Neuroengineering 2021/22

COMPUTATIONAL NEUROSCIENCE 1 –

Part 3- Neural bases of Motor Control – Focus on the Cerebellum

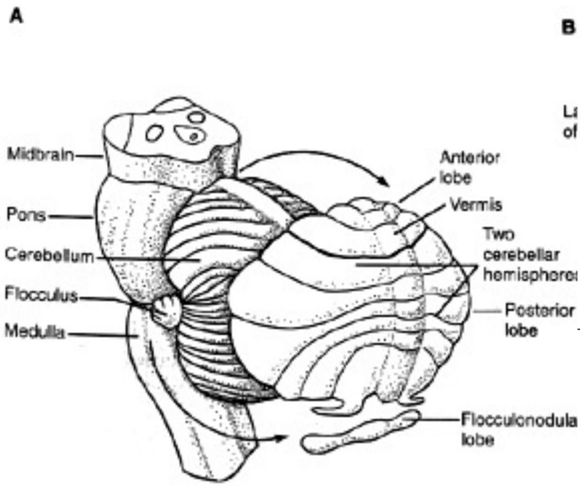
Cerebellum

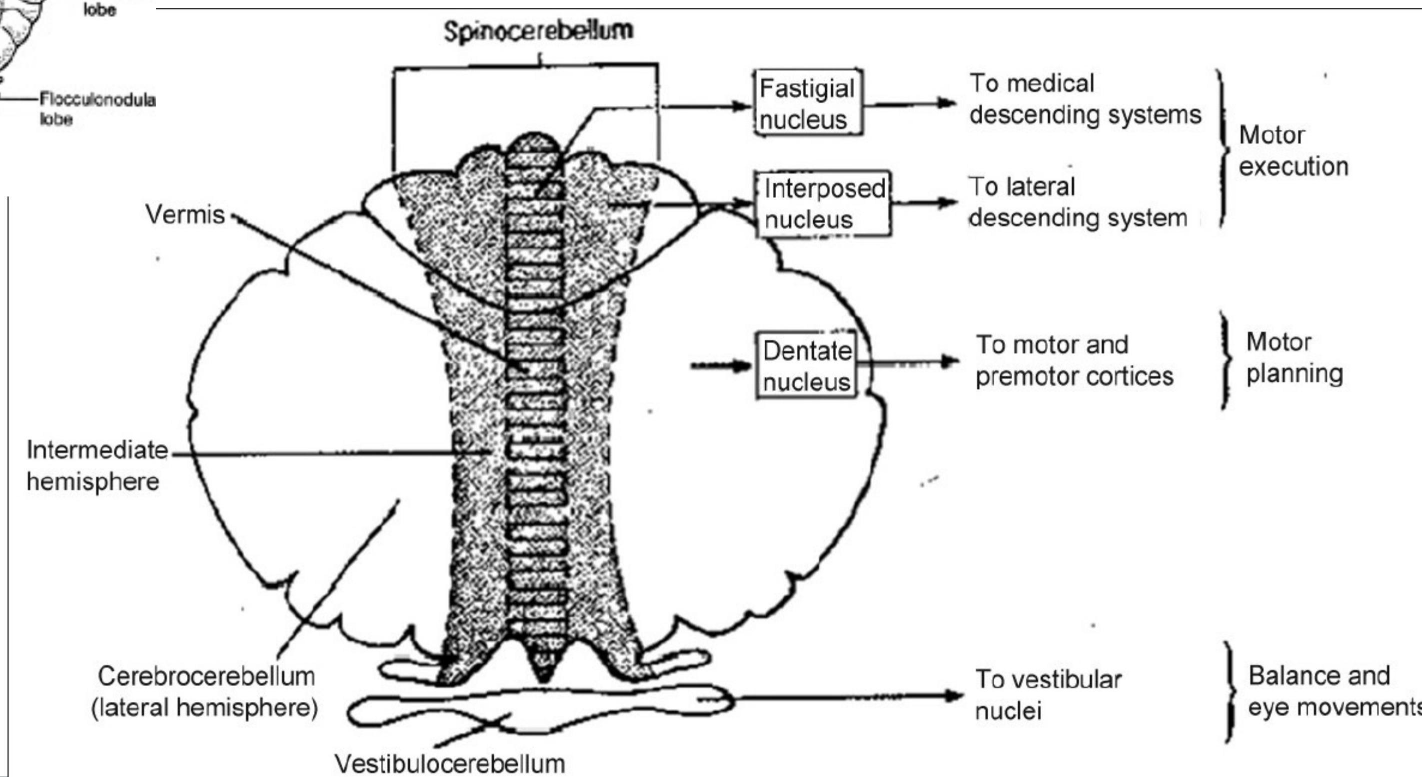
- What does it receive as input? (Inputs=40*outputs)
  - Info on the objective of motor actions
  - Info on the motor commands
  - Sensorial feedback signals associated to the planning and execution of movements

- What does it produce as output?
  - The output projections of the cerebellum are focused mainly on the premotor and motor systems of the cerebral cortex and brain stem, systems that control spinal interneurons, and motor neurons directly
- It has the property of modulation of the input/output connections (adaptation and motor learning: synaptic plasticity)

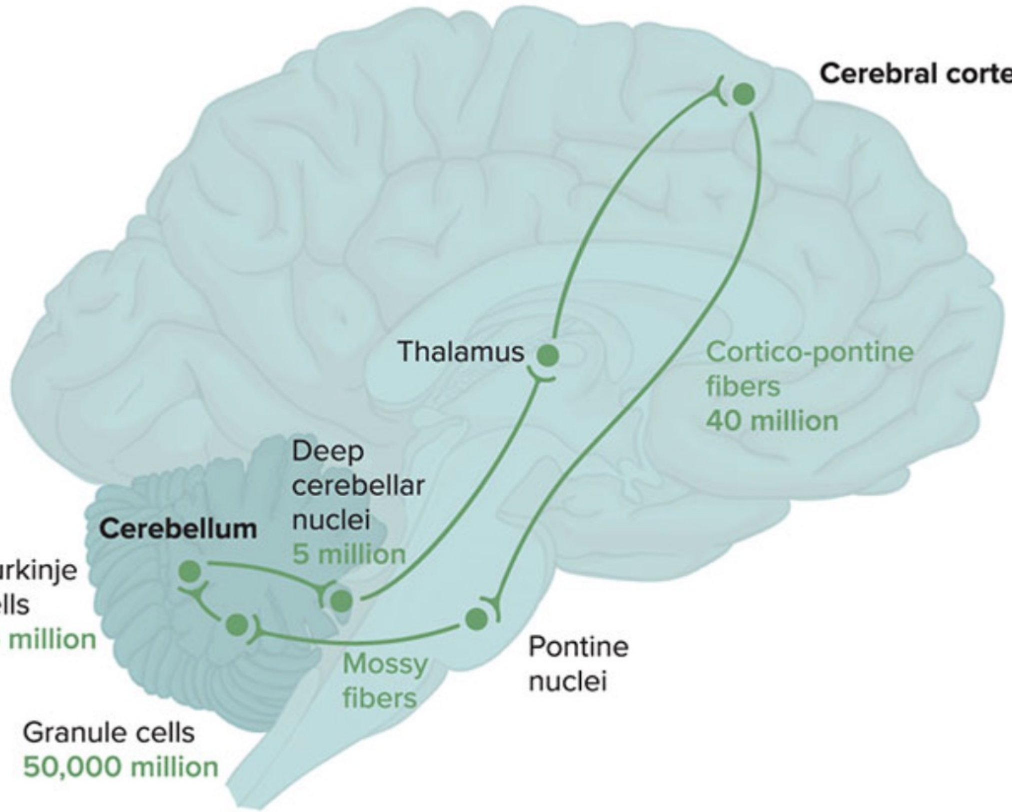
- The cerebellum makes up only about 10 percent of the mass of the human brain but contains more than half of its neurons. Stretched out, its surface area would be nearly 80% that of the cerebral cortex.

Anatomical structure





The cerebellum-cerebral cortex loop



SOURCE: J. DIEDRICHSEN *ET AL* / *NEURON* 2019 KNOWABLE MAGAZINE

While the cerebral cortex's role in cognition has long been recognized, the cerebellum's role has largely been ignored. But these two parts of the brain share an elaborate network of connections. Some 40 million neurons in the cerebral cortex have fiber-like axons extending to the pontine nuclei in the brainstem, an area intimately connected to the cerebellum. Extensive connections go in the other direction, too, from the cerebellum up to the cortex.

Functions of the cerebellum

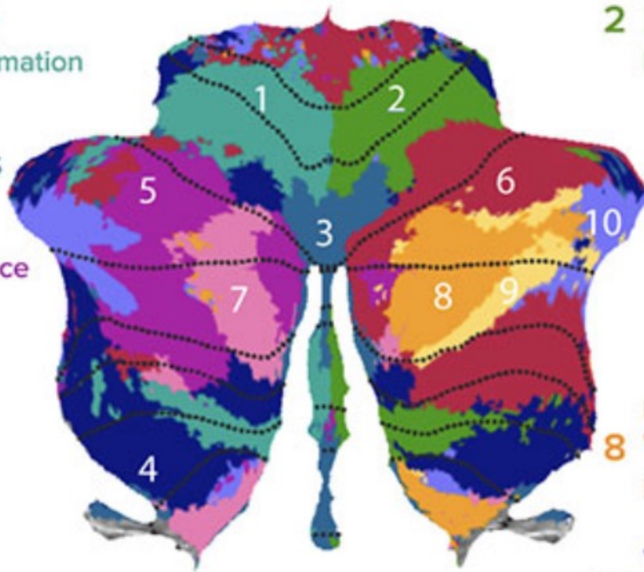
Motor planning
1 Left hand movements
Resolution of conflicting information

Visual working memory
3 Rapid eye movements
Visual letter recognition

Active information maintenance
5 Divided attention
Mental arithmetic

Emotion processing
7 Narrative
Language processing

Word comprehension
9 Verbal fluency
Mental arithmetic



Motor planning
2 Right hand movements
Divided attention

Divided attention
4 Action observation
Motor planning

Active information maintenance
6 Divided attention
Verbal fluency

Language processing
8 Word comprehension
Narrative

Visual letter recognition
10 Autobiographical recall
Resolution of conflicting information

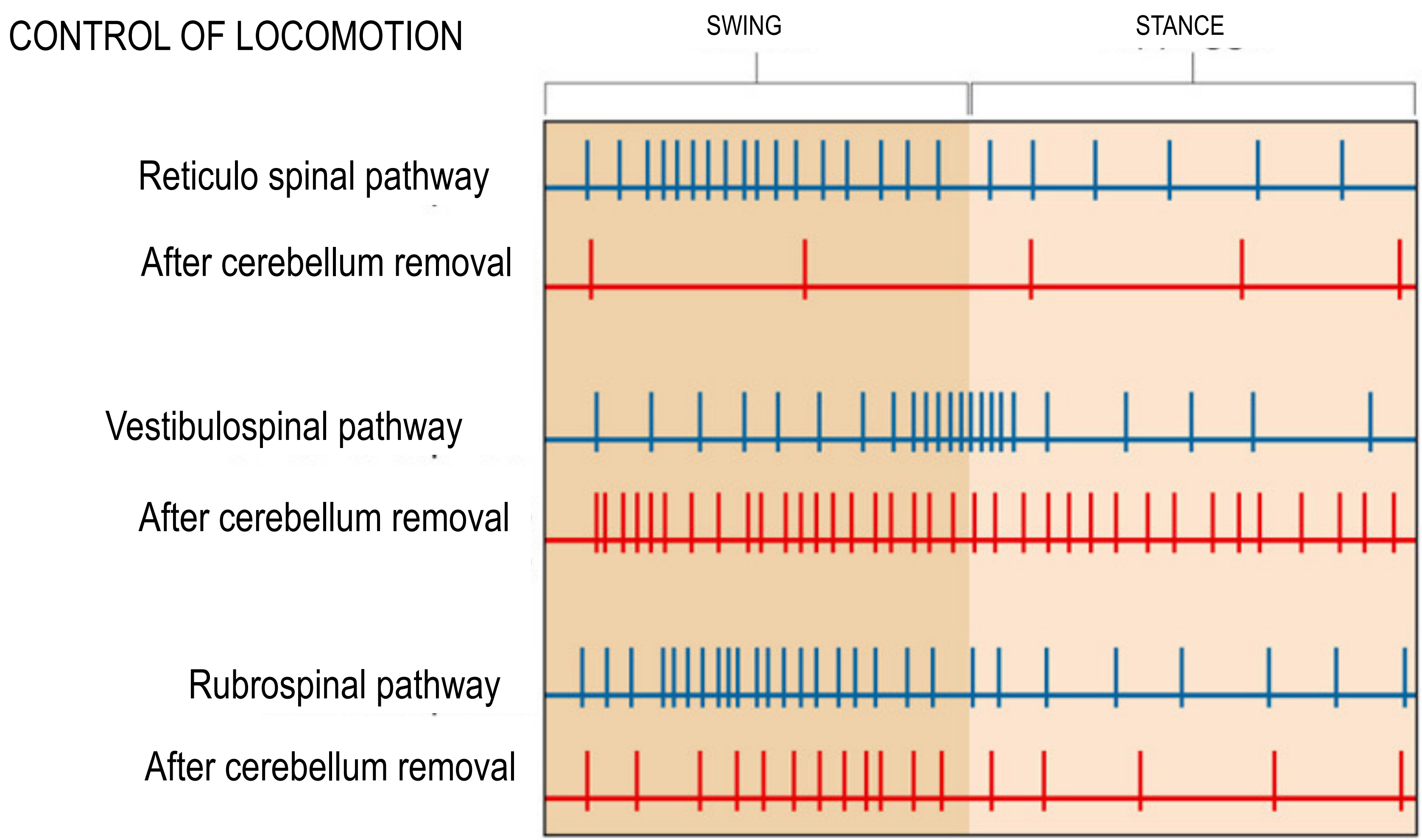
SOURCE: M. KING *ET AL / NATURE NEUROSCIENCE* 2019

KNOWABLE MAGAZINE

The cerebellum plays a role in several motor and cognitive tasks. Neuroscientists used functional magnetic resonance imaging to scan people's brains while they carried out a wide variety of activities. The researchers then mapped key functions associated with different regions of the cerebellum. Stronger associations are indicated by larger text in this flattened version of the cerebellum's surface.

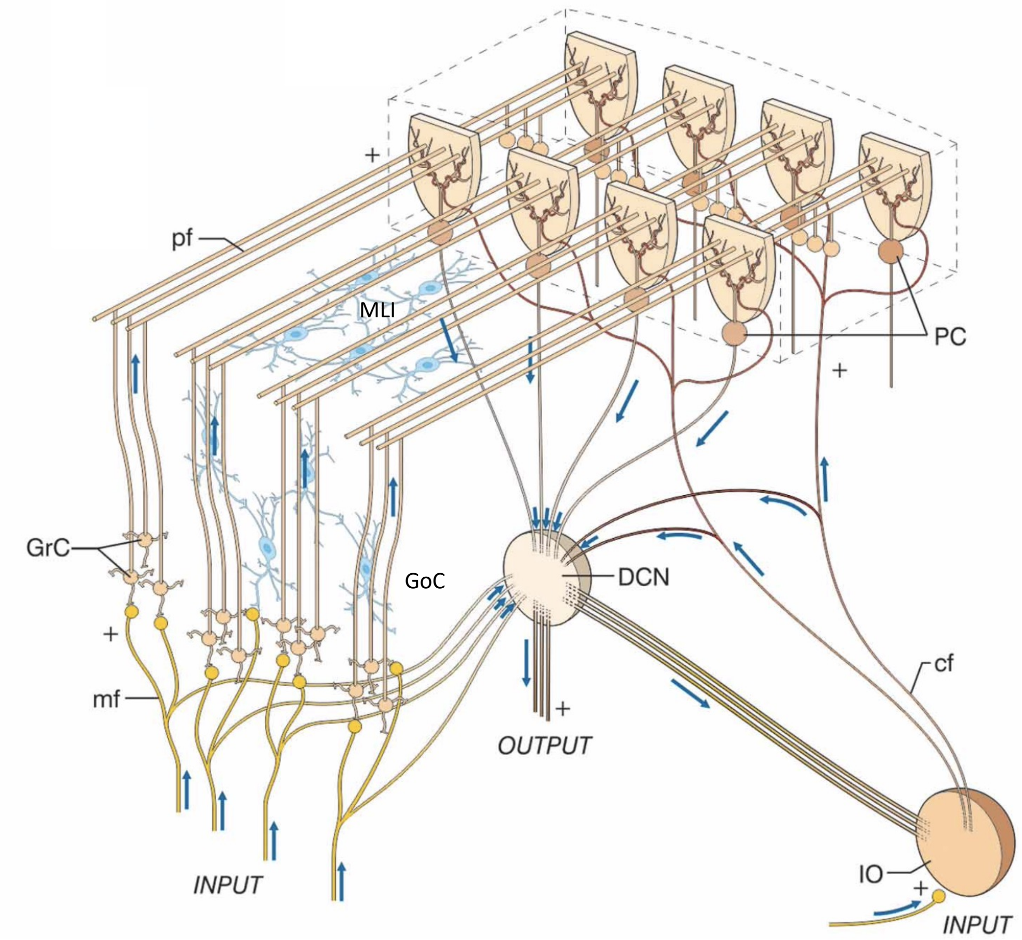
https://www.brainfacts.org/brain-anatomy-and-function/anatomy/2020/the-mysterious-multifaceted-cerebellum-120320

