



IST-2001-35271 Project SpikeFORCE: Real-time Spiking Networks for Robot Control



**Project funded by the Future and Emerging Technologies
arm of the IST Programme FET-Life-like Perception
Systems (LPS) Proactive Initiative 2001 in Bionics**





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Boris Barbour
ÉCOLE NORMALE SUPÉRIEURE



Olivier J.-M. D. Coenen

Sony CSL Neuroscience
Sony Computer Science Laboratory Paris



Eduardo Ros Vidal



Universidad de Granada
Fundada en 1531

Egidio D'Angelo

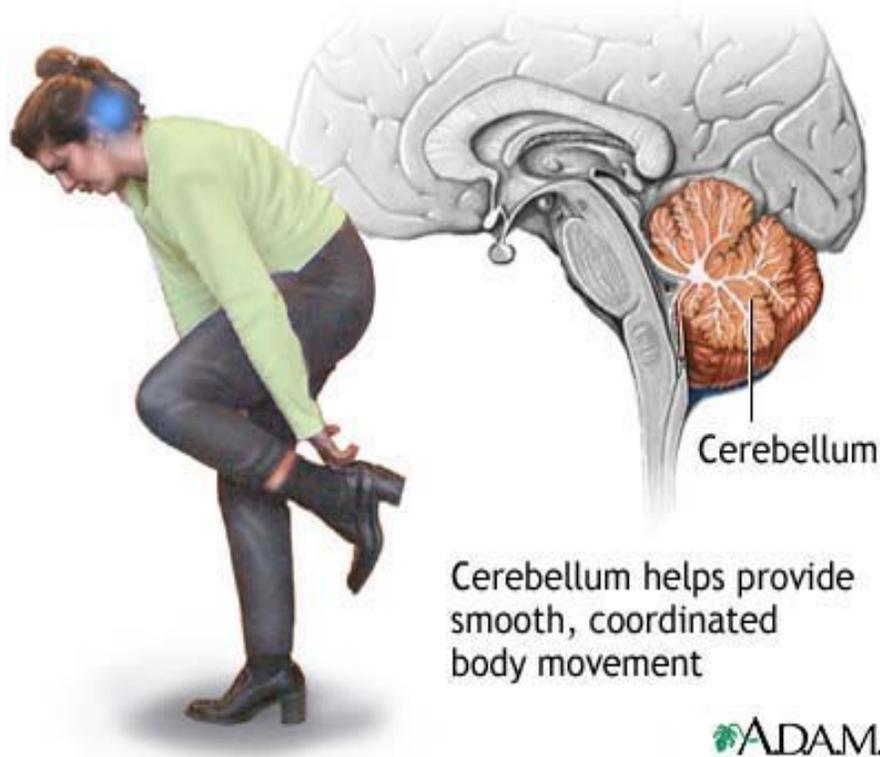


UNIVERSITÀ DEGLI STUDI DI PAVIA
 Corso Strada Nuova, 65 - 27100 Pavia
 tel. 0382.504223 - fax 0382.504287 - e-mail: relest@unipv.it
 webmaster: Anna Cemiglia

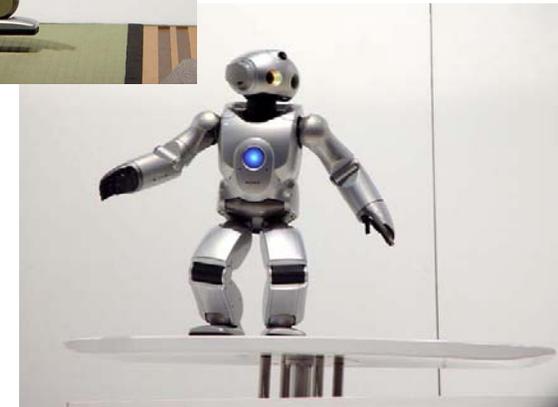
<http://www.spikeforce.org>

Project Objectives

Produce a model of the cerebellum based on known physiology and latest analytical and computational results that can be implemented efficiently in software/hardware for running real-time robotic experiments.

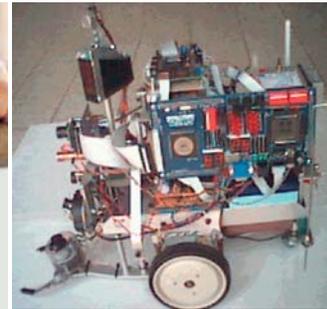
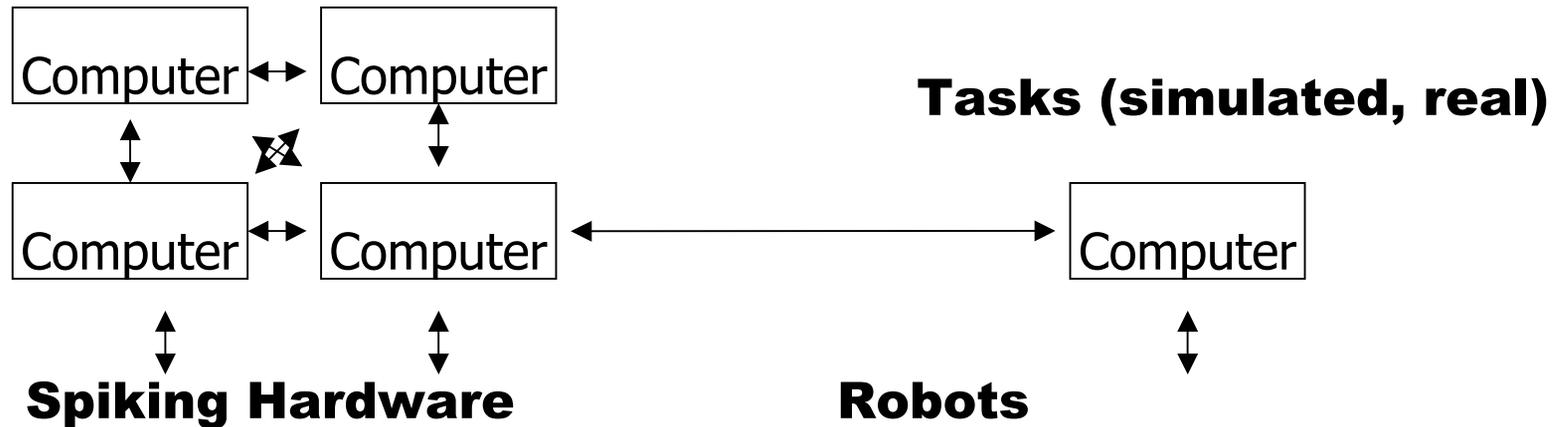


Sony SDR-4X



Real-time Spiking Network for Robot Control

Spiking Cerebellar Model





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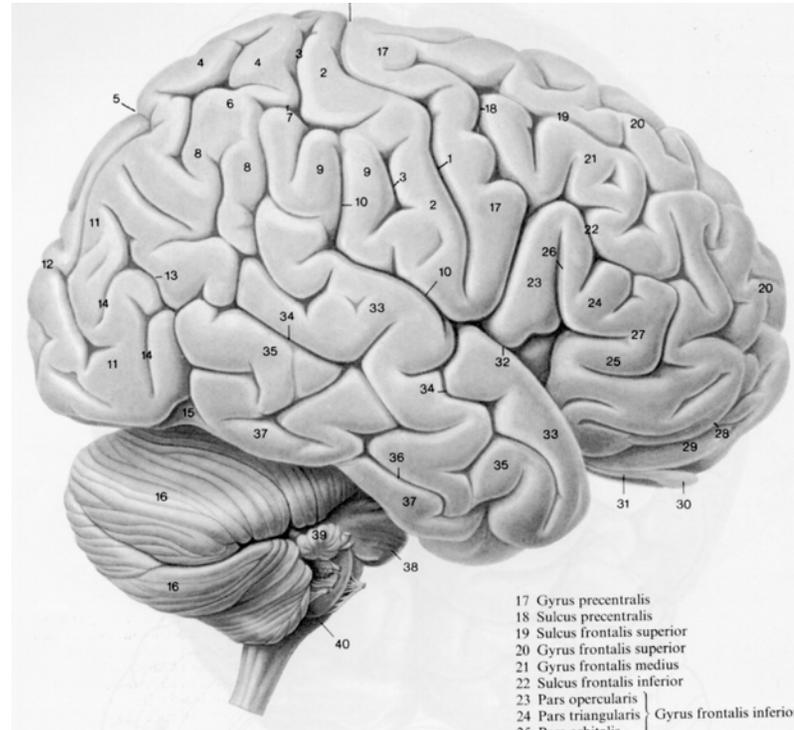
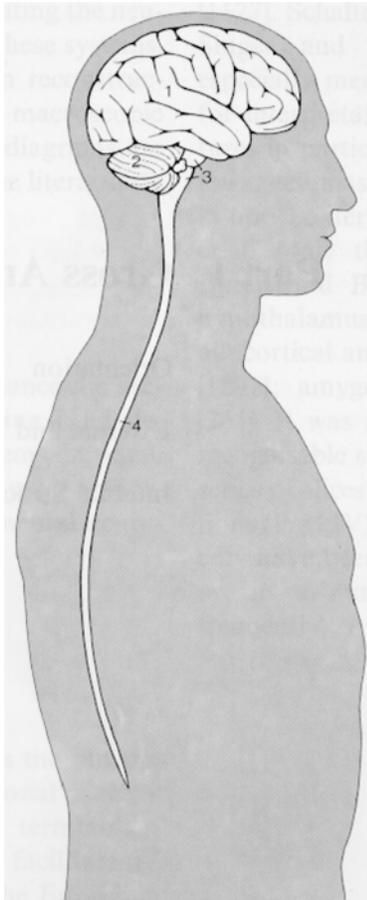


Impacts:

- Advances in robot learning
fine response modulation/anticipation with context
- Improve cerebellar neurophysiological knowledge
- Spiking representation
- Improve knowledge of action-perception loop
cerebellum participation
- Real-time spiking hardware technology
- Potential use in human rehabilitation

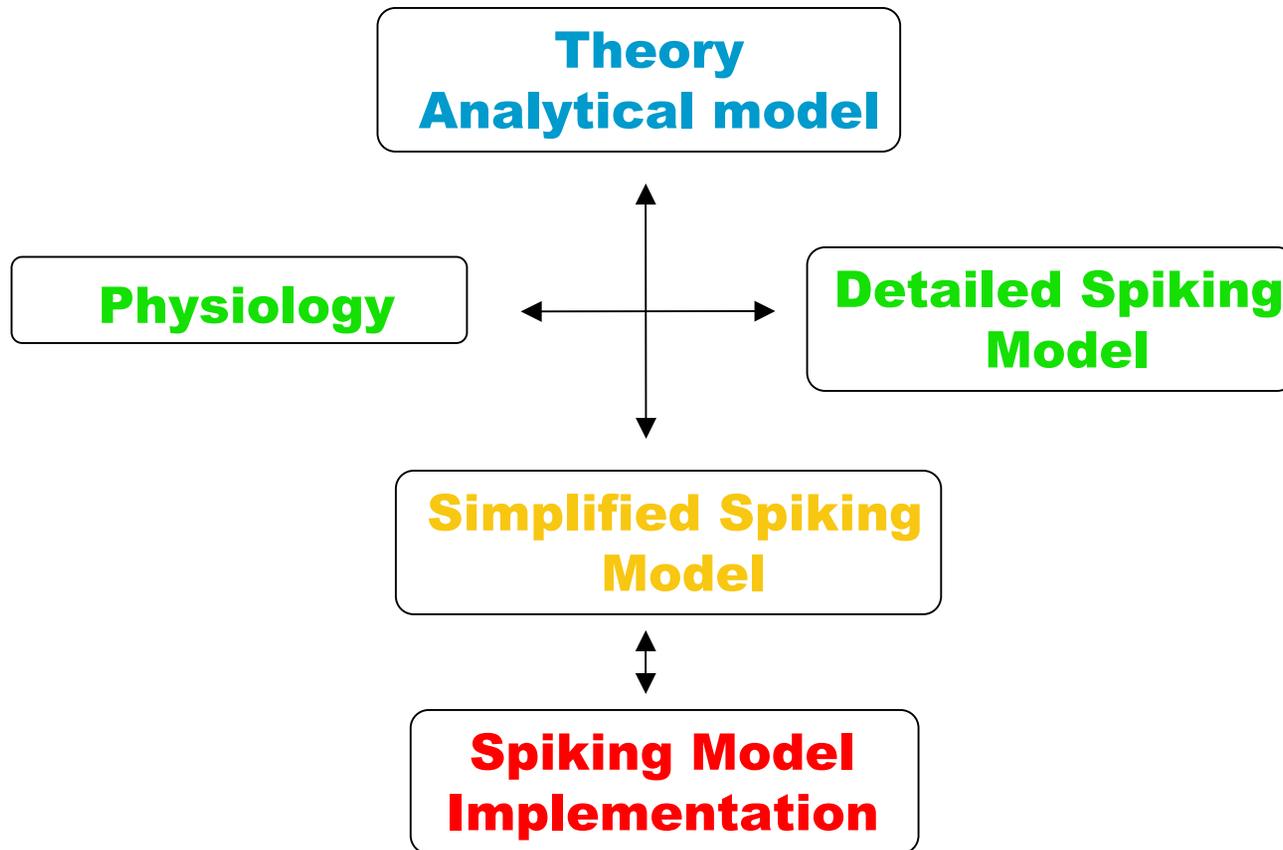
The Cerebellum

The human central nervous system, Nieuwenhuys *et al.*, 1988



- 17 Gyrus precentralis
- 18 Sulcus precentralis
- 19 Sulcus frontalis superior
- 20 Gyrus frontalis superior
- 21 Gyrus frontalis medius
- 22 Sulcus frontalis inferior
- 23 Pars opercularis
- 24 Pars triangularis
- 25 Pars orbitalis
- 26 Pars orbitalis
- 27 Gyrus frontalis inferior
- 28 Gyrus frontalis inferior
- 29 Gyrus frontalis inferior
- 30 Gyrus frontalis inferior
- 31 Gyrus frontalis inferior
- 32 Gyrus frontalis inferior
- 33 Gyrus frontalis inferior
- 34 Gyrus frontalis inferior
- 35 Gyrus frontalis inferior
- 36 Gyrus frontalis inferior
- 37 Gyrus frontalis inferior
- 38 Gyrus frontalis inferior
- 39 Gyrus frontalis inferior
- 40 Gyrus frontalis inferior

