Sensorimotor control via counterfactual errors

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specs-lab.com
eodyne.com
futurememoryfoundation.com

Barcelona Institute of Science and Technology

SPECS
Synthetic, Perceptive, Emotive and Cognitive Systems group

European Commission

HORIZON 2020

European Research Council
Established by the European Commission

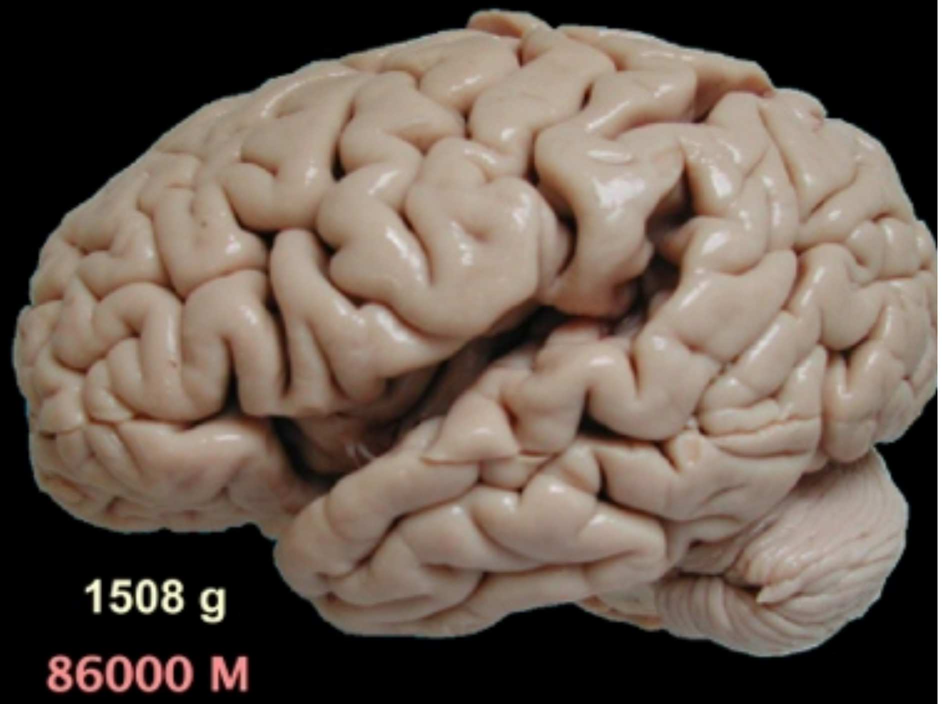
ANITA
ADVANCED TOOLS FOR FIGHTING ONLINE ILLEGAL TRAFFICKING

VirtualBrainCloud

RobotRecycler

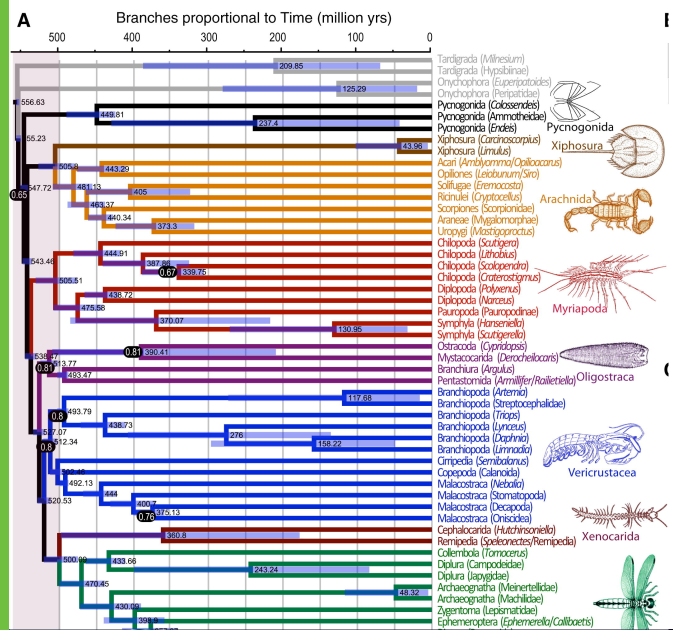
SANaR

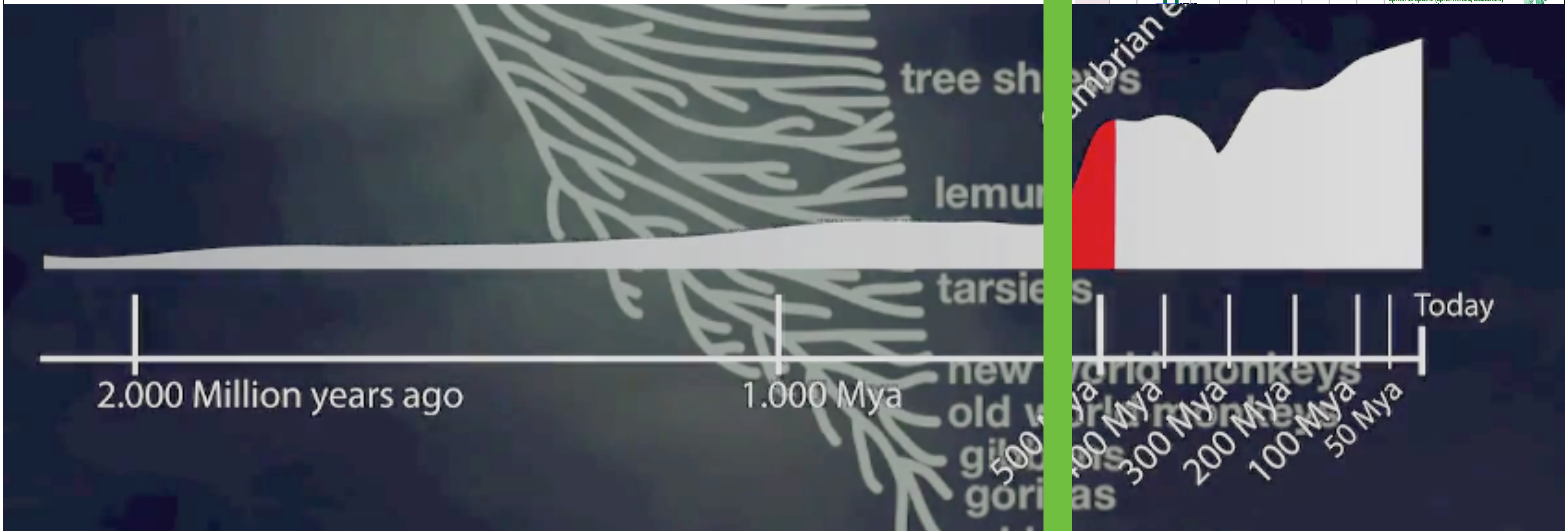
psyche



flesh

Herculano-Houzel

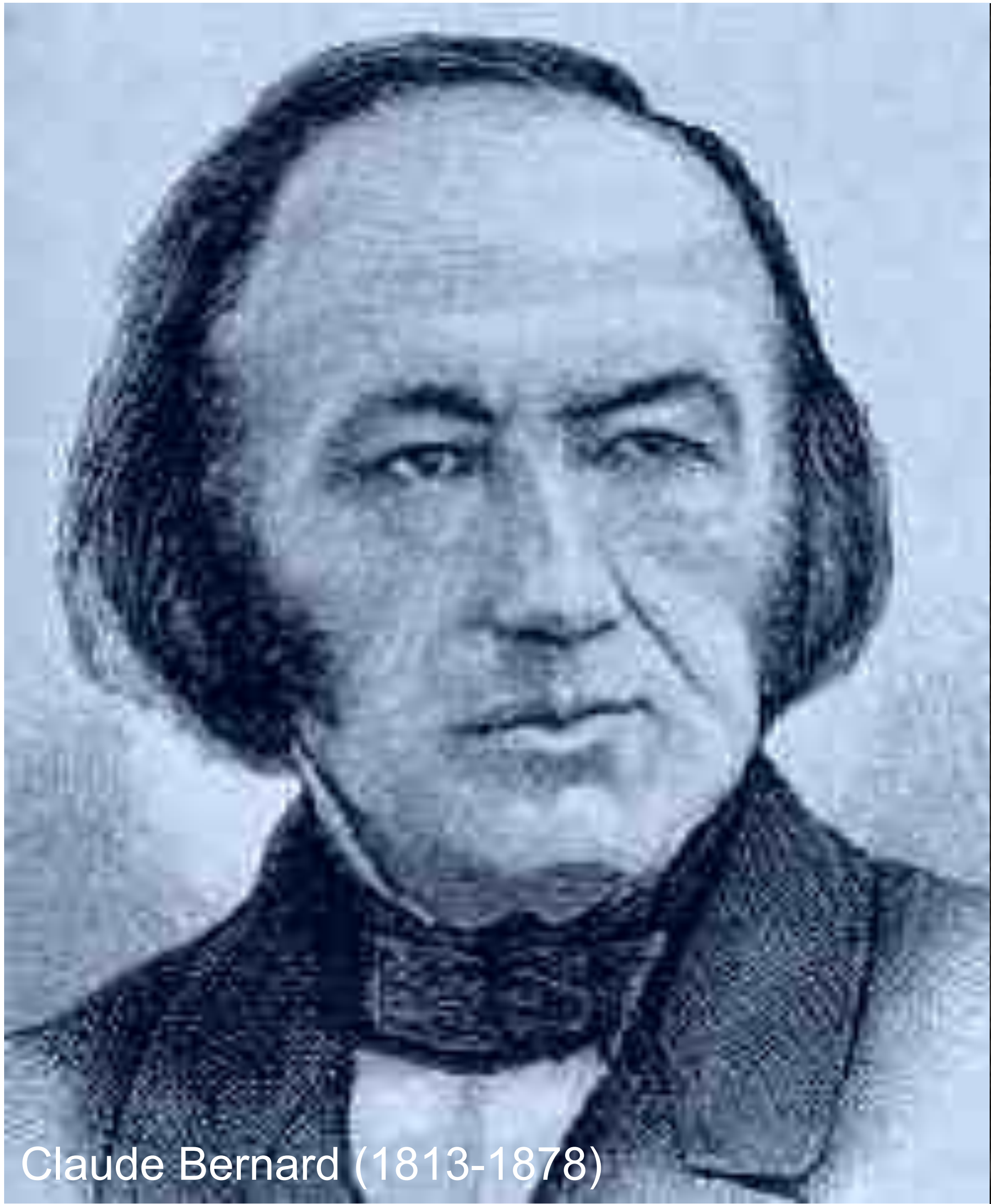

A
Branches proportional to Time (million yrs)
500
400
300
200
100
0
Tardigrada (Milnesium)
Tardigrada (Hypsibiinae)
Onychophora (Euperipatoides)
Onychophora (Peripatidae)
Pycnogonida (Colossendeis)
Pycnogonida (Ammotheidae)
Pycnogonida (Endeis)
Xiphosura (Carcinoscorpius)
Xiphosura (Limulus)
Acari (Amblyomma/Opilioacarus)
Opiliones (Leiobunum/Siro)
Solifugae (Eremocosta)
Ricinulei (Cryptocellus)
Scorpiones (Scorpionidae)
Araneae (Mygalomorphae)
Uropygi (Mastigoproctus)
Chilopoda (Scutigera)
Chilopoda (Lithobius)
Chilopoda (Scolopendra)