Effects of cerebellar removal



Cerebellar microcircuits

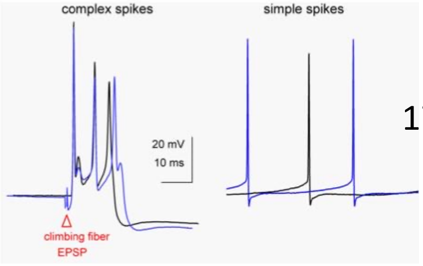
Mossy Fibers (mf)
Granule cells (GrC),
parallel fibers (pf)
Golgi cells (GoC),
Molecular Interneurons (MLI)
    Stellate cells(SC)
    Basket cells (BC).
Inferior Olive cells (IO-C)
Purkinje cells (PC),
Deep Cerebellar Nuclei cells (DCN-C)



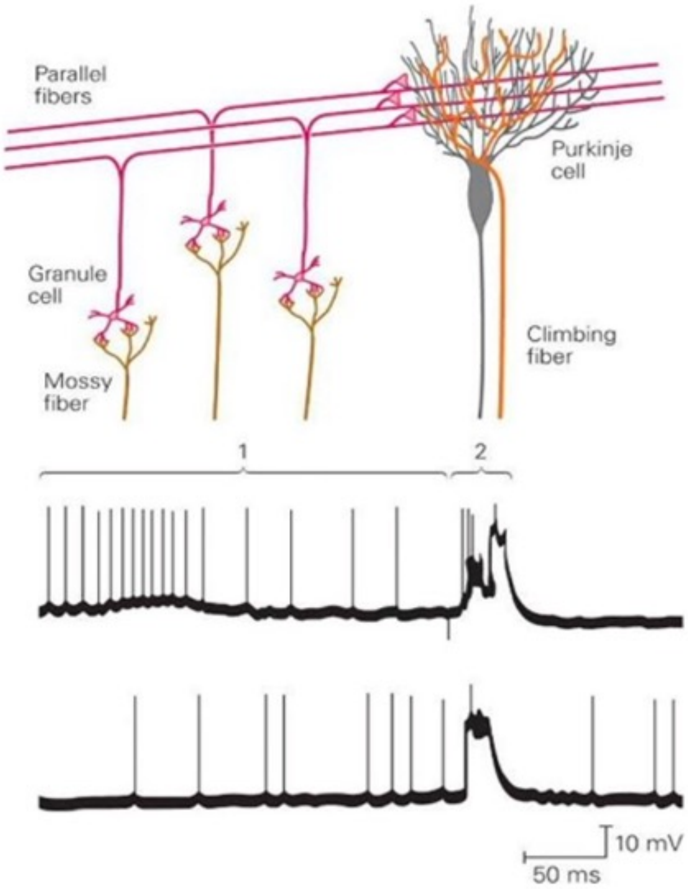
[Ito 2006]

Electrical Activity of Purknjie Cells

1-3 Hz

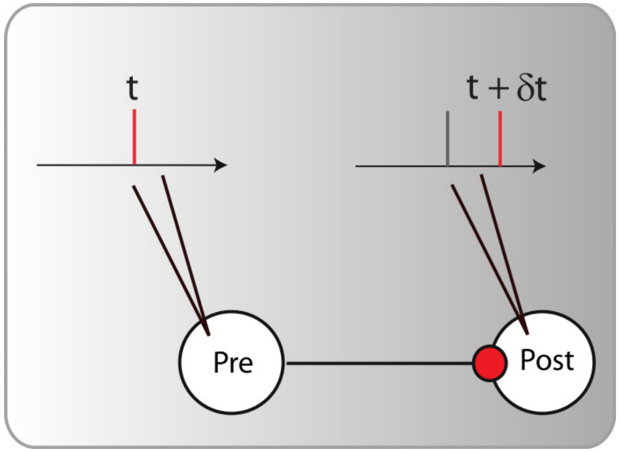


17 – 150 Hz

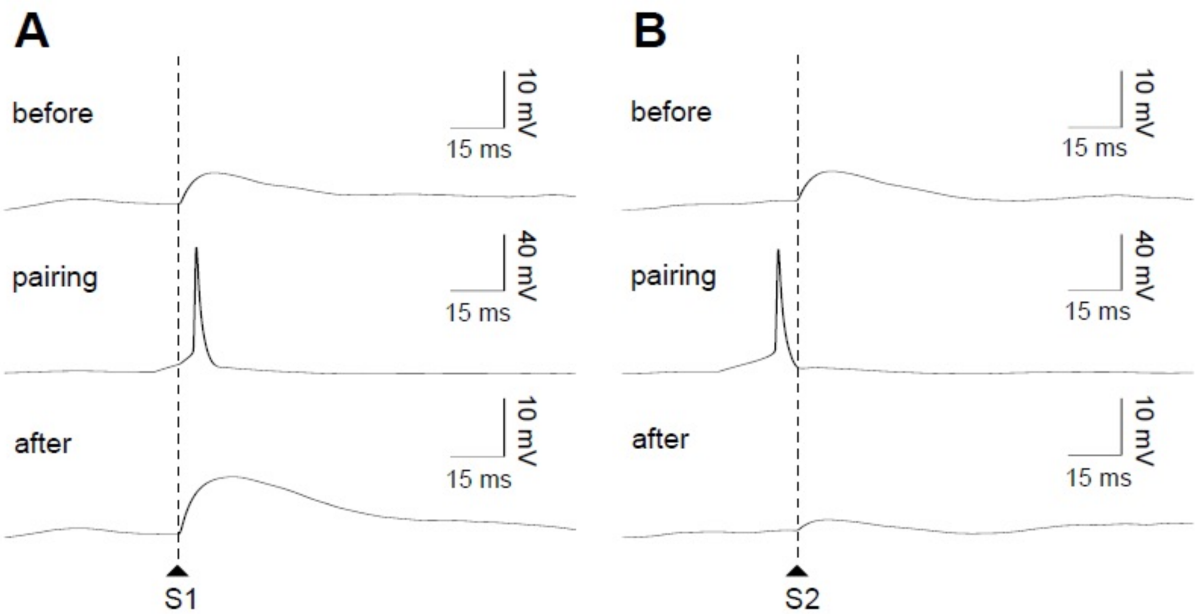


Hebbian plasticity: Spike Timing Dependent Plasticity (STDP)

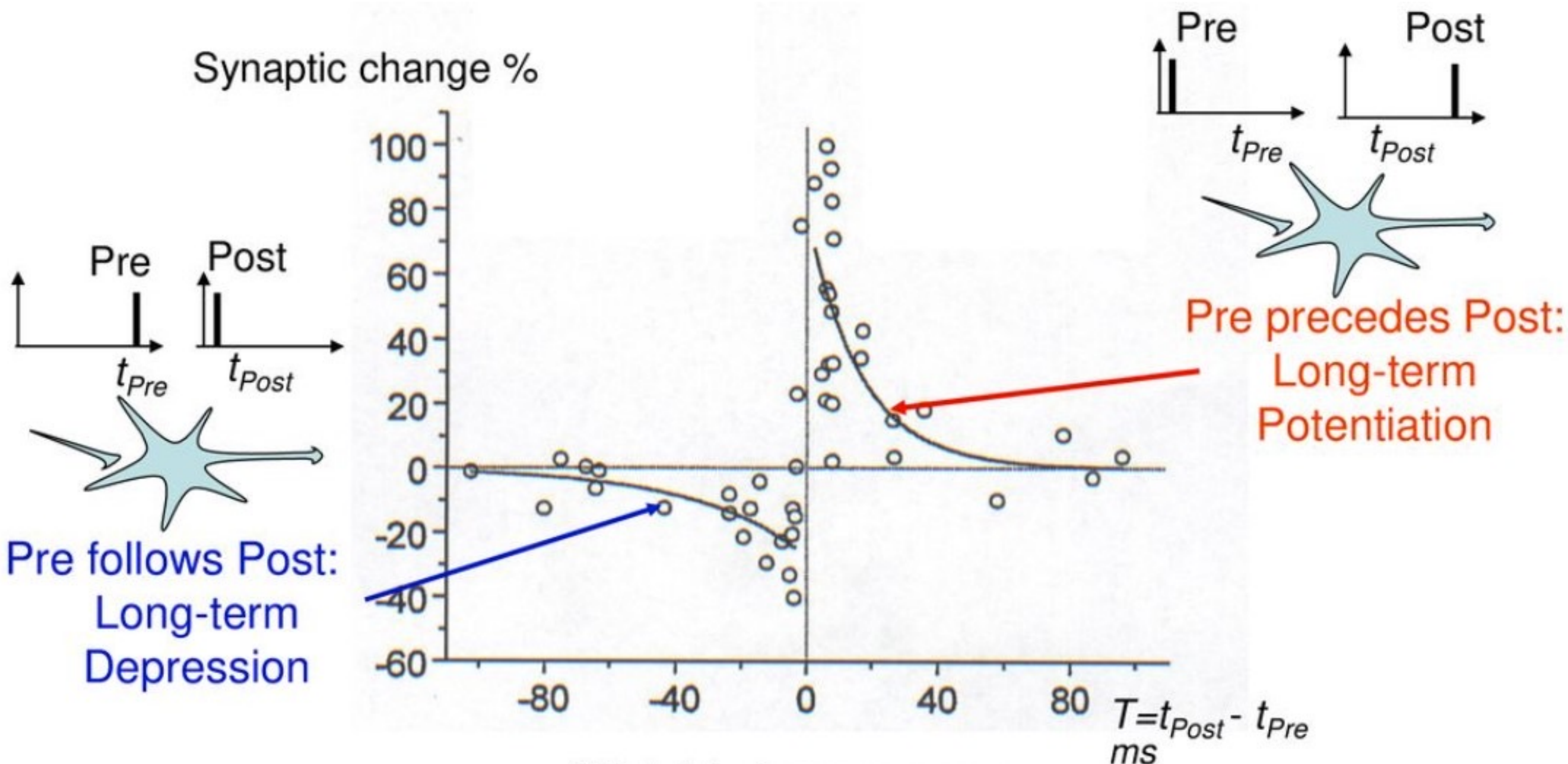
Hebb hypothesis 1949
Experimental proofs:
Bi 1998, Markram 1997,
Gerstner 1996



Experimental protocol of Spike Timing Dependent Plasticity in vitro. Pre and Post synaptic neurons are patched and forced to fire with a time difference, while the modification of the synaptic strength is monitored

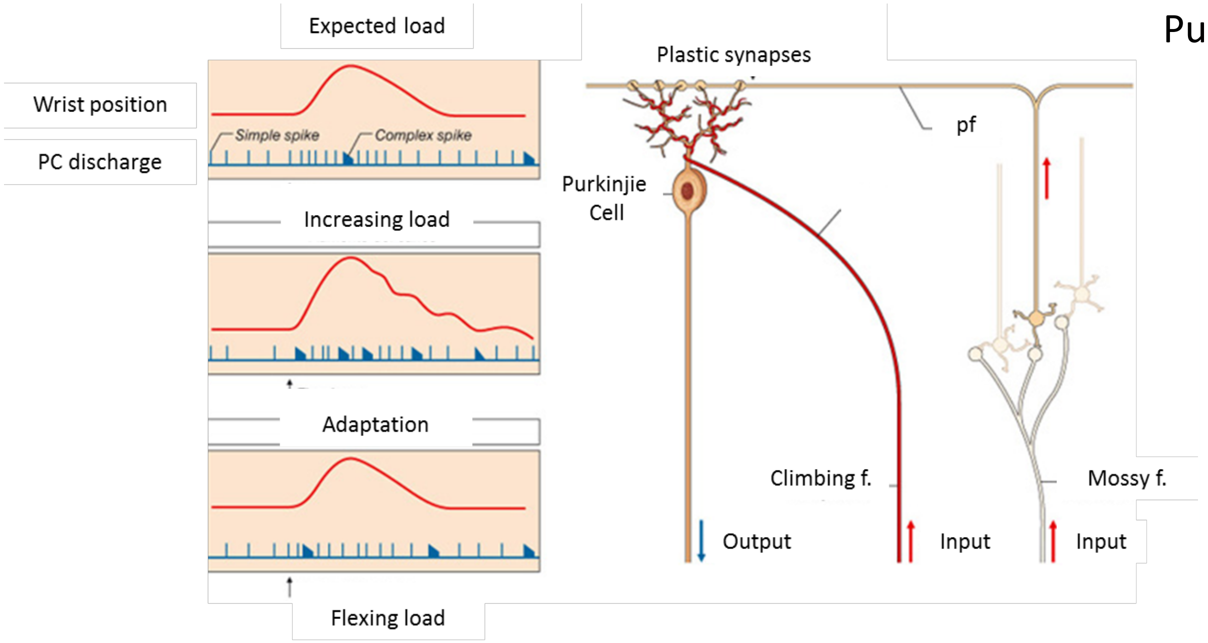


STDP

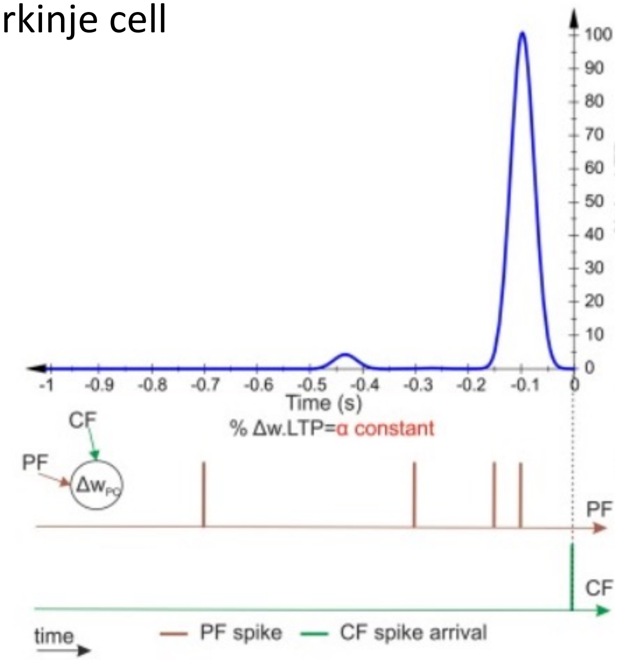


Weight-change curve

Cerebellum output



Synapic plasticity at parallel fiber–Purkinje cell



Changes in the strengths of parallel fiber–Purkinje cell synapses could store stimulus-response associations by linking inputs with appropriate motor outputs, following a **Hebbian learning** approach but with supervision of Cf discharge.

Summary

Structure and organization of the brain suggest computational analogies:

•INFORMATION STORAGE: Physical and chemical structure of neurons and synapses
•INFORMATION TRANSMISSION: electrical and chemical signaling
•PRIMARY COMPUTING ELEMENT: the neuron
•COMPUTATIONAL BASIS: still unknown!!!

Summary

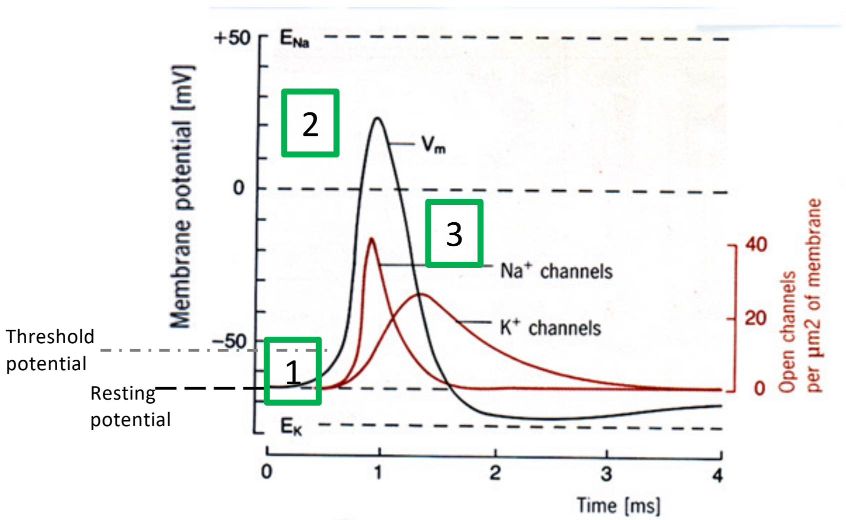
- What is motor control and motor learning and high level models of motor control by the Human Brain
- The human brain areas involved in motor control
- Focus on Cerebellum
- The physiology of the cerebellum accounting for its functional features

Neuroengineering 2021/22

COMPUTATIONAL NEUROSCIENCE - Part 4 Modelling and Simulations

Neuronal communication: the Action Potential

Neurons communicate through Action Potentials (AP) = change in membrane voltage depending on subcellular ion channel-mediated mechanisms



1 *Resting condition*

2 *Depolarization*

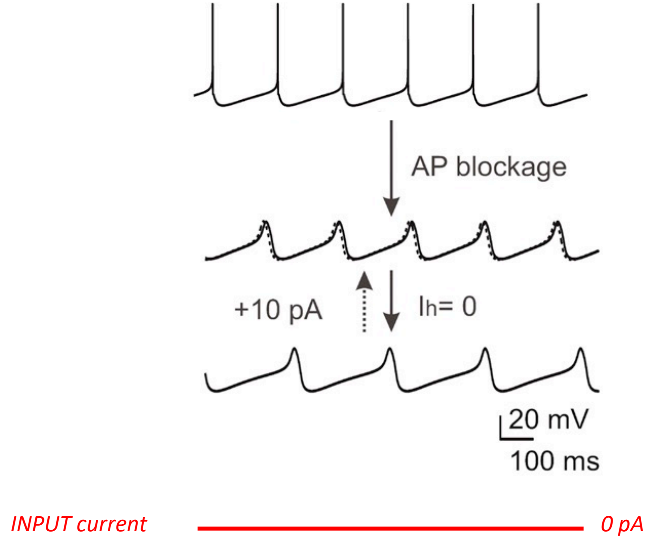
3 *Repolarization and hyperpolarization*

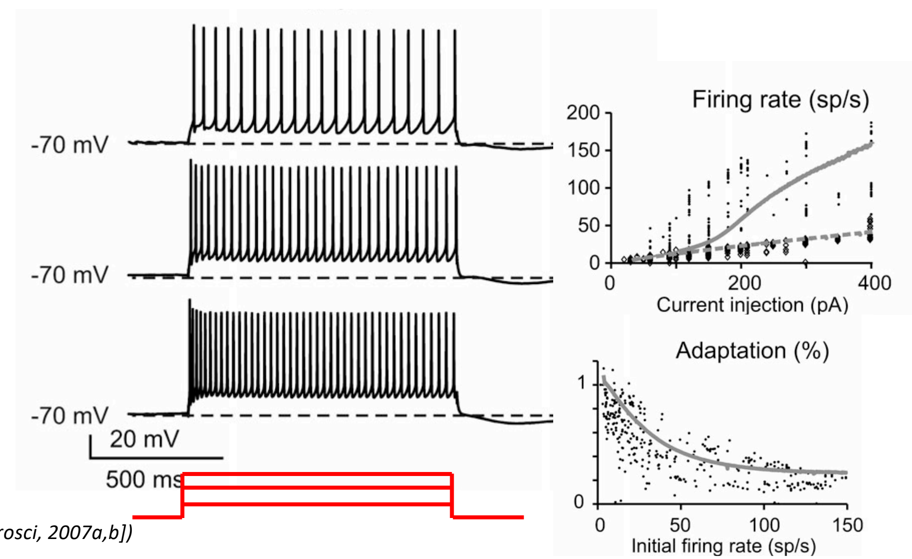
AP can be approximated with SPIKES, the basic units of neuronal coding

Neuronal communication: single neuron dynamics

Neurons can exhibit different **spiking** patterns (**electroresponsive properties**):

- Autorhythm = spontaneous firing of neurons due to neurons' intrinsic electro-responsiveness
- SubThreshold Oscillations (STO) = sinusoidal oscillations of the membrane potential around the threshold potential value
- Depolarization induced bursting = increased firing rate of neurons following the starting of a depolarizing external stimulation
- Linear current-frequency relationship
- Spike-Frequency Adaptation (SFA) = Decrease in the neuron's firing rate when stimulated with a constant input.



