synthetic perceptive, emotive and cognitive systems

Distributed Adaptive Control: A proposal on the architecture of mind, brain and behavior

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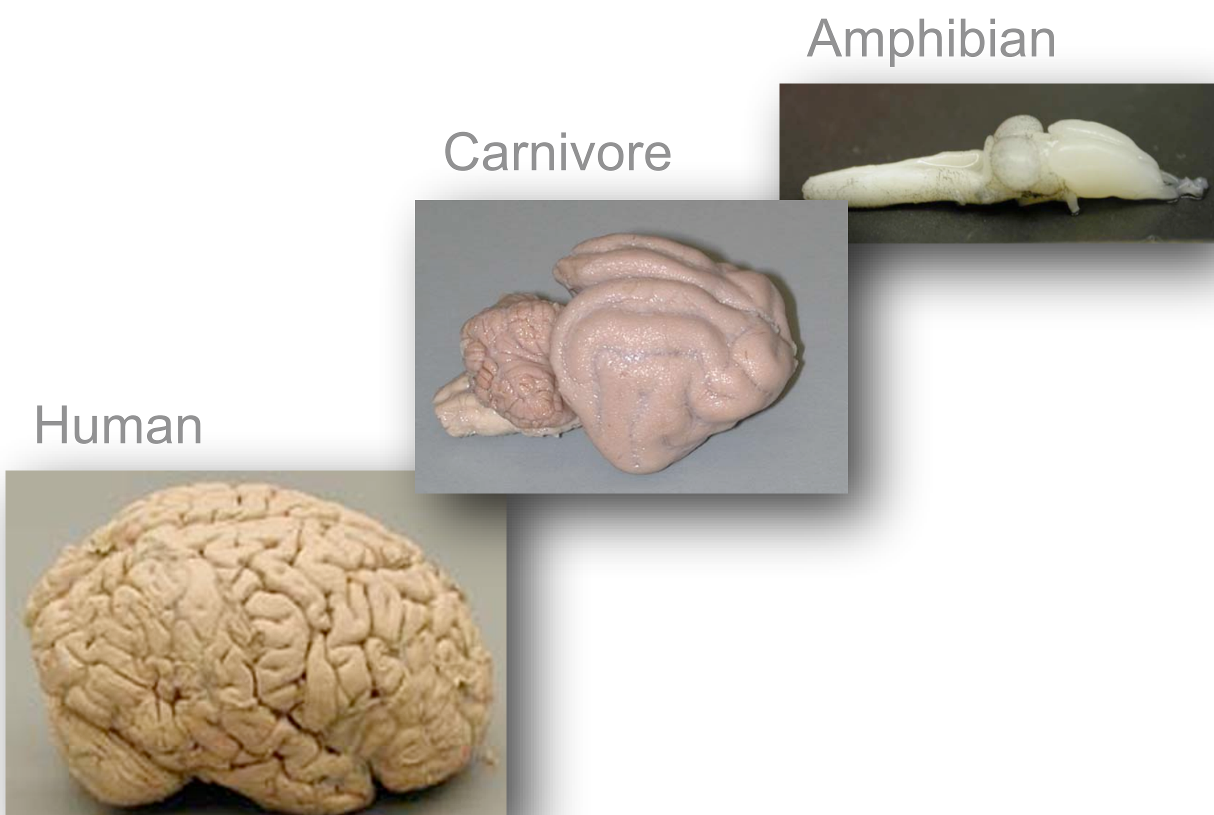
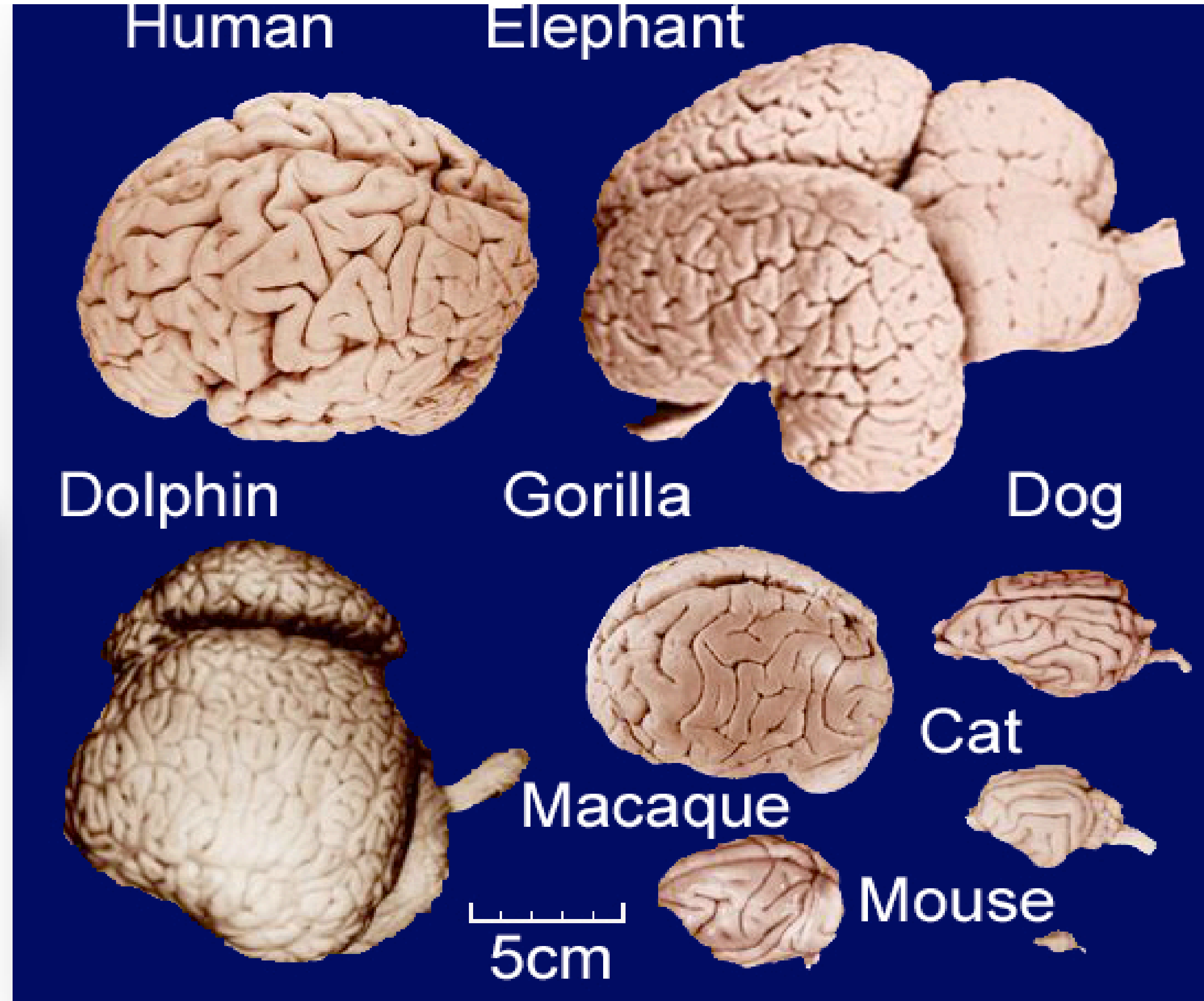
GoalLeader

eSMC

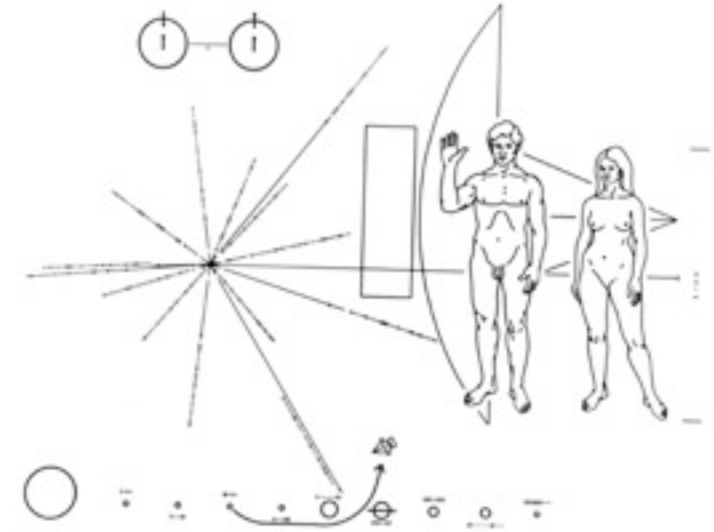
Brains big and small

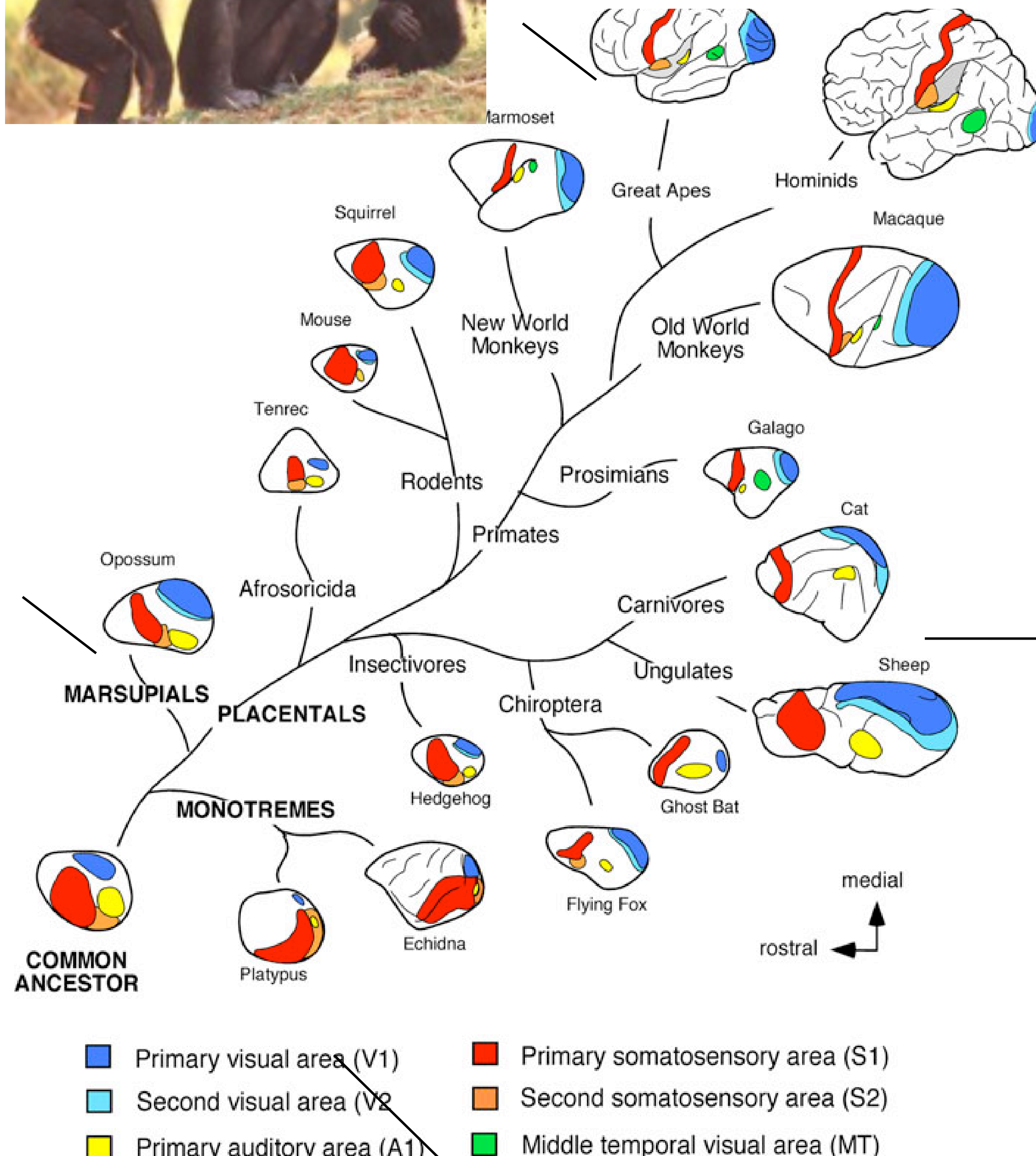




Moth

I set of underlying principles?





Kubitzer, 2007

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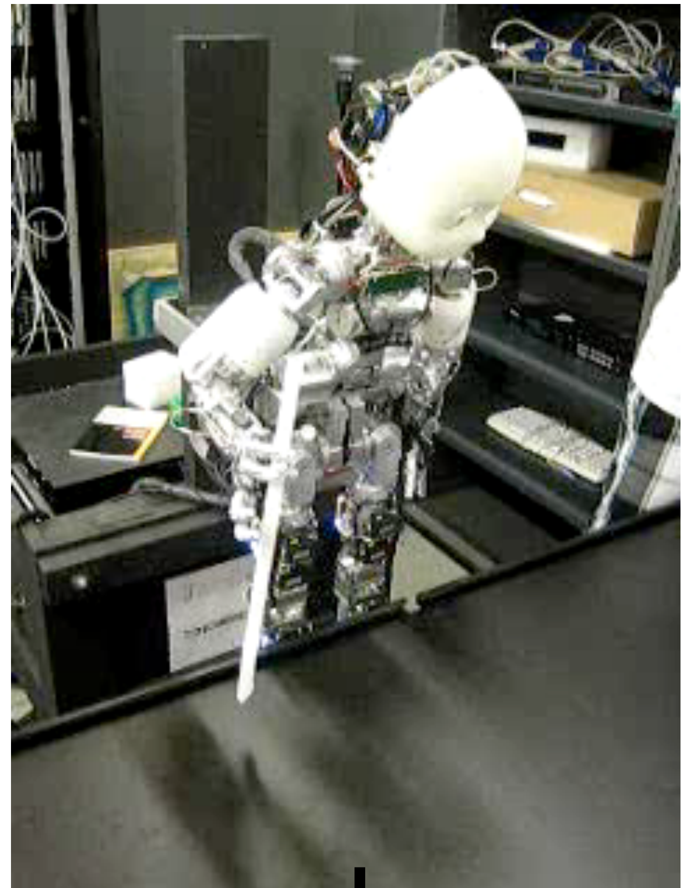
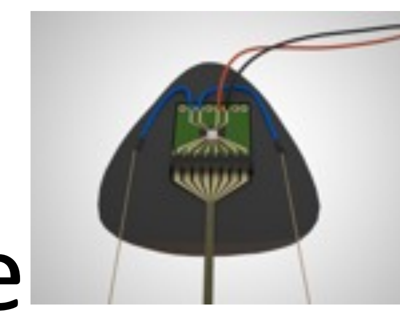
Brain = Action = Embodiment



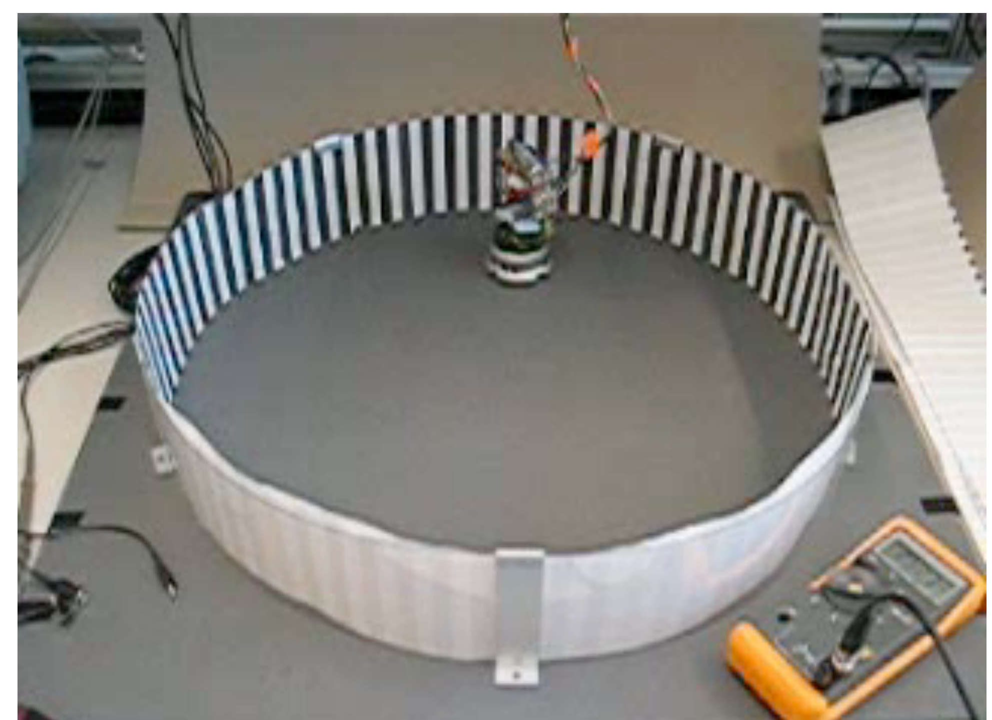
Mathews et al (2010) Inf. Sci.

Events

Time



Reno Costa et al (2010) Neuron

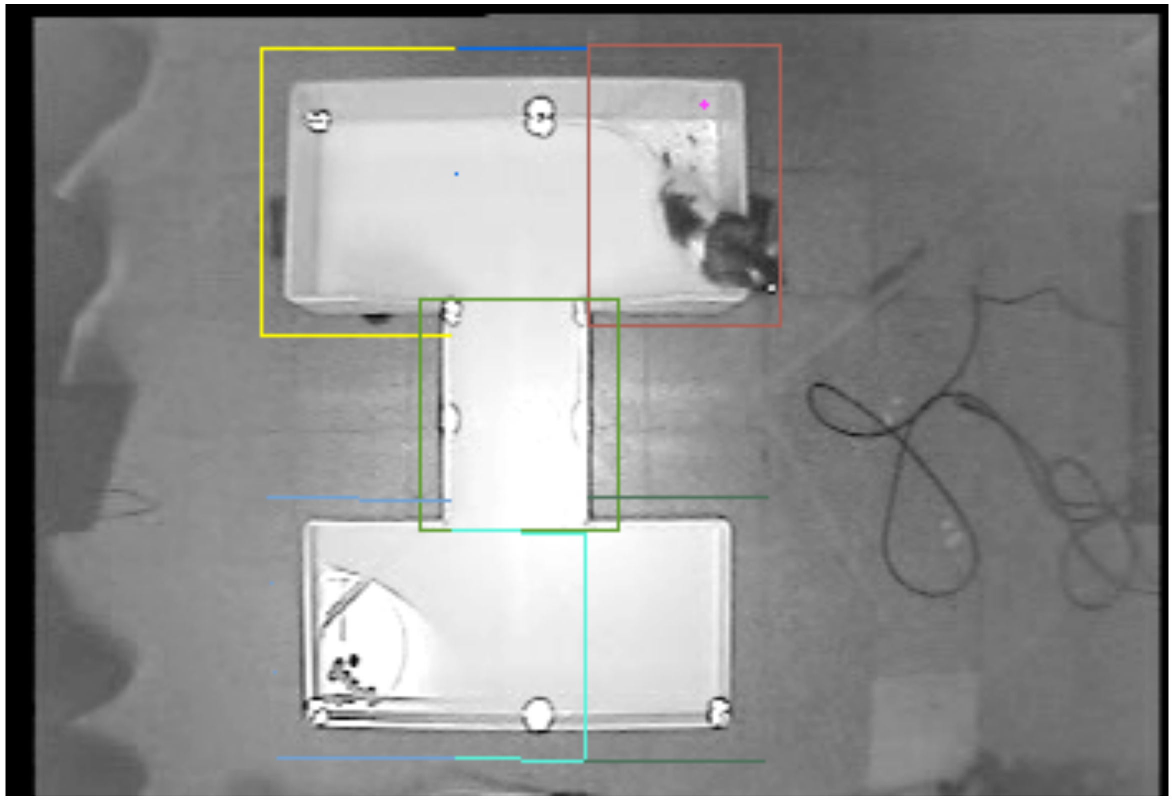


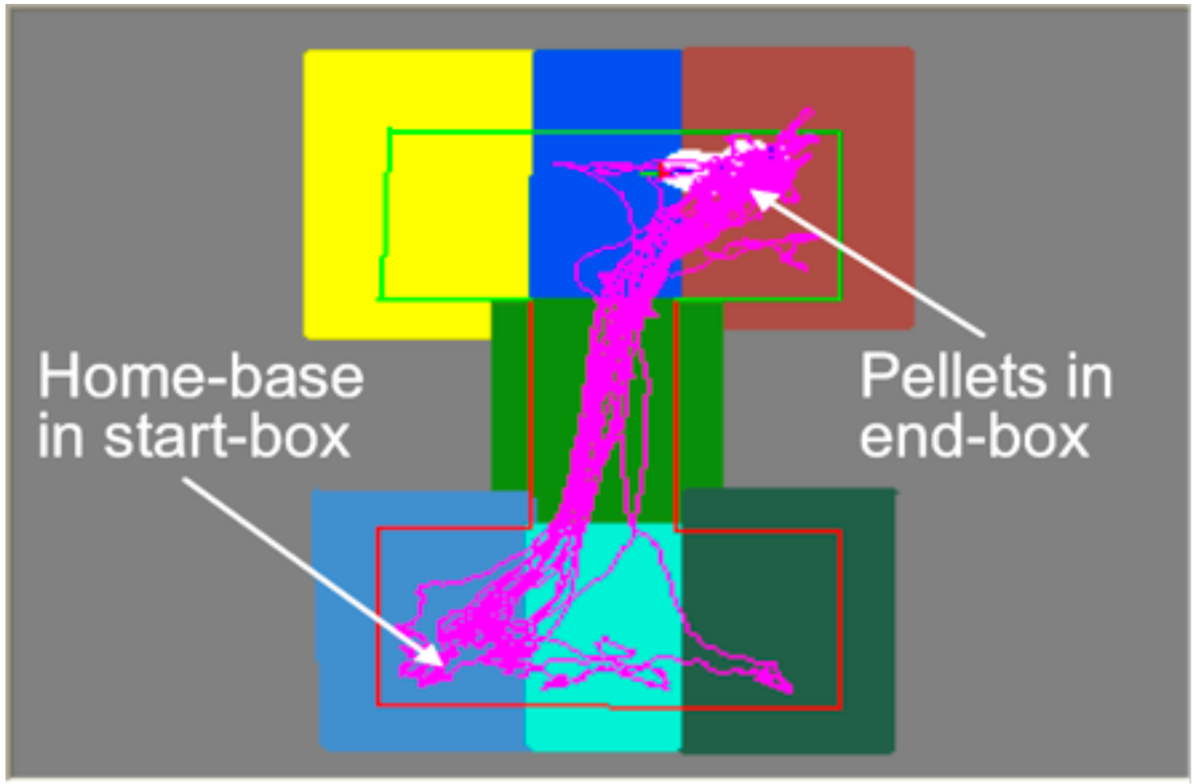
Hofstodter et al (2003;2005) Eur J. Neurosci;NIPS

Acting means solving the **H4W** problem

- Why: goal
- What: objects
- Where: space
- When: time

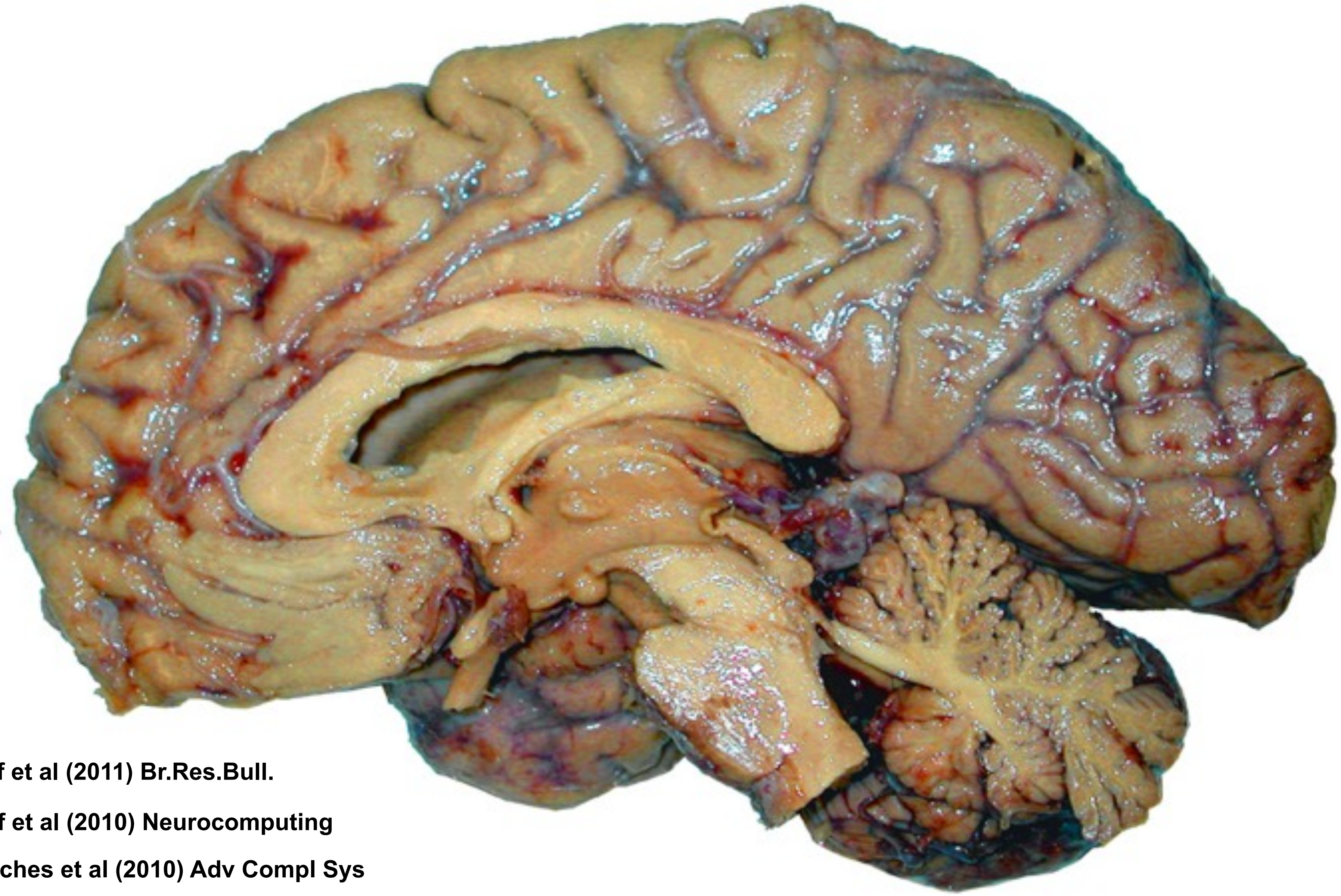
→ Act (How)





Courtesy Mintz lab, Univ. Tel Aviv

Distributed Adaptive Control



Contextual layer

Planning
Operant conditioning

Adaptive layer

Stimulus/Action shaping
Classical conditioning

Reactive layer

Reflex
Action selection
Autonomic control

Duff et al (2011) Br.Res.Bull.

Duff et al (2010) Neurocomputing

Sanches et al (2010) Adv Compl Sys

Mathews et al (2009;2010) IROS09;ICRA10

Eng et al (2003;2005) ICRA; IEEE Tr Sys, Man, Cyb

Verschure et al (2003) Nature (425) 620

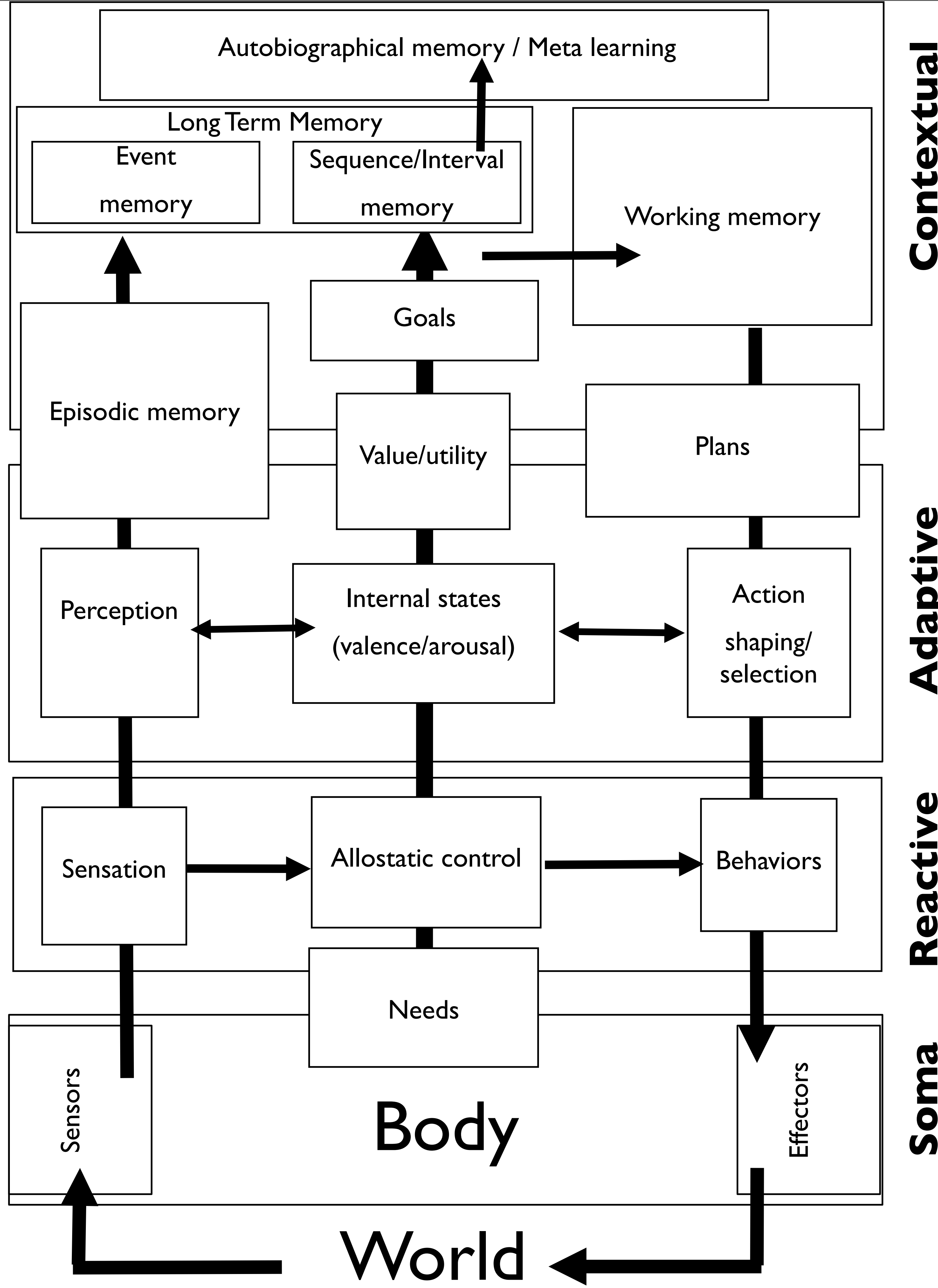
Verschure et al (2003) Cogn. Sci. (27) 561

Verschure & Voegtlin (1998) Neural Netw

Verschure et al (1992) Rob. Aut. Sys.

Verschure & Coolen (1991) Network

The Distributed Adaptive Control Architecture



Duff et al (2011) Br.Res.Bull.
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Verschure & Althaus (2003) Cogn. S
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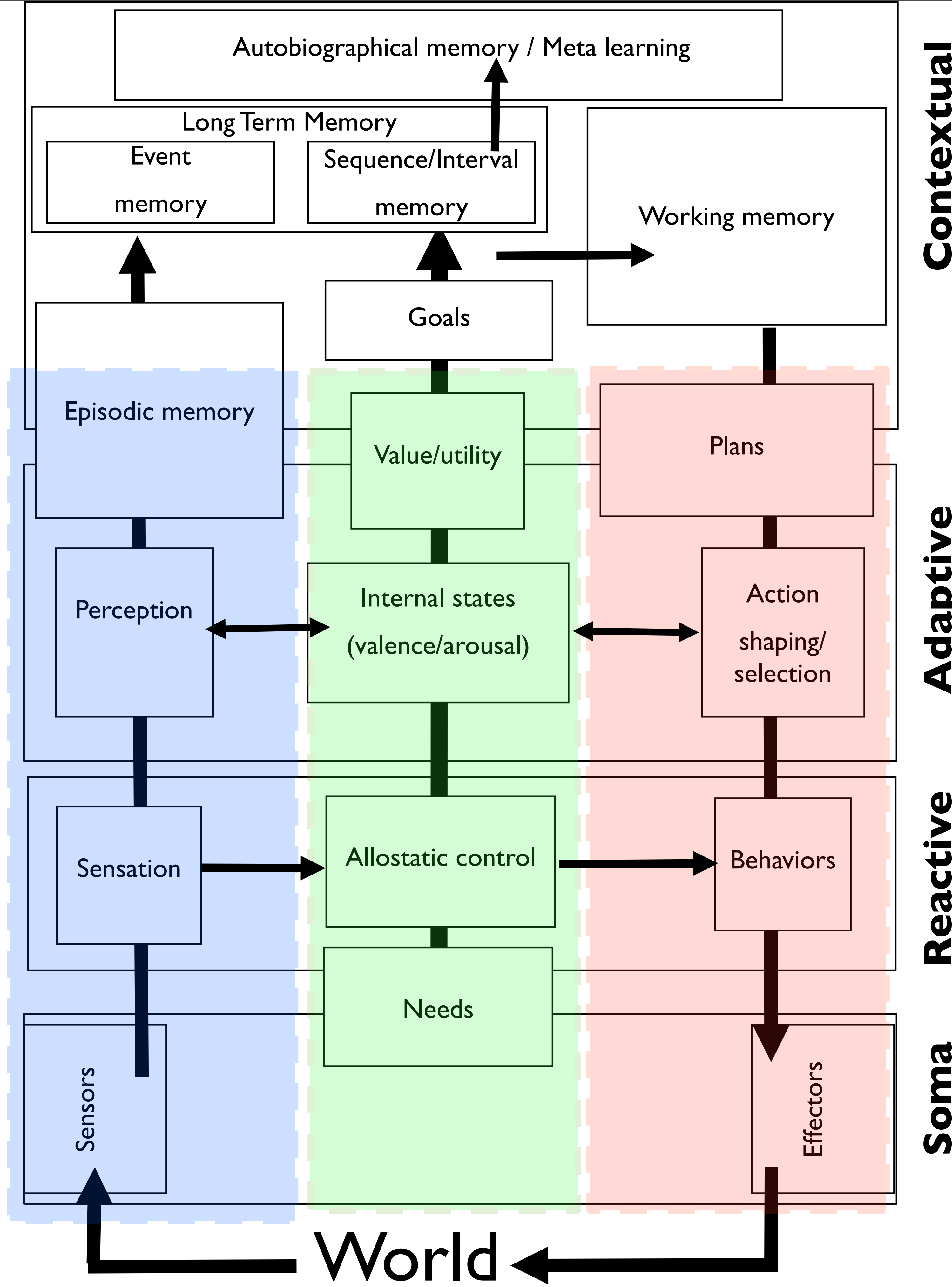
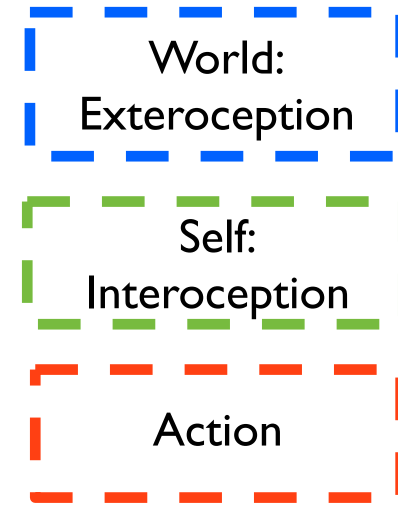
The Distributed Adaptive Control Architecture





Duff et al (2011) Br.Res.Bull.
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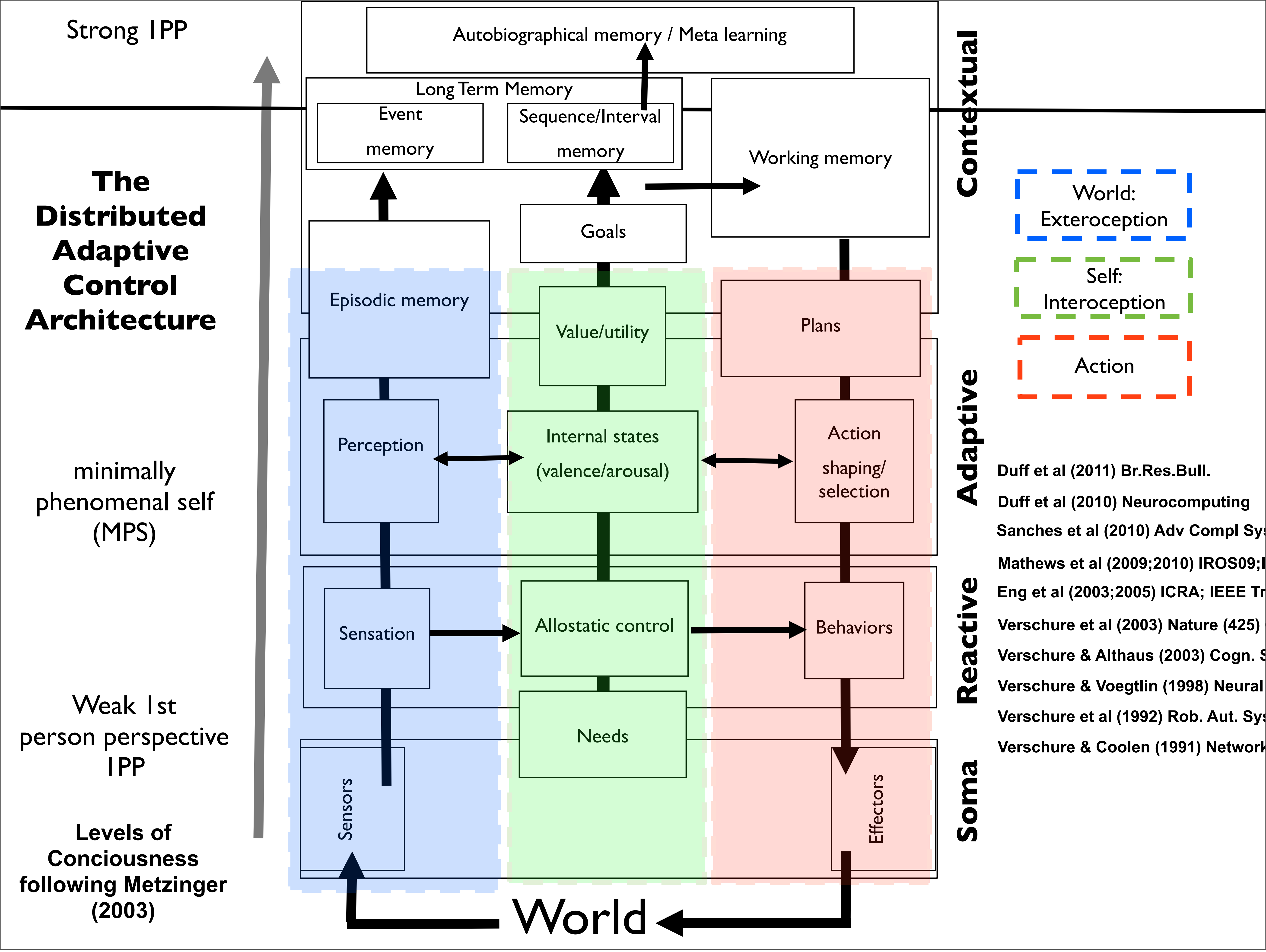
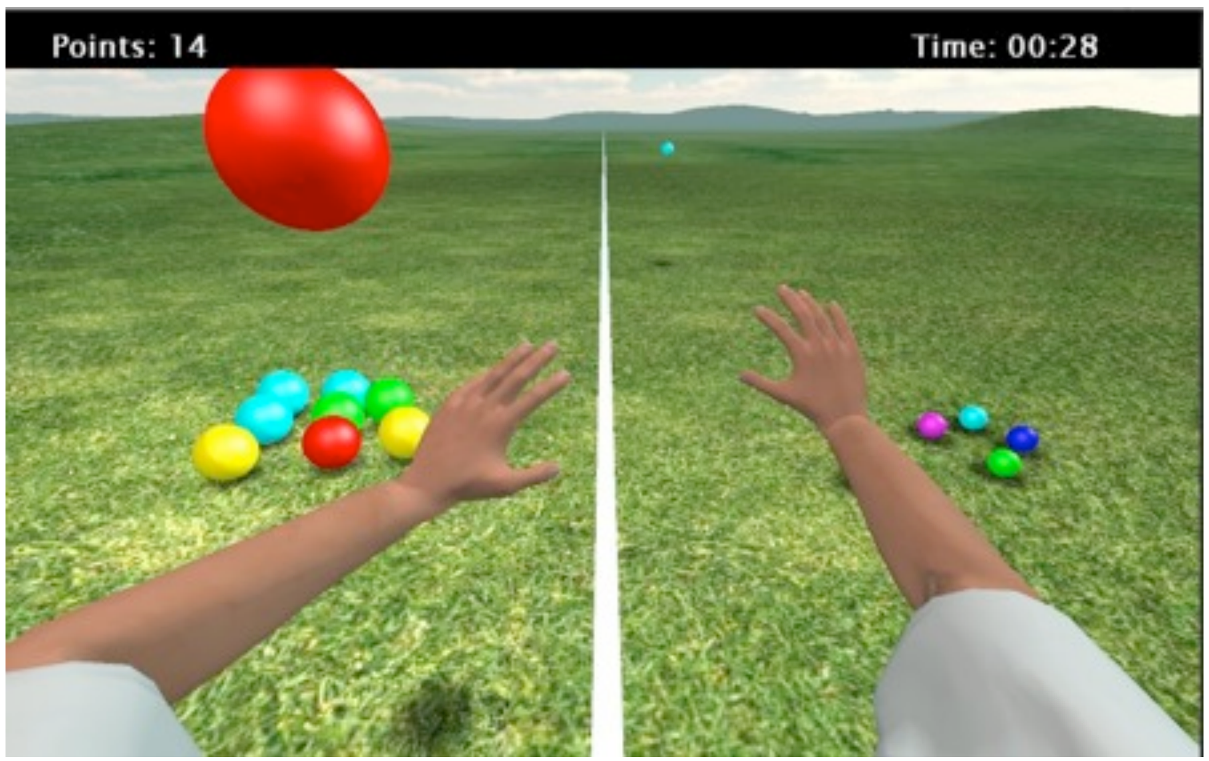
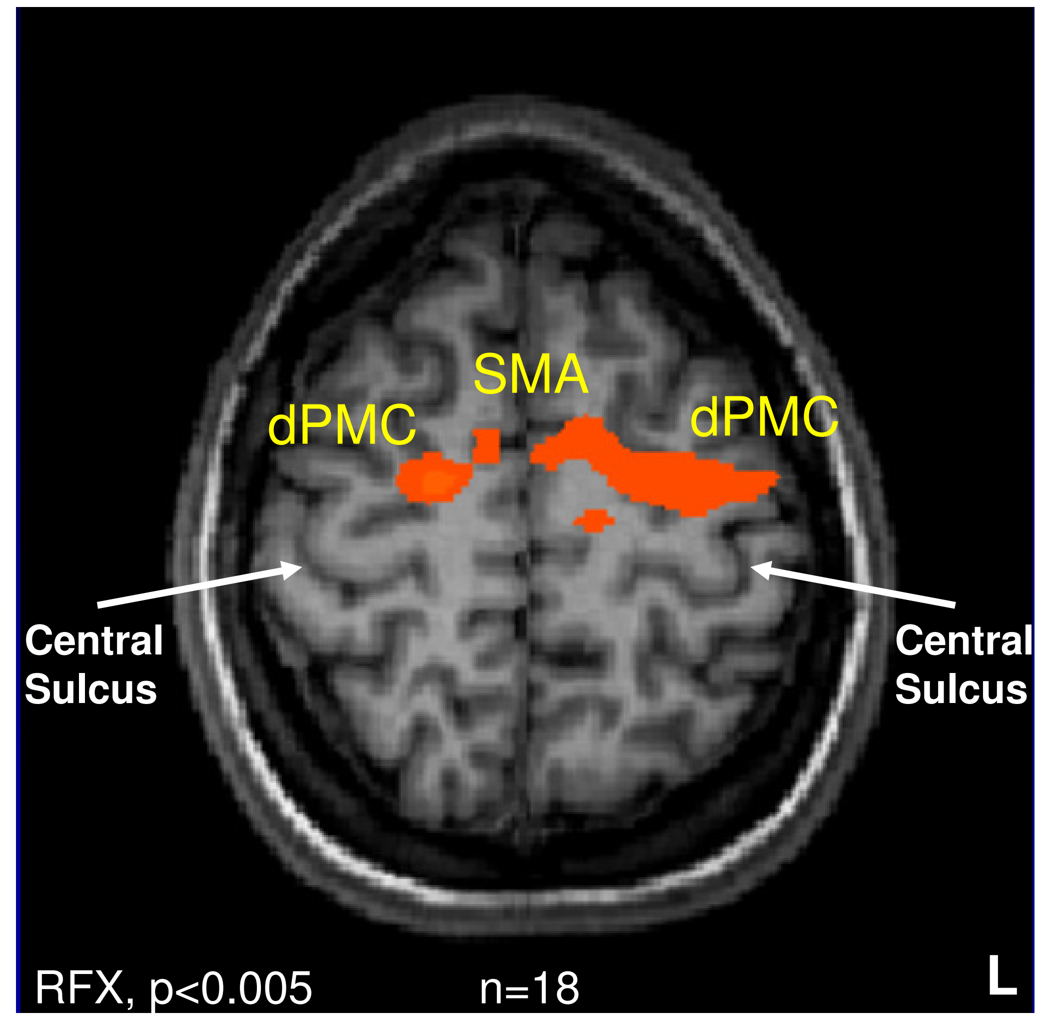

Strong 1PP
The Distributed Adaptive Control Architecture
minimally phenomenal self (MPS)
Weak 1st person perspective 1PP
Levels of Conciousness following Metzinger (2003)
Autobiographical memory / Meta learning
Long Term Memory
Event memory
Sequence/Interval memory
Working memory
Goals
Episodic memory
Value/utility
Plans
Perception
Internal states (valence/arousal)
Action shaping/ selection
Sensation
Allostatic control
Behaviors
Needs
Sensors
Effectors
World
Contextual
Adaptive
Reactive
Soma
World: Exteroception
Self: Interoception
Action
Duff et al (2011) Br.Res.Bull.
Duff et al (2010) Neurocomputing
Mathews et al (2009;2010) IROS09;I
Verschure et al (2003) Nature (425)
Verschure & Voegtlin (1998) Neural
Verschure et al (1992) Rob. Aut. Sys
Verschure & Coolen (1991) Network

Principles of DAC have been translated to an effective stroke rehabilitation system



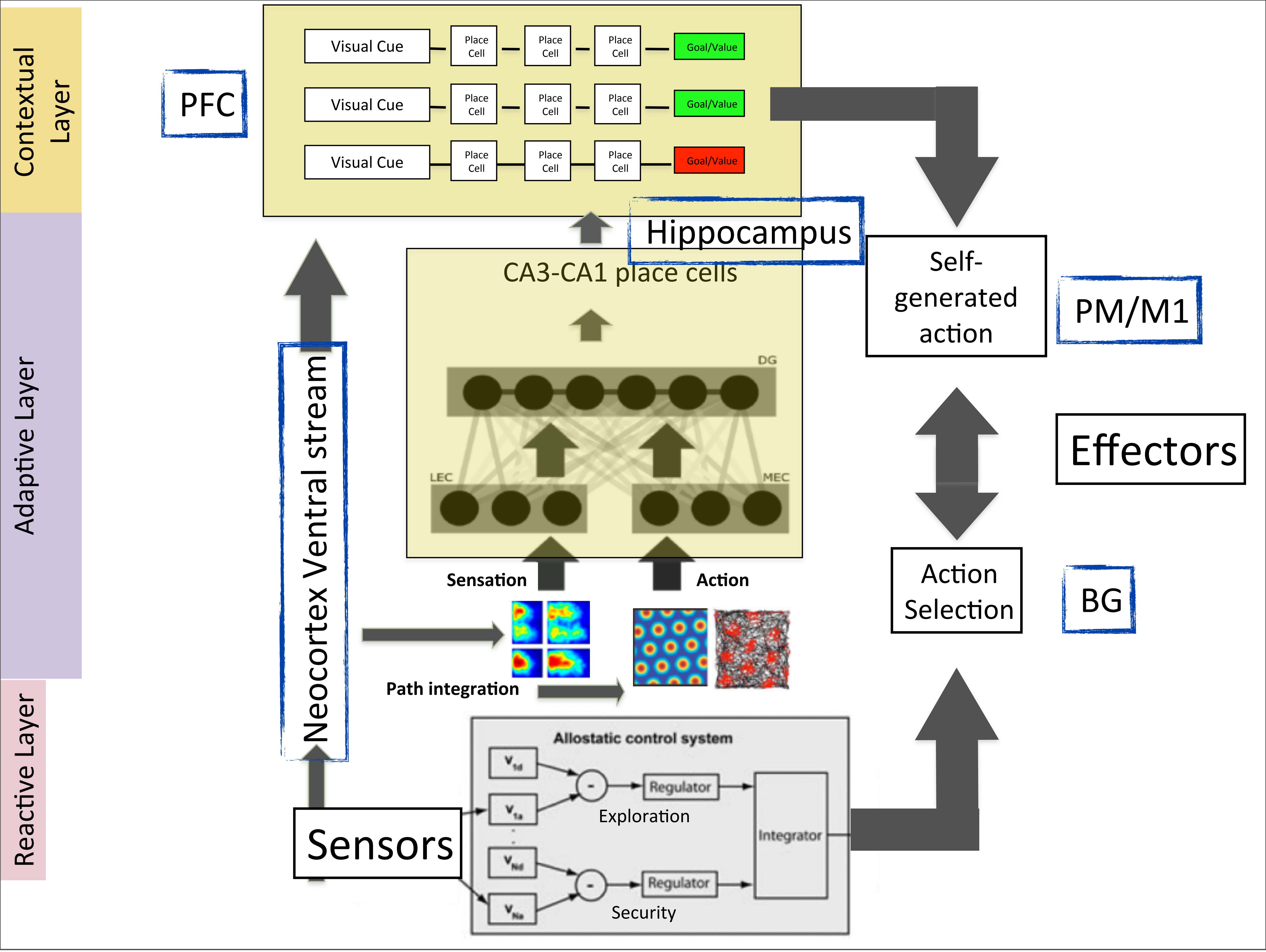
Cameirao et al (2011) Rest.Neurol.Neurosci.