Chilopoda (Craterostigmus)
Diplopoda (Polyxenus)
Diplopoda (Narceus)
Pauropoda (Pauropodinae)
Symphyla (Hanseniella)
Symphyla (Scutigerella)
Ostracoda (Cypridopsis)
Mystacocarida (Derocheilocaris)
Branchiura (Argulus)
Pentastomida (Armillifer/Raillietiella)
Branchiopoda (Artemia)
Branchiopoda (Streptocephalidae)
Branchiopoda (Triops)
Branchiopoda (Lynceus)
Branchiopoda (Daphnia)
Branchiopoda (Limnadia)
Cirripedia (Semibalanus)
Copepoda (Calanoida)
Malacostraca (Nebalia)
Malacostraca (Stomatopoda)
Malacostraca (Decapoda)
Malacostraca (Oniscidea)
Cephalocarida (Hutchinsoniella)
Remipedia (Speleonectes/Remipedia)
Collembola (Tomocerus)
Diplura (Campodeidae)
Diplura (Japygidae)
Archaeognatha (Meinertellidae)
Archaeognatha (Machilidae)
Zygentoma (Lepismatidae)
Ephemeroptera (Ephemerella/Callibaetis)
Pycnogonida
Xiphosura
Arachnida
Myriapoda
Oligostraca
Vericrustacea
Xenocarida

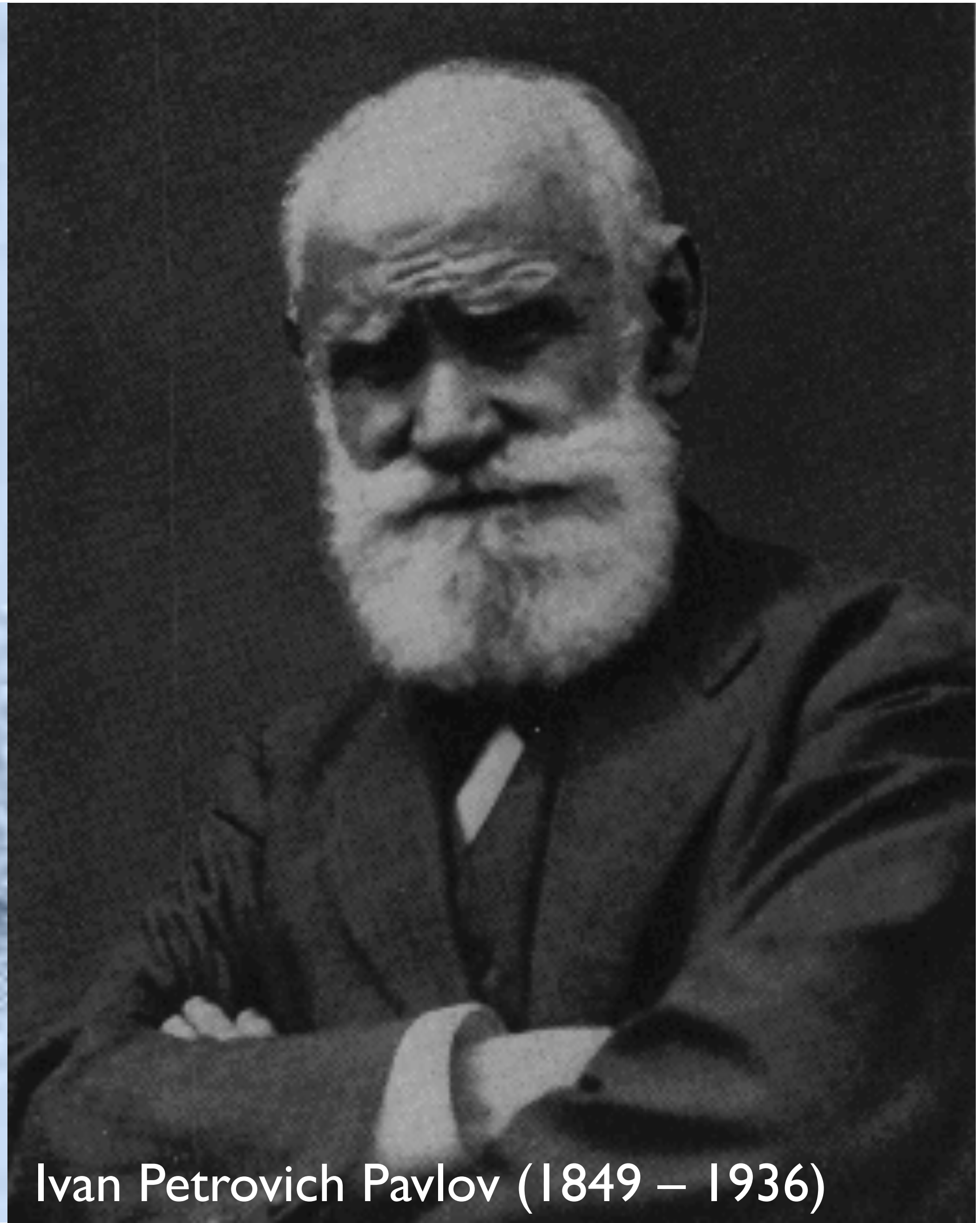

tree shrews
lemurs
tarsiers
new world monkeys
old world monkeys
gibbons
gorillas
Cambrian e
2.000 Million years ago
1.000 Mya
500 Mya
400 Mya
300 Mya
200 Mya
100 Mya
50 Mya
Today

560M ya

action

"The brain maintains
the equilibrium between
the organism and its environment"