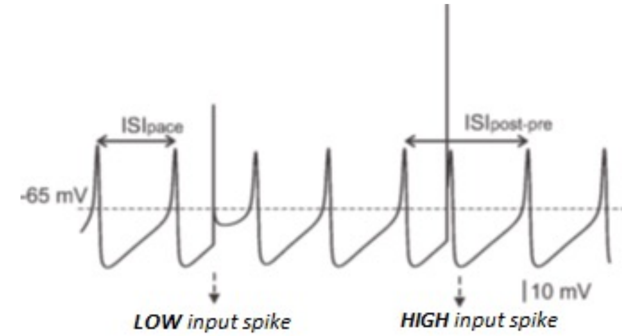


Membrane voltage of a cerebellar Golgi cell *(adapted from [Solinas et al, Front Cell Neurosci, 2007a,b])*

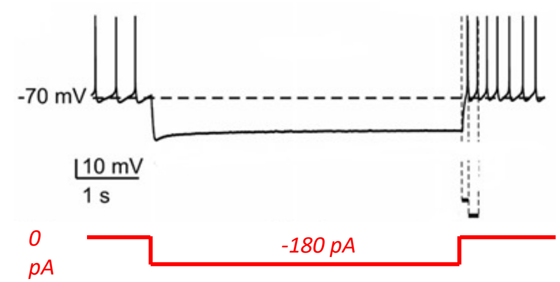
Neuronal communication: single neuron dynamics

Neurons can exhibit different **spiking** patterns (**electroresponsive properties**):

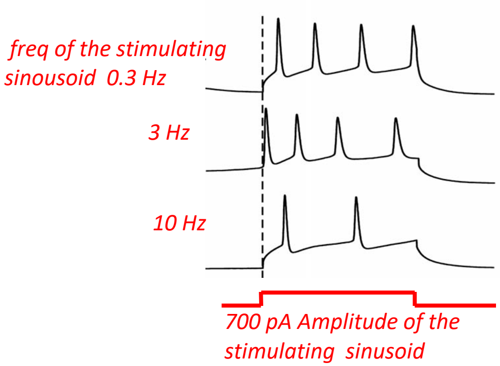
- Phase reset

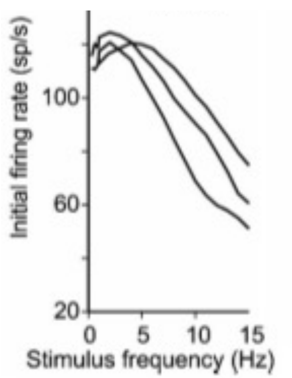


- Post-inhibitory rebound burst = increased firing rate following the end of a negative hyperpolarizing input (amplitude and duration of the negative input are fundamental to cause the rebound burst)



- Resonance = maximum firing response of a neuron at a preferred frequency of the input current stimulus



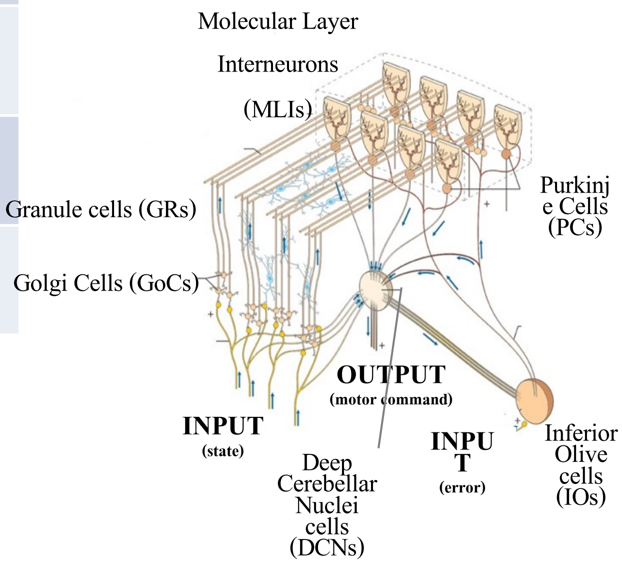


Initial firing rate is the inverse of the ISI between the first two spikes after the stimulus

FUNDAMENTAL for:
✓Generating network dynamics
✓Noise filtering
✓Plasticity enhancement
✓Communication within and among brain areas

Cerebellar single neuron dynamics

CEREBELLAR CELLS	Auto-rhythm	Sub-Threshold Oscillations	Depolarization-induced burst	SFA	Phase reset	Post-inhibitory rebound burst	Resonance
Golgi Cell	✓ 5-15 Hz	✓	✓	✓	✓	✓	✓ (ϑ band)
Granule Cell	-	✓	-	-	-	-	✓ ϑ band)
Purkinje Cell	✓ 40-80 Hz	-	✓		-	-	-
Molecular Layer Interneurons	✓ 10-20 Hz	-	-	-	-	-	-
Deep Cerebellar Nuclei	✓ 10-30 Hz	-	✓	✓	-	✓	-
Inferior Olive cells	-	✓ 1-4 Hz	n.a.	n.a.	✓	-	-

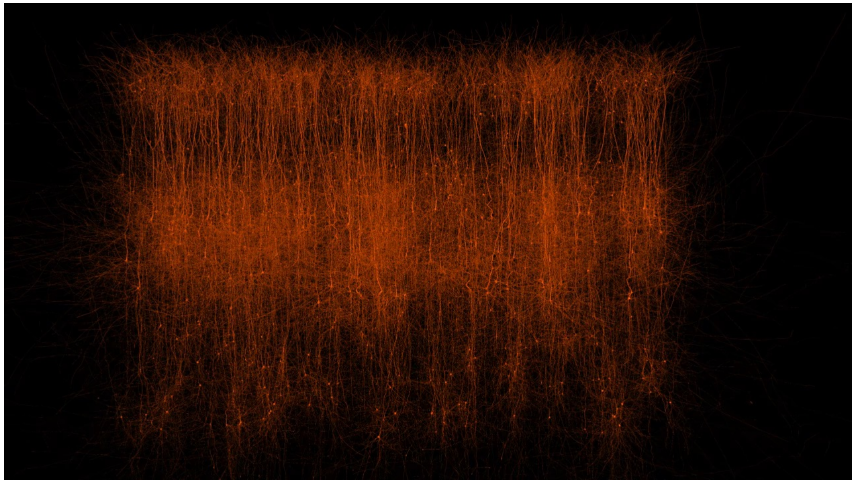


Θ band = 1-4 Hz; fundamental for brain oscillations and communication with the cerebral cortex

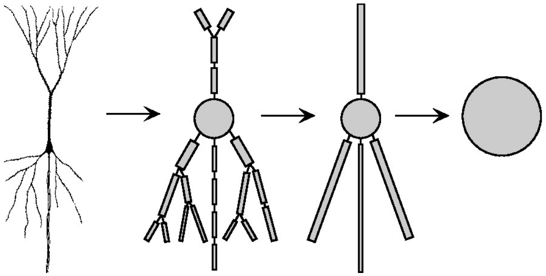
Modelling single neurons

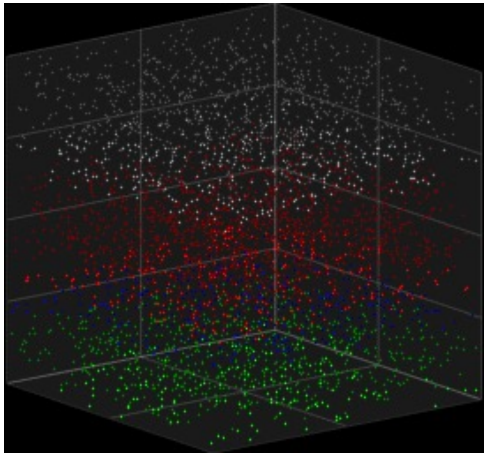
Different levels of *morphological* detail: from multi-compartment to point neuron models

Multi-compartment neuron models describe the activity of each neuron element (dendrites, axons, …) taking into account morphological features. Example from the neo-cortex microcircuit [Markram et al., *Cell Reports*, 2015]:



Point neuron models describe the activity of neurons as collapsed in a single point, neglecting compartment differences and morphological features. They represent more the computational properties of neurons, than the electrical activity and its spatial distribution



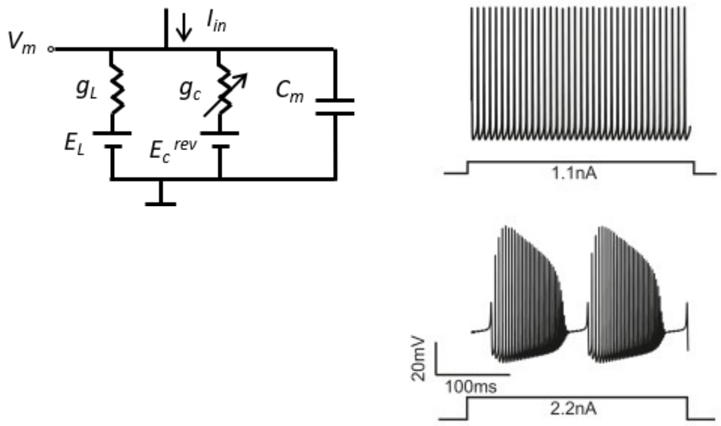


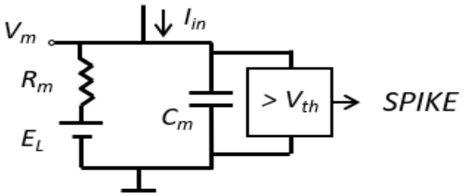
Modelling single neurons

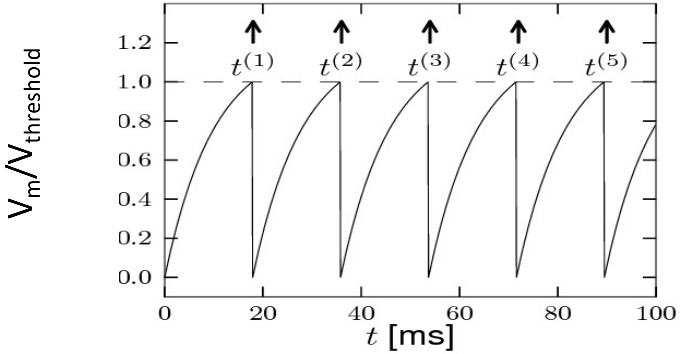
Different levels of *electrical* detail: Hodgkin-Huxley (HH) and Leaky Integrate-and-Fire (LIF)

HH: membrane potential V_m computed considering the resting potential (E_L) and the contribution of each membrane **ion channel** (represented by the conductance g_c and reversal potential E_c^{rev}).

LIF: Only **passive** membrane properties are considered (capacitance C_m and resistance R_m). The output is a spike train, corresponding to time instants of threshold overcoming







Modelling the neuron: HH Compartimental models

The above HH description is for a single compartment. If one wants to describes propagation of the spike in the axon, one has to couple the compartments like we did in the cable equation. The equation holds for each compartment in the axon.

HIGH PERFORMING COMPUTERS (CINECA)

Stefano Masoli, Sergio Solinas,and Egidio D'Angelo

Front Cell Neurosci. 2015; 9: 47.

In each compartment, membrane voltage was obtained as the time integral of the equation (Yamada, 1989):

$$\frac{dV}{dt} = -\frac{1}{C_m} * \left\{ \sum [g_i * \ (V - V_i)] + i_{inj} \right\}$$

Adjacent compartments communicated through an internal coupling resistance (Diwakar et al., 2009).

Modelling the Purkinje Cell (PC): HH Compartimental models

Section name	Diameter (µm)	Length (µm)	N° sections
Dendrites	0.67–9.22	1–10	1599
Soma	29.8	29.8	1
AIS Axon Initial Segment	0.97	17	1
ParaAIS	0.97	4	1
Myelin	0.73	100	4
Ranvier Nodes	0.73	4	3
Collateral	0.6	100	2

Table 1 -Electrotonic compartments in the PC model.
The table shows the sections of the PC model along with their number, diameter and length.

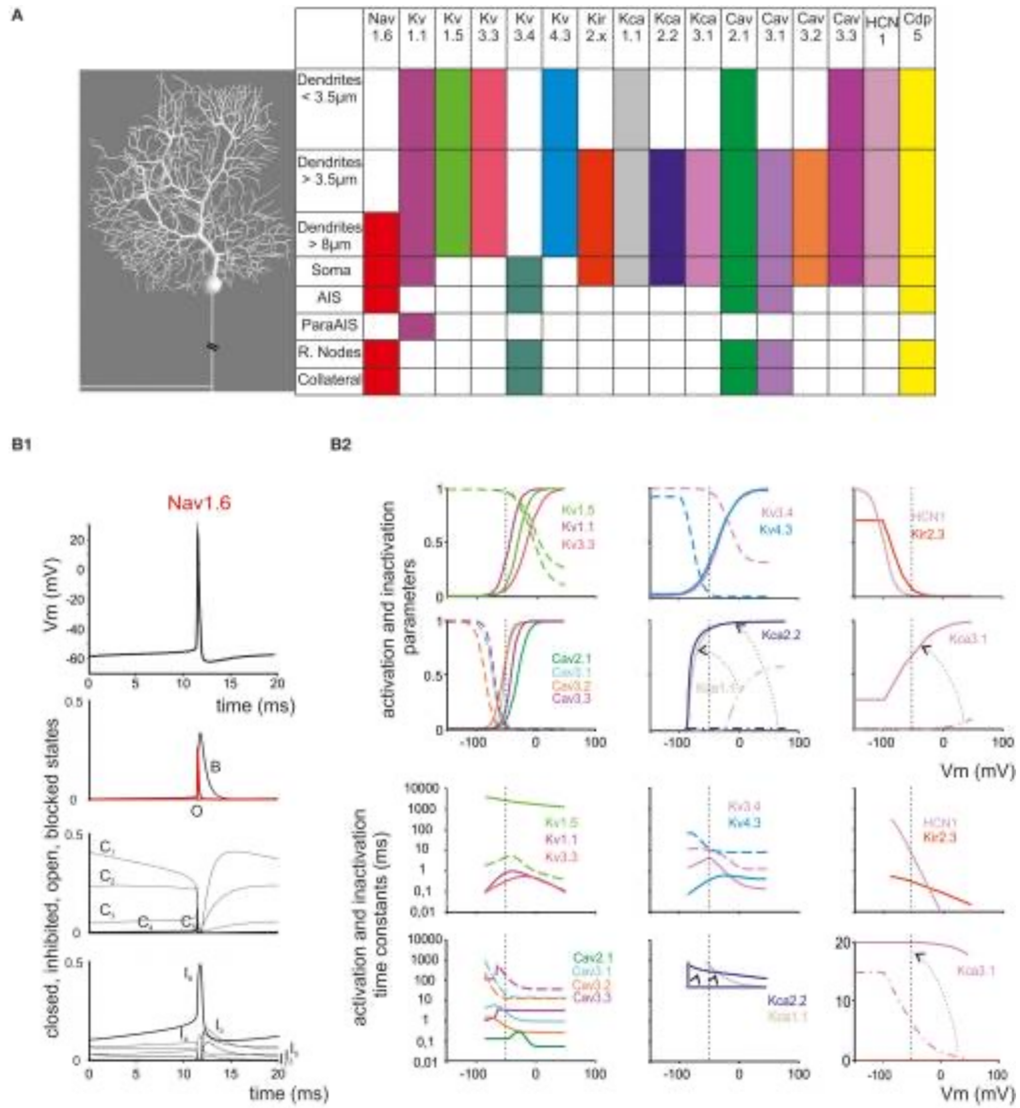


Table 2

Ionic mechanisms in the PC model: I.