Route to a spiking cerebellar model



The Cerebellum

Principles of Neural Science, Kandel *et al.*, 4th Ed., 2000

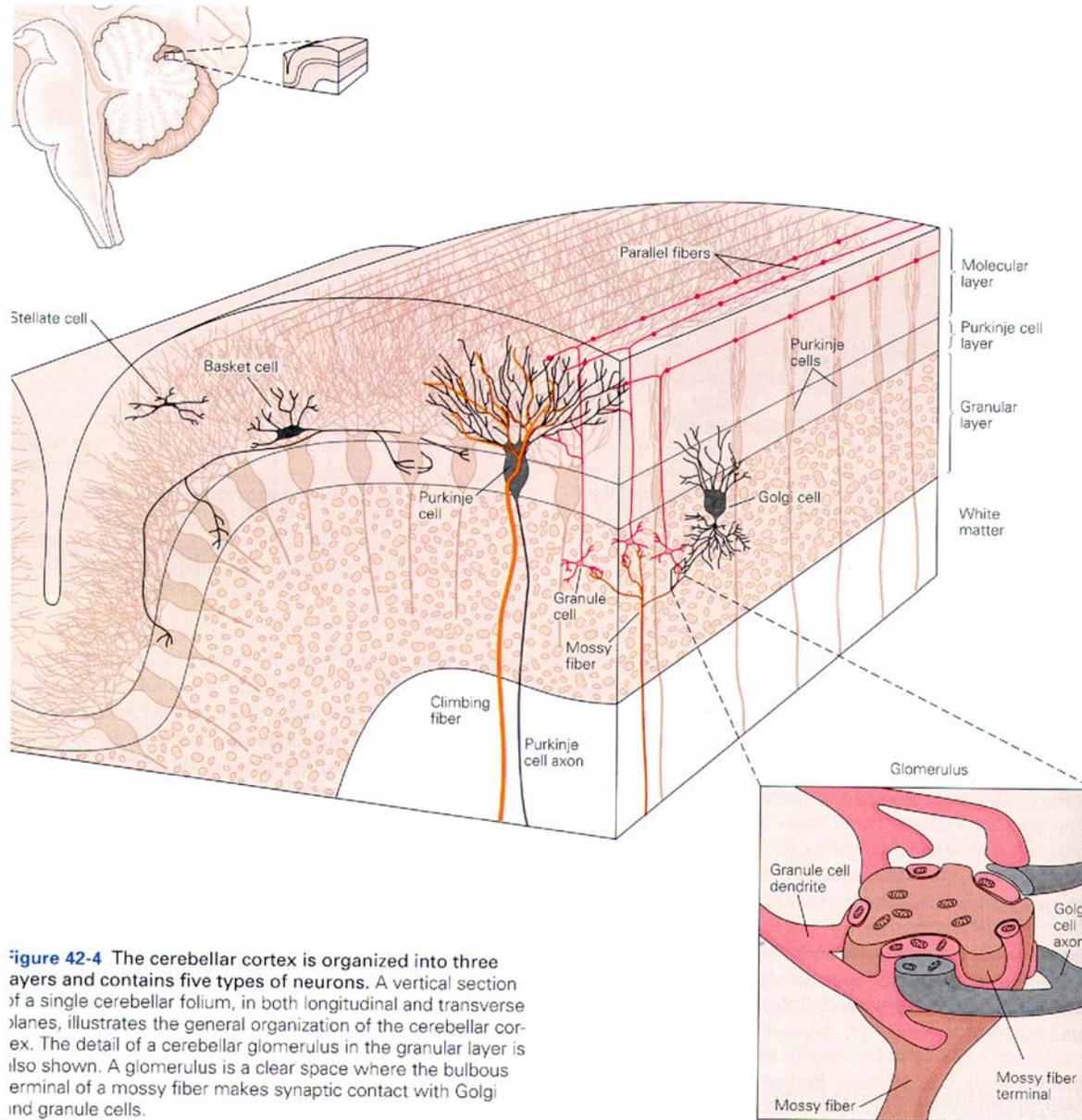


Figure 42-4 The cerebellar cortex is organized into three layers and contains five types of neurons. A vertical section of a single cerebellar folium, in both longitudinal and transverse planes, illustrates the general organization of the cerebellar cortex. The detail of a cerebellar glomerulus in the granular layer is also shown. A glomerulus is a clear space where the bulbous terminal of a mossy fiber makes synaptic contact with Golgi and granule cells.

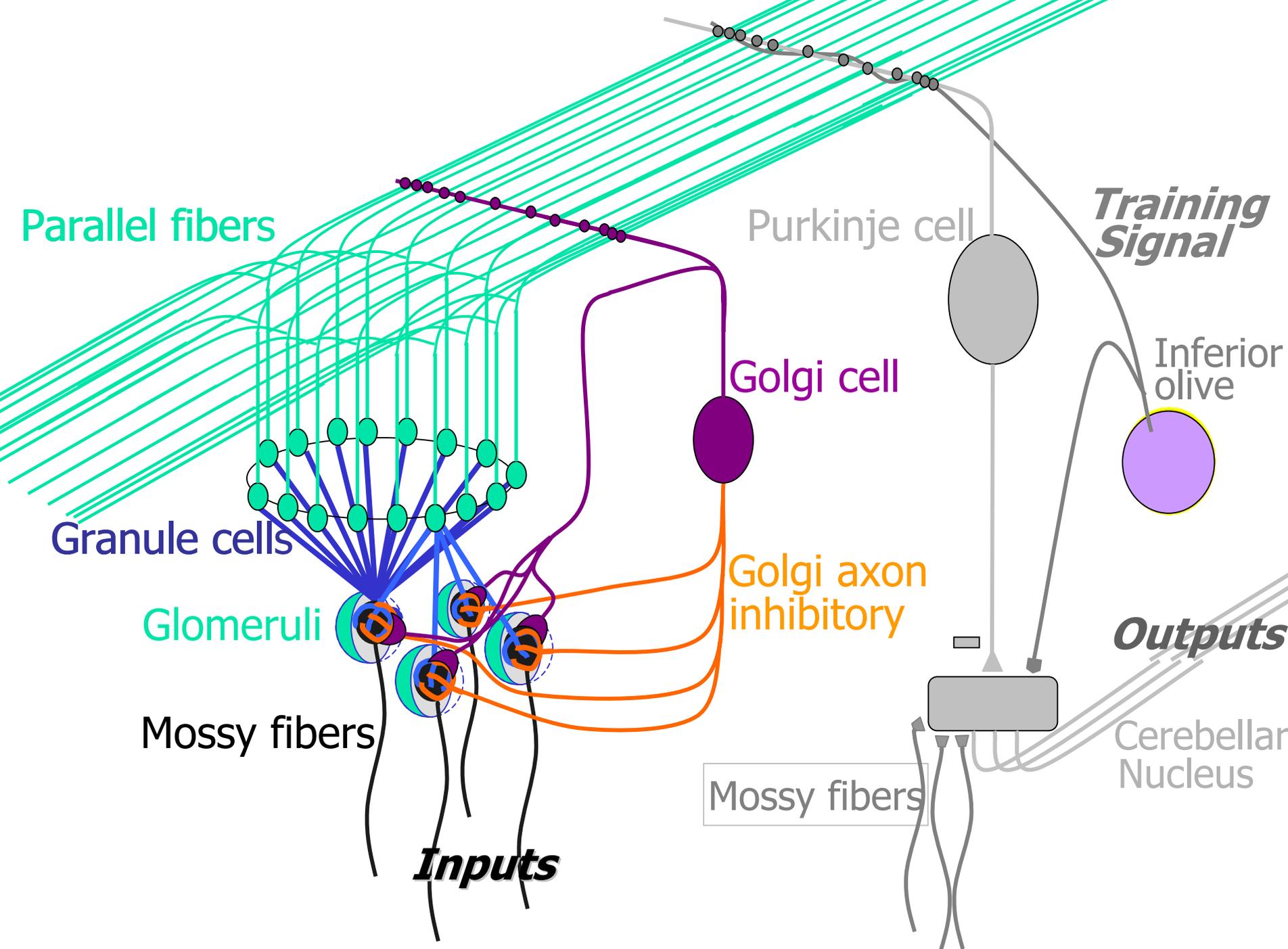


Granular layer

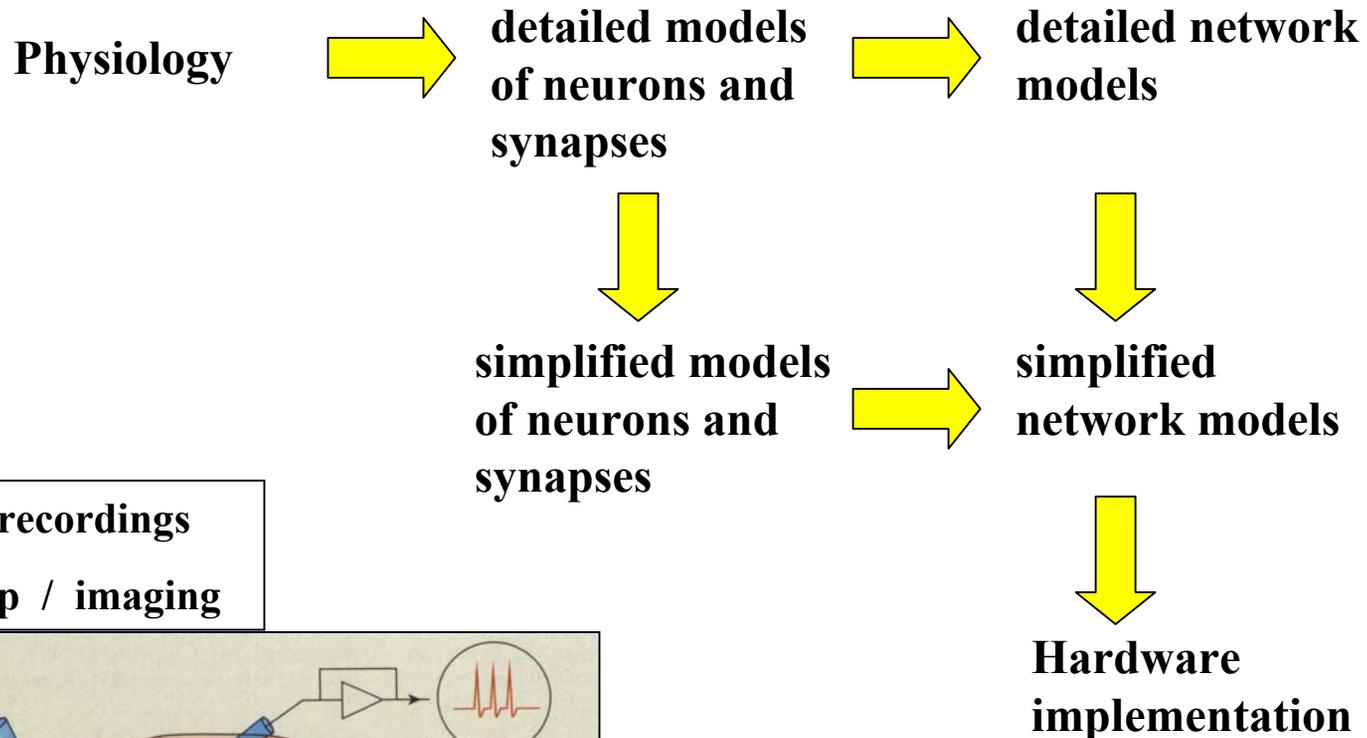


Outline:

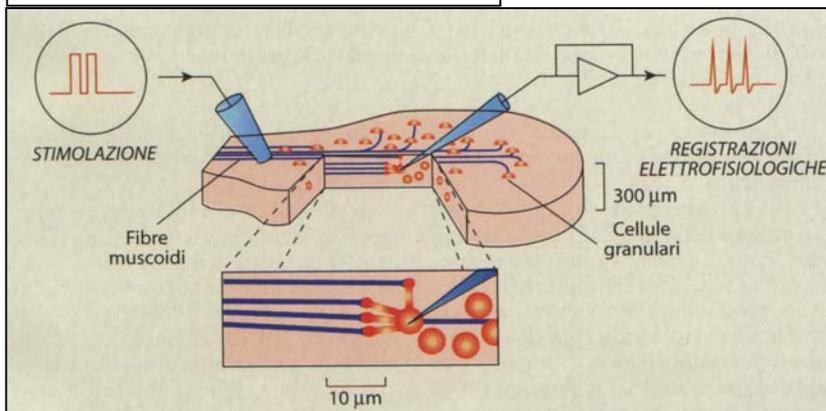
- **Physiology**
- **Computer models**
- **Theoretical models**



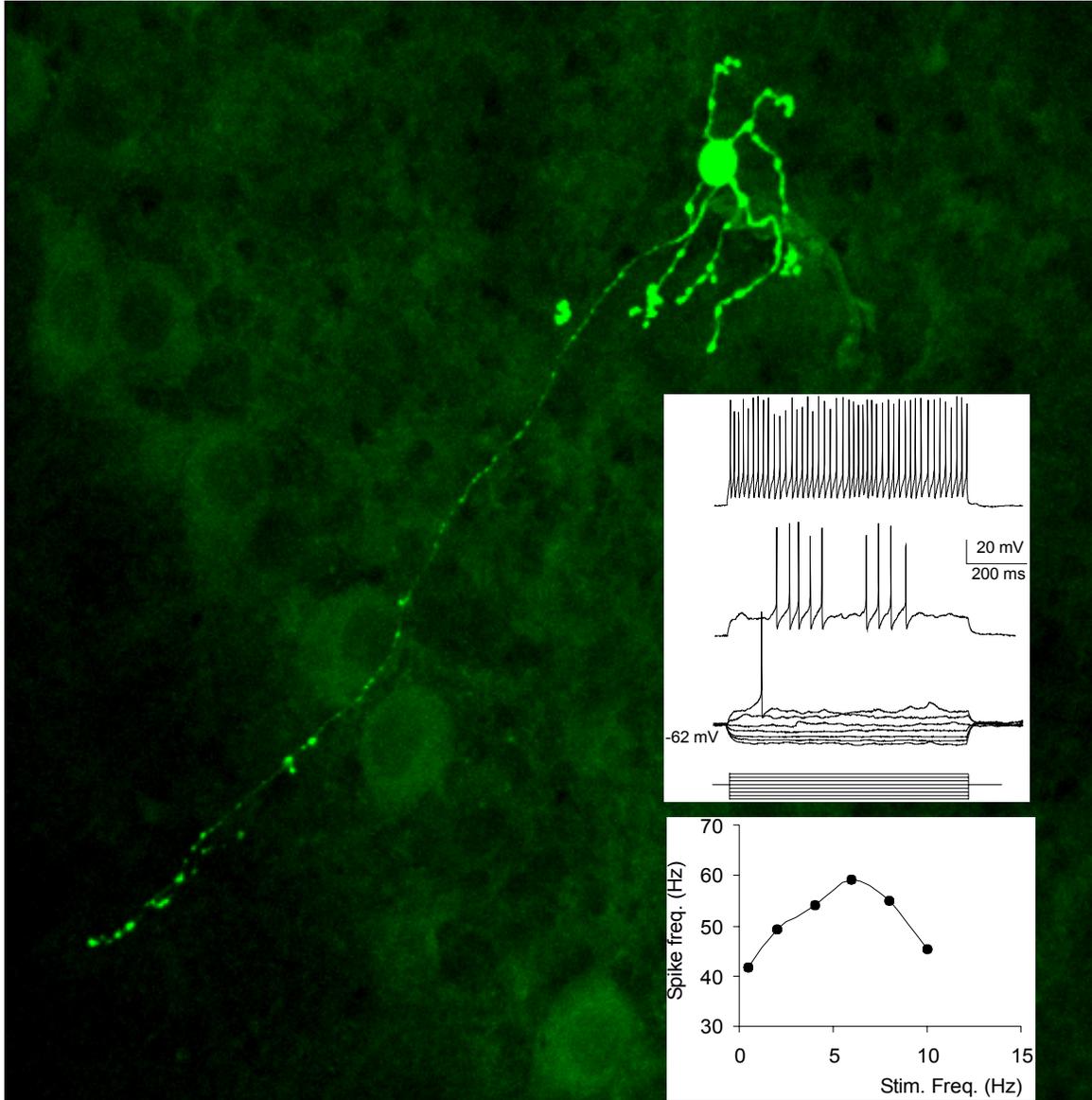
Modeling: from physiological complexity to simplified hardware implementation retaining the salient biophysical properties of neurons and synapses