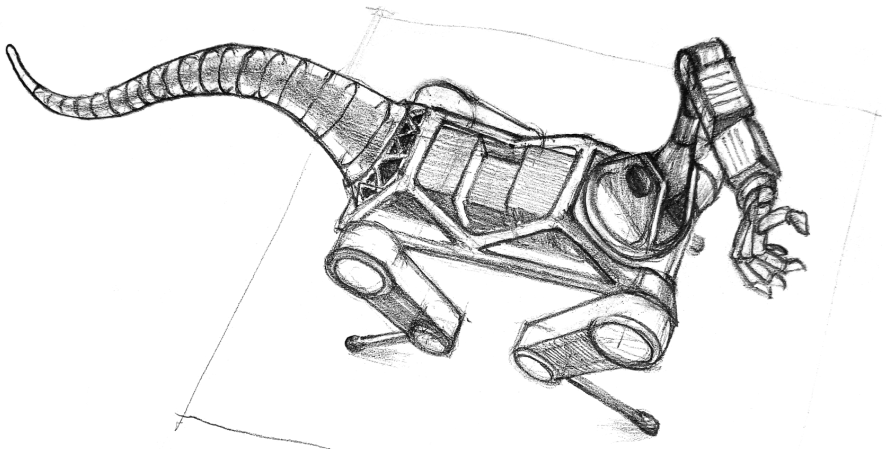


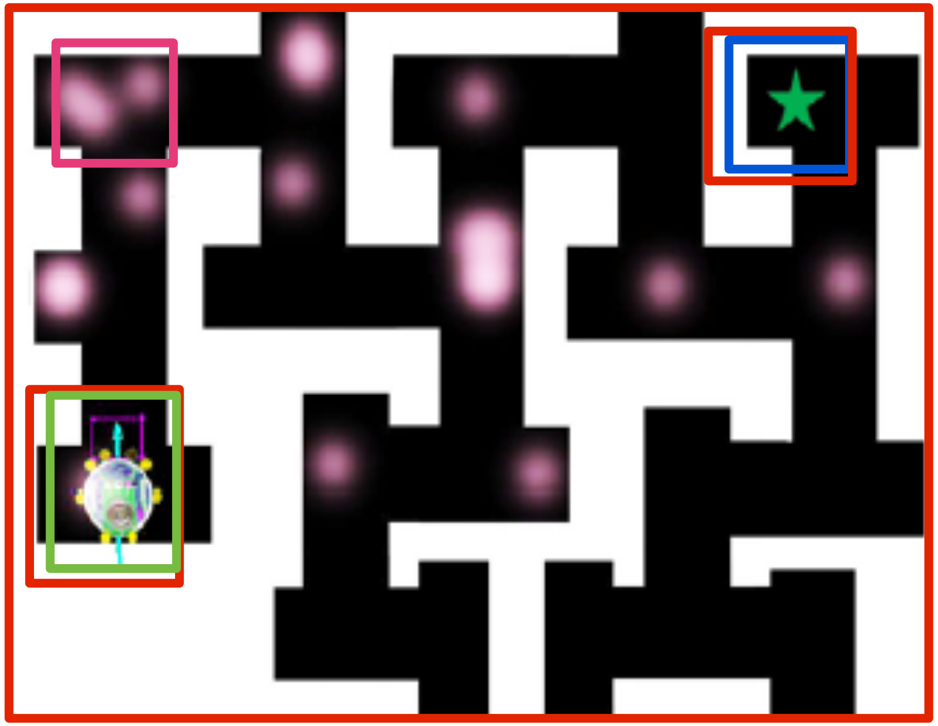


Acting = solving the **H4W** problem

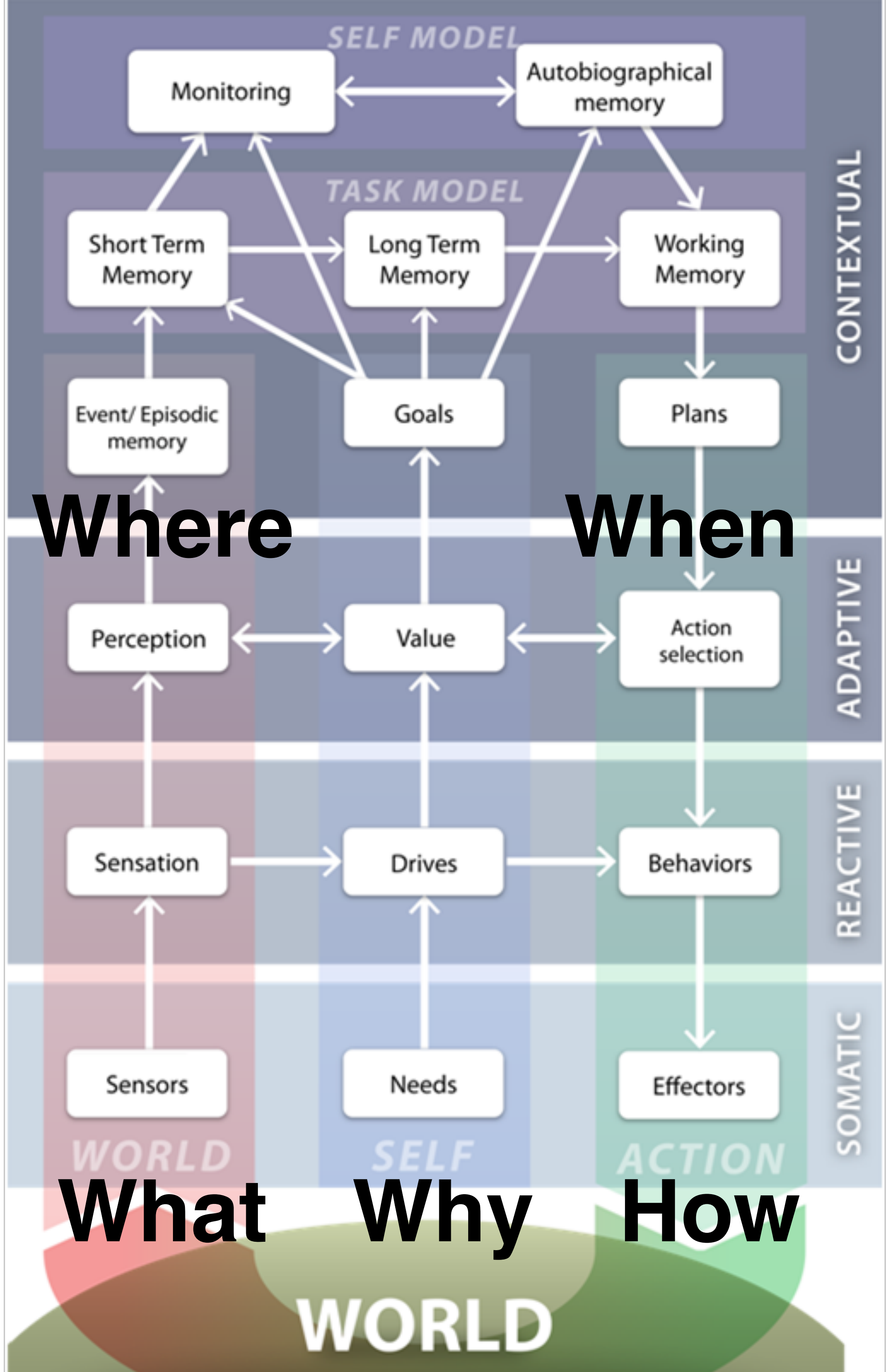
- **Why**: goal
- **What**: objects
- **Where**: space
- **When**: time

→ Act (**How**)



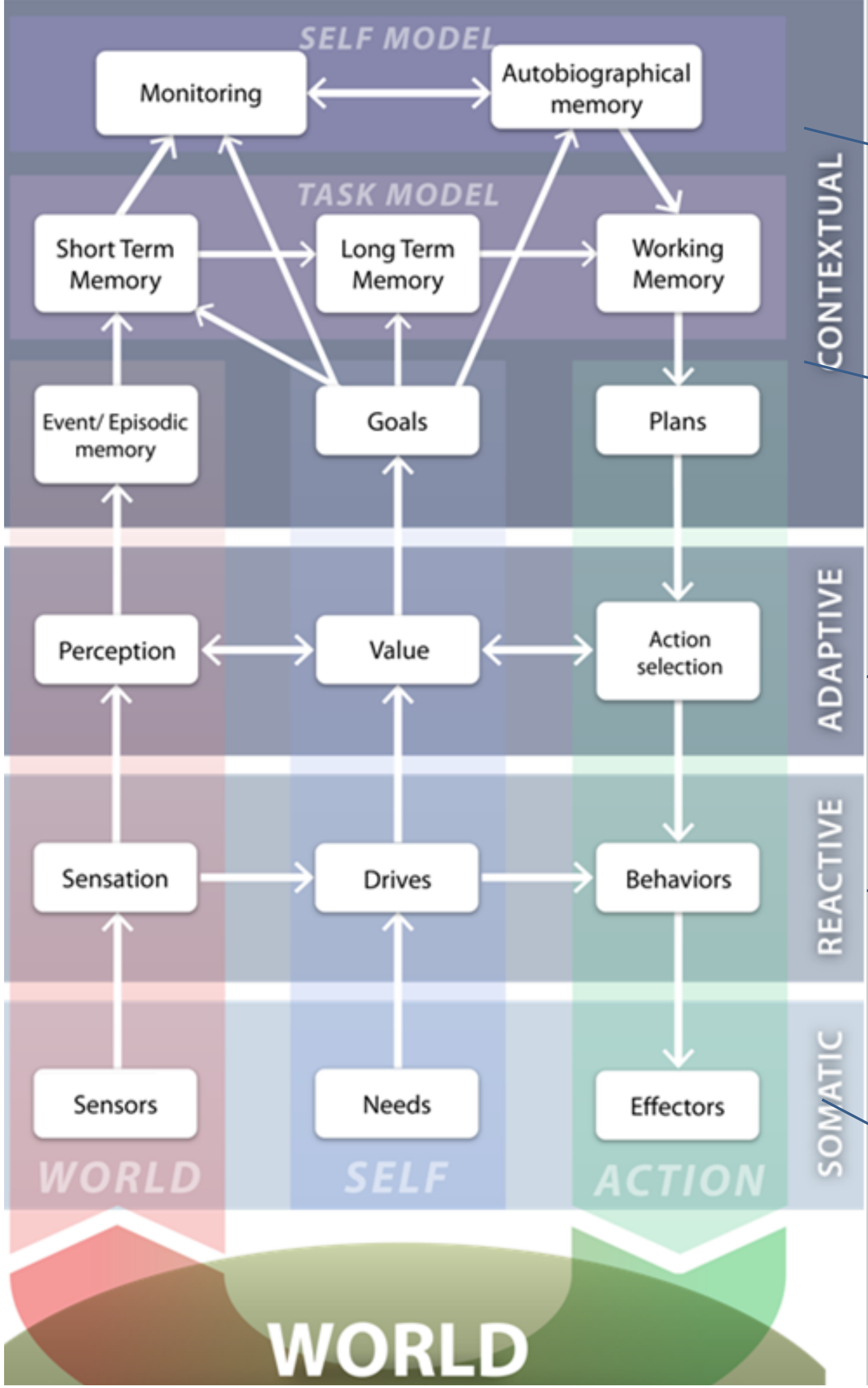


Verschure (2012) BICA



Verschure 1993;1998 NN; 2003 Cog Sci; Nature; 2012 Biol. Insp.Cog.Arch. 2013 IEEE Expert; 2014/2016 TrRoySoc