The table shows ionic channel localization, maximum conductance and reversal potential. Gating equations were written either in Hodgkin-Huxley (HH) style or Markovian style according to indicated references.

Conductance/Location		Gmax (S/cm^2)	Erev (mV)	Description of channel (H.H or Markovian)	References
Na CHANNEL					
Nav1.6	Dendrites	0.016	60	Markovian 13 states	Raman and Bean, 2001
	Soma	0.214			
	AIS	0.5			
	Nodes	0.03			
	Collateral	0.03			

Modelling PC: HH Compartimental models

Conductance/Location		Gmax (S/cm²)	Erev (mV)	Description of channel (H.H or Markovian)	References
K CHANNELS					
Kv1.1	Dendrites	0.0012	−88	HH	Akemann and Knopfel, 2006
	Soma	0.002			
	ParaAIS	0.01			
Kv1.5	Dendrites	$1.3*10^{-4}$	−88	HH	Courtemanche et al., 1998
Kv3.3	Dendrites	0.01	−88	HH	Akemann and Knopfel, 2006
Kv3.4	Soma	0.05	−88	HH	Raman and Bean, 2001; Khaliq et al., 2003
	AIS	0.01			
	Nodes	0.01			
	Collateral	0.02			
Kv4.3	Dendrites	0.001	−88	HH	Diwakar et al., 2009
Kir2.x	Dendrites	0.00001	−88	HH	Diwakar et al., 2009
	Soma	0.00003			

Modelling PC: HH Compartimental models

Conductance/Location		Gmax (S/cm²)	Erev (mV)	Description of channel (H.H or Markovian)	References
Ca DEPENDENT K CHANNELS					
Kca1.1	Dendrites	$3.5*10^{-2}$	−88	Markovian	Anwar et al., 2010
	Soma	0.01			
Kca2.2	Dendrites	$1*10^{-3}$	−88	Markovian	Solinas et al., 2007a,b
	Soma	$1*10^{-3}$			
Kca3.1	Dendrites	0.002	−88	HH	Rubin and Cleland, 2006
	Soma	0.01			
Ca CHANNELS					
Cav2.1	Dendrites	$1*10^{-3}$	137.5	HH	Swensen and Bean, 2005; Anwar et al., 2010
	Soma	$2.2*10^{-4}$			
	AIS	$2.2*10^{-4}$			
	Nodes	$2.2*10^{-4}$			
	Collateral	$2.2*10^{-4}$			

Modelling PC: HH Compartimental models

Ca CHANNELS	Conductance/Location	Gmax (S/cm²)	Erev (mV)	Description of channel (H.H or Markovian)	References
Cav2.1	Dendrites	$1*10^{-3}$	137.5	HH	Swensen and Bean, 2005; Anwar et al., 2010
	Soma	$2.2*10^{-4}$			
	AIS	$2.2*10^{-4}$			
	Nodes	$2.2*10^{-4}$			
	Collateral	$2.2*10^{-4}$			
Cav3.1	Dendrites	$5*10^{-6}$	137.5	HH	Anwar et al., 2010
	Soma	$7*10^{-6}$			
	AIS	$1*10^{-5}$			
	Nodes	$1*10^{-5}$			
	Collateral	$1*10^{-5}$			
Cav3.2	Dendrites	0.0012	137.5	HH	Huguenard and McCormick, 1992
	Soma	0.0008			
Cav3.3	Dendrites	0.0001	137.5	HH	Xu and Clancy, 2008
	Soma	0.0001			

Modelling PC: HH Compartimental models

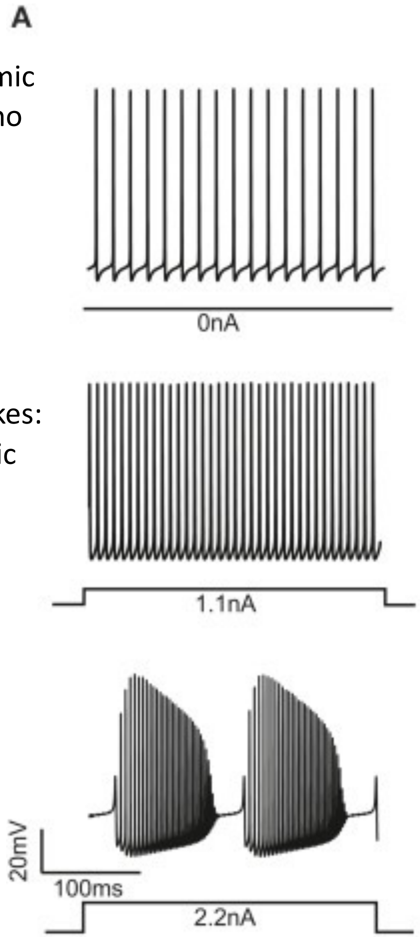
Conductance/Location		Gmax (S/cm^2)	Erev (mV)	Description of channel (H.H or Markovian)	References
MIXED CATIONIC CHANNEL					
HCN1	Dendrites	0.000004	−34.4	HH	Angelo et al., 2007; Larkum et al., 2009
	Soma	0.0004			
CALCIUM BUFFER—PUMPS DENSITY					
Ca Buffer	Dendrites	$2*10^{-8}$		Markovian	Anwar et al., 2010
	Soma	$5*10^{-8}$			
	AIS	$5*10^{-8}$			
	Nodes	$5*10^{-7}$			
	Collateral	$5*10^{-8}$			

Modelling PC: HH Compartimental models

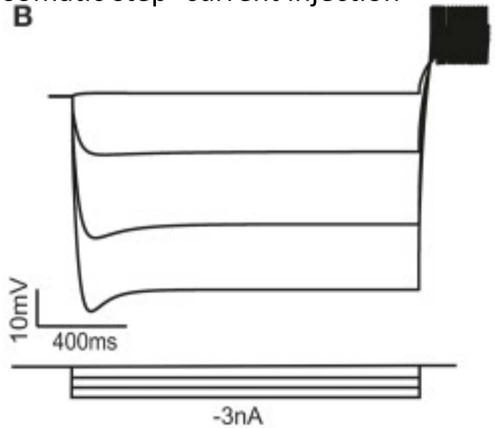
Auto-rhythmic properties no current injection

Simple spikes: low somatic current injection

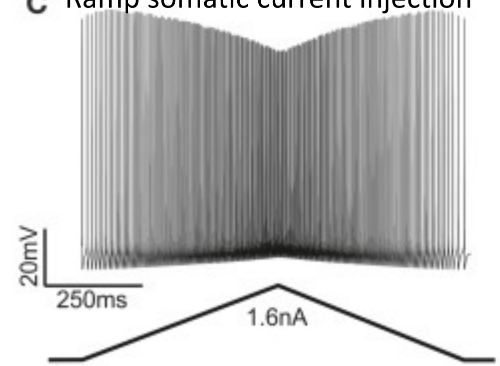
Complex spikes: high somatic current injection



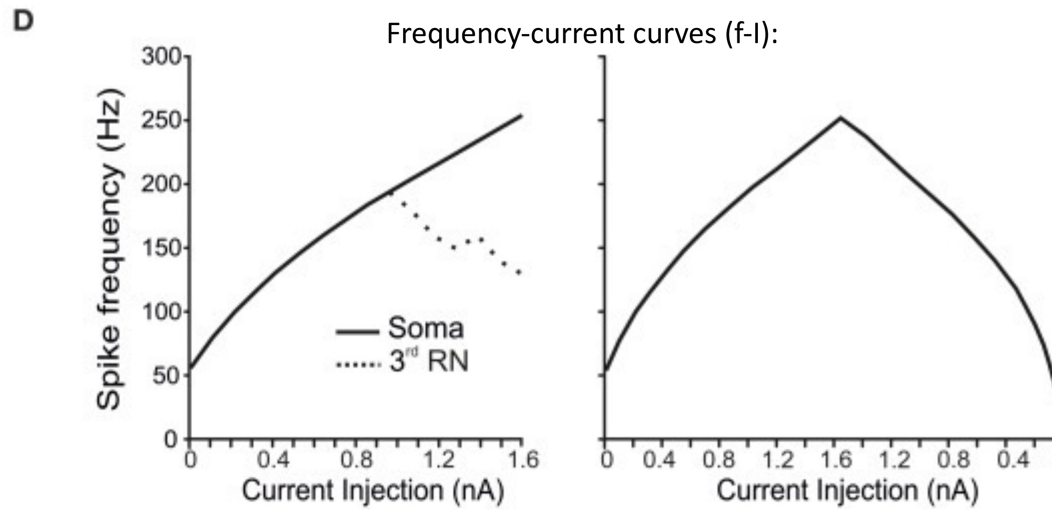
sag and rebound depolarization: Negative somatic step -current injection



Frequency modulation:
Ramp somatic current injection



Frequency-current curves (f-I):



ramp current induces a linear frequency modulation of Soma (up to about 300Hz while RNs are unable to sustain firing frequencies above 200 Hz

up and down ramp current non perfectly symmetrical

Modelling single neurons: the Leaky Integrate and Fire neuron

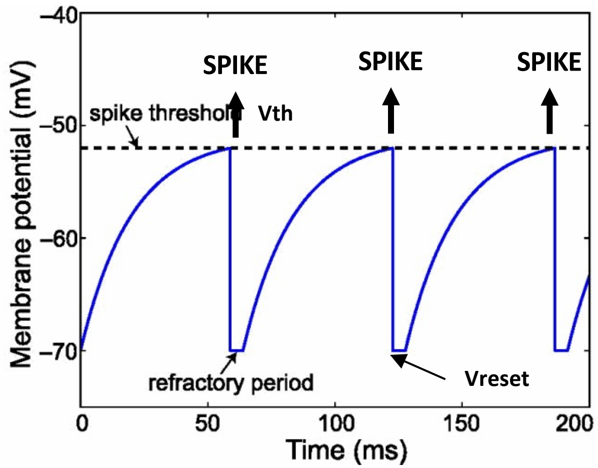
In the Leaky Integrate-and-Fire (LIF) neuron, the subthreshold dynamics of the membrane potential is modelled through a single passive term:

Membrane potential dynamics

$$\tau_m \frac{dV_m(t)}{dt} = -(V_m(t) - E_L) + R_m \cdot I_{in}(t)$$

Spike condition

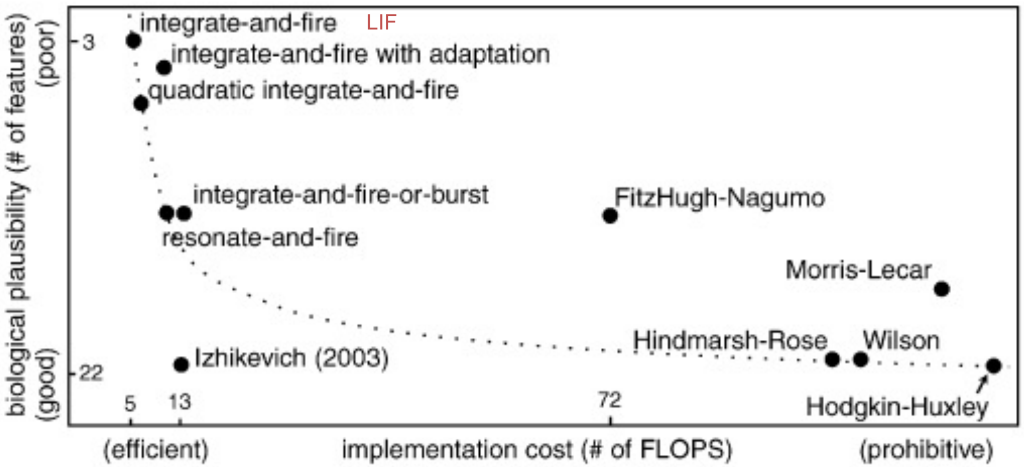
$$If\ V_m > V_{th}, then\ V_m = V_{reset}$$



- τ_m is the membrane time constant ($\tau_m = R_m \cdot C_m$, where R_m and C_m are the membrane resistance and capacitance, respectively), and it accounts for how fast the Vm curve increases
- E_L is the resting potential and it represents the steady-state value of V_m in absence of external input current
- I_{in} is the input current.

Action potentials are approximated as **single spike instants**: whenever V_m reaches a firing threshold V_{th}, the membrane potential is reset to a fixed value V_{reset}. After the spike, V_m remains at V_{reset} value (constant) during the refractory period and it is not possible to emit spikes.

Modelling single neurons: biological plausibility vs computational load



[Izhikevich, *IEEE Trans Neural Networks*, 2003]

Compromise between biological plausibility and implementation cost:

– HH multi-compartment models with morphology representation ✓ biological plausibility ✗ computational load
– LIF point neuron models ✗ biological plausibility ✓ computational load

– Multi-dimensional LIF models:
  - Izhikevich (non linear)
  - Adaptive Exponential Leaky Integrate and Fire (LIF) model (non linear)
  - Generalized LIF (linear)
– Fitting with experimental traces for OPTIMIZATION – also optimization has a cost!

Multi-dimensional LIF models: Izhikevich neuron

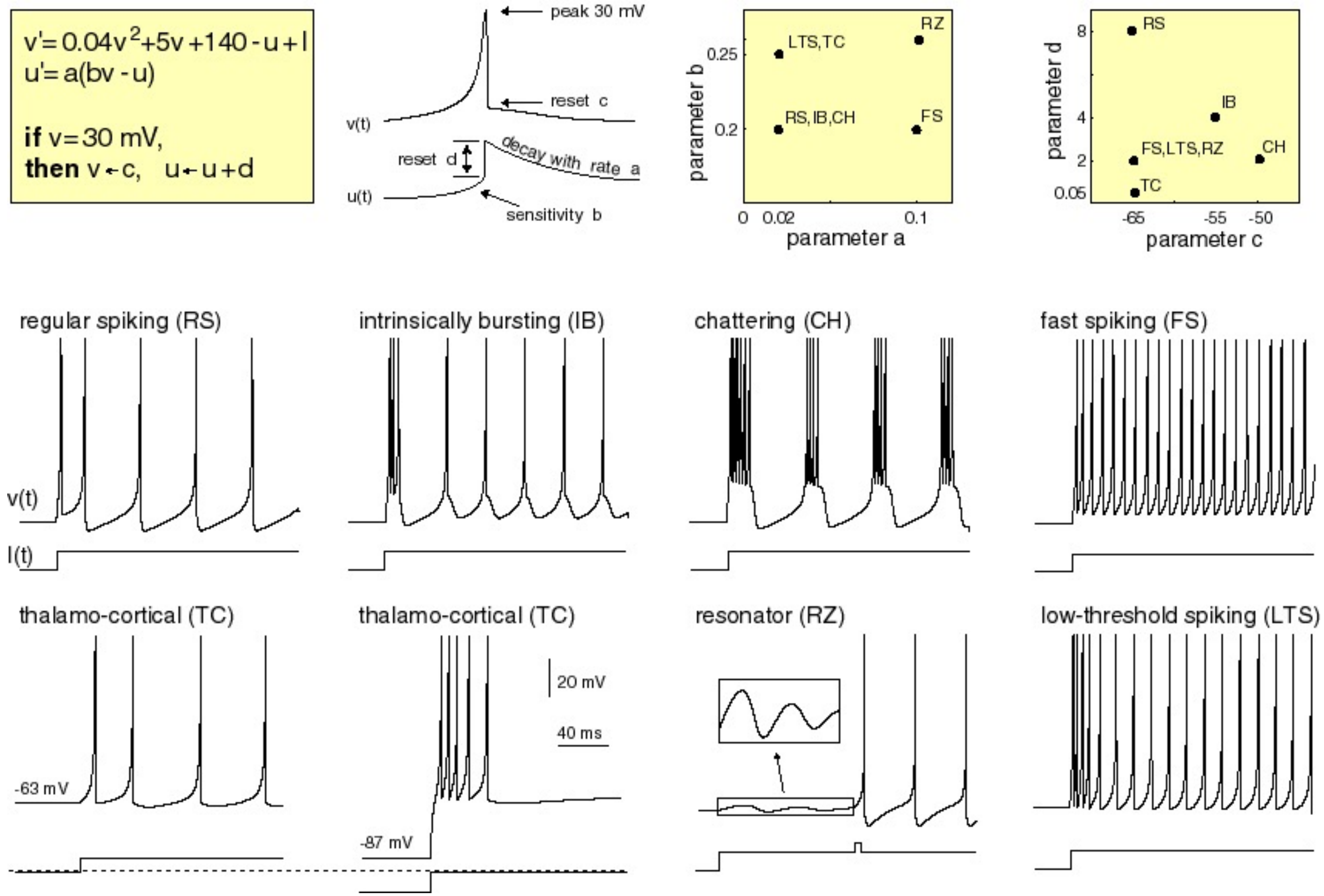
$$\begin{cases} \dfrac{dV_m(t)}{dt} = 0.04 * V_m^2(t) + 5 * V_m] + 150 - u(t) + 1 \\ \dfrac{du(t)}{dt} = a * b(V_m(t) - u(t)) \end{cases}$$

Membrane Potential

Membrane Recovery variable u(t)

If $V(t) > 30mV \rightarrow$ Spikes.

$$\begin{cases} V_m(t+1) = c \\ u(t+1) = u(t) + d \end{cases}$$



[Izhikevich, *IEEE Trans Neural Networks*, 2003]