Acute slice recordings
Patch-clamp / imaging

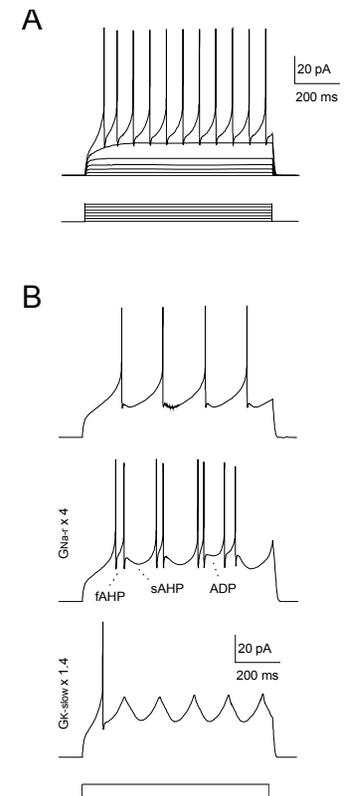


Granule cell

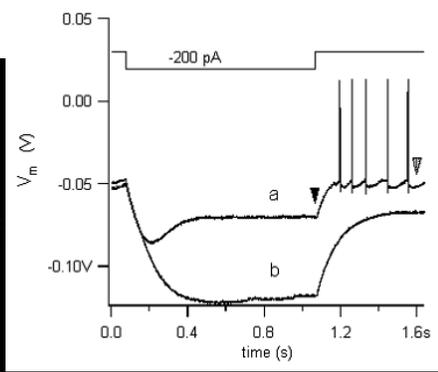
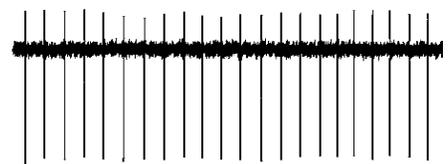
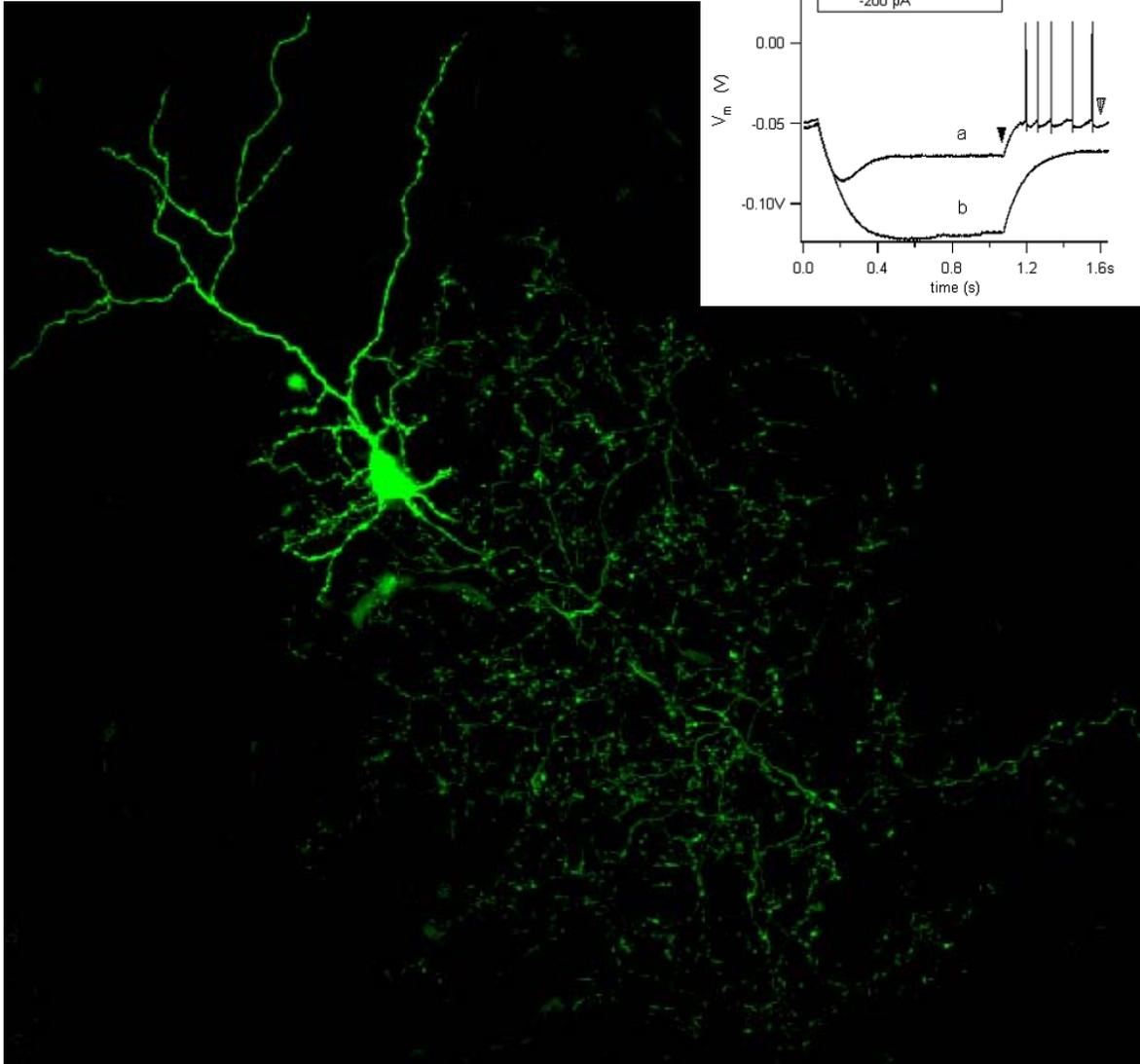


- 1) *Repetitive firing*
- 2) *Inward rectification*
- 3) *Bursting*
- 4) *Resonance*

model

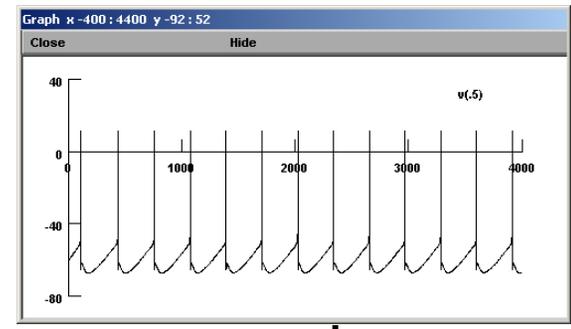


Golgi cell

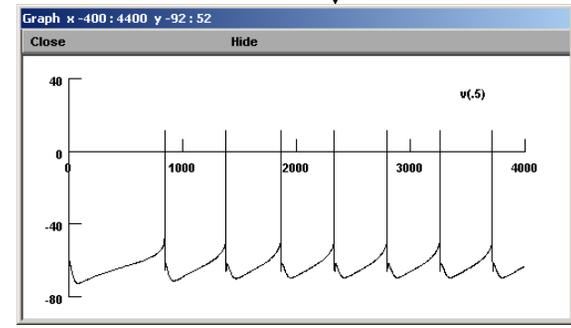


- 1) *Autorhythmic firing*
- 2) *Subthreshold oscillations*
- 3) *Postinhibitory rebound*
- 4) *Post-burst pause*
- 5) *Inward rectification*

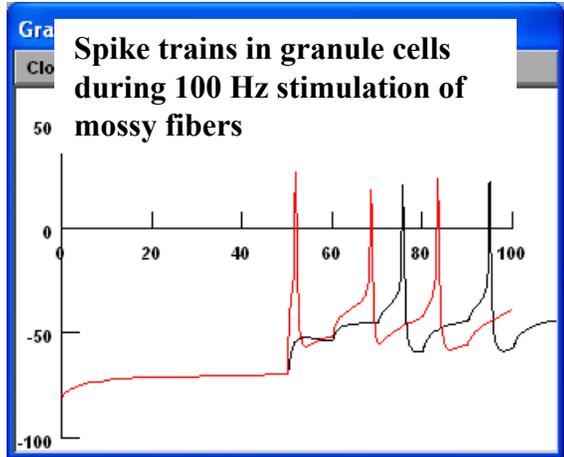
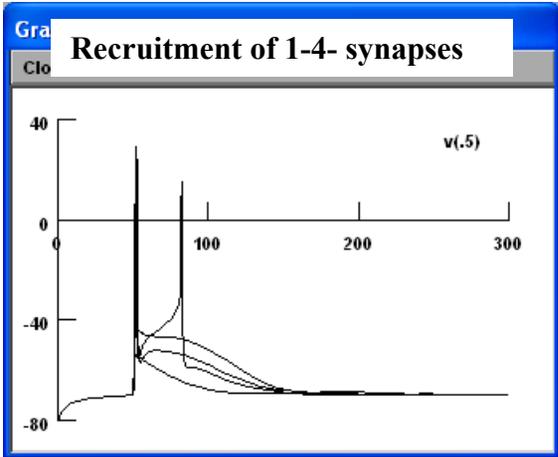
model



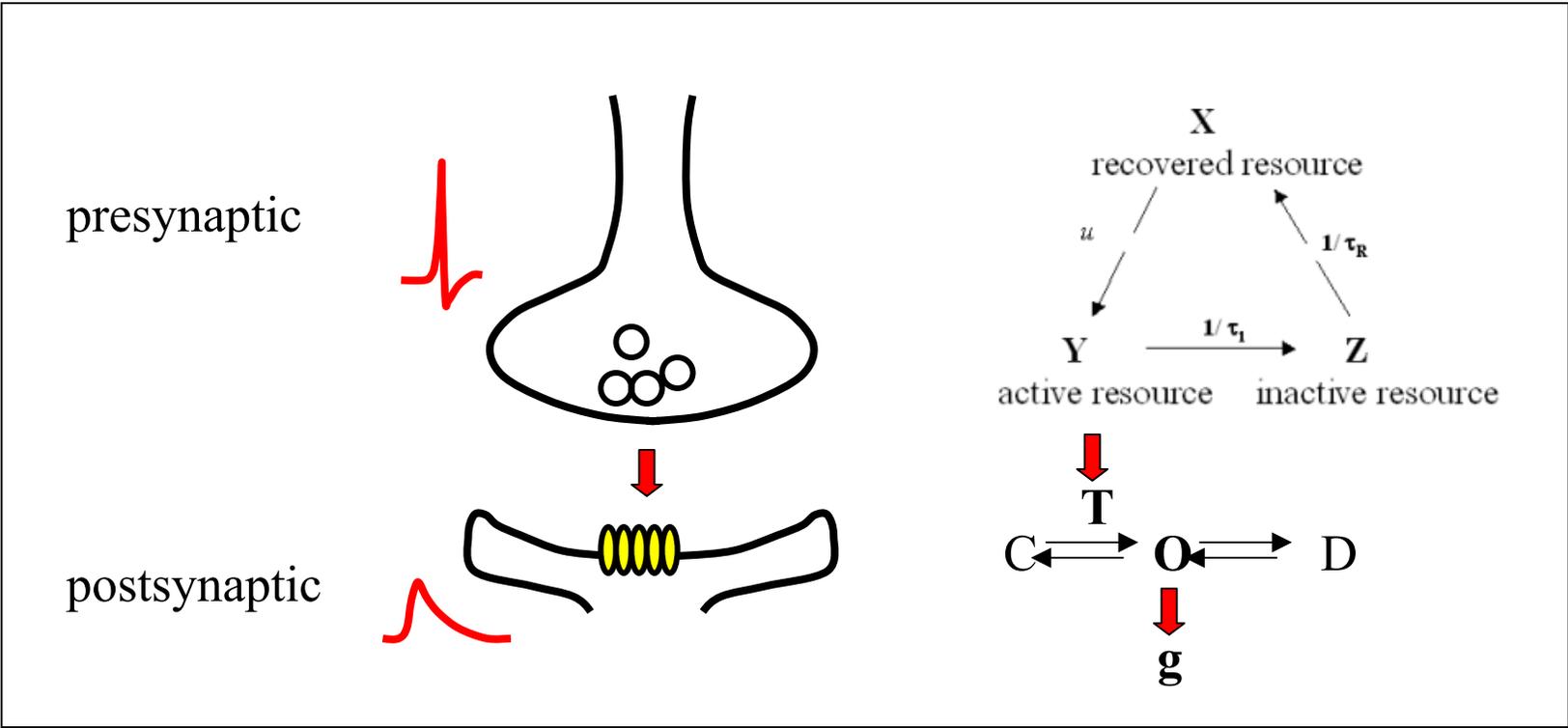
I_H 50% ↓



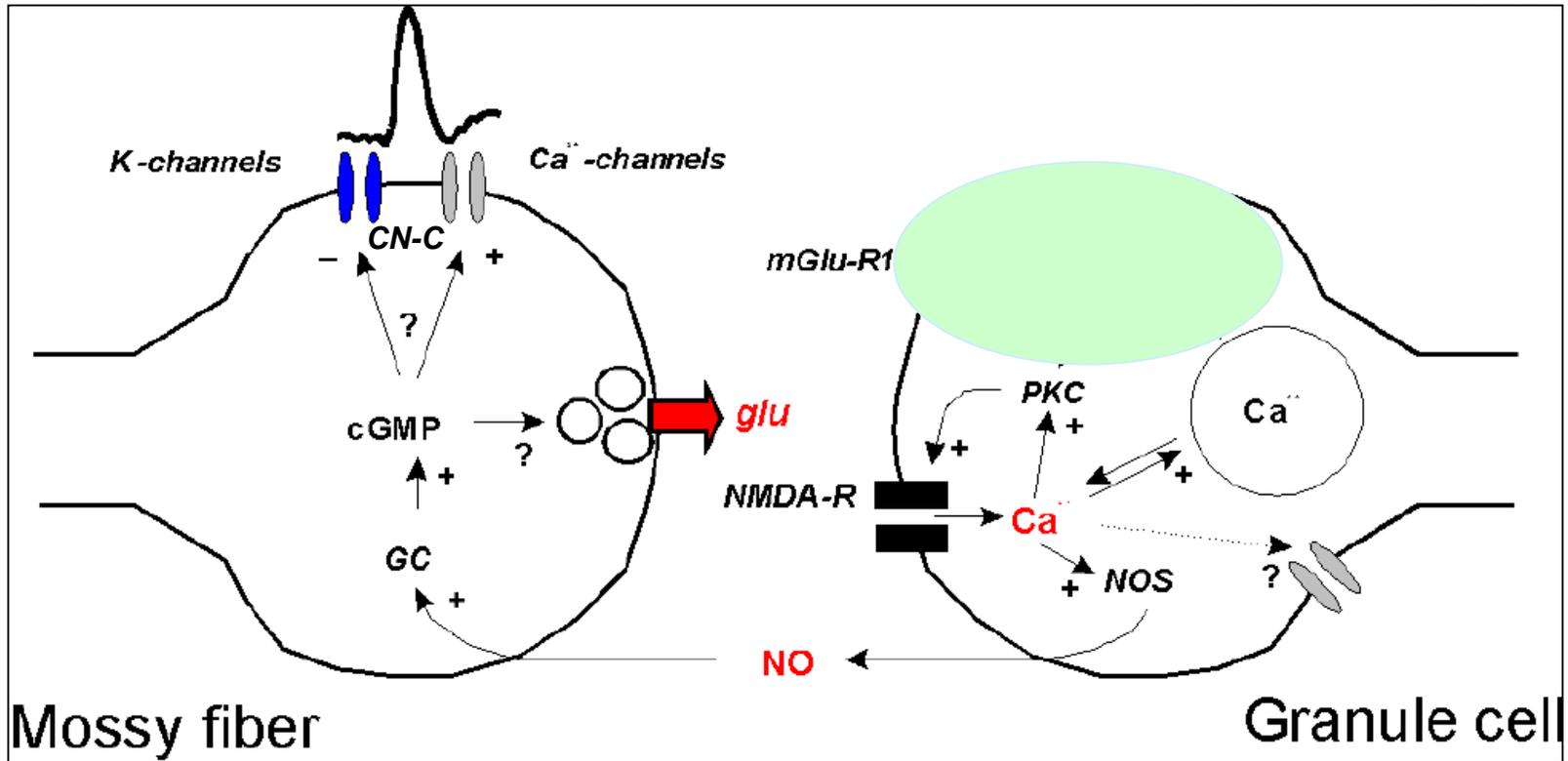
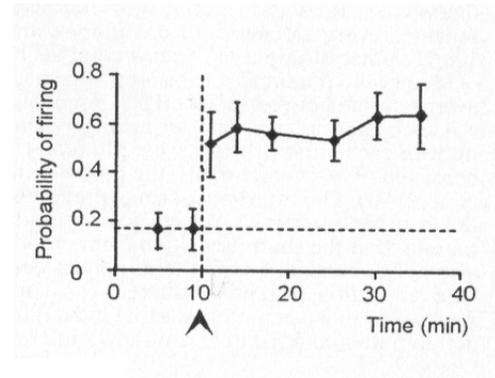
Modeling neurotransmission dynamics by conductance-based models



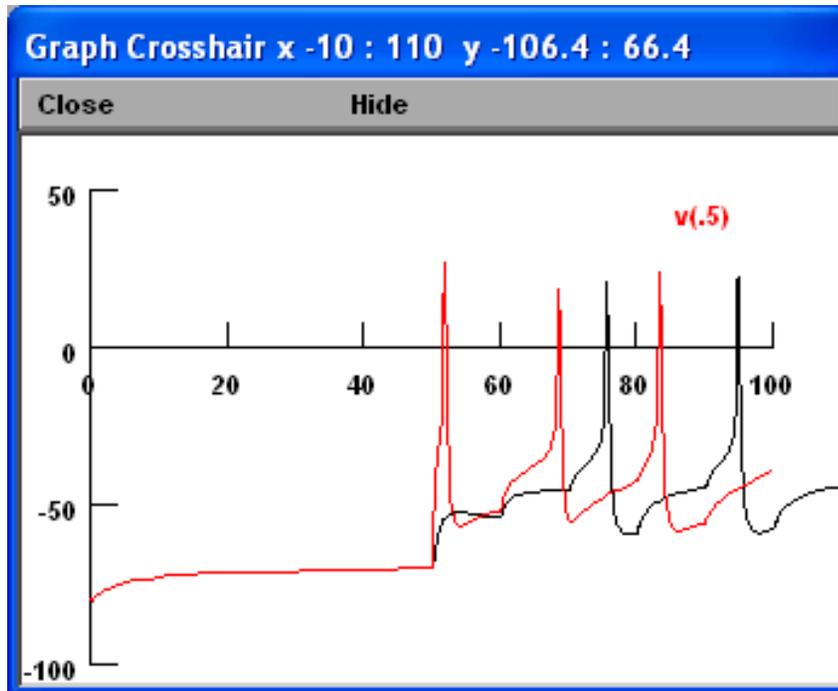
Mossy fiber - granule cell neurotransmission



Mossy fibre – granule cell LTP



The presynaptic expression mechanism implies that neurotransmission dynamics are modified during LTP



Control of spike initiation in the model by changing release probability

$p = 0.1$

$p = 0.5$

The influence of dynamics changes caused by LTP are currently under testing in a detailed model network comprising 2000 Granule Cells.