Distributed Adaptive Control



autonoetic memory, **consciousness**

goal-oriented policies from sequence learning on state-affect-action triads (model based RL)

state space acquisition of agent-environment interaction from dynamics of the reactive level and action shaping (deep learning & model free RL)

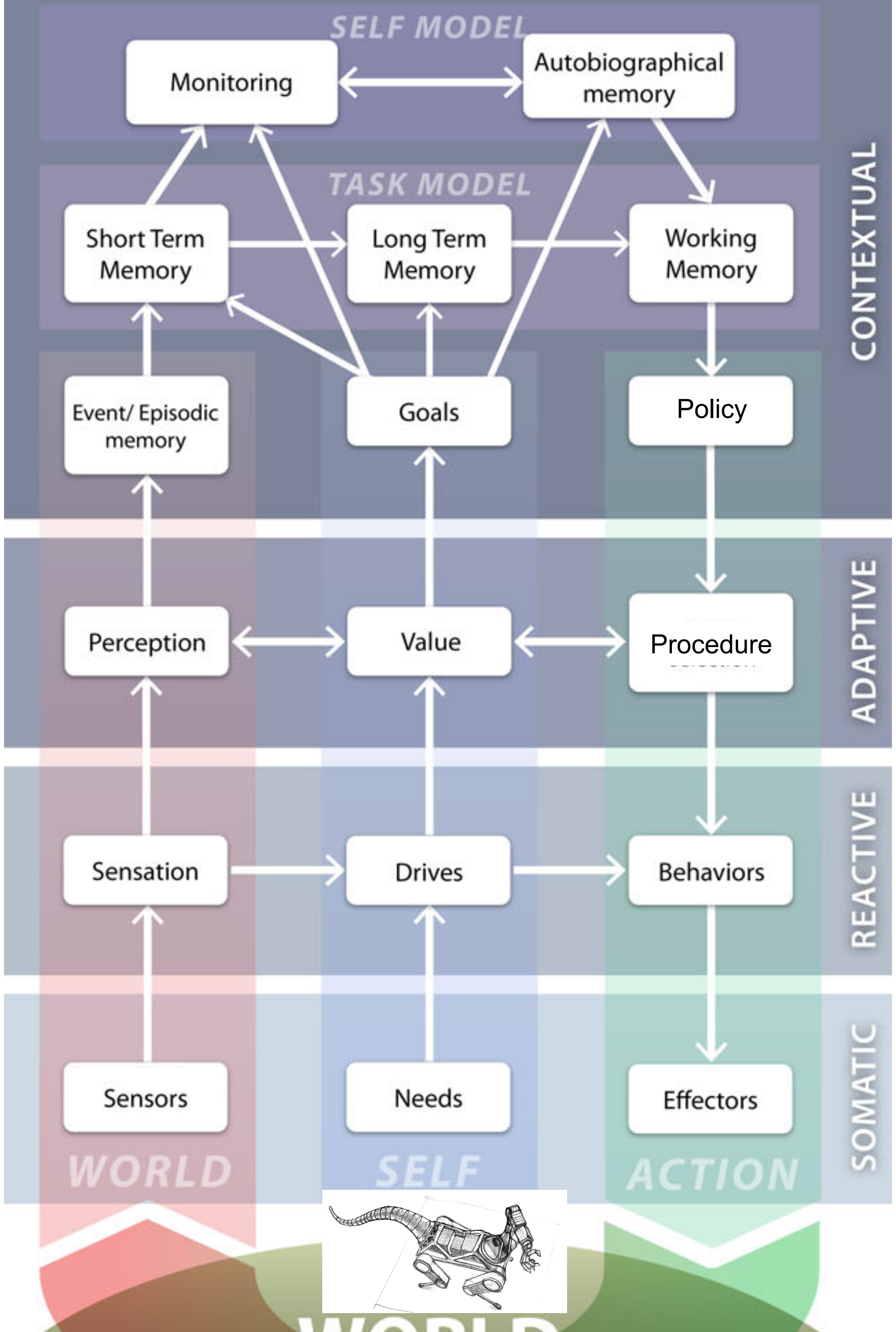
reactive interaction with the environment through **drive regulation, homeostasis, allostasis**

the **physical agent** with sensors, effectors, intrinsic dynamics and needs

Verschure et al 1993;1998 NN; 2003 Cog Sci; Nature; 2012 Biol. Insp.Cog.Arch. 2013 IEEE Expert; 2014/2016 TrRoySoc

Distributed Adaptive Control

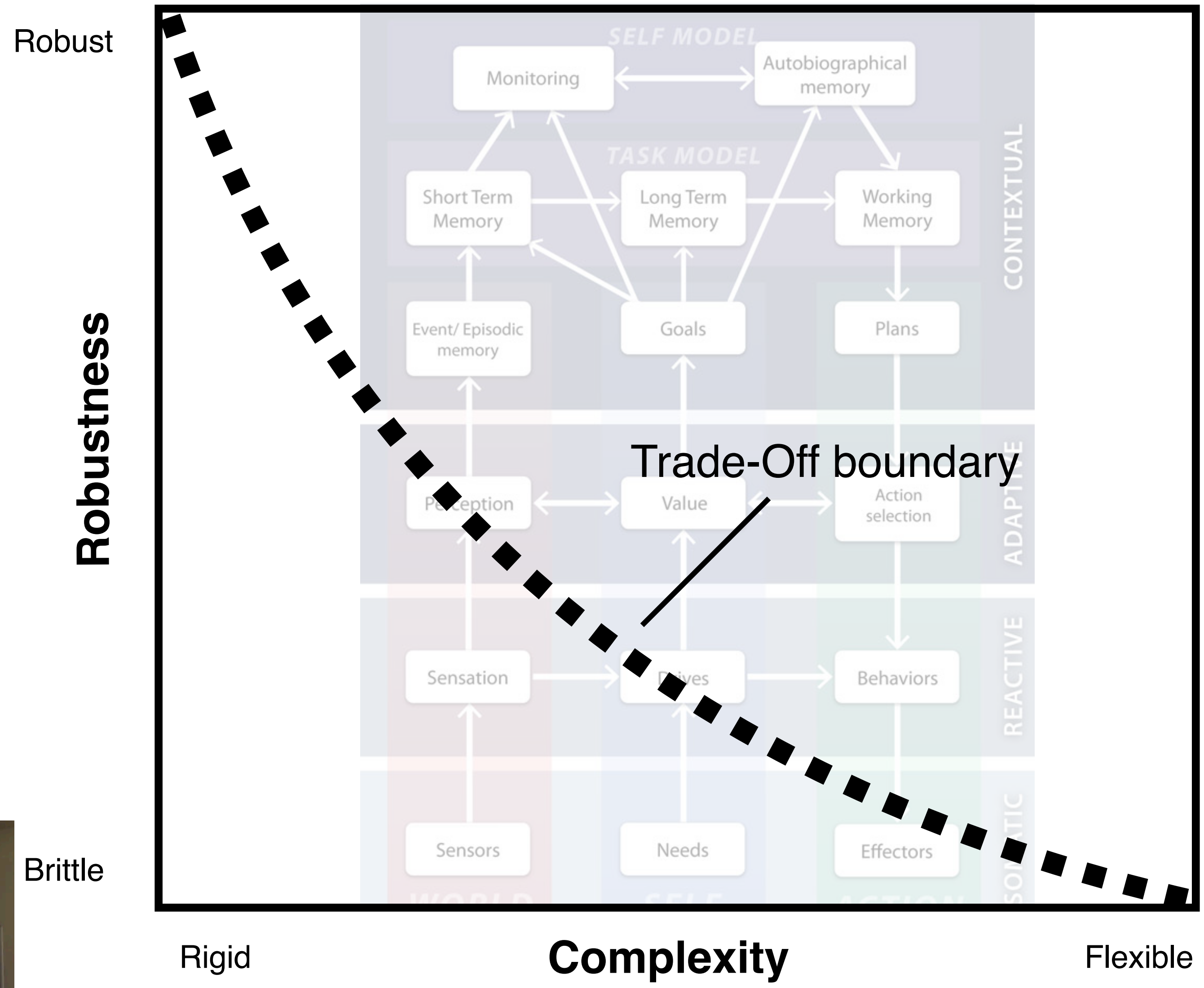
Sequential
Acquired
Flexible
Virtualisation

