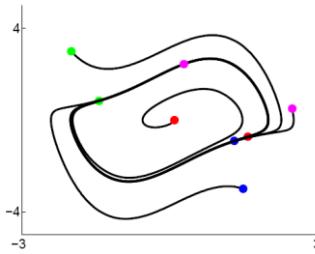
In addition to responding only to stimuli in a circumscribed region of the visual space, **neurons in the visual cortex typically only respond to some specific classes of stimuli** (e.g., of given color, orientation, spatial frequency).

A neuron exhibits a ***tuning curve*** that describes the decrease of its response to stimuli increasingly different from the preferred stimulus.

## Spatial Orientation Selectivity (Tuning) of Simple Cells



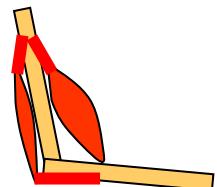
# Contents of lectures



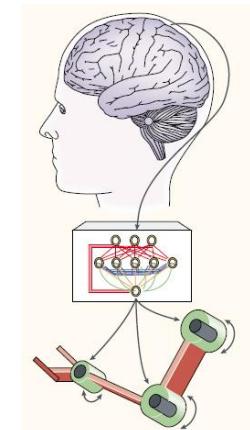
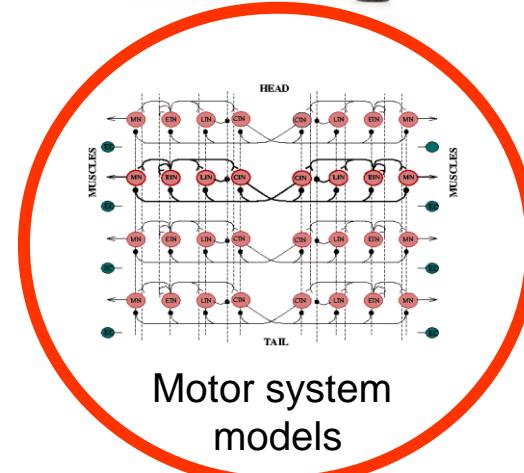
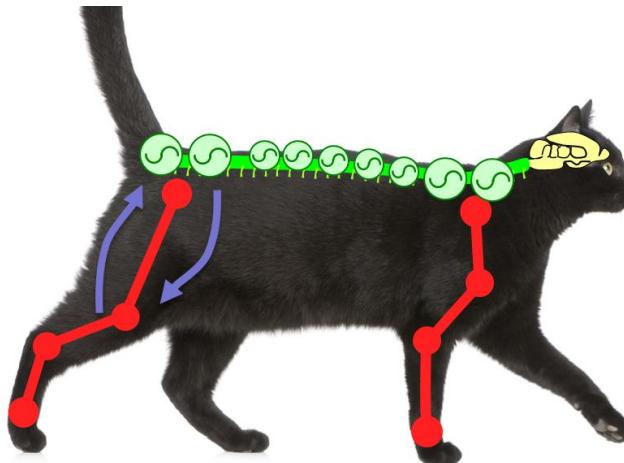
Dynamical systems



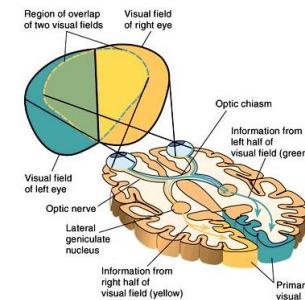
Neuron models



Muscle and  
Biomech. models



Neuroprosthetics



Visual system  
models

# Models of arm movements

Topics:

- Invariants of movements
- Different school of thoughts:
  - Internal Models
  - Equilibrium Point Trajectory
  - Muscle synergies

# Invariants of movements

Despite the large variety of movements that humans can make, most of our (typical) movements show several invariants.