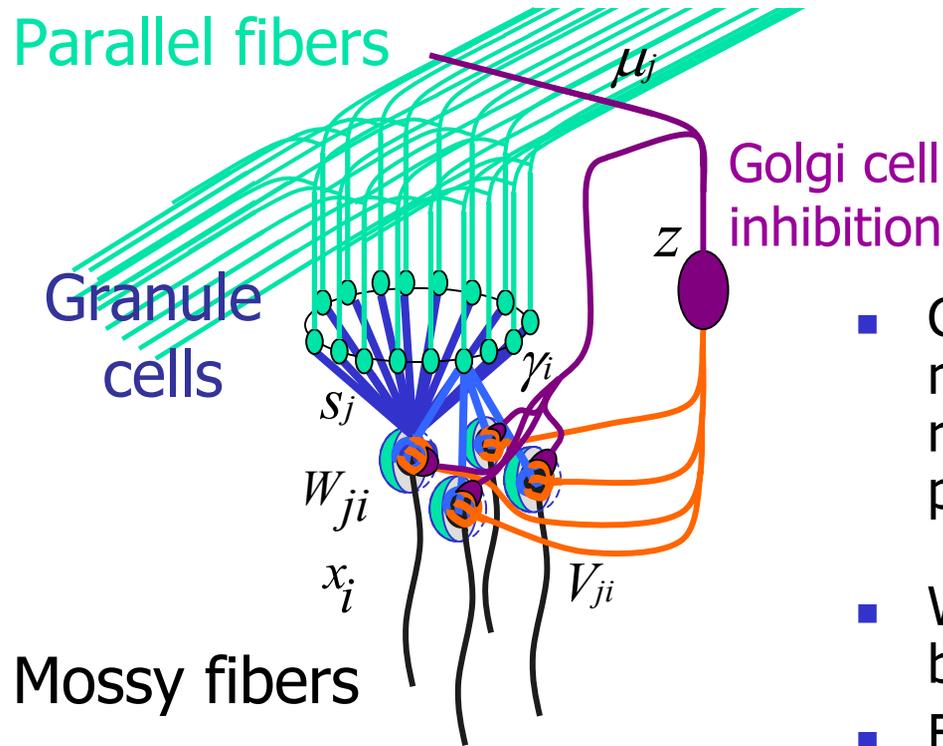
Granular layer



Outline:

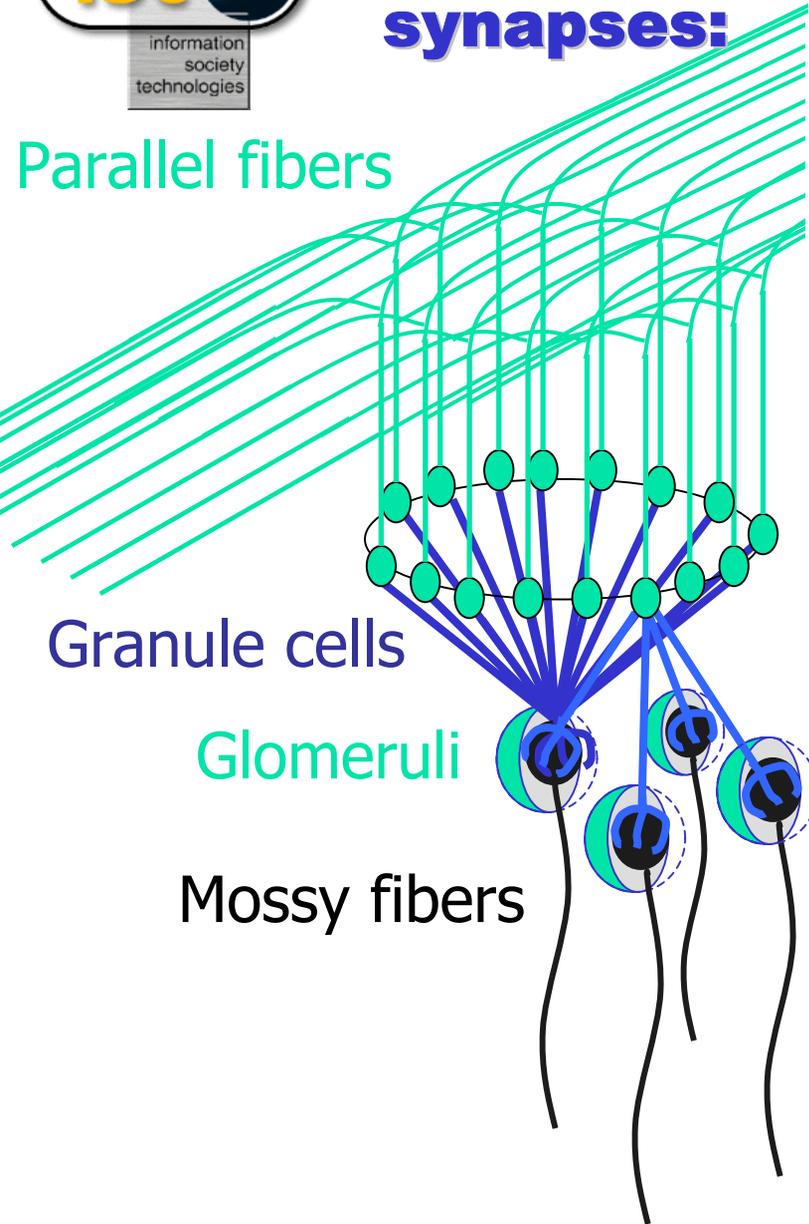
- Physiology
- Computer models
- **Theoretical models**

Denoising: A new role for the Golgi cells



- Granule cells perform a recoding of the mossy fibers inputs into a sparse representation using a biologically plausible ICA (Coenen *et al.*, 2001; Eagleman *et al.*, 2001)
- Which permits optimal noise reduction by the Golgi cell &
- Facilitates learning in the Purkinje and molecular layer of the cerebellum (simplifies credit assignment problem)

Plasticity at granule cell synapses:



Experimental evidence:

mossy fiber-granule cell

synaptic weight changes:

Long-term potentiation (LTP)

synaptic weight increase

EPSPs, presynaptic currents

Long-term depression (LTD)

synaptic weight decrease

(D'Angelo, 1999; Maffei *et al.*, 2002; etc.)

Changes in cell excitability

intrinsic cell properties

(Armano *et al.*, 2000)

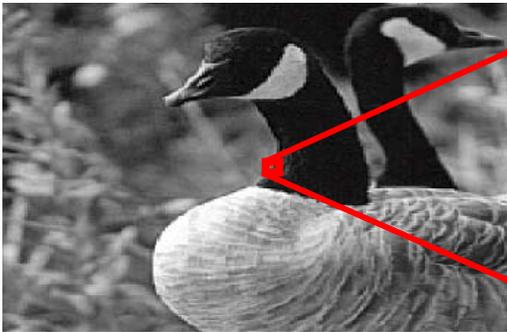
S_j

w_{ji}

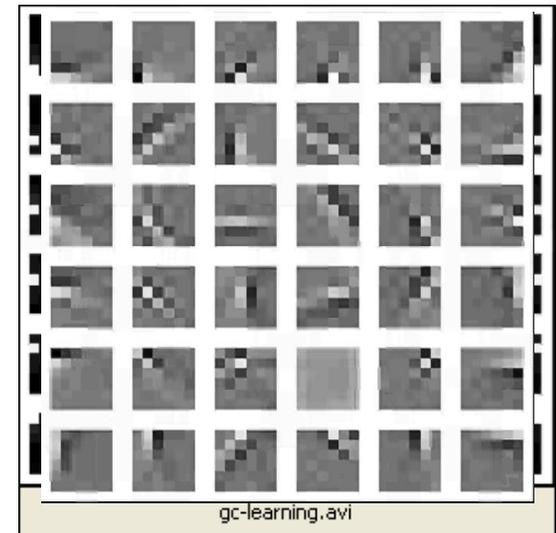
x_i

Images as mossy fiber inputs to illustrate putative 'statistical structure'

granule cell
receptive field



one pixel = one mossy fiber input



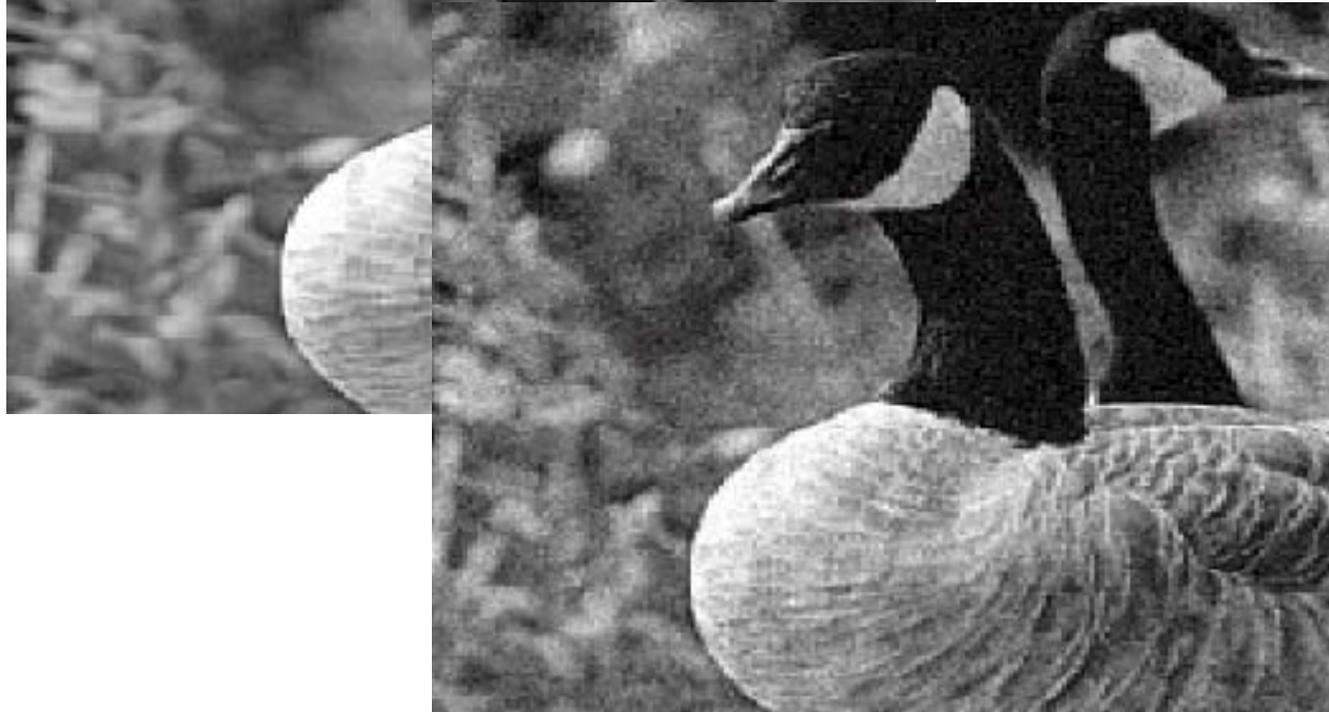
granule cell weights adapt to become independent as much as possible using the mossy fibers statistical structure

Cerebellar inputs will contain noise:

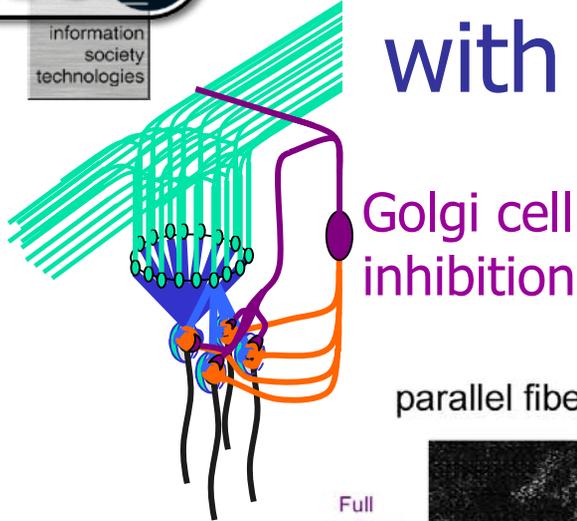
original image



noisy mossy fibers inputs



Encoding by granule cells with Golgi cell inhibition



parallel fibers output

activity over a subset of parallel fibers

probability of the number of active granule cells in the subset

retained information (decoded output)

noisy mossy fibers inputs



Full coding

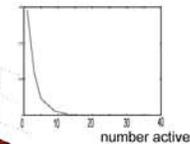
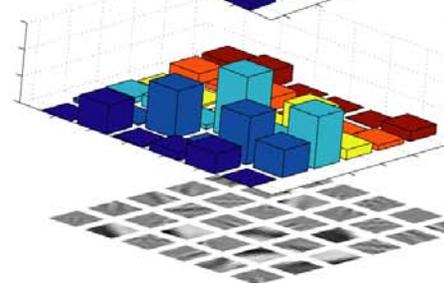
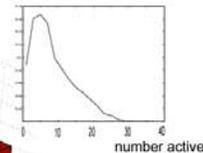
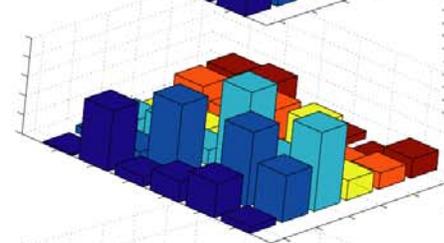
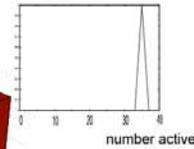
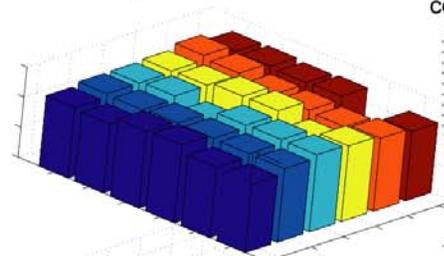


Optimal denoising



increased level of inhibition

Robust coding



Receptive fields for the subset of granule cells



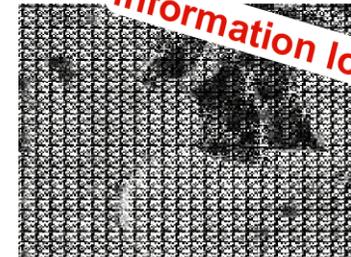
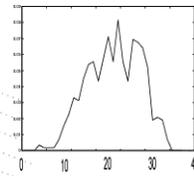
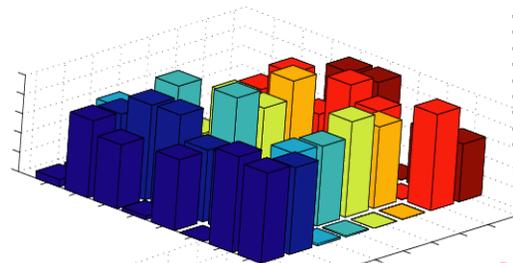
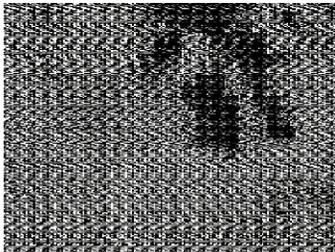
Encoding by granule cells: robust coding?