Rehabilitation
Gaming System

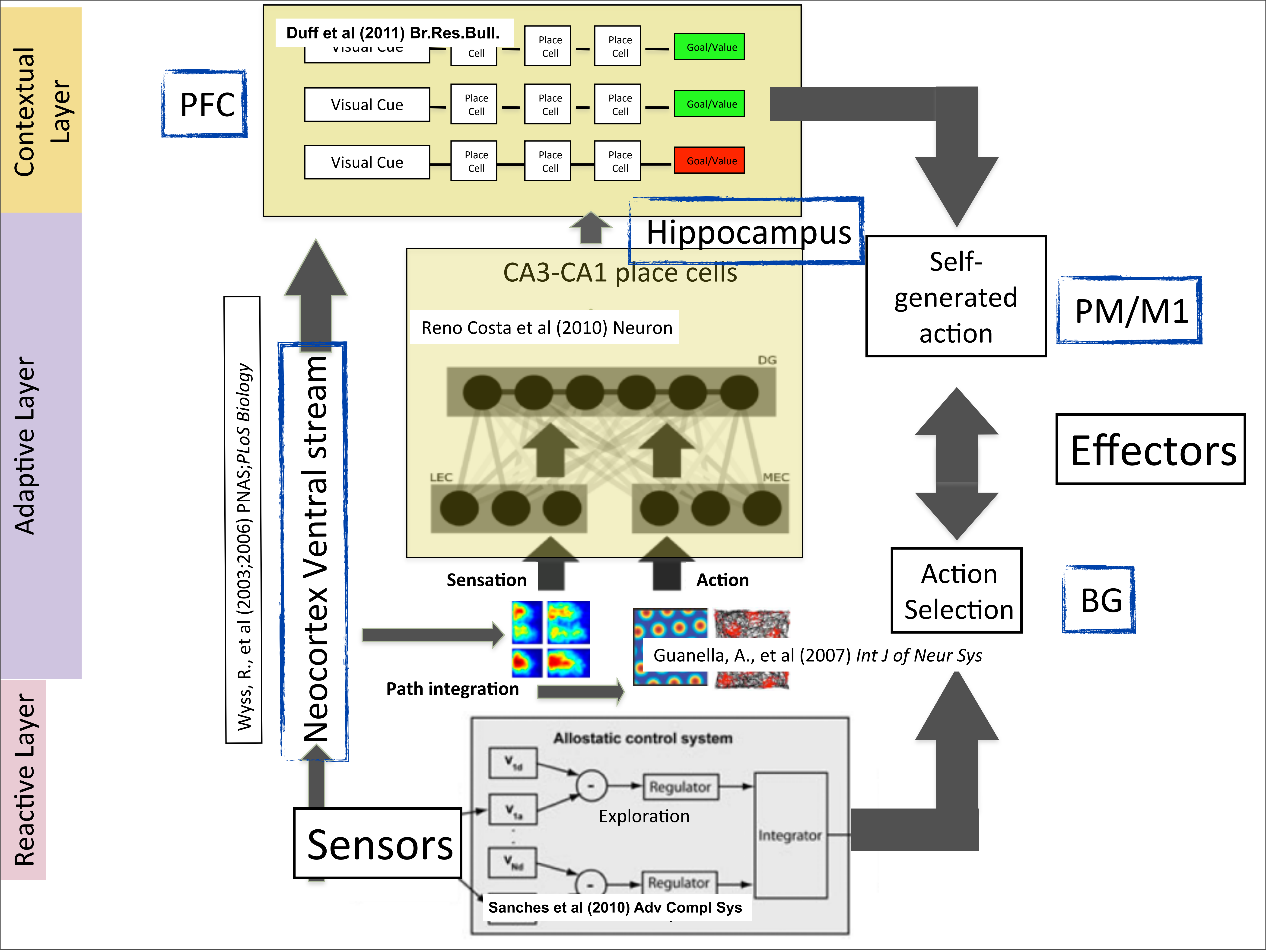


With
Ruediger Seitz

synthetic forager



Contextual Layer
Adaptive Layer
Reactive Layer
PFC
Visual Cue
Place Cell
Goal/Value
Hippocampus
CA3-CA1 place cells
DG
LEC
MEC
Sensation
Action
Path integration
Neocortex Ventral stream
Sensors
Allostatic control system
Regulator
Exploration
Security
Integrator
Self-generated action
PM/M1
Effectors
Action Selection
BG



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CA3-CA1 place cells
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LEC
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Sensation
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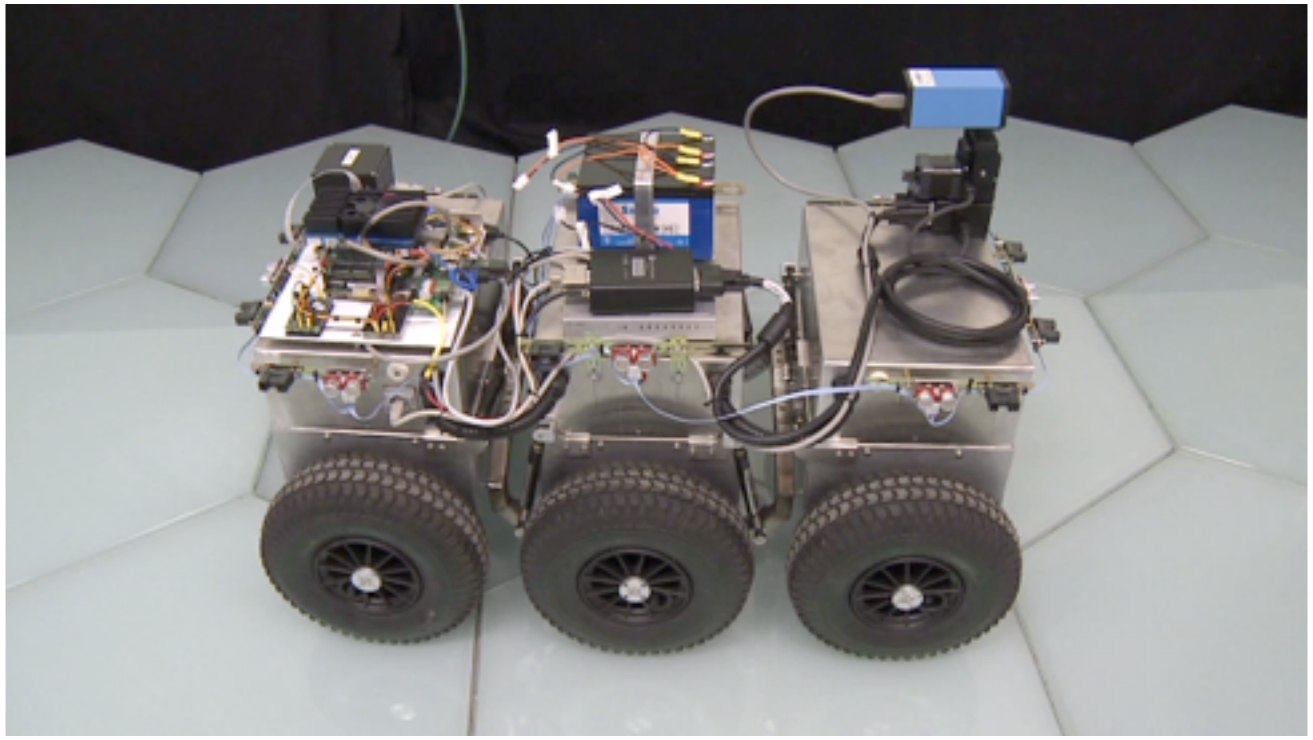
Path integration
Guanella, A., et al (2007) *Int J of Neur Sys*
Wyss, R., et al (2003;2006) PNAS;*PLoS Biology*
Neocortex Ventral stream
Sensors
Allostatic control system
Regulator
Exploration
Integrator
Sanches et al (2010) Adv Compl Sys
Self-generated action
PM/M1
Effectors
Action Selection
BG

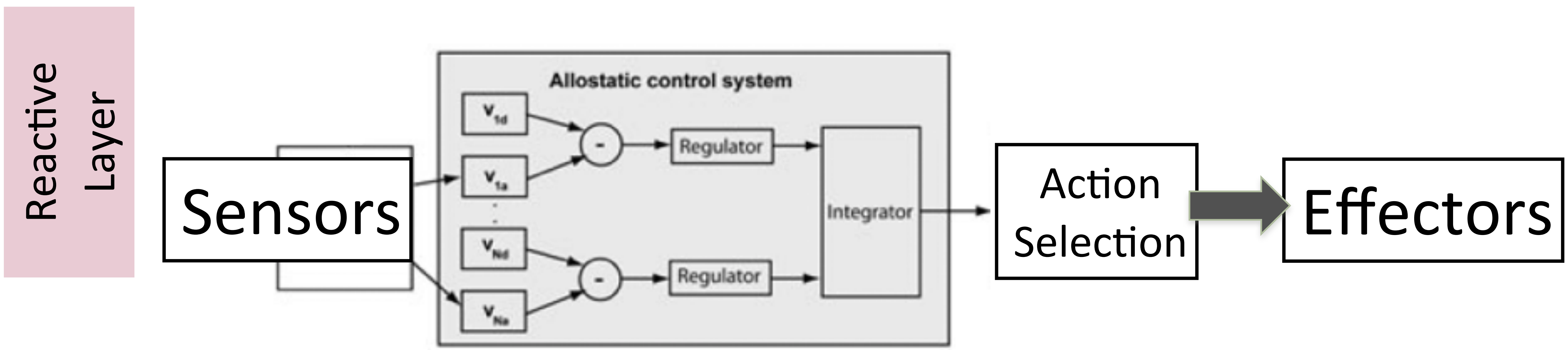

Outdoor Tests of
Experimental Protocol

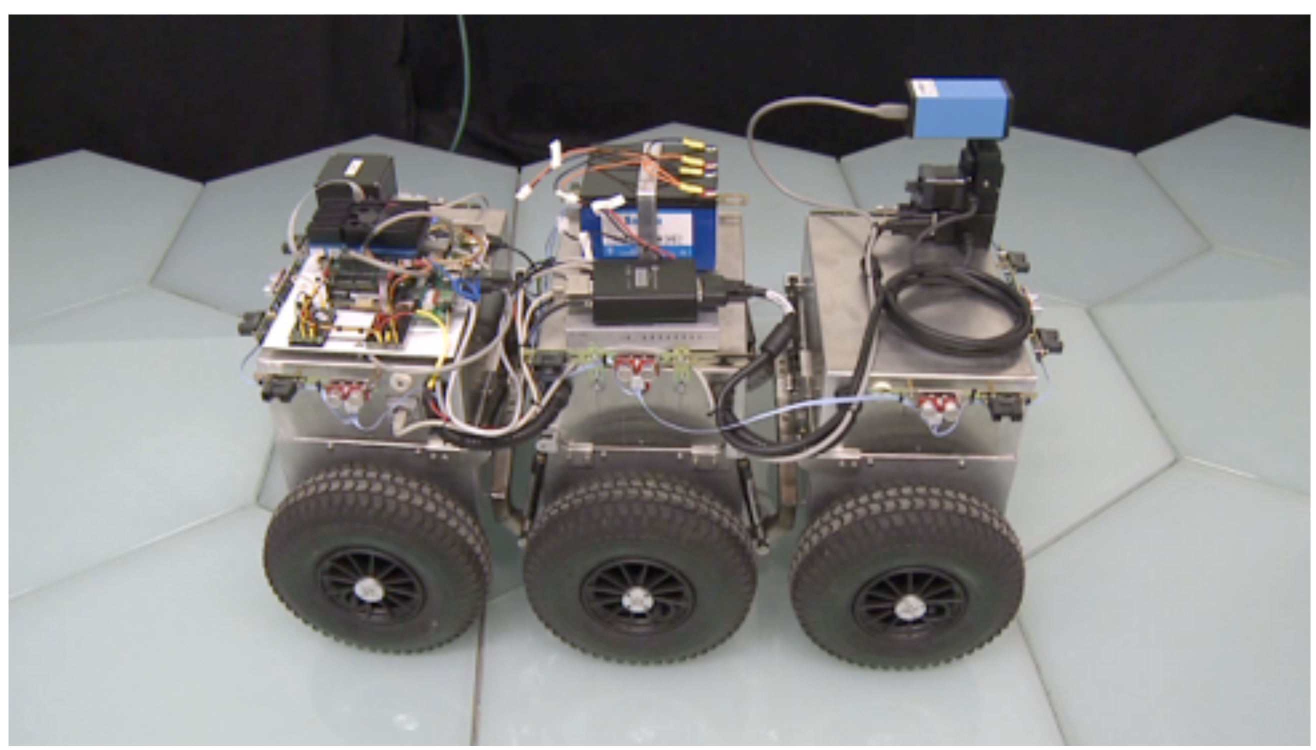
DAC: Reactive Layer



With Robosoft

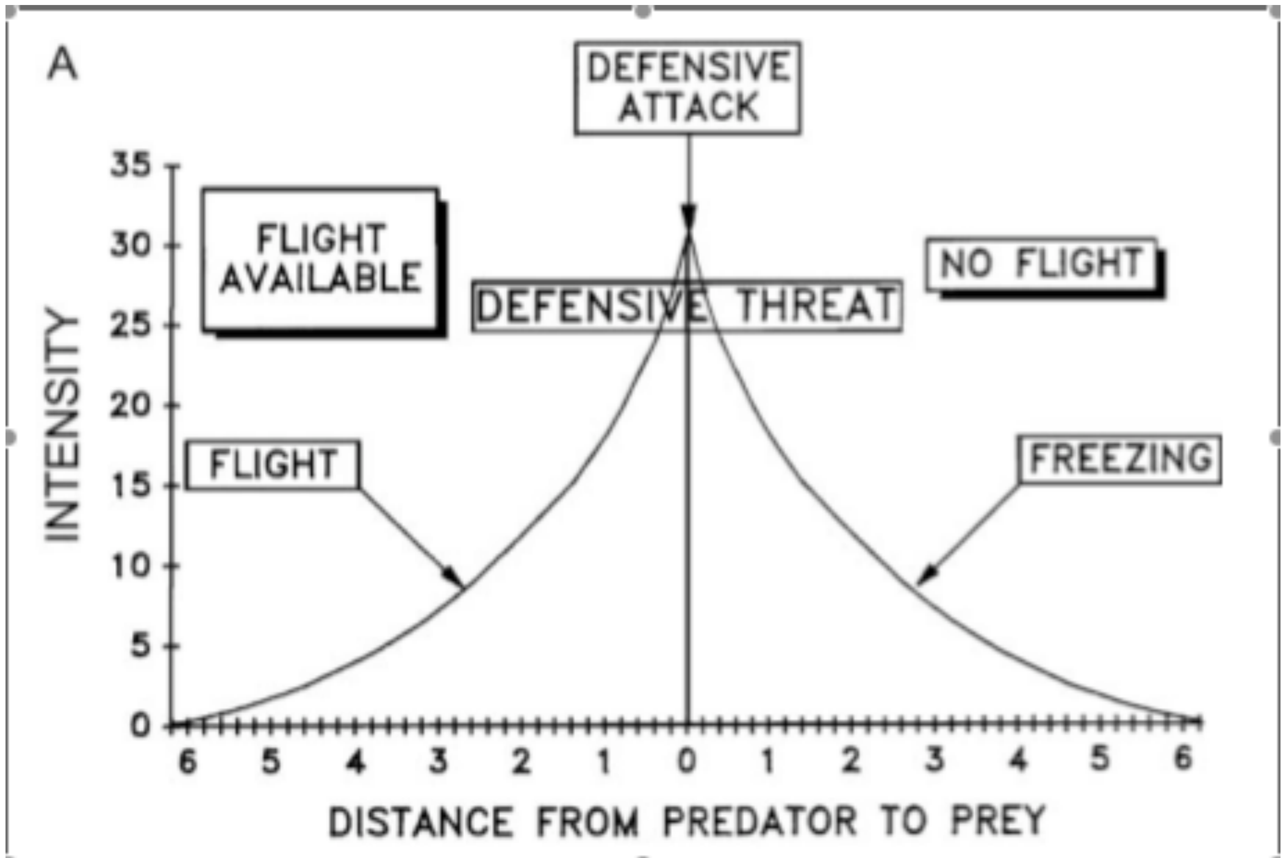
DAC: Reactive Layer



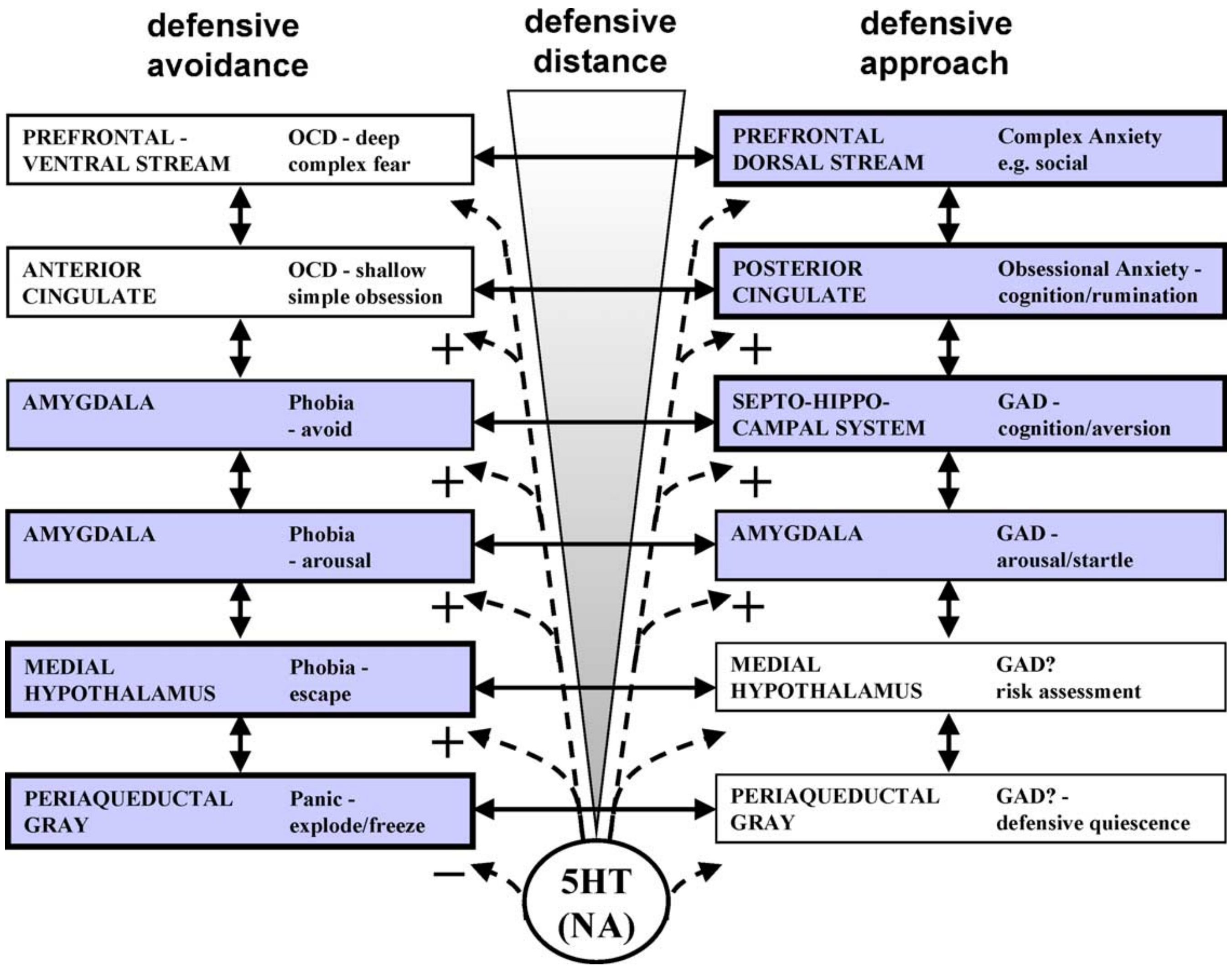


With Robosoft

Regulating the 5Fs in the real world

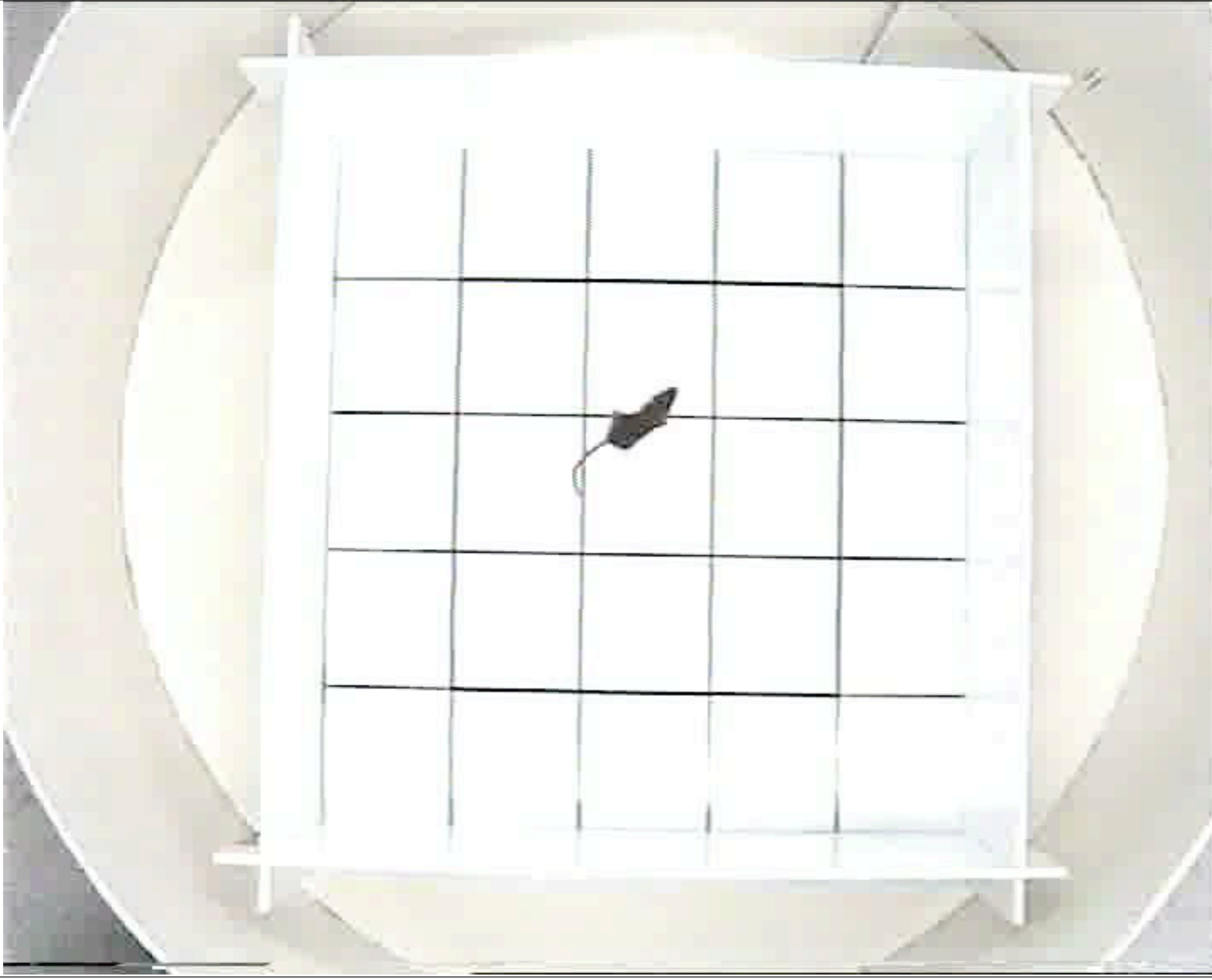


Blanchard & Blanchard (1989) J Comp Psychol

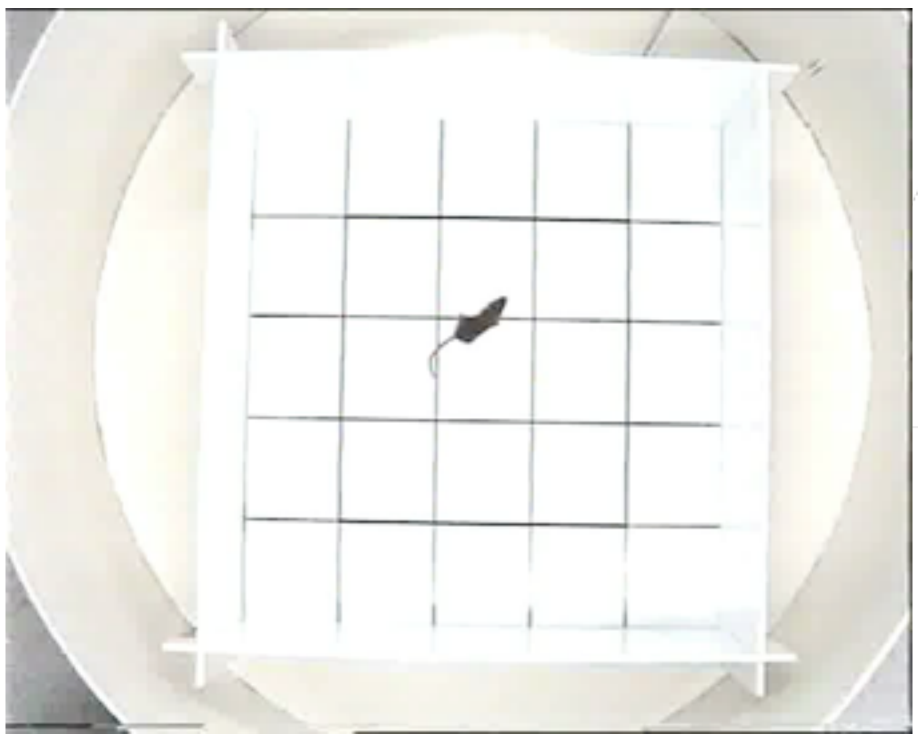


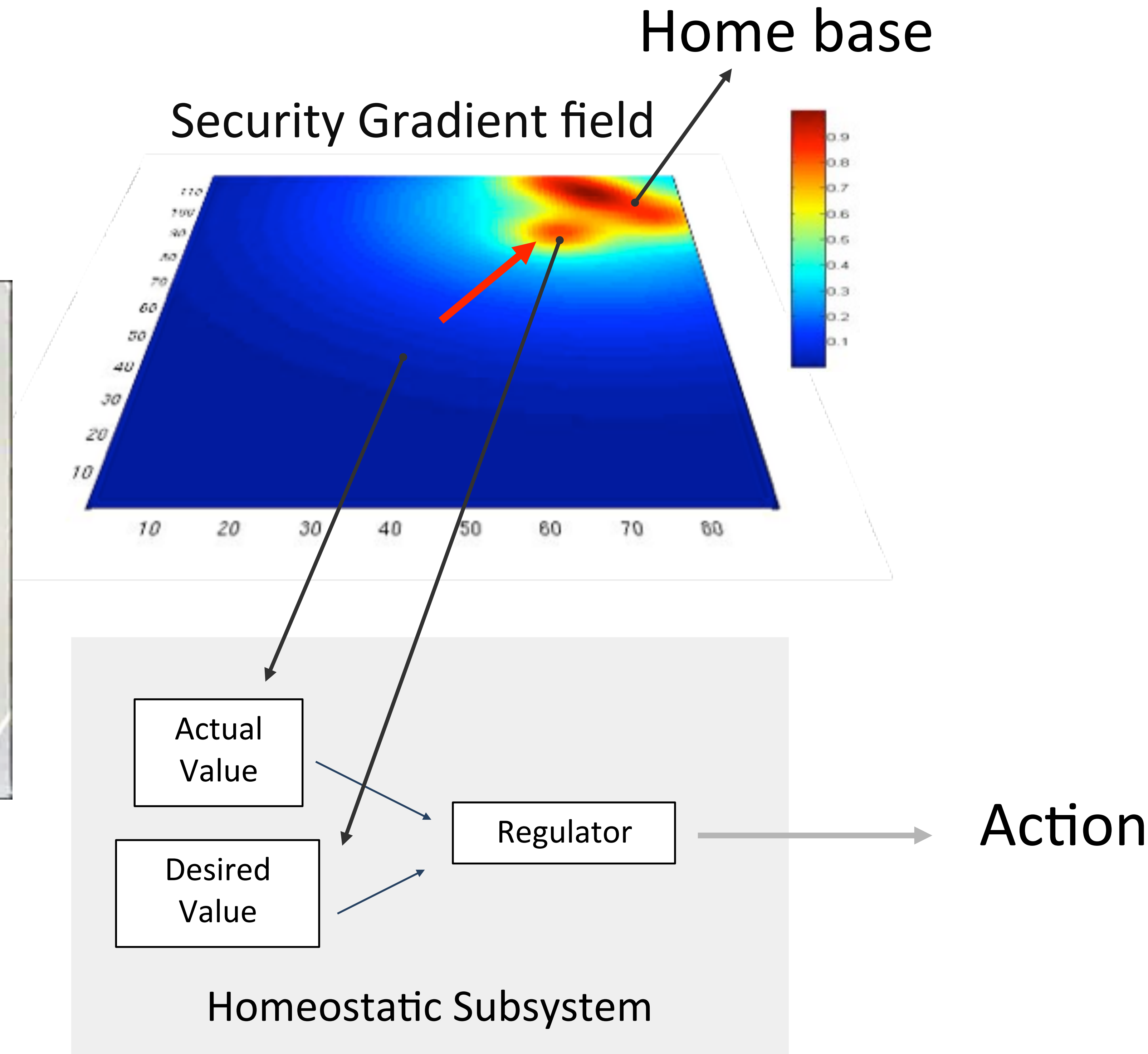
Gray's 2D model of defense as shown in McNaughton & Corr (2004)

RC Requires:
- behavioral repertoire (UR)
- stimulus repertoire (US)
- assessment of state of the world
- assessment of state of the organism
- integration of information
- action selection
- behavioral sustain



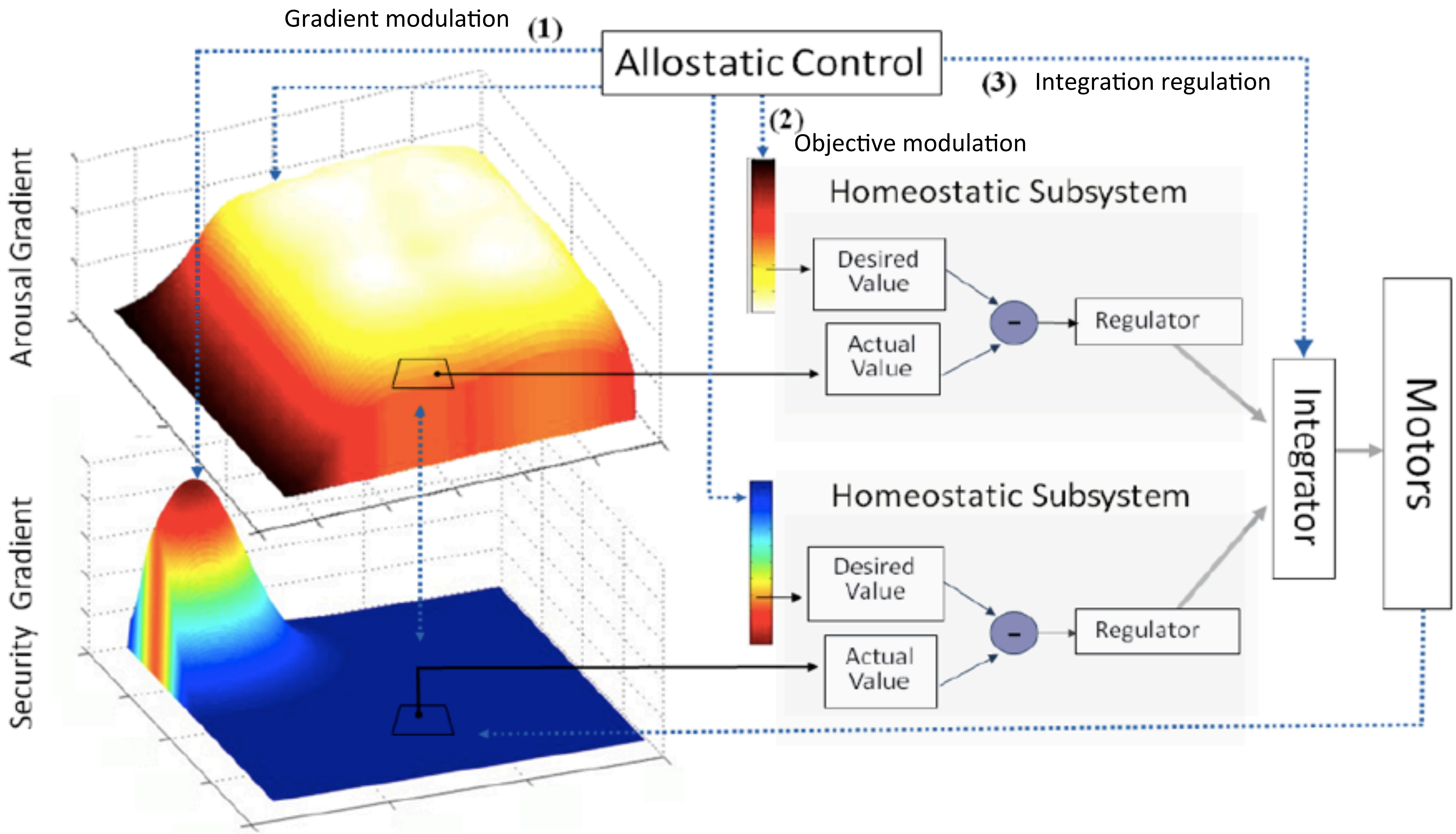
Reactive Layer: Behavioral Control as Homeostasis





Sanchez et al (2010) Advances Compl Sys / IROS

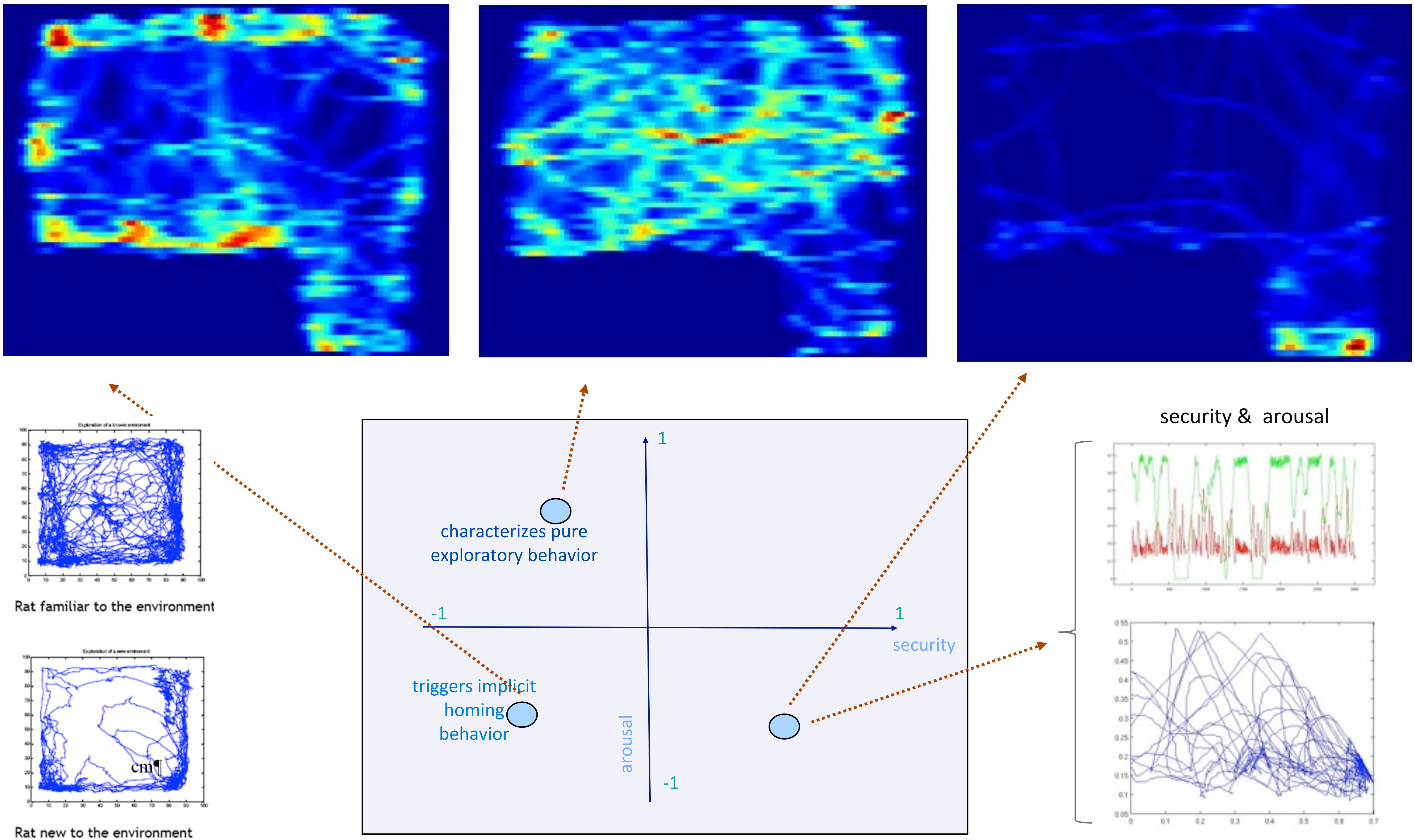
Reactive Layer: Allostatic control system



Sanchez et al (2010) Advances Compl Sys / IROS

Behavioral Results

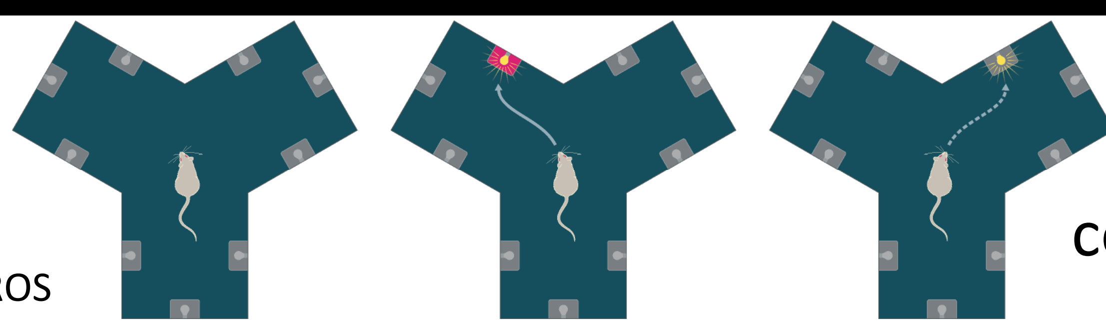
P(x,y) of robot in arena



Sanchez lab IDIBAPS

Sanchez et al (2010) Advances Compl Sys / IROS

Reactive Layer: Behavioral Control as **Allostasis**

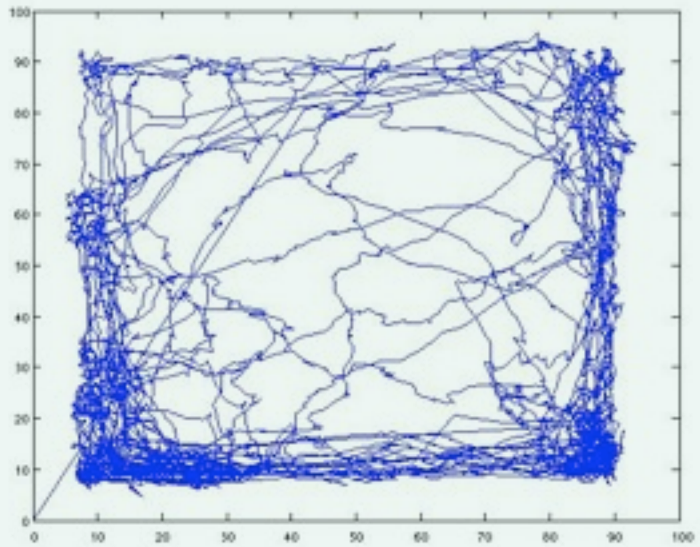


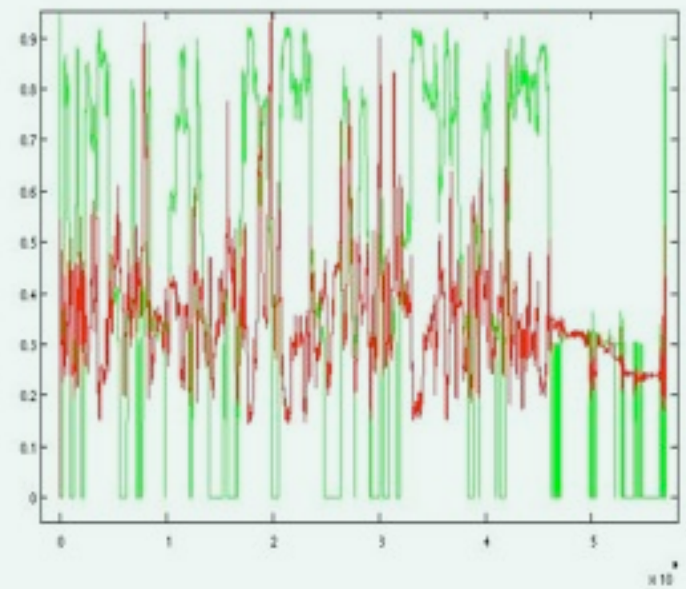
courtesy Pennaertz lab, UvA

Sanchez et al (2010) Advances Compl Sys / IROS

Comparative Behavioral Results: Model predicts arousal/security of the animal

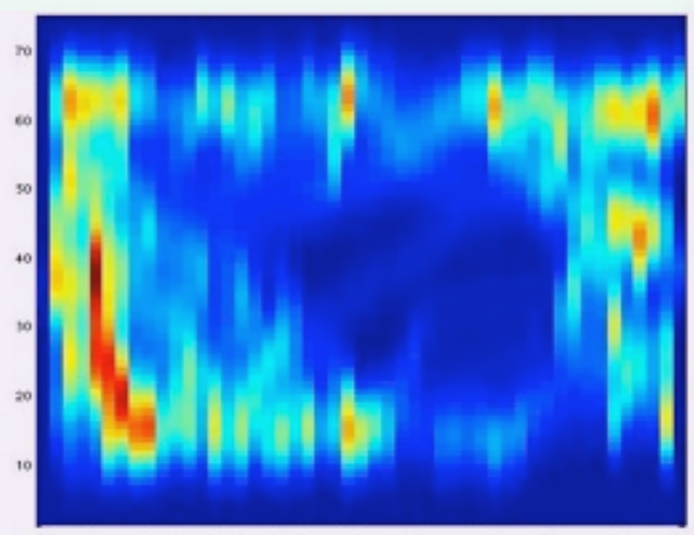
rat1

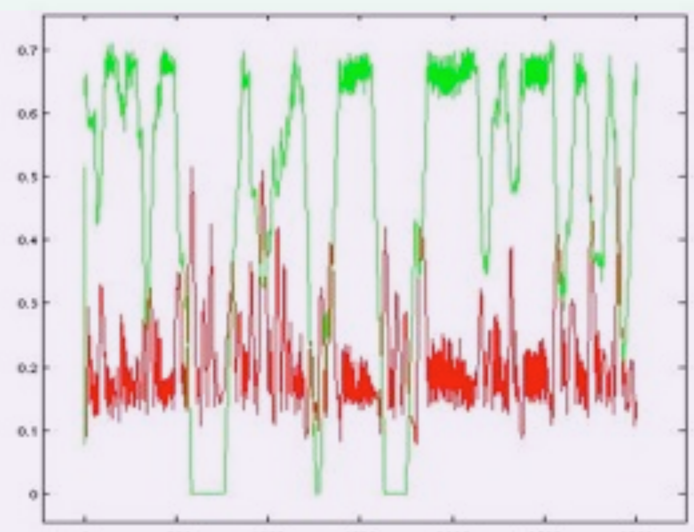




security & arousal

robot1



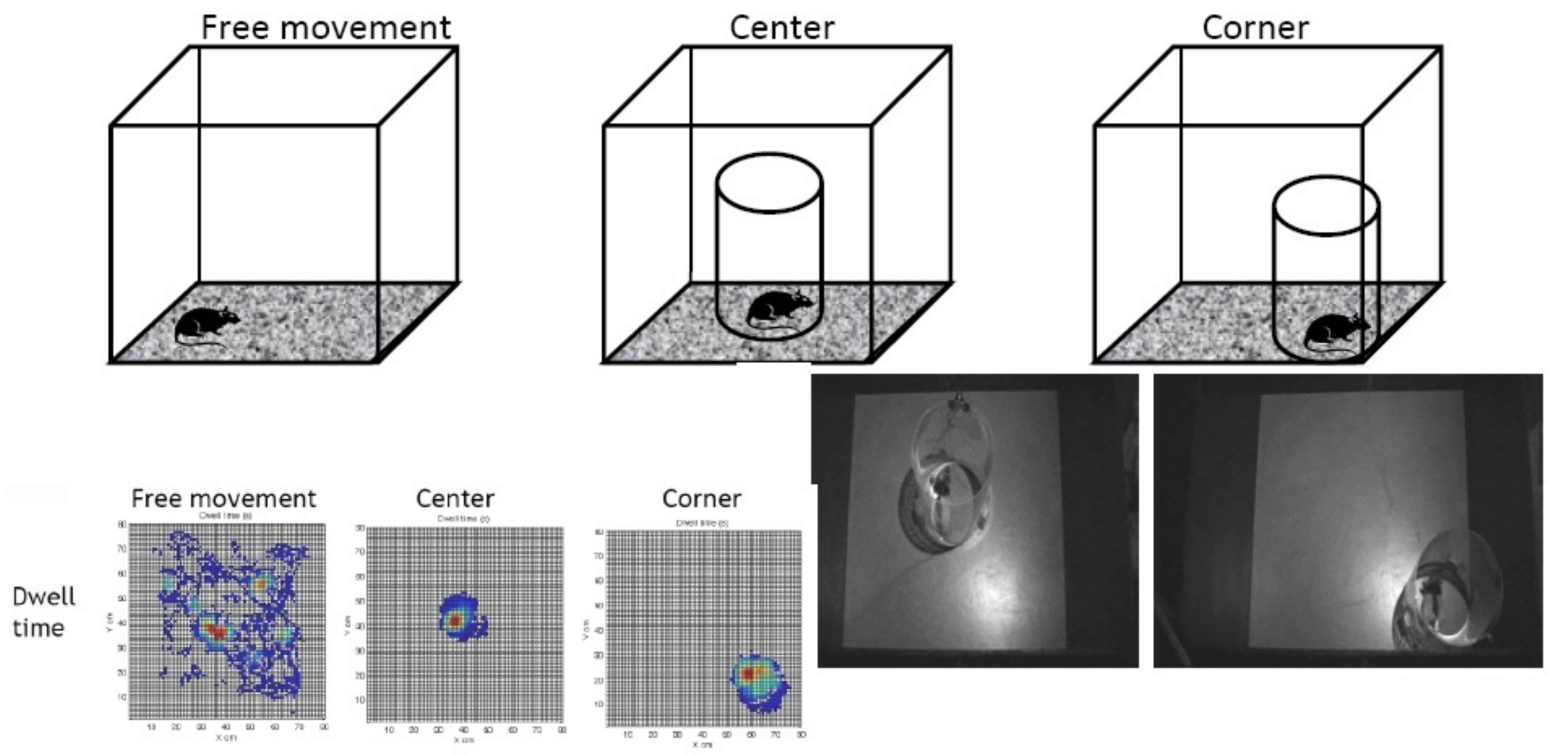


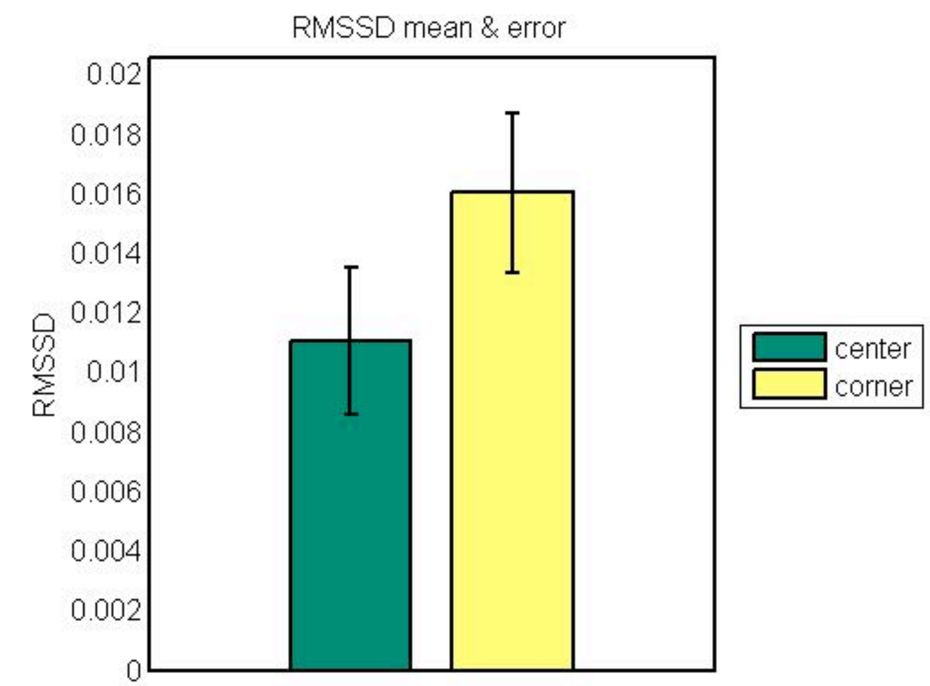
security & arousal

Visited field

Sanchez et al (2010) Advances Compl Sys / IROS

Testing the prediction using HRV





Arousal (HRV) varies with the position in space consistent with the model prediction

Courtesy Sanchez lab IDIBAPS

DAC: Reactive Layer

- 5F system acts in space of gradients defined by the motivational affordance of the environment:
  - **affordance gradient**
- Behavioral regulation as allostatic control of homeostatic subsystems
  - reactive behaviors are structured around gradients
  - gradients provide a common currency
- Robot and rat behavior seem consistent
- Robot model generates explicit and testable predictions

Optomotor system

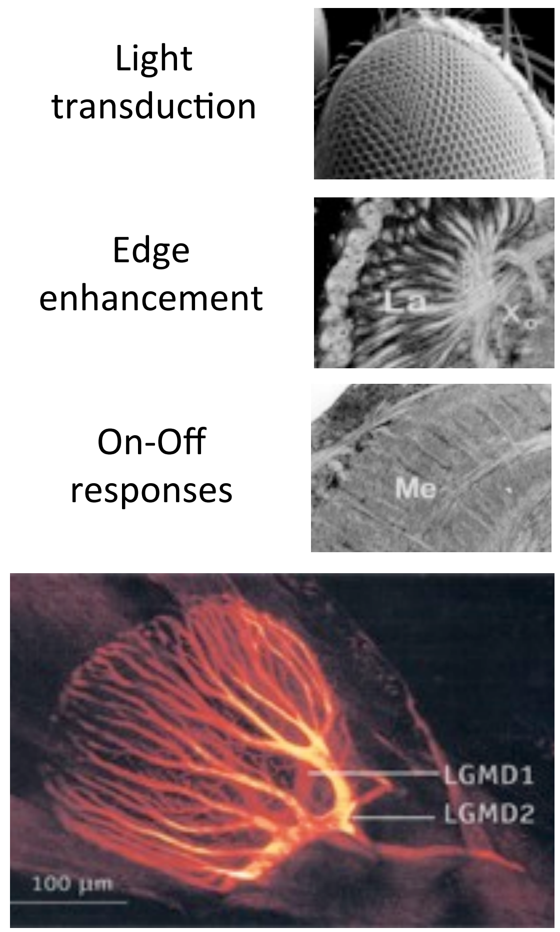
PHOTO RECEPTORS Light transduction

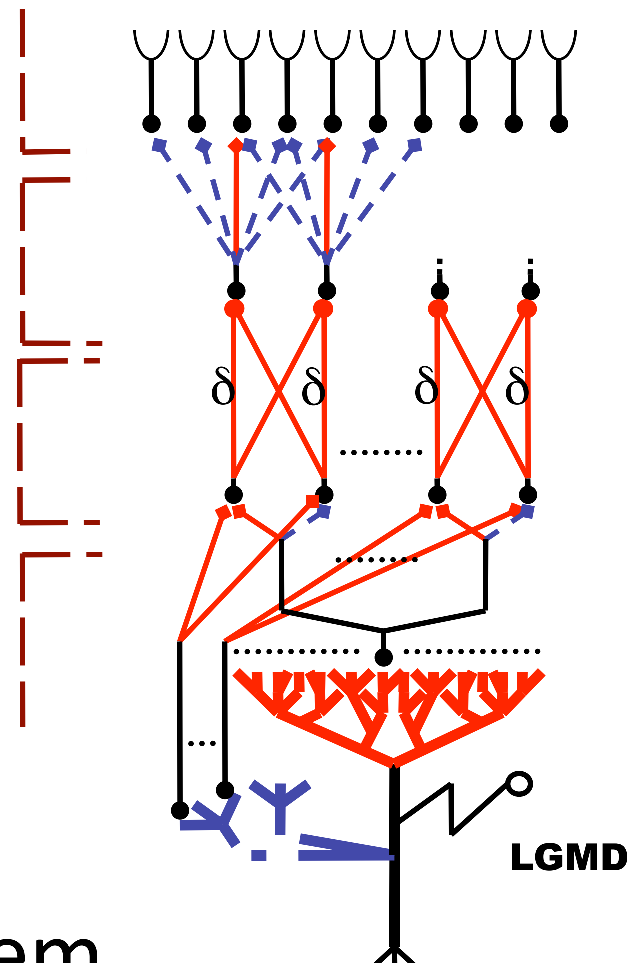
LAMINA Edge enhancement

MEDULLA On-Off responses

LOBULA

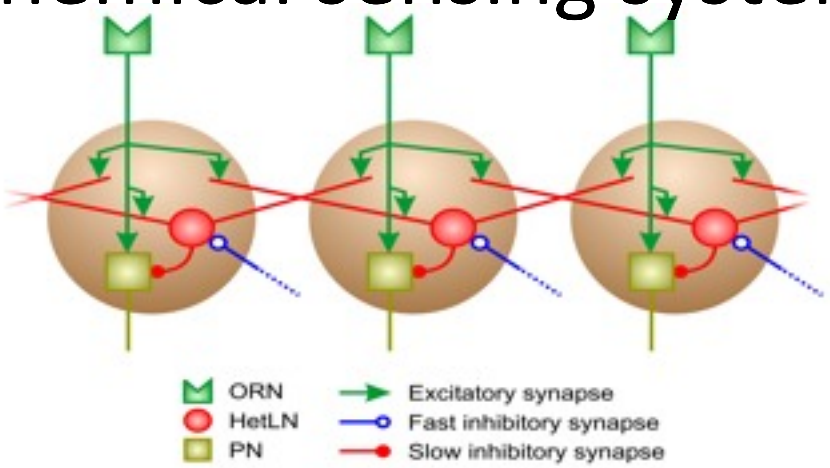
Looming sensitivity

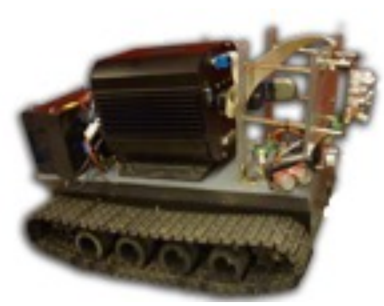




Courtesy Bill Hansson, MPI Jena

Chemical sensing system





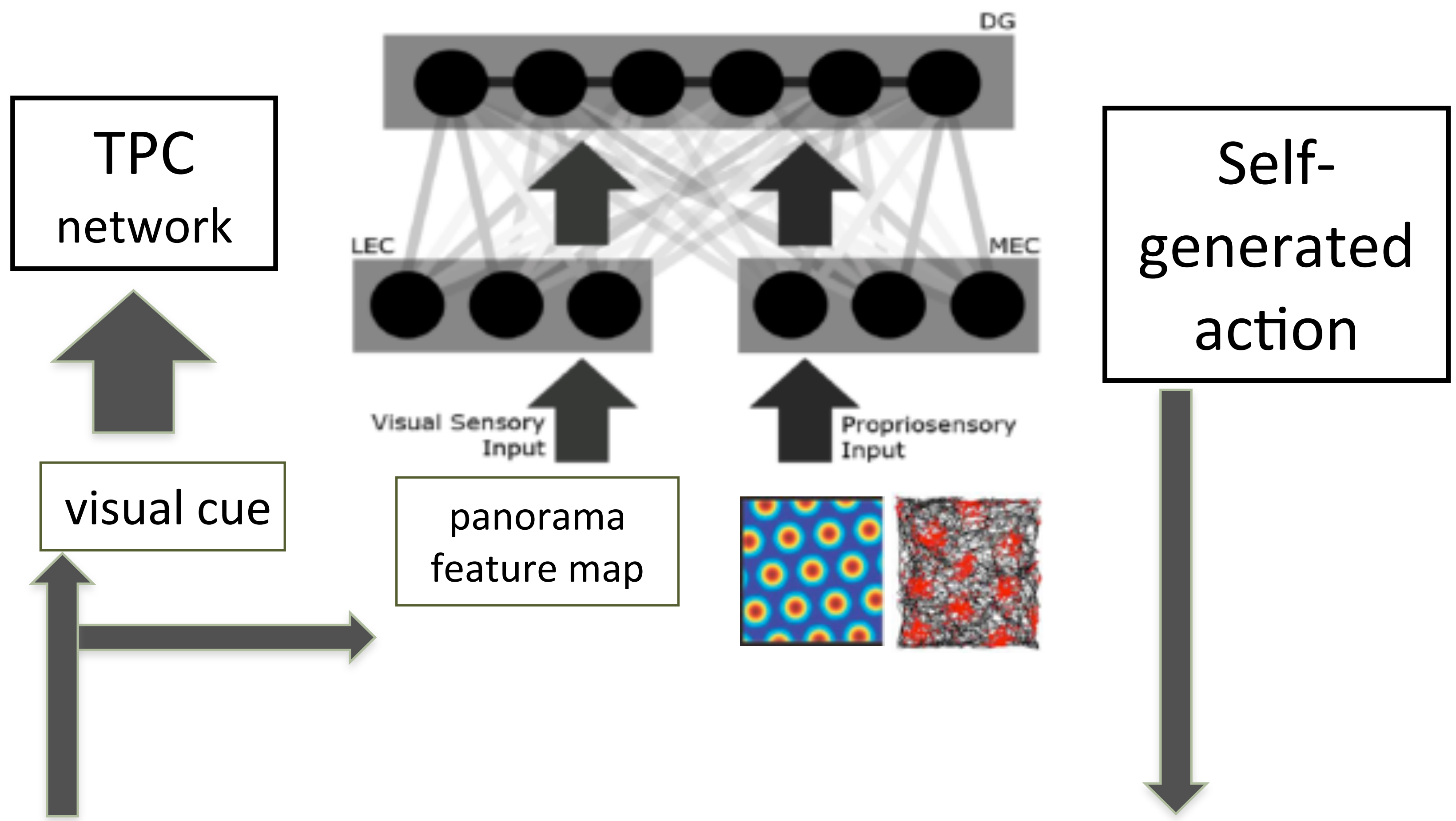
Carlsson, M. A.,et al (2005). European Journal of Neuroscience,
Knüsel, P., et al (2007). Network: Computation in Neural Systems,

Bermúdez I Badia, S., et al (2010). PLoS Computational Biology,
Mathews, Z., et al (2009). IEEE/RSJ International Conference on Intelligent RObots and Systems IROS.
Bermudez I Badia, S., et al (2007). The International Journal of Robotics Research,
Bermúdez i Badia, S., et al (2007). International Journal of Advanced Robotic Systems,
Bernardet, U, et al (2008). Theory in biosciences 127(2),
Pyk, P, et al (2006). Autonomous Robots, 20(3),

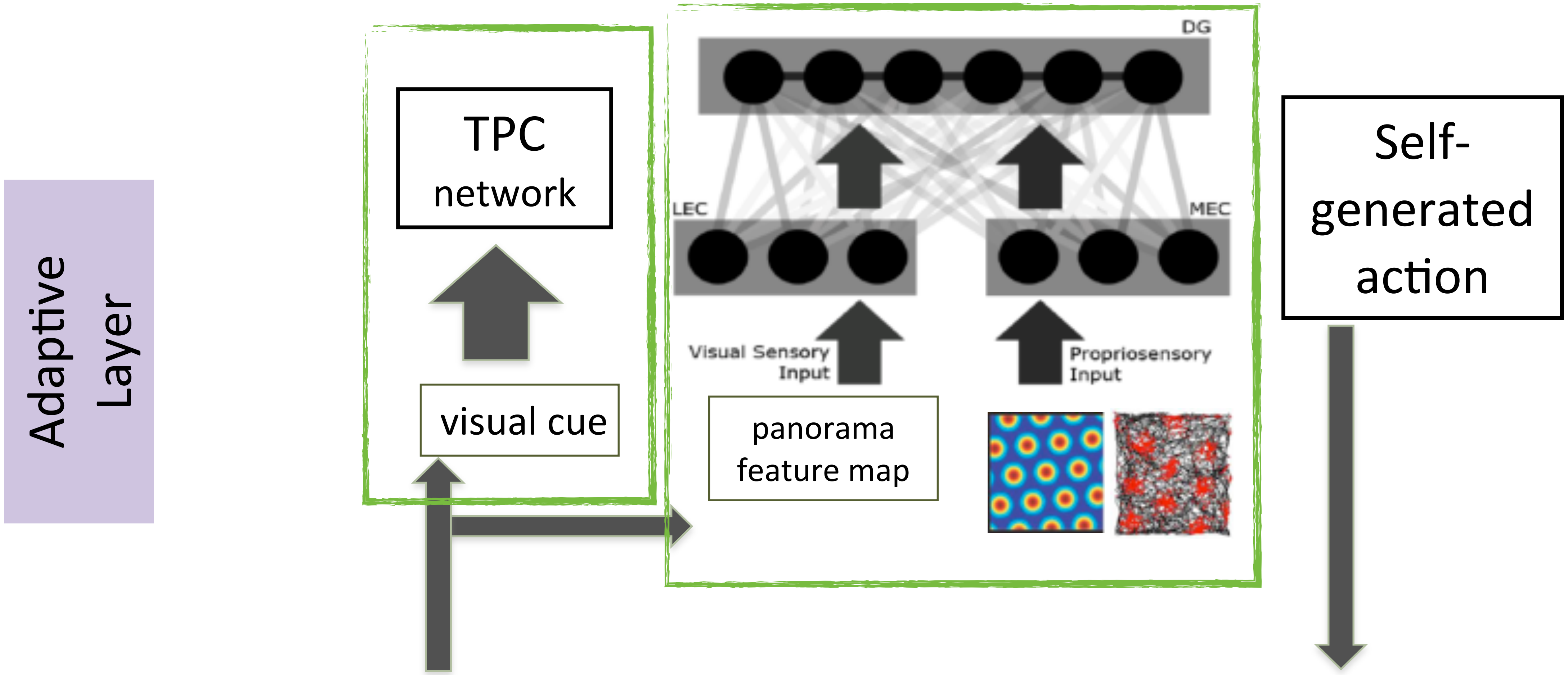
DAC: Adaptive Layer

DAC: Adaptive Layer

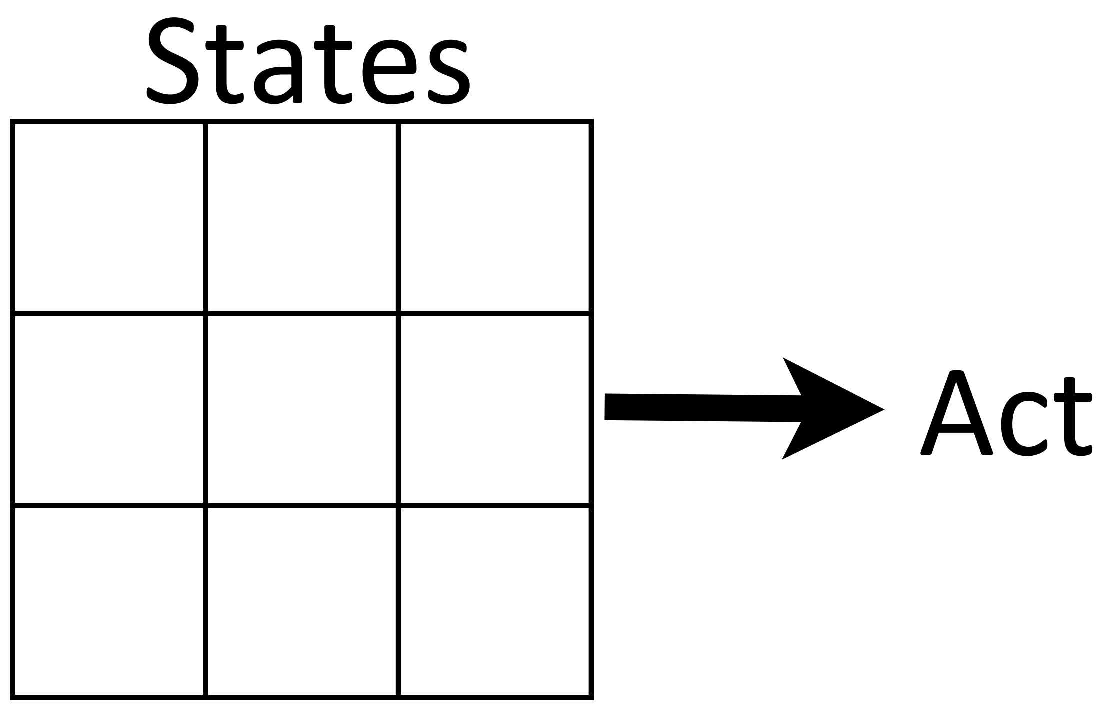
Adaptive Layer



DAC: Adaptive Layer



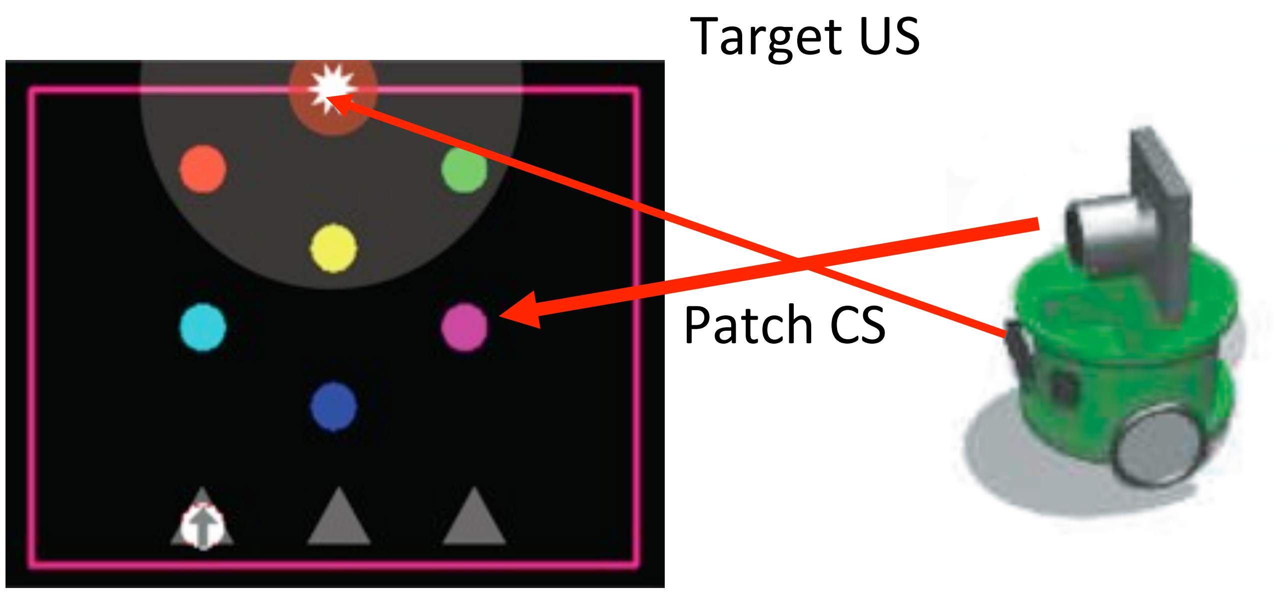
The problem of Priors



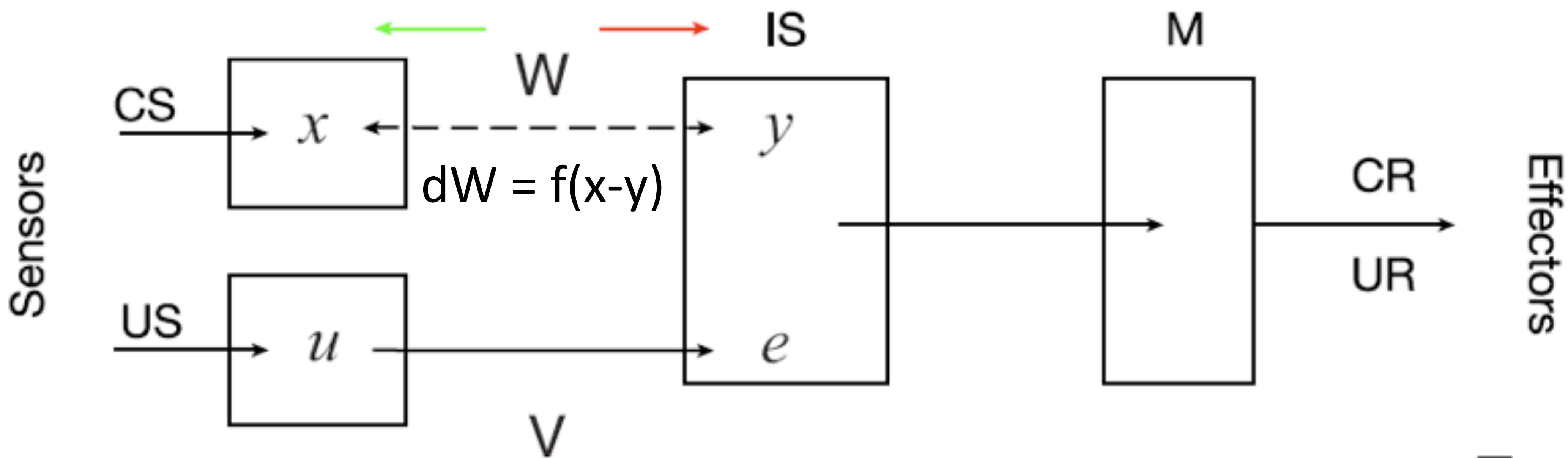
How to acquire states and policies in parallel?