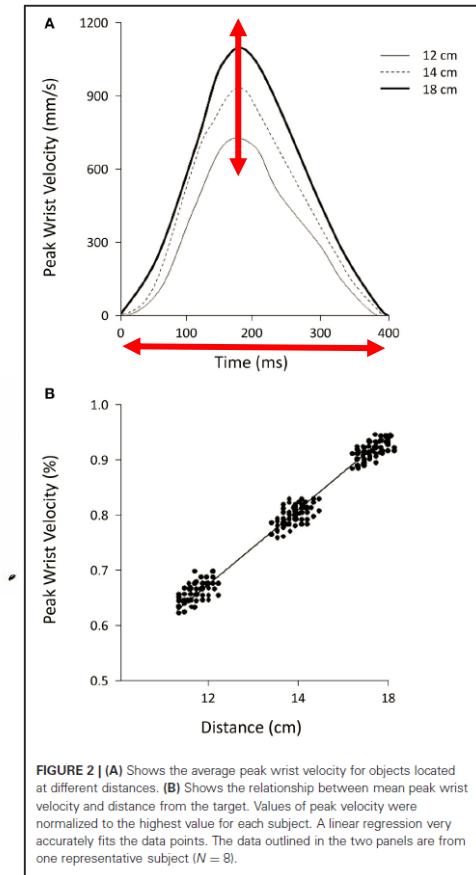
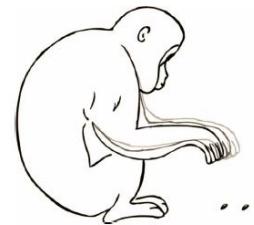
- Bell-Shaped Velocity Profile and Straight Trajectory
- Isochrony principle
- Fitts's Law
- Two Third Power Law
- Minimum Jerk hypothesis

# Isochrony principle in reaching movements

## Isochrony principle:

Spontaneous tendency to increase the velocity of movements depending on the distance in order to keep **execution time approximately constant**.

In other words: the velocity of voluntary movements increases proportionally with their linear extension

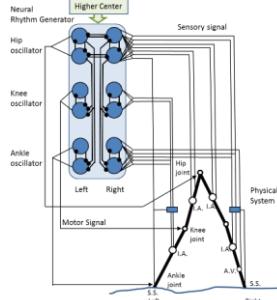


Viviani, P., and McCollum, G. (1983). The relation between linear extent and velocity in drawing movements.

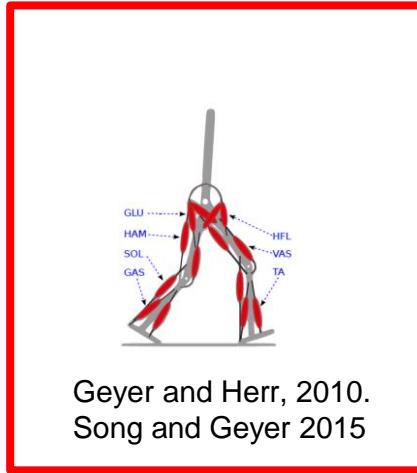
Sartori, L., Camperio-Ciani, A., Bulgheroni, M., & Castiello, U. (2013). Reach-to-grasp movements in *Macaca fascicularis* monkeys: the Isochrony Principle at work. *Frontiers in psychology*, 4.

FIGURE 2 | (A) Shows the average peak wrist velocity for objects located at different distances. (B) Shows the relationship between mean peak wrist velocity and distance from the target. Values of peak velocity were normalized to the highest value for each subject. A linear regression very accurately fits the data points. The data outlined in the two panels are from one representative subject ( $N = 8$ ).