Multi-dimensional LIF models: Adaptive Exponential LIF neuron

The model:

$$\begin{cases} C_m \cdot V_m{}'(t) = -g_L \cdot (V_m(t) - E_L) + g_L \cdot \Delta_T \cdot e^{\frac{V_m(t)-V_{th}}{\Delta_T}} - w(t) + I_m(t) \\ \tau_w \cdot w'(t) = a \cdot (V(t) - E_L) - w(t) \end{cases}$$

$V_m(t)$ Membrane Potential

$w(t)$ Adaptive current

If $V_m(t) \geq V_{th} \rightarrow SPIKE$:

$$\begin{cases} V_m(t+1) = V_r \\ w(t+1) = w(t) + b \end{cases}$$

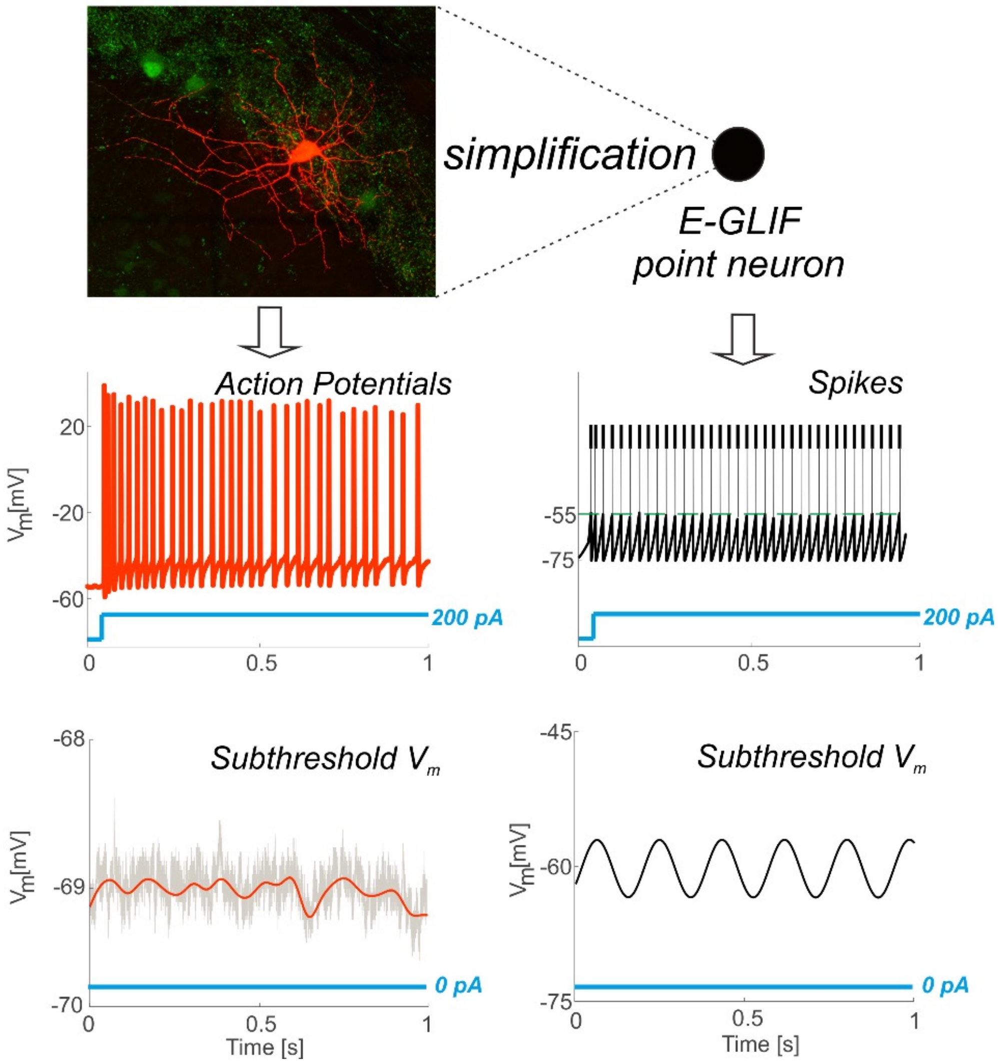
Properties:

- multiple electroresponsive properties based on parameter values
- replacement of the strict voltage threshold by a more realistic smooth spike initiation zone.
- subthreshold resonances or adaptation as in the Izhikevich model.

[Brette and Gerstner, *J Neurophysiol*, 2005]

Towards a unified point neuron model for cerebellar neurons

- Aim: a model able to reproduce all the cerebellar electroresponsive mechanisms, while keeping:
  - **Neurophysiological realism** (elements in the model ↔ biophysical mechanisms)
  - **Low computational load** (→ linear and analytically solvable, to increase simulation step without loosing precision within large-scale Spiking Neural Networks - SNNs)
  - **Generalized features** (not fitting on single traces)
  - Different **sets of parameters** for different cells, reproducing **all** the electrophysiological properties of each population, i.e. **spike patterns** more than sub/supra-threshold mechanisms (since within SNN)



Extended-Generalized LIF neuron model (E-GLIF)

Membrane potential V_m

Adaptive current I_{adapt}

Spike-triggered depolarizing current I_{dep}

$$\begin{cases} V_m'(t) = \dfrac{1}{C_m}\left(\dfrac{C_m}{\tau_m}(V_m(t) - E_L) + I_{stim} + I_e + I_{dep}(t) - I_{adap}(t)\right) \\ I_{adap}'(t) = k_{adap}(V_m(t) - E_L) - k_2 I_{adap}(t) \\ I_{dep}'(t) = -k_1 I_{dep}(t) \end{cases}$$

Refractory period T_{ref}
Stocasticity in spike generation

$$\begin{cases} t_{spk} \notin \Delta t_{ref} \\ rng < (1 - e^{-\lambda(t_{spk})t_{spk}}) \end{cases}$$

$$\lambda(t) = \lambda_0 e^{\frac{V_m(t) - V_{th}}{\tau_V}}$$

Updates at spike event

$$\begin{cases} V_m(t_{spk}) \leftarrow V_r \\ I_{dep}(t_{spk}) \leftarrow A_1 \\ I_{adap}(t_{spk}) \leftarrow I_{adap}(t_{spk} - 1) + A_2 \end{cases}$$

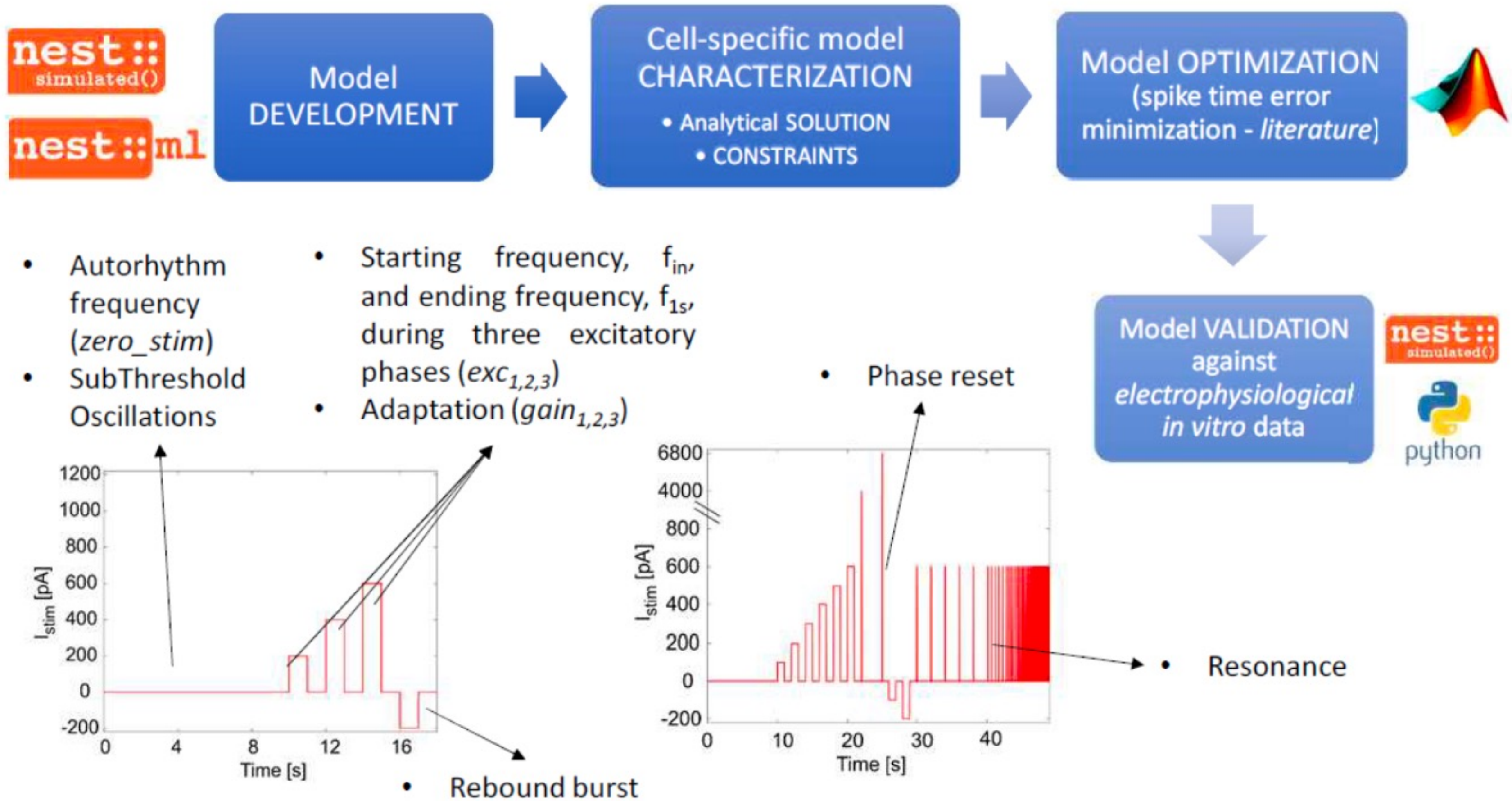
Biological quantities/parameters

Artificial parameter

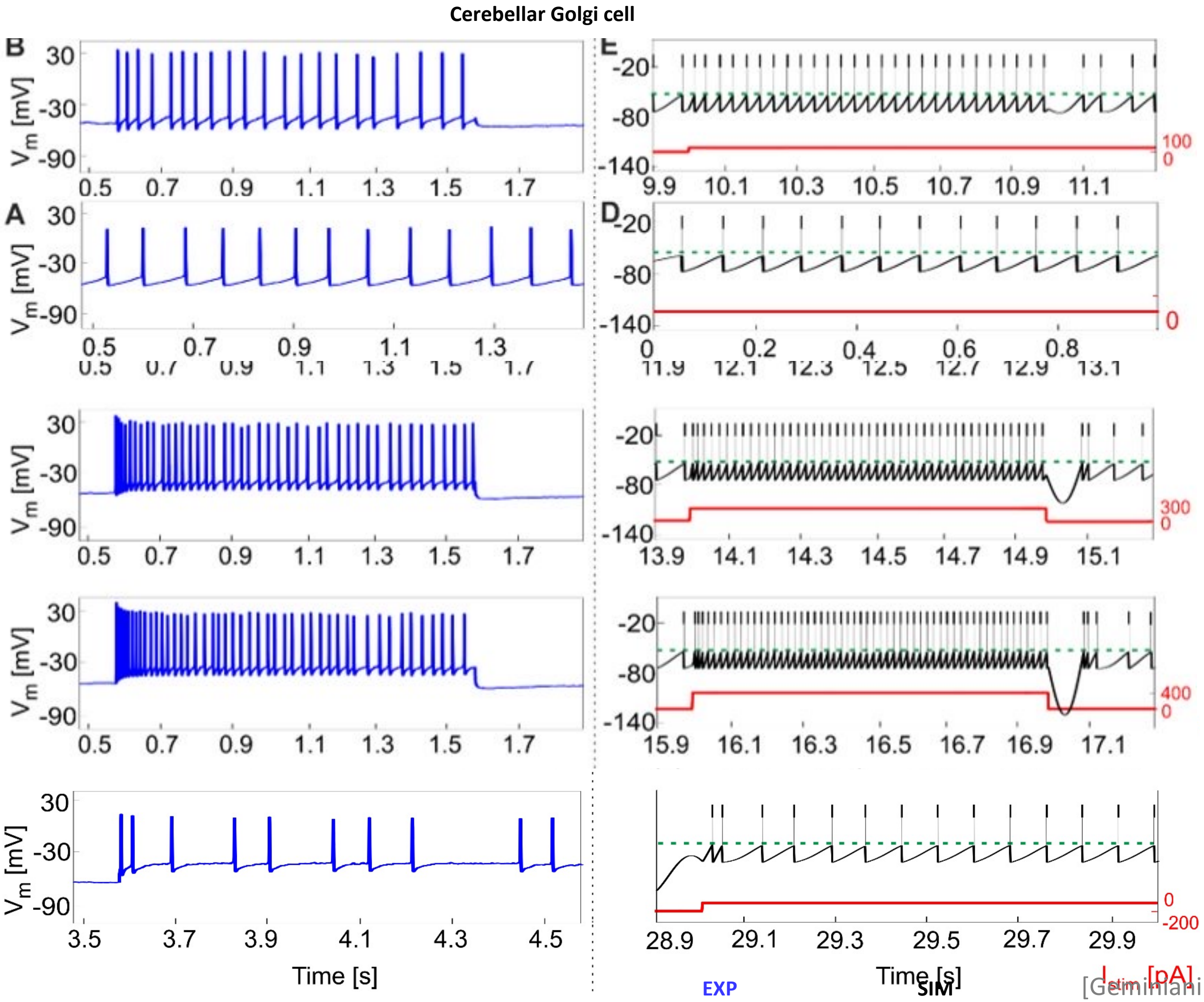
I_{stim} = external stimulation current;
C_m = membrane capacitance;
τ_m = membrane time constant;
E_L = resting potential;
I_e = endogenous current;
k_{adap}, k_2 = adaptation constants;
k_1 = I_{dep} decay rate;
V_{th} = threshold potential;
λ_0, τ_V = escape rate parameters;
t_{spk}^+ = time instant immediately following the spike
V_r = reset potential;
A_2, A_1 = model currents update constants.

[Geminiani et al, *Front Neuroinform*, 2018]

E-GLIF – implementation, optimization and validation



E-GLIF for cerebellar Golgi cells: validation against experimental data



Autorhythm

Depolarization-induced bursting

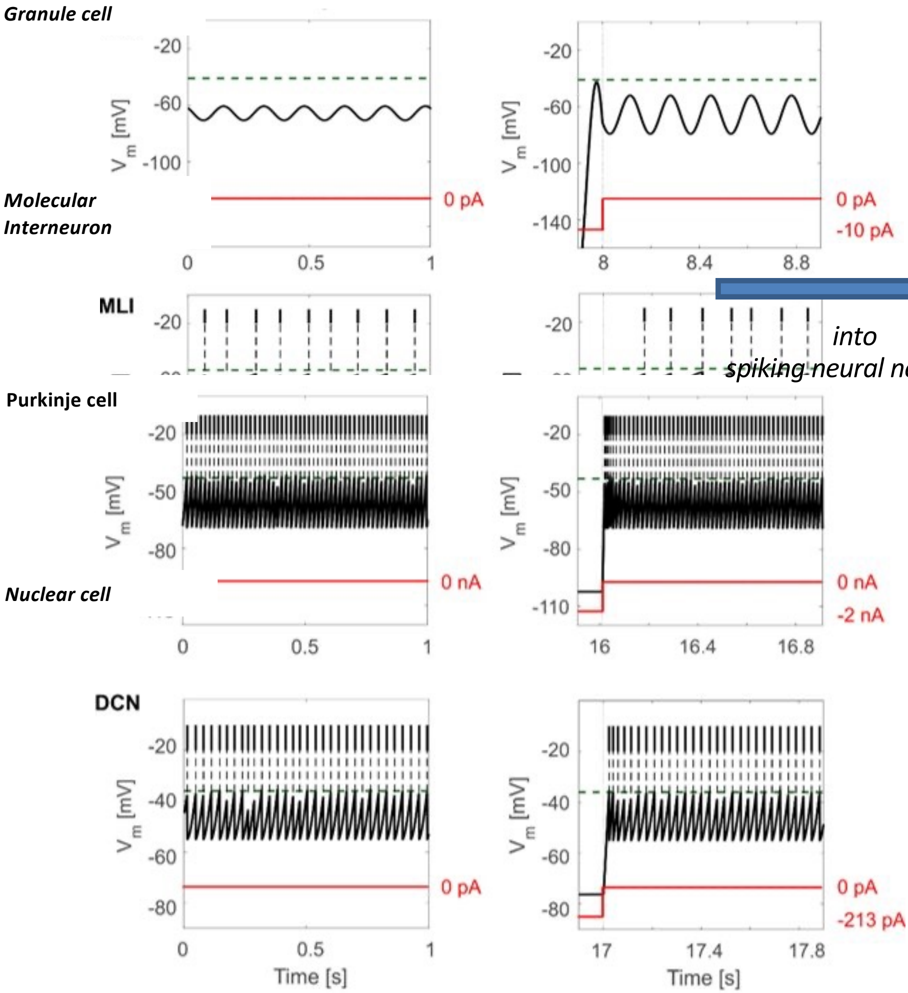
Post-inhibitory rebound bursting

… subthreshold oscillations, resonance, phase-reset

[Geminiani et al, Front Neuroinform, 2018]