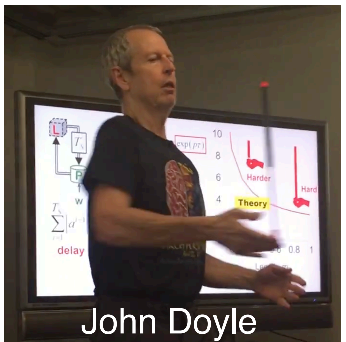


Rigid
Speed
Prior
Parallel

Verschure et al 1993 Rob Aut Sys; 2003 Cog Sci.; 2003 Nature; 2012 Biol. Insp.Cog.Arch.; 2013 IEEE Expert; 2014;2016 Phil.Tr.Roy.Soc. B

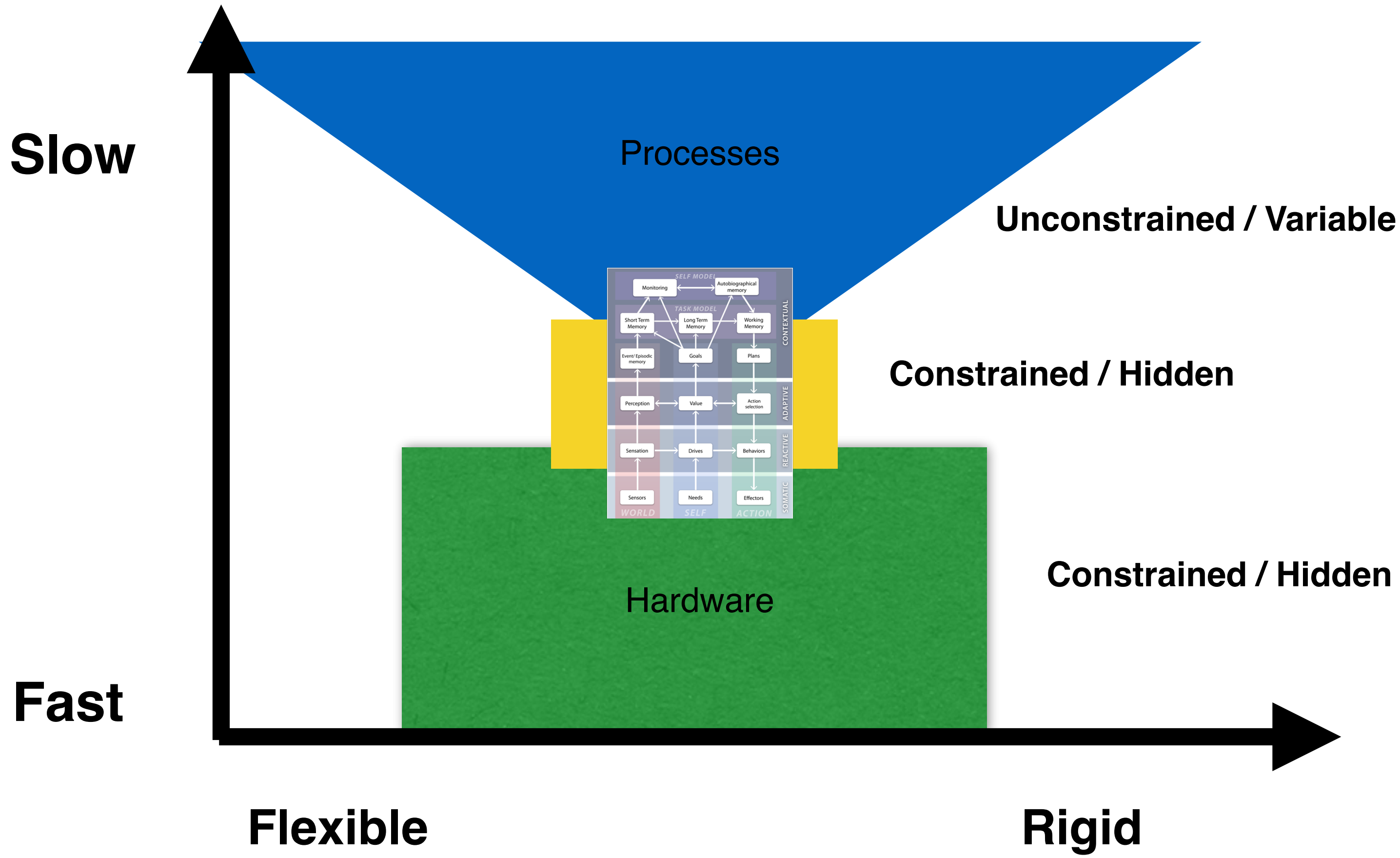
Architectures optimise trade-offs



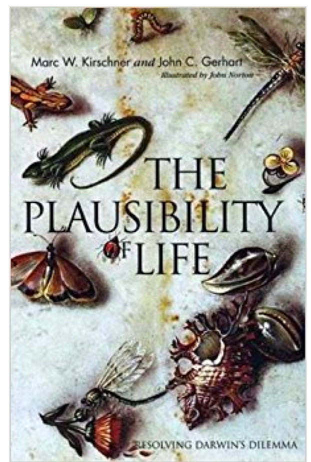


Doyle & Cseste 2011 PNAS

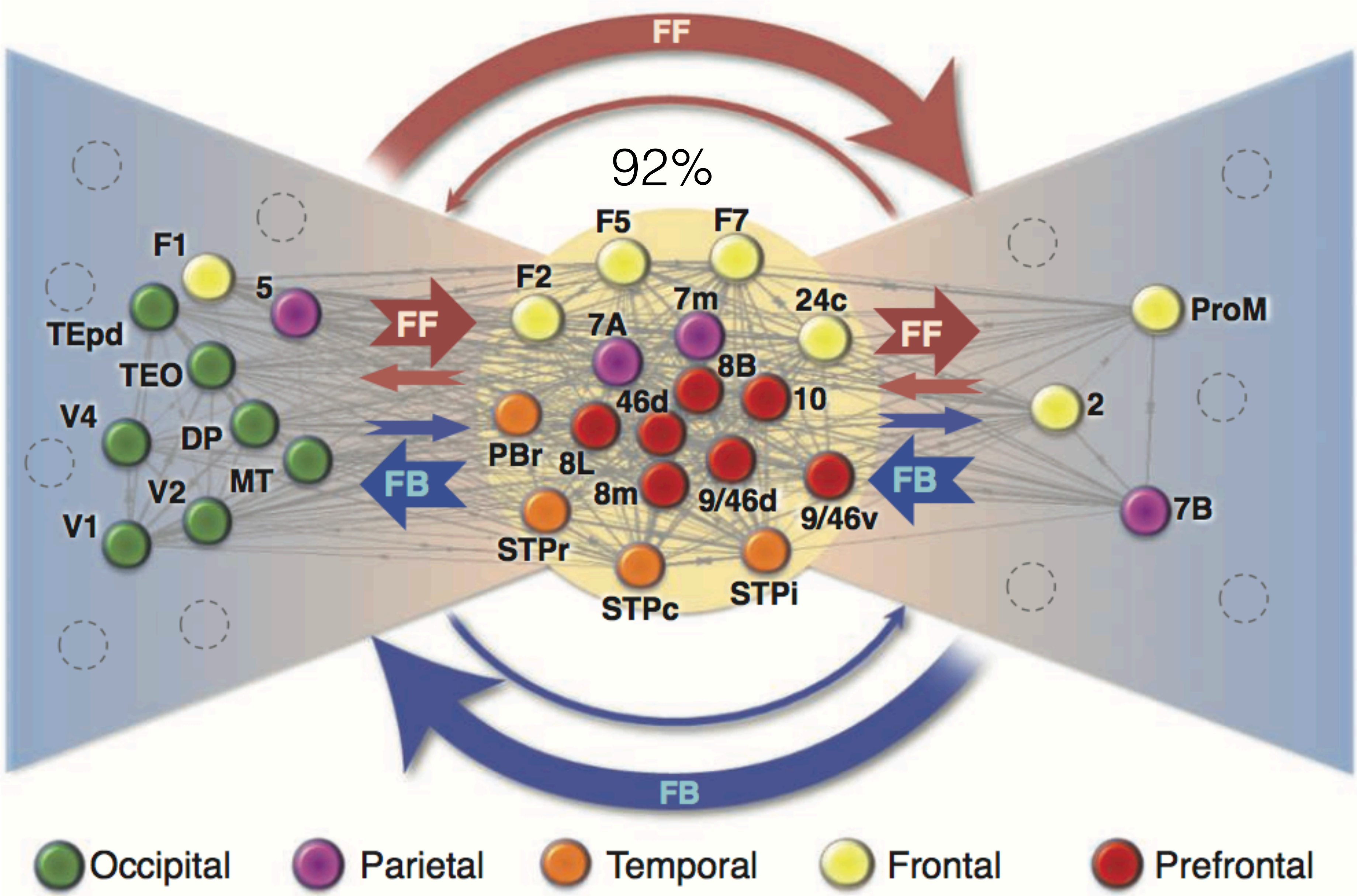
Architectures provide Constraints that Deconstrain