Verschure (1996;1998) wcci

DAC Adaptive Layer: Learning Dynamics



Remember: Rescorla & Wagner (1972)



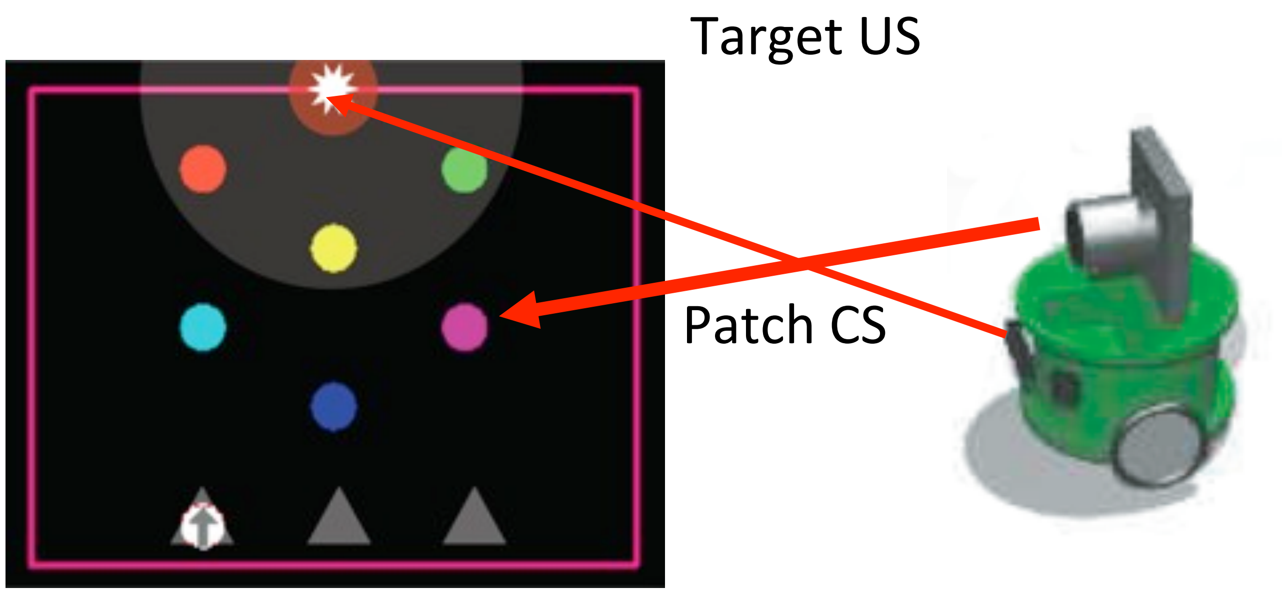
$$e = V^{\mathsf{T}} u$$

$$y = W^{\mathsf{T}} x$$

Verschure & Voegtlin (1998) Neural Netw

Verschure & Pfeifer (1992) SAB

DAC Adaptive Layer: Learning Dynamics



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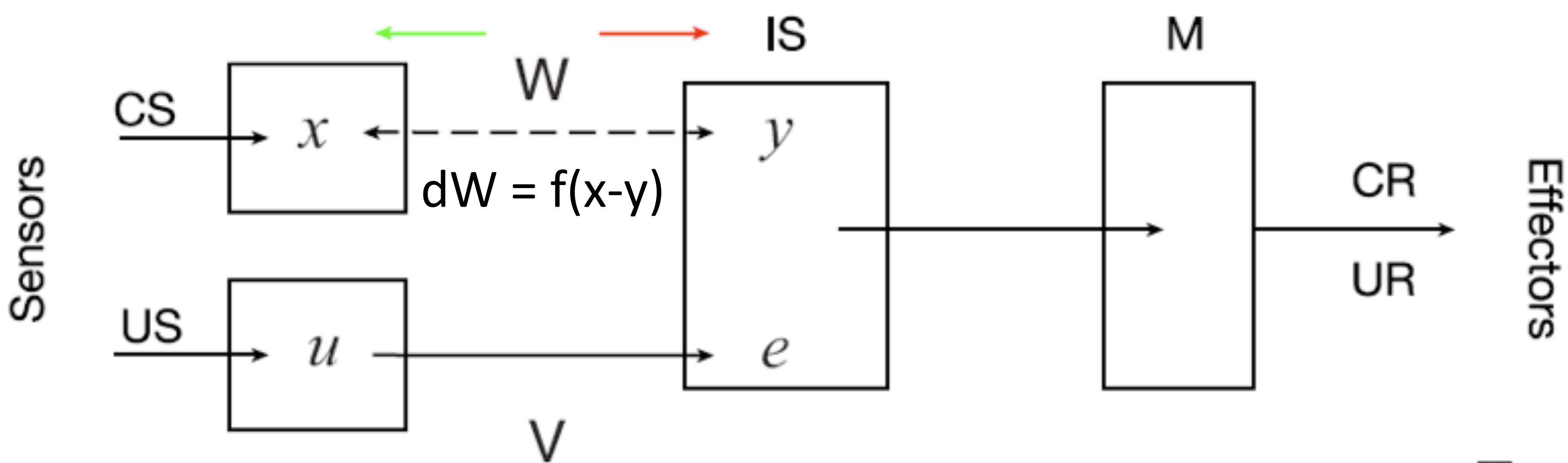

V defines the reactive Layer
W is plastic and changes according to the slow dynamics
Learning is modulated by the internal/motivational state (IS)

$$e = V^{\mathsf{T}} u$$

$$y = W^{\mathsf{T}} x$$

Verschure & Voegtlin (1998) Neural Netw
Verschure & Pfeifer (1992) SAB

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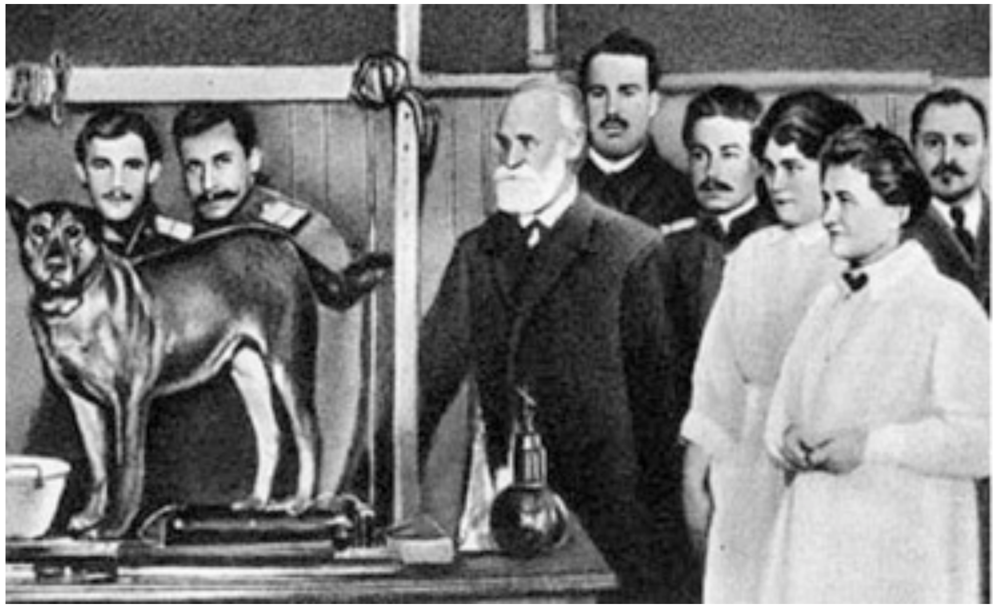
The behavioral law of associative competition

$V_{ab} = V_a + V_b$

$\Delta V_i = \alpha_{cs}\, \gamma_{us}\, (\lambda - \Sigma_j V_j)$

Rescorla & Wagner (1972)



Ivan Pavlov (1849-1936)

The behavioral law of associative competition

$V_{ab} = V_a + V_b$

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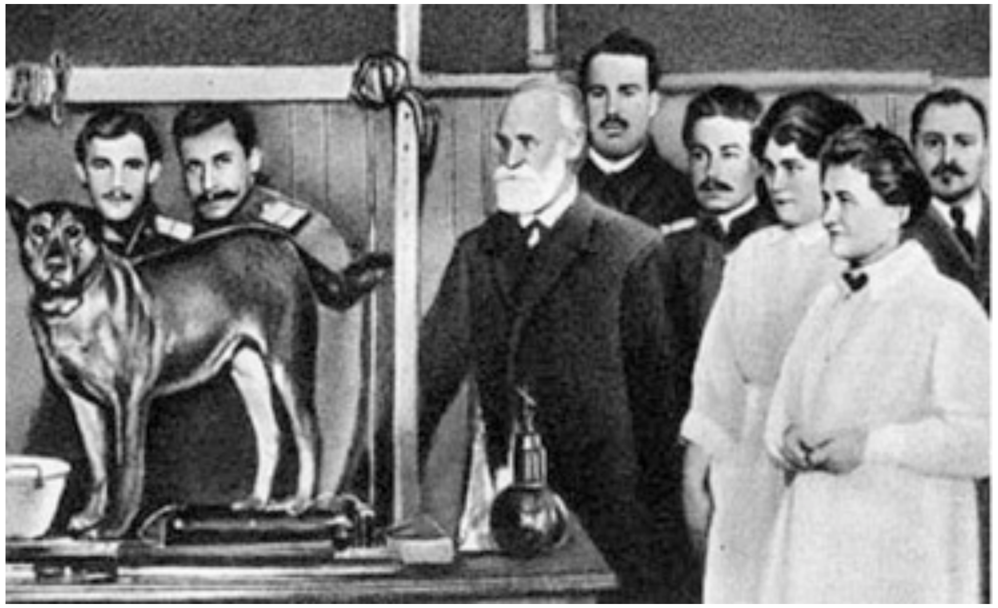


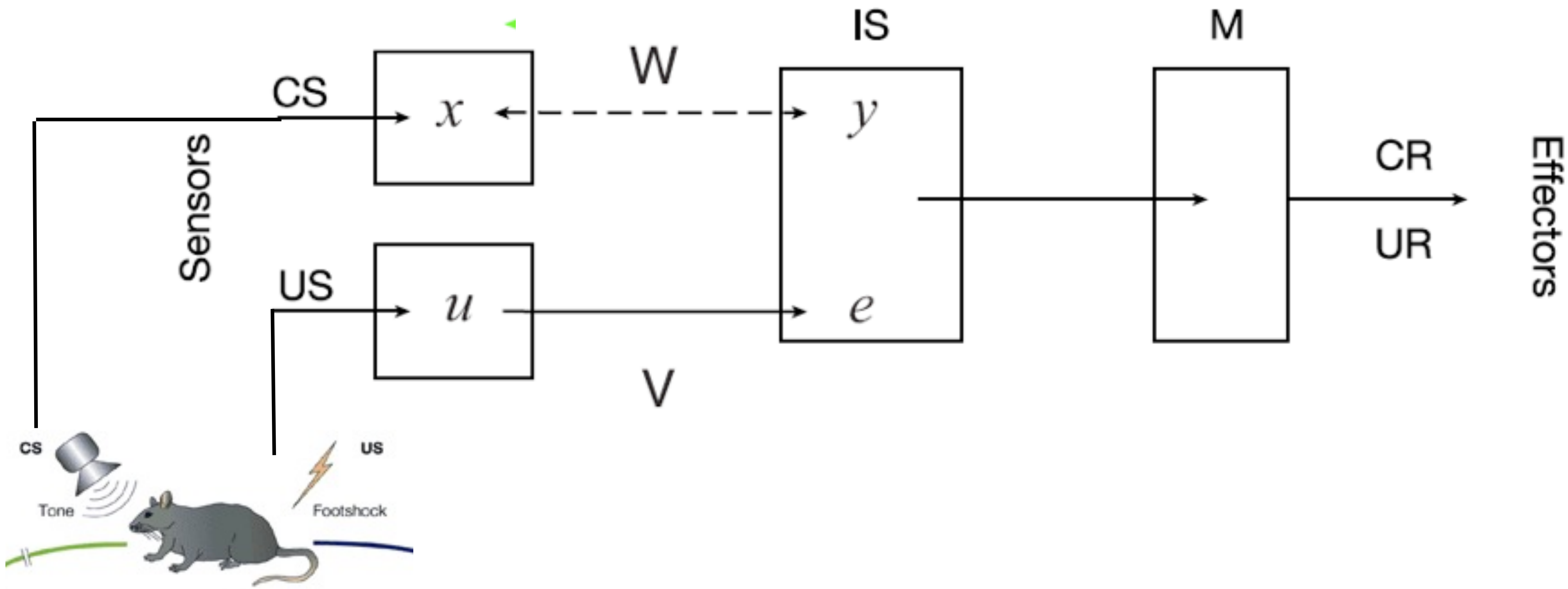
Ivan Pavlov (1849-1936)

animals only learn when events violate their expectations

Optimization Objective:
Correlation, Perceptual and Behavioral prediction

$$e = V^{\mathsf{T}} u$$

$$y = W^{\mathsf{T}} x$$

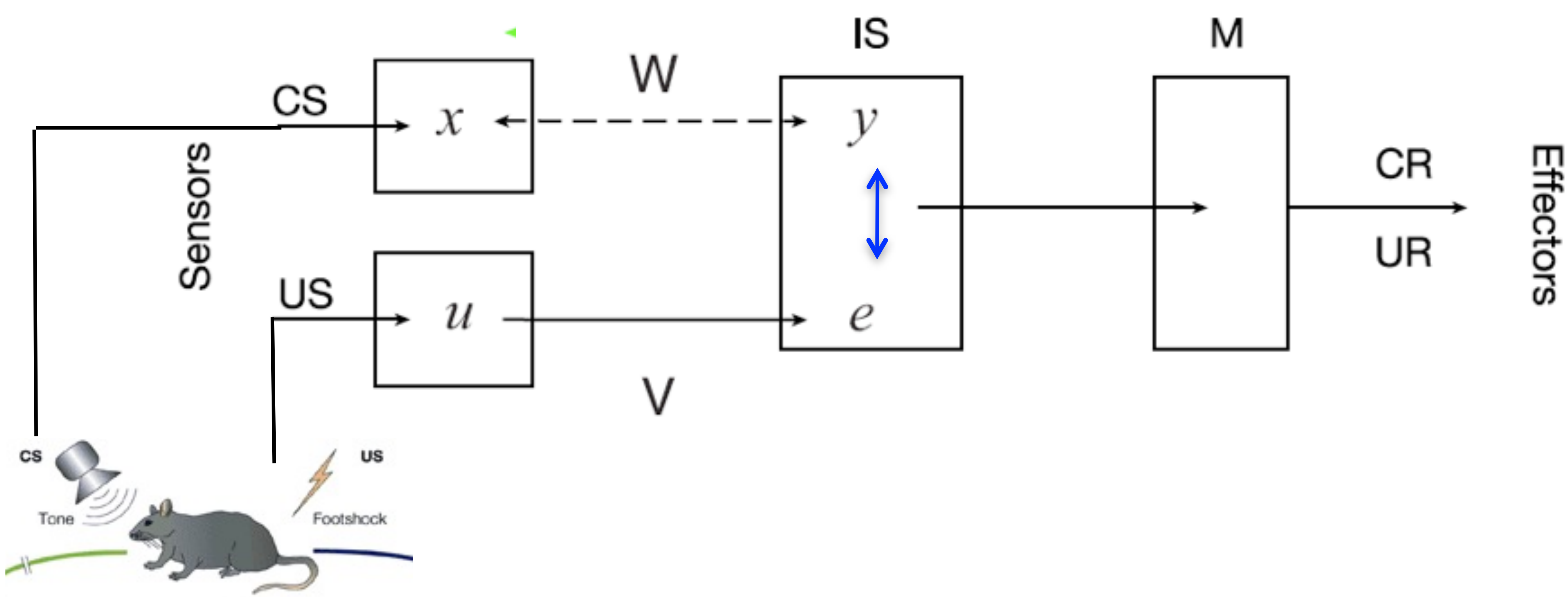


Duff et al (2010) Neurocomputing

Optimization Objective:
Correlation, Perceptual and Behavioral prediction

correlation

$$J_C(W) = E[trace(ye^{\mathsf{T}})|W] \qquad WW^{\mathsf{T}} = I \qquad e = V^{\mathsf{T}}u \quad y = W^{\mathsf{T}}x$$



Duff et al (2010) Neurocomputing

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Optimization Objective:
Correlation, Perceptual and Behavioral prediction

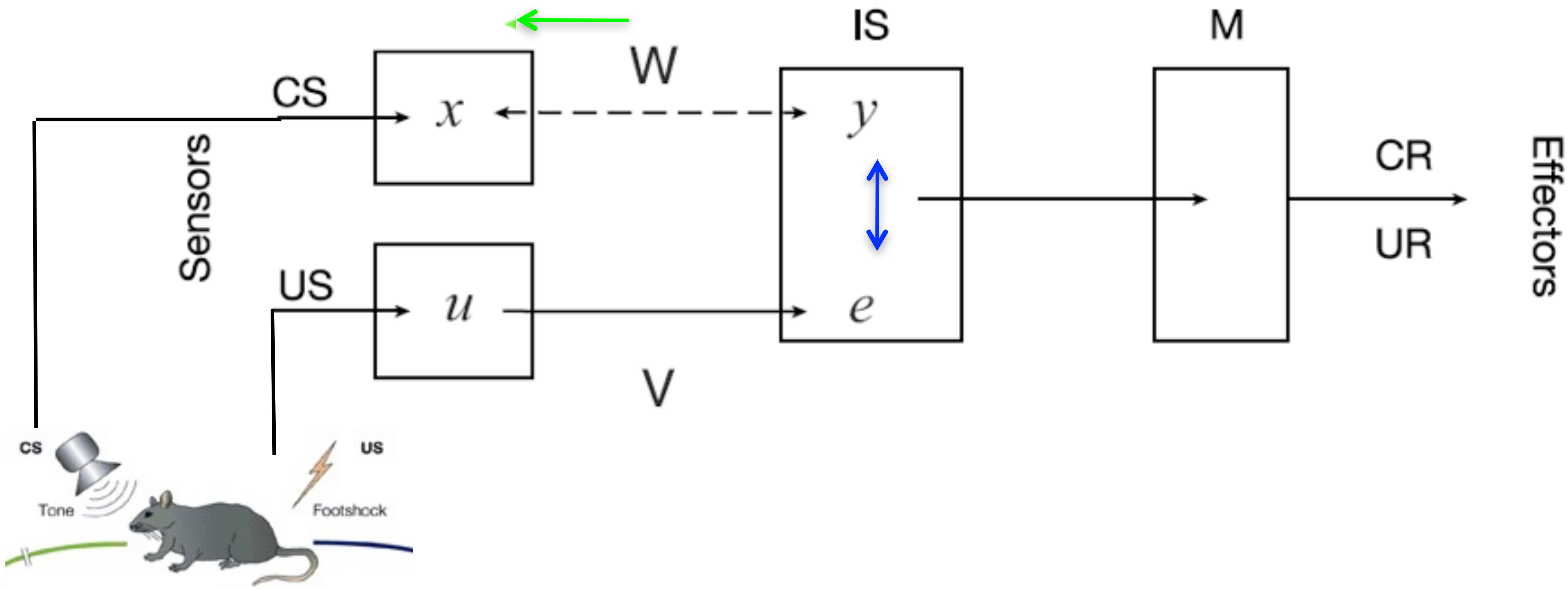
$$e = V^{\mathsf{T}} u$$

correlation

$$J_C(W) = E[trace(ye^{\mathsf{T}})|W] \qquad WW^{\mathsf{T}} = I \qquad y = W^{\mathsf{T}} x$$

perceptual prediction

$$J_P(W) = E[||x - WW^{\mathsf{T}}x||^2|W]$$



Duff et al (2010) Neurocomputing

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Optimization Objective: Correlation, Perceptual and Behavioral prediction

$$e = V^{\mathsf{T}} u$$

correlation

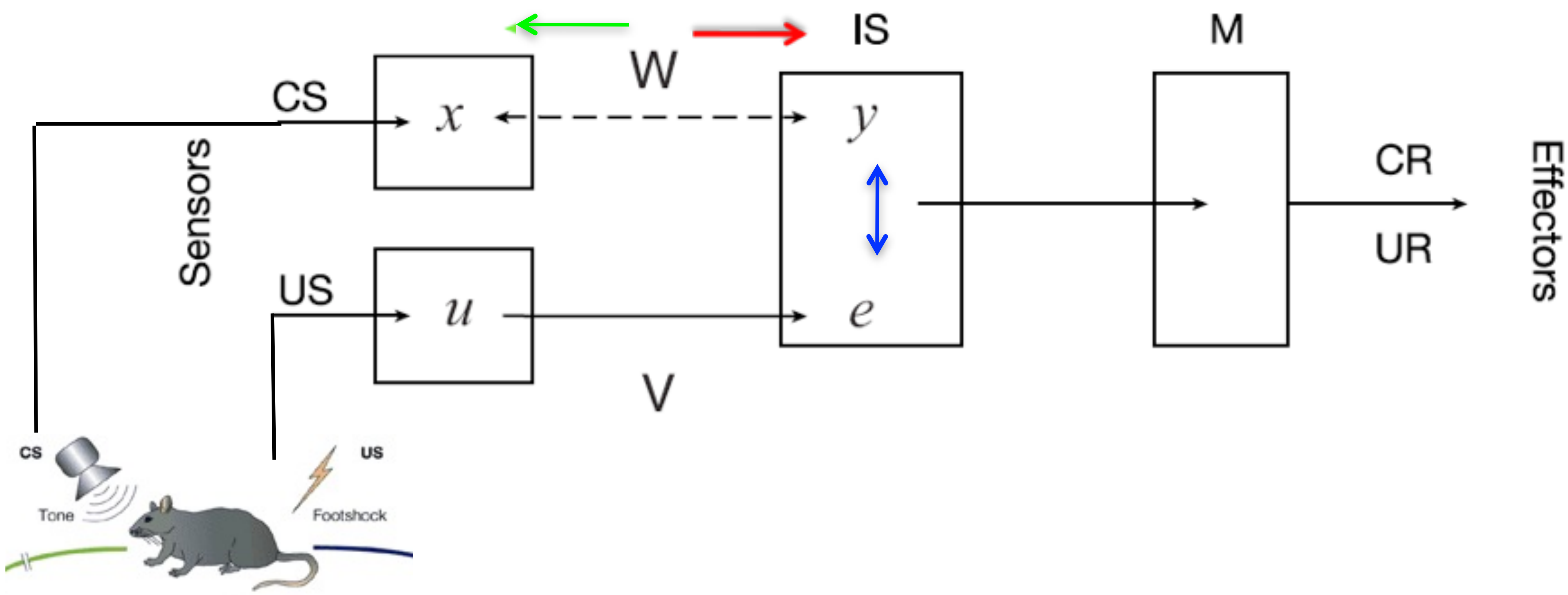
$$J_C(W) = E[trace(ye^{\mathsf{T}})|W] \qquad WW^{\mathsf{T}} = I \qquad y = W^{\mathsf{T}} x$$

perceptual prediction

$$J_P(W) = E[||x - WW^{\mathsf{T}}x||^2|W]$$

behavioral prediction

$$J_B(W) = E[||e - W^{\mathsf{T}}x||^2|W]$$



Duff et al (2010) Neurocomputing

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Correlation, Perceptual and Behavioral prediction

correlation

$$J_C(W) = E[trace(ye^{\mathsf{T}})|W]$$

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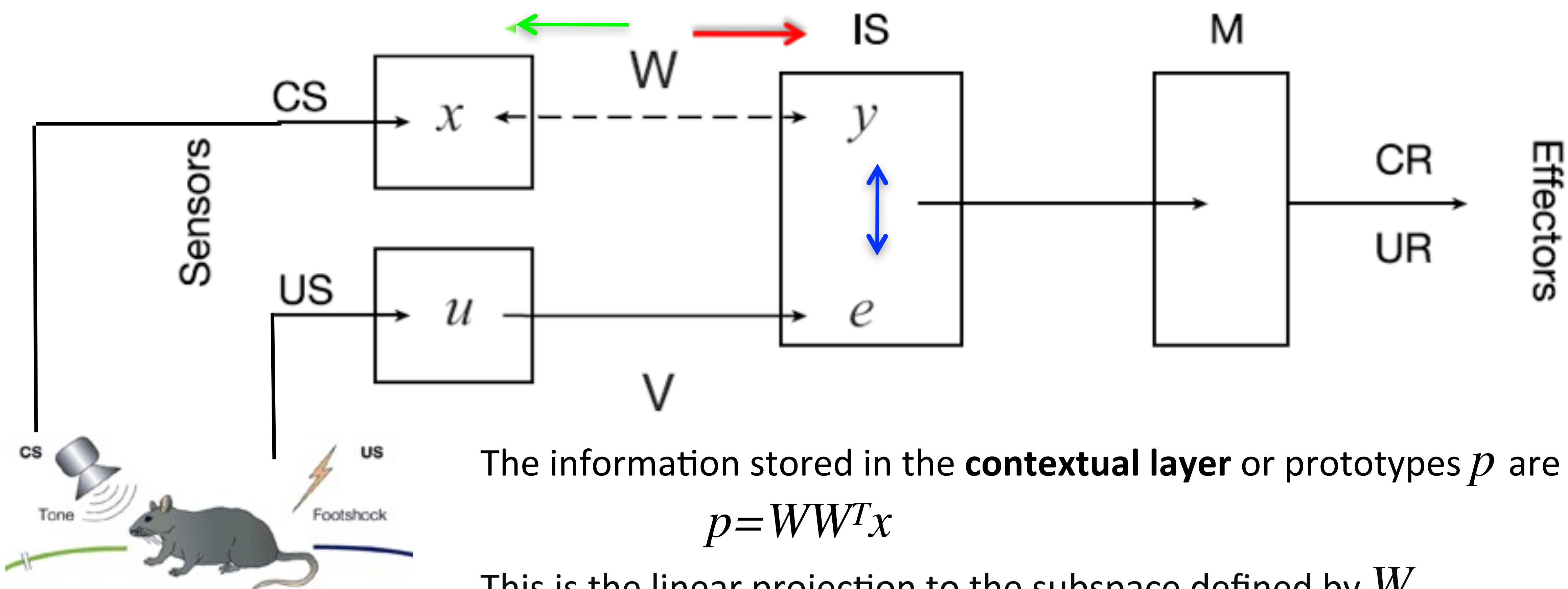

The information stored in the **contextual layer** or prototypes p are defined as:

$$p = WW^T x$$

This is the linear projection to the subspace defined by W.

Duff et al (2010) Neurocomputing

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Performance as the trade-off between perceptual and behavioral learning

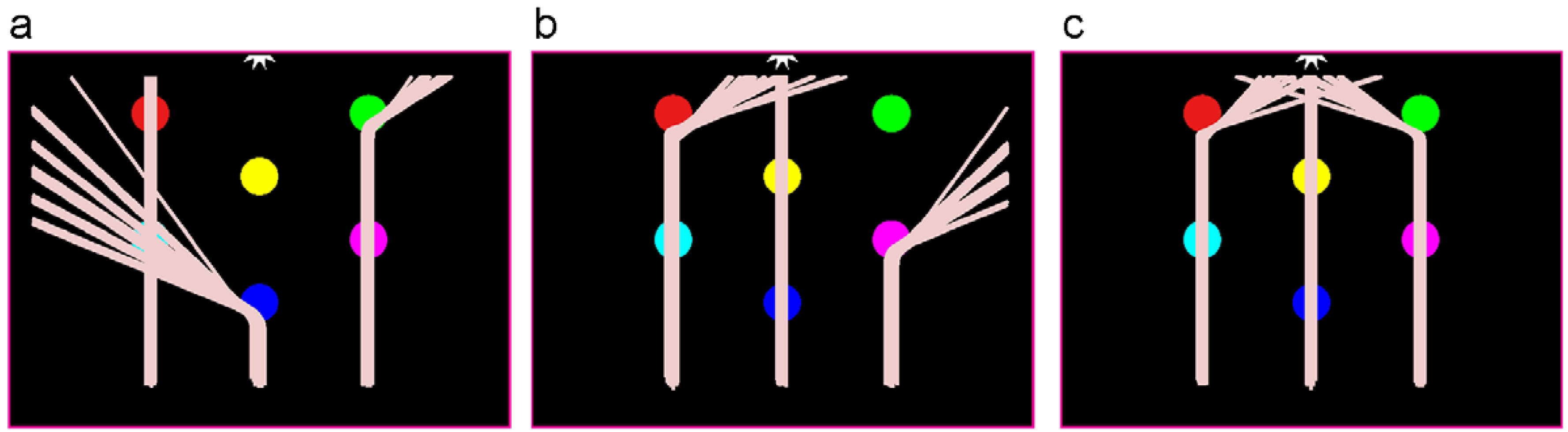
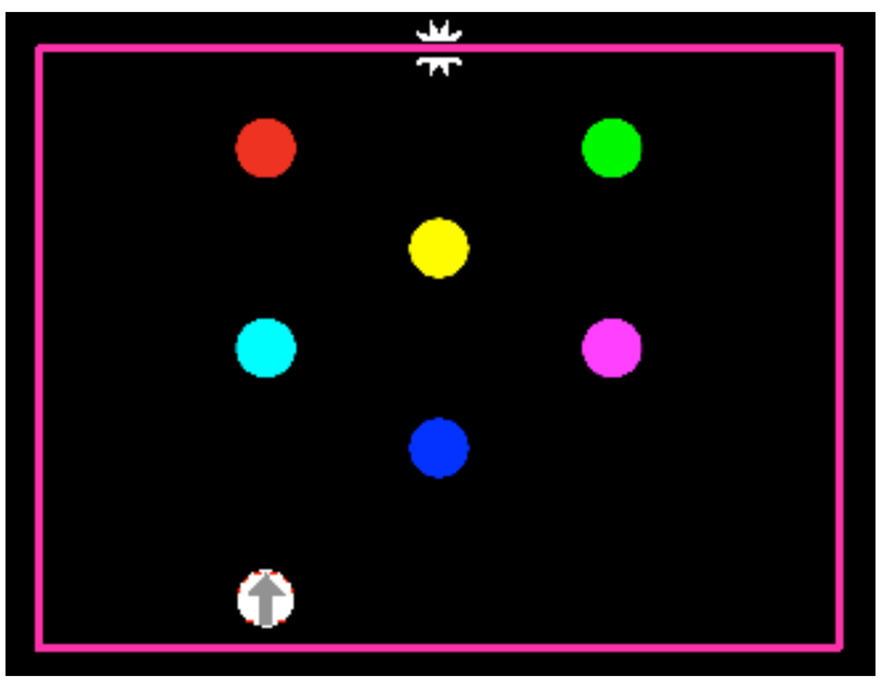


Fig. 5. Example trajectories of the robot for different values of ζ after learning: (a) perceptual learning only $\zeta = -1$, (b) behavioral and perceptual learning $\zeta = 0.9$, and (c) behavioral learning only $\zeta = 1$.



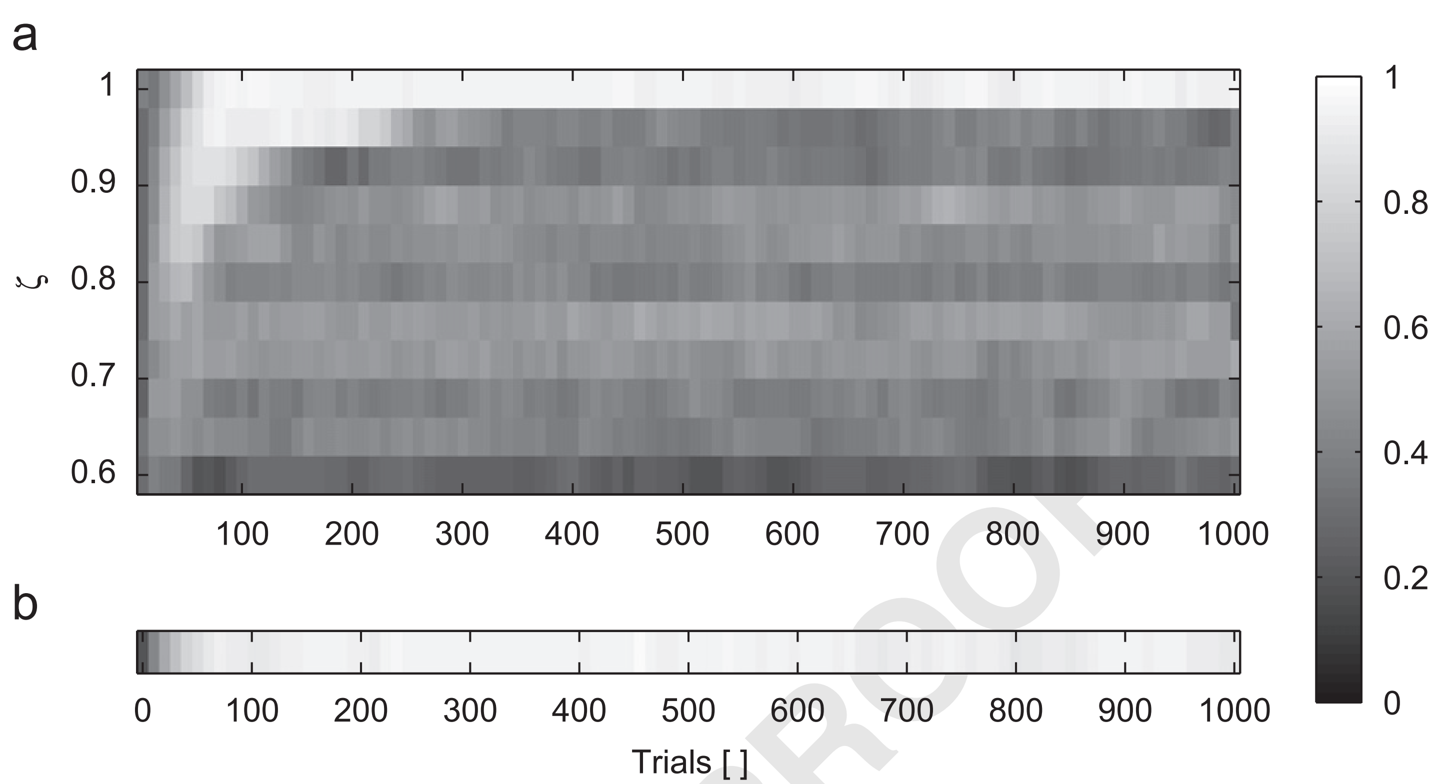


Fig. 6. Floating behavioral performance over 1000 trials with a time bin of 50 trials: (a) performance for different values of ζ and (b) performance for an actively modulated ζ.

Duff et al (2010) Neurocomputing

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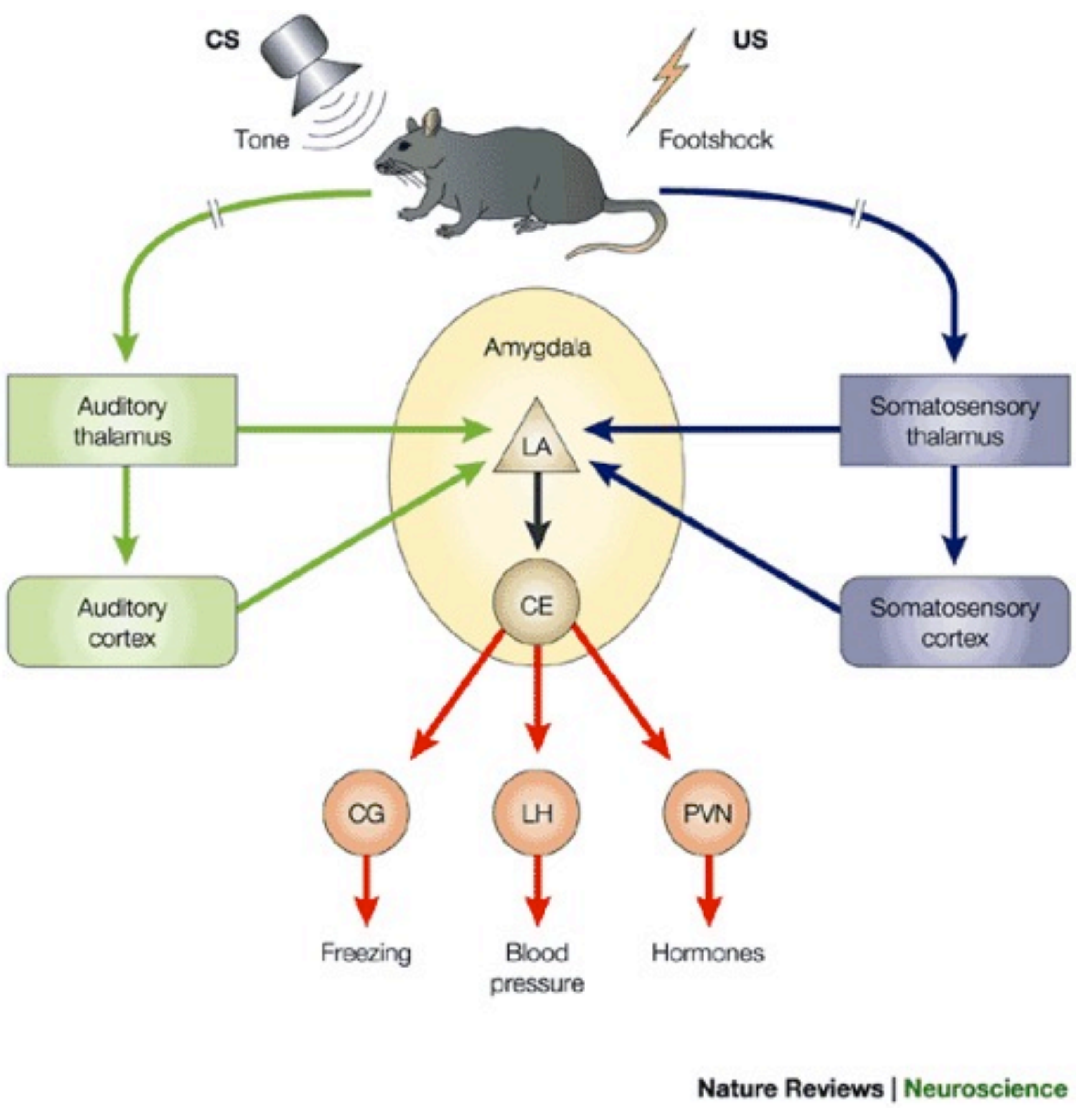
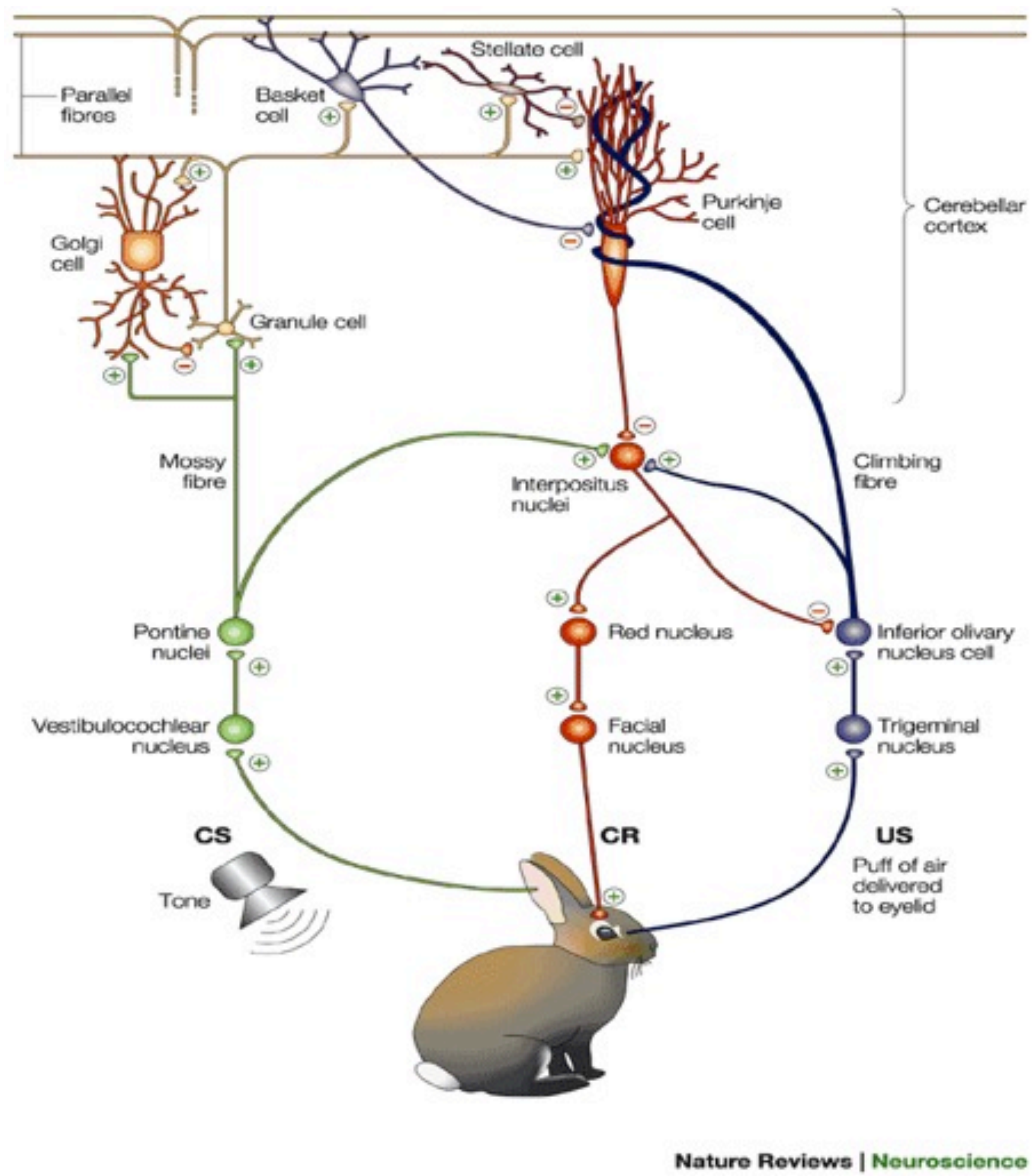
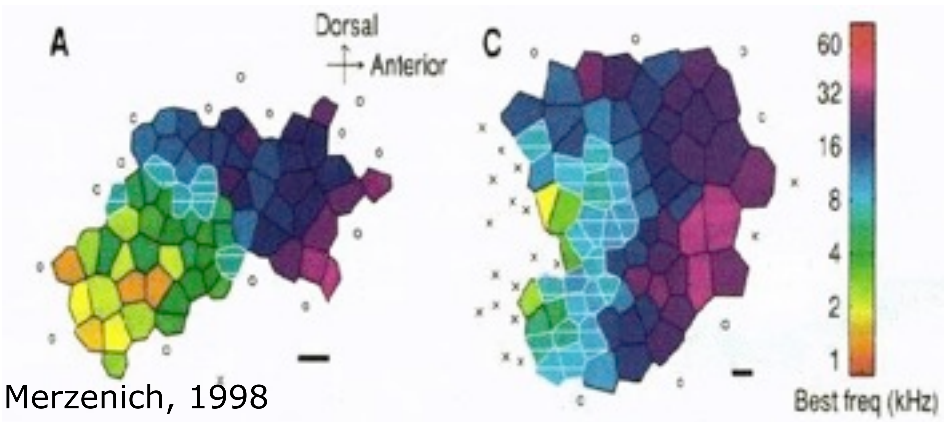
The neuronal substrate of the AL : prediction and correlation in the amygdala and the cerebellum



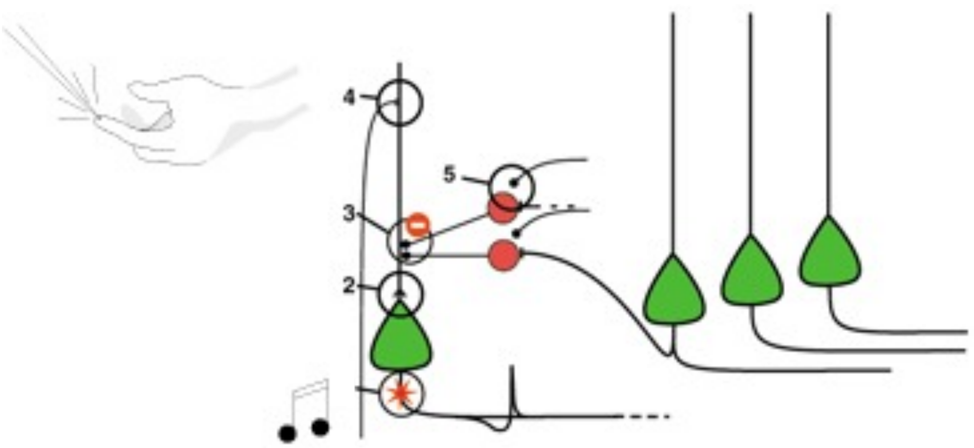


Medina et al, Nat Rev Neurosci, 2001

Models of AL



Kilgard & Merzenich, 1998

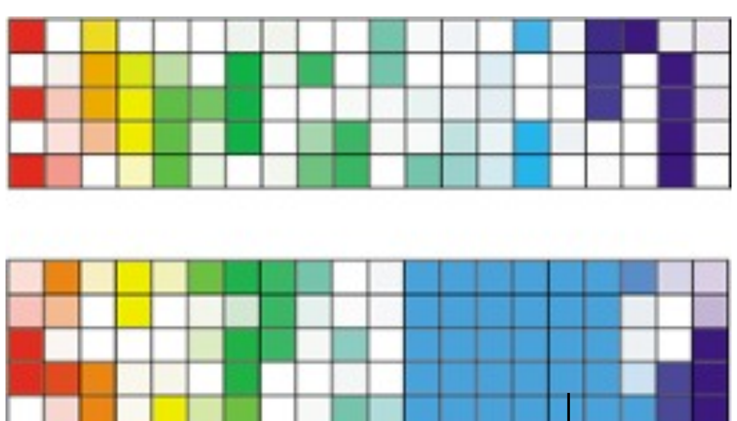


0.74 kHz

2.96 kHz

Naive

Trained

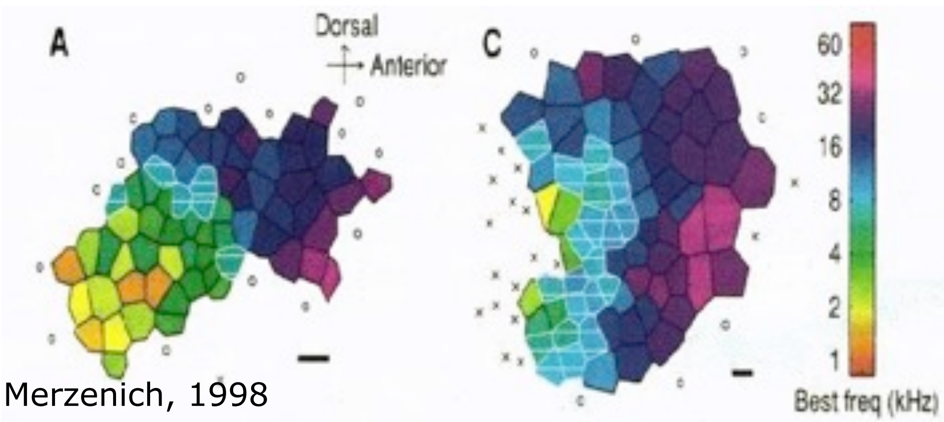


Sanchez-Montanes et al (2000/2002)

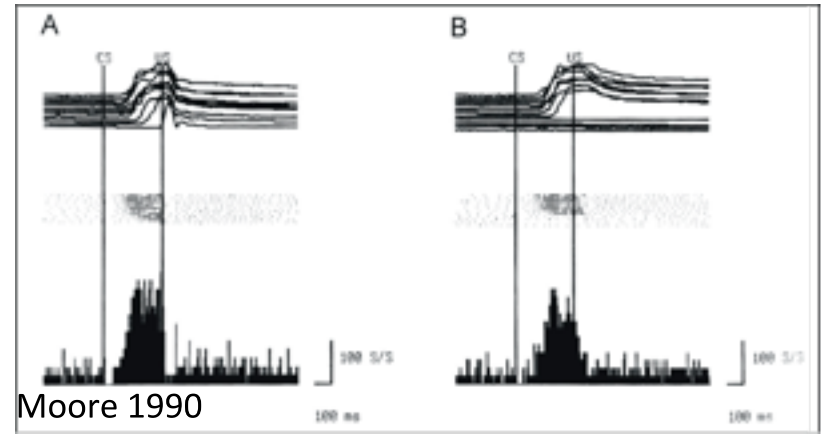
22 CS-US trials

Sanchez-Montanes et al (2000/2002)