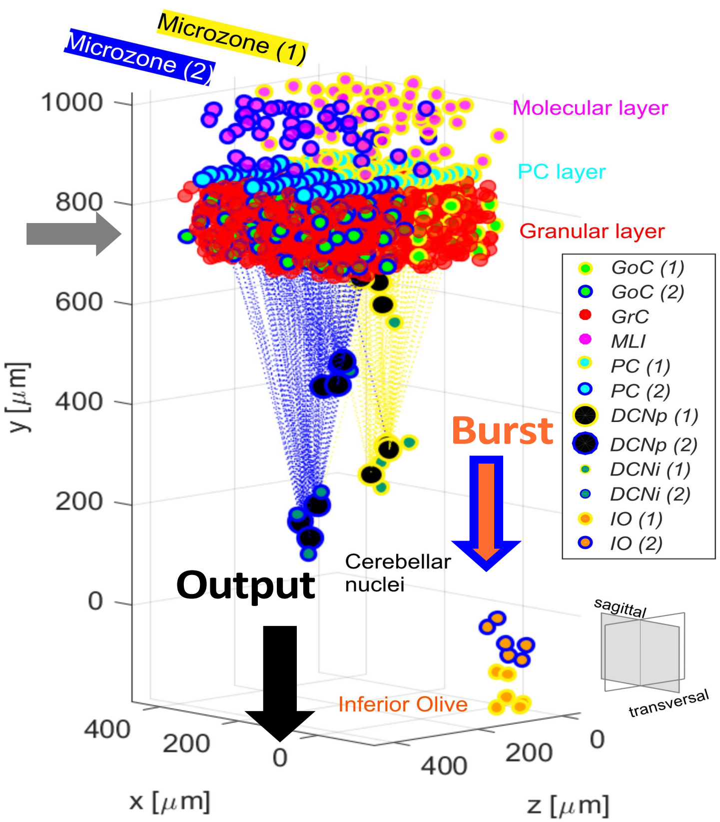
E-GLIF for other cerebellar neurons

*Tuned on experimental data for the **other cerebellar neurons***



into spiking neural network

40 Hz Pois son



Single neuron properties propagate to network dynamics: pause-burst responses enhance the time precision of the output

Modelling plasticities (pf-PC)

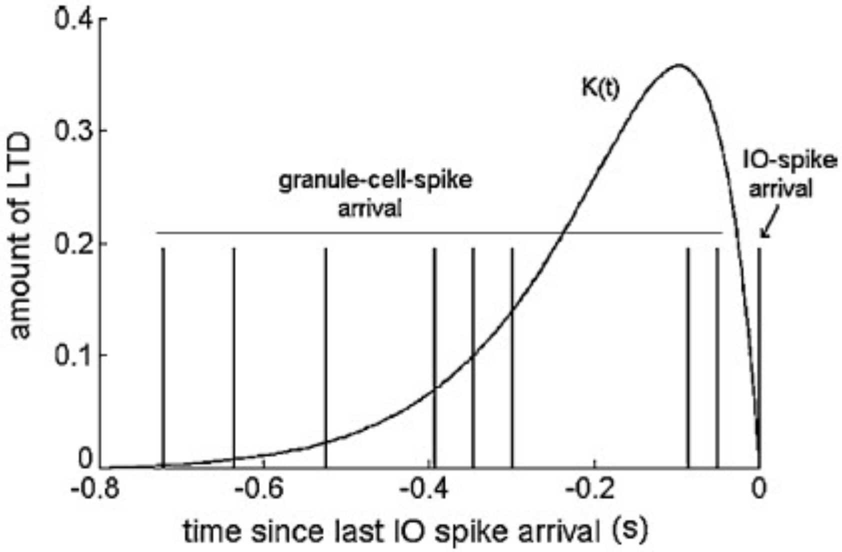
LTD

$$\Delta w_i = \beta \int_{-\infty}^{t_{IOSPIKE}} k(t_{IOSPIKE} - \mathrm{t})\mathrm{h}(t)_{PF_i} dt$$

$$k(t) = e^{-\left(\frac{t-t_0}{\tau}\right)} sin\left(2\pi\left(\frac{t-t_0}{\tau}\right)\right)^{20}$$

$$\mathrm{h(t)}\begin{cases} 1 & if\ PF_i\ is\ active\ at\ time\ t \\ 0 & otherwise \end{cases}$$

LTP $\Delta w_i = \alpha$



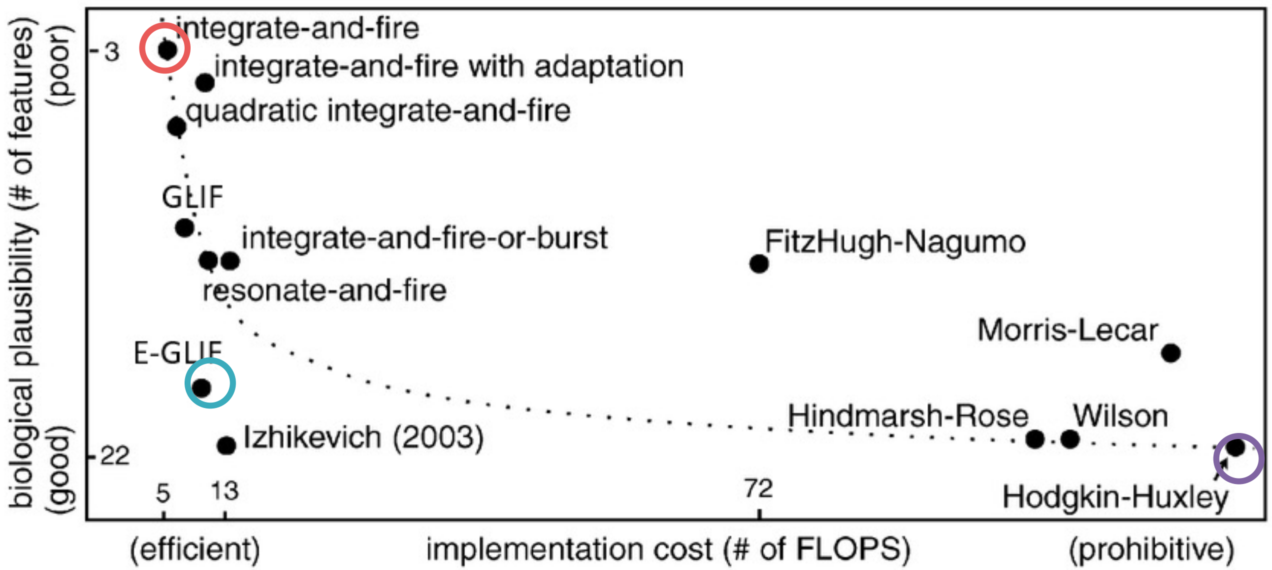
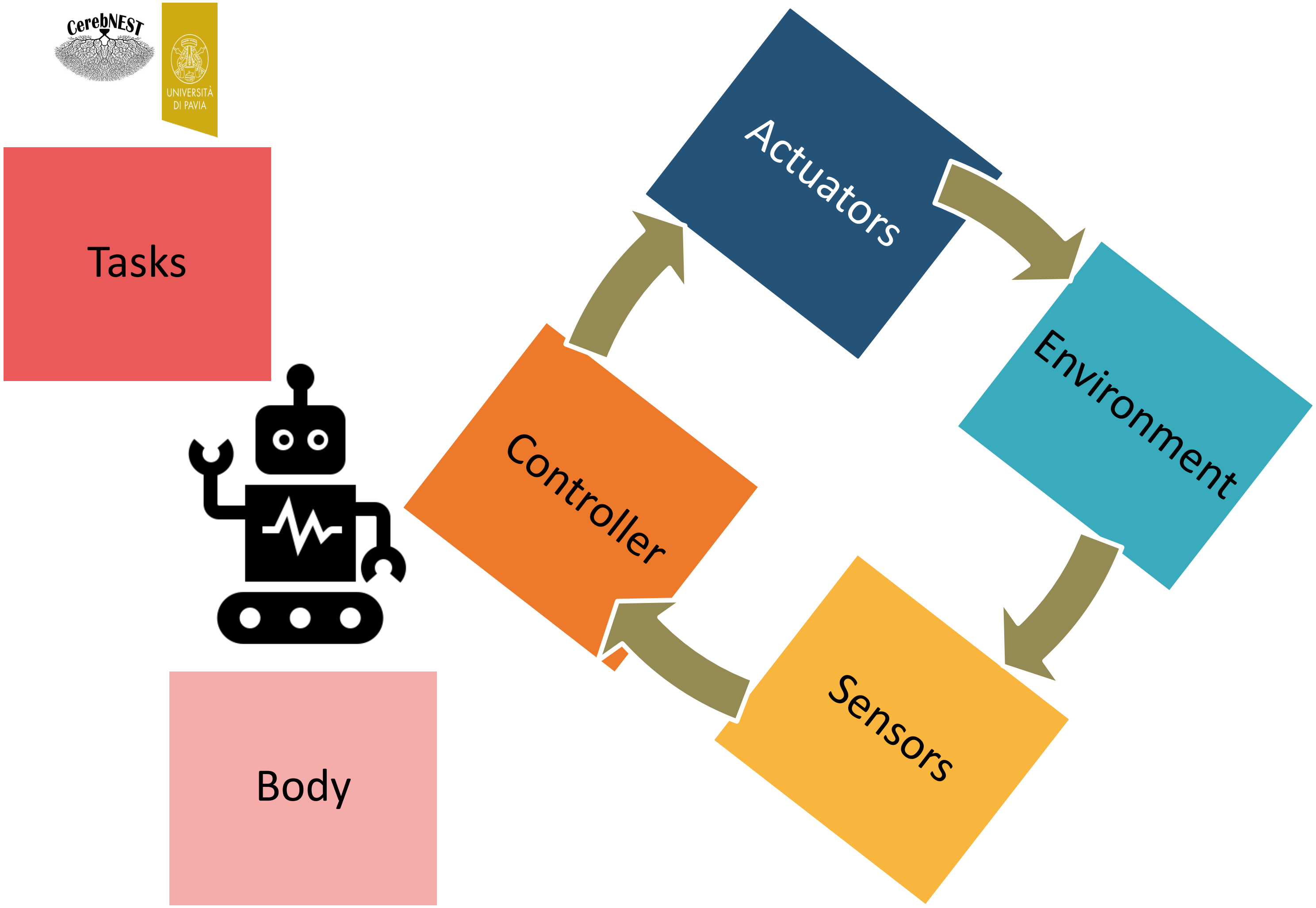


Figure 2.1 Trade-off between biological plausibility and computational load in single neuron models. Basic IF and HH models are at the two extreme cases. GLIF and E-GLIF approximate values have been added. The E-GLIF simplifies the action potential representation, but approaches the Izhikevich and HH precision in terms of firing patterns, outperforming the other multidimensional LIF models. In multi-compartment models, the HH representation remains the standard and amplifies by orders of magnitude both computational capability and biological plausibility. Modified from (Izhikevich, 2004).

Neuroengineering 2021/22

COMPUTATIONAL NEUROSCIENCE - Part 5 Neurorobotics

Neurorobotics



Human Brain Project

CerebNEST

UNIVERSITÀ DI PAVIA

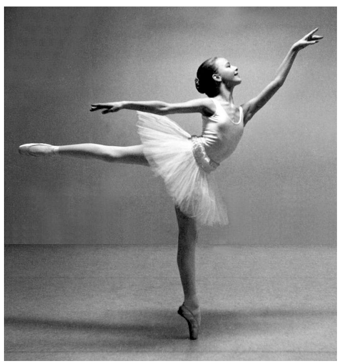
CONTROLLER

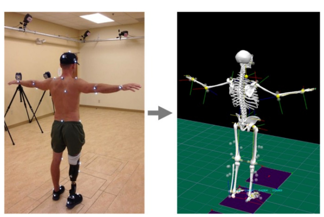
MIMICKS BRAIN CRICUITS

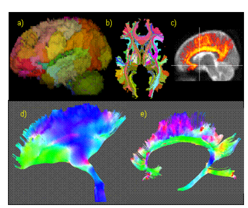
TASKS

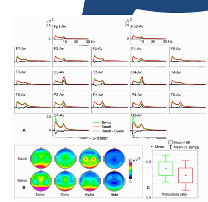
MIMICK THE HUMAN ONE

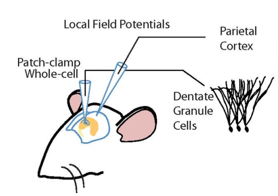
A MULTI SCALE PROBLEM

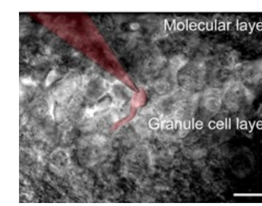










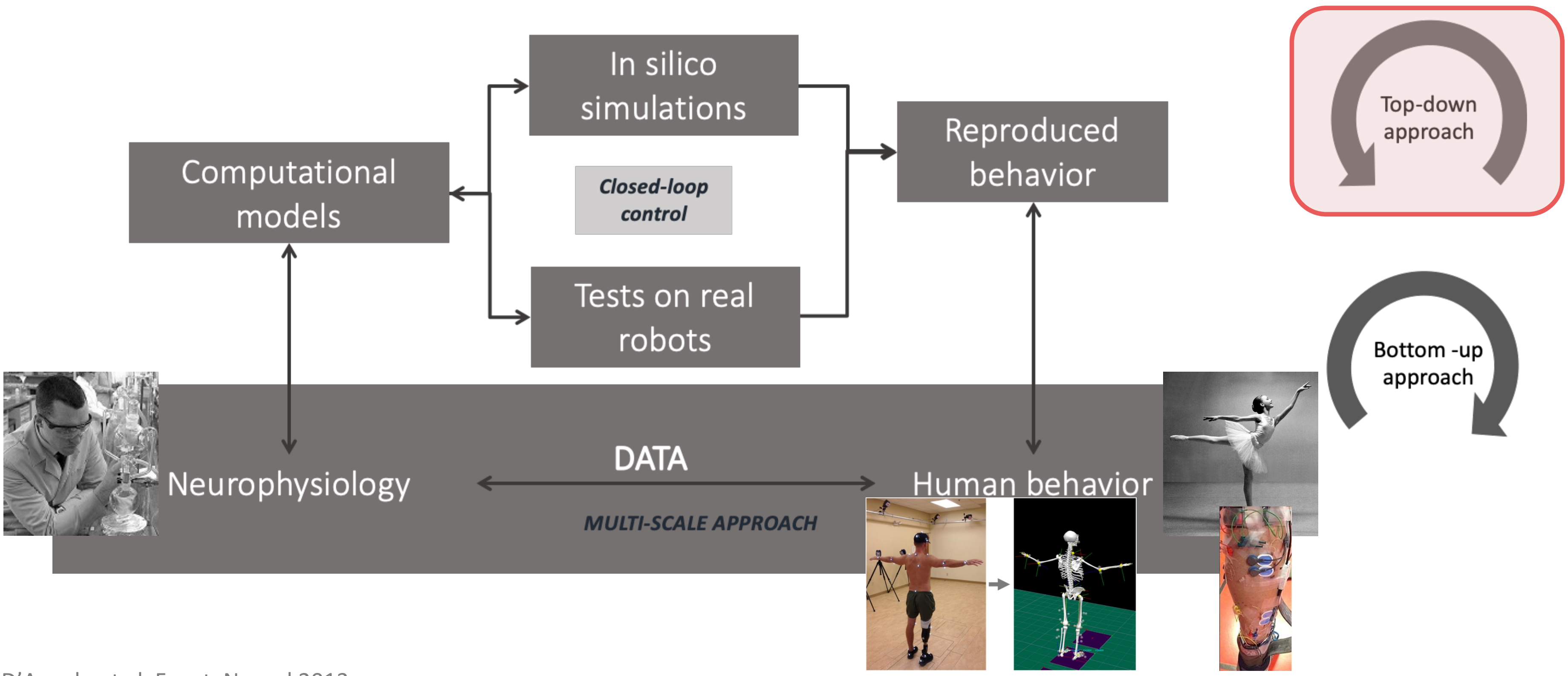


Approaches to neurorobotics design

Human Brain Project

CerebNEST

UNIVERSITÀ DI PAVIA



D'Angelo et al. Funct. Neurol 2013

D'Angelo et al. Front. Cell. Neuroscience, 2016

Approaches to neurorobotics design

Human Brain Project

D’Angelo et al. Funct. Neurol 2013
D’Angelo et al. Front. Cell. Neuroscience, 2016