Kettner *et al.*, JNeurophys., 1997

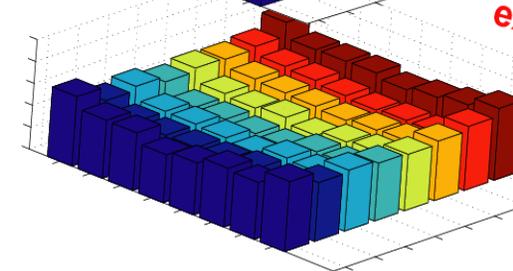
Other models:

Random weights

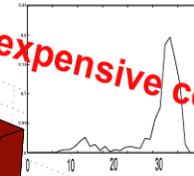


Information loss

Decorrelating weights

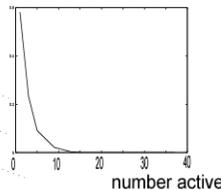
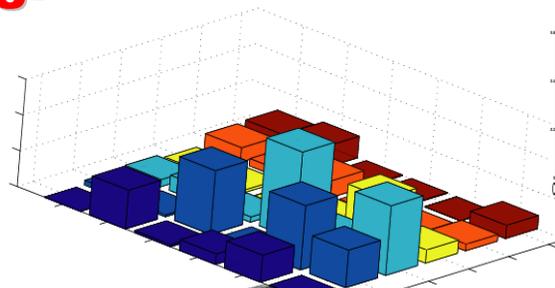


expensive coding



Robust sparse coding:

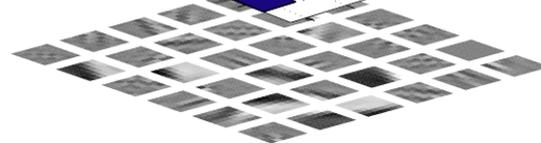
Robust coding



Schweighofer *et al.*, Neurosci., 2001
Chauvet, 1986; Jonker *et al.*, 1998



Receptive fields for the subset of granule cells



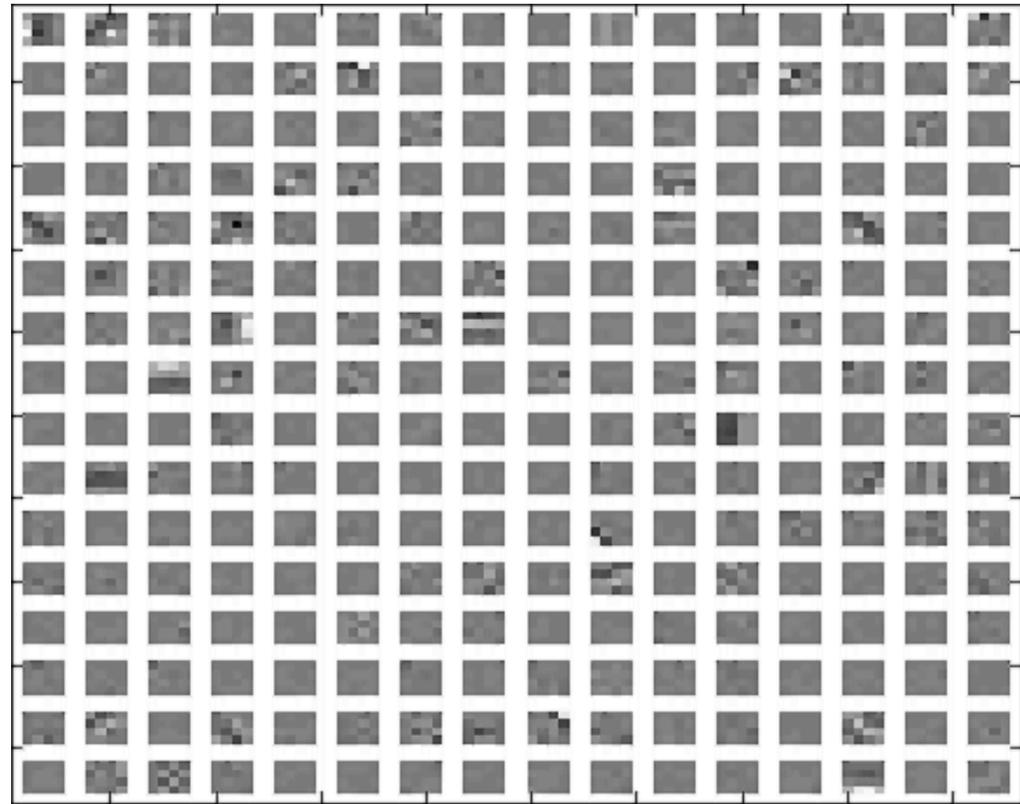
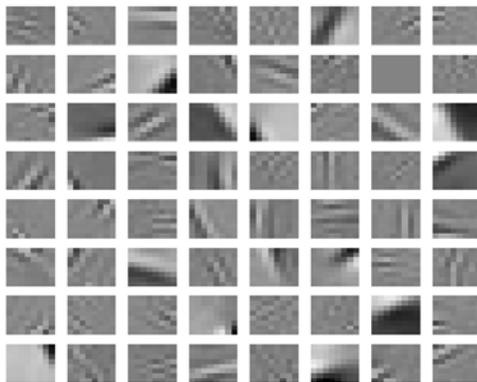
**Granule cells display
facilitating and depressing
synapses**
(D'Angelo, personal communication)

**Preferred mossy fibers stimulus
for a set of granule cells**

**Constructing temporal basis
function from experience**

(Bell & Sejnowski, 1995; Lewicki, 2002;
Olshausen, 2002;
van Hateren & Ruderman, 1998)

Static



$$s_j(t) = \sum_n \sum_i w_{ji}(n) x_i(t-n)$$



Purkinje/molecular layer

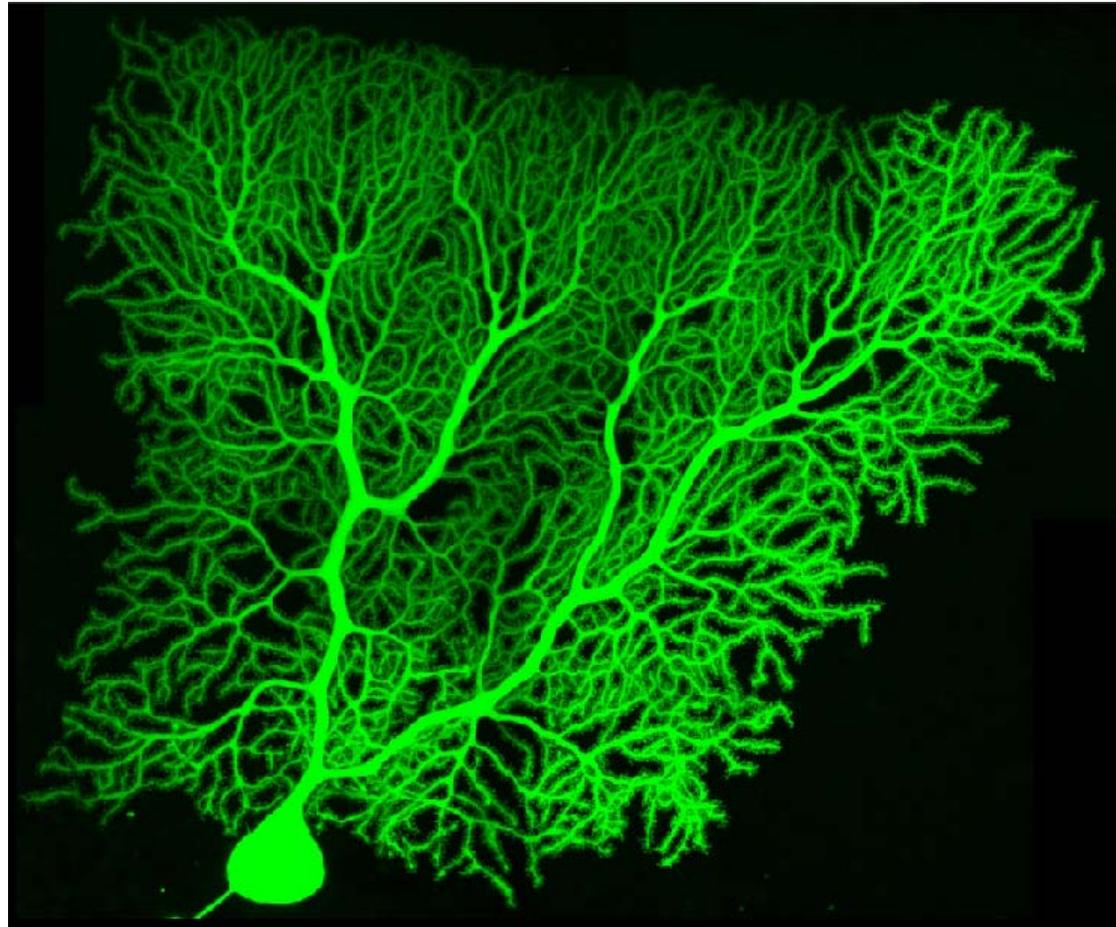


Outline:

- **Physiology**
- **Theoretical models**

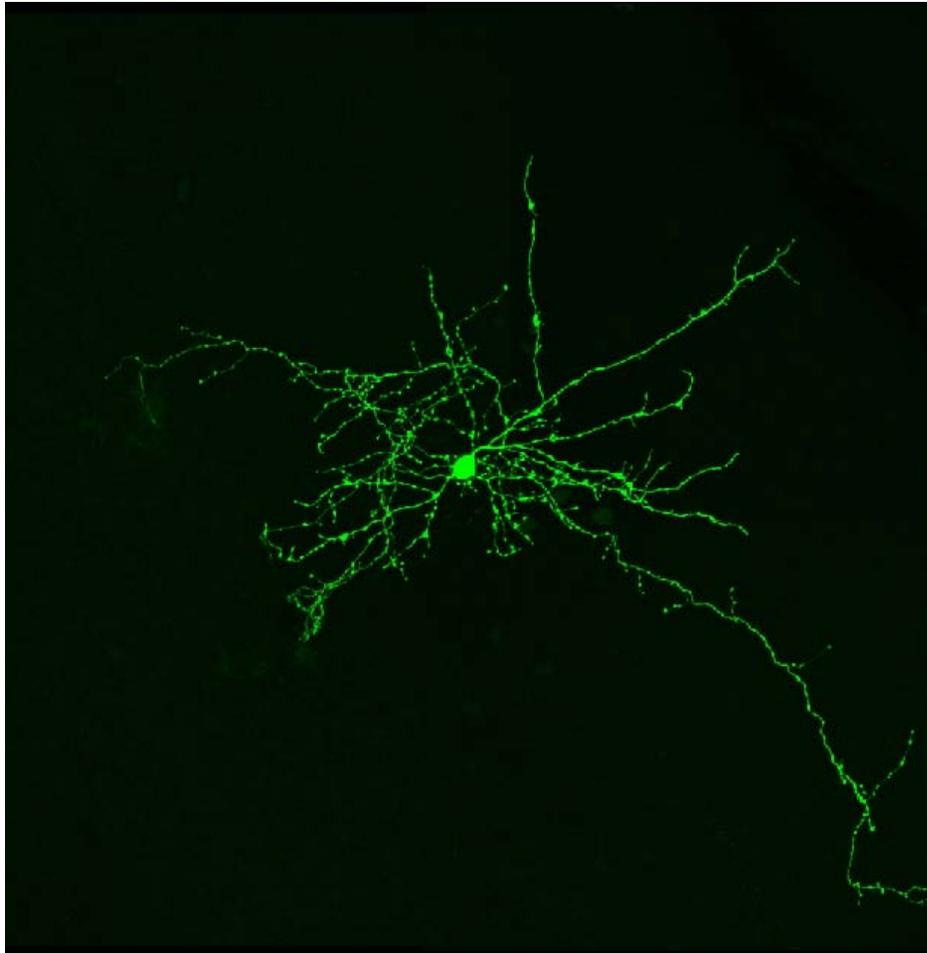
Purkinje cell

High resolution fluorescence confocal image stacks (3D)

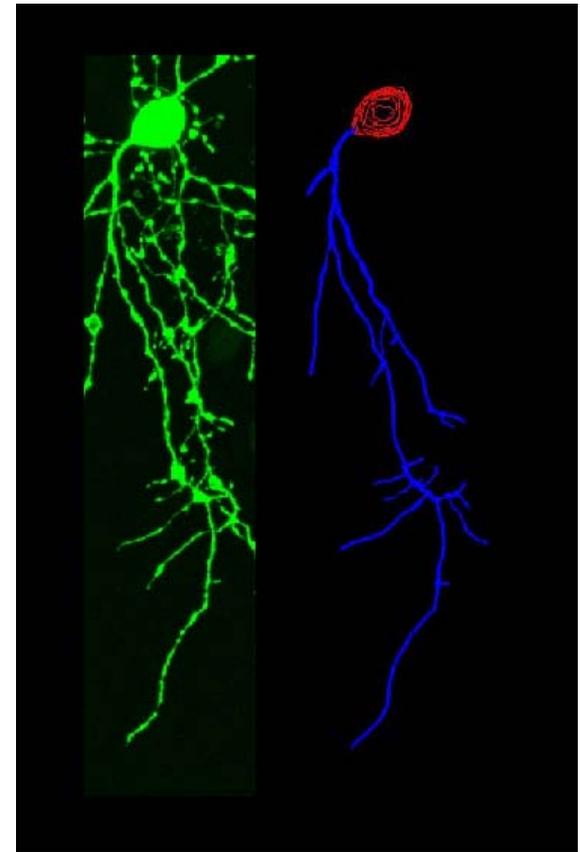


Inhibitory interneuron

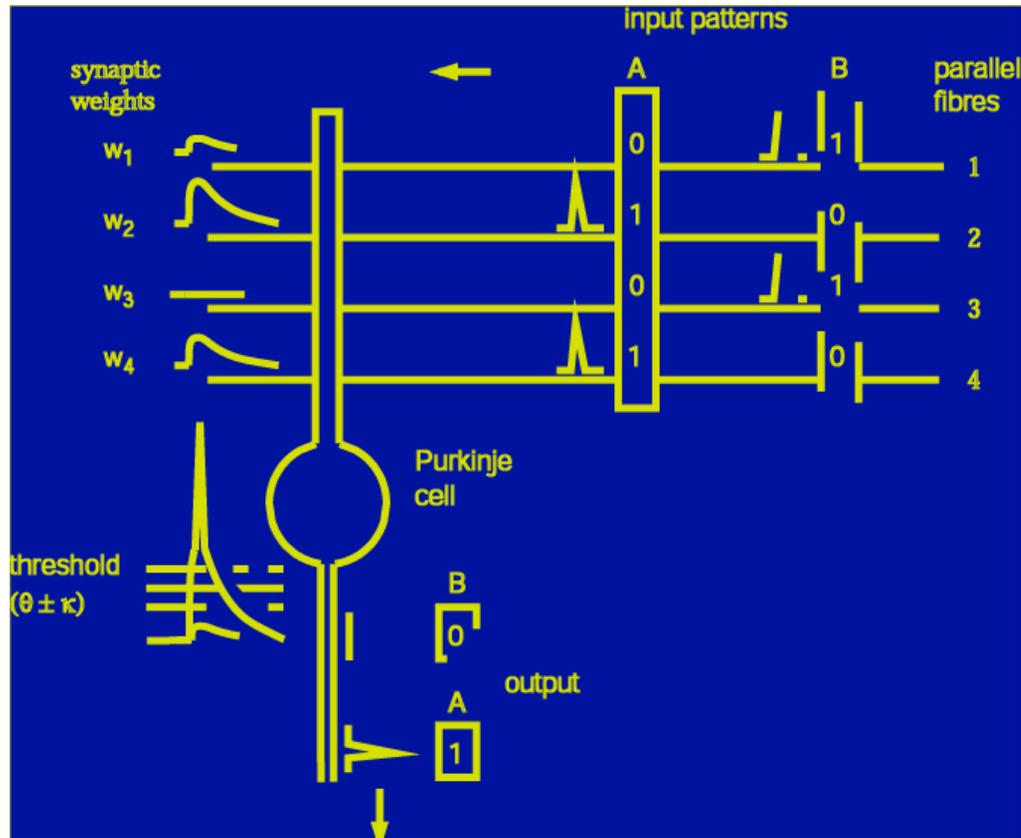
High resolution fluorescence confocal image stacks (3D)