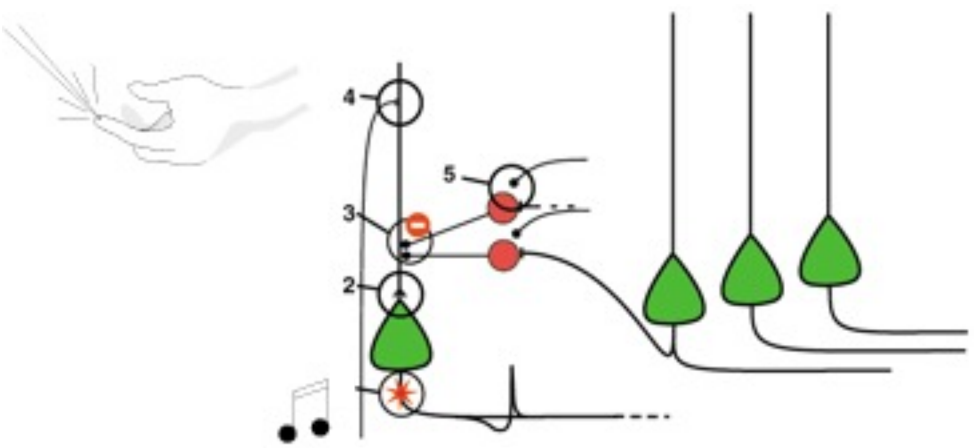
Models of AL



Kilgard & Merzenich, 1998



Moore 1990



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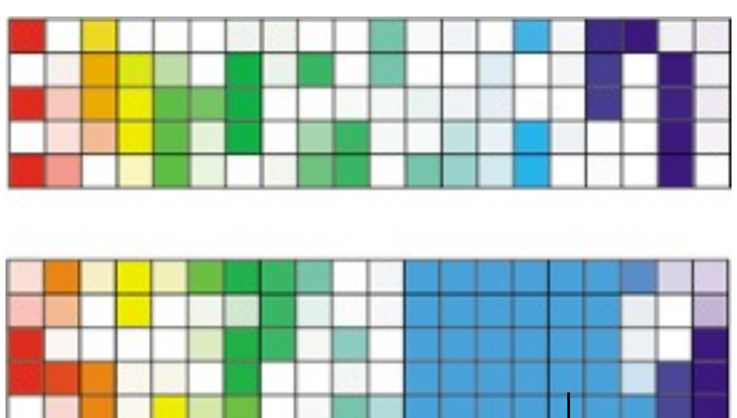
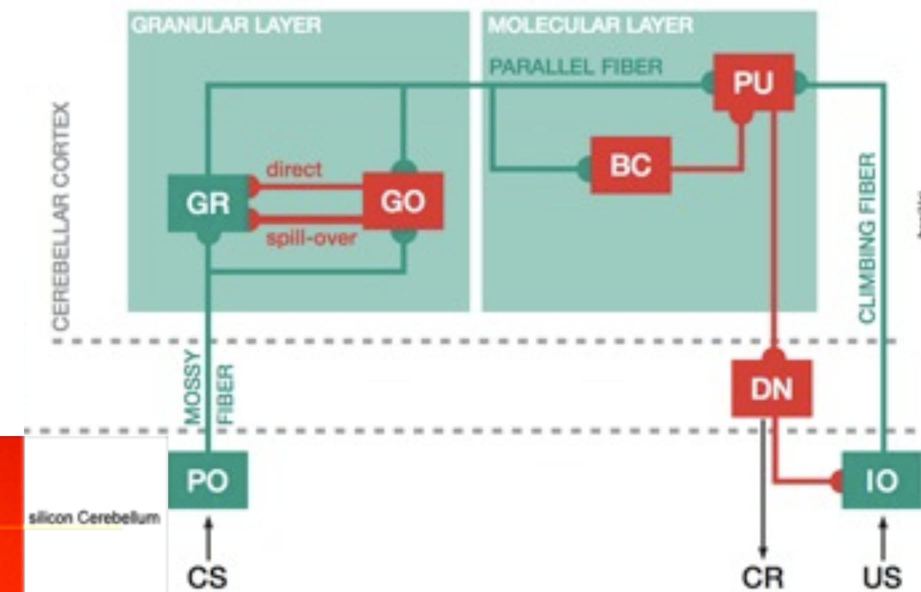
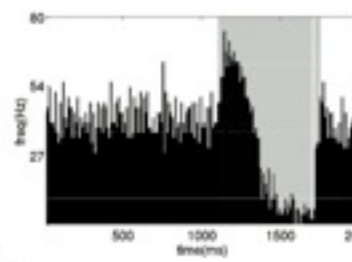
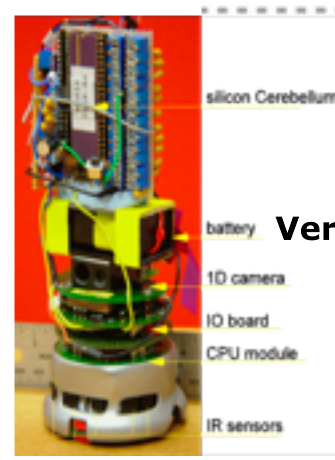


Trained







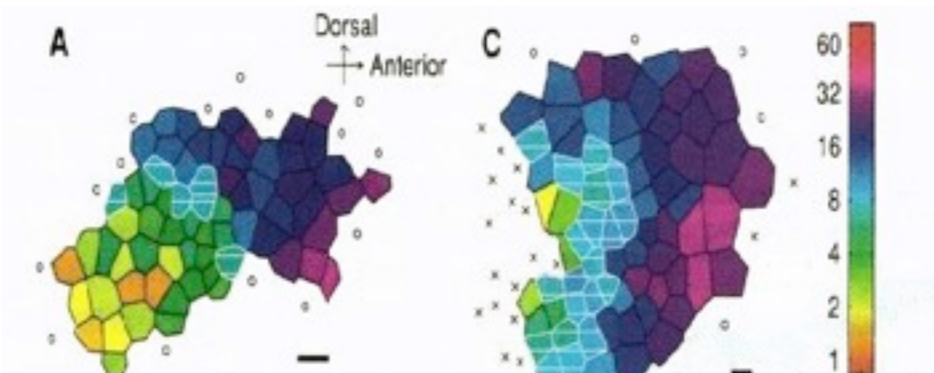
Verschure & Mintz (2000); Hofstotter et al (2003) Eur. J. Neurosci

Sanchez-Montanes et al (2000/2002)

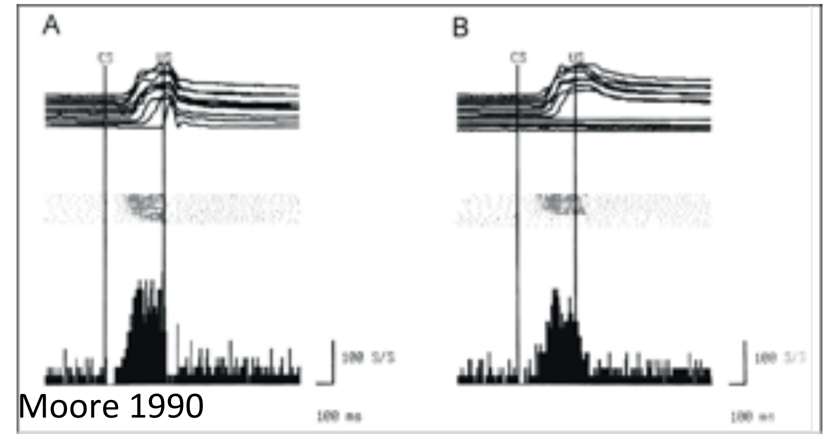
22 CS-US trials

Hofstotter et al (2005) NIPS

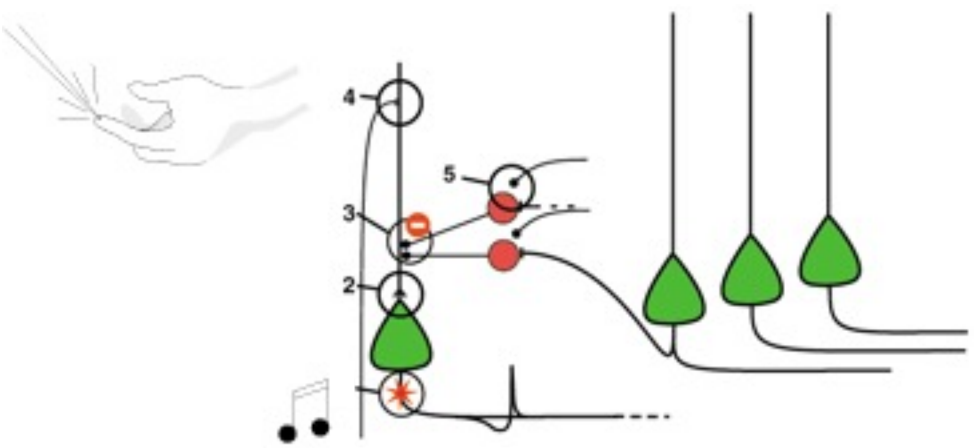
Models of AL



Kilgard & Merzenich, 1998



Moore 1990



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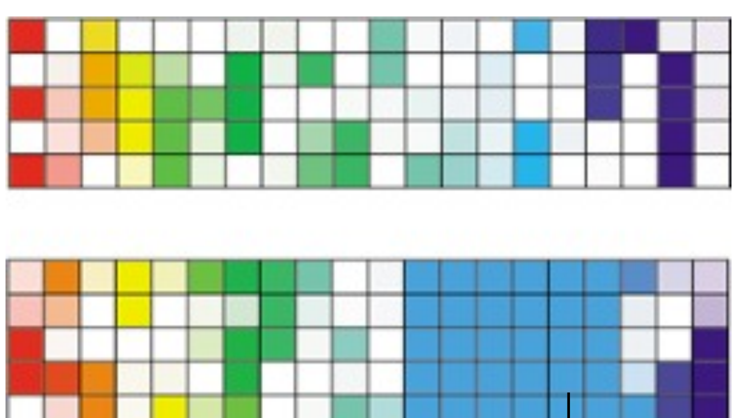

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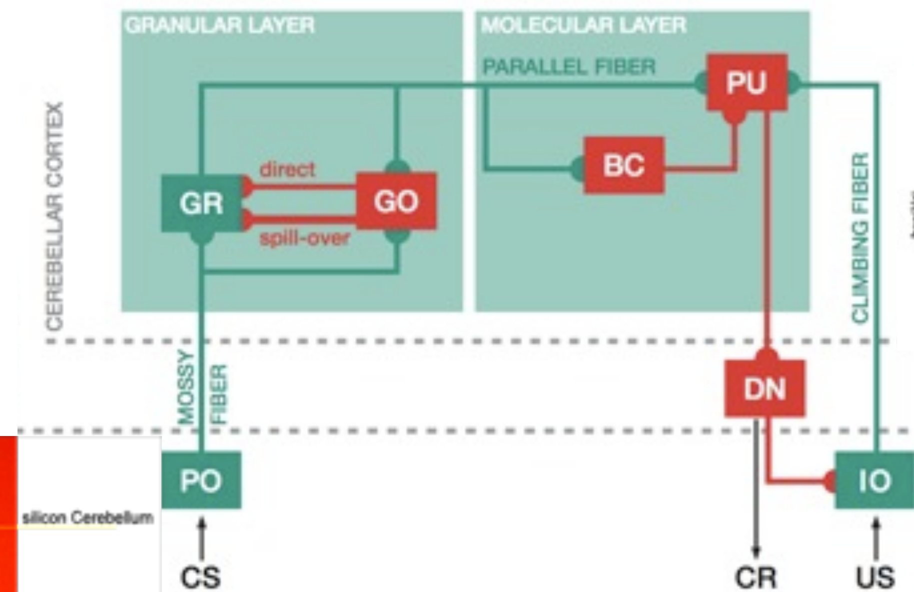
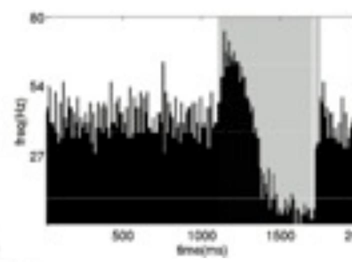
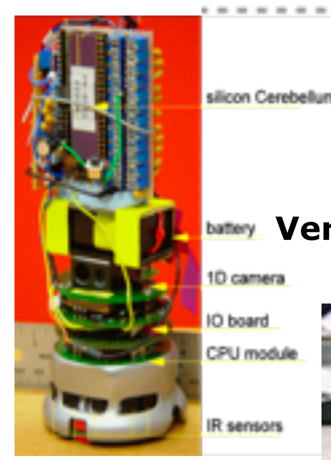
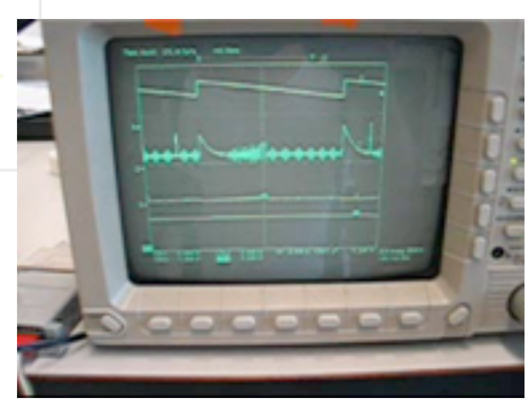
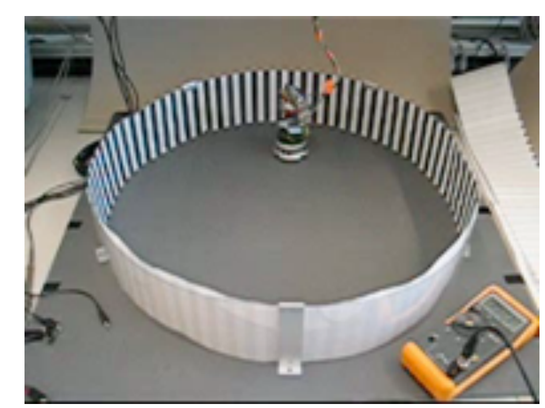






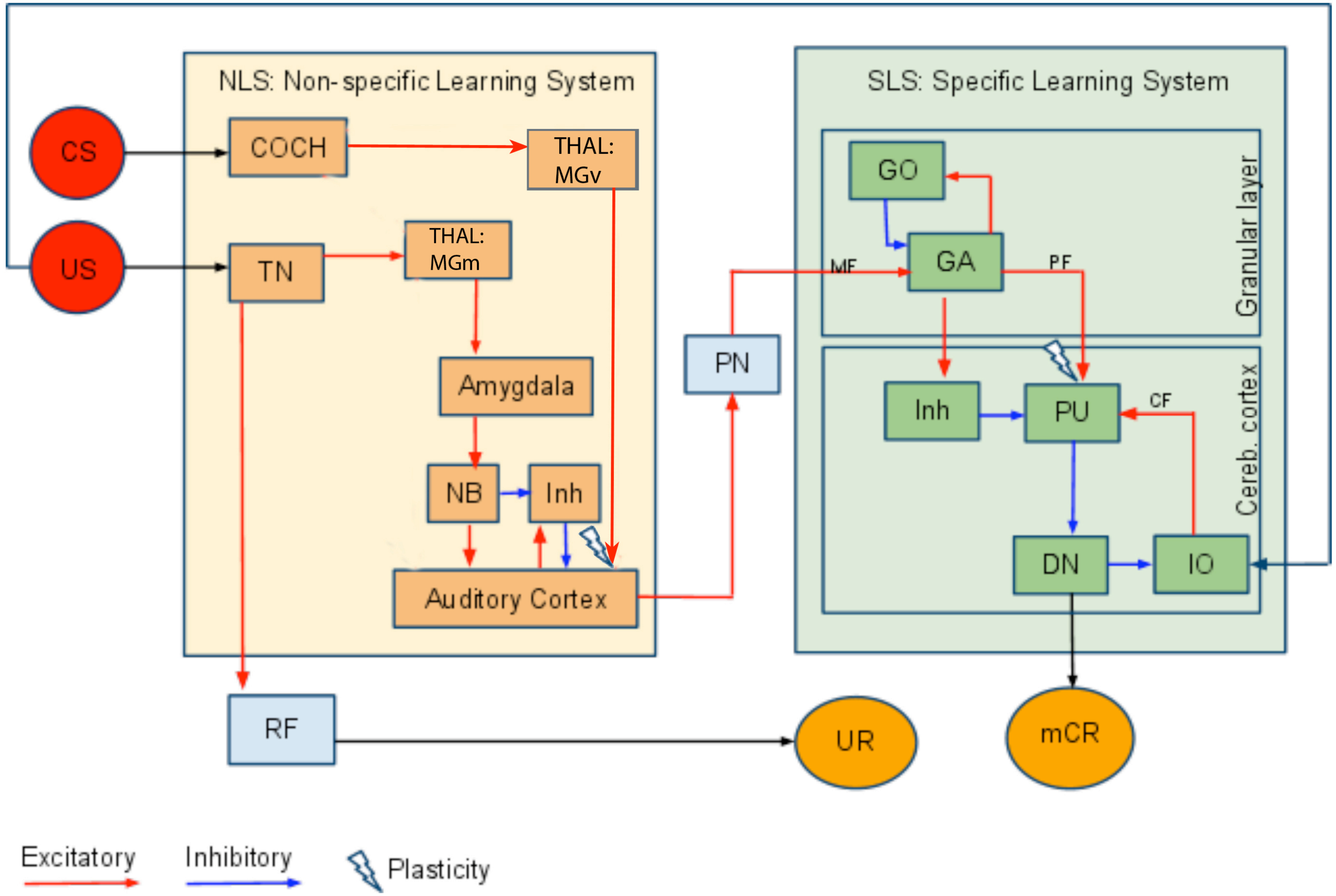
Verschure & Mintz (2000); Hofstotter et al (2003) Eur. J. Neurosci



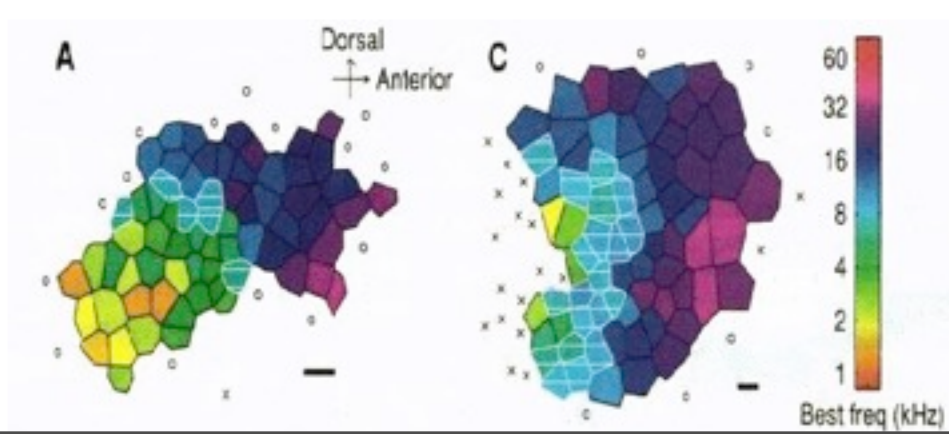


Hofstotter et al (2005) NIPS

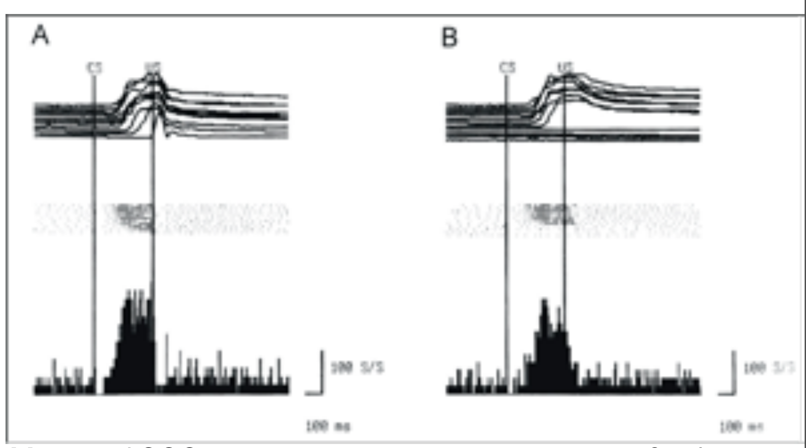
Konorski's 2 phase theory of conditioning



Kilgard & Merzenich, 1998



Inderbizin et al (2010) WCCI



Moore 1990

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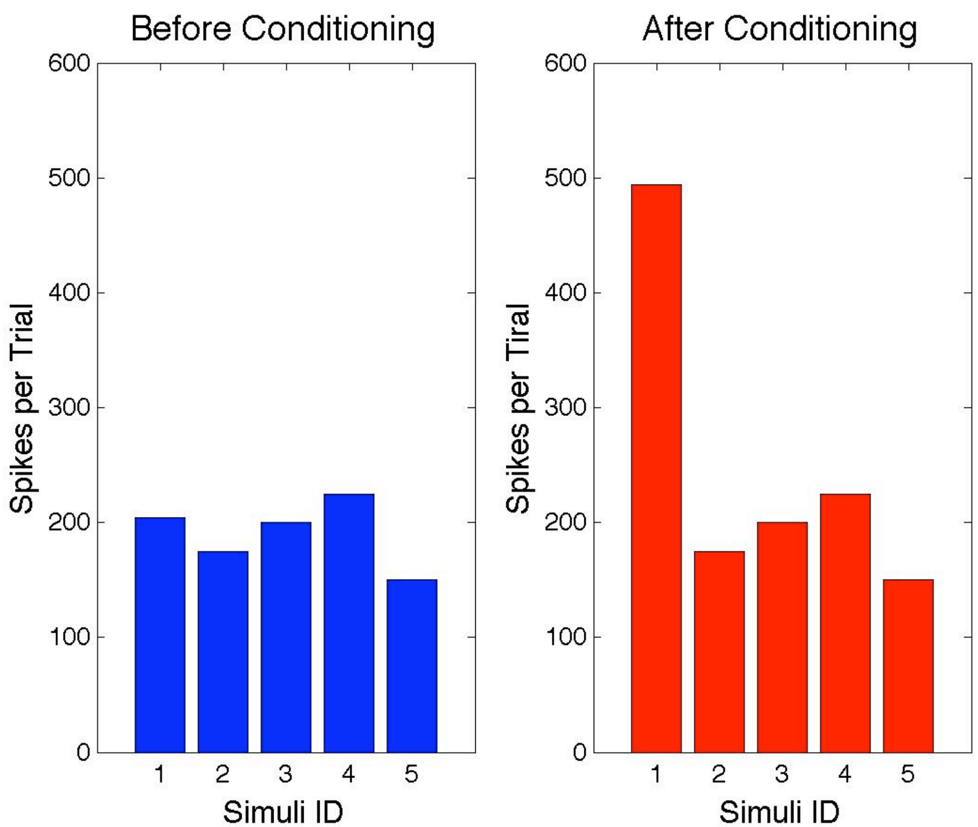
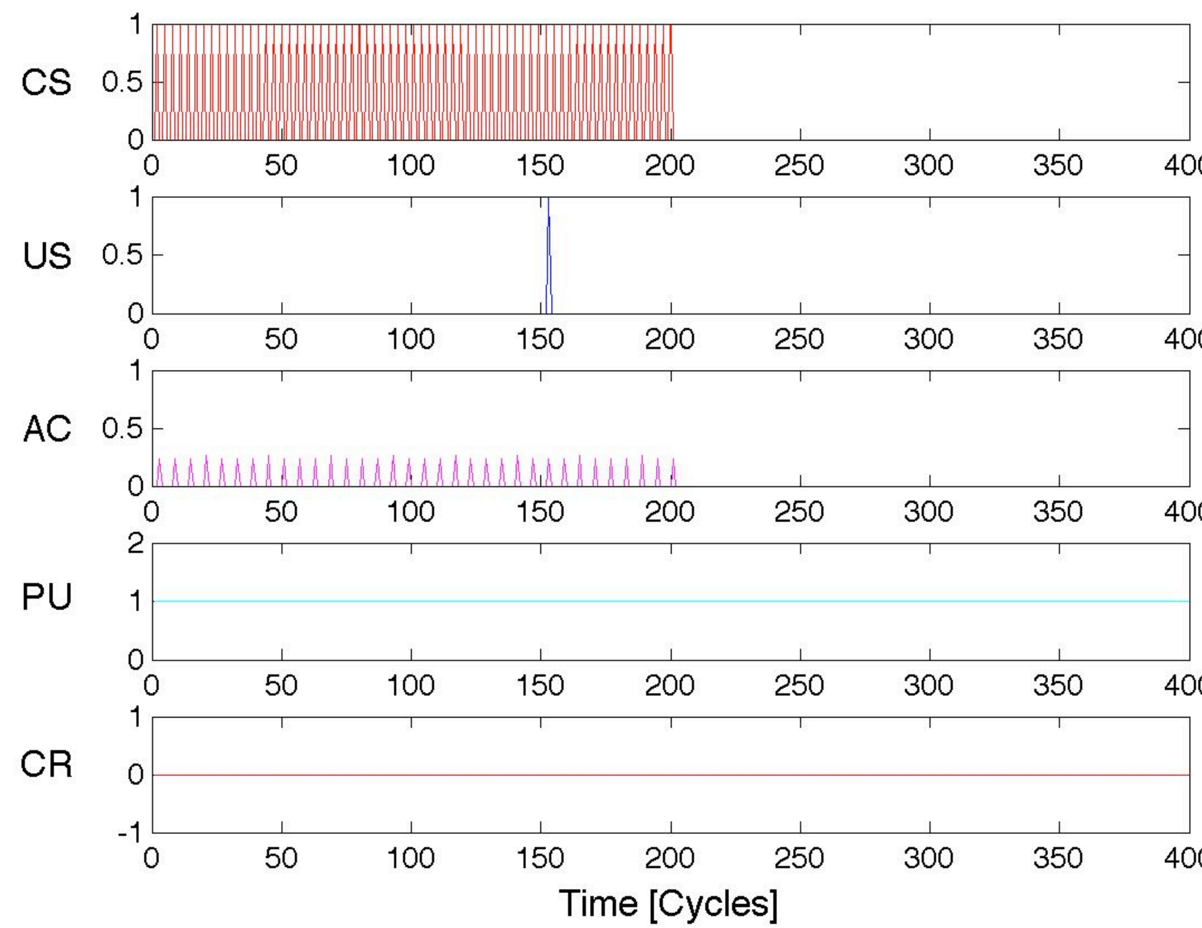
Event and time acquisition

Auditory cortex

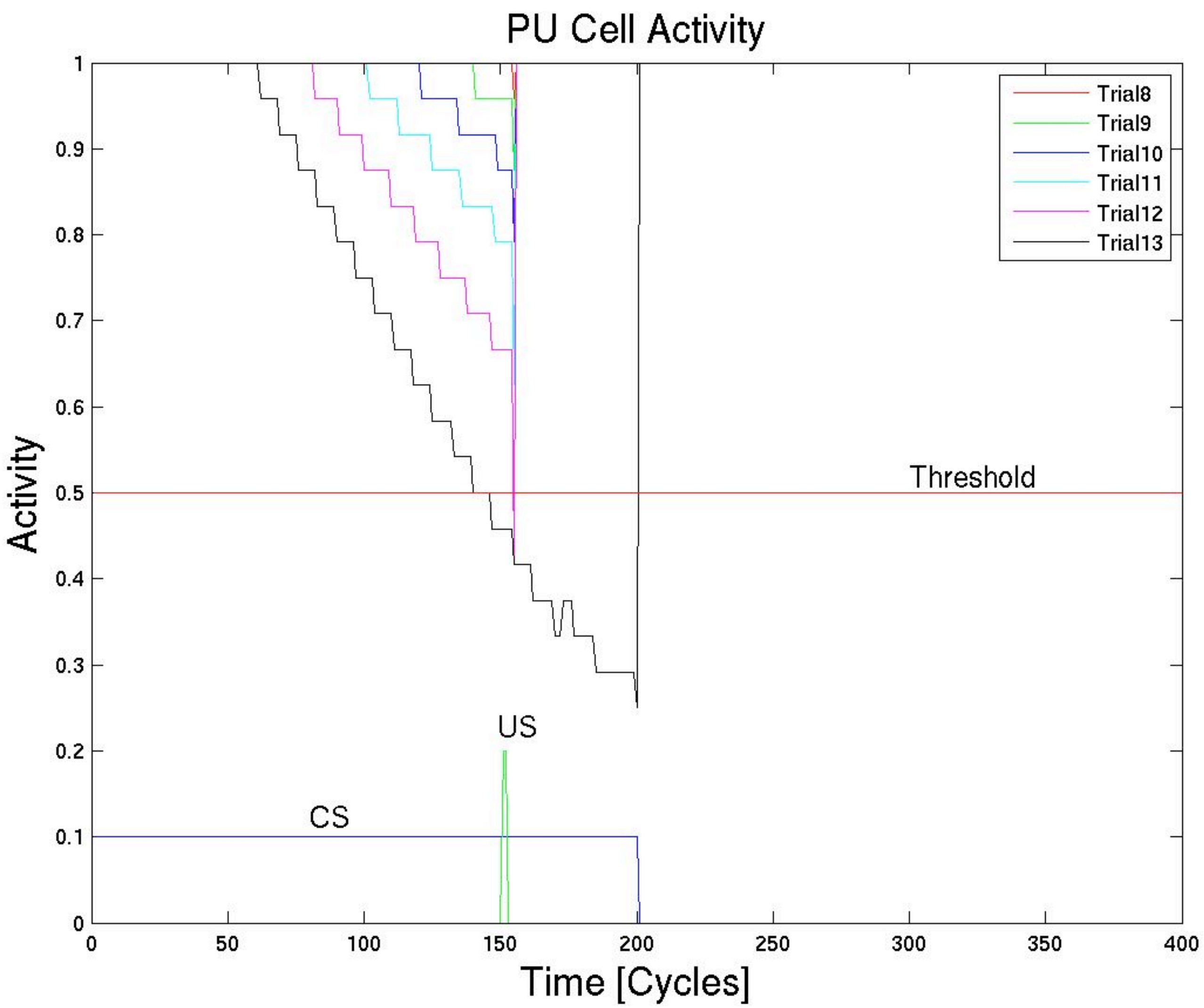


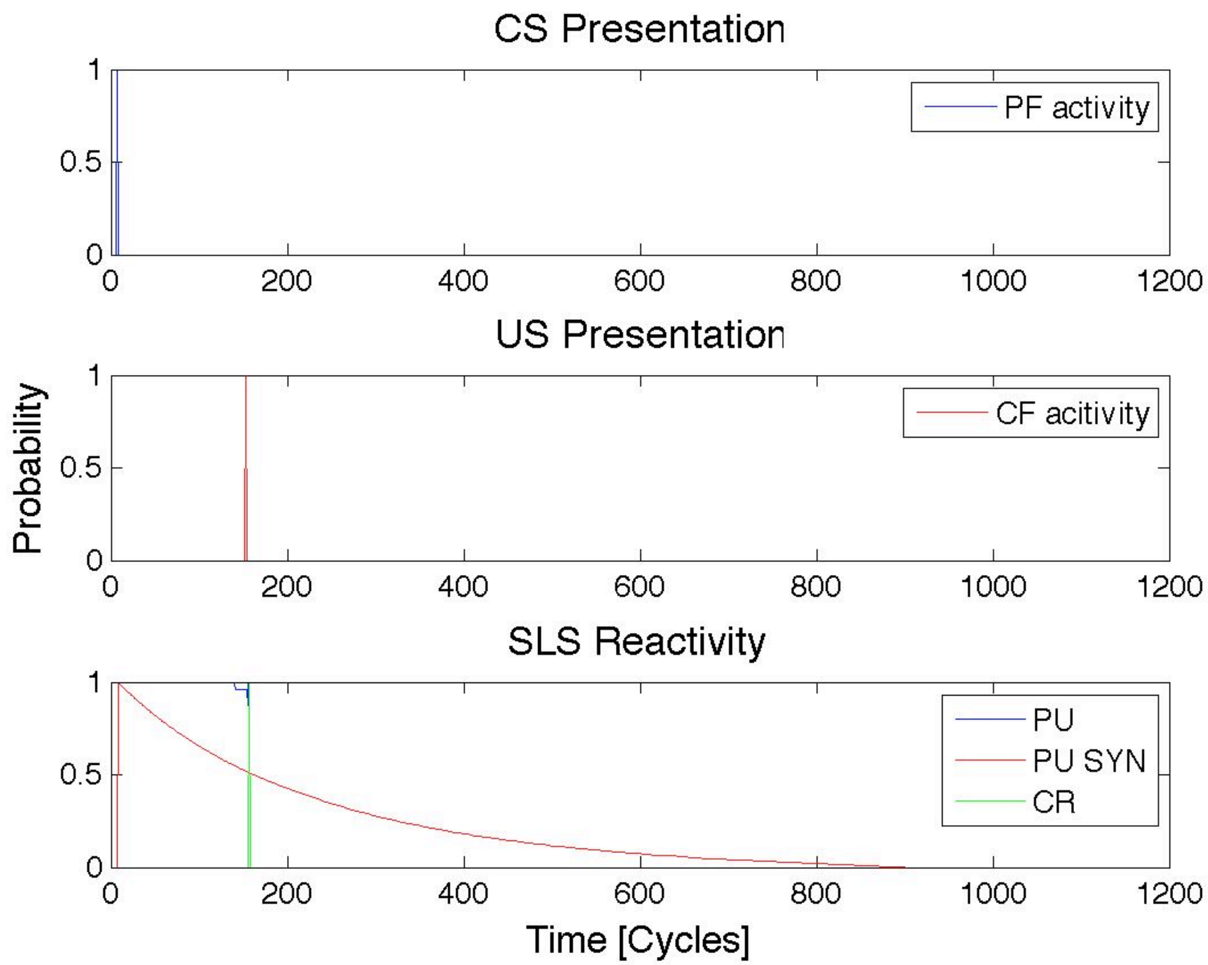
Cerebellum
Trial 1



Sanches Montanes et al 01 Neur Comp; Hofstotter et al 2003; Inderbizin et al 2010
WCCI

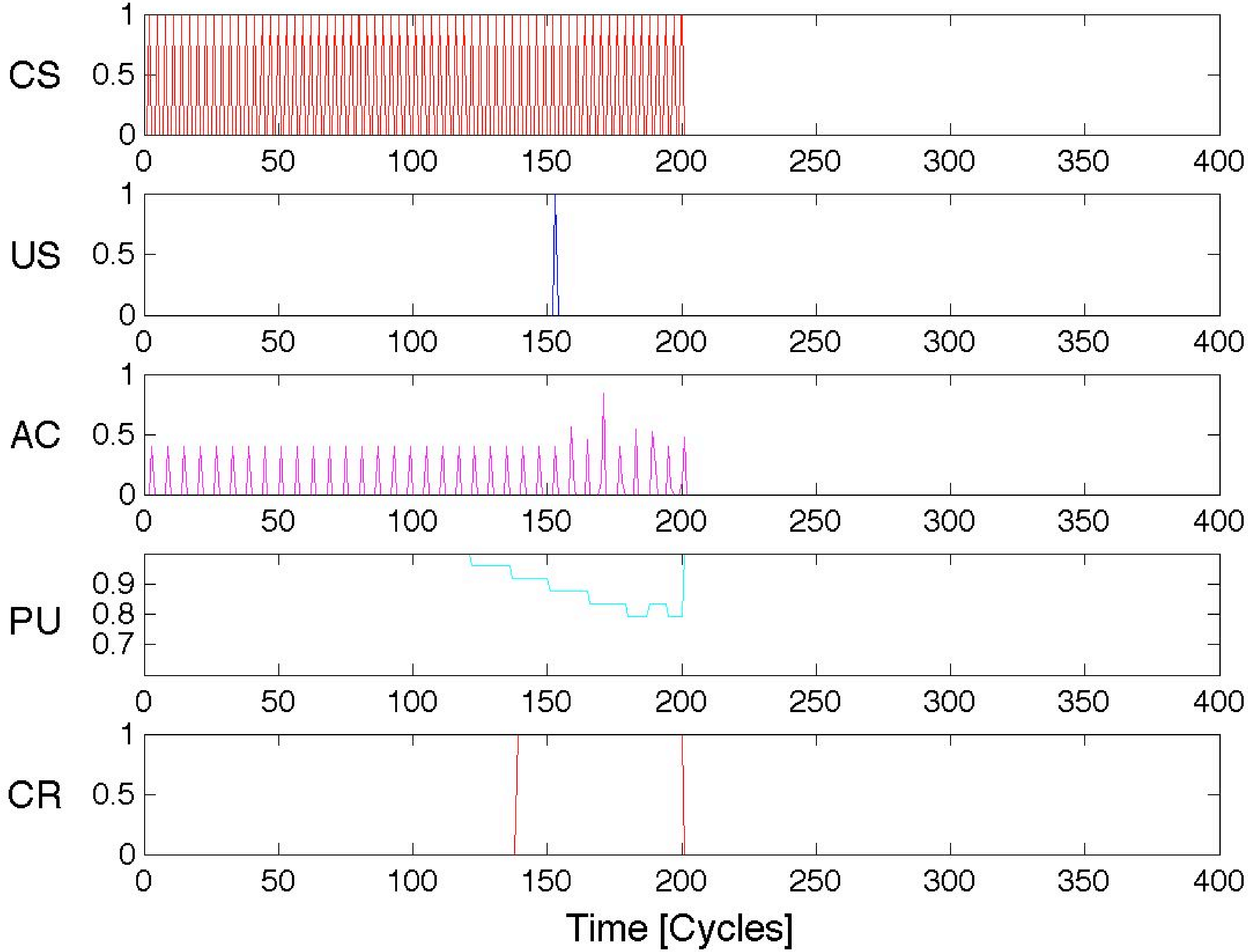
Event and time acquisition





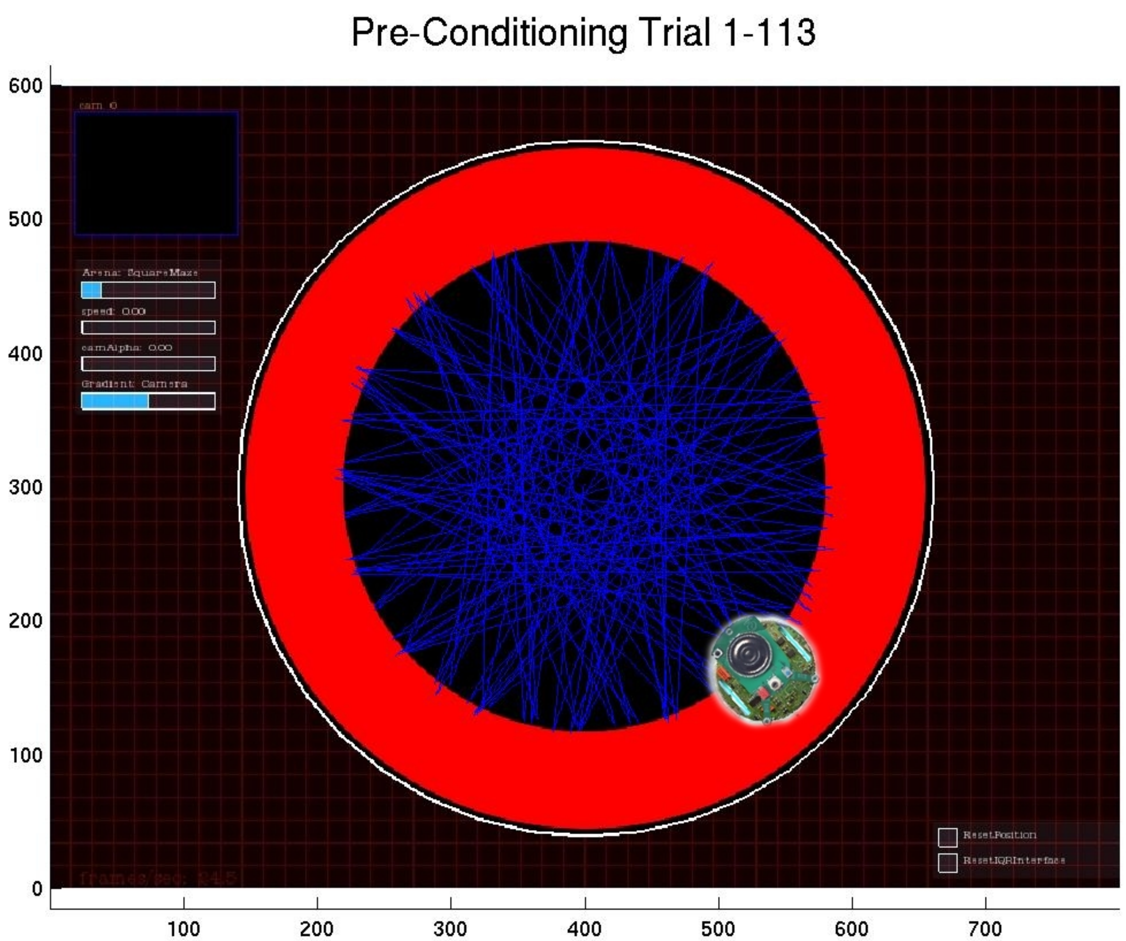
Sanches Montanes et al 01 Neur Comp; Hofstotter et al 2003; Inderbizin et al 2010 WCCI

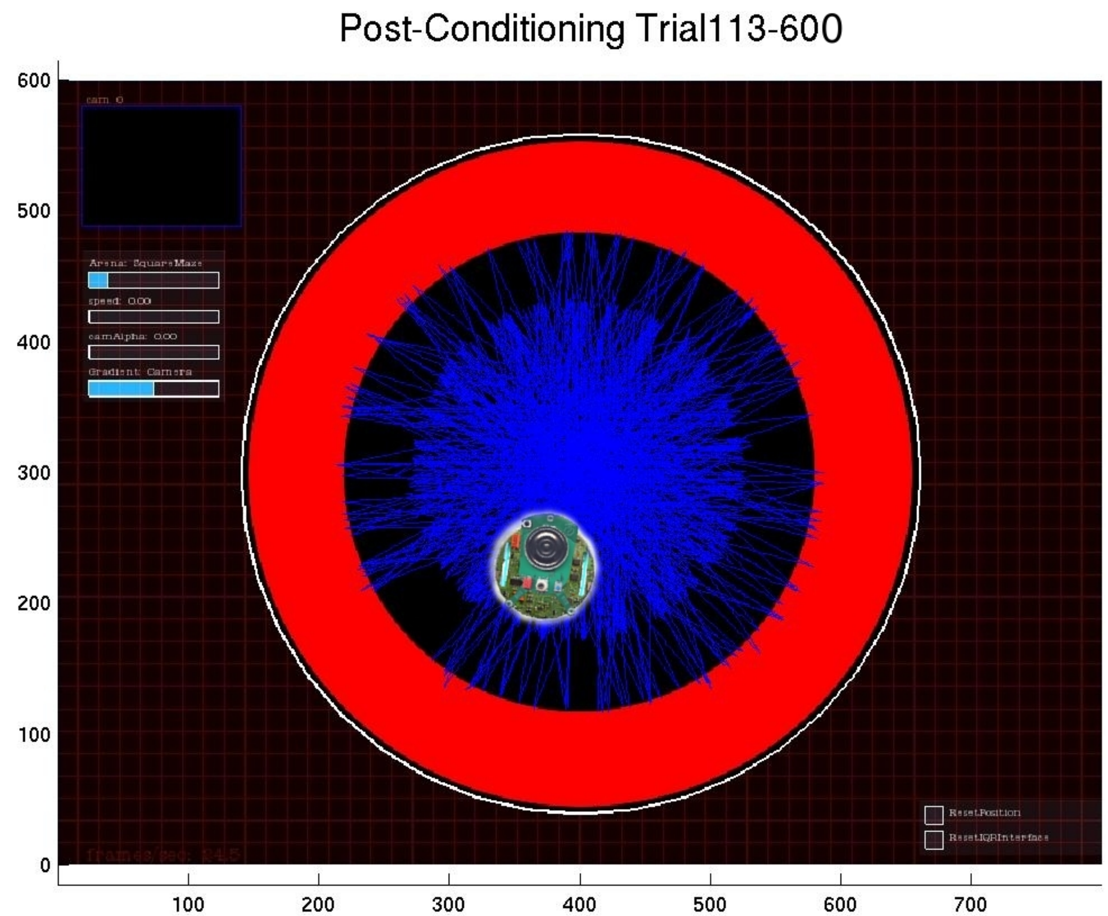
After training

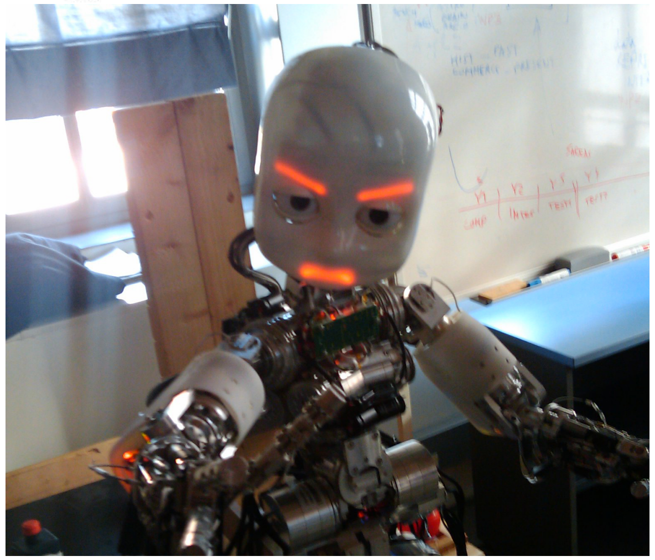


Sanches Montanes et al 01 Neur Comp; Hofstotter et al 2003; Inderbizin et al 2010
WCCI

Robot Validation

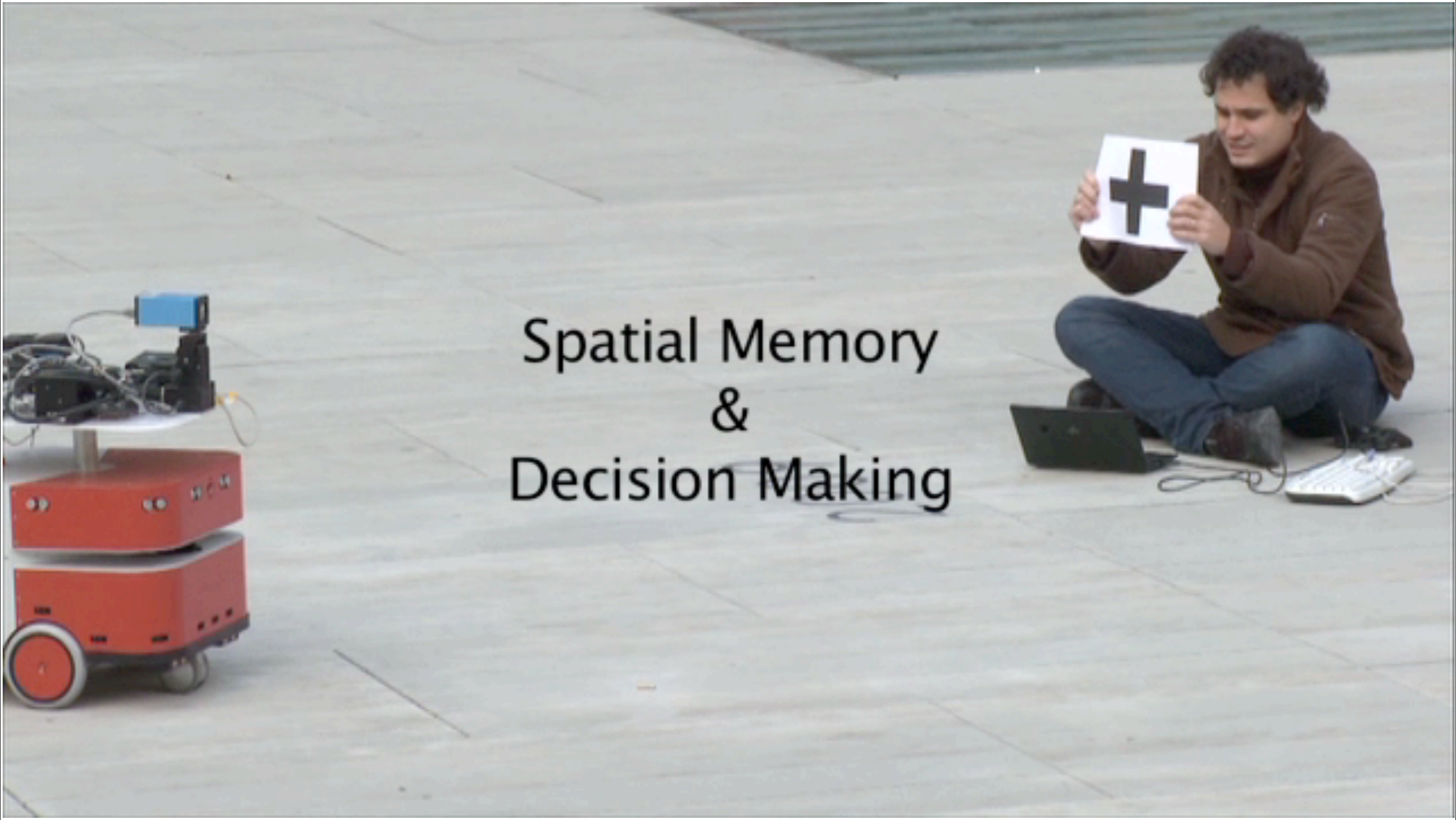




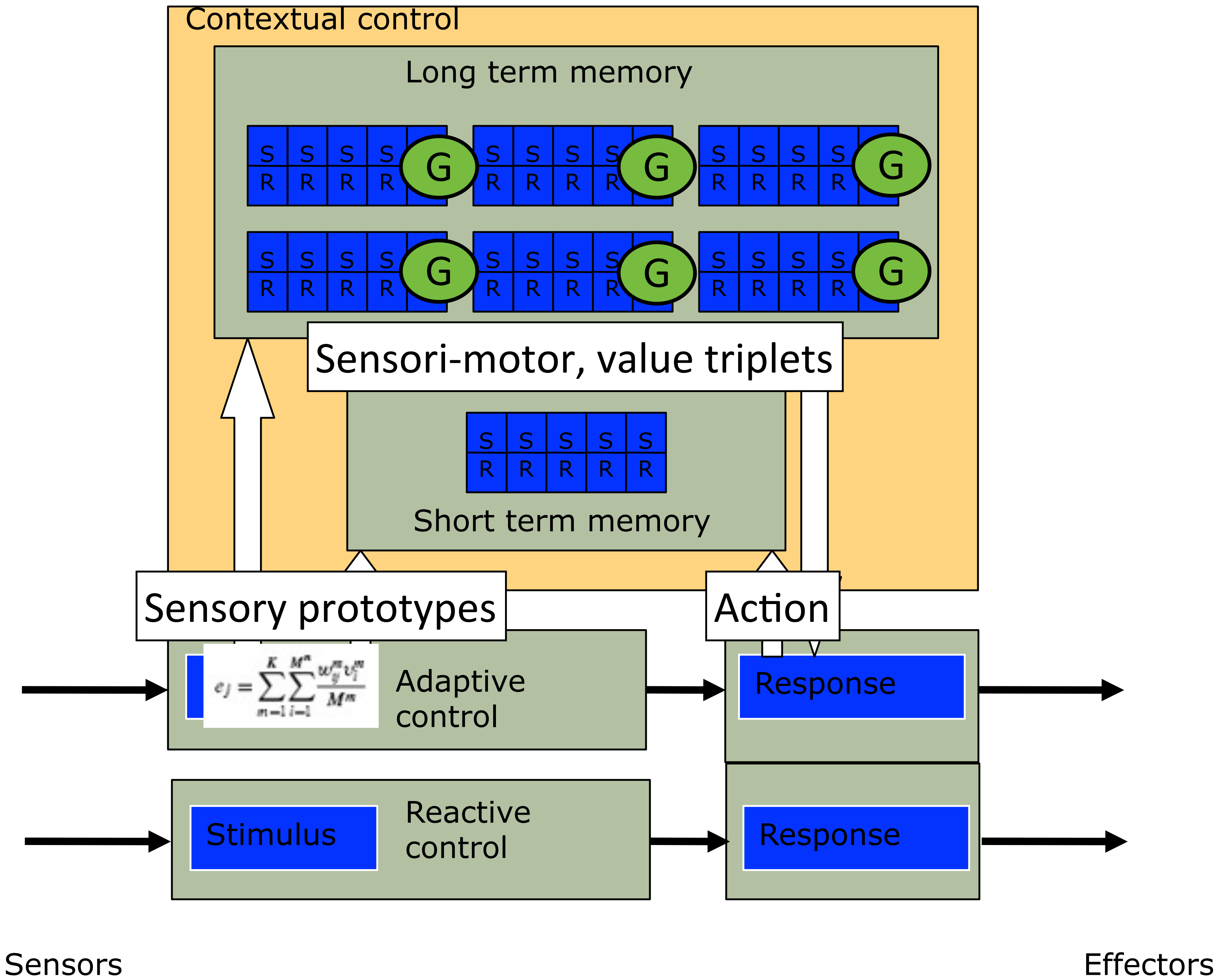


DAC AL: Intermediate conclusion

- From sensing to symbols, percepts and actions
- Interaction of perceptual and behavioral learning
  - PL & BL are both prediction based
  - Interaction of PL & BL are dynamically regulated
- Konorski's 2 phase theory emphasizes the fundamental distinction between event and interval representations
- The objectives of the adaptive layer are perceptual and behavioral prediction
- AL maps onto the neuronal substrate of classical conditioning: amygdala and cerebellum

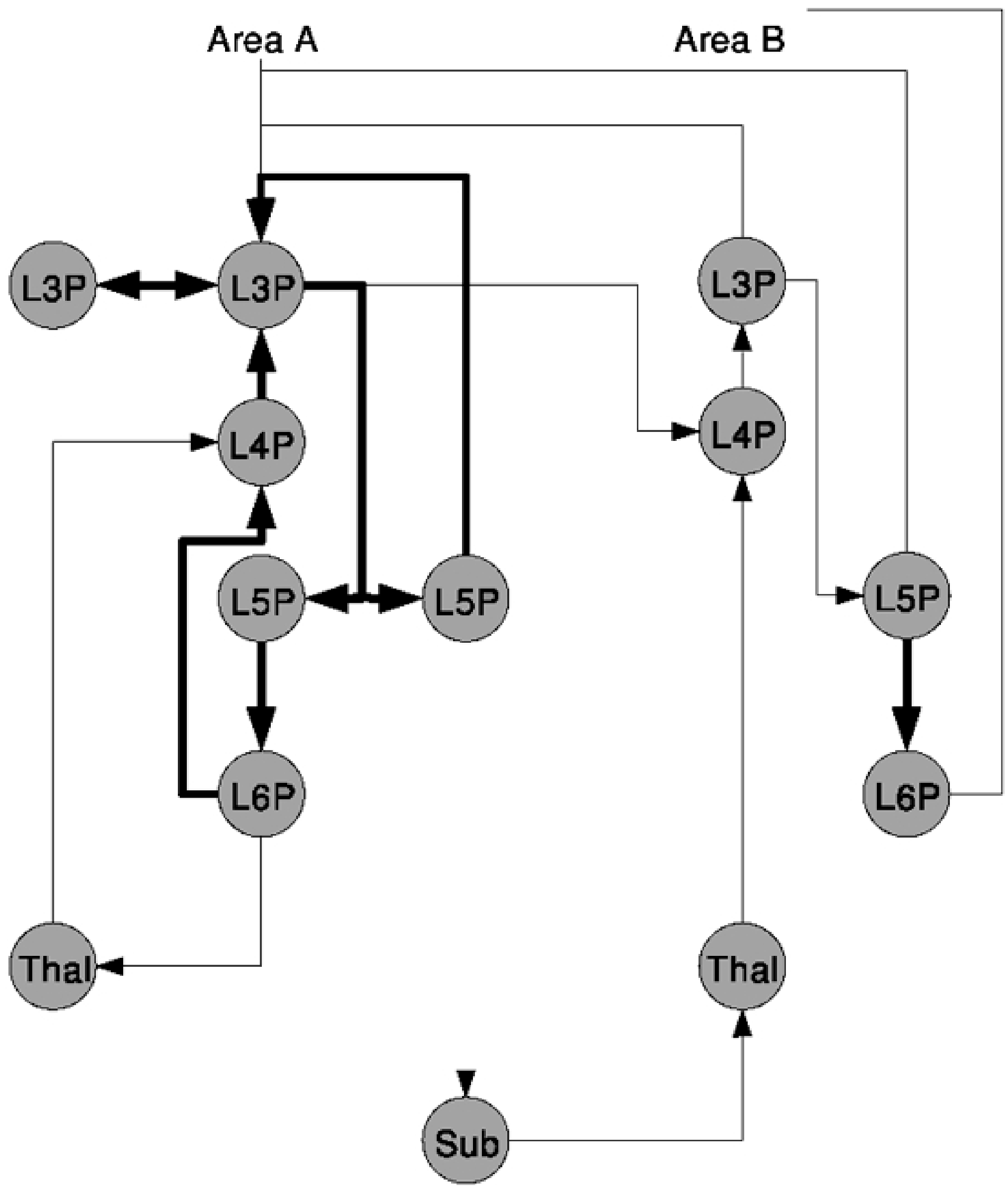

Spatial Memory
&
Decision Making

Inter-layer control signals and protocols of DAC



Verschure & Voegtlin (1998) Neur.Netw. Verschure & Althaus (2003) Cog.Sci., 27: 561-590 Verschure et al (2003)
[Duff et al., Brain Res Bull 2011]

Cortical networks are characterized by dense local and sparse long-range inter-area connectivity

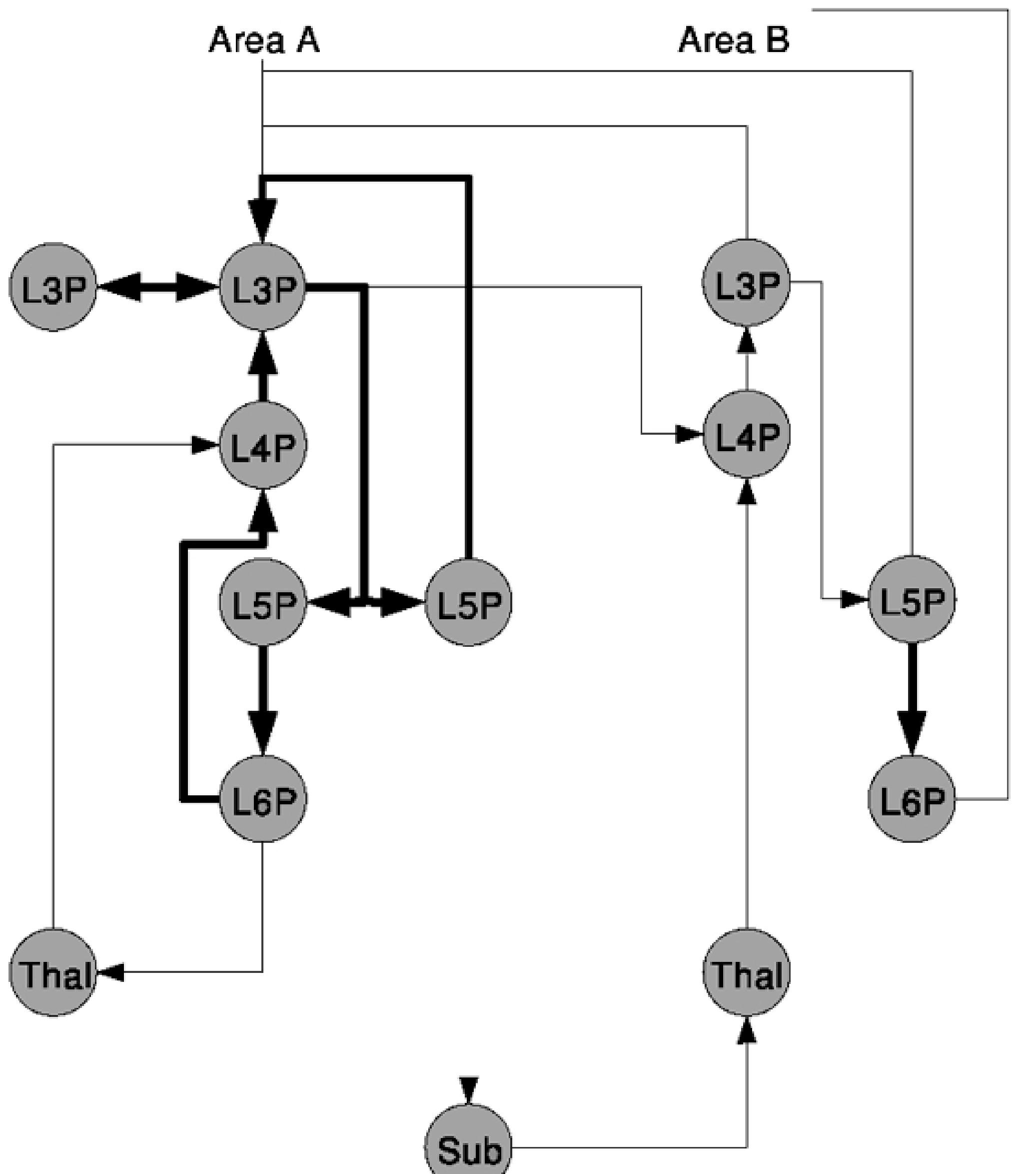


Douglas & Martin (2004) Ann Rev Neurosci.