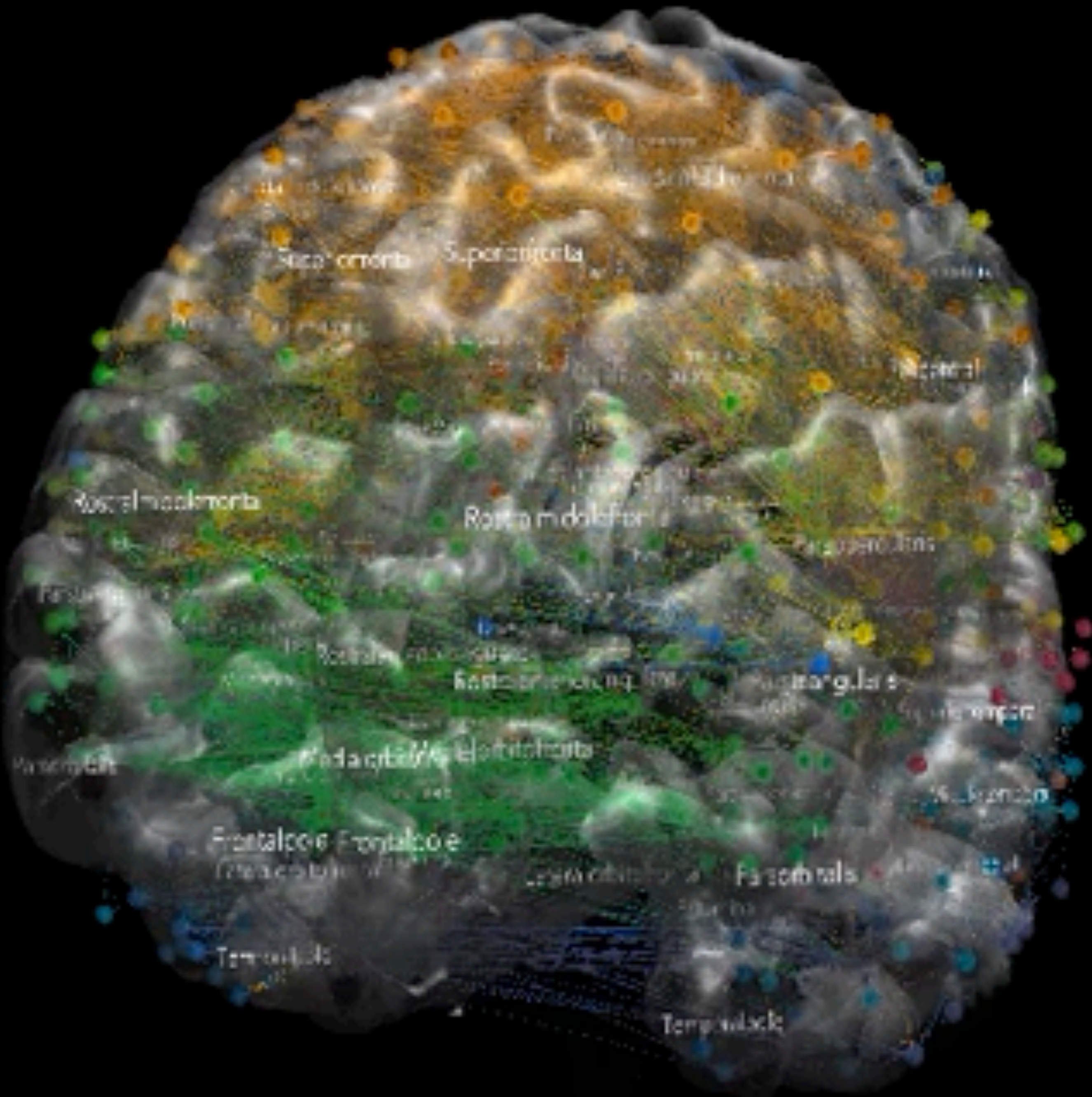
Bowtie architectures



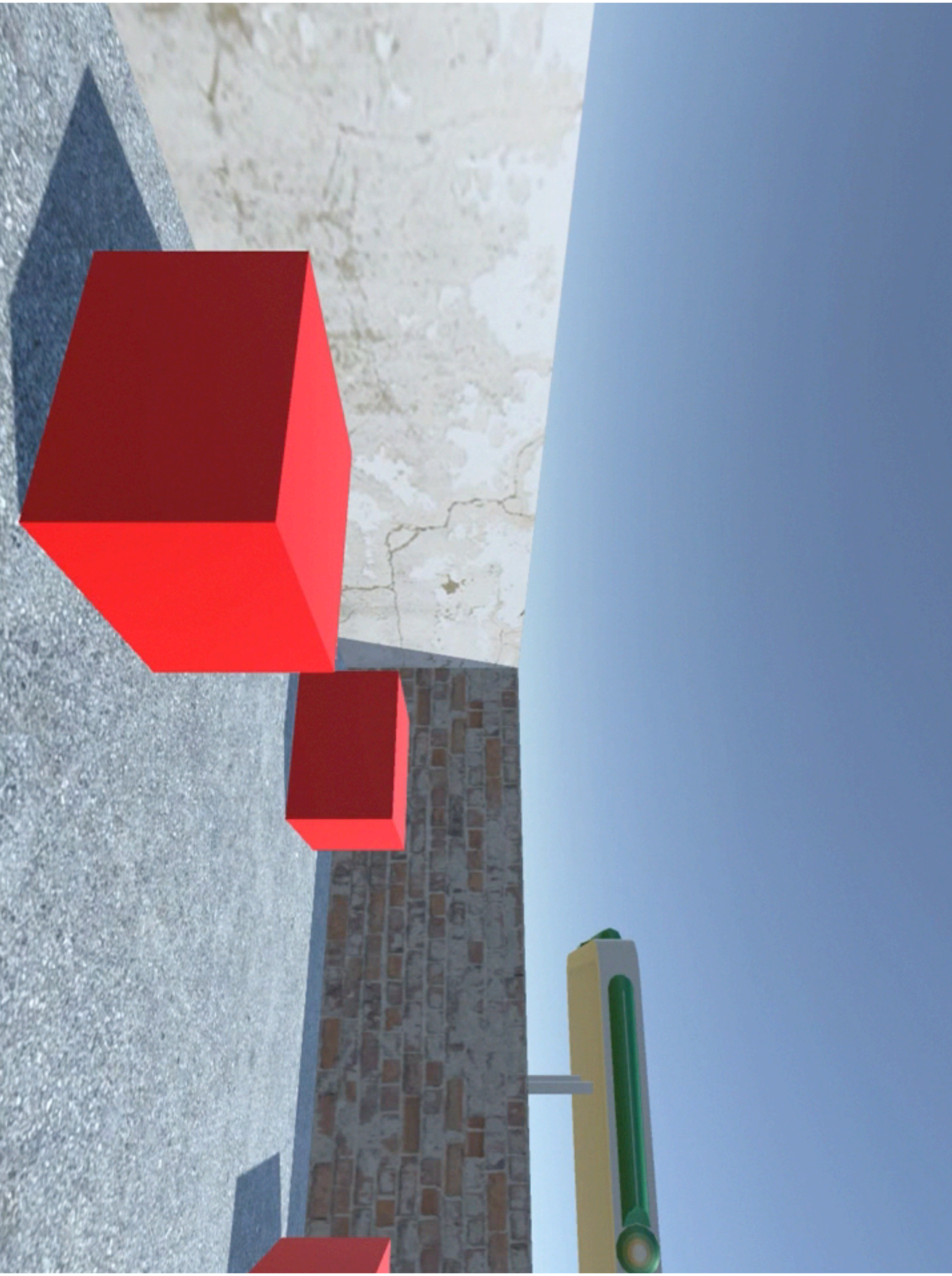
Neocortical Bowtie architecture



Markov et al 2013 Science

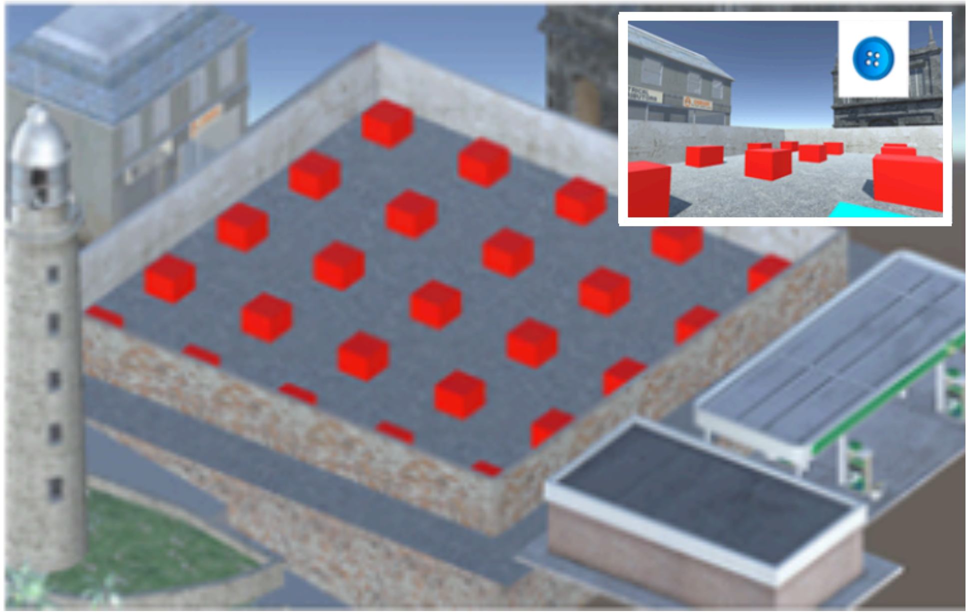


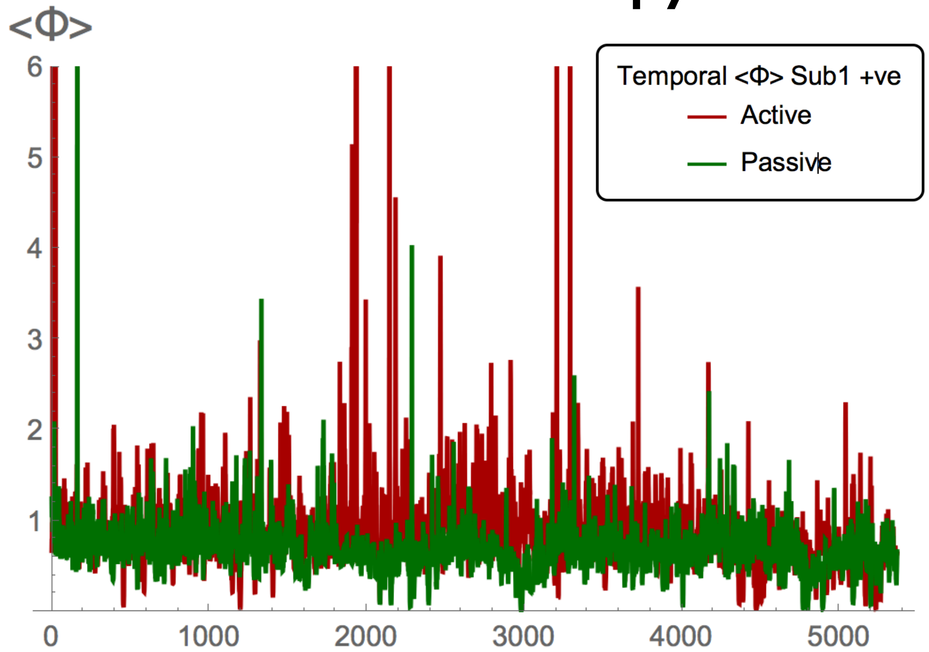
brainx3.com

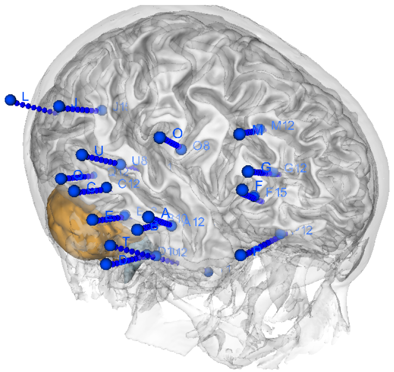


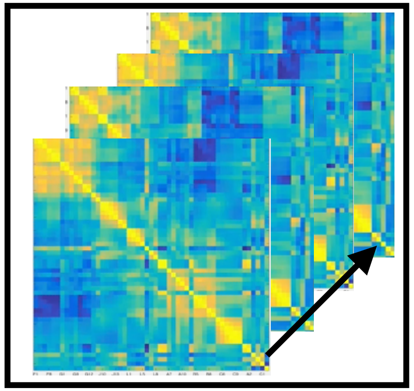
The architecture of the human brain is highly dynamic