# Neuromechanical models of human locomotion



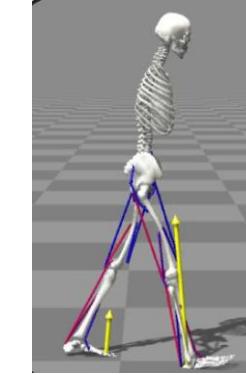
Taga 1991, 1995



Geyer and Herr, 2010.  
Song and Geyer 2015



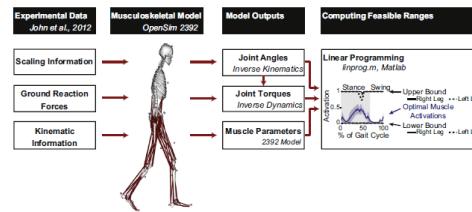
Lee et al 2019



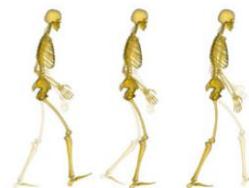
Ong et al 2019



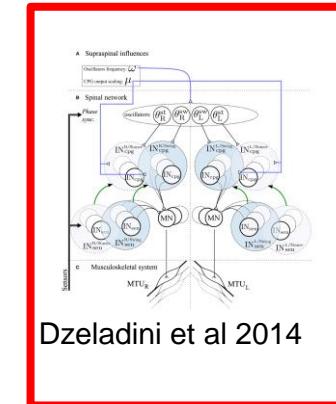
Y. Nakamura lab  
(Sreenivasa et al 2012)