Reconstruction



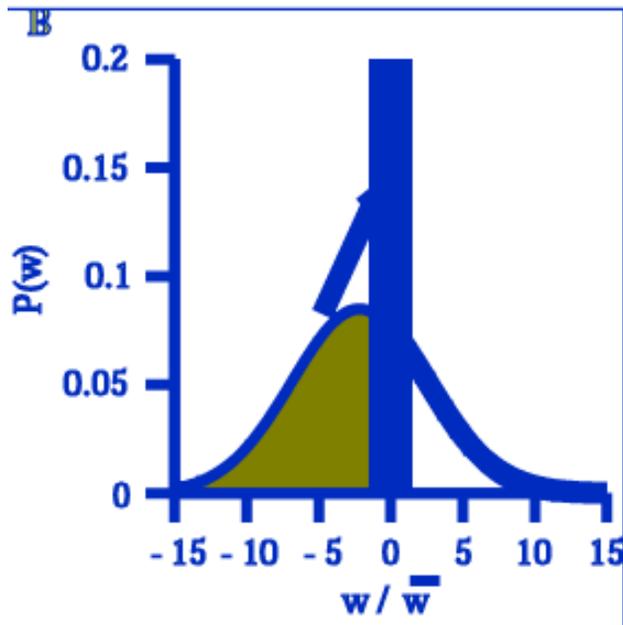
Purkinje cell as a perceptron



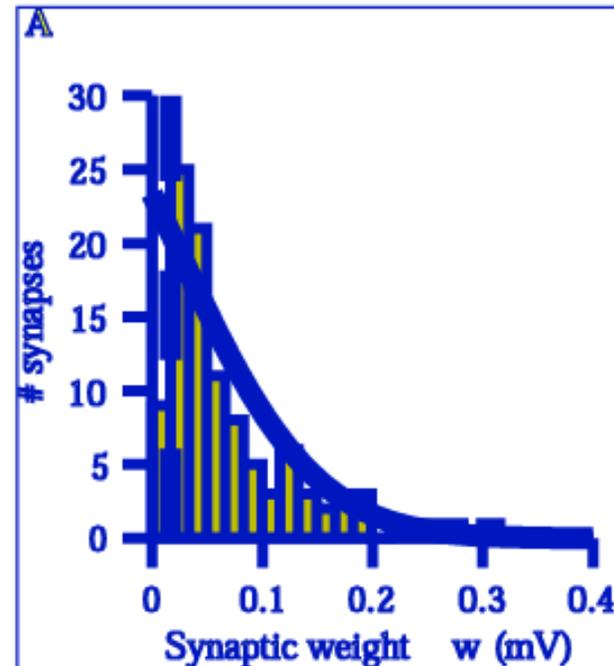
Brunel *et al.*, submitted

Purkinje weight distributions & silent synapses

Perceptron weight distrib.



Experimental vs Theoretical



Capacity analysis: ~ 50000 patterns/Purkinje cell



Cerebellar Task Development



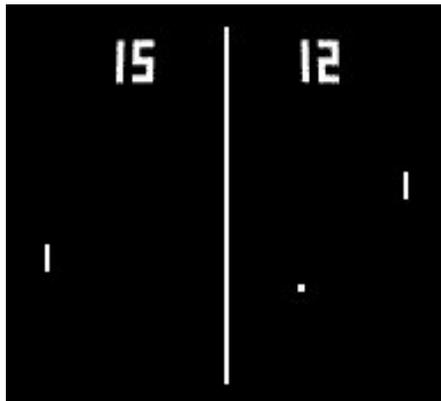
Outline:

- **Task description**
- **Cerebellar simulation results**

Task description: cerebellar pong player



Pong - 1972



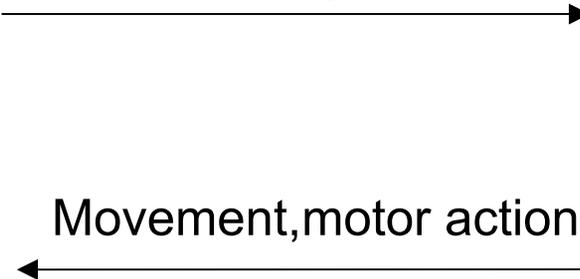
Computer

Simulated sensory
systems:
visual, auditory, touch

**Spiking cerebellar
model**

Computer, FPGA

Movement, motor actions



Task description: cerebellar pong player



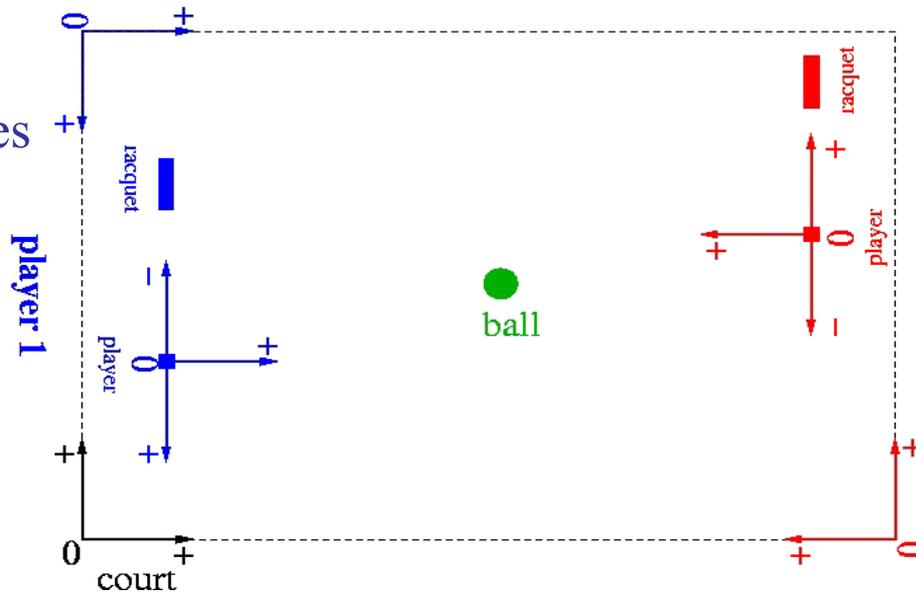
One player
-racquet move
with player



Different configurations possible:

- ball dynamics (speed, spin, rebound effects)
- racquet dynamics
- racquet in 1D, 2D or 3D
- control strategies:

Two players
-racquet moves
wrt player



tracking/pursuit
colliding trajectory
controller imitation

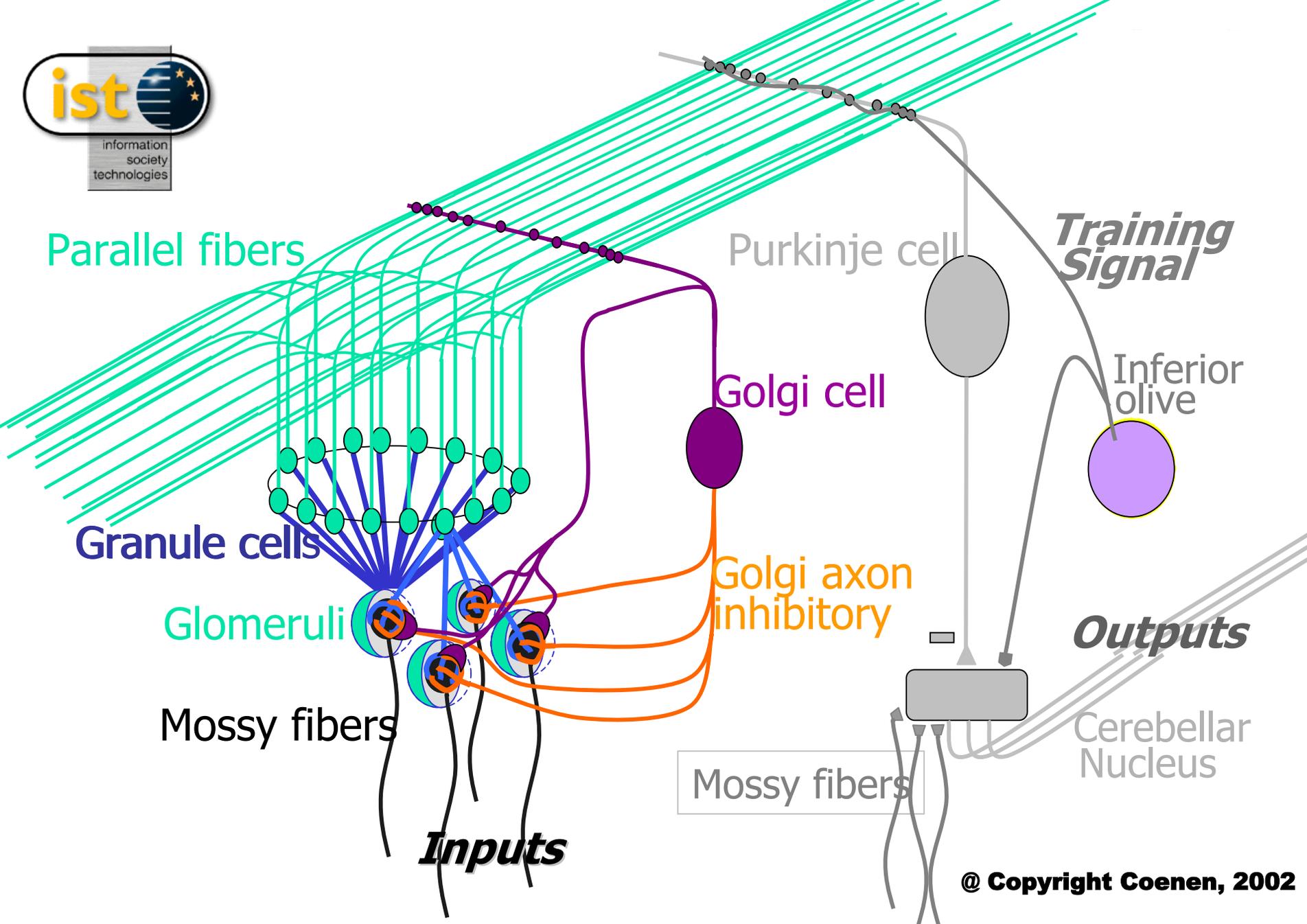
- etc.

Cerebellar pong player



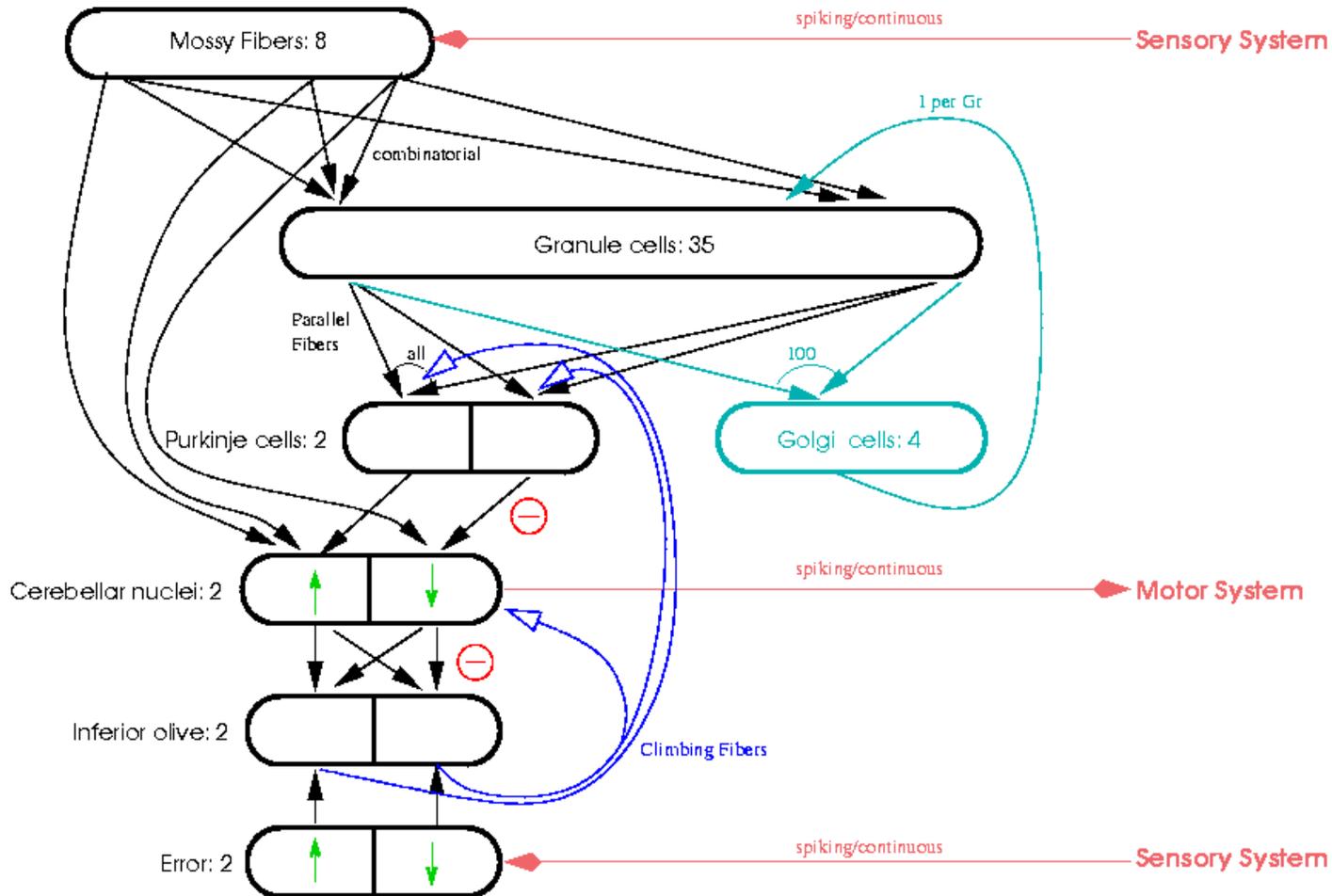
Look for:

- Learning multiple tasks -> learning multiple games
or one game with different dynamics
- Min interference -> fast switching/modulation btw games
with no need to relearn
- Flexible, possibly large sensorimotor context
- Cerebellar encoding: useful for high numbers of games/dynamics
to learn



Cerebellar pong player: smooth pursuer

Tenns spiking neural network simulator (Altjira Software)

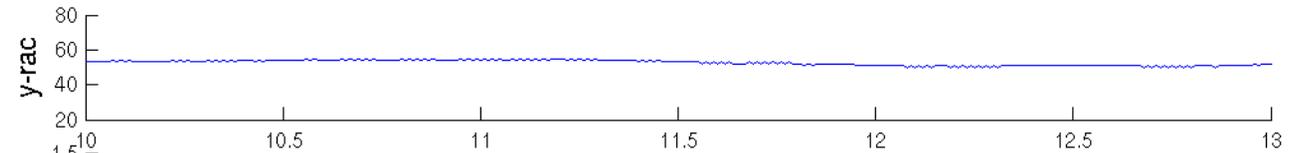


Cerebellar pong player: cell responses during tracking **before** learning

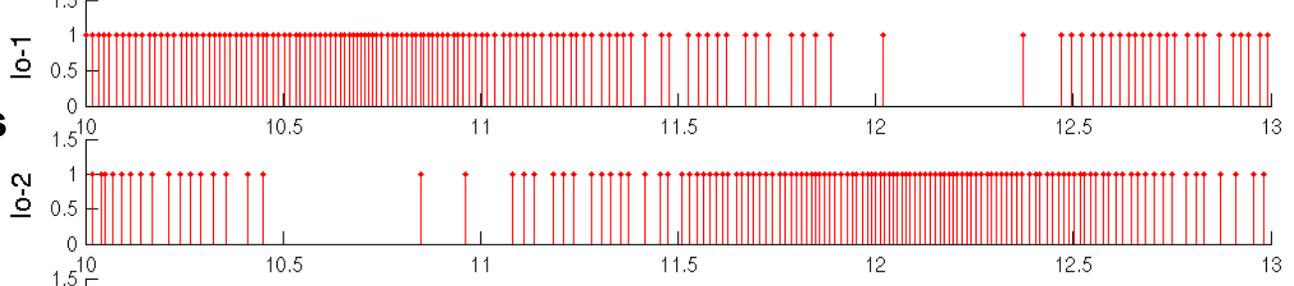


Tennis spiking neural network simulator (Altjira Software)