In silico simulations

Computational models

Closed-loop control

Tests on real robots

Reproduced behavior

Top-down approach

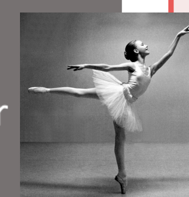
Bottom -up approach

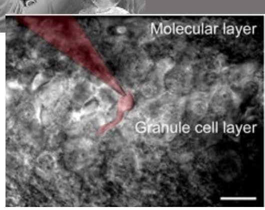
Neurophysiology

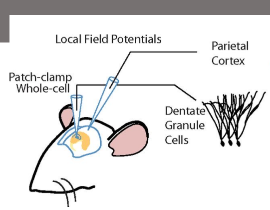
DATA

MULTI-SCALE APPROACH

Human behavior





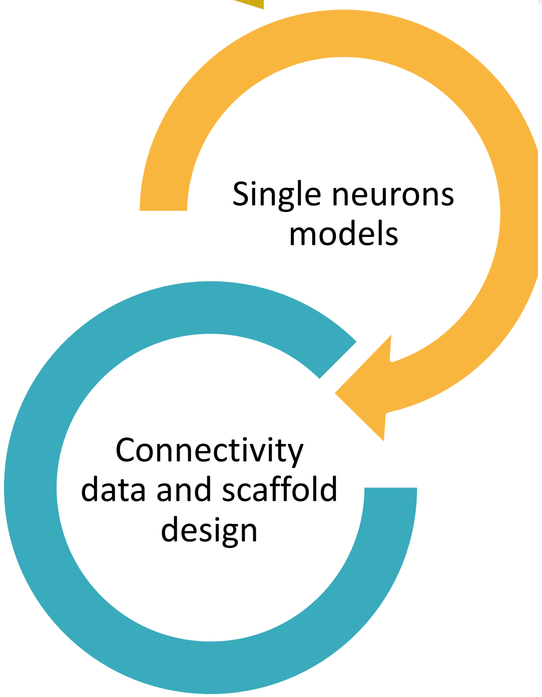


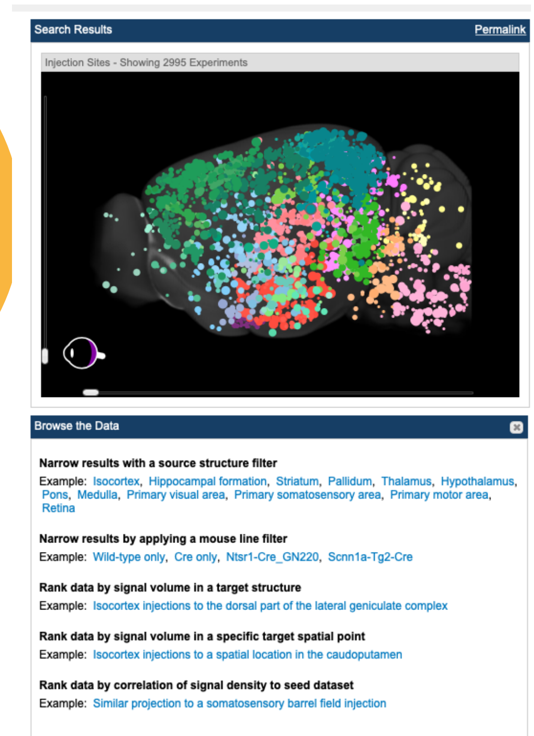
Data-driven spiking NN

Human Brain Project

CerebNEST

UNIVERSITÀ DI PAVIA




Search Results
Permalink
Injection Sites - Showing 2995 Experiments

Browse the Data

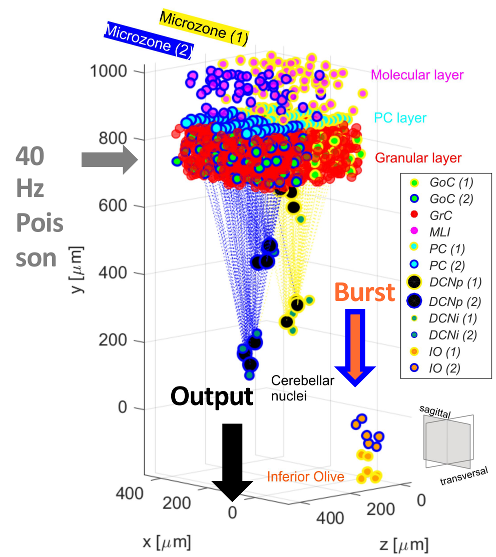
Narrow results with a source structure filter
Example: Isocortex, Hippocampal formation, Striatum, Pallidum, Thalamus, Hypothalamus, Pons, Medulla, Primary visual area, Primary somatosensory area, Primary motor area, Retina

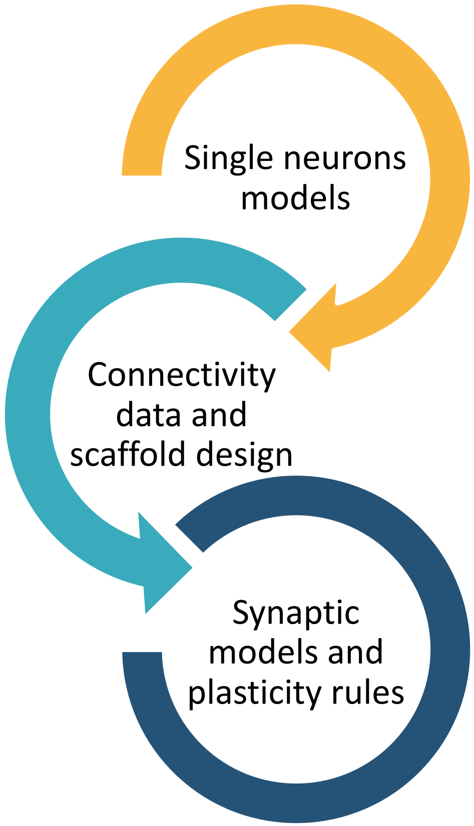
Narrow results by applying a mouse line filter
Example: Wild-type only, Cre only, Ntsr1-Cre_GN220, Scnn1a-Tg2-Cre

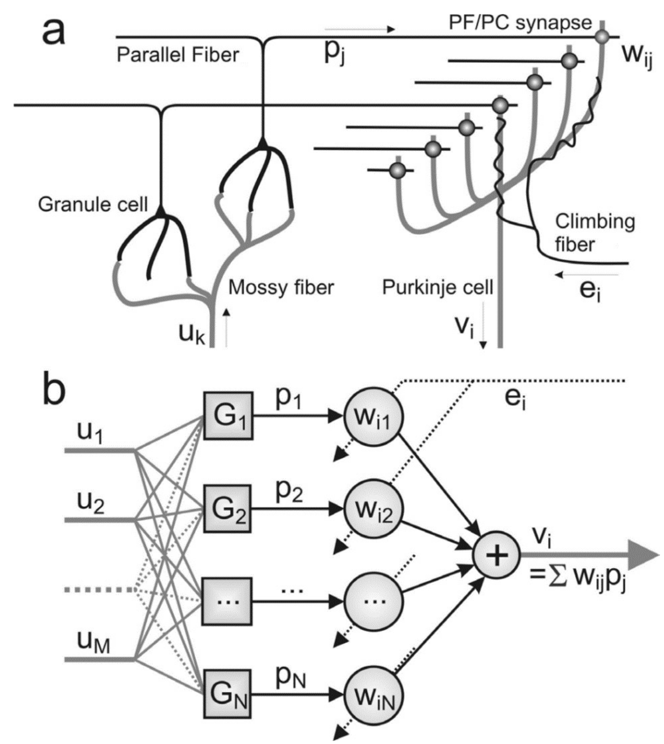
Rank data by signal volume in a target structure
Example: Isocortex injections to the dorsal part of the lateral geniculate complex

Rank data by signal volume in a specific target spatial point
Example: Isocortex injections to a spatial location in the caudoputamen

Rank data by correlation of signal density to seed dataset
Example: Similar projection to a somatosensory barrel field injection

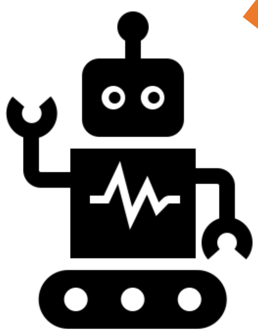



Single neurons models
Connectivity data and scaffold design
Synaptic models and plasticity rules

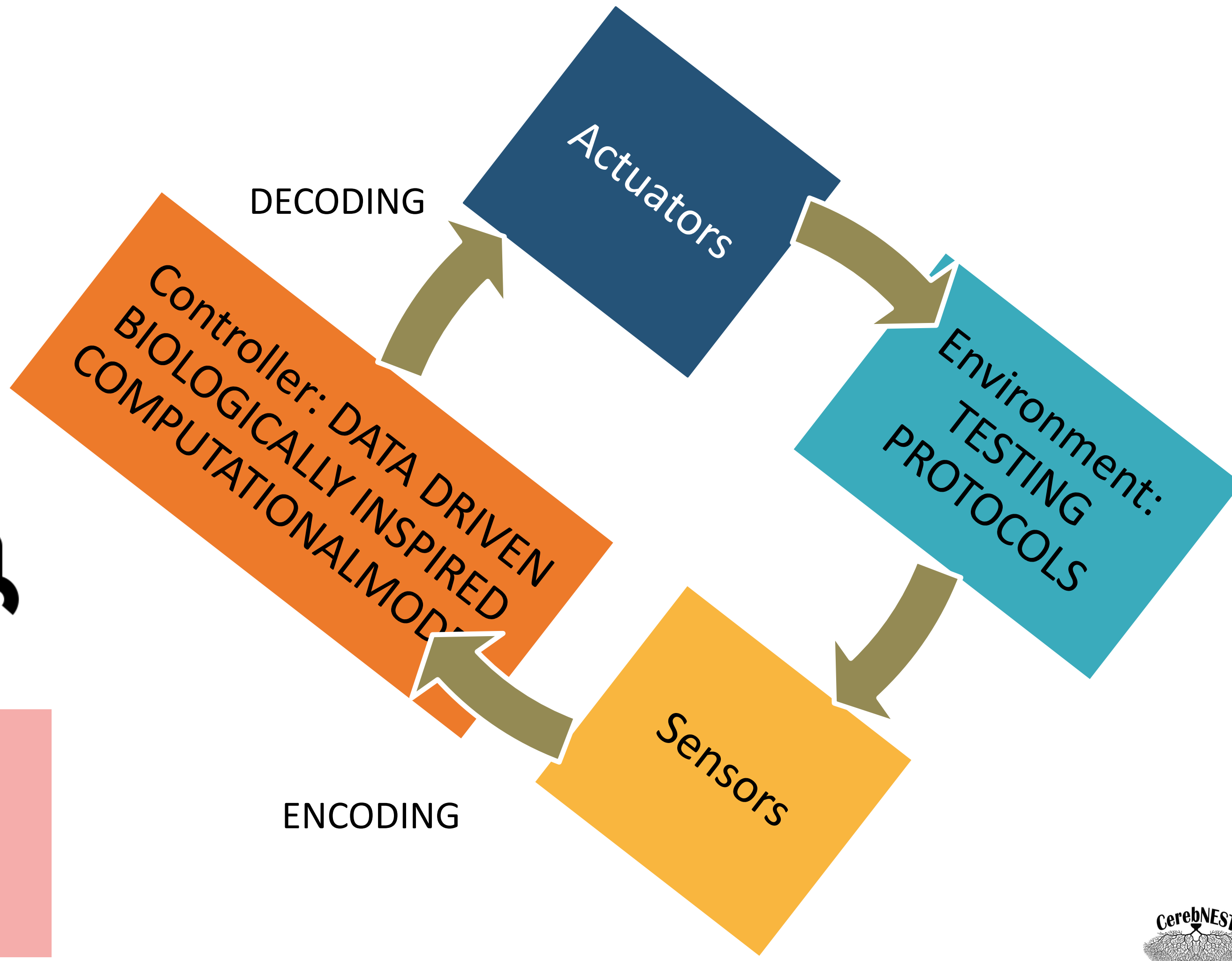

a
Parallel Fiber
p_j
PF/PC synapse
w_{ij}
Granule cell
Mossy fiber
Purkinje cell
Climbing fiber
e_i
u_k
v_i
b
u_1
u_2
u_M
G_1
G_2
...
G_N
p_1
p_2
...
p_N
w_{i1}
w_{i2}
...
w_{iN}
e_i
+
v_i
$=\sum w_{ij}p_j$

Tasks:

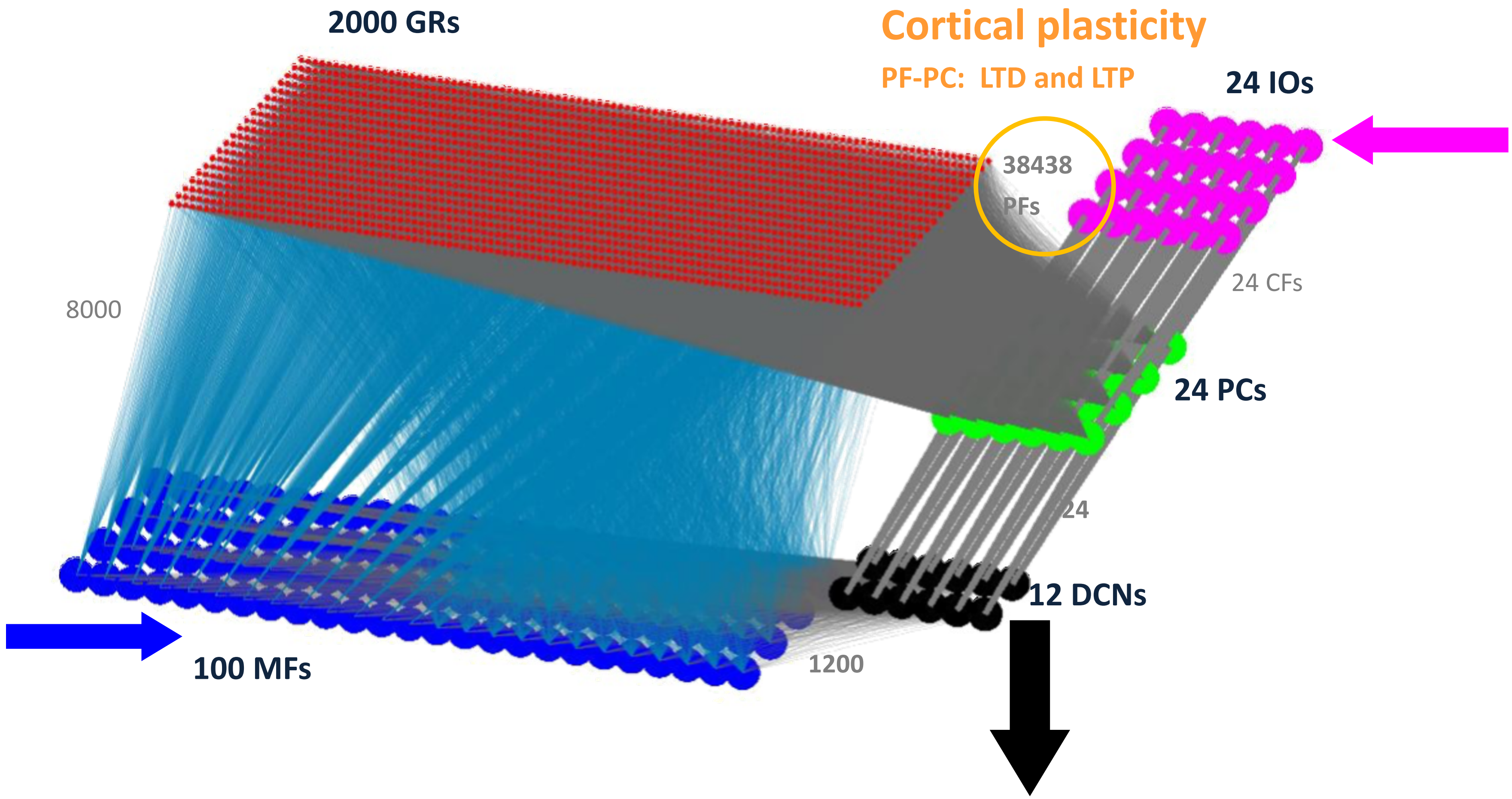
TESTING PROTOCOLS



Body



Cerebellar spiking NN

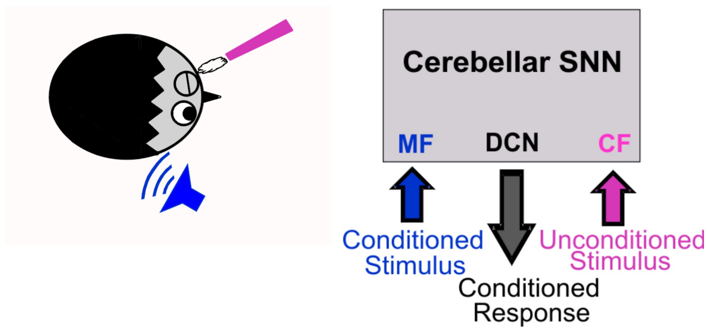


Spiking Neural Network (EDLUT-based)

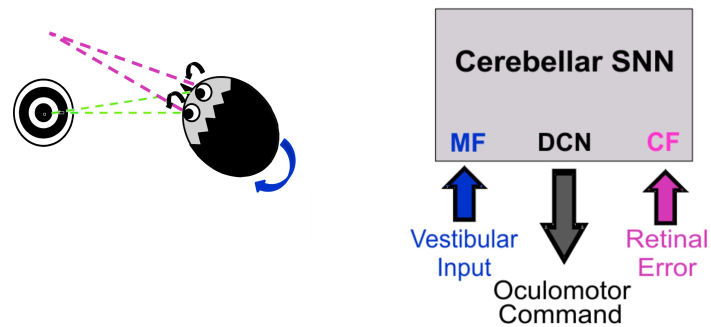
Testing protocols of the Cerebellar Models

Casellato et al., PlosOne 2014;
Antonietti et al., IEEE TMBE 2015

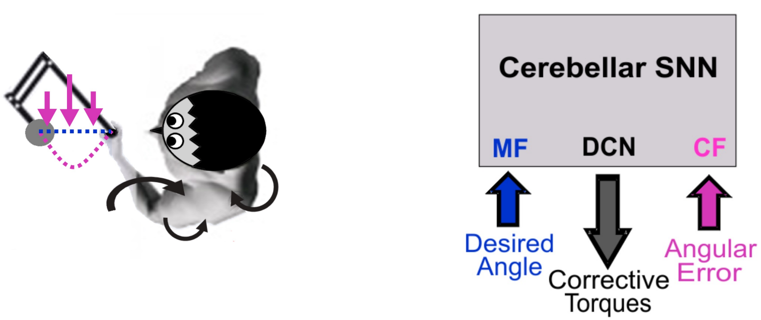
Eye Blink Classical Conditioning (EBCC)



Vestibulo-Ocular Reflex (VOR)



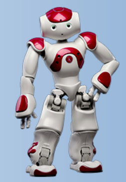
Movements perturbed by Force Fields (FF)