L. Ting lab (Simpson et al 2015)



Falisse et al 2019



Dzeladini et al 2014

# Geyer and Herr's sensory-driven model

## Sensory-driven model

+

7 muscles per leg

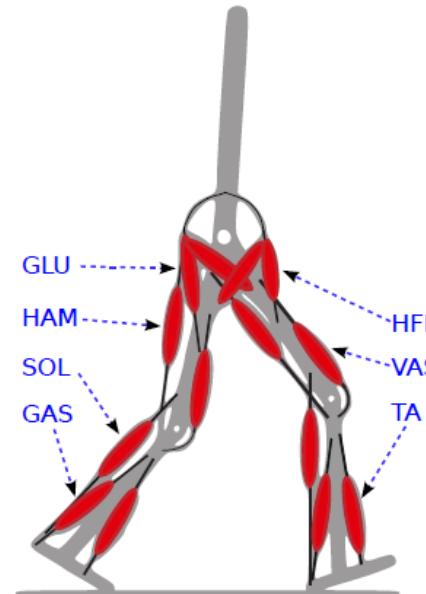
+

Different reflexes

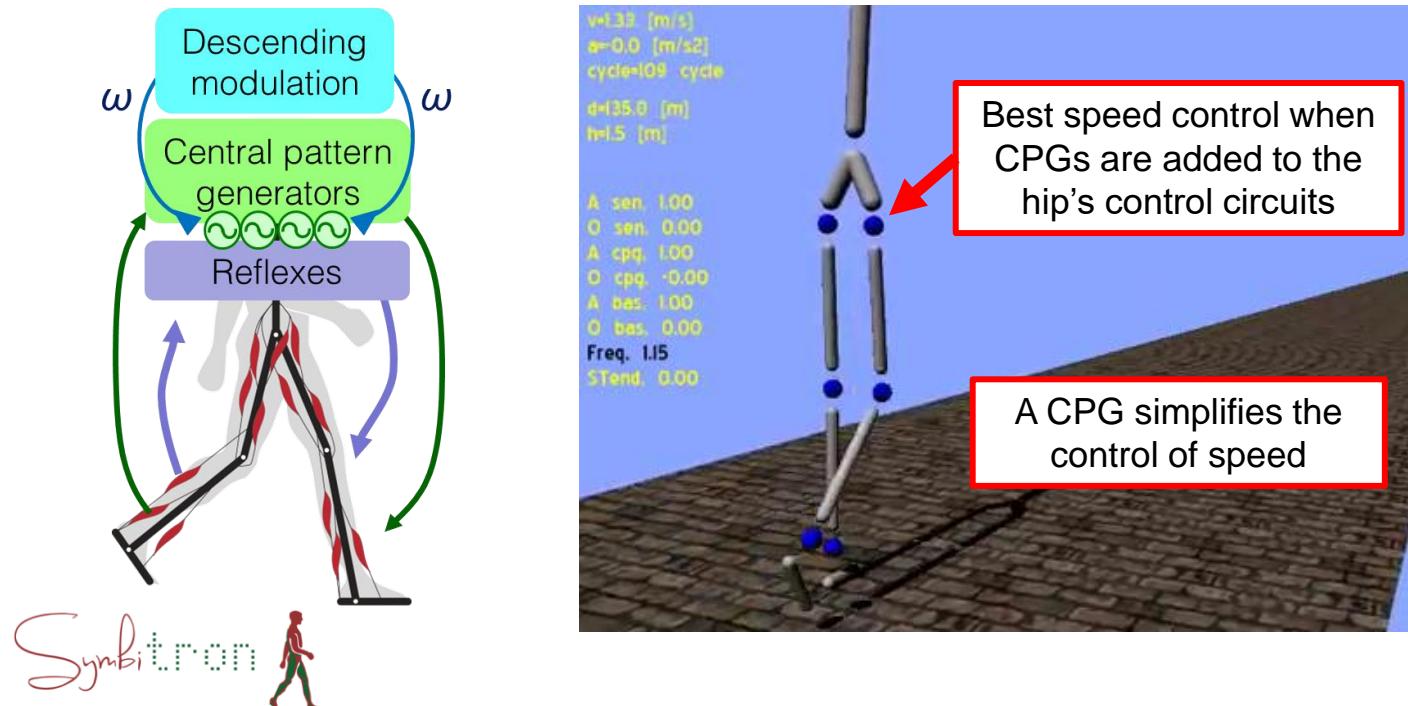
(positive and negative force feedback,  
limits of overextension, ...)

+

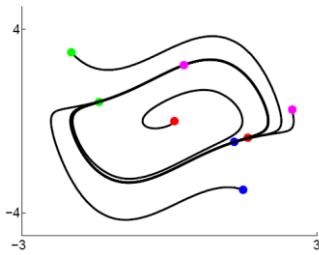
Posture control (torso angle)