Integrated Information: Conditional Entropy





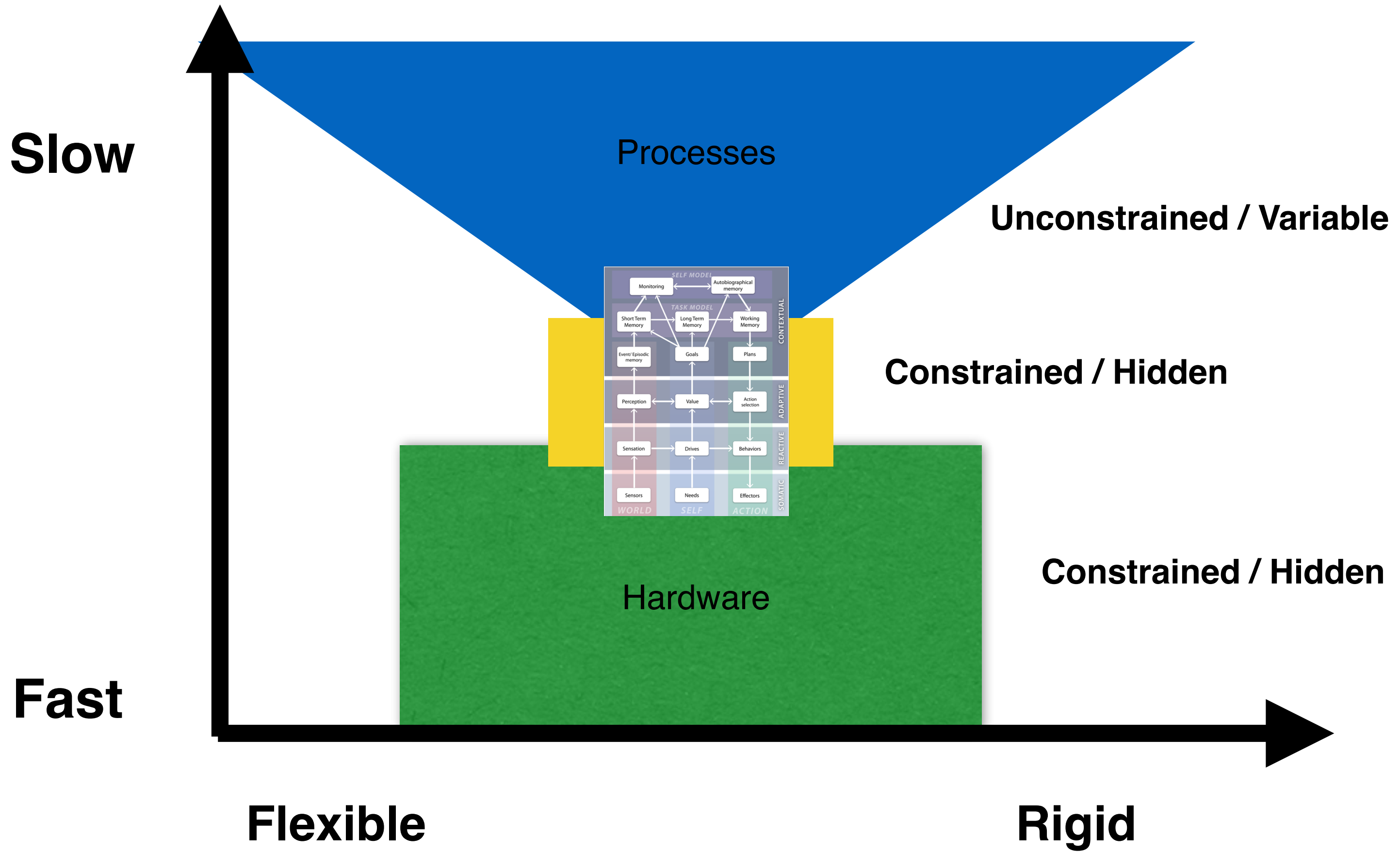




500 msec

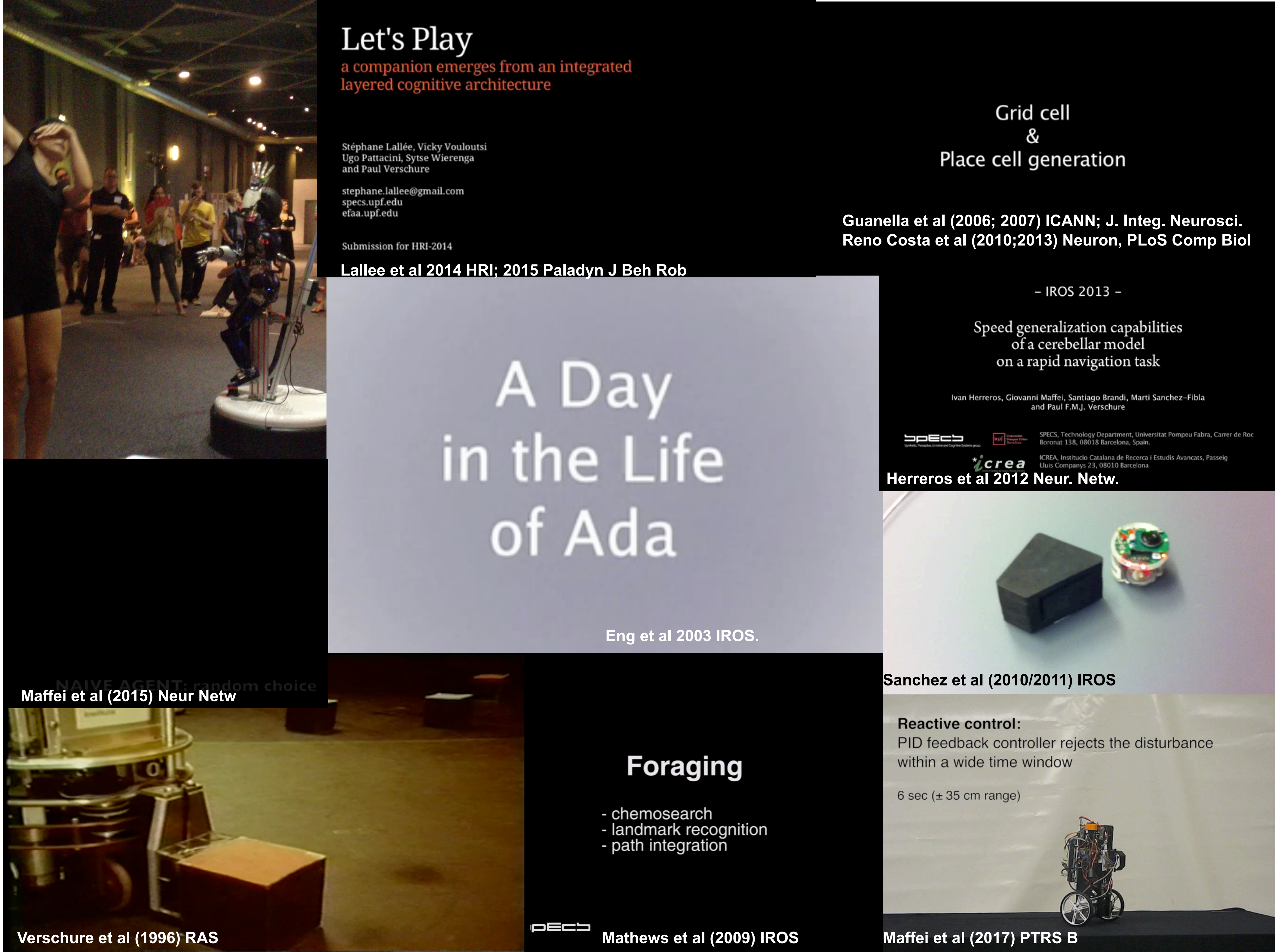
Arsiwalla, Pacheco & Verschure (2016; 2018). App Netw. Sci, ICANN

Brain architecture is dynamic

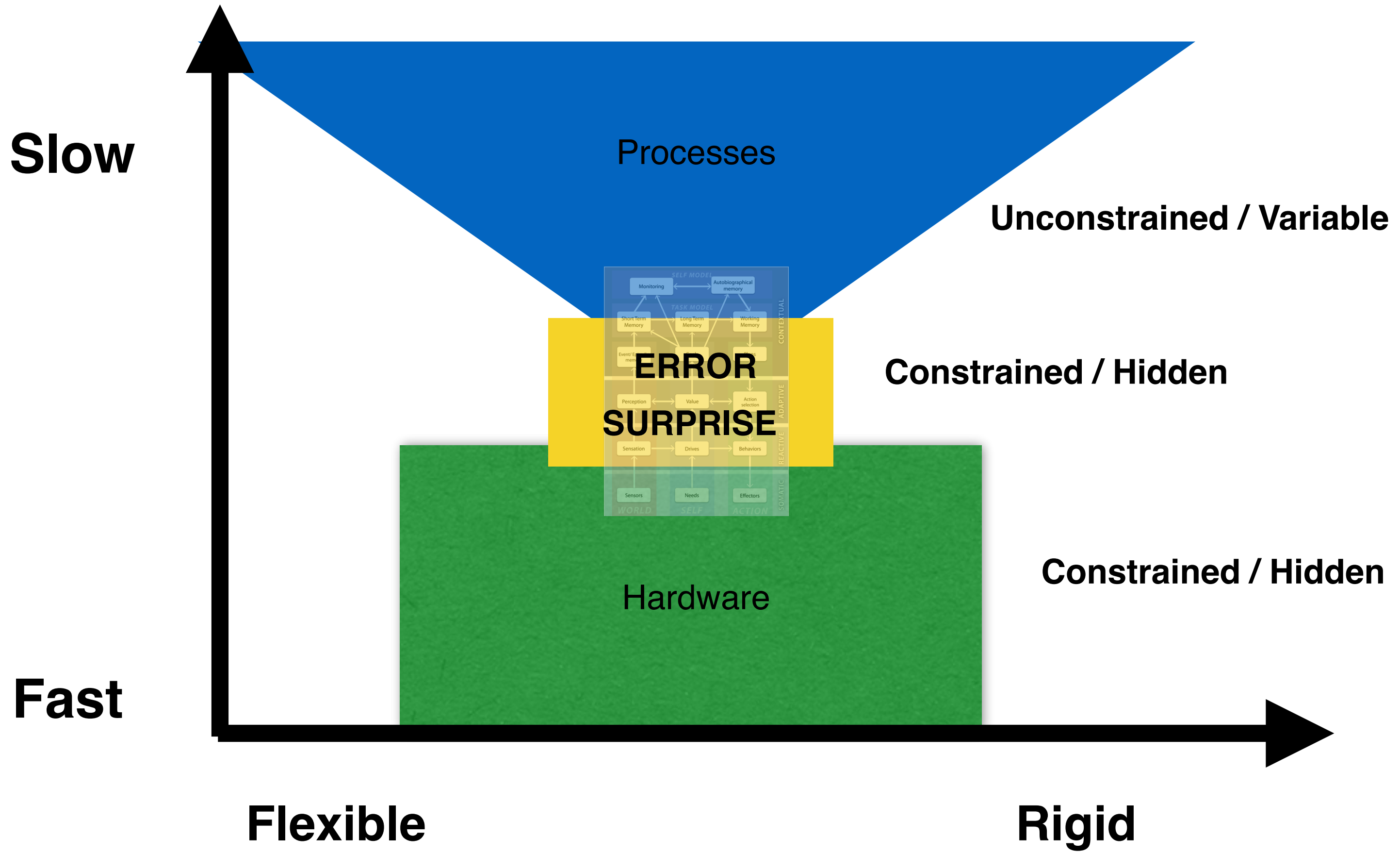


Bowtie architectures

Paul Verschure