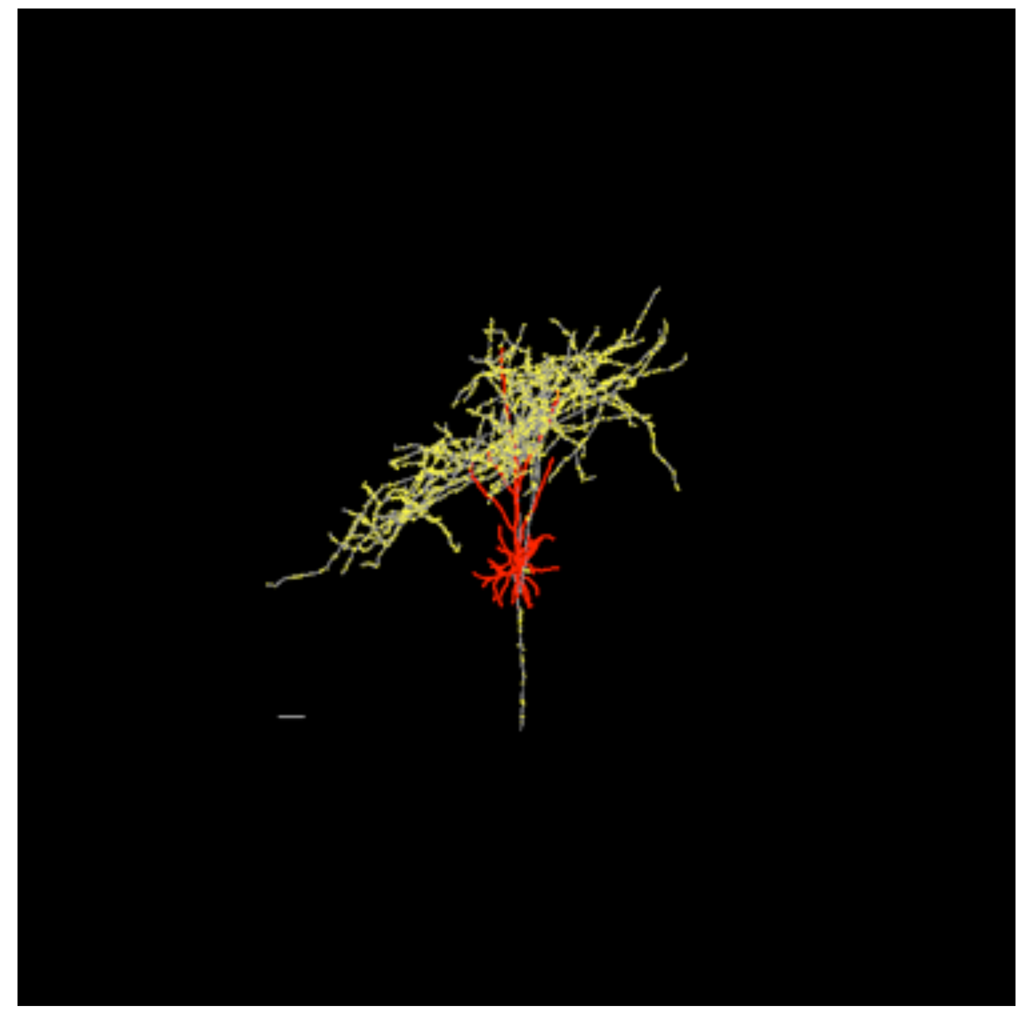
Reconstruction: Kevan Martin & John Anderson INI-Zurich

The brain might not have the wires to implement hierarchical systems

Cortical networks are characterized by dense local and sparse long-range inter-area connectivity



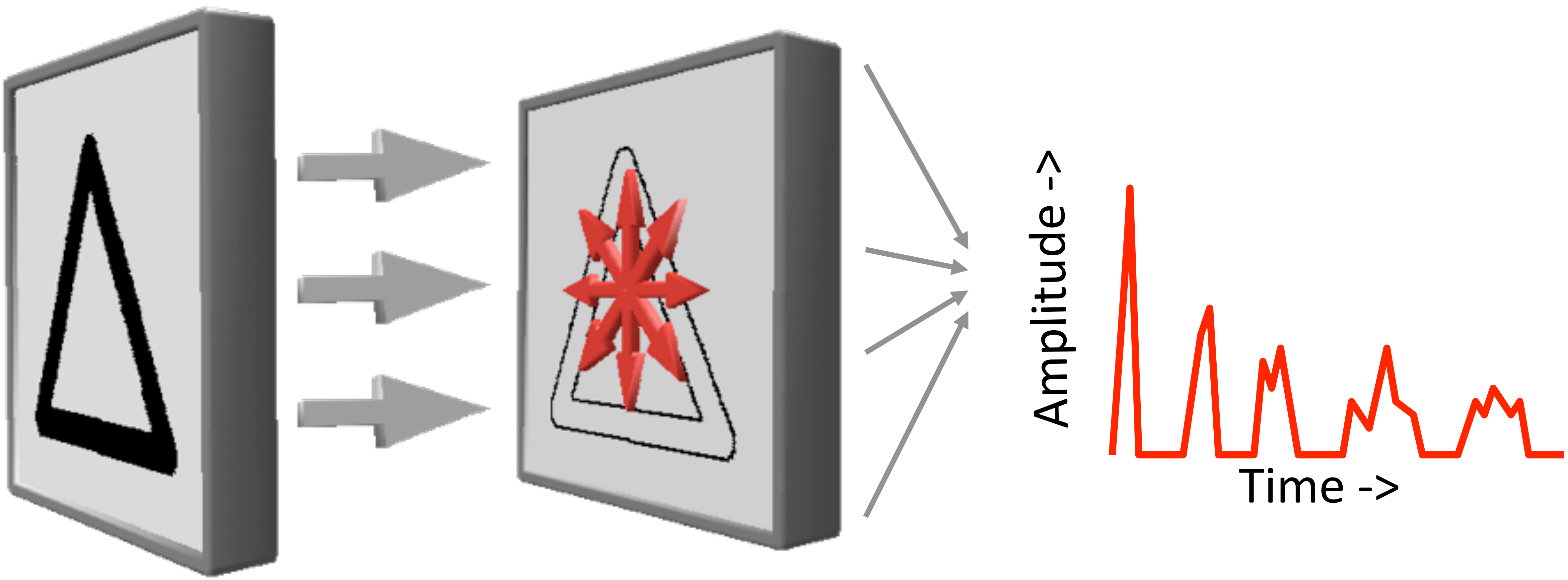
Douglas & Martin (2004) Ann Rev Neurosci.

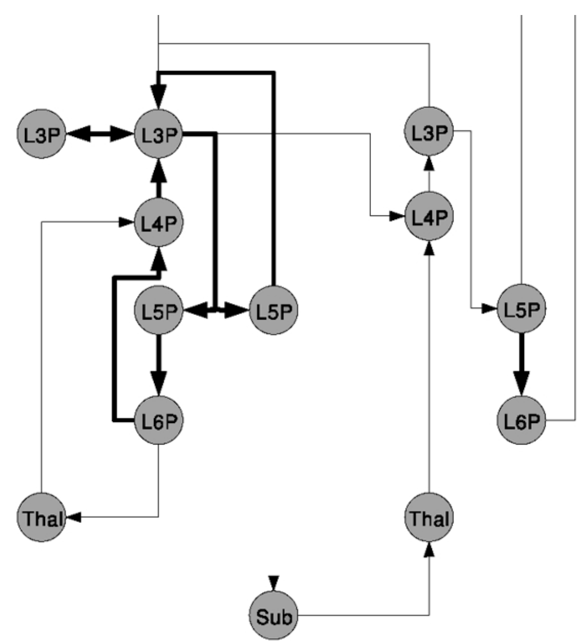


Reconstruction: Kevan Martin & John Anderson INI-Zurich

The brain might not have the wires to implement hierarchical systems

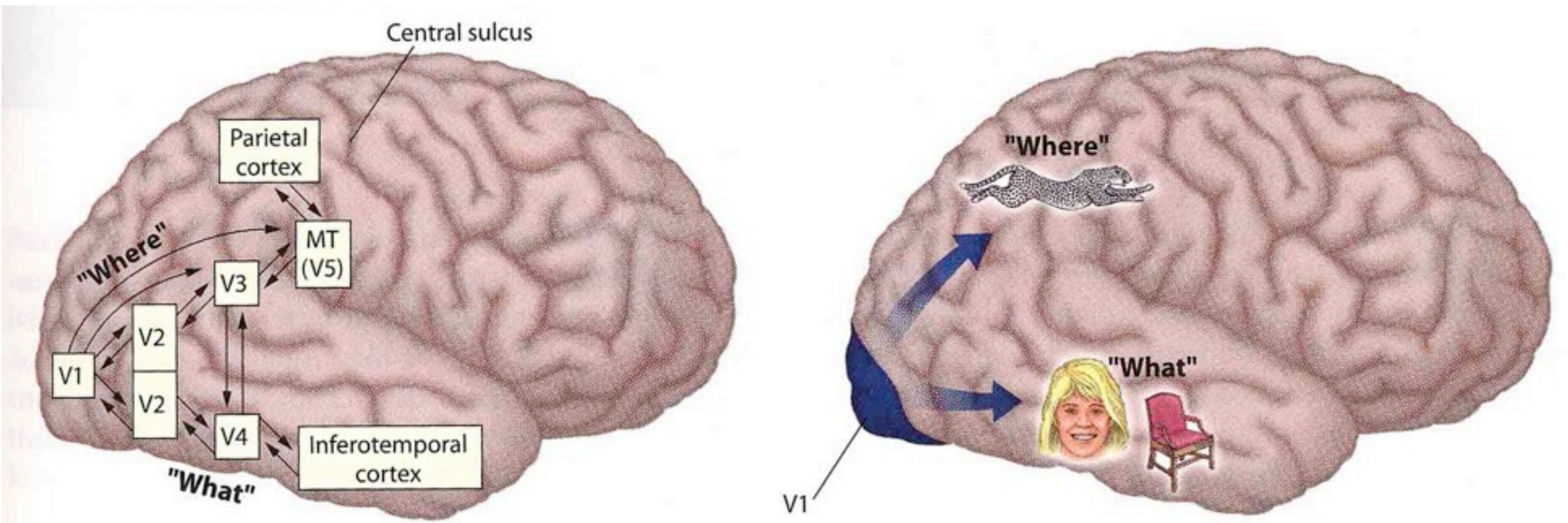
Temporal Population Code



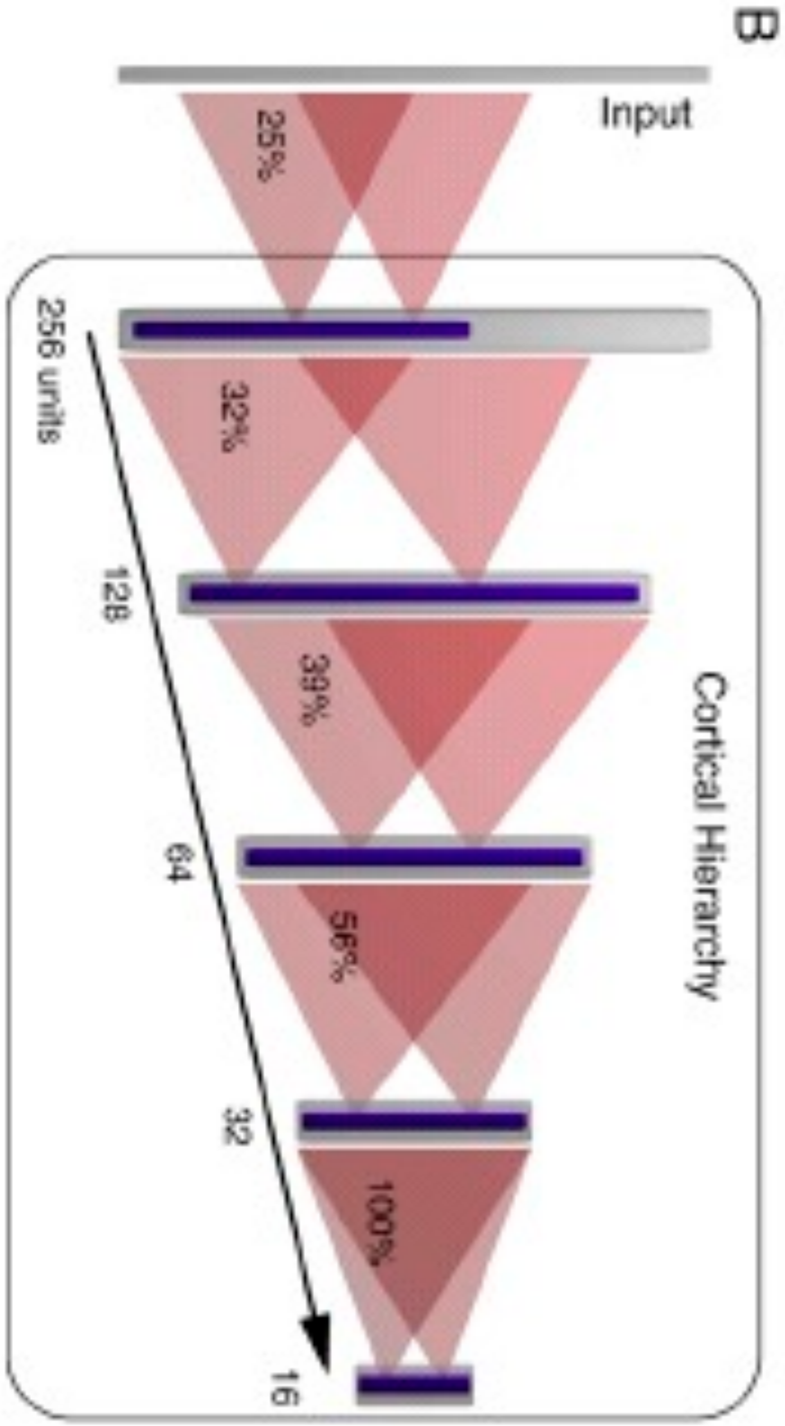


Wyss et al (2002) PNAS 100: 324-329

How to wire up the visual hierarchy?



A model of the ventral visual system:



- Sparseness: Learning sparse codes explains simple cell receptive fields in V1 (Olshausen 1996) and the formation of adequate auditory filters (Lewicki 2002).

- Stability: Optimizing for temporal stability in visual system leads to invariant representations similar to V1 complex cells (Kayser 2001, Einhäuser 2003, Körding 2003, Berkes 2003, Wyss).

Wyss et al, 2006, Public Library of Science

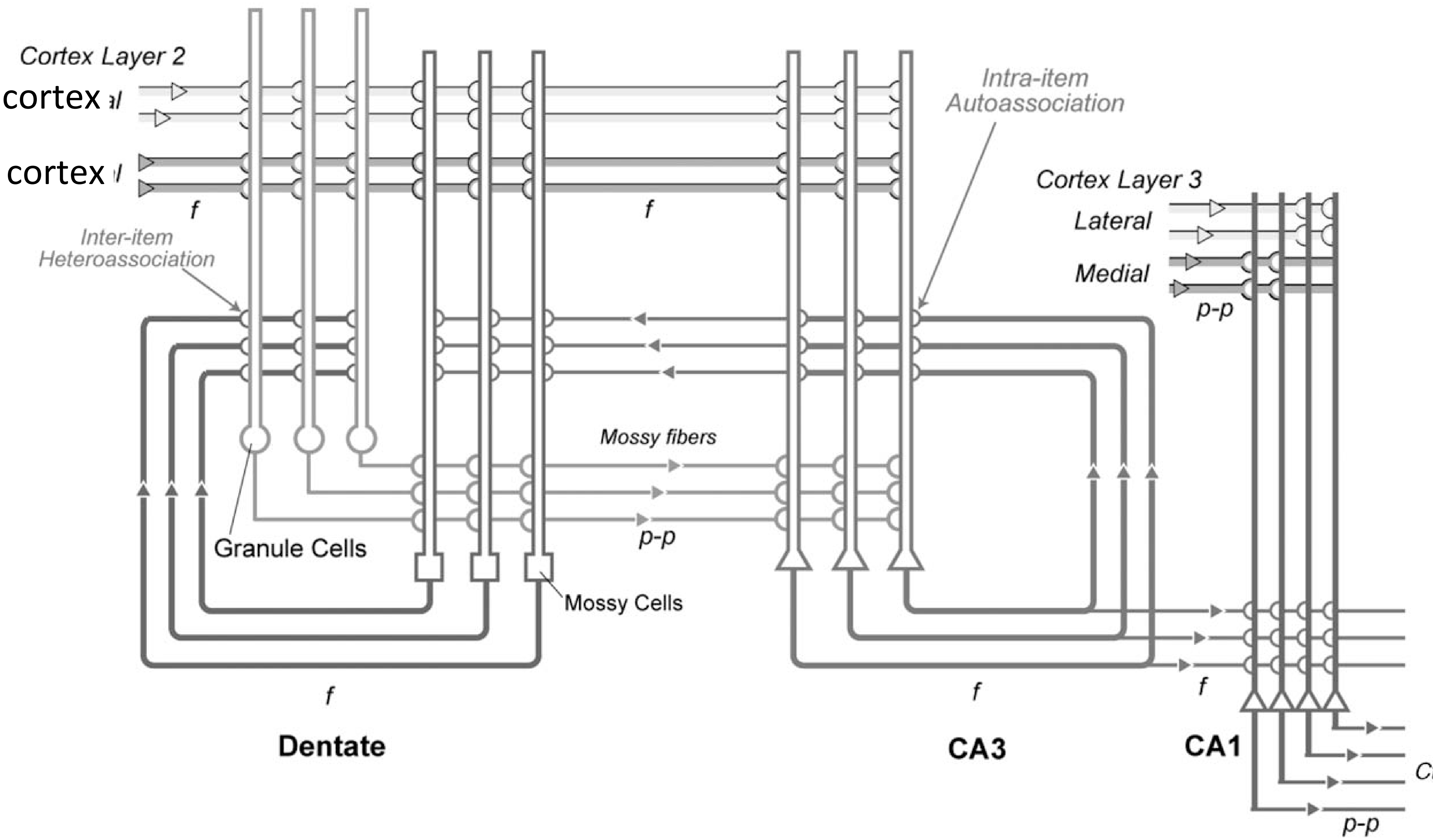
Mixing **what** and **how** into sensori-motor couplets

Sense

lateral entorhinal cortex

medial entorhinal cortex

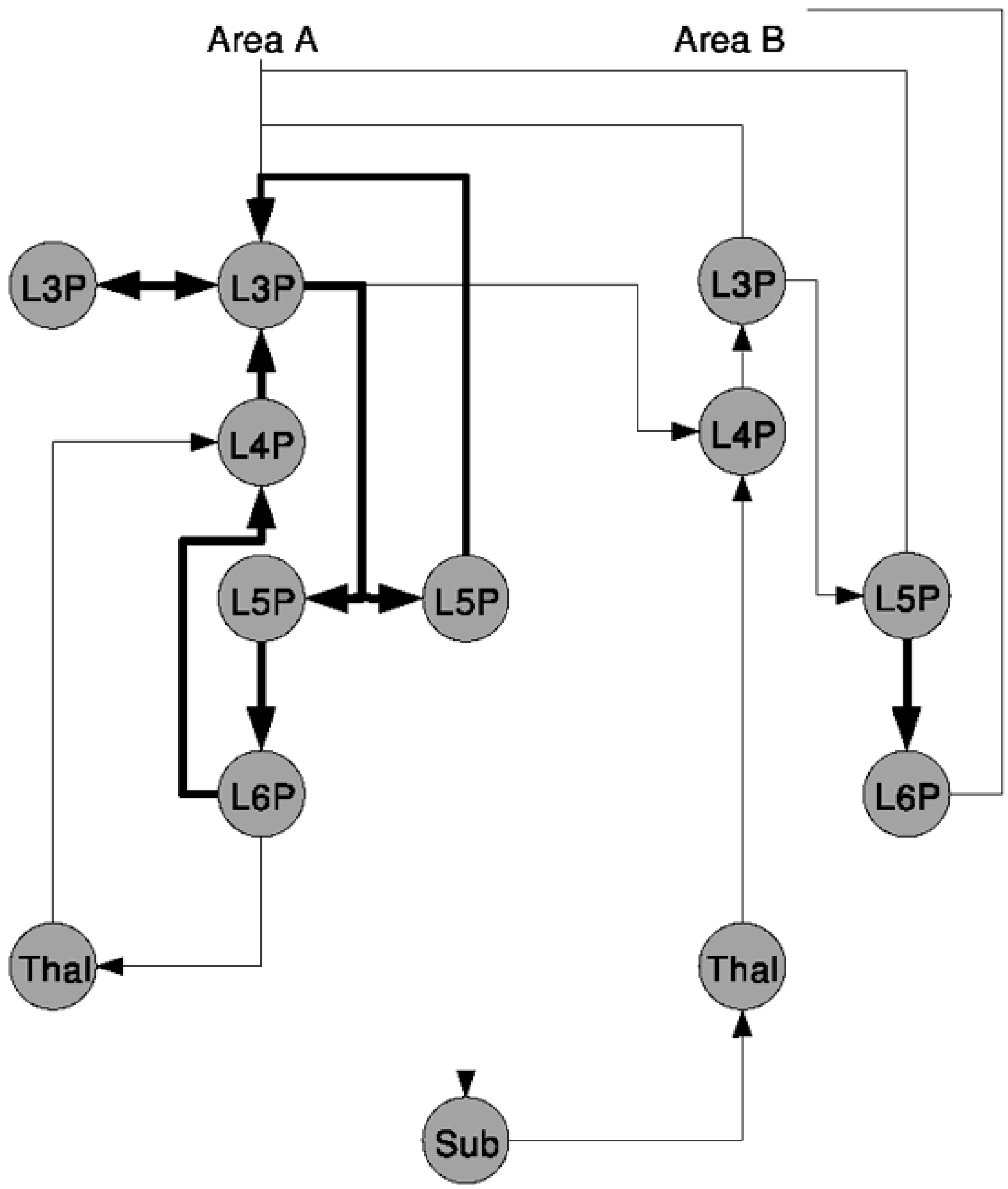
Act



Lisman (2007) Prog in Br Res

Defining "**what**"

Cortical networks are characterized by dense local and sparse long-range inter-area connectivity



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The brain might not have the wires to implement hierarchical systems

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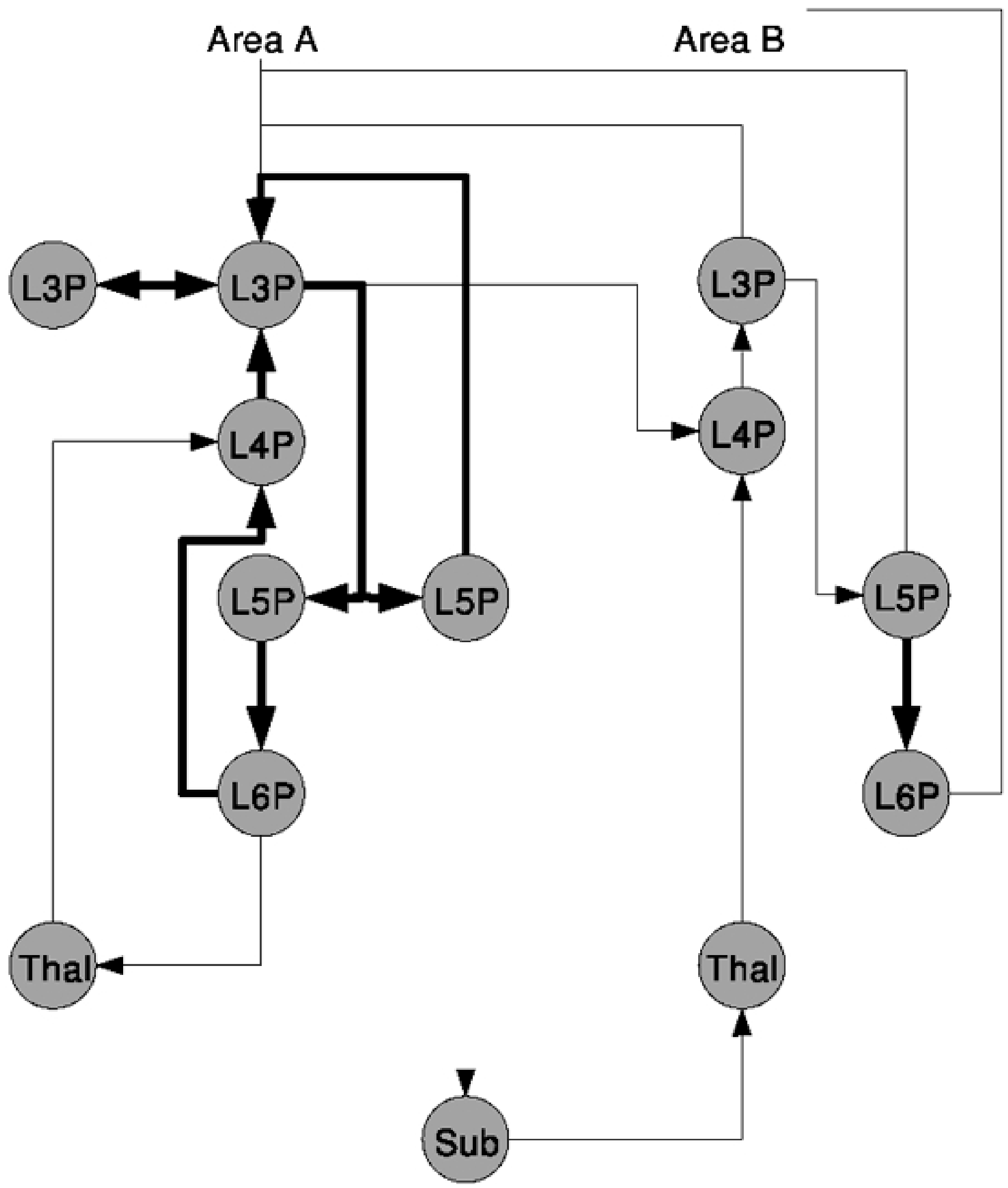

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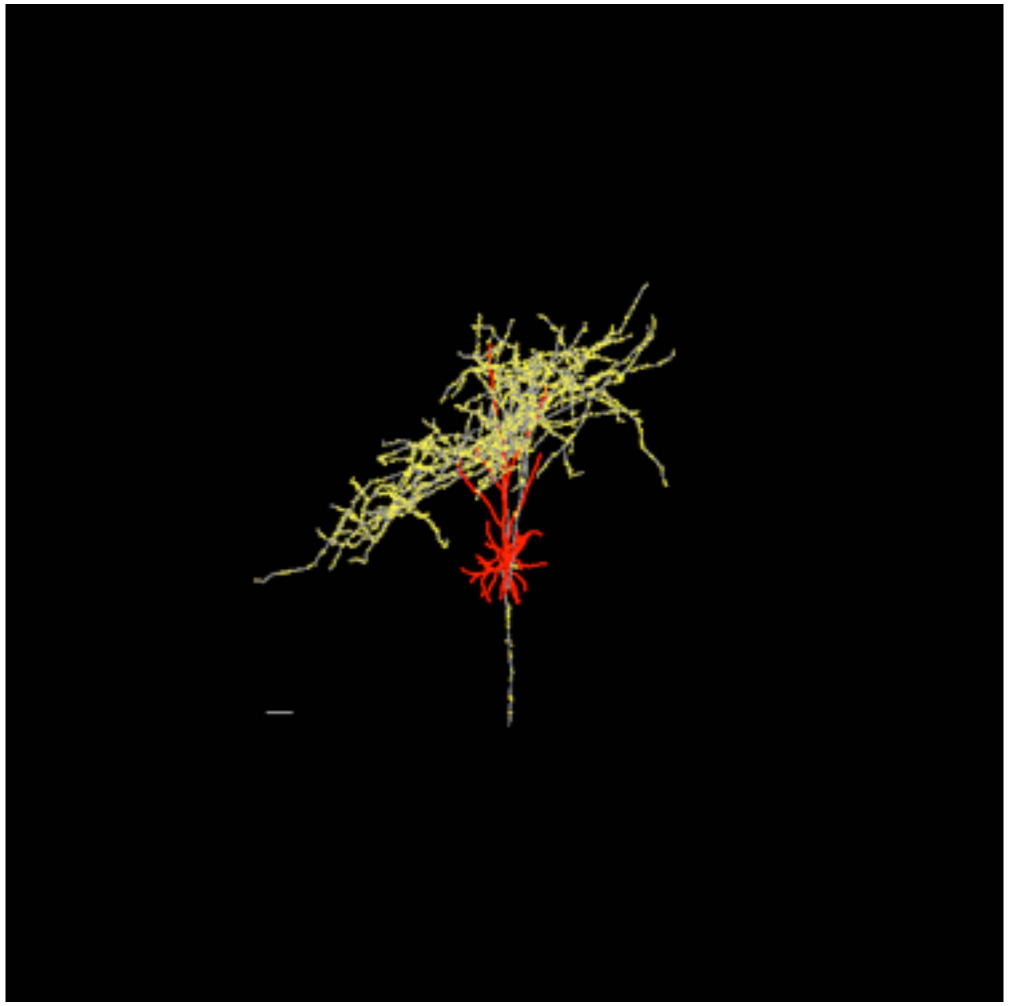

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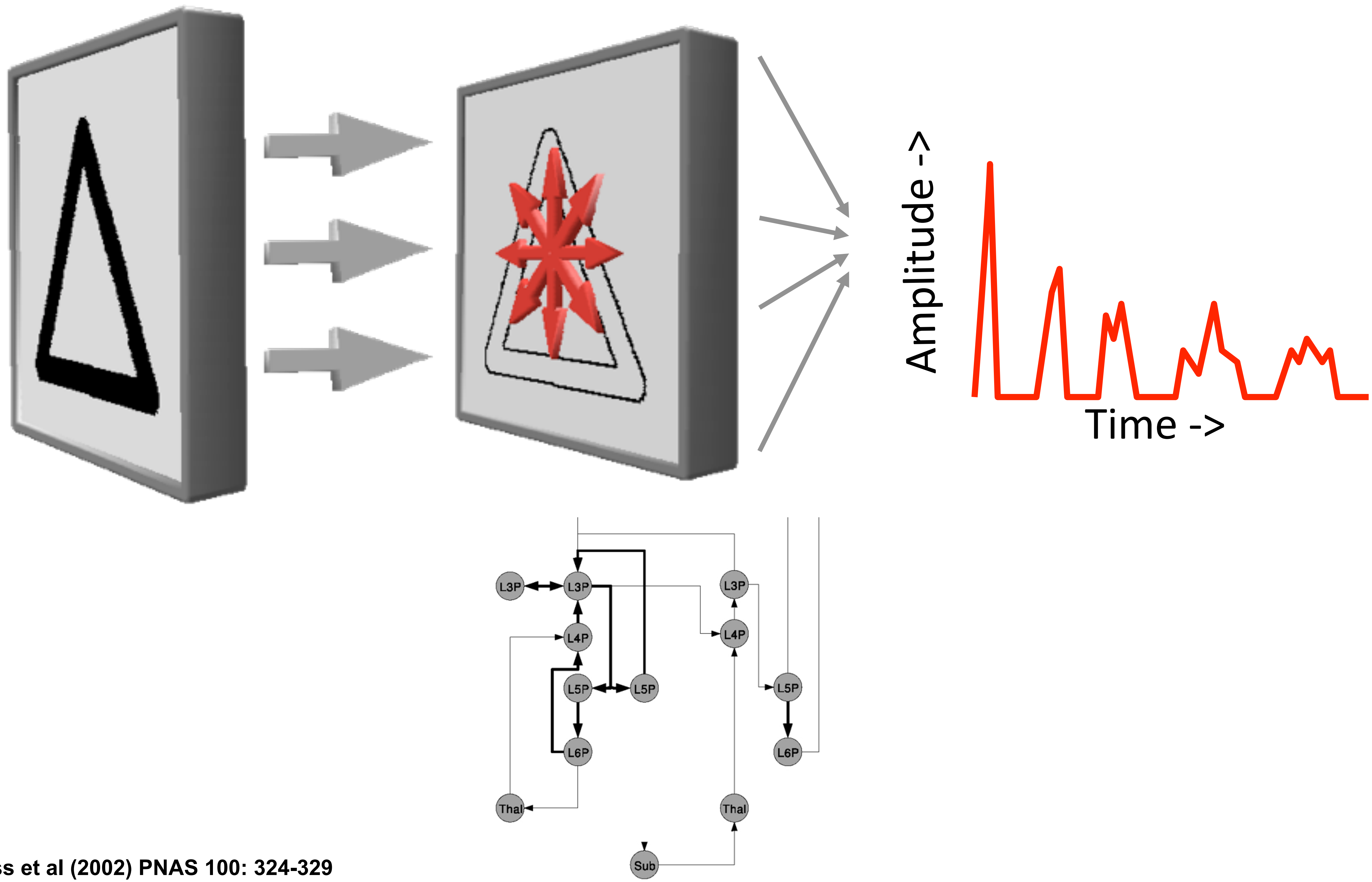
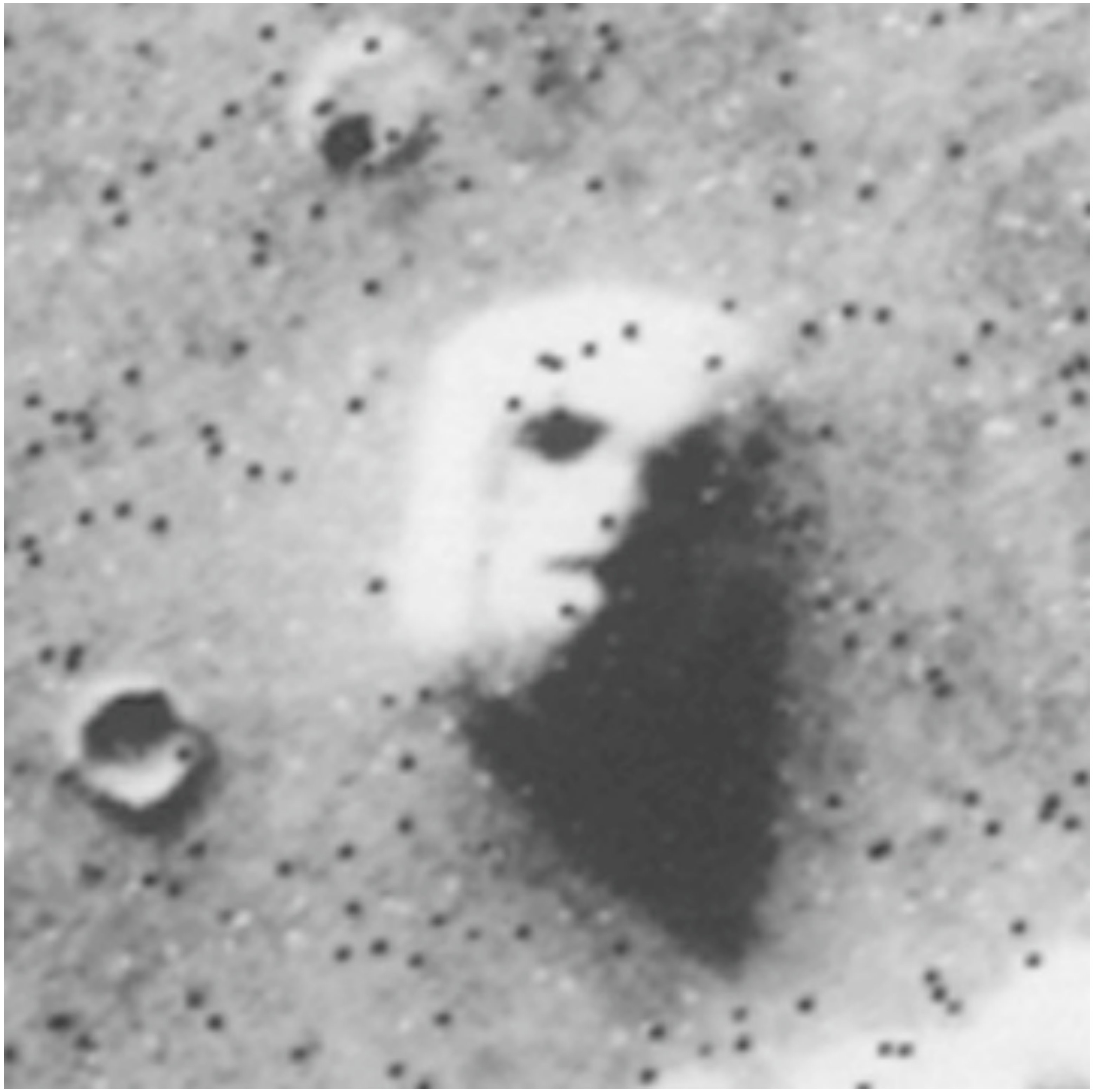
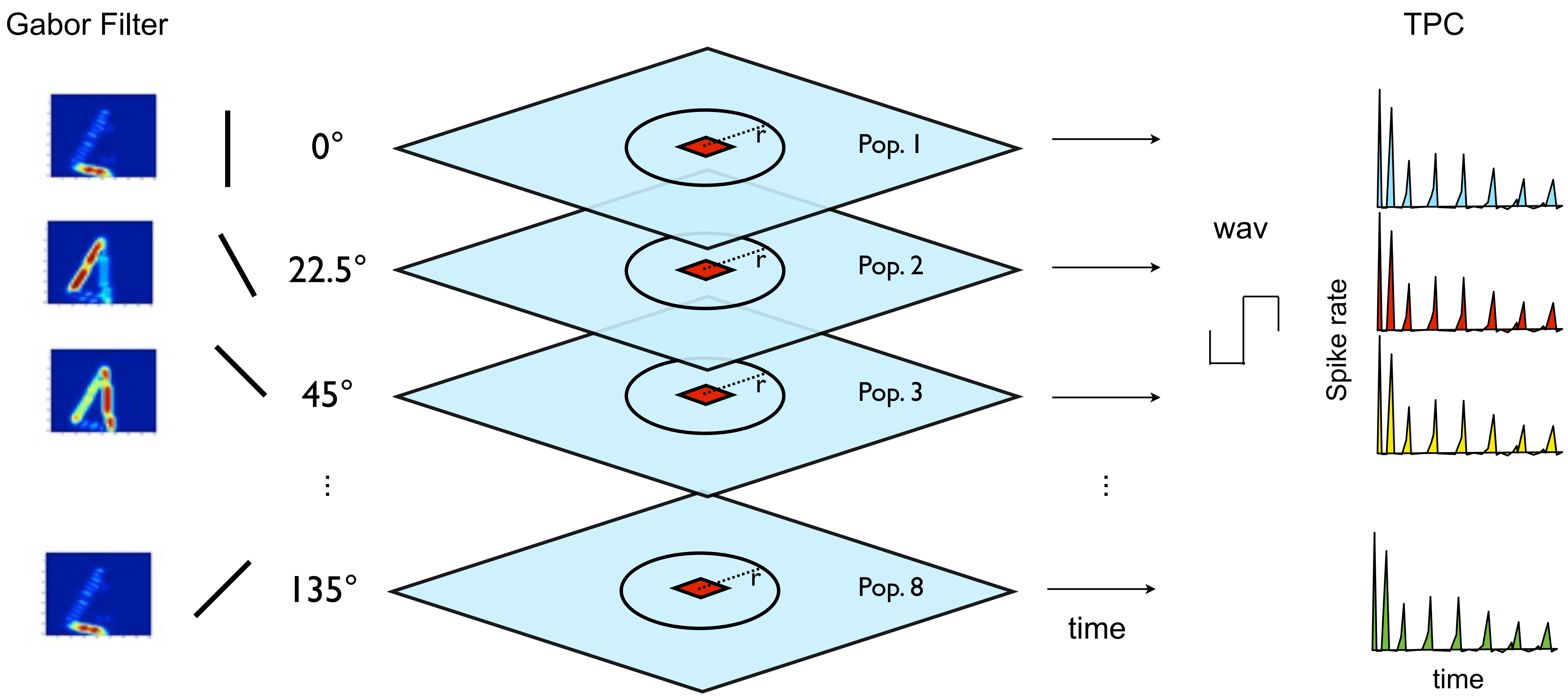


Wyss et al (2002) PNAS 100: 324-329

TPC Generalization to face recognition

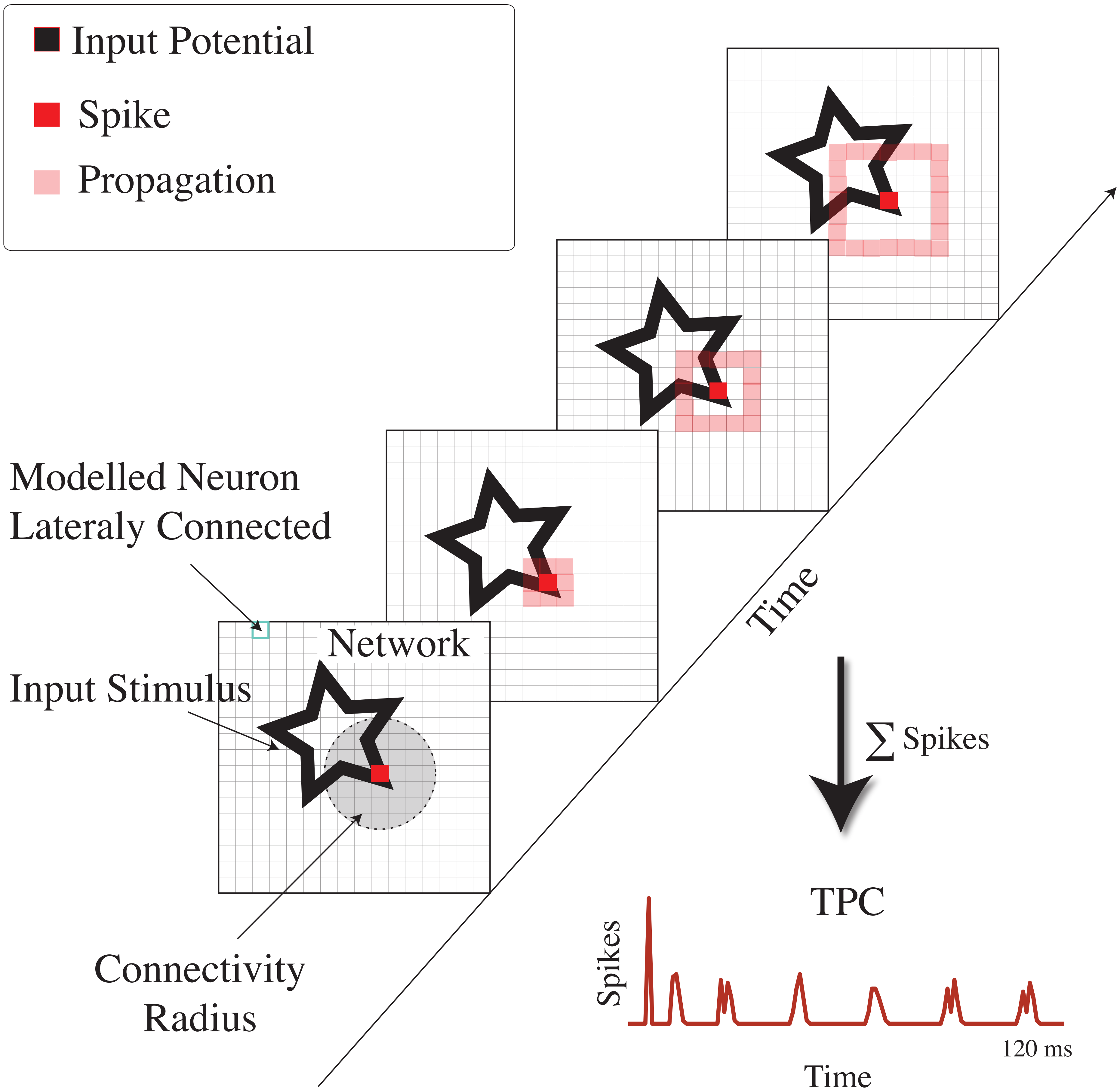


V1 TPC Model



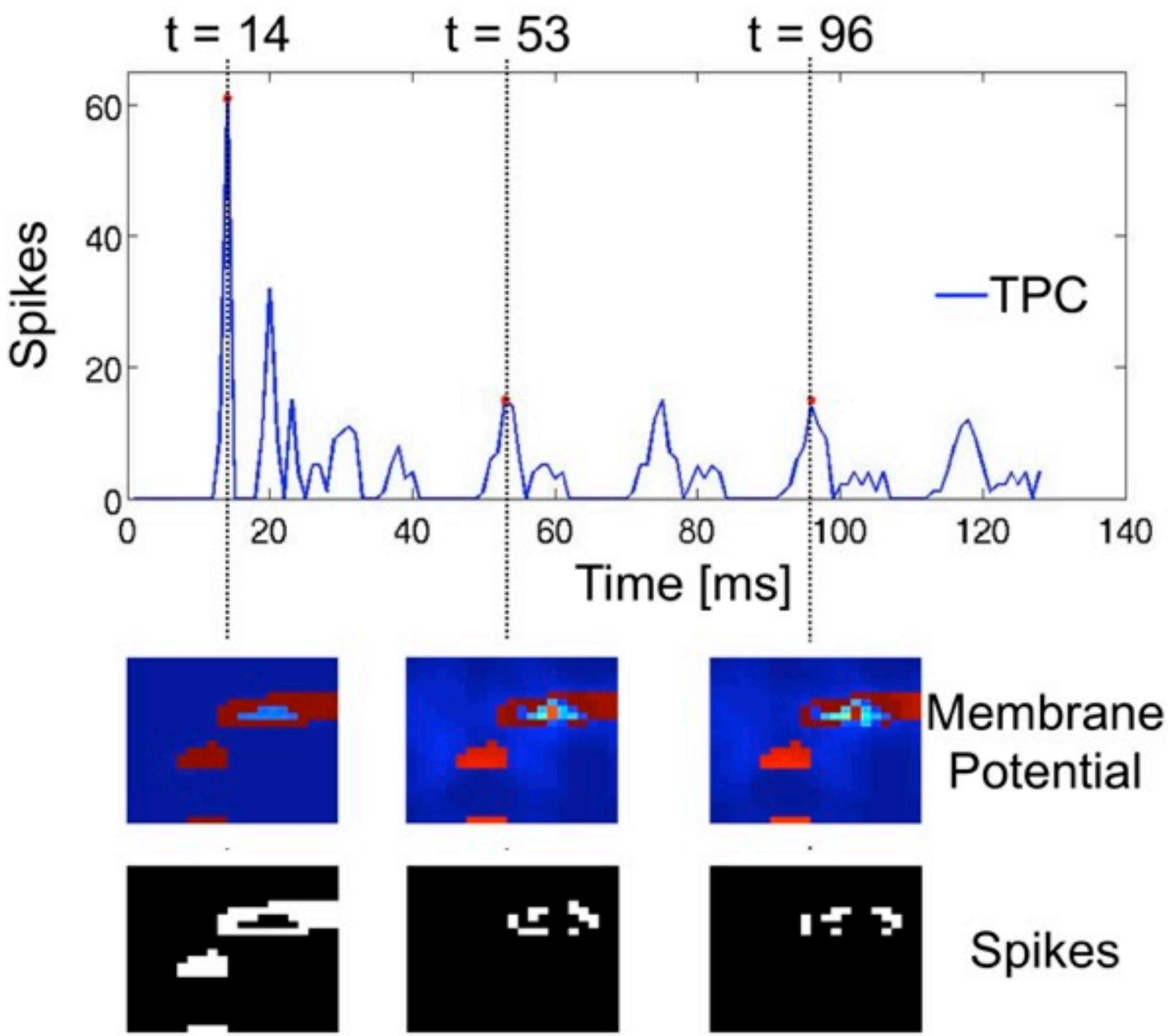
- Each orientation defines a population of pyramidal cells.
- R: radius (11) of connected cells in the same population.
- A neural representation in which information is conveyed by relative amounts of activity across multiple elements of an array.

Luvizotto et al (submitted)



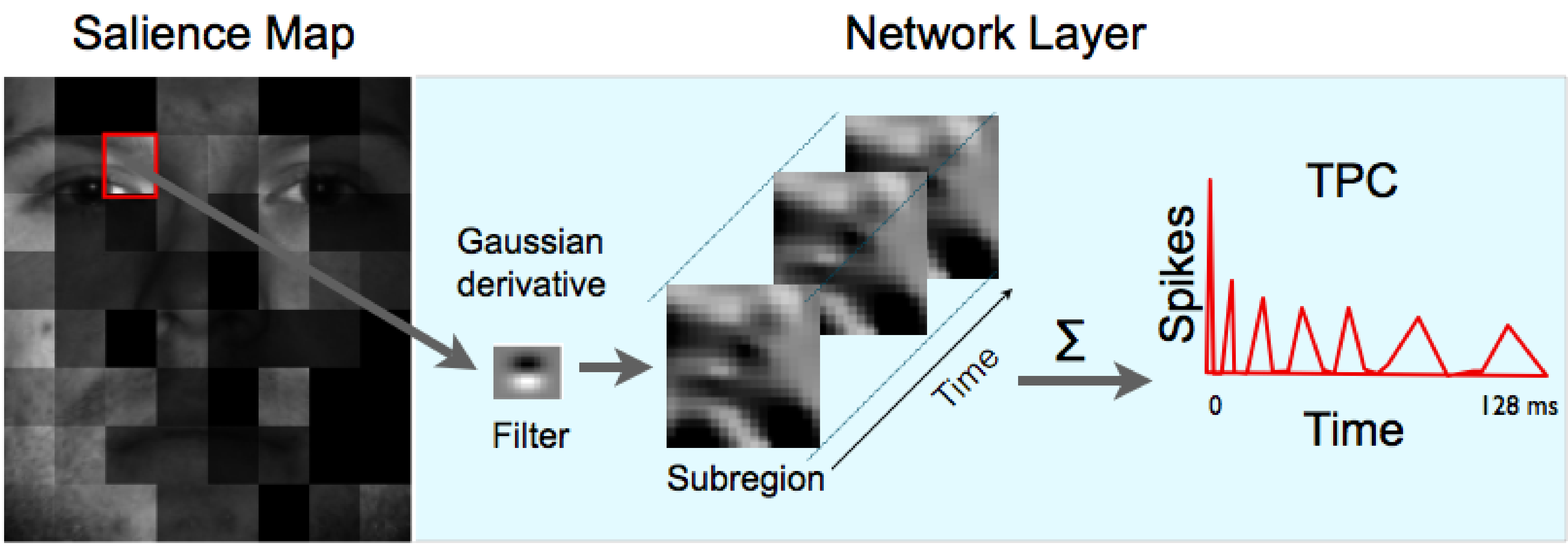
Luvizotto et al (submitted)

Network Responses



Luvizotto et al (submitted)

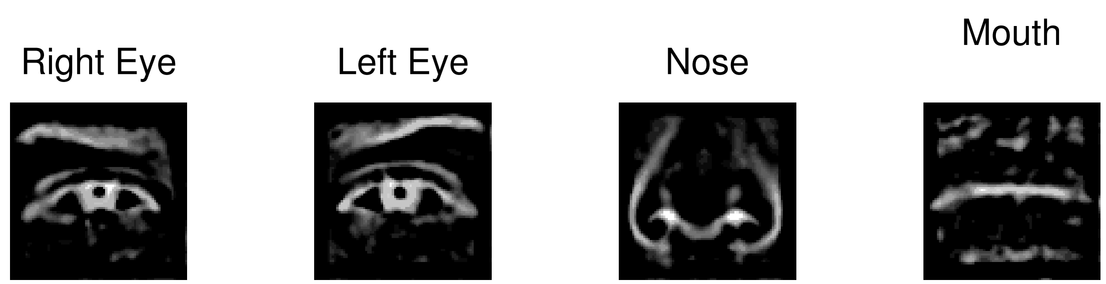
Attention based processing



Luvizotto et al (submitted)

Yale Face Database

(a)

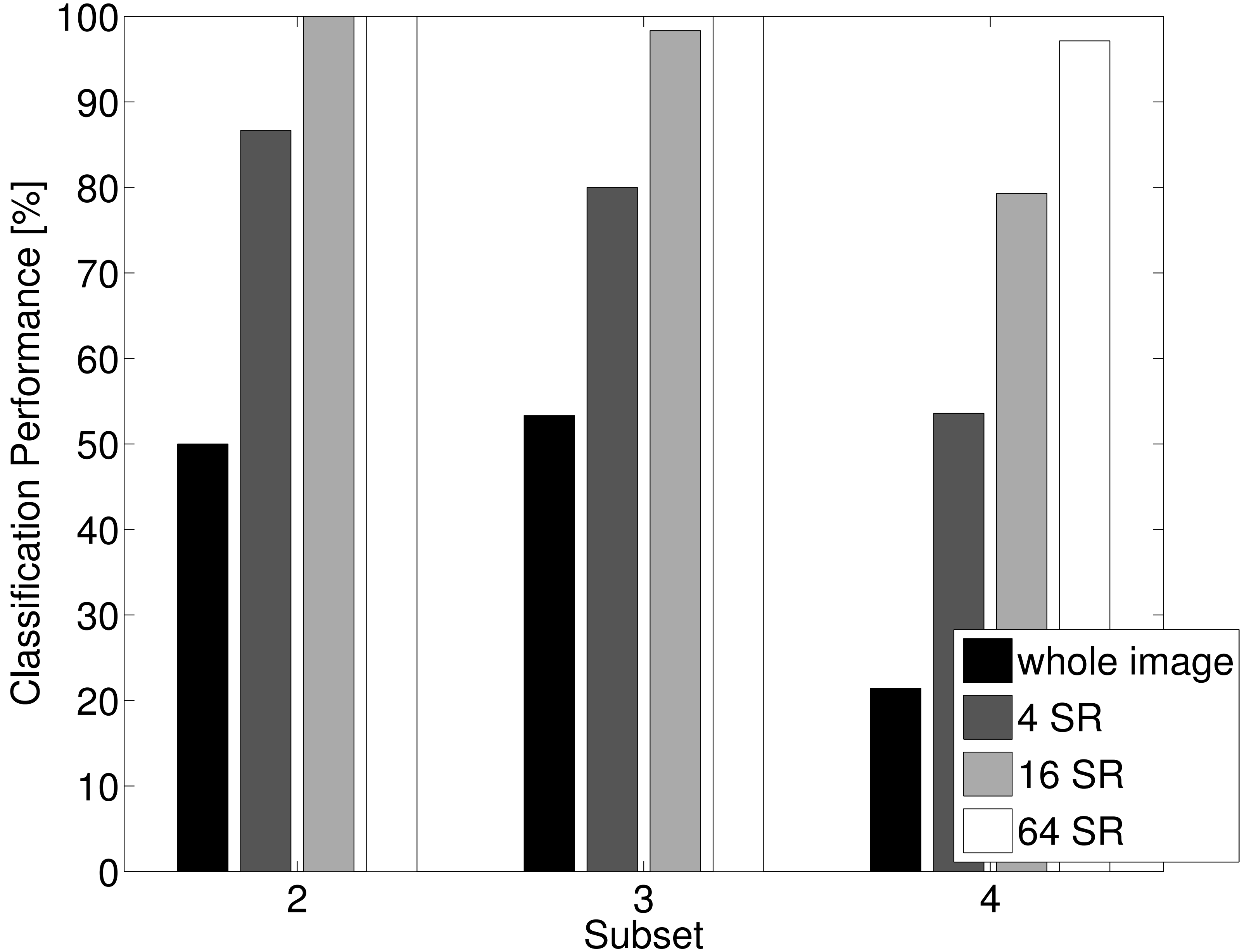


(b) Subregions of the first face class.