LEARNING FEATURES EMERGE
FROM PLASTICITY CHANGES IN THE SNN

Embodiment with real robots

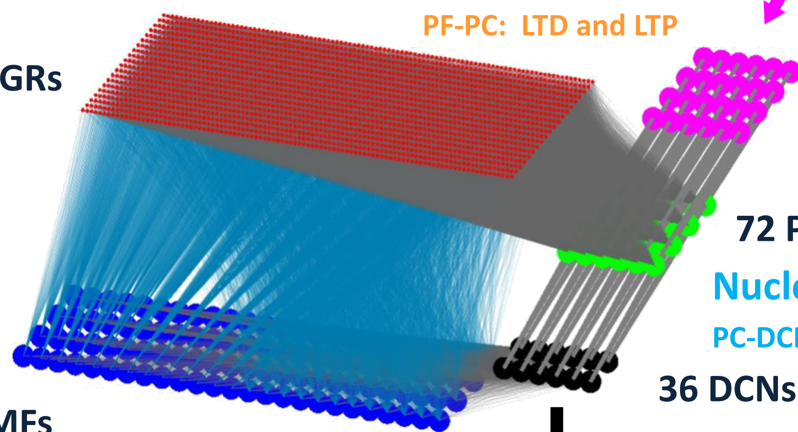
Ros et al. Neural Computation 2006
Luque et al. Int. J. Neural Syst. 2011
Antonietti et al., IEEE TMBE 2015
Antonietti et al. IEEE TNNLS 2018

Simulator	EDLUT				
Number of Neurons	6480	2160	6480	1480	6480
Plasticity (1 vs 3)					
Parameter Optimization	GA	GA	GA	Brute Force	GA Inherited
Testing paradigms	EBCC	EBCC	EBCC	EBCC VOR FF	EBCC FF
Embedding or Data Fitting	Healthy Standard	22 Human subjects TMS dataset	36 Human subjects TMS dataset		

Embodiment with real robots

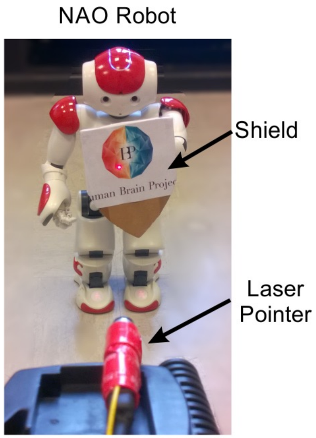
Ros et al. Neural Computation 2006
Luque et al. Int. J. Neural Syst. 2011
Antonietti et al., IEEE TMBE 2015
Antonietti et al. IEEE TNNLS 2018

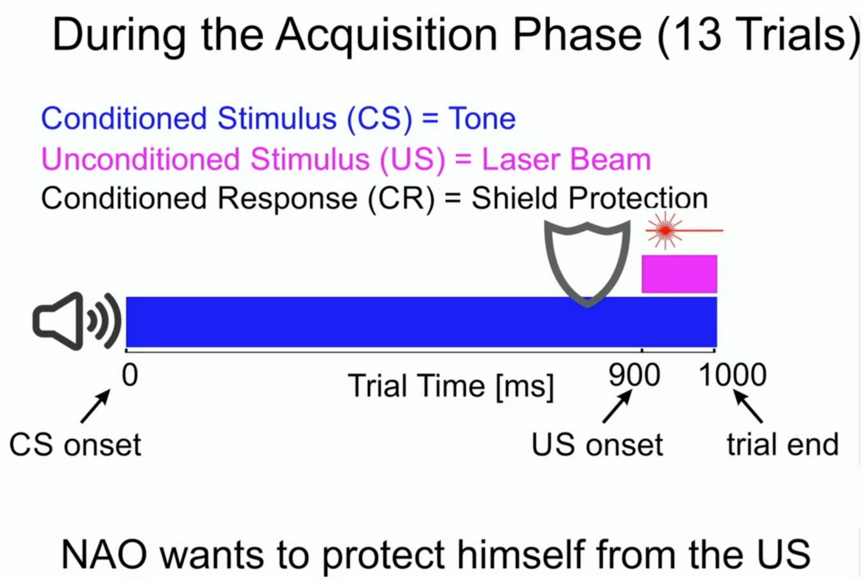
Simulator	
Number of Neurons	6480
Plasticity (1 vs 3)	
Parameter Optimization	GA Inherited
Testing paradigms	EBCC FF
Embedding or Data Fitting	



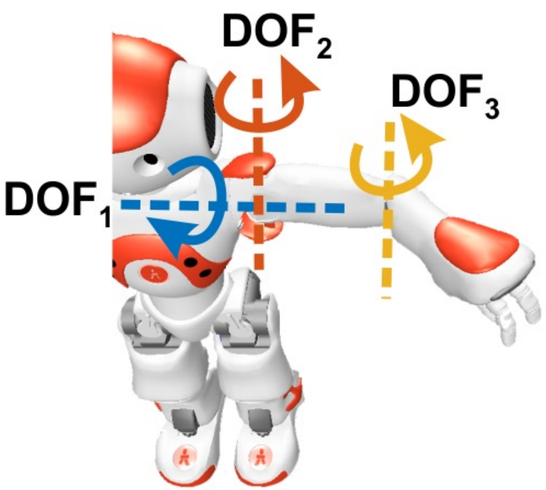
EBCC with Nao robot

Antonietti et al., IEEE TMBE 2015;
Antonietti et al., IEEE TNNLS 2018





Multi-joint Force Field with NAO Robot

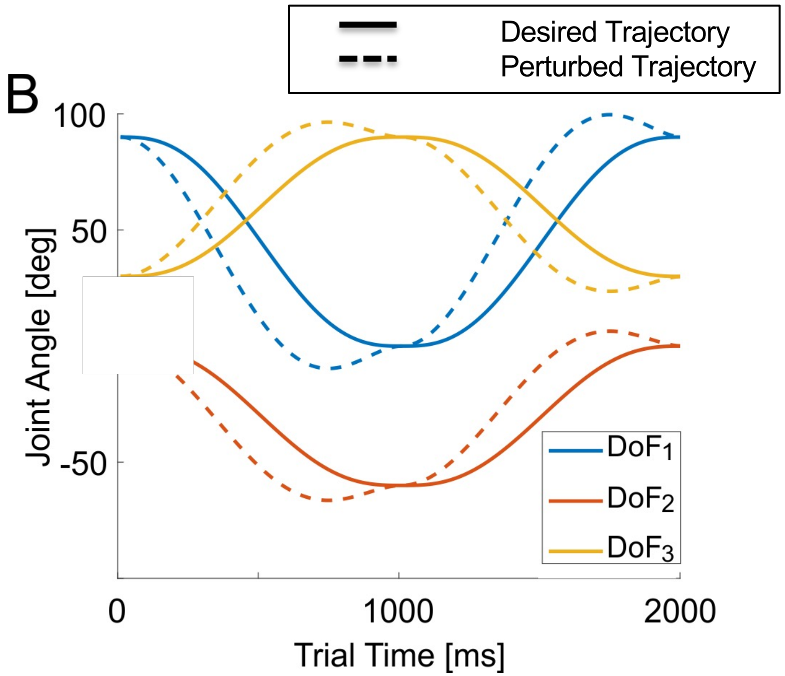


Protocol

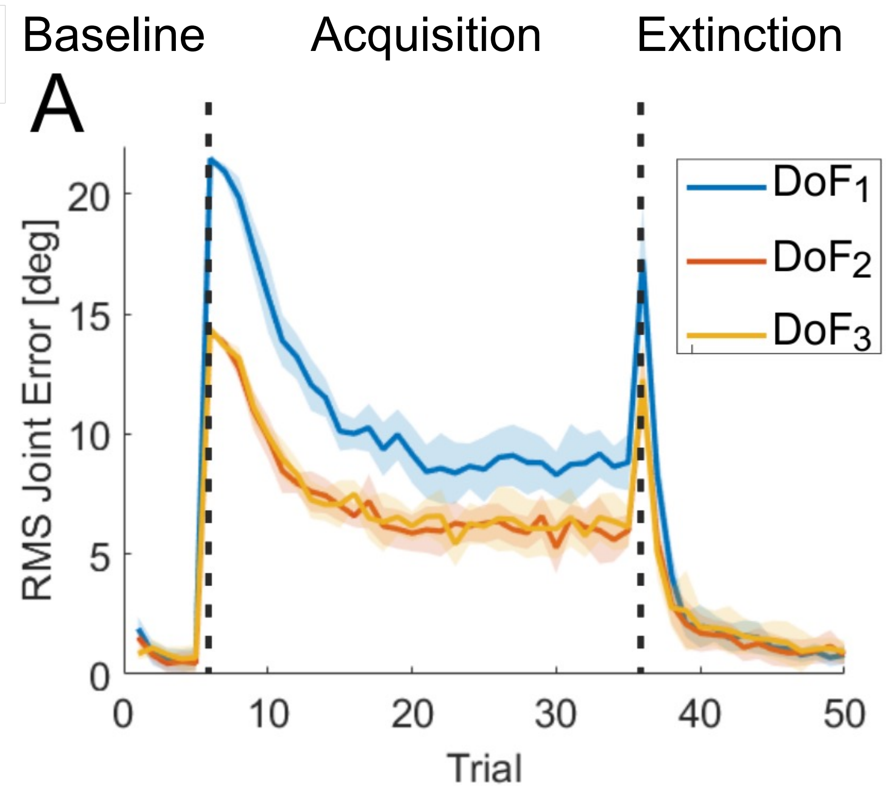
5 trials of Baseline
(No perturbation)

30 trials of Acquisition
(Perturbation starts)

15 trials of Extinction
(Perturbation ends)



5 trials of Baseline
(No perturbation)



Antonietti et al., Comp. Int. And Neurosc. 2019;

Embodiment with virtual robots: NRP

- Brain simulators at increasing computation load (more features, more neurons, more plasticity,…)
- Physics simulator (virtual robots)
- Robot controller
- Experiment pipeline

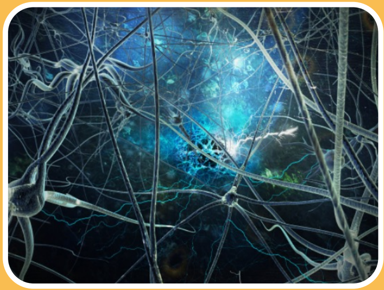
GAZEBO

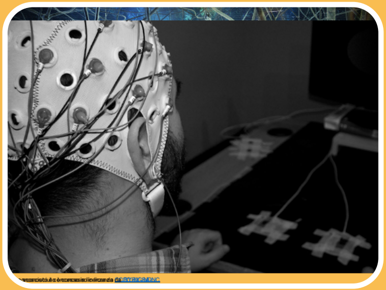
nest::
simulated()

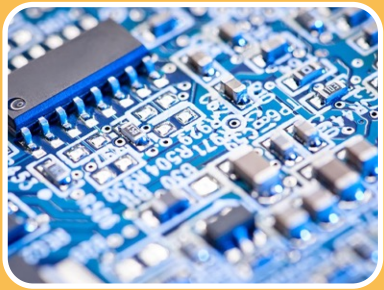
ROS

PyNN

Impacts







Impacts on Basic Neuroscience

Impacts on Applied Neuroscience

Impacts on Robotics and Computer Science

Impacts on basic neuroscience

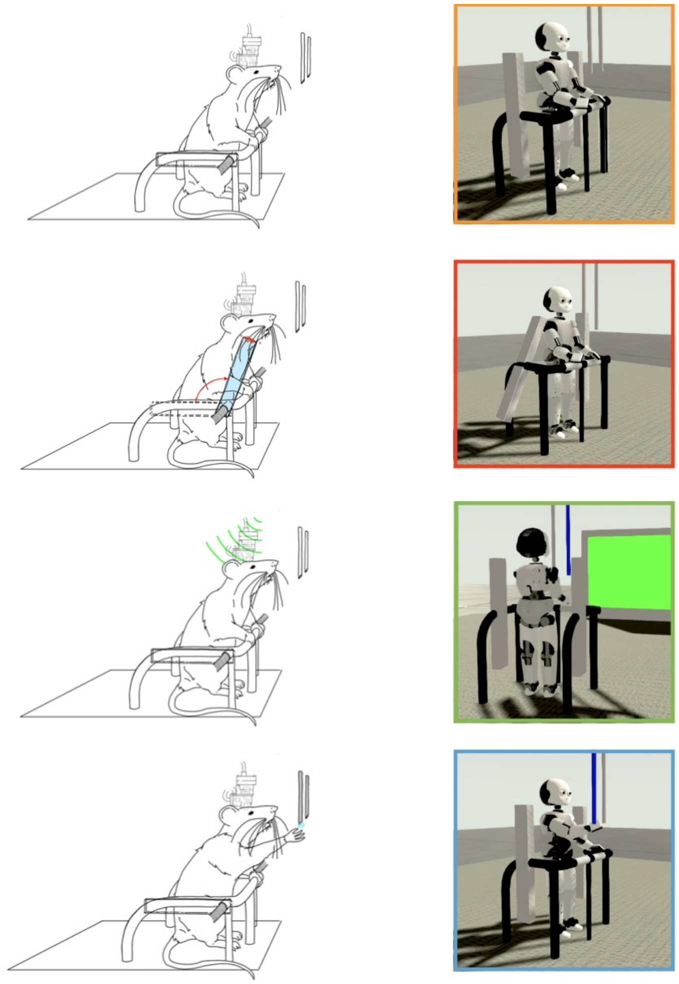
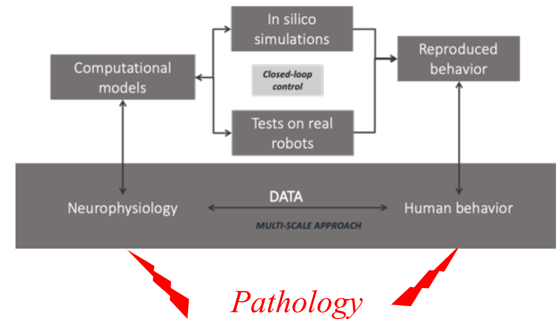


Figure 9: *In vivo and in silico protocol co-execution.* *The robotic subject successfully performs the protocol as it was designed to be executed in vivo. The colored frames are used to mark a temporal reference on the spiking plot in Figure 8.*

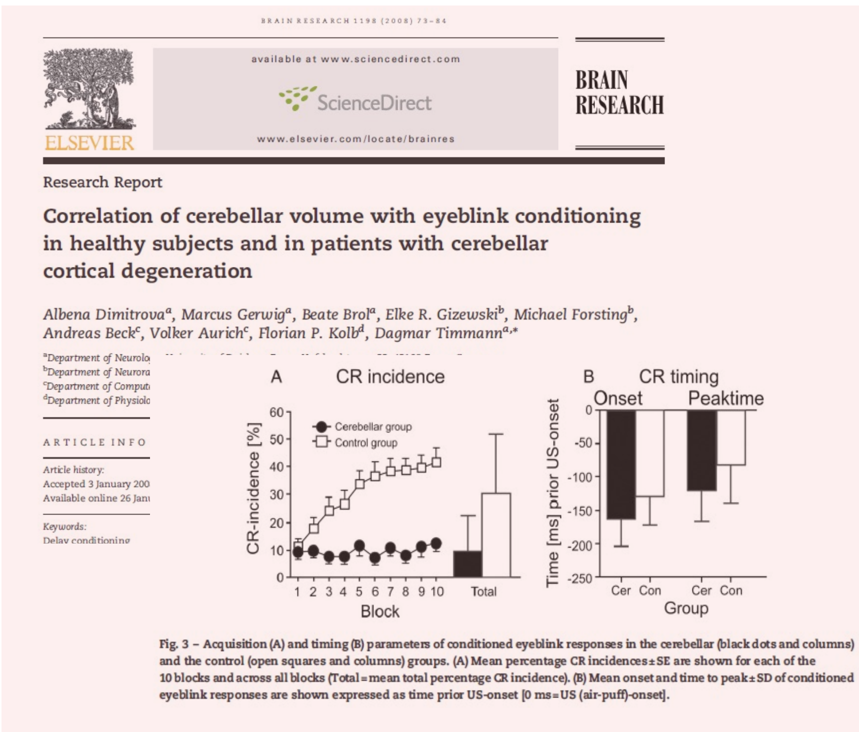
Impacts on applied neuroscience

Geminiani et al., Int J Neural Syst 2018

EBRAINS



- From physiological to pathological models



BRAIN RESEARCH 1198 (2008) 73–84
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BRAIN RESEARCH

Research Report

Correlation of cerebellar volume with eyeblink conditioning in healthy subjects and in patients with cerebellar cortical degeneration

Albena Dimitrova[a], Marcus Gerwig[a], Beate Brol[a], Elke R. Gizewski[b], Michael Forsting[b], Andreas Beck[c], Volker Aurich[c], Florian P. Kolb[d], Dagmar Timmann[a,]*
[a]Department of Neurolo…
[b]Department of Neurora…
[c]Department of Comput…
[d]Department of Physiolo…

ARTICLE INFO
Article history:
Accepted 3 January 200…
Available online 26 Janu…
Keywords:
Delay conditioning

Fig. 3 – Acquisition (A) and timing (B) parameters of conditioned eyeblink responses in the cerebellar (black dots and columns) and the control (open squares and columns) groups. (A) Mean percentage CR incidences±SE are shown for each of the 10 blocks and across all blocks (Total=mean total percentage CR incidence). (B) Mean onset and time to peak±SD of conditioned eyeblink responses are shown expressed as time prior US-onset [0 ms=US (air-puff)-onset].