# Speed control



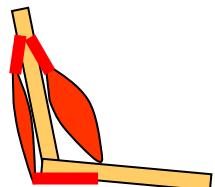
# Contents of lectures



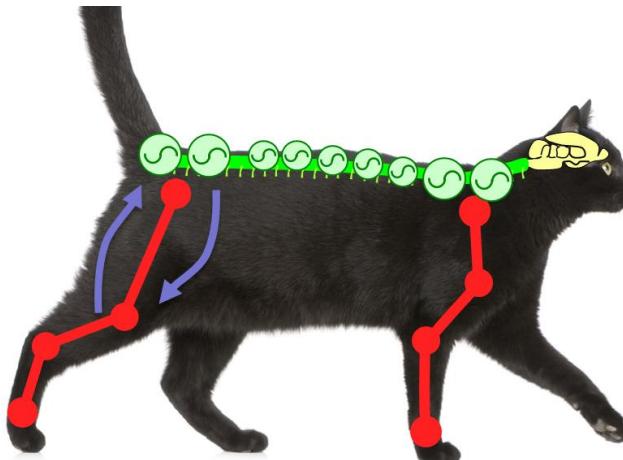
Dynamical systems



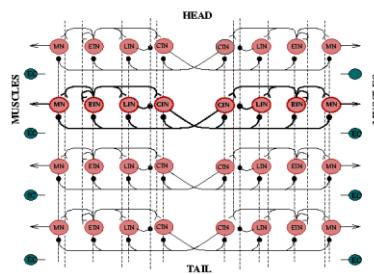
Neuron models



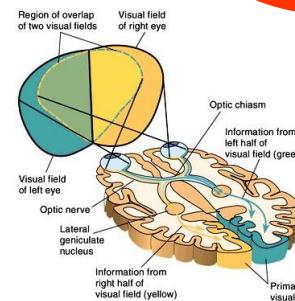
Muscle and  
Biomech. models



Motor system  
models

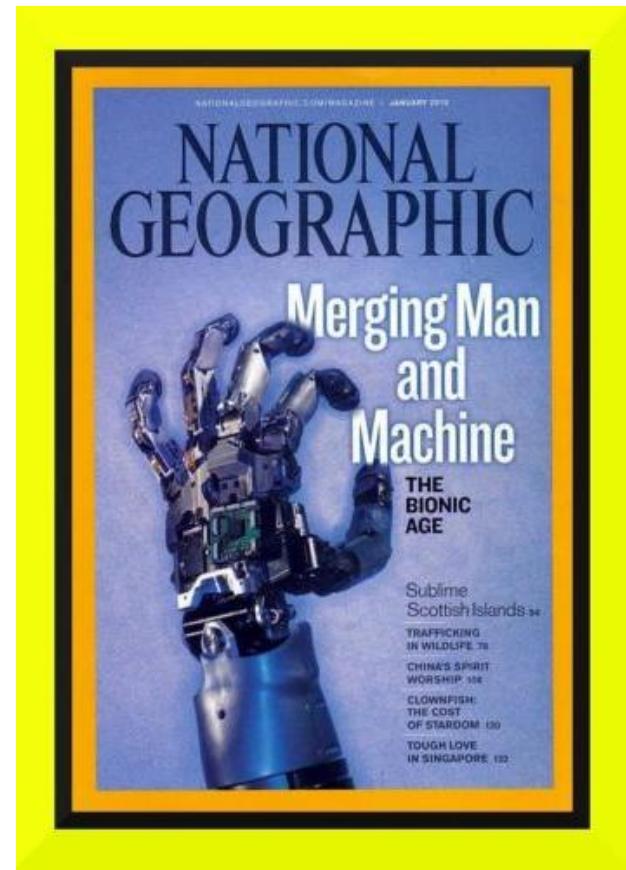


Visual system  
models



Neuroprosthetics

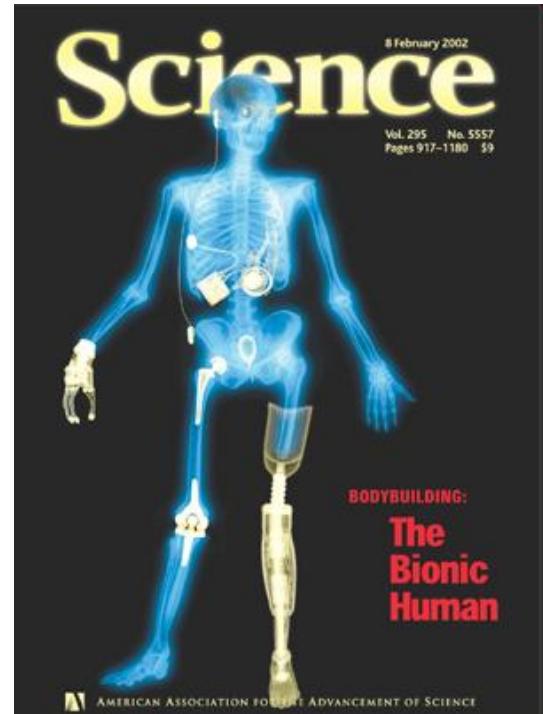
# Neuroprosthetics



# Neuroprosthetics

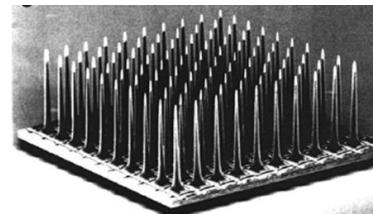
Topics:

- Restoring mobility:
  - Prosthesis versus orthosis
  - Spinal cord stimulation
  - Functional Electromyographic stimulation
  - Control of lower limb orthosis
- Restoring upper limb movements:
  - Arm/hand replacement
  - Cortical implants and population coding



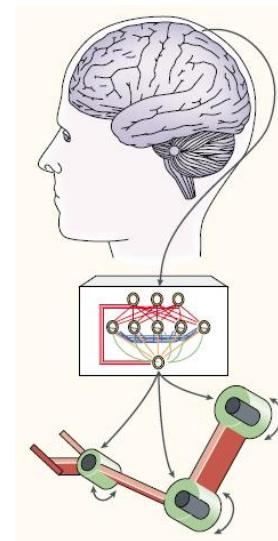
# Cortical implants and population coding

Advances in **multi-array electrodes**



And in the **understanding of movement coding in the cortex**

have allowed the design of **cortical interfaces**



(Nicolelis 2003)

# Population Vector

**E.g. encoding  
of arm  
movements  
in the motor  
cortex**

$$\vec{v}_{\text{pop}} = \sum_{a=1}^4 \left( \frac{r}{r_{\text{max}}} \right)_a \vec{c}_a .$$

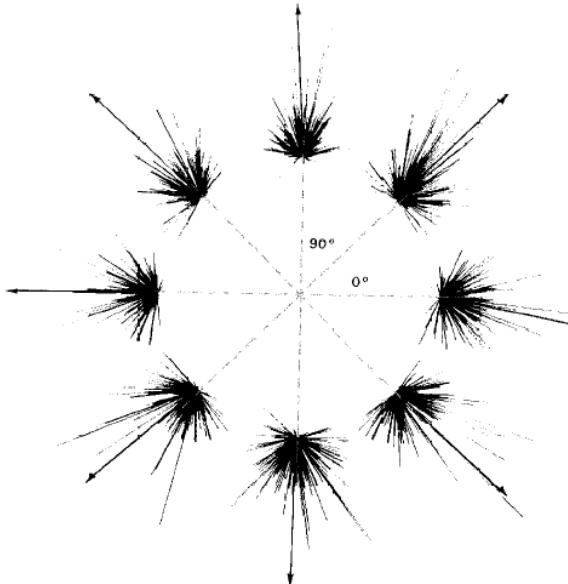


Figure 3.6: Comparison of population vectors with actual arm movement directions. Results are shown for eight different movement directions. Actual arm movement directions are radially outward at angles that are multiples of  $45^\circ$ . The groups of lines without arrows show the preferred direction vectors of the recorded neurons multiplied by their firing rates. Vector sums of these terms for each movement direction are indicated by the arrows. The fact that the arrows point approximately radially outward shows that the population vector reconstructs the actual movement direction fairly accurately. (Figure adapted from Kandel et al., 1991 based on data from Kalaska et al., 1983.)