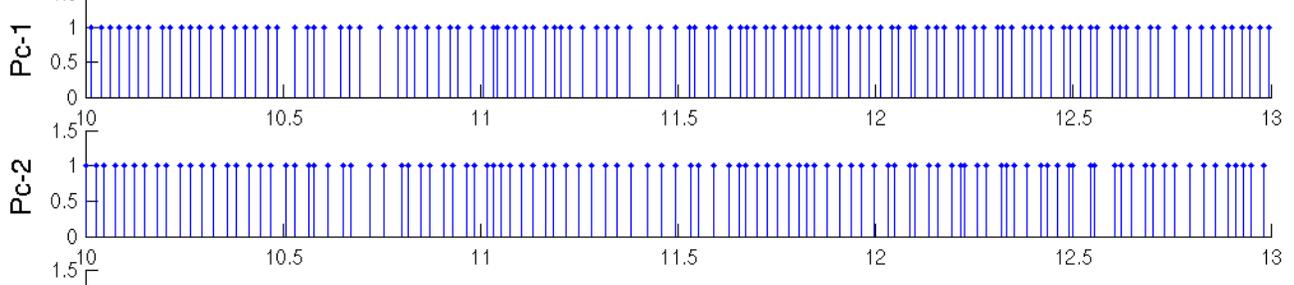
Racquet position



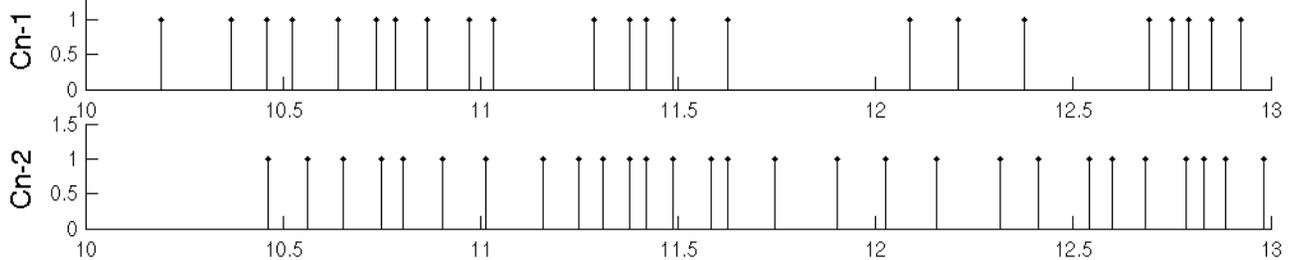
Inferior olive neurons



Purkinje cells



Cerebellar nucleus neurons

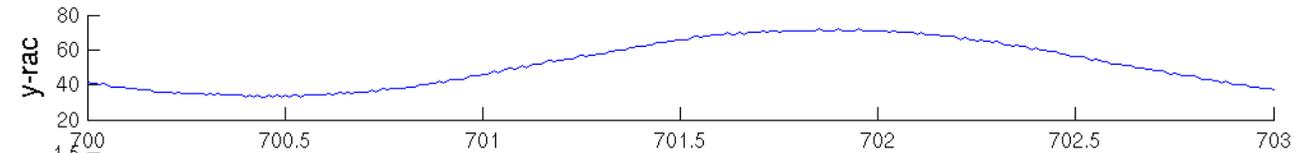


Cerebellar pong player: cell responses during tracking **after** learning

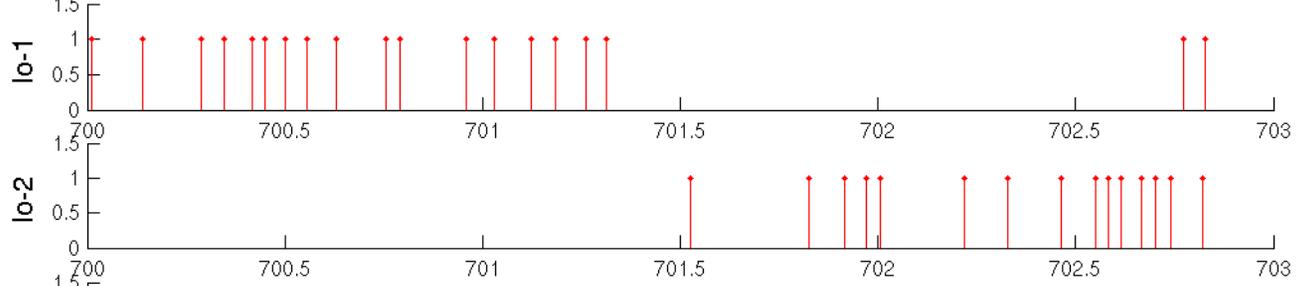


Tennis spiking neural network simulator (Altjira Software)

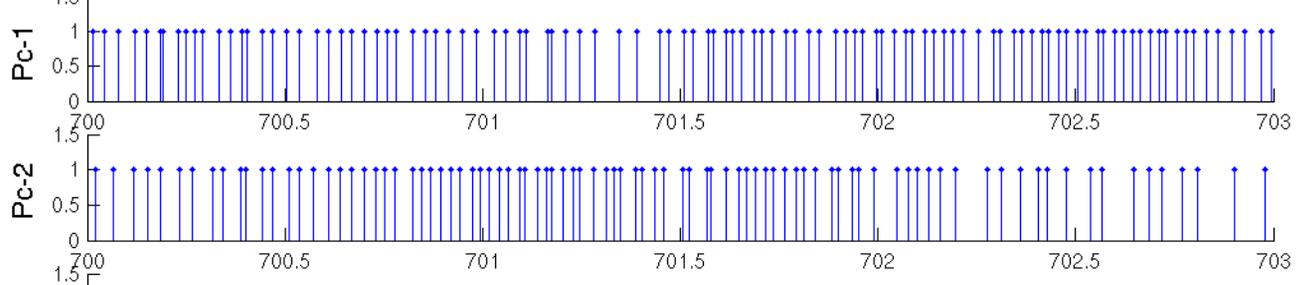
Racquet position



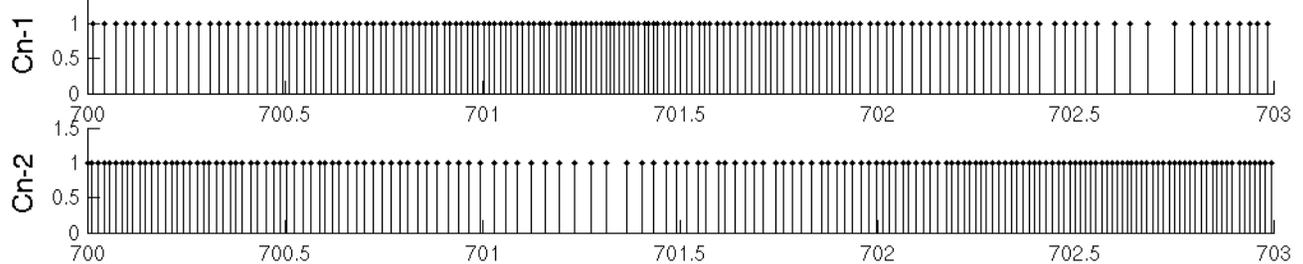
Inferior olive neurons



Purkinje cells



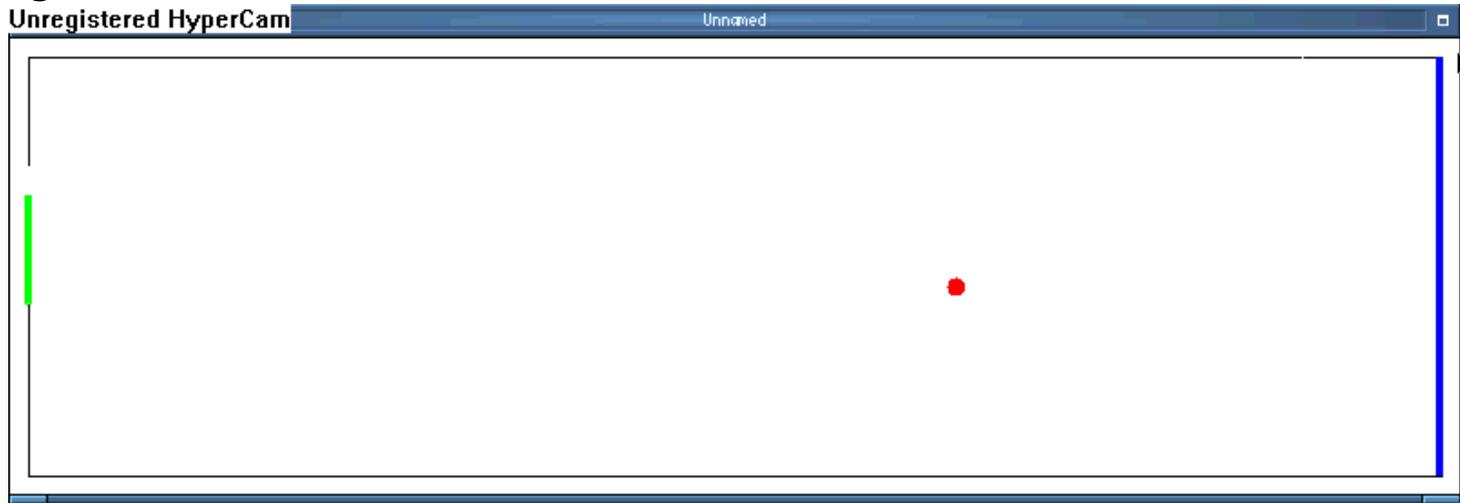
Cerebellar nucleus neurons



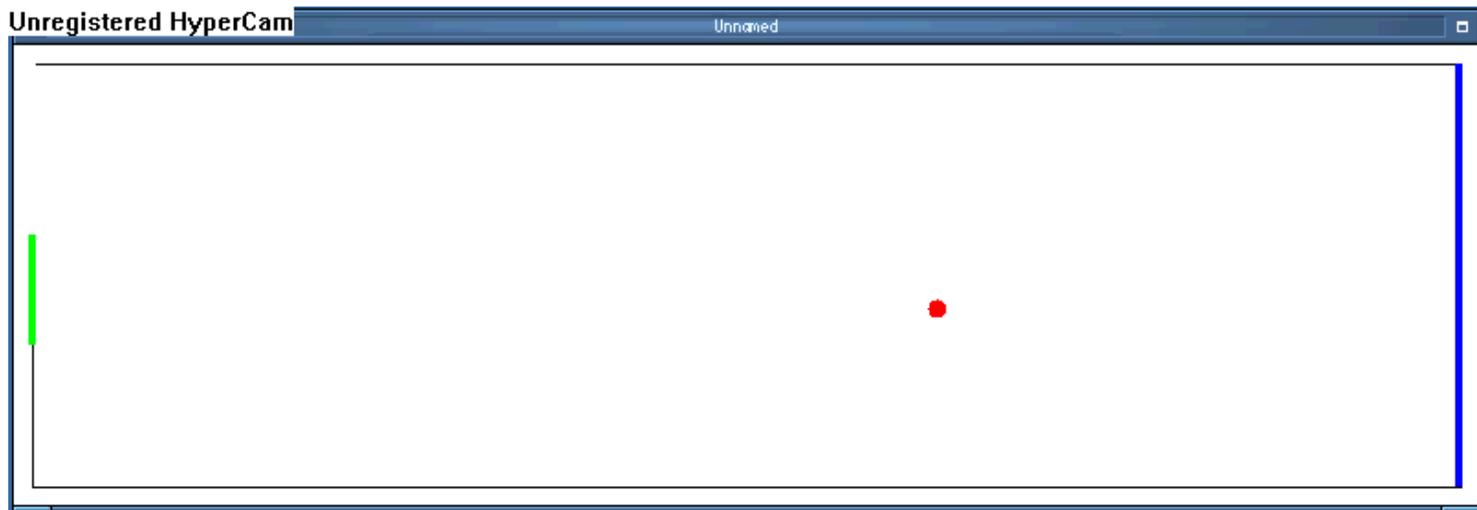
Cerebellar pong player



Before learning



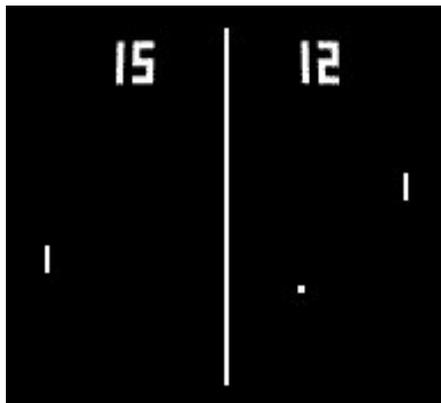
After



Task extension: mixing simulated with real

A robot playing videogames

Pong, 1972



Computer

simulated/ real systems:
visual, auditory, touch

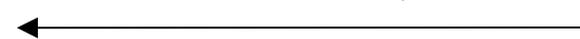


Spiking cerebellar model

Computer, FPGA

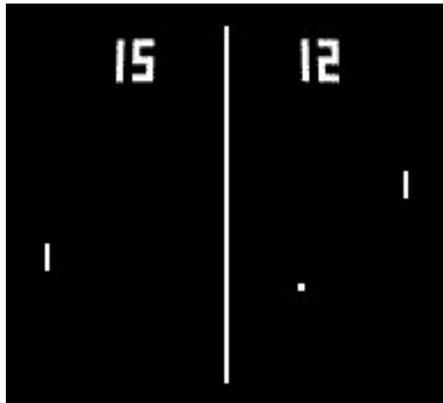


Robot movement, action



Further extension: air-table hockey

Air-table hockey



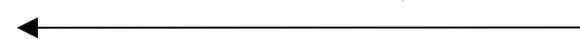
real systems:
visual, auditory, touch

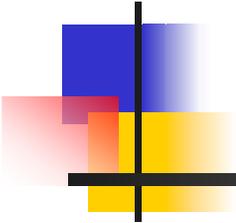


Spiking cerebellar model



Robot movement, action





Efficient Implementation

Hardware

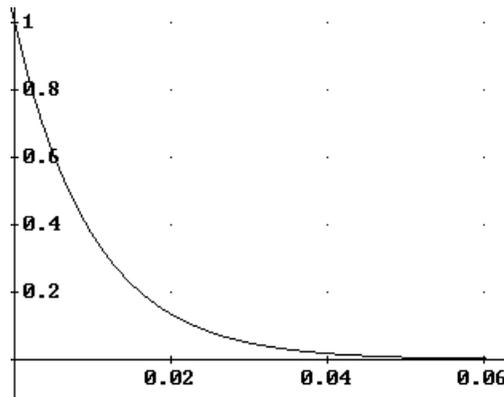
Natural Neuron characteristics incorporated in developed hardware

Synapses as conductances (shunting or multiplicative synapses)

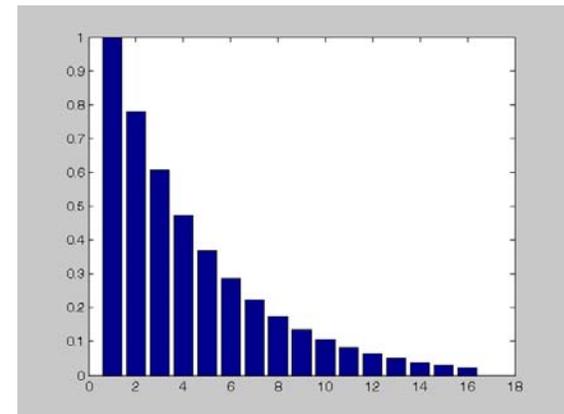
$$V_x = V_x + (E_{exc} - V_x) \cdot \sum I_i^{exc} \cdot \omega_{ij}^{exc} + (V_x - E_{inh}) \cdot \sum I_i^{inh} \cdot \omega_{ij}^{inh}$$

Time-dependent synaptic characteristic: gradual injection of charge.