- 10 subjects
- 4 subsets of increasingly difficult light conditions.
- Standard face recognition data set.

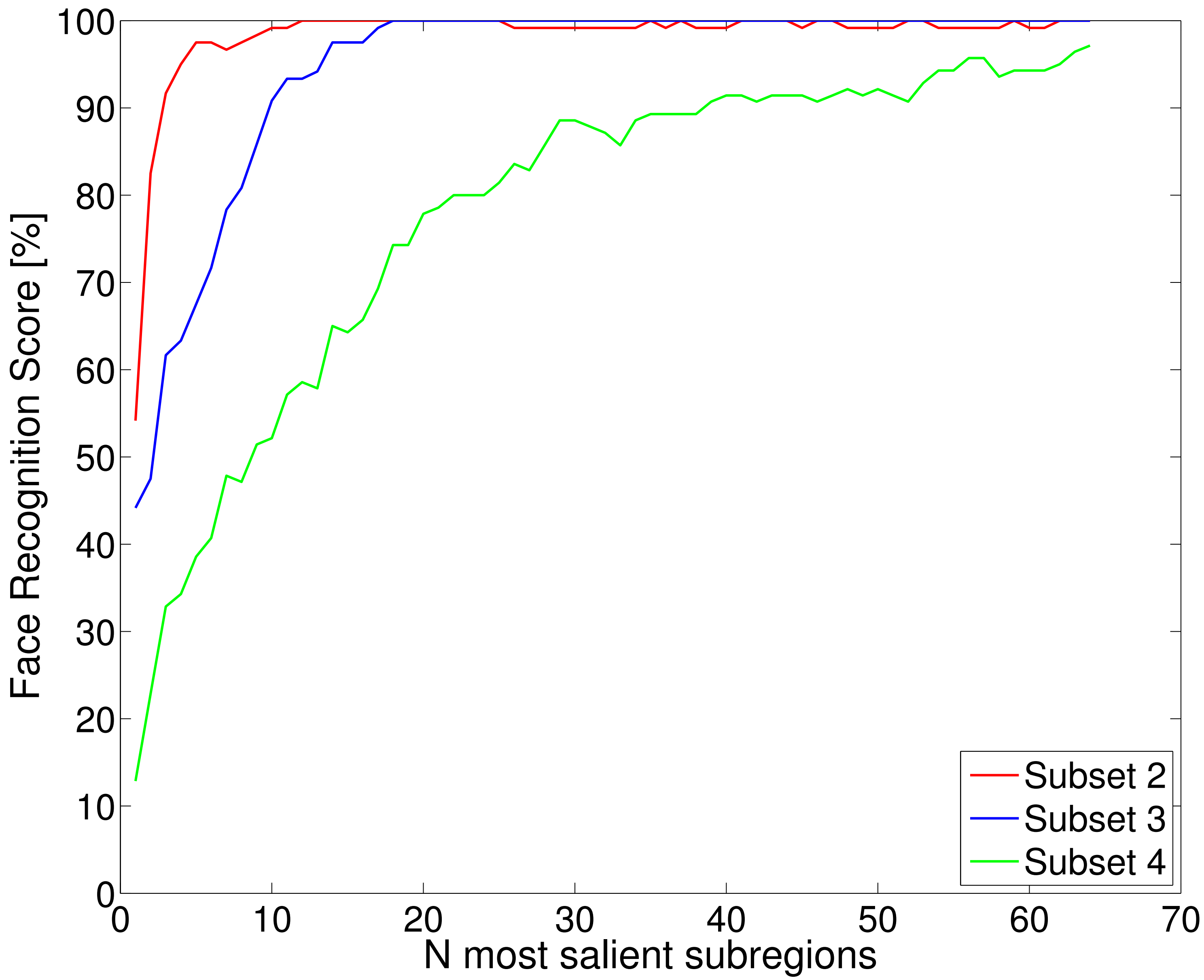
Luvizotto et al (submitted)

Performance



Luvizotto et al (submitted)

Performance



Method	Classification (%) vs. Ilum.		
	ss1 & ss2	ss3	ss4
Correlation	100.0	76.7	23.7
Eigenfaces	100.0	74.2	24.3
Cones-attached	100.0	100.0	91.4
TPC	**100.0**	**100.0**	**97.14**
9PL (simulated images)	100.0	100.0	97.2
9PL (real images)	100.0	100.0	100.0

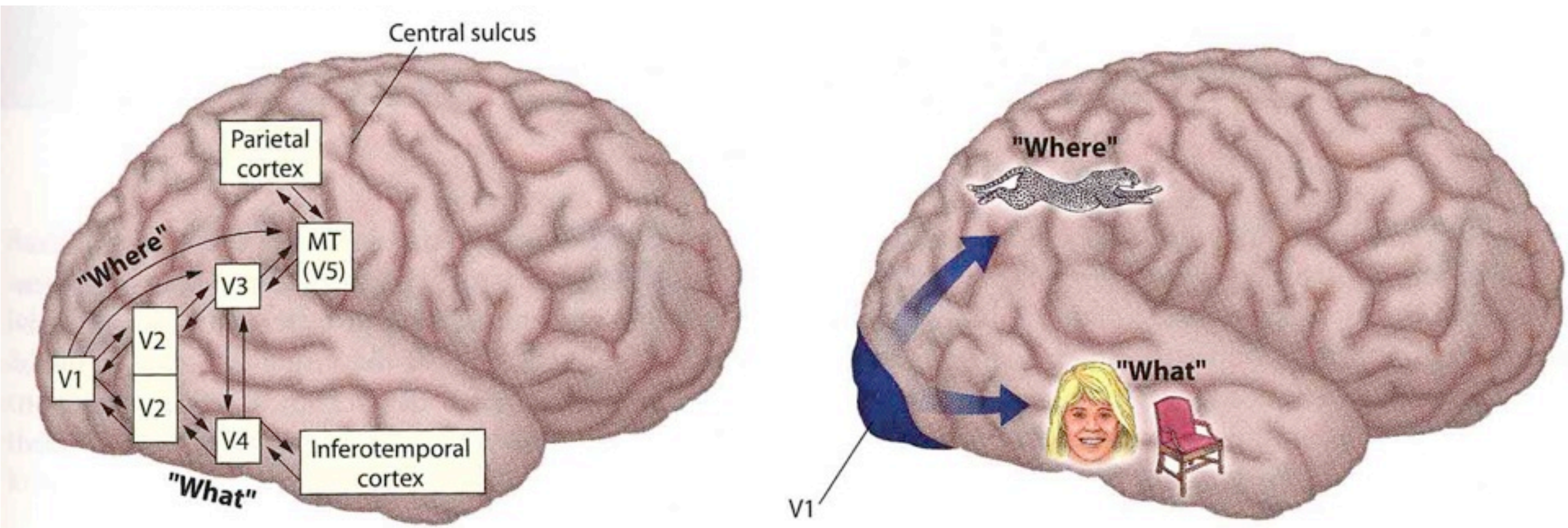
Lee, K. C., Ho, J. & Kriegman, D. Acquiring Linear Subspaces for Face Recognition under Variable Lighting. IEEE Trans.
Pattern Anal. Mach. Intelligence 27, 684–698 (2005).

Defining “**what**” using TPC

- TPC incorporates basic wiring templates of the cortex
- TPC aims at solving the basic inter-area wiring bottle neck
- TPC provides multiplexing
- Generalizes to face recognition
- Performance depends on active input sampling: attention

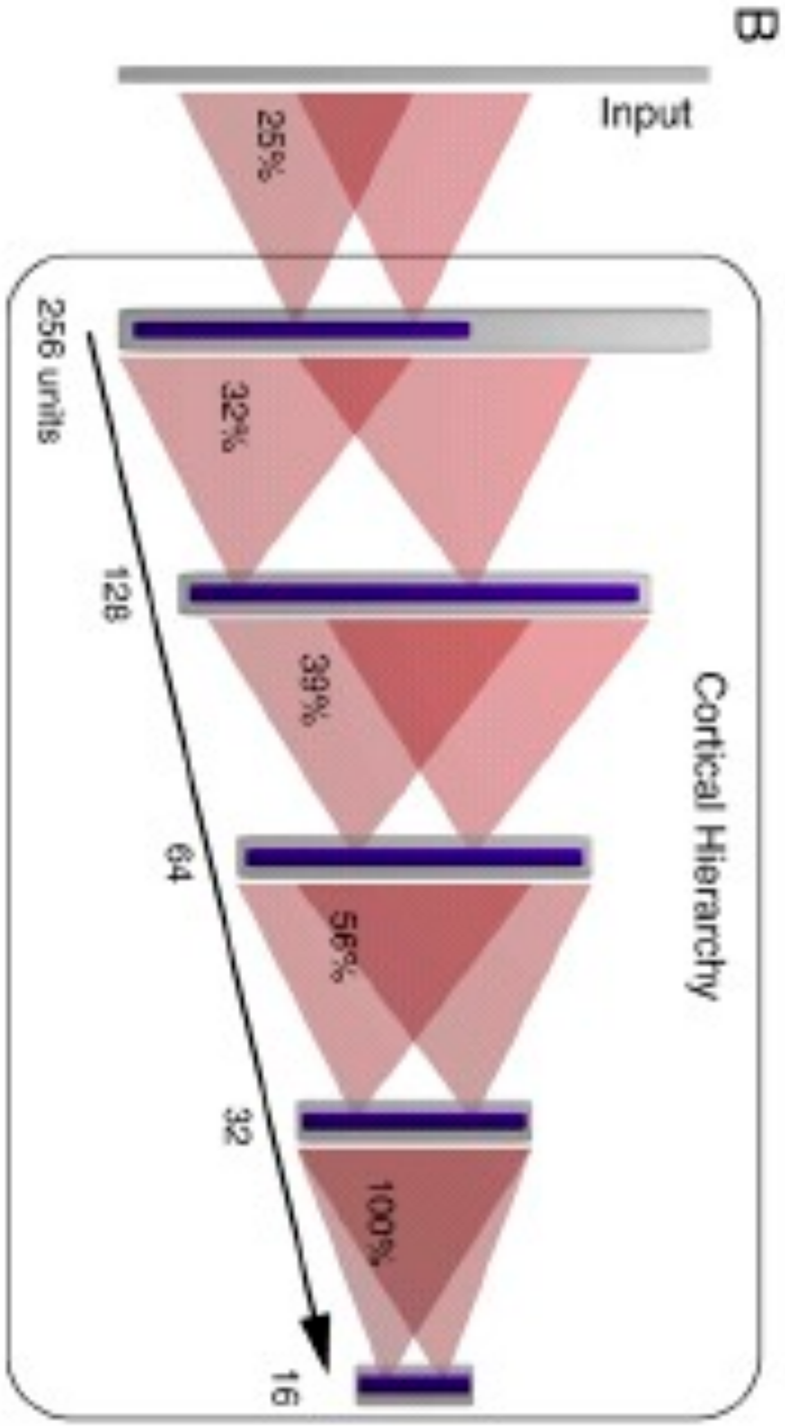

10

How to wire up the visual hierarchy?



specs.upf.edu

A model of the ventral visual system:

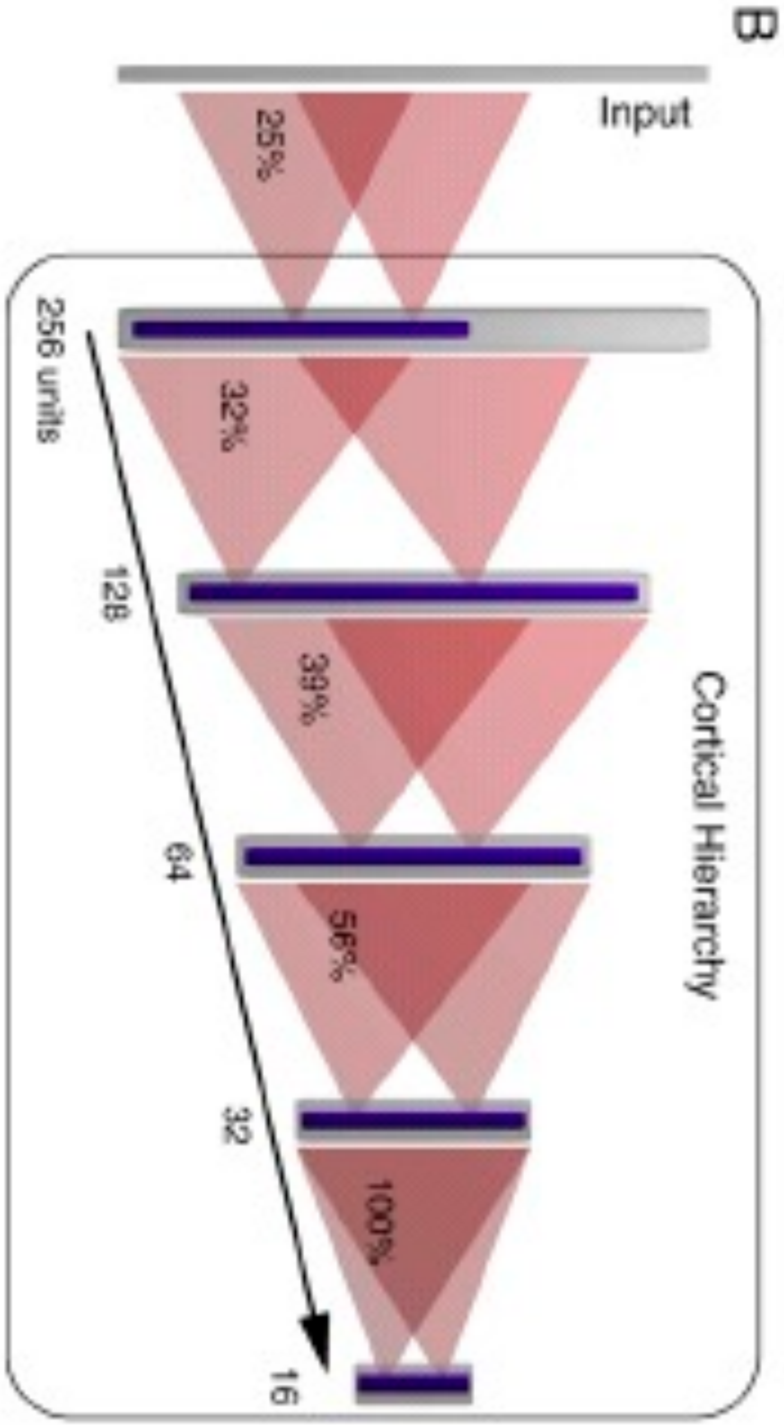


- Sparseness: Learning sparse codes explains simple cell receptive fields in V1 (Olshausen 1996) and the formation of adequate auditory filters (Lewicki 2002).

- Stability: Optimizing for temporal stability in visual system leads to invariant representations similar to V1 complex cells (Kayser 2001, Einhäuser 2003, Körding 2003, Berkes 2003, Wyss).

Wyss et al, 2006, Public Library of Science

Objectives: stability and decorrelation



$$\Psi = (1-\gamma)\Psi_{stab} + \gamma\Psi_{decor}$$

Stability:

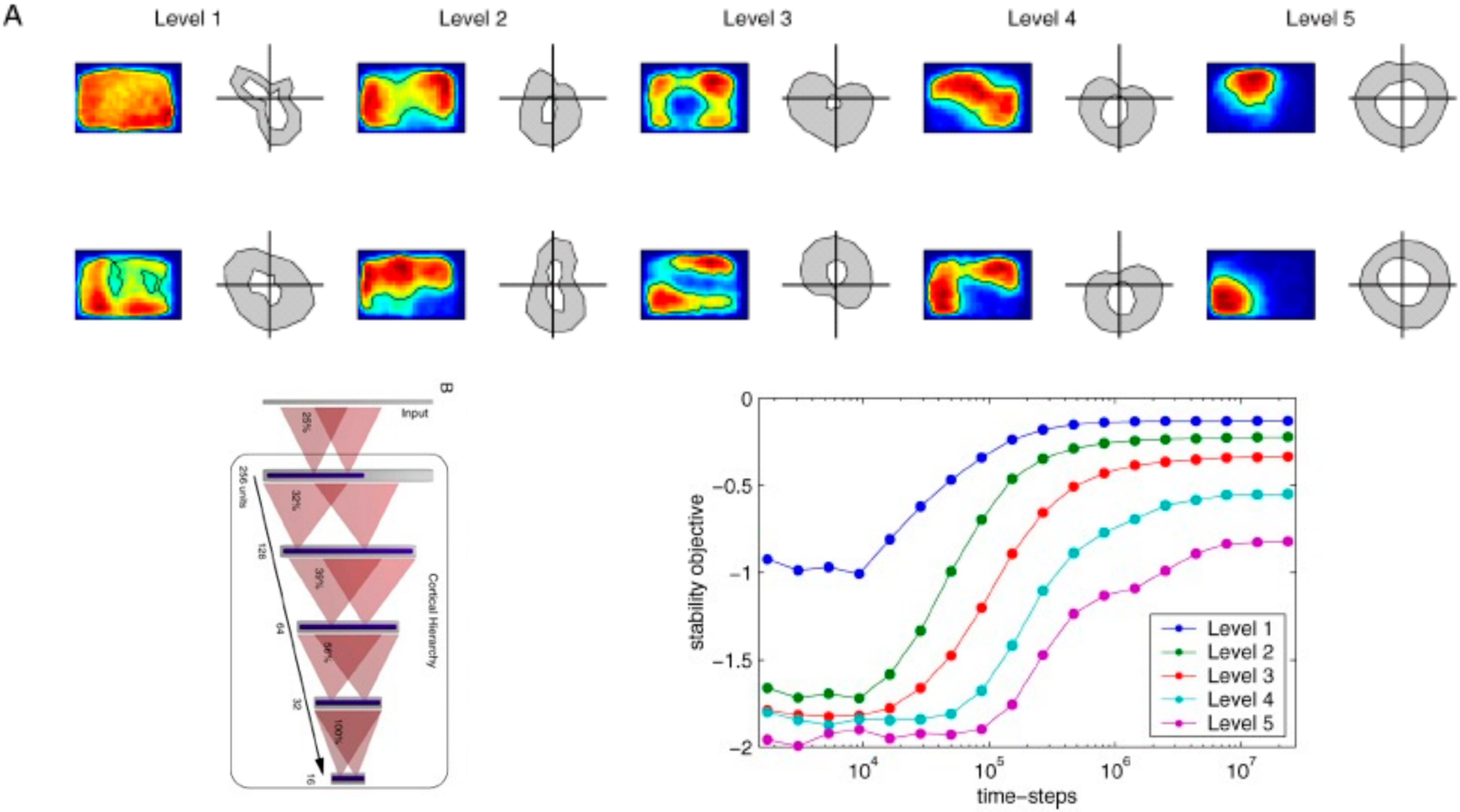
$$\Psi_{stab} = -\sum_i \frac{\left\langle \dot{A}_i^{2} \right\rangle_t}{\mathrm{var}_t(A_i)}$$

Decorrelation:

$$\Psi_{decor} = -\sum_i \sum_{i\neq j} \left(\rho_{ij}(A_i, A_j)\right)^2$$

Wyss et al, 2006, Public Library of Science

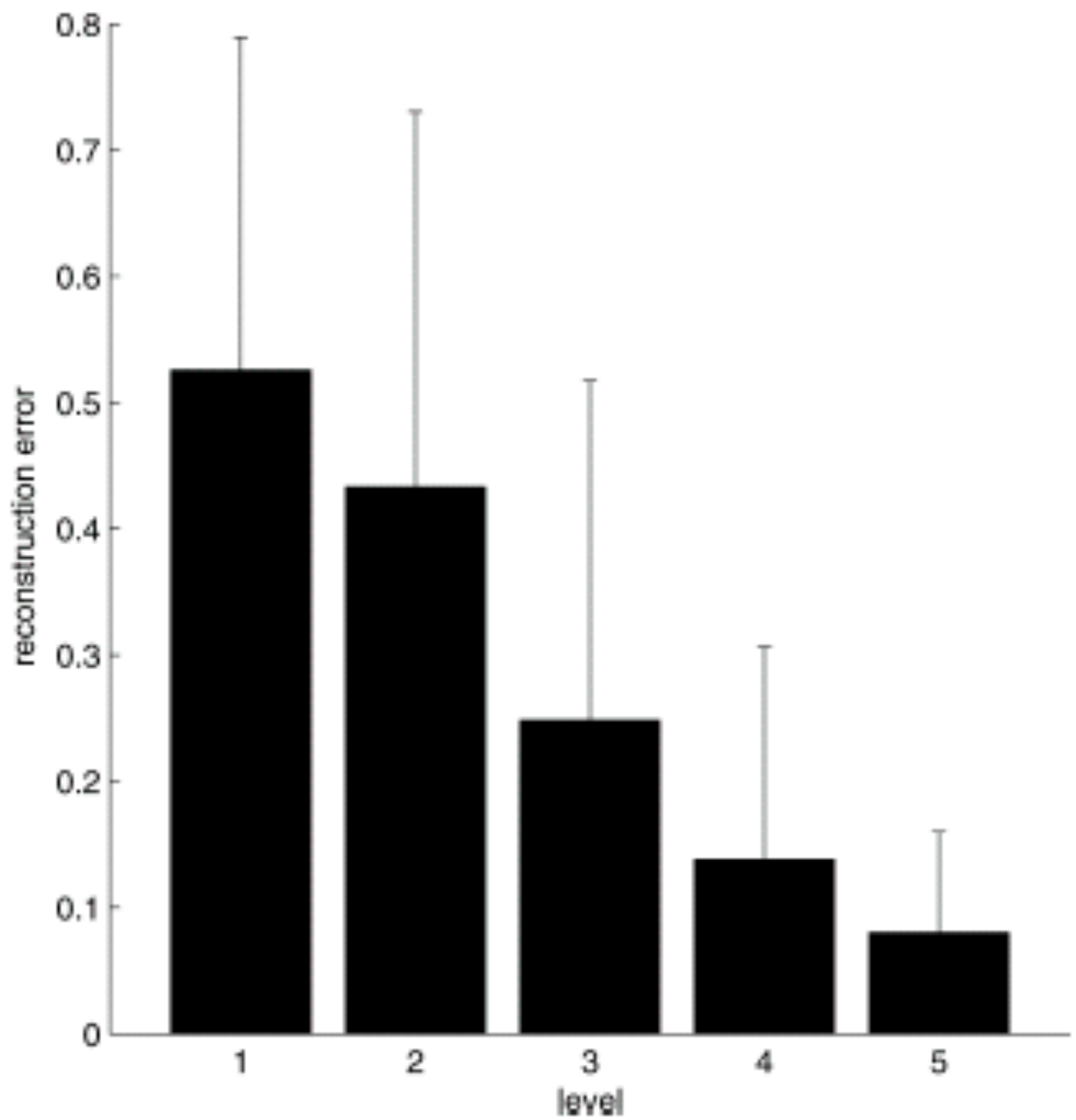
Hierarchy of representations

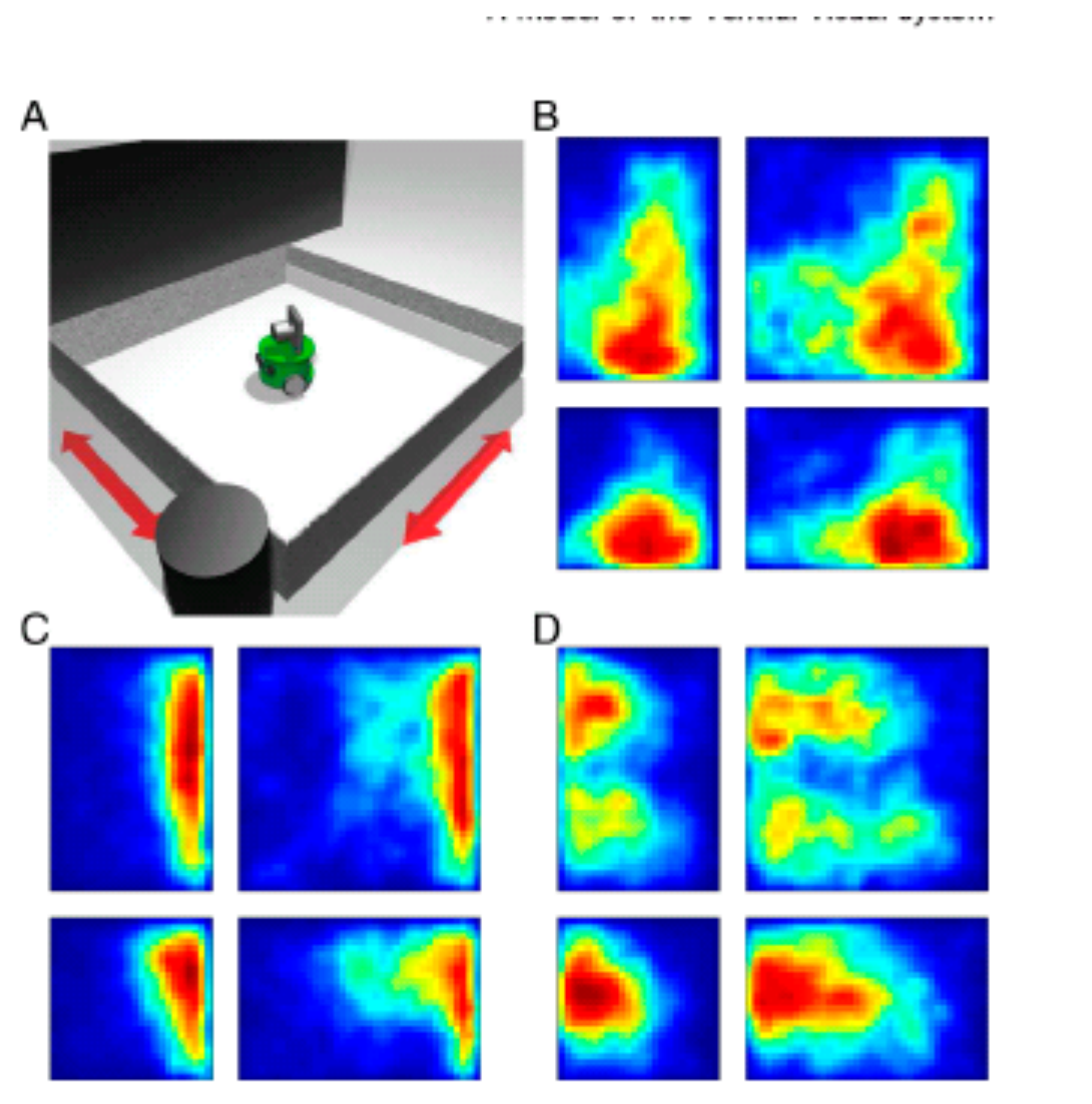


Wyss et al, 2006, Public Library of Science

specs.upf.edu

Position reconstruction environment stretching





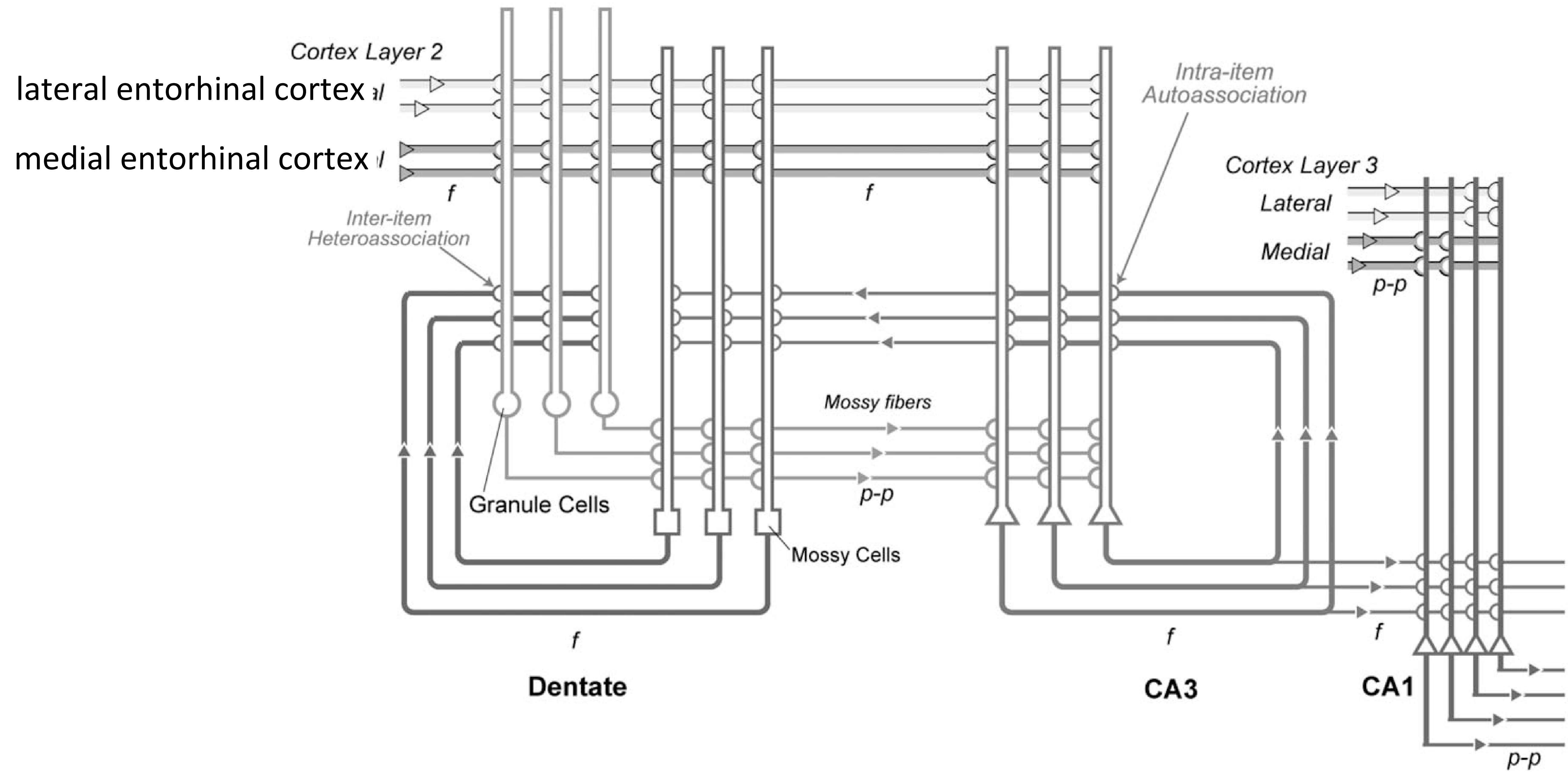
Wyss et al, 2006, Public Library of Science

Defining "**what**" using cortical networks

Complex real-world physiologically realistic representations can be acquired on the basis of few cortical-like rules:

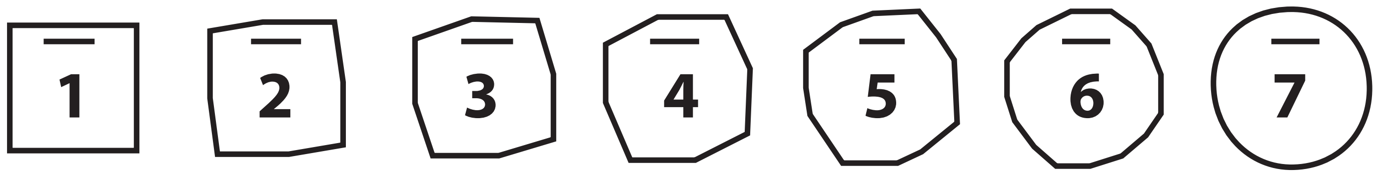
decorrelation & smoothness

Mixing **what** and **how** into sensori-motor couplets

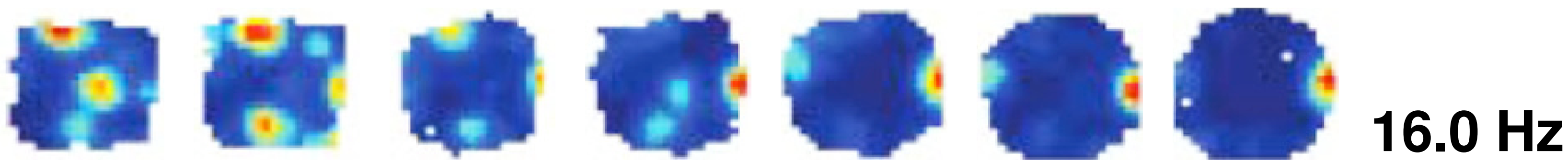


Lisman (2007) Prog in Br Res

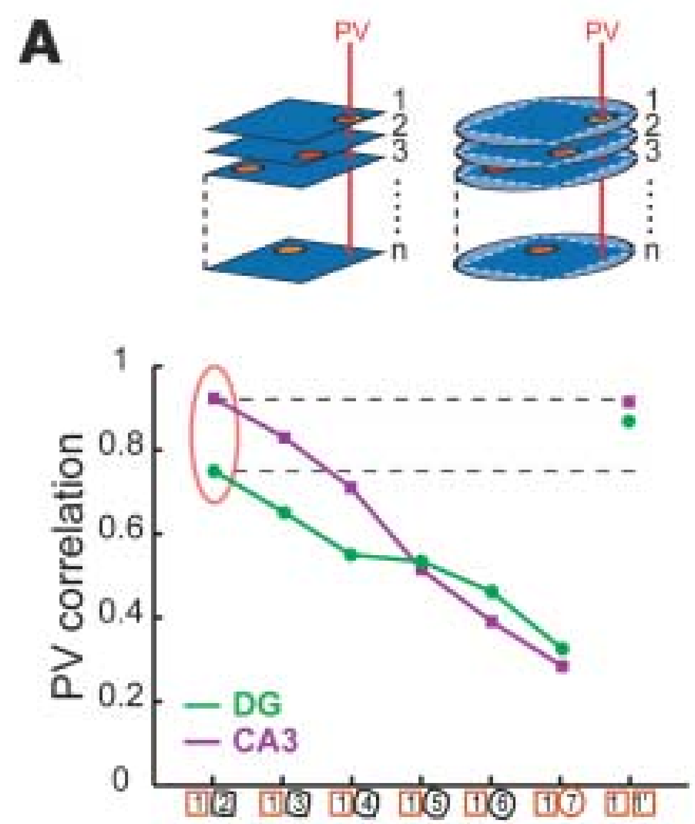
Rate remapping in the DG



(a)

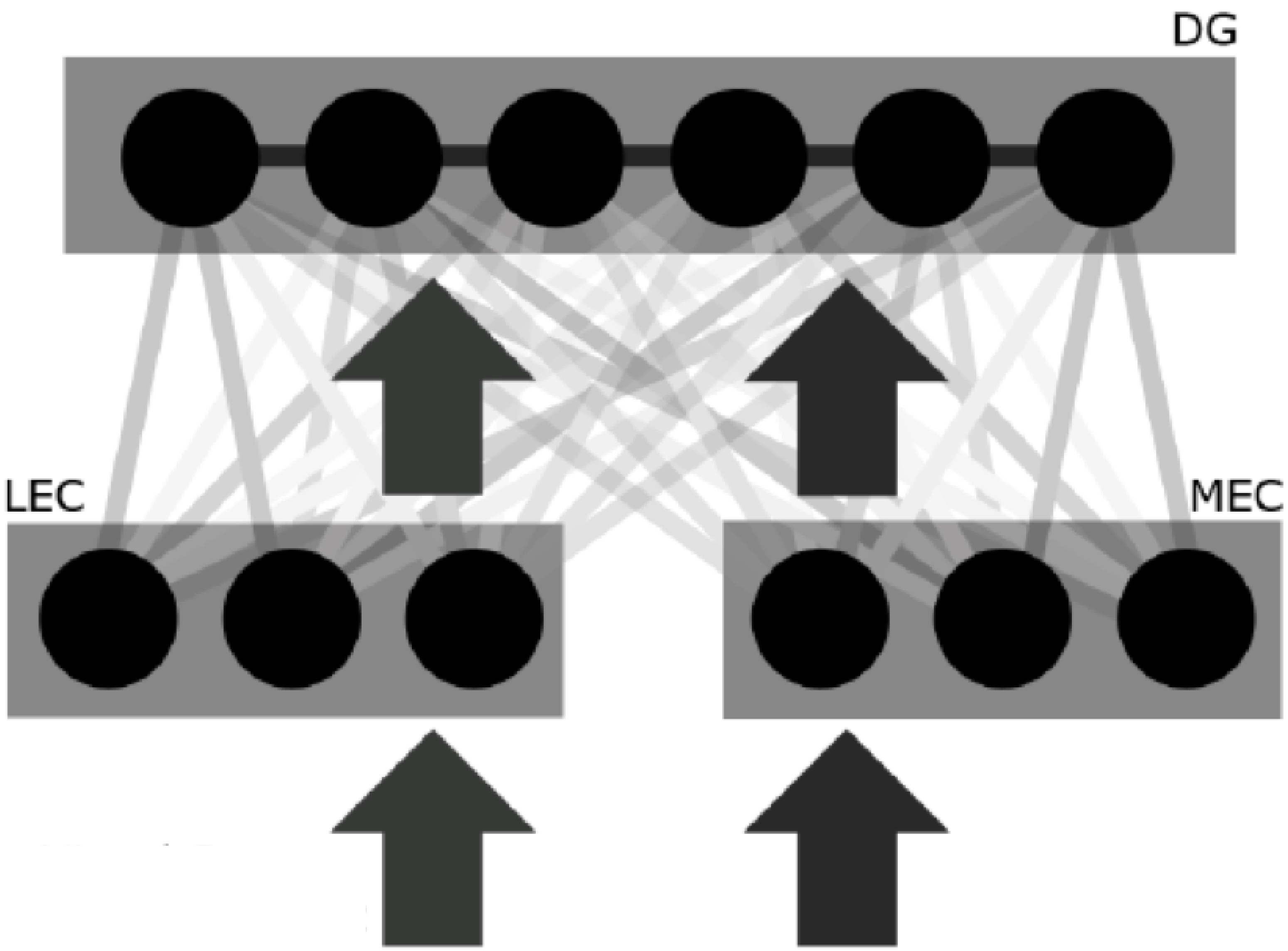


(b)



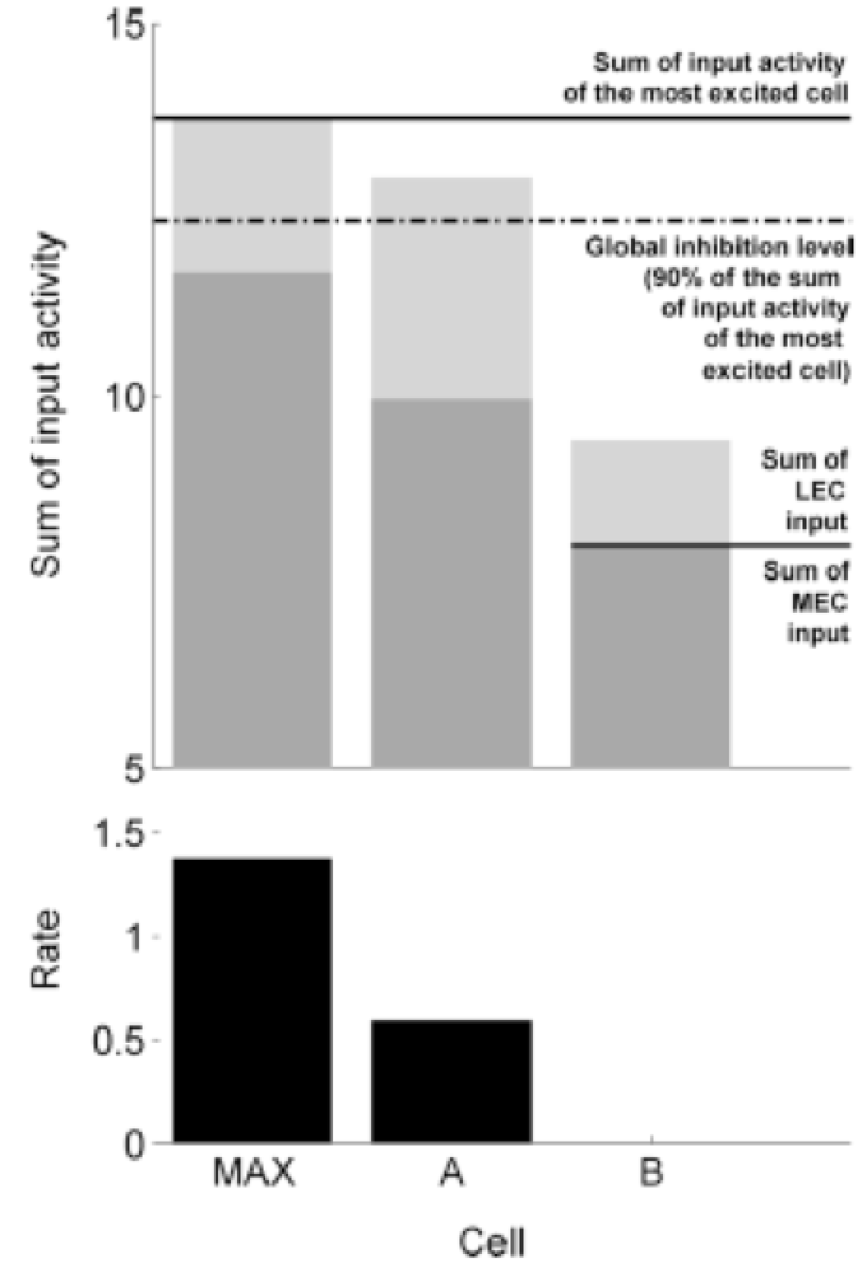
Leutgebetal., 2007, Science.

EC-DG Model



Vision

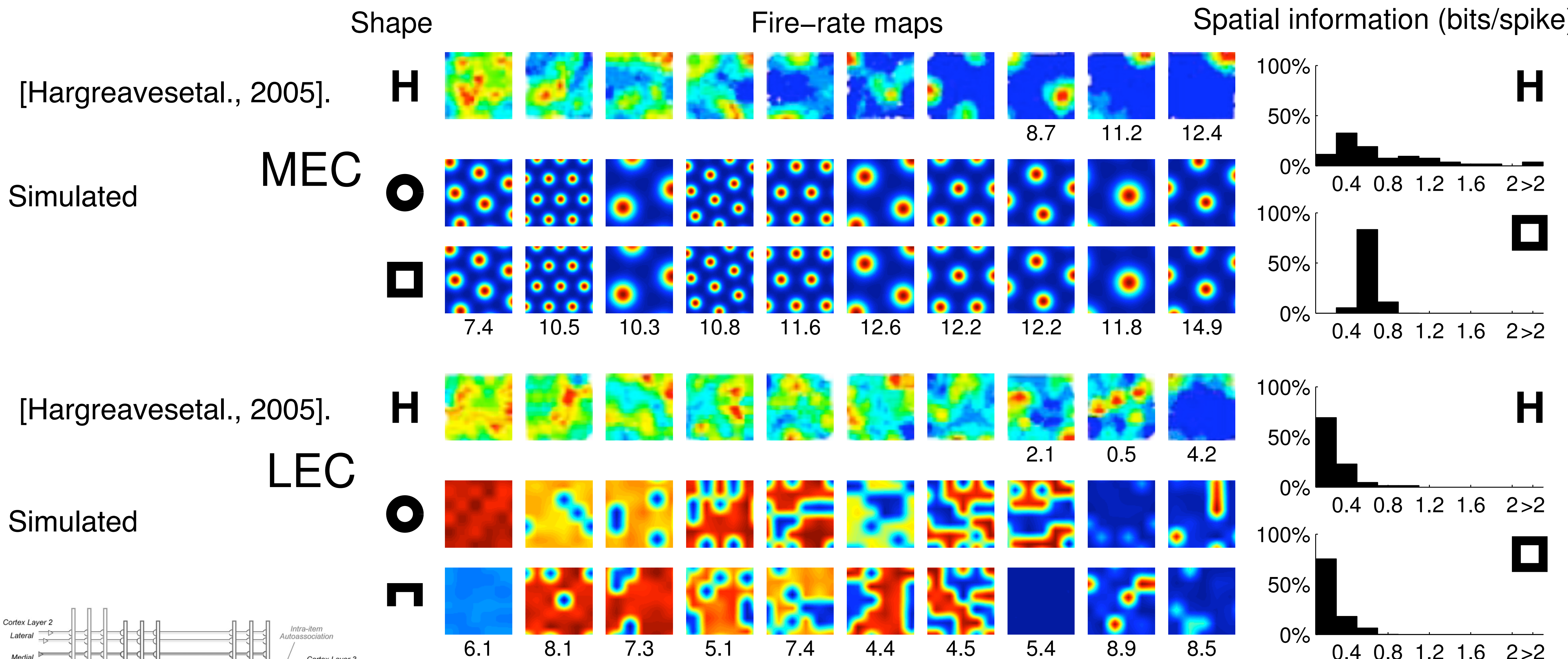
Path integration

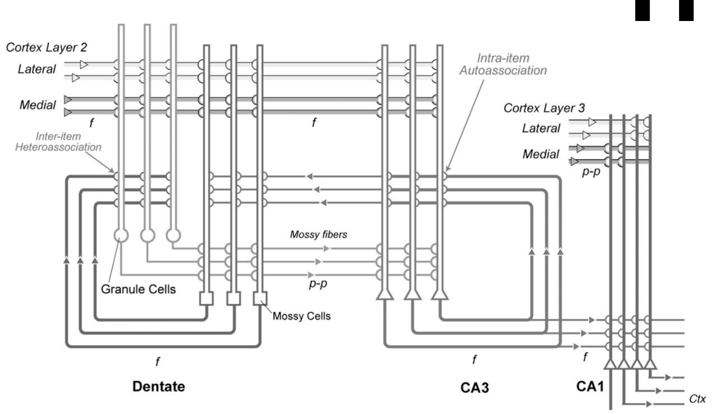


The E% MAX winner-take-all dynamics takes place in the DG

Reno Costa et al (2010) Neuron

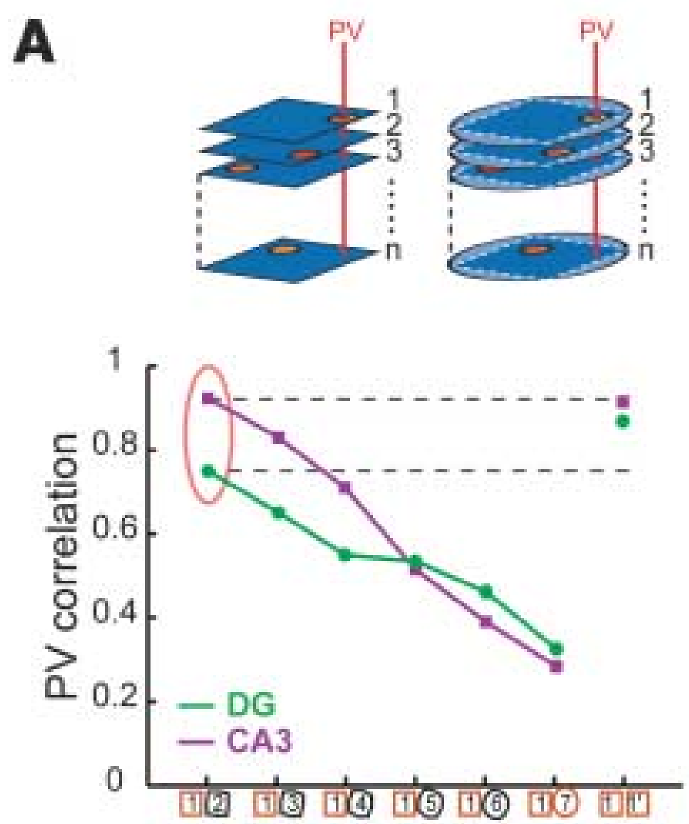
Rate remapping in the DG: LEC & MEC

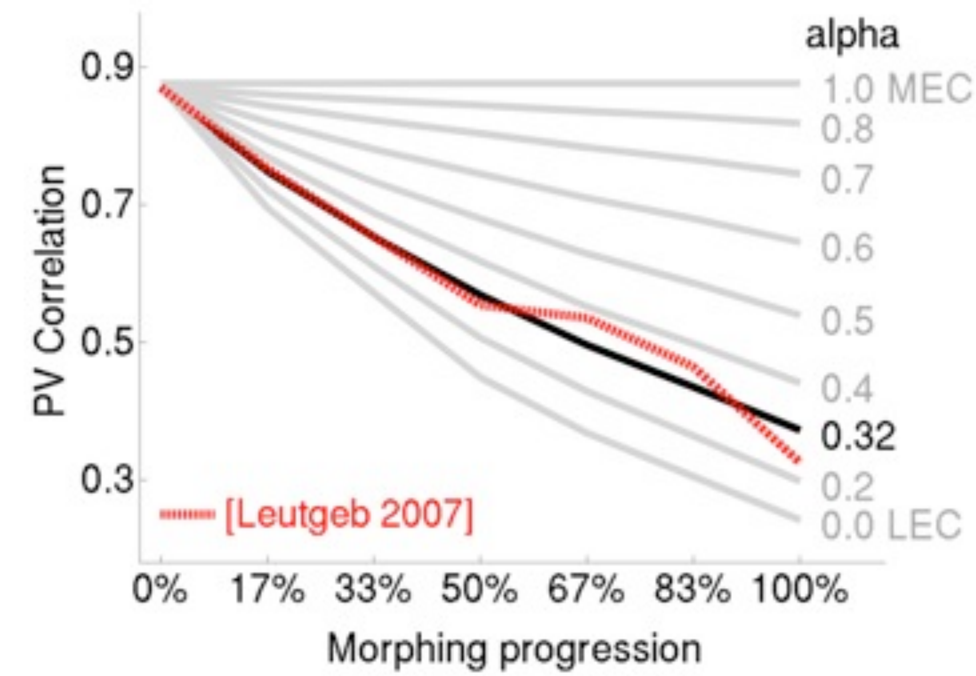


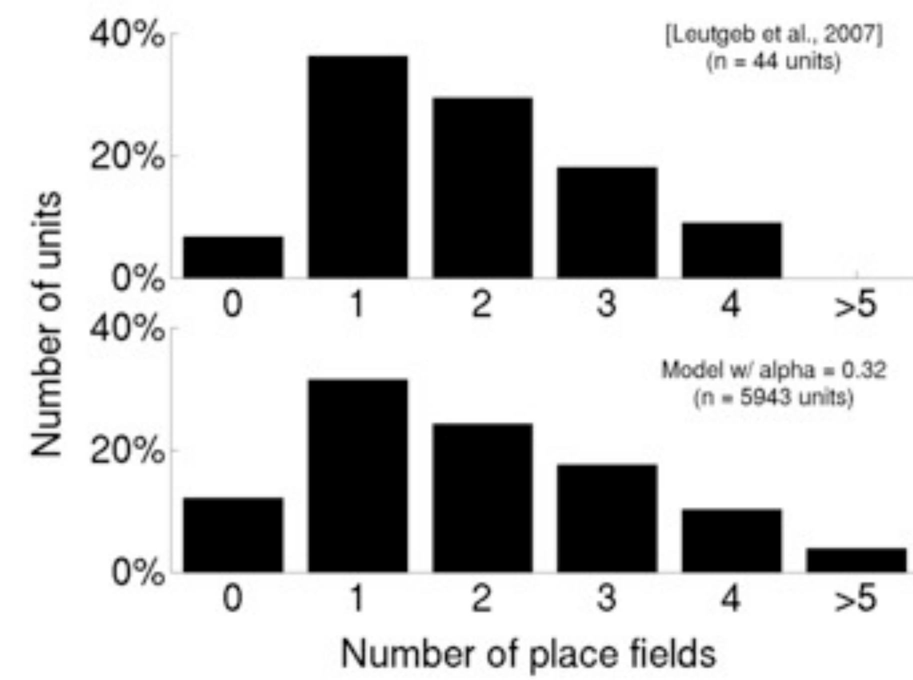


Reno Costa et al (2010) Neuron

DG forms sense-act couplets by instantaneous mapping of LEC and MEC inputs







Reno Costa et al (2010) Neuron

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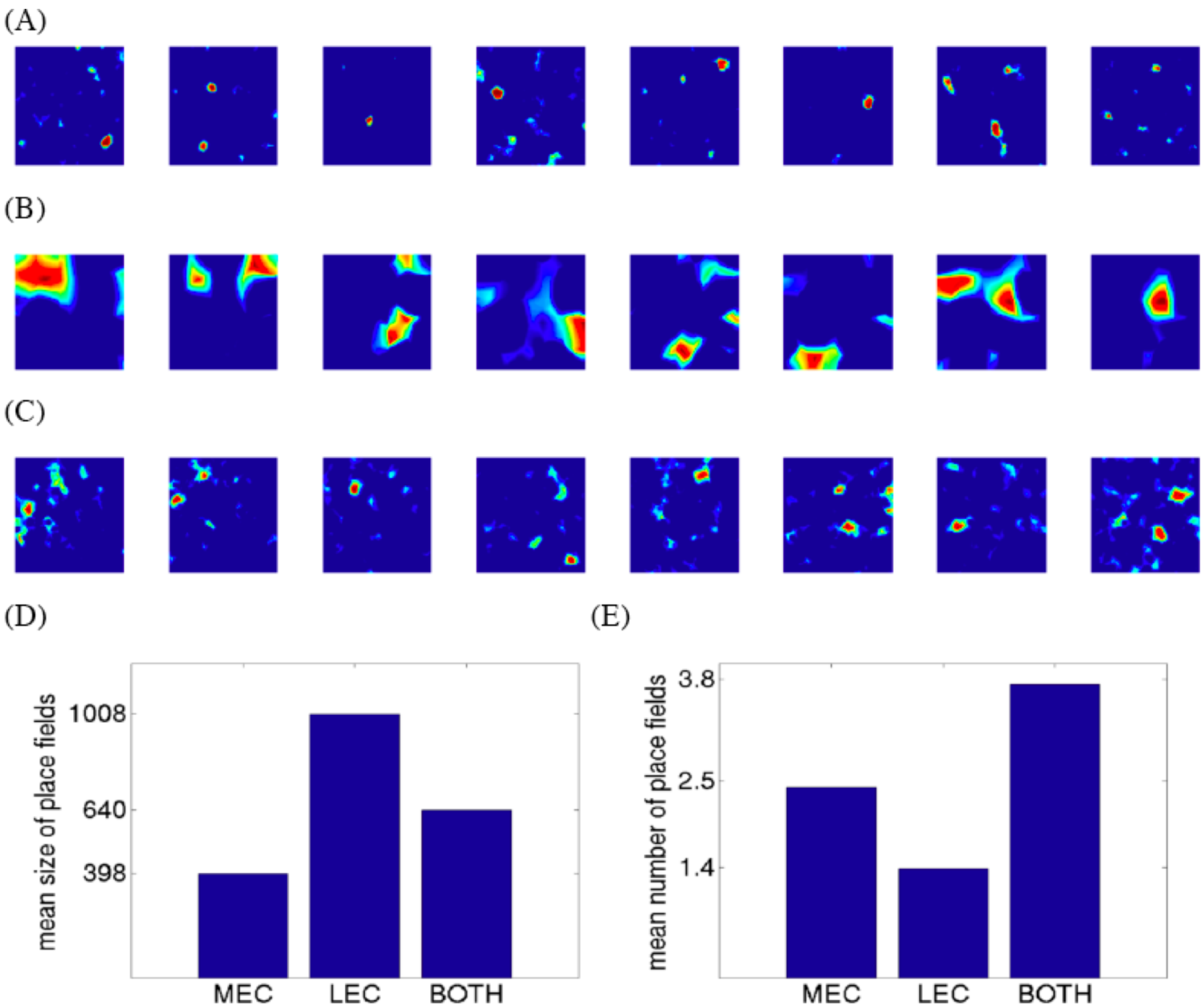


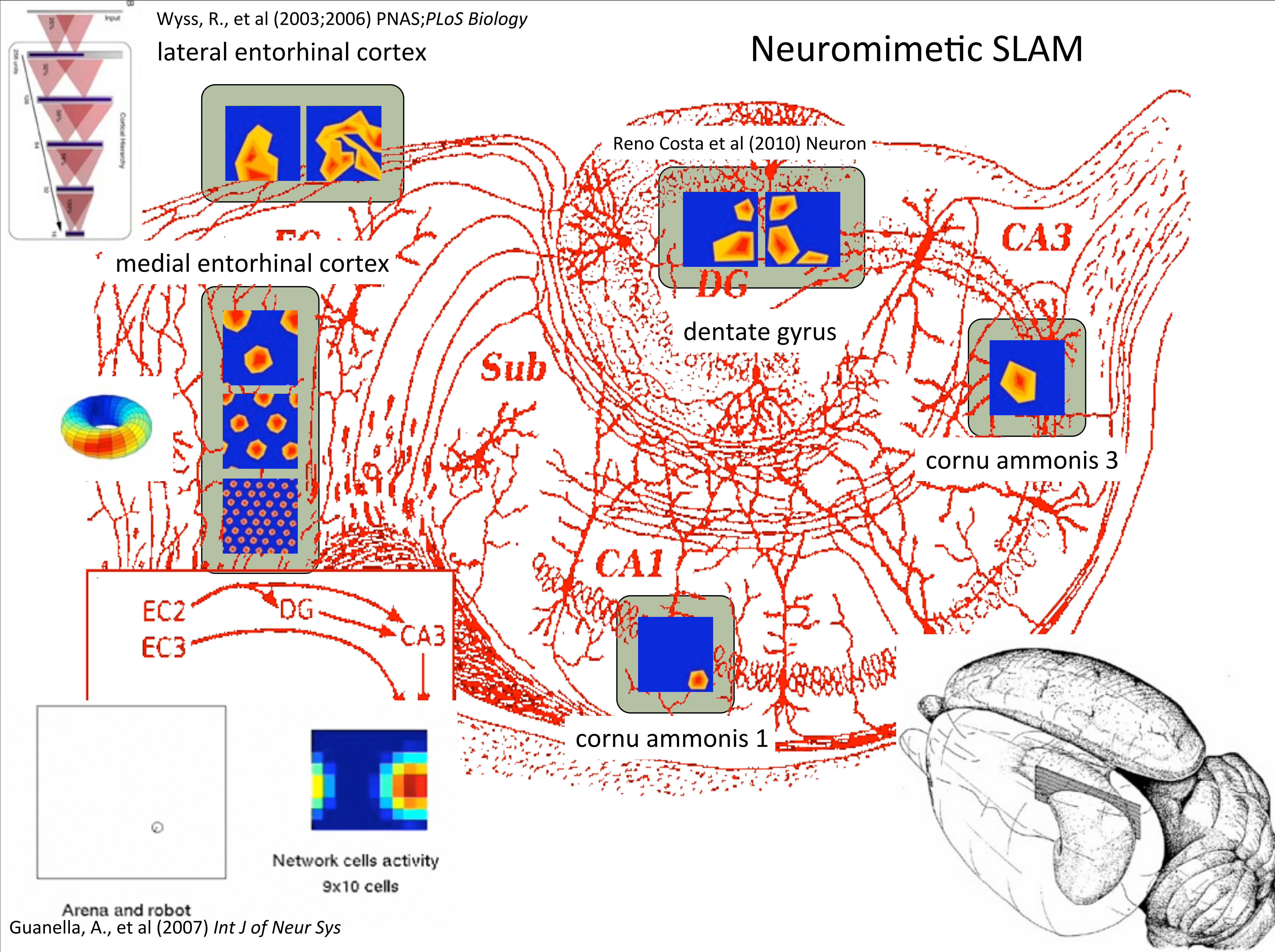
Place cells emerging from model interaction.