# Interfacing with a robot



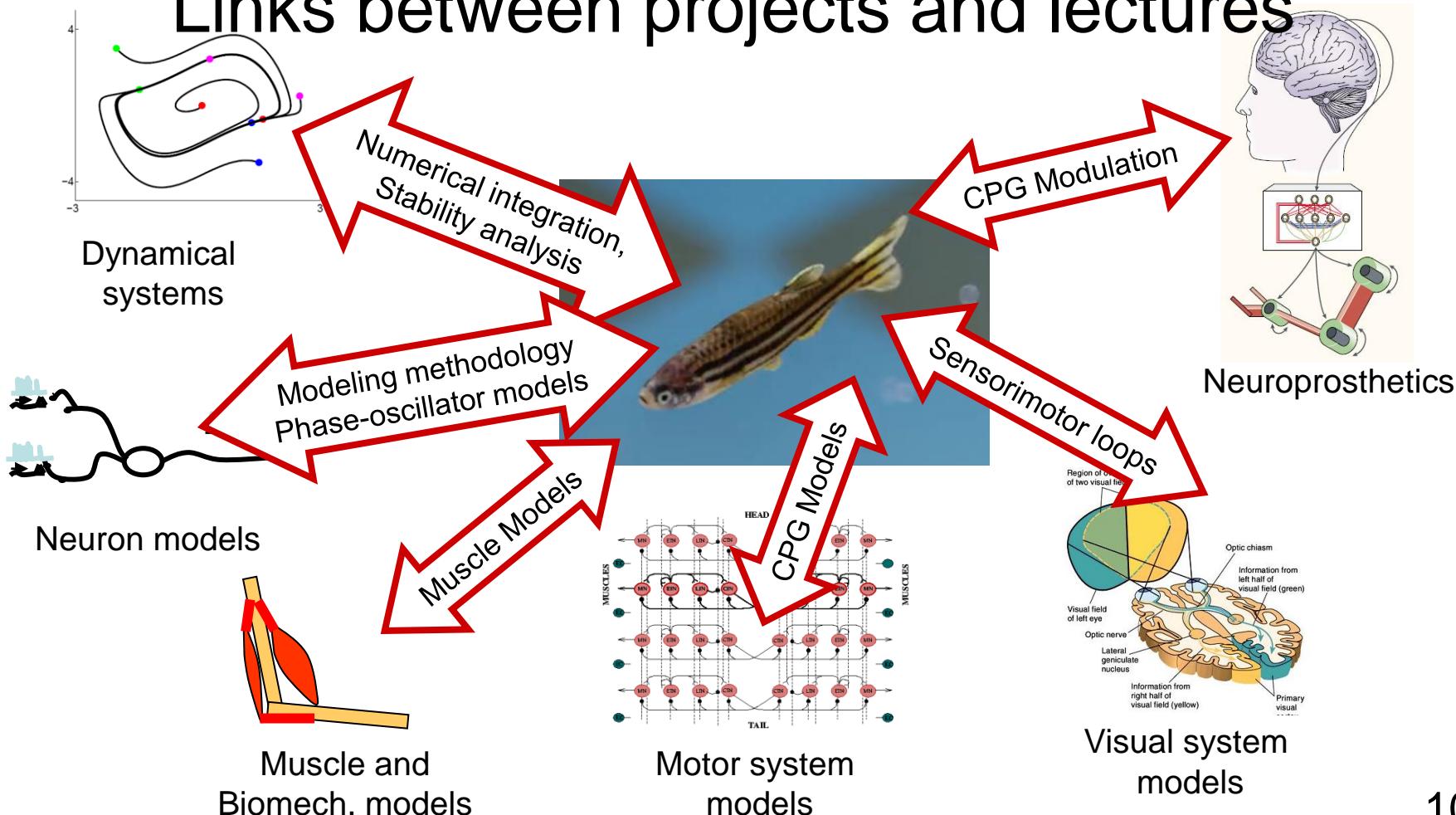
Andrew Schwarz and colleagues, U. of Pittsburgh

# Expected outcomes of this course

You will (hopefully) get:

- An **overview of how numerical tools are used in biology**, as part of a scientific methodology
- A **mathematical background** for designing and analyzing models
- Illustrations of interesting **interactions between biology and robotics/computer science**
- **Practical experience of designing, programming, and testing your own models**
- Practical experience of **writing scientific reports**

# Links between projects and lectures



# Possible exam questions

- What is a **computational model** and why is it useful in biology?
- What is the **difference between inductive and deductive reasoning**? Which approach is typically used in computational motor control (answer: inductive reasoning)
- **Methodology of modeling:** What are the key steps in developing a computational model?
- **Discuss how models have been used to investigate the lamprey locomotor circuit.** Give two different examples of models at different levels of abstraction and how they were selected to answer specific scientific questions (see also next lectures).

End of Lecture 1:

Practicals start this afternoon at 13:15 in INF2