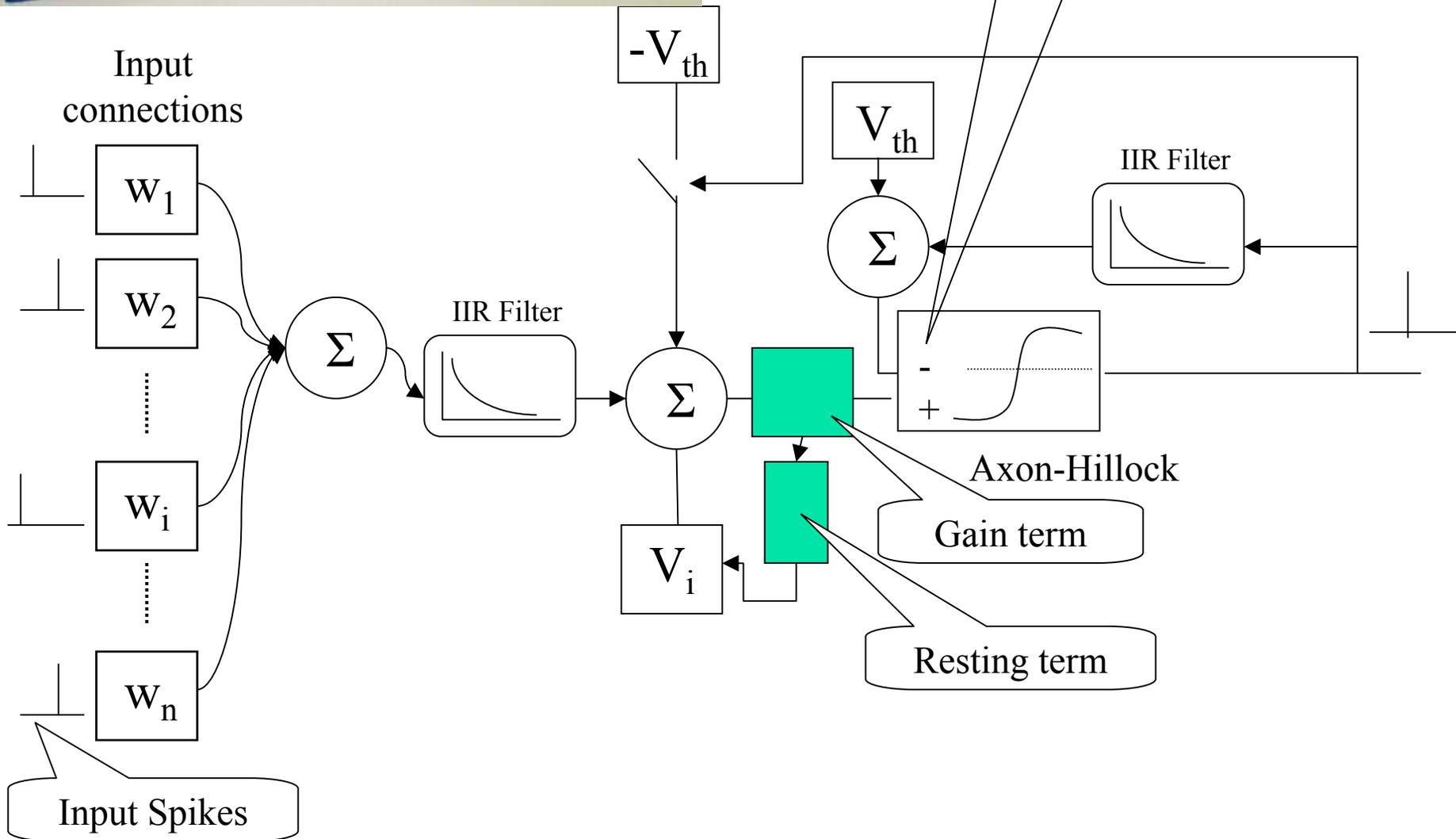
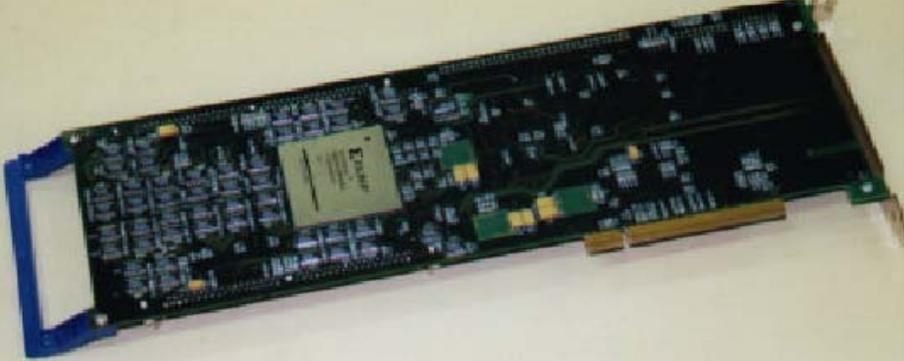
$$F_{syn} = \overline{F_{syn}} \cdot e^{-\frac{(t-t^{(f)})}{\tau}}$$



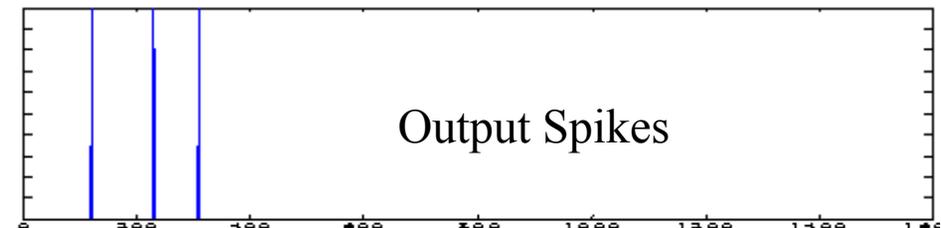
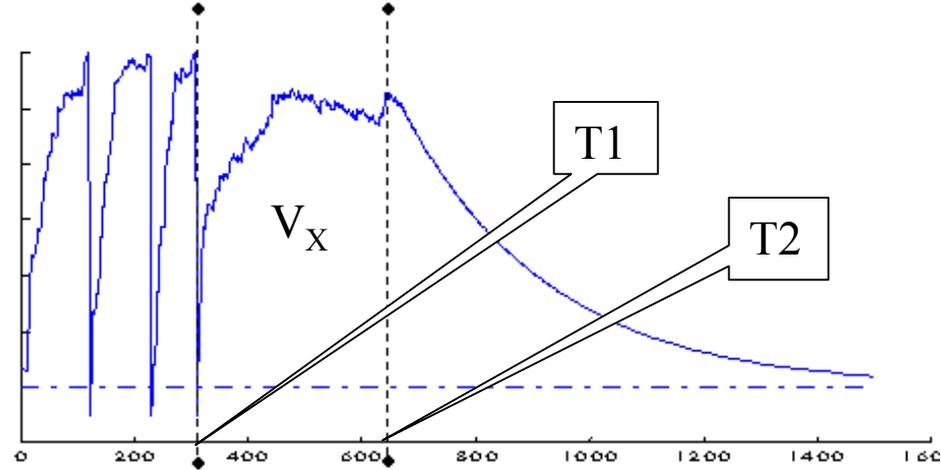
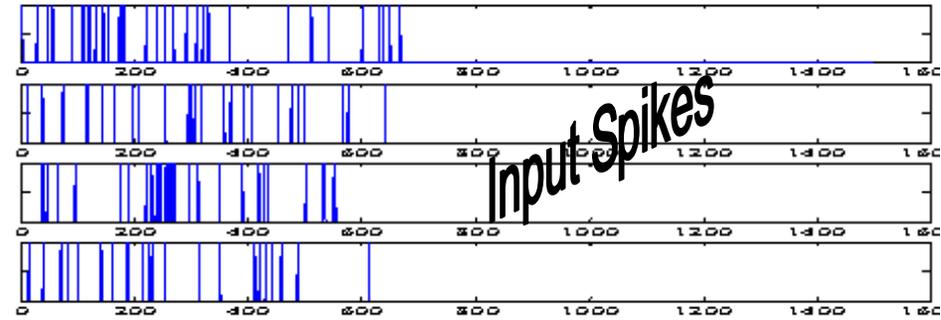
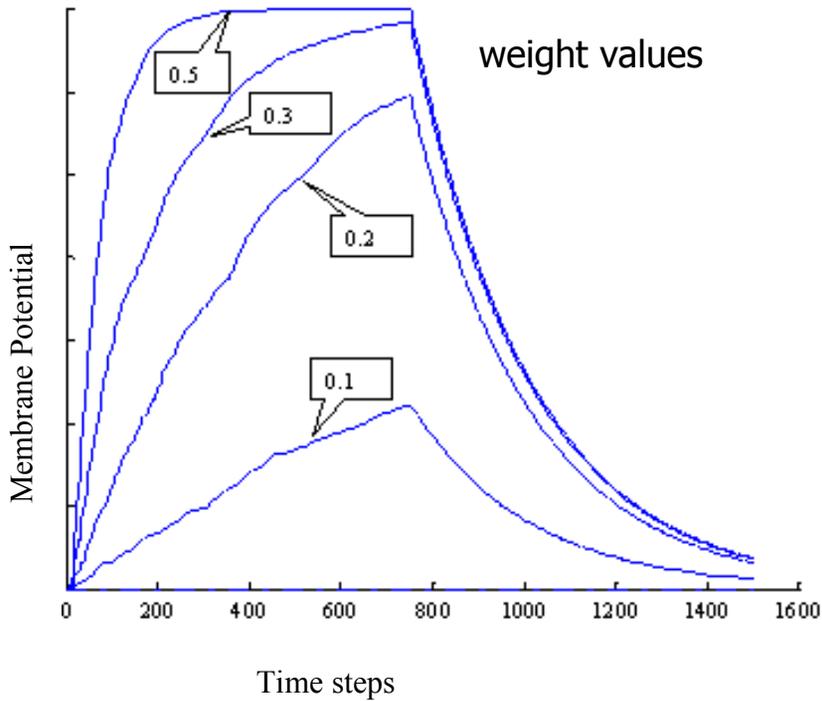
Analytical expression



16 values approach



Experimental Results



Preliminary Implementation (NRH approach)

Table 1. Implementation cost and computing time of different neural configurations.

Inputs per Neuron	Functional Units	Total Num. of Neu.	Number of Slices	Max. Clock freq. (Mhz)	Computing time (ms)	Embedded Memory Blocks (EMB)
2	2	4	1832 (9%)	23.3	0.0055	24 (15%)
2	2	1024	1966 (10%)	20.2	1.4	65 (60%)
8	4	8	5476 (28%)	20.9	0.0011	36 (22%)
8	4	1760	5595 (29%)	20.5	2.9	160 (100%)
8	8	16	12011 (62%)	18.7	0.0018	36 (22%)
8	8	1760	12010 (62%)	18.7	4.5	160 (100%)

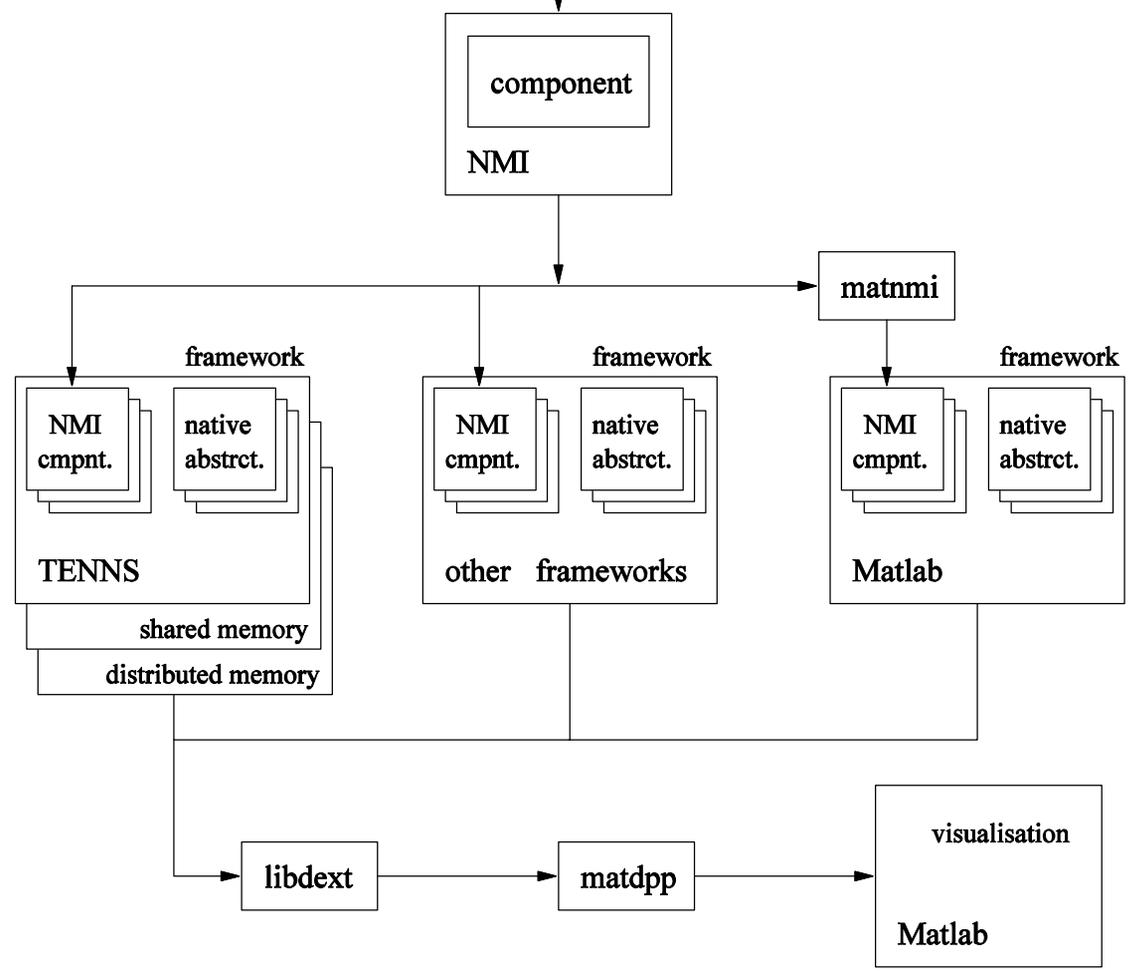
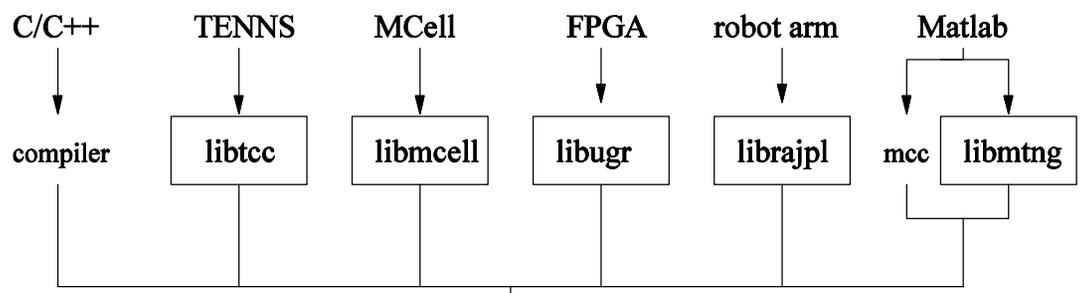


Supporting Focus Group Software Framework



Outline:

- **Network Model Interface (NMI)**





Principal Investigators

- Dr. Boris Barbour (ENS, Paris)
- Dr. Olivier J.-M. D. Coenen (SONY, Paris)
- Associate Prof. Eduardo Ros (Univ of Granada)
- Prof. Egidio D'Angelo (INFM, Pavia)
- Dr. Michael P. Arnold (SONY subcontractor - Altjira Software)

Staff

- Dr. Eva M. Ortigosa (UGR)
- Dr. Paola Rossi (INFM)
- Dr. Lia Forti (INFM)
- Dr. David Gall (INFM)
- Dr. Michele Bezzi (SONY)
- Dr. Eric Ronco (SONY)

Students

- Francesca Porestori (INFM)
- Leda Roggieri (INFM)
- Jonathan Mapelli (INFM)
- Thierry Nieuus (INFM)
- Richard Carrillo (UGR)
- Rodrigo Agis (UGR)
- David Philipona (SONY)
- David Marchal (SONY)
- Jérôme Lecoq (SONY)
- Edouard Dognin (SONY)



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