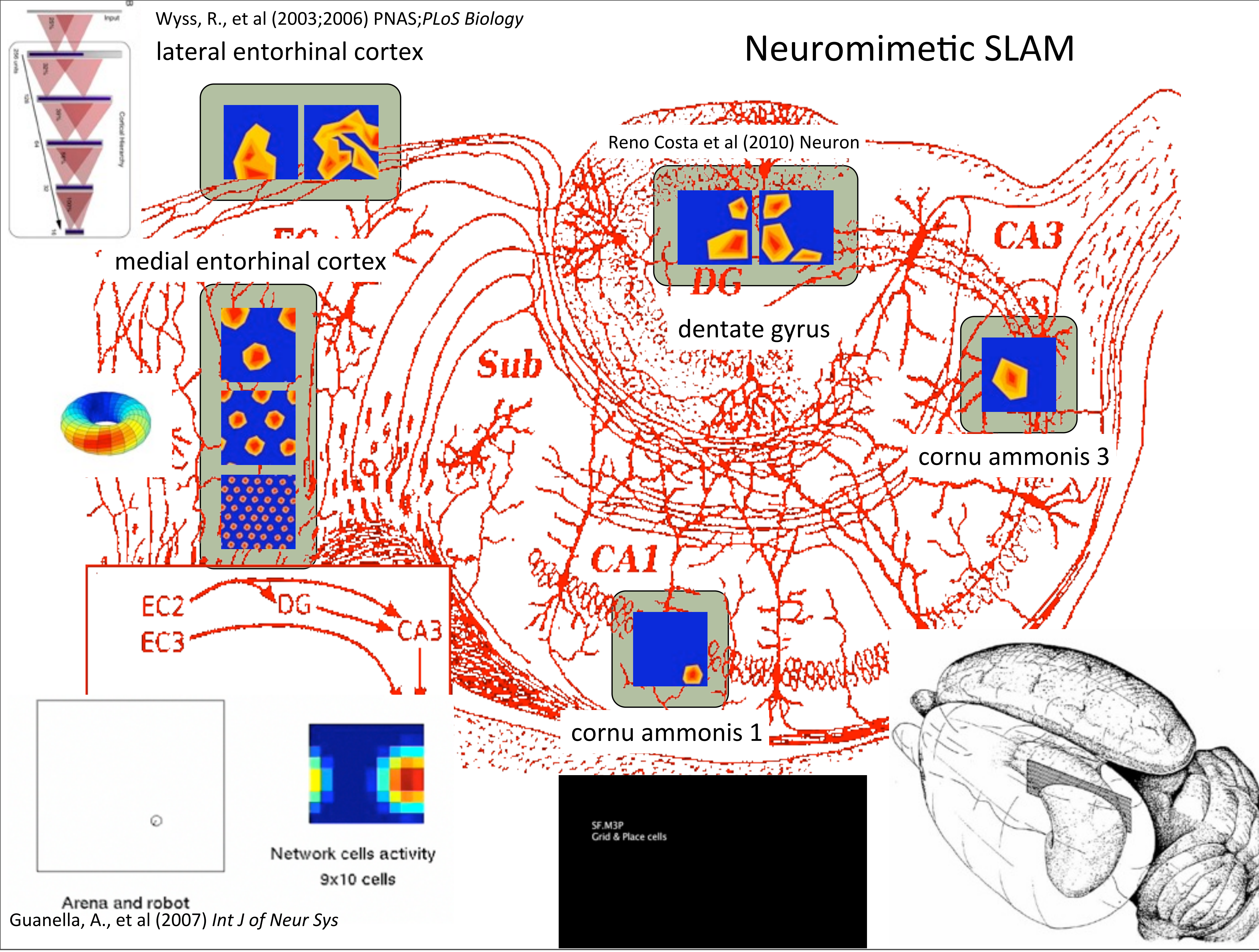
Rate map of simulated granule cells with:

(A)only MEC Input
(B)only LEC input
(C)both MEC and LEC inputs.

Reno Costa et al (2010) Neuron

Neuromimetic SLAM




Wyss, R., et al (2003;2006) PNAS;*PLoS Biology*
lateral entorhinal cortex
Neuromimetic SLAM
Reno Costa et al (2010) Neuron
medial entorhinal cortex
DG
dentate gyrus
CA3
Sub
cornu ammonis 3
CA1
EC2
EC3
DG
CA3
cornu ammonis 1
Network cells activity
9x10 cells
Arena and robot
SF.M3P
Grid & Place cells
Guanella, A., et al (2007) *Int J of Neur Sys*

Biological evidence for gradient based planning

Johnson & Redish (2007) J Neurosci

At a decision point place cell activity correlates with possible forward paths at the bifurcation

Biological evidence for gradient based planning

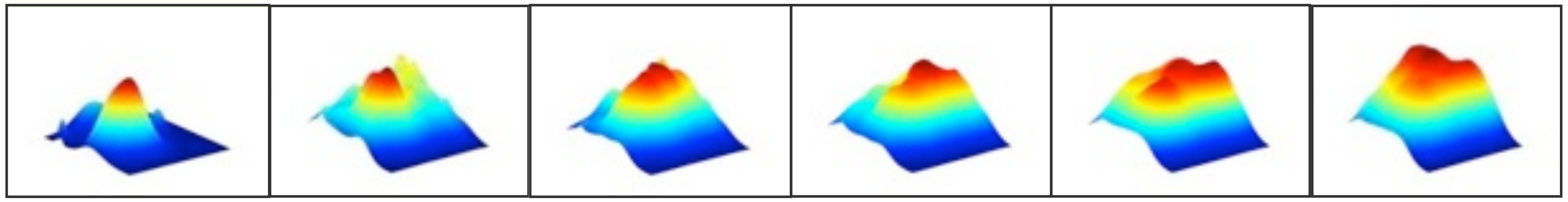
Johnson & Redish (2007) J Neurosci

At a decision point place cell activity correlates with possible forward paths at the bifurcation

Constructing gradients from a hippocampal cognitive map

- Can we dynamically build and modify gradients?

Sum of 2D Gaussians $f(x,y) = Ae^{-\left(\frac{(x-x_o)^2}{2\sigma_x^2}+\frac{(y-y_o)^2}{2\sigma_y^2}\right)}.$



Sanchez et al (2010) IROS

We can use Gaussians as being the basis for building gradients

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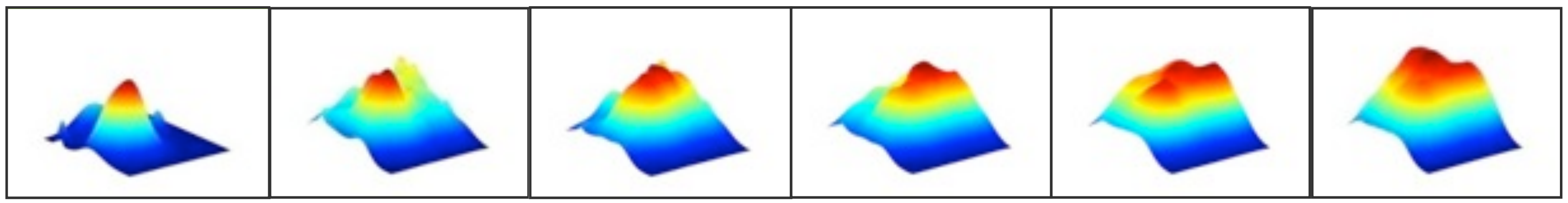
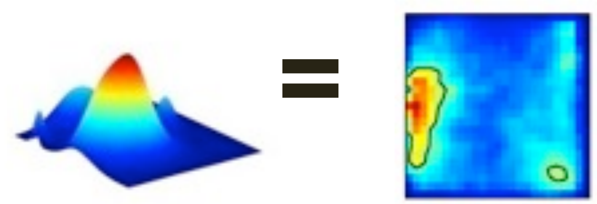


- Place/Grid Cells are often approximated by Gaussians



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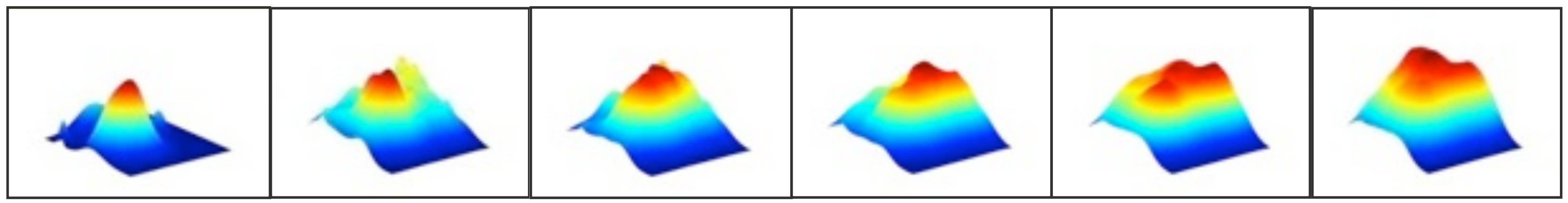

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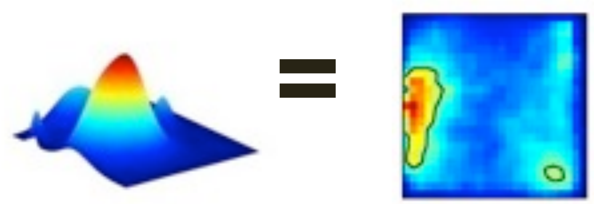
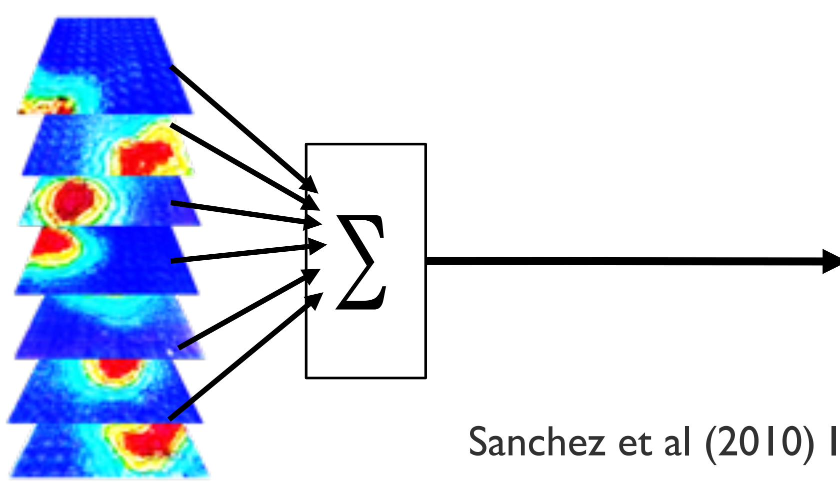
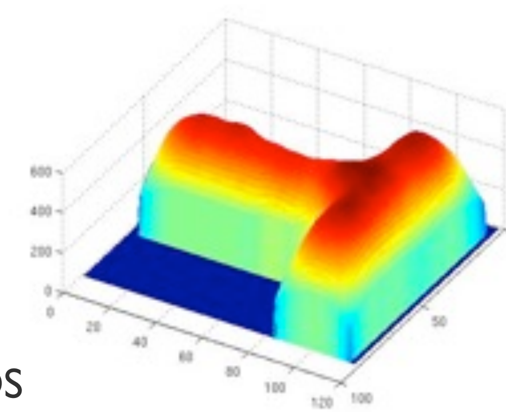


- Place/Grid Cells as basis function for generating Affordance Gradients





Sanchez et al (2010) IROS

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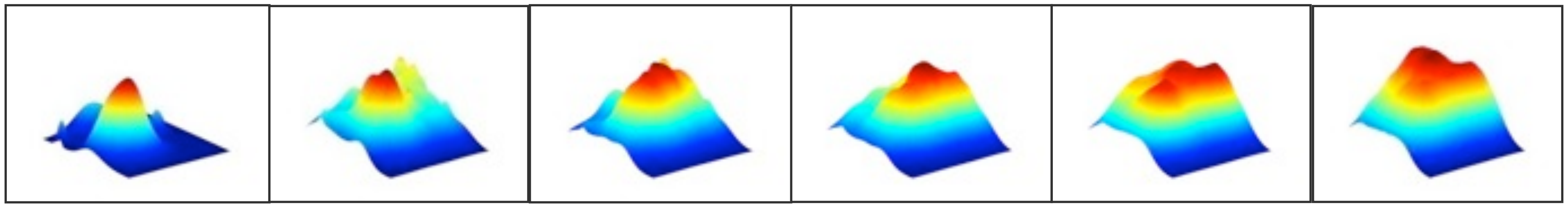

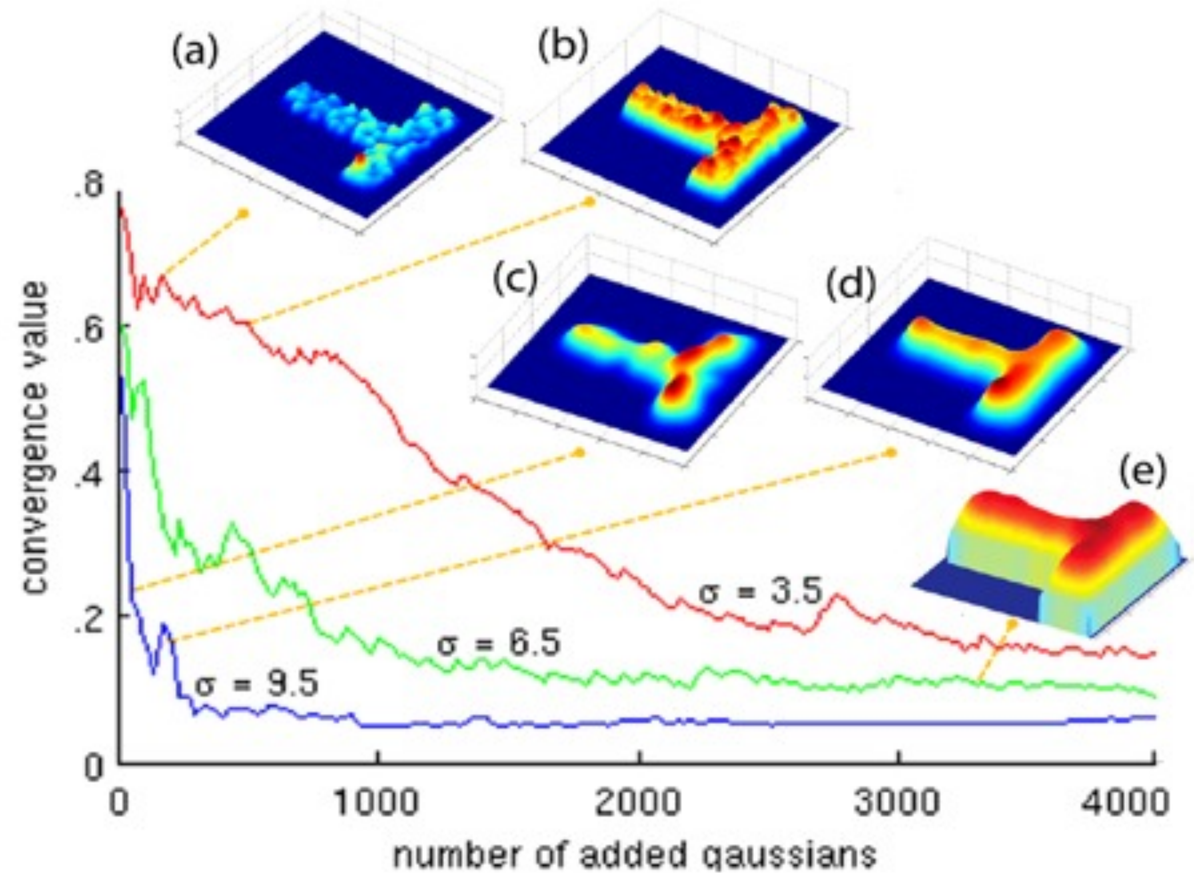

Sanchez et al (2010) IROS

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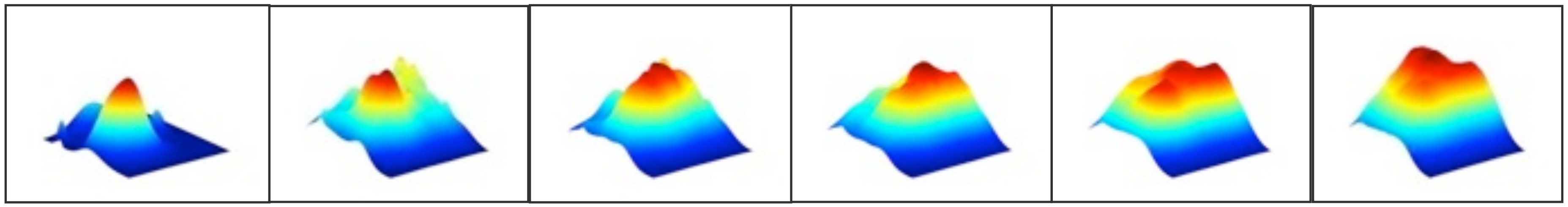
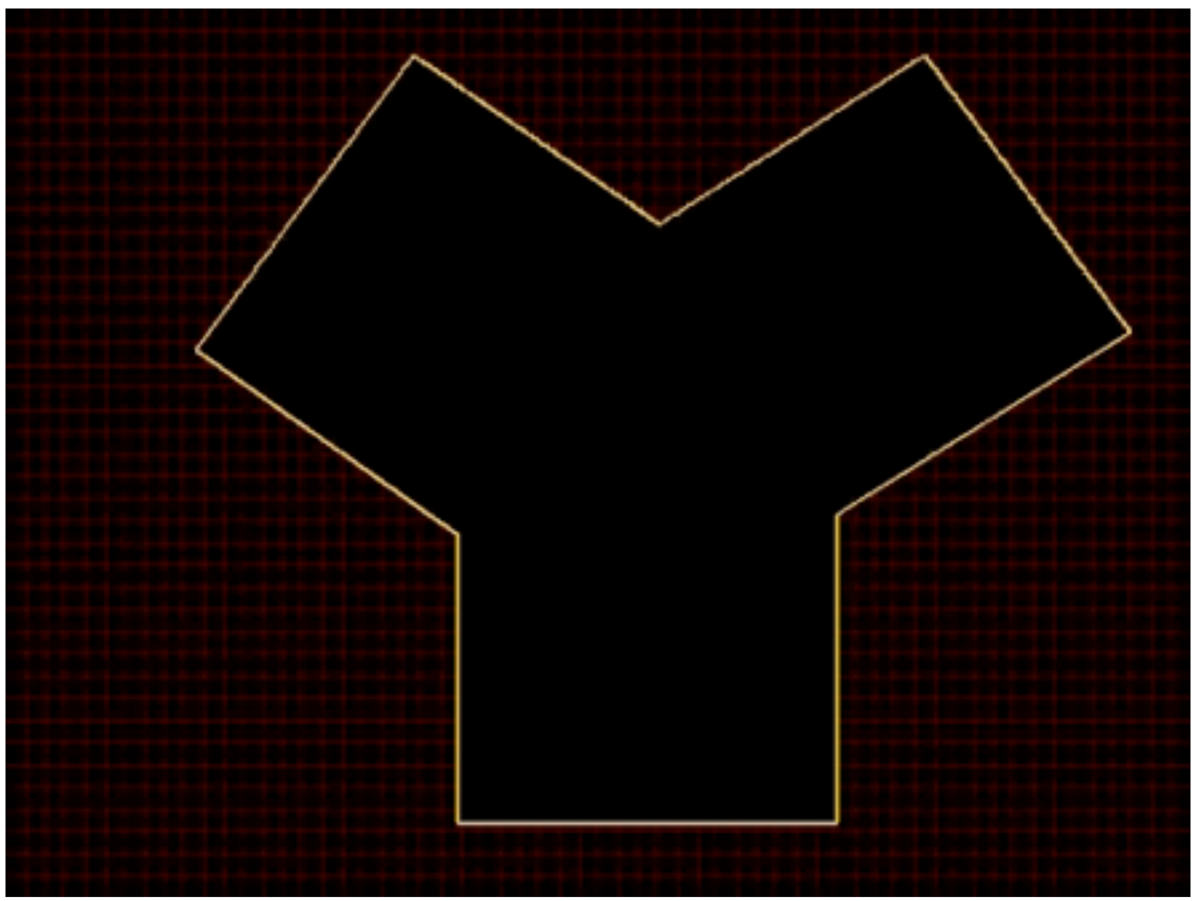
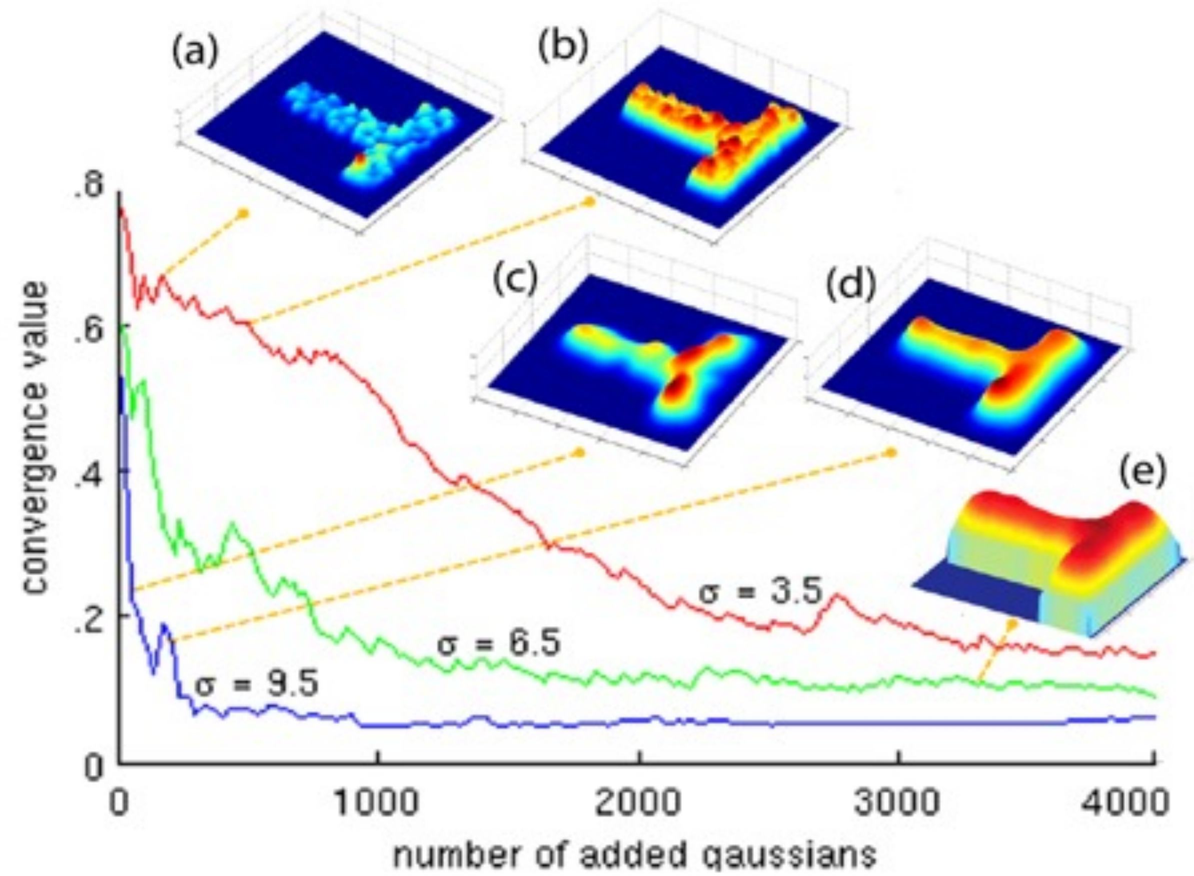






Sanchez et al (2010) IROS

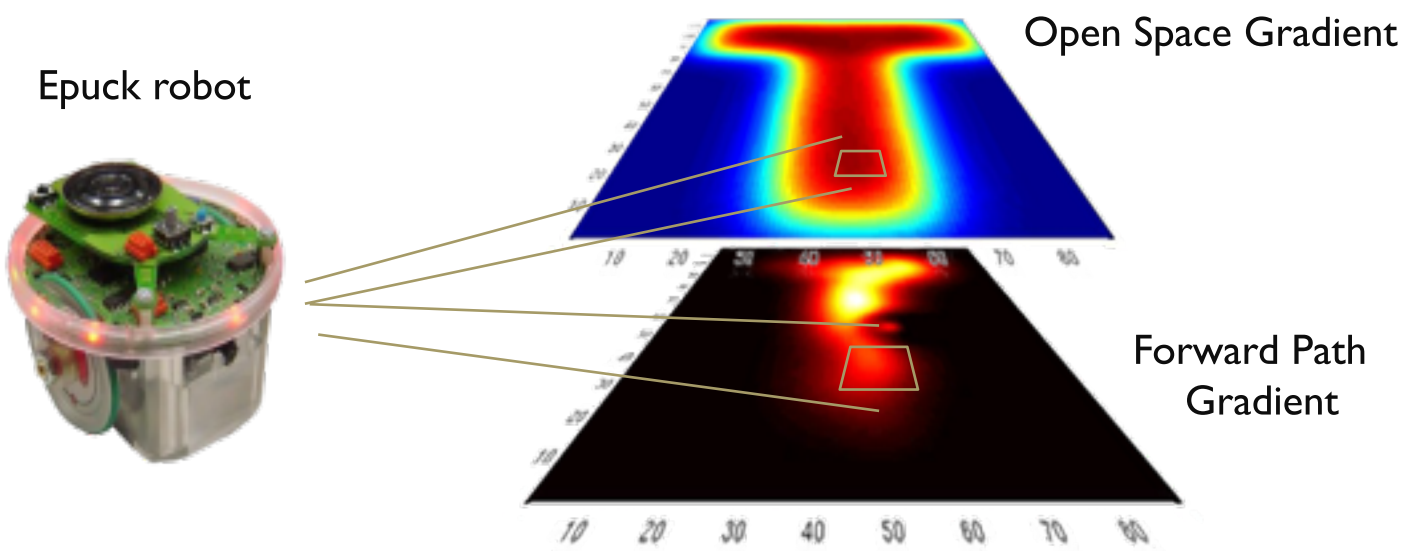
Allocentric Goal oriented Navigation using affordance gradients

- Can we then translate graph search into a problem of gradient ascent/descent?

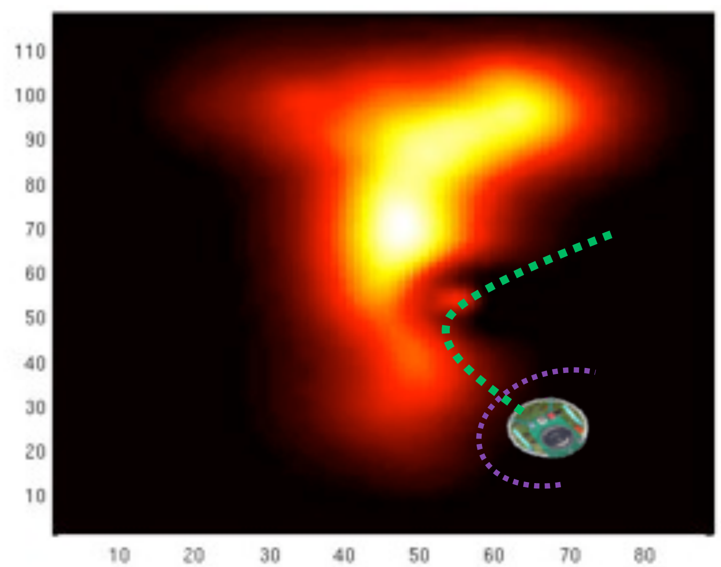
1 build the gradient connecting the initial position to the goal.

2 sequentially generate random paths among place cells (Gaussians) covering overlapping space

3 accumulate in a gradient the generated path if it was successful (if it reached the memorized goal).



Forward Path Gradient



Sanchez et al (2010) IROS

Goal-Directed Behavior

- We detect bifurcations by abrupt changes in the direction of a generated path of Gaussians

M_{path} : gradient of each generated path

M_{bif} : gradient of the accumulated bifurcations and corners

: Goal

Sanchez et al (2010) IROS

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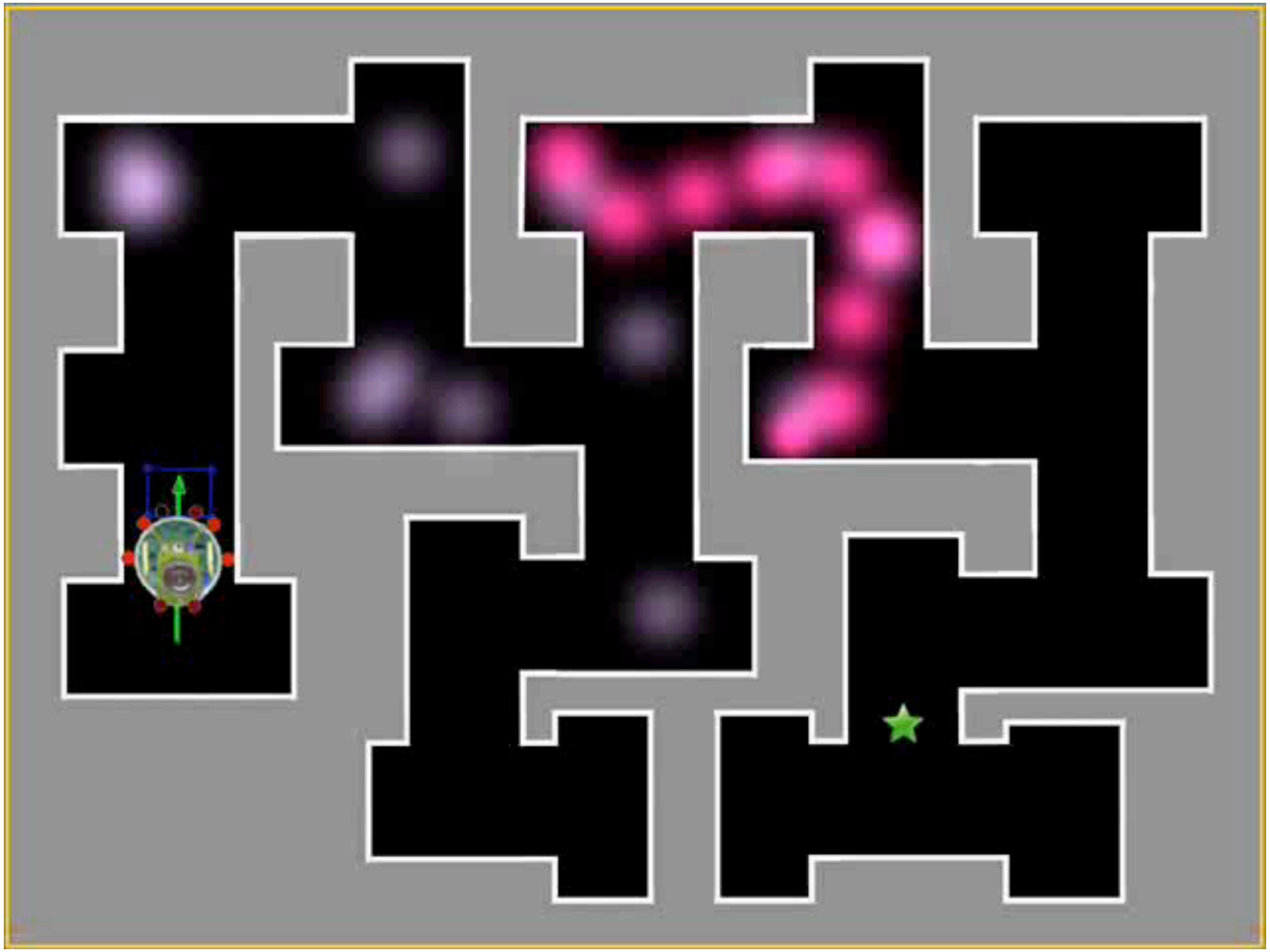


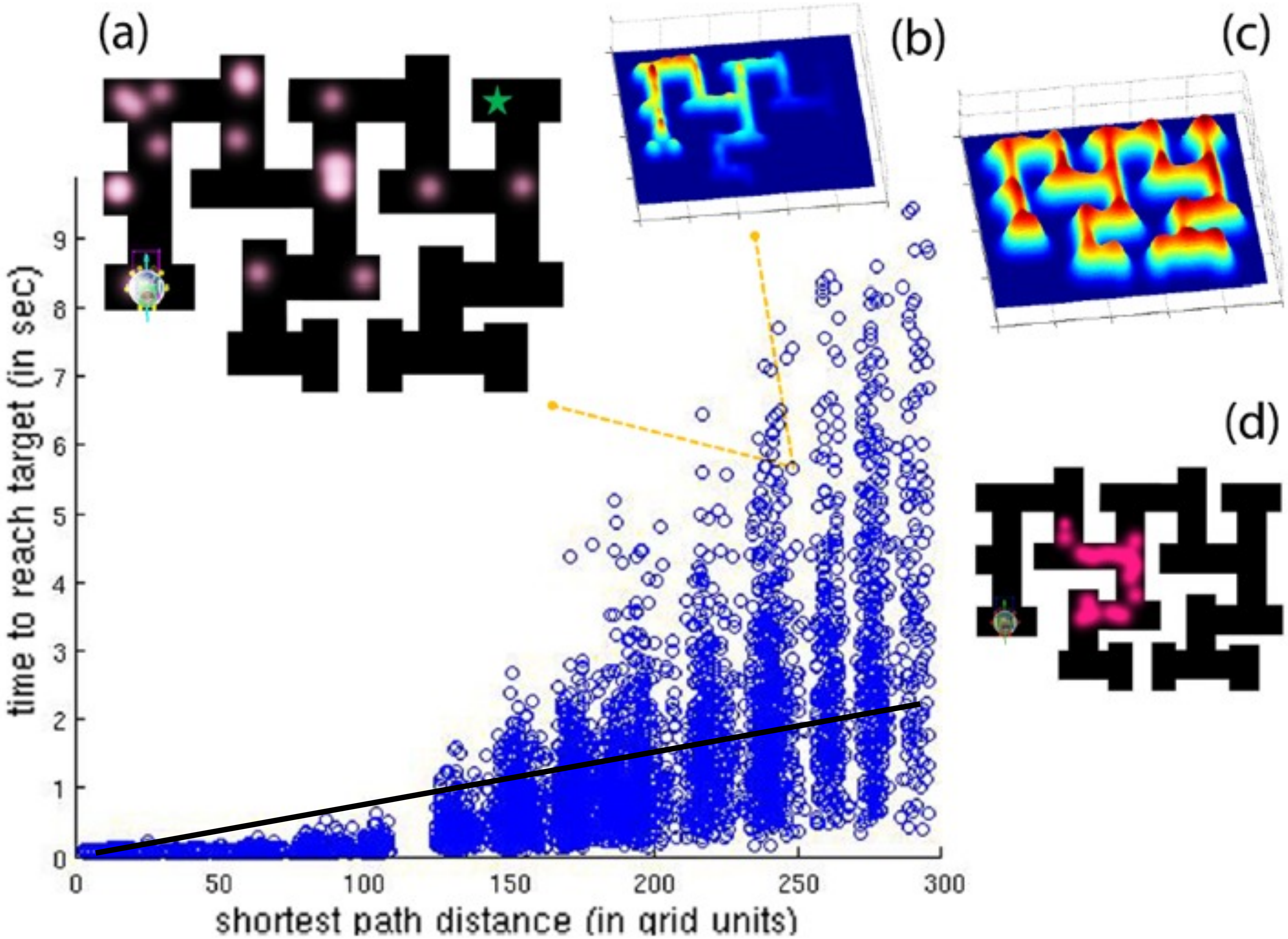
M_{path} : gradient of each generated path

M_{bif} : gradient of the accumulated bifurcations and corners

: Goal

Sanchez et al (2010) IROS

Goal-Directed Behavior: Finding a random target



- The majority of searches show a monotonic relation between "time to target" versus "shortest path"

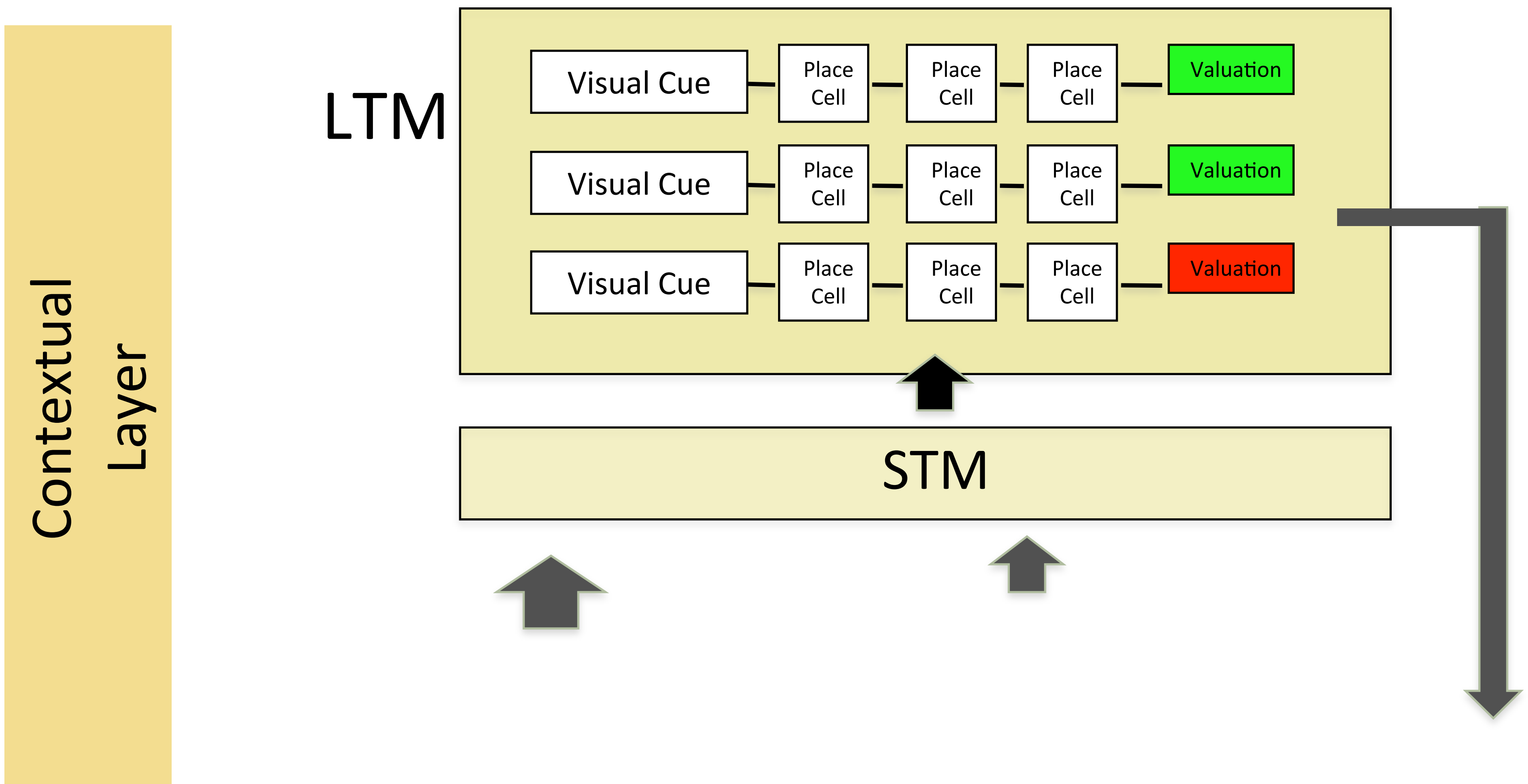
Sanchez et al (2010) IROS

Dac AL: Mixing **what** and **how** into sensori-motor couplets

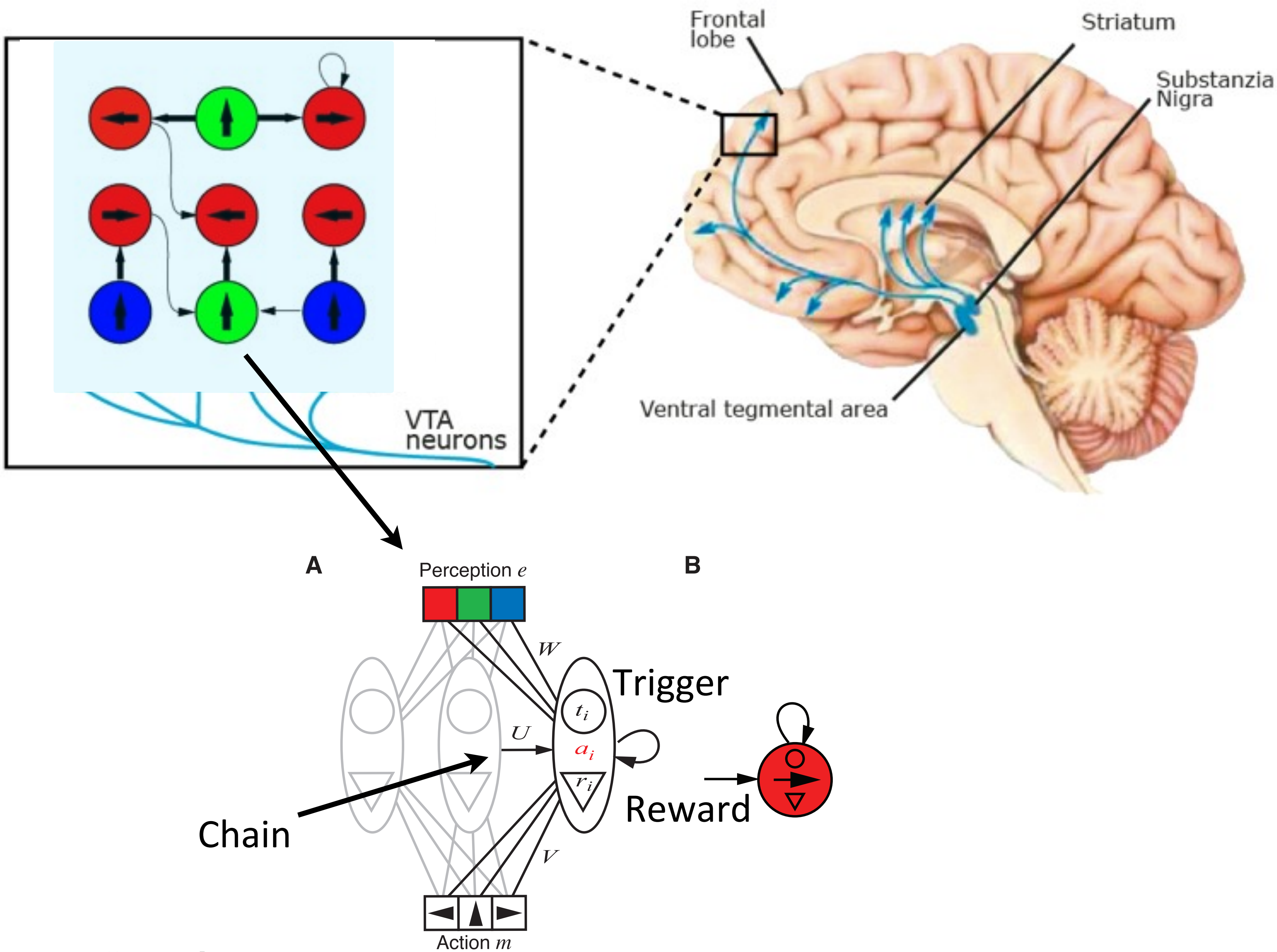
- DG provides instantaneous what and how mapping into an integrated representation
- MEC (how) provides a basic metric modulated by LEC (what)
- This can be read out into dedicated representations of space
- Hippocampal representations can be used to construct affordance gradients linking to the reactive layer allostatic control systems

DAC: Contextual Layer

DAC: Contextual Layer



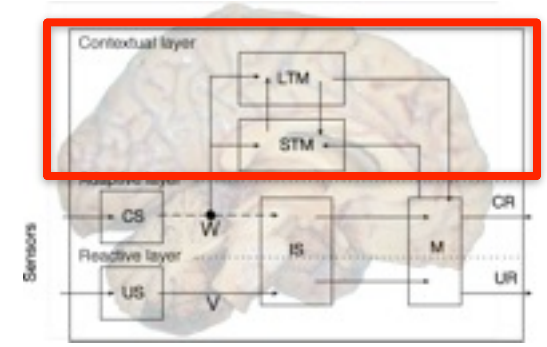
Contextual layer generalized to model of PFC



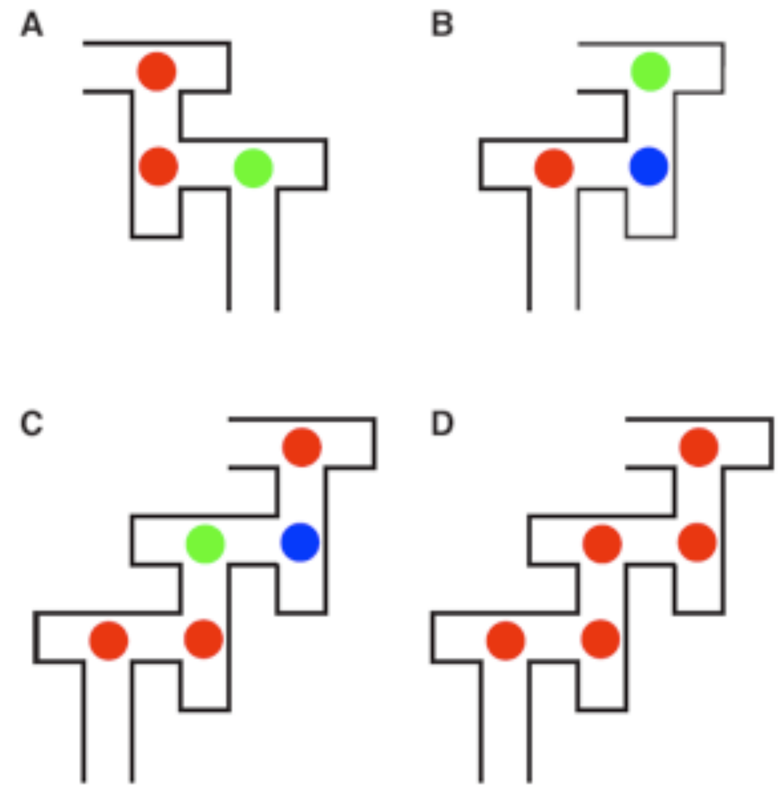
[Duff et al., Brain Res Bull 2011]

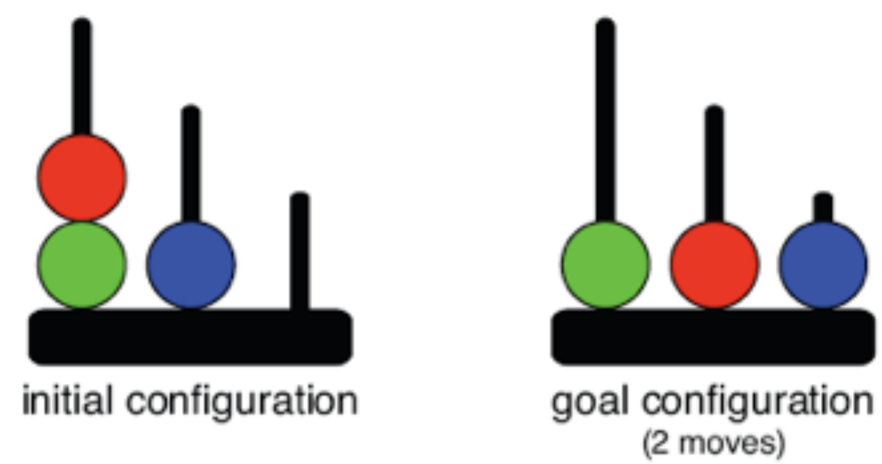
Contextual Layer:

Rule learning and switching



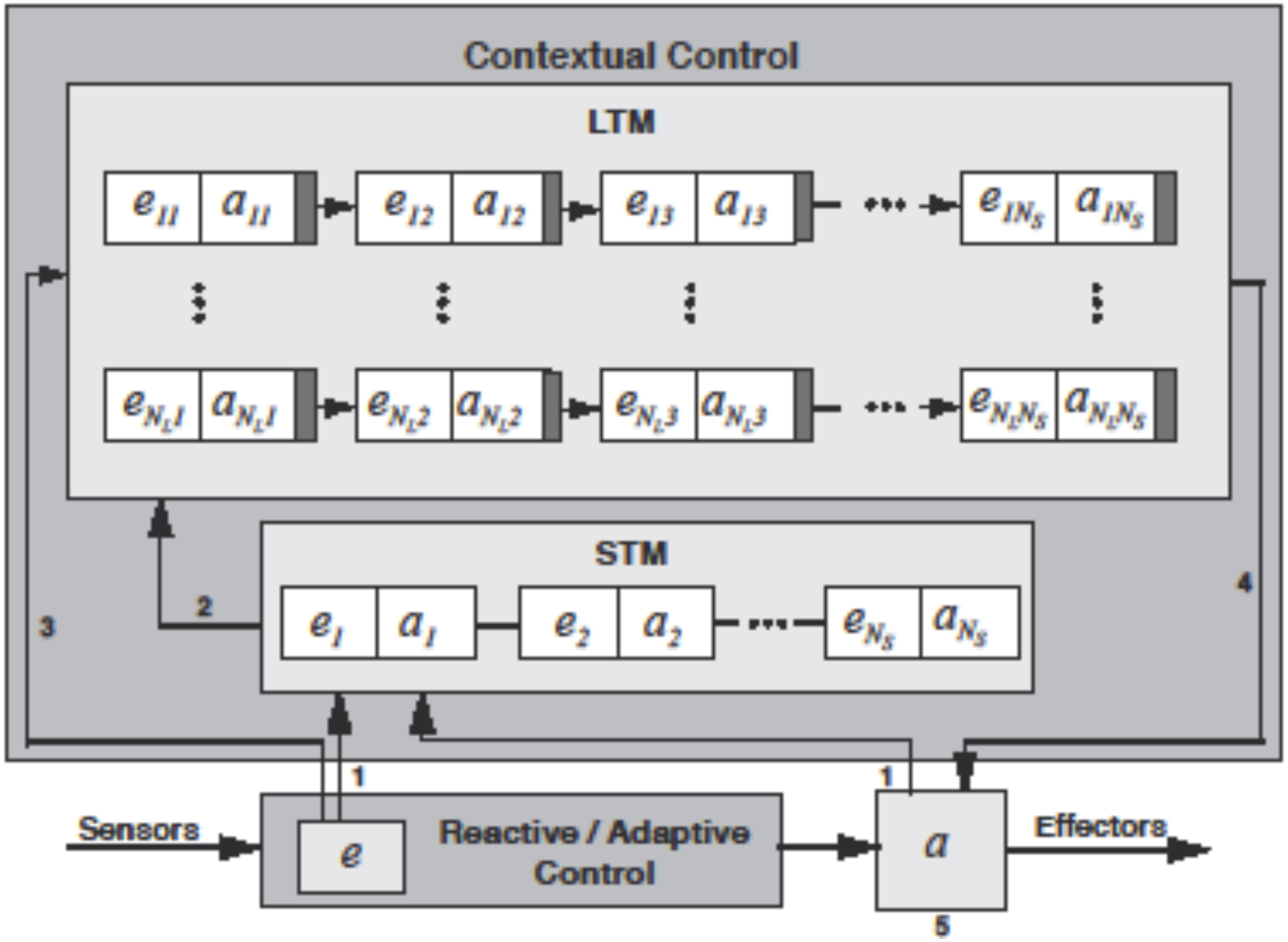
- PFC-grounded contextual layer
  - Sustained activity
  - Lateral connectivity
  - Reward modulation
- Single/Multiple T-Maze, Tower of London
- SMC can be manipulated and adapted to express sequential rules and plans

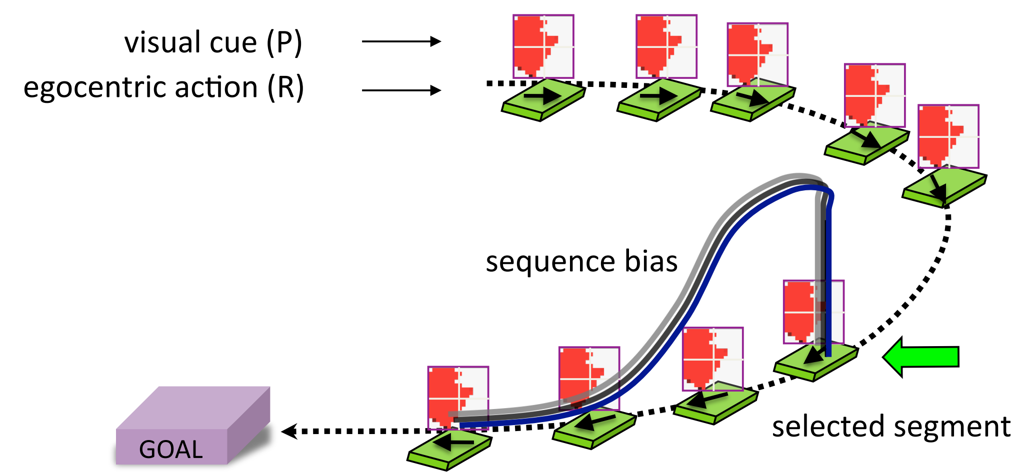




[Duff et al., Brain Res Bull 2003]

Integration perception and memory in decision making





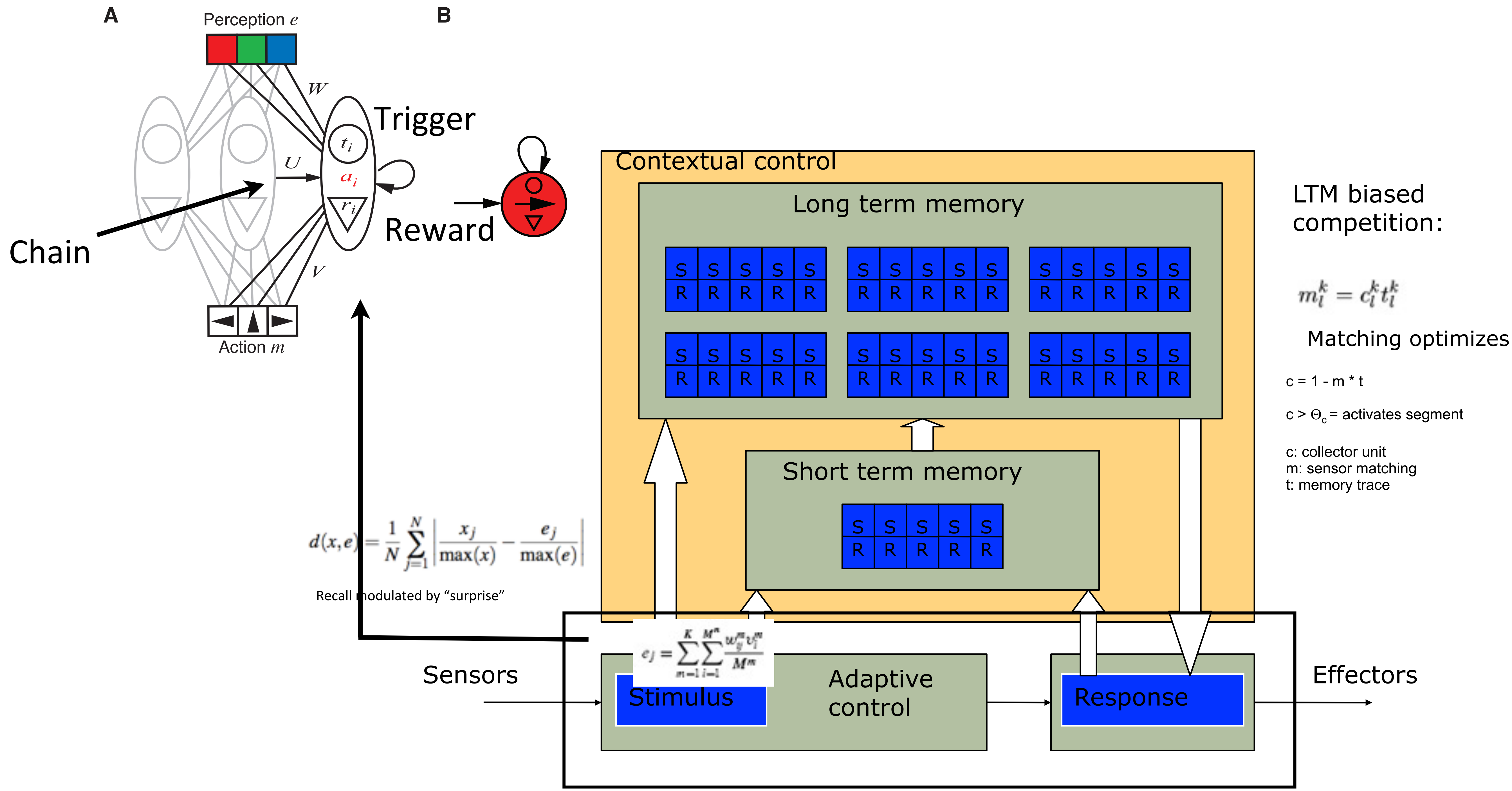
$$m_l^k = c_l^k t_l^k$$

(1) perceptual matching through **membrane potential** modulation (t);

(2) memory biasing and chaining through **threshold** modulation (c)

[Verschure et al., Nature 2003]

Certainty/novelty assessed at level of RL modulates the memory units of CL



Verschure & Voegtlin (1998) Neur.Netw. Verschure & Althaus (2003) Cog.Sci., 27: 561-590 Verschure et al (2003) Nature

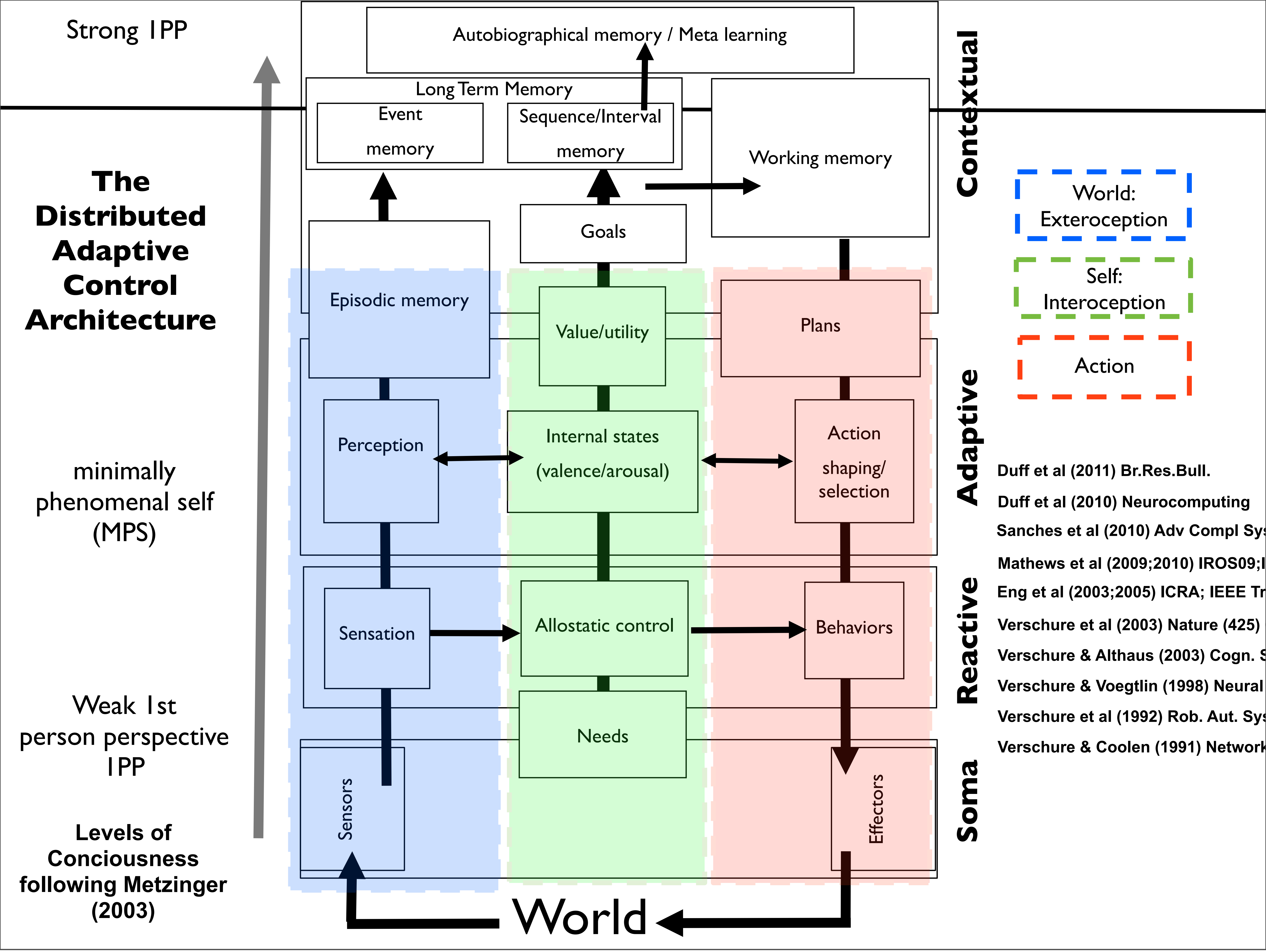
[Duff et al., Brain Res Bull 2011]

Contextual layer: integrating perception and memory

- Our previous prediction: sensory information and memory bias are integrated using separate decision variables: rate and threshold.
- We analyzed responses from neurons in the PMd
- Observed:
  - Rate does not vary with certainty
  - Neural variability and RT increases with uncertainty.
  - Mean and SE of the RT can be predicted from the neural variability.

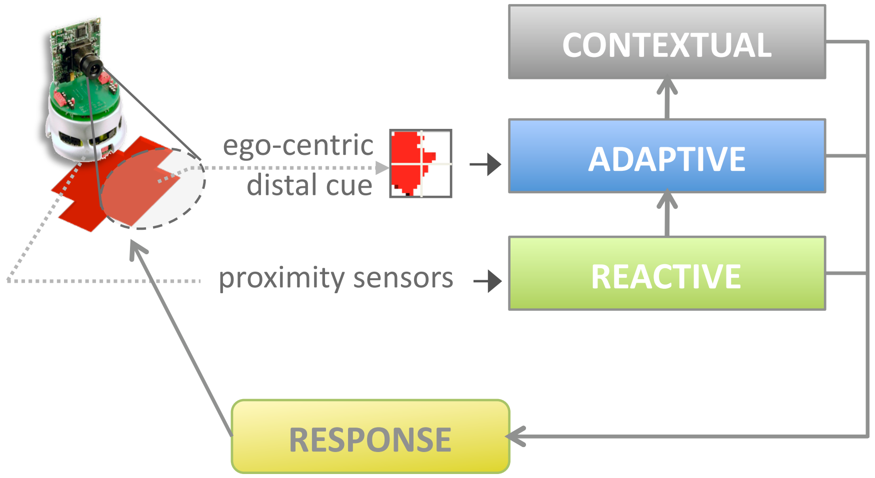
$$m_l^k = c_l^k t_l^k$$

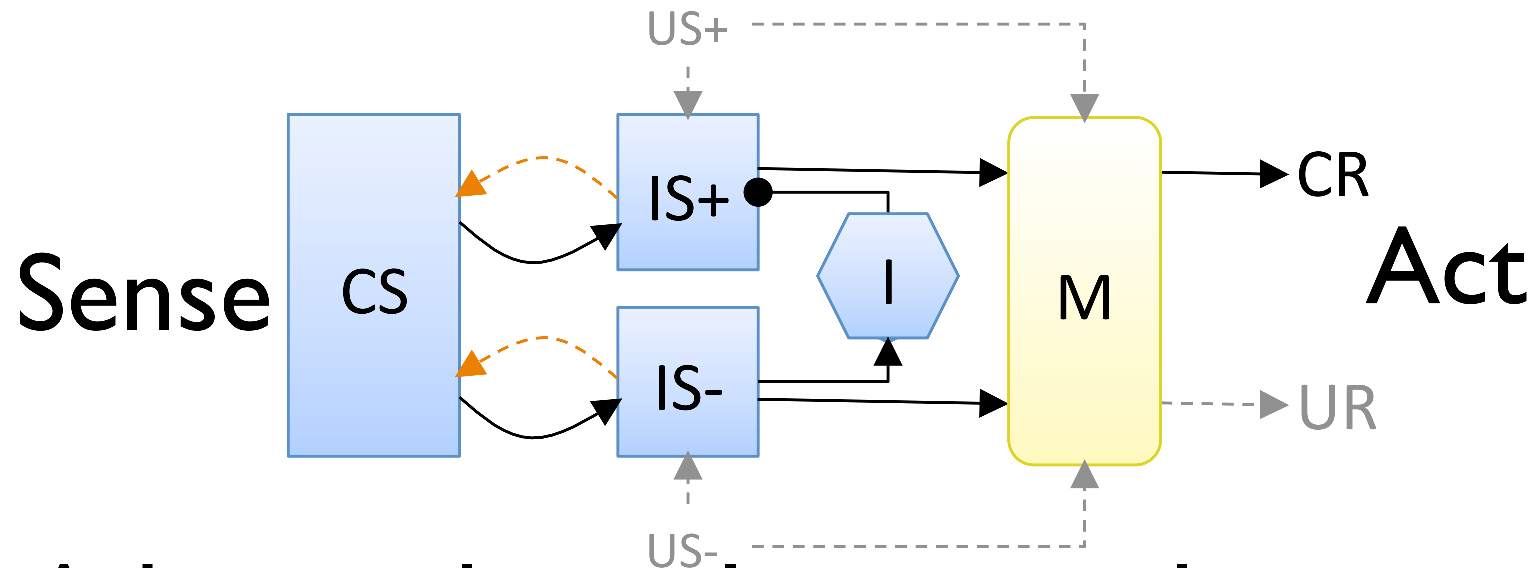
Control signals and protocols in DAC



Strong 1PP
The Distributed Adaptive Control Architecture
minimally phenomenal self (MPS)
Weak 1st person perspective 1PP
Levels of Conciousness following Metzinger (2003)
Autobiographical memory / Meta learning
Long Term Memory
Event memory
Sequence/Interval memory
Working memory
Goals
Episodic memory
Value/utility
Plans
Perception
Internal states (valence/arousal)
Action shaping/ selection
Sensation
Allostatic control
Behaviors
Needs
Sensors
Effectors
World
Contextual
Adaptive
Reactive
Soma
World: Exteroception
Self: Interoception
Action
Duff et al (2011) Br.Res.Bull.
Duff et al (2010) Neurocomputing
Sanches et al (2010) Adv Compl Sys
Mathews et al (2009;2010) IROS09;I
Eng et al (2003;2005) ICRA; IEEE Tr
Verschure et al (2003) Nature (425)
Verschure & Althaus (2003) Cogn. S
Verschure & Voegtlin (1998) Neural
Verschure et al (1992) Rob. Aut. Sys
Verschure & Coolen (1991) Network

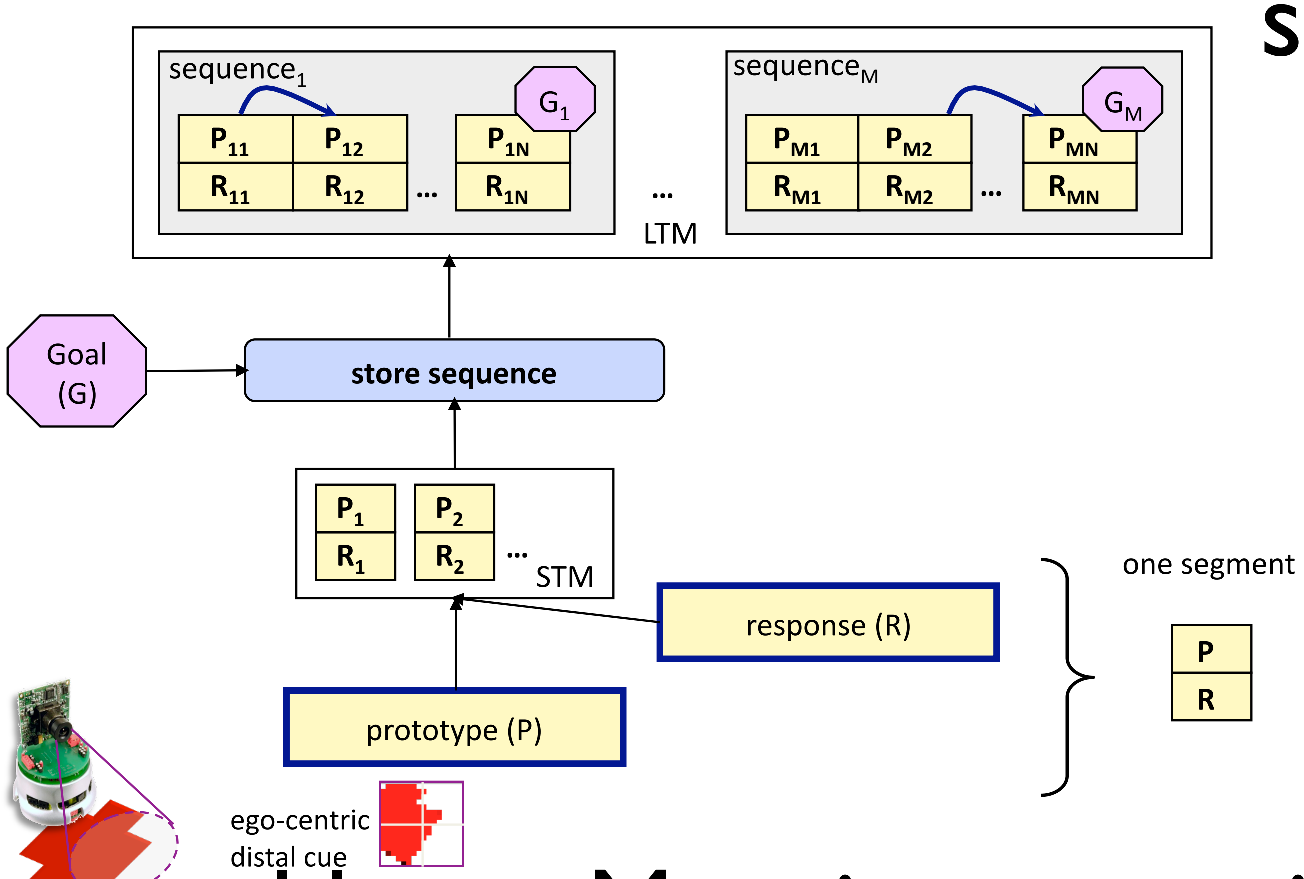
3 layers of DAC





Adaptive layer: Learning the state space

CS: Conditioned stimulus
US: Unconditioned stimulus
CR: Conditioned response
UR: Unconditioned response



Contextual layer: Mapping states into plans for goal oriented action

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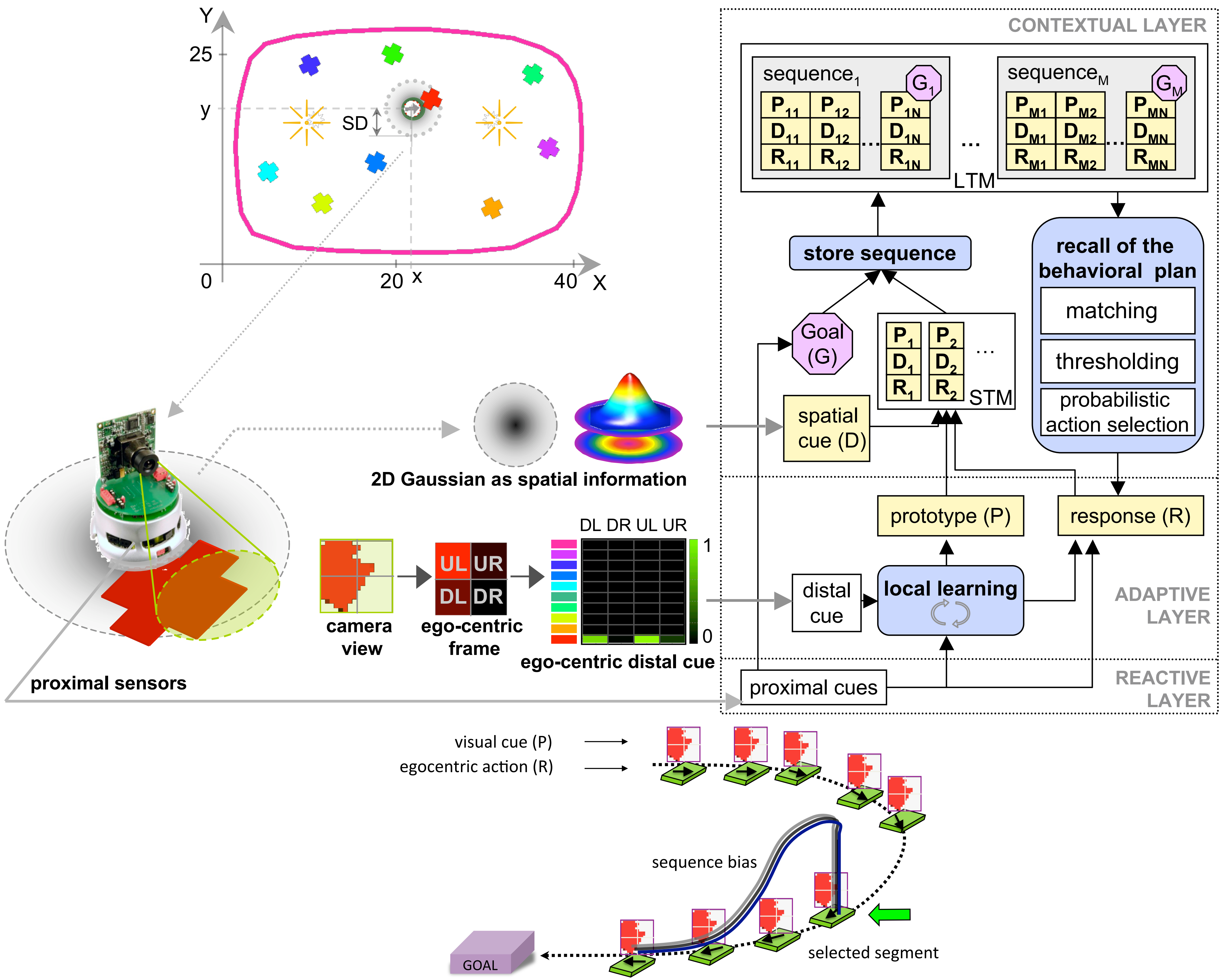
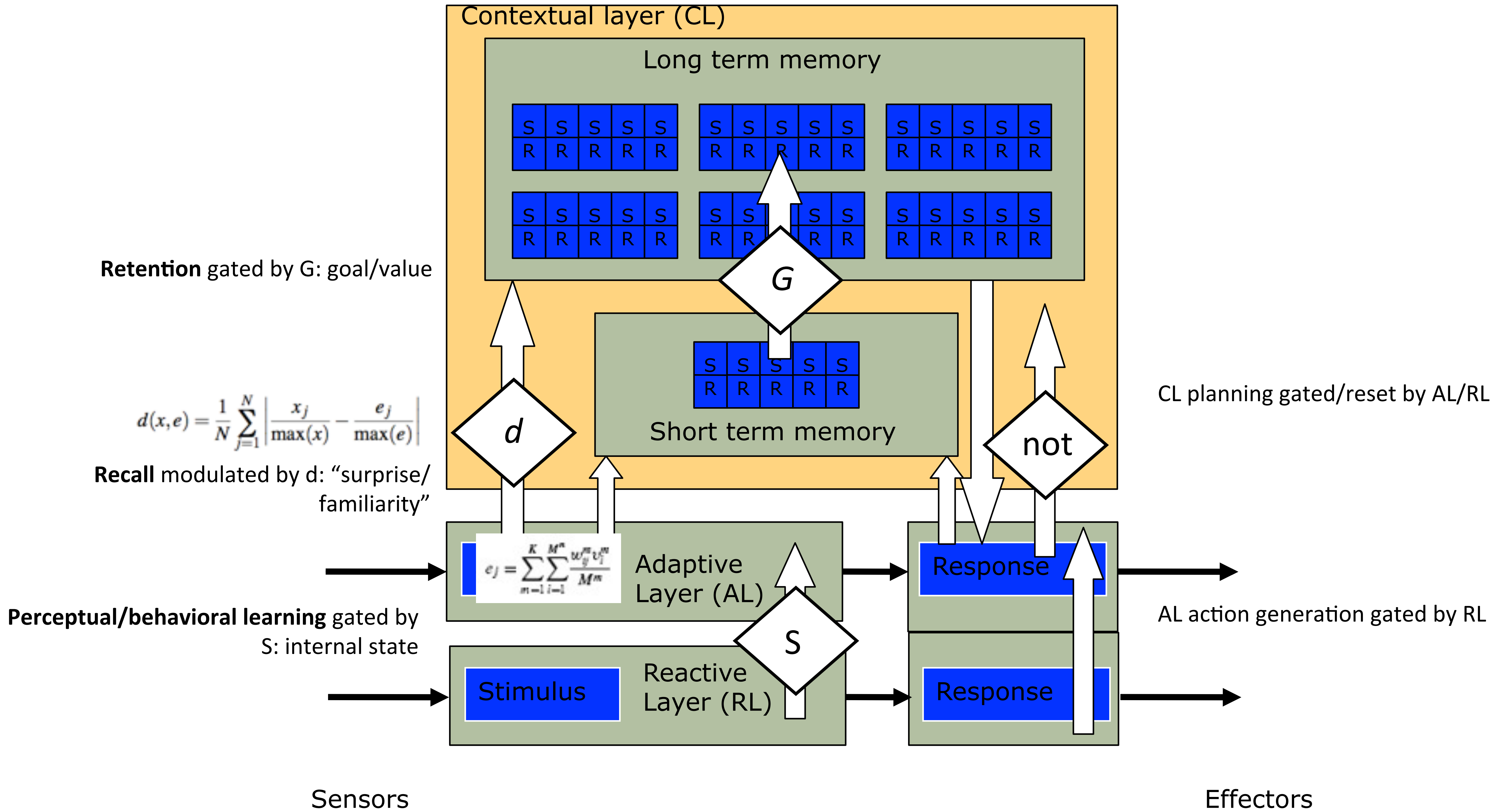


Inter-layer control signals and protocols of DAC



Verschure & Voegtlin (1998) Neur.Netw. Verschure & Althaus (2003) Cog.Sci., 27: 561-590 Verschure et al (2003) Nature

[Duff et al., Brain Res Bull 2011]

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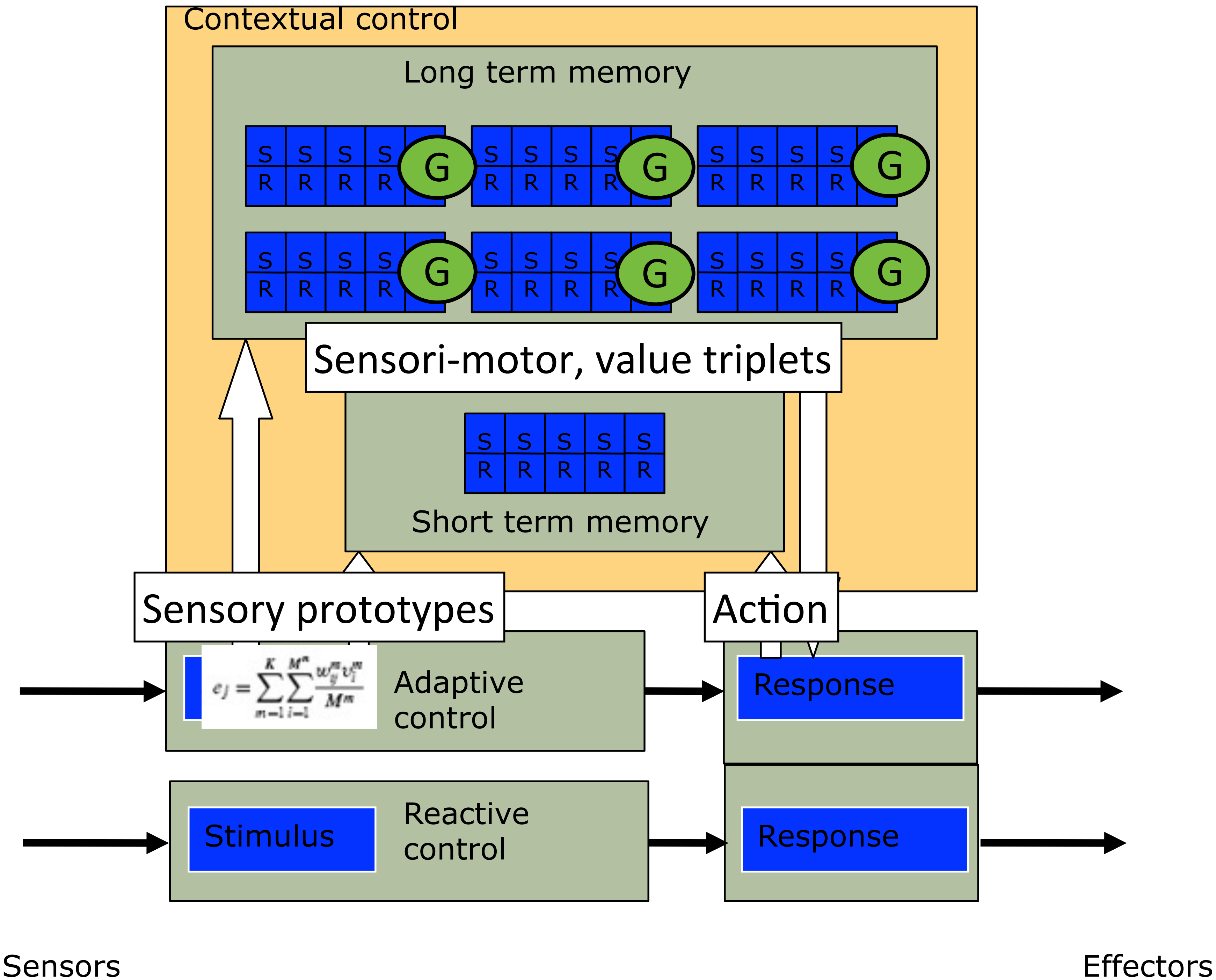

[Duff et al., Brain Res Bull 2011]

Verschure & Voegtlin (1998) Neur.Netw. Verschure & Althaus (2003) Cog.Sci., 27: 561-590 Verschure et al (2003) Nature

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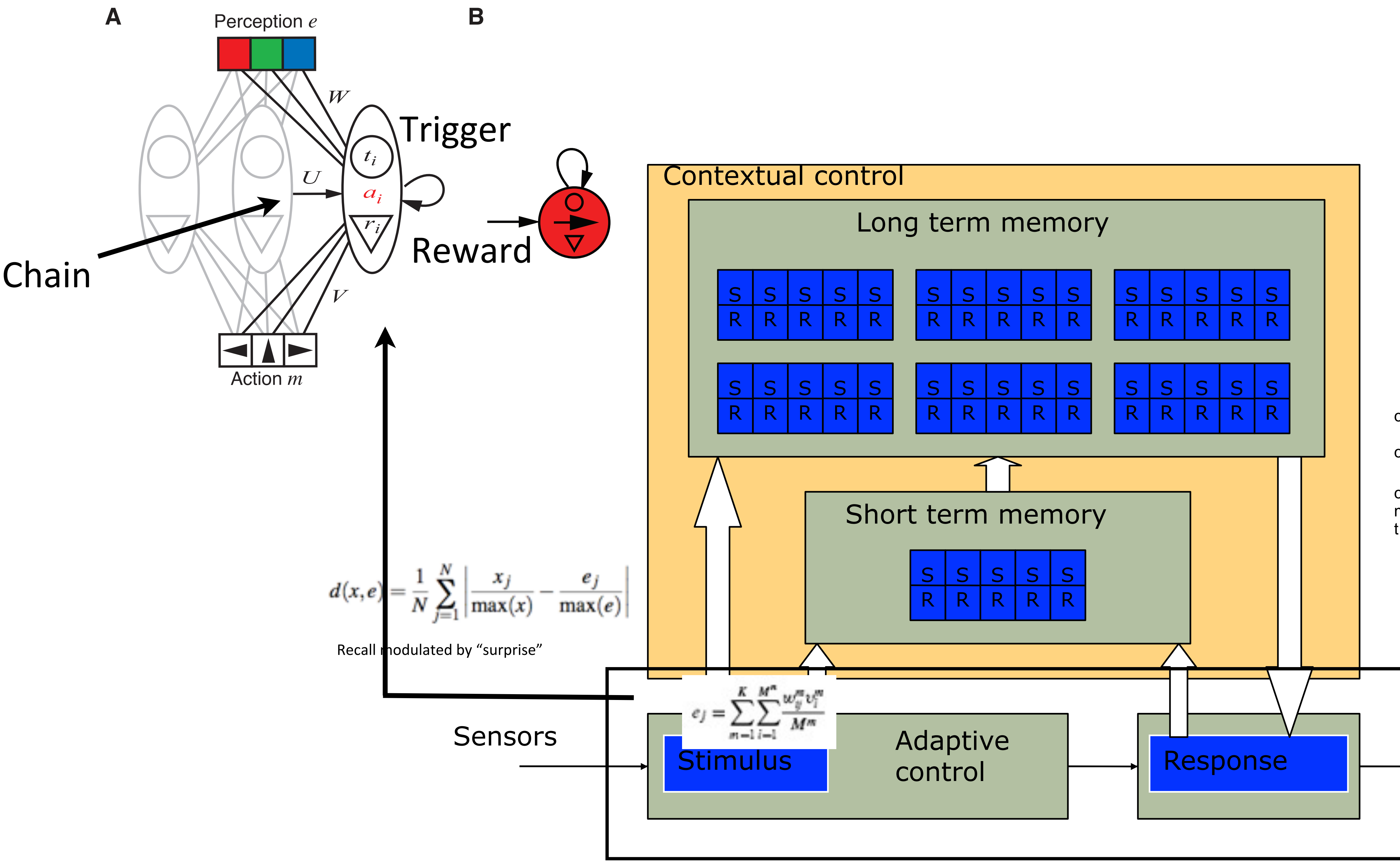

LTM biased competition:

$$m_l^k = c_l^k t_l^k$$

Matching optimizes:

c = 1 - m * t

c > Θ_c = activates segment

c: collector unit
m: sensor matching
t: memory trace

[Duff et al., Brain Res Bull 2011]

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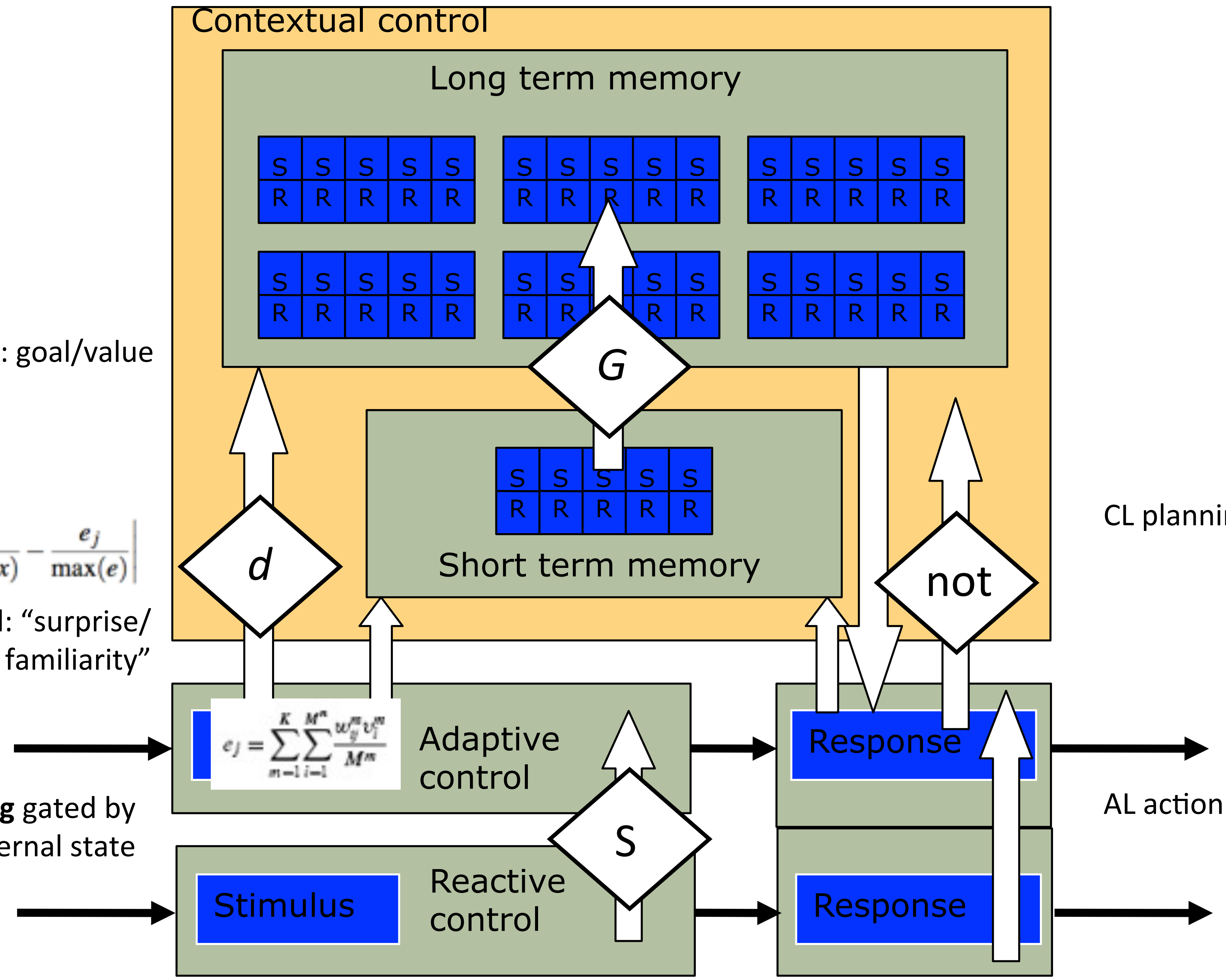
Inter-layer control signals and protocols of DAC

Retention gated by G: goal/value

$$d(x,e) = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{x_j}{\max(x)} - \frac{e_j}{\max(e)}\right|$$

Recall modulated by d: "surprise/ familiarity"

Perceptual/behavioral learning gated by S: internal state



CL planning gated/reset by AL/RL

AL action generation gated by RL

Sensors

Effectors

[Duff et al., Brain Res Bull 2011]

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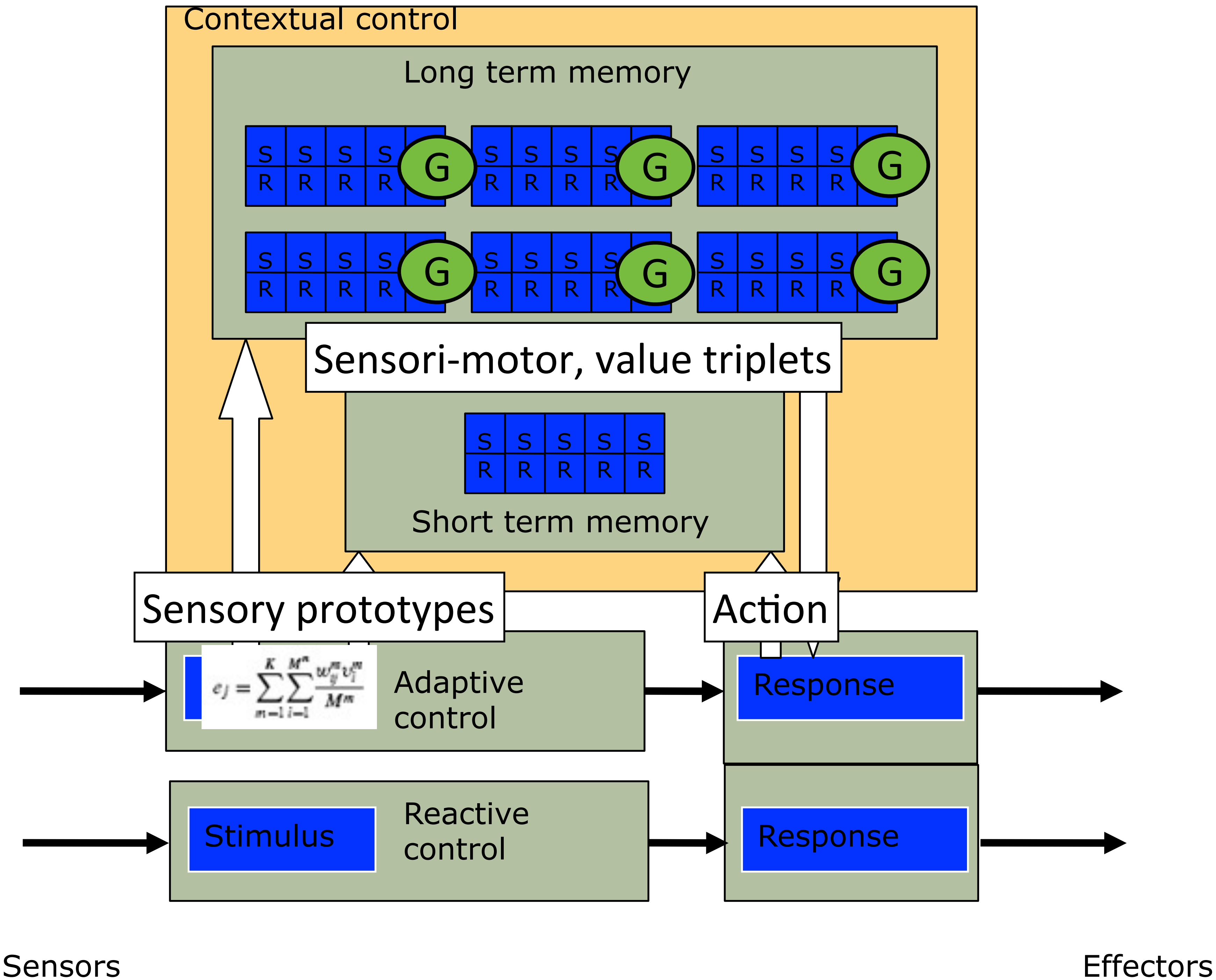

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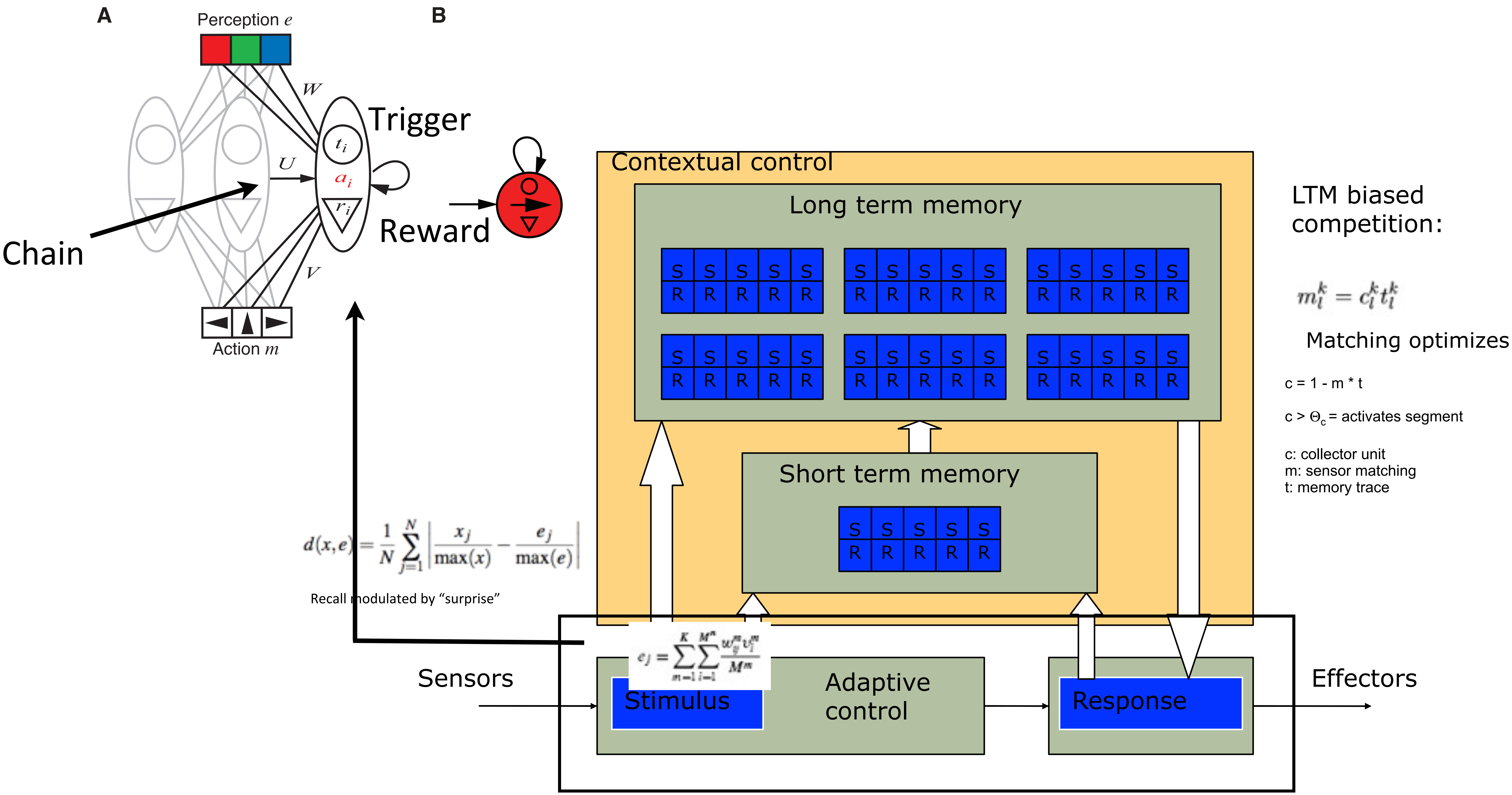

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[Duff et al., Brain Res Bull 2011]

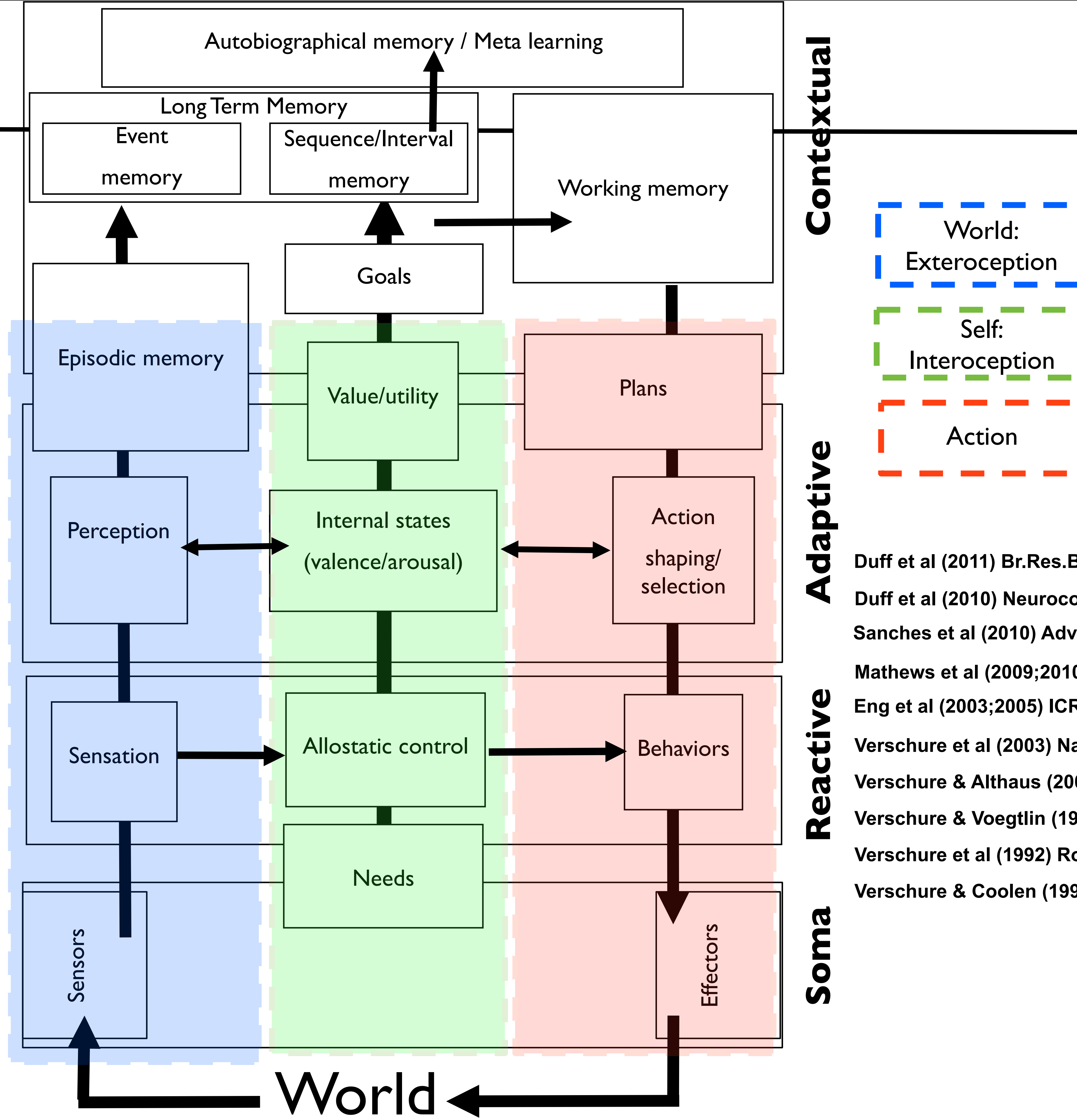
Strong 1PP

The Distributed Adaptive Control Architecture

minimally phenomenal self (MPS)

Weak 1st person perspective 1PP

Levels of Conciousness following Metzinger (2003)



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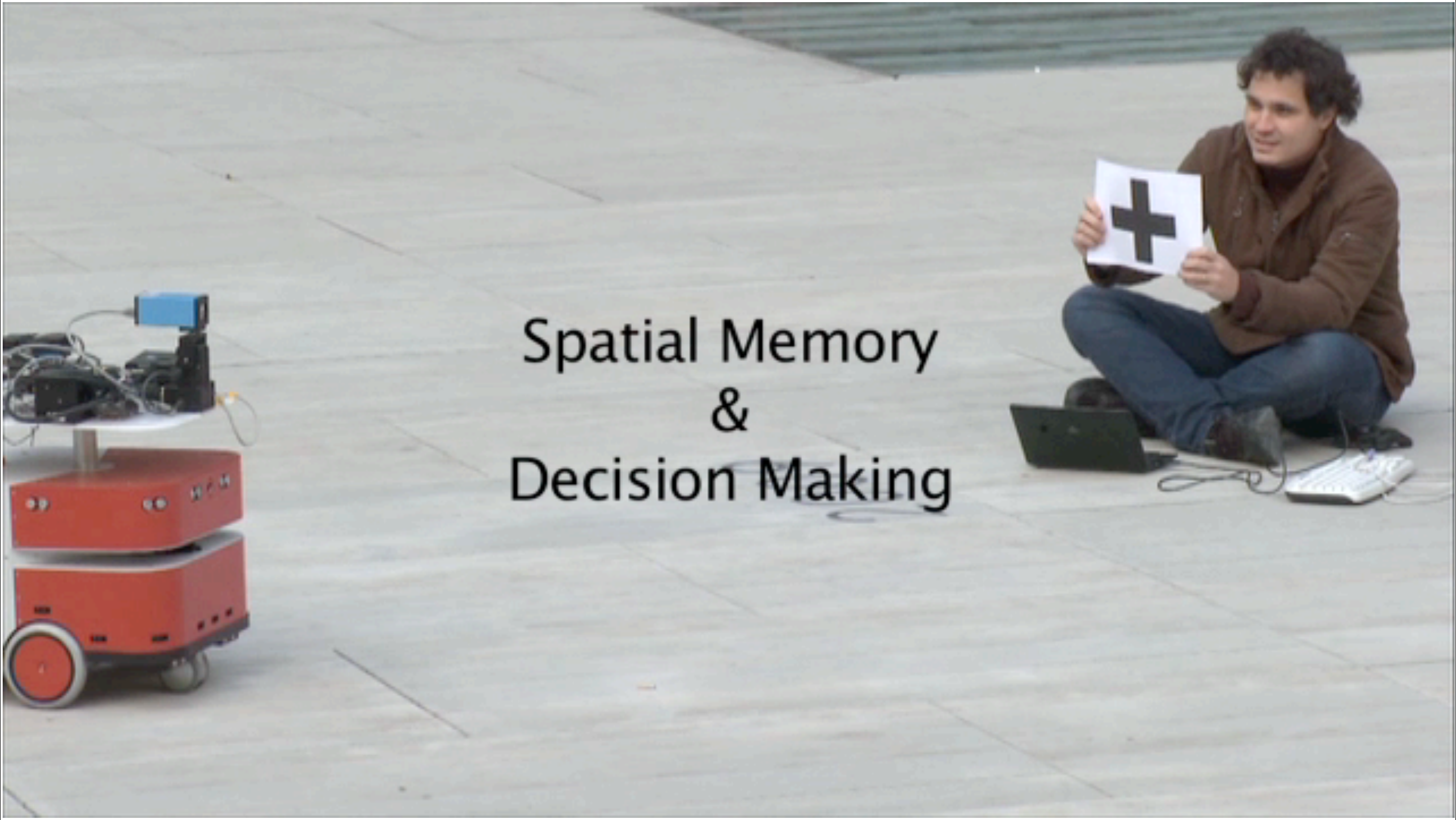
Spatial Memory
&
Decision Making

Conclusions 1

- DAC is an architecture that integrates mind and brain
- It is validated in the context of foraging behavior
- The functional decomposition of foraging has been mapped onto the brain through detailed models of:
  - Brainstem, amygdala, cerebellum, hippocampus and visual, entorhinal and prefrontal cortex
- Reactive layer: provides the regulation of species specific behaviors through **affordance gradients**
- Adaptive layer 1:
  - acquires the sense-act state space
  - model of ventral visual system, TPC coupled to active input sampling for face recognition
- Adaptive layer 2:
  - Compresses sense and act states into sense-act couplets
  - representational primitive of the hippocampus

Conclusions 2

- Adaptive layer 2:
  - Compresses sense and act states into sense-act couplets
  - These representational primitives are formed in the dentate gyrus of the hippocampus
- Contextual layer:
  - sensory information and memory based prediction are integrated using separate decision variables: rate and threshold in PFC
- DAC has been validated using
  - mobile and humanoid robots
  - Neuroprosthetics (cerebellum)
  - Neurorehabilitation (Rehabilitation Gaming Station)