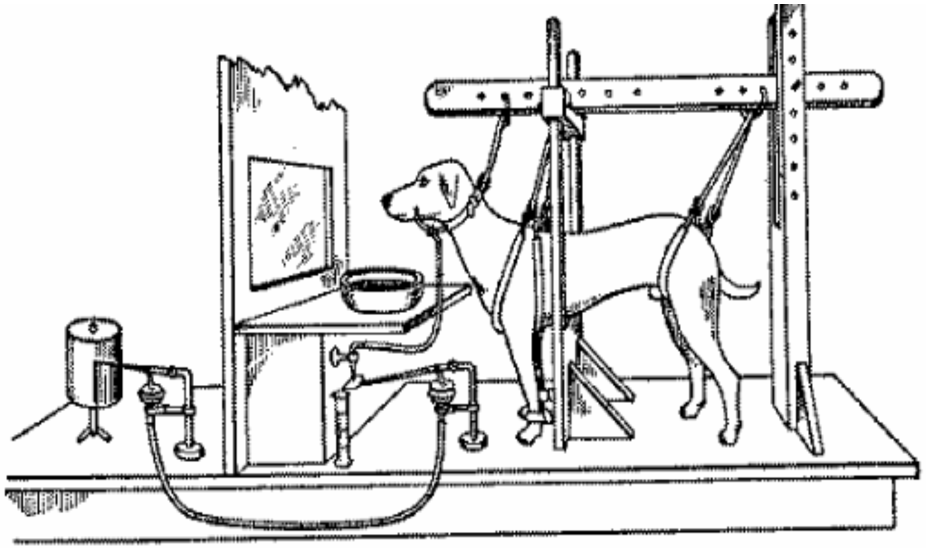

Let's Play
a companion emerges from an integrated layered cognitive architecture
Stéphane Lallée, Vicky Vouloutsi
Ugo Pattacini, Sytse Wierenga
and Paul Verschure
stephane.lallee@gmail.com
specs.upf.edu
efaa.upf.edu
Submission for HRI-2014
Lallee et al 2014 HRI; 2015 Paladyn J Beh Rob
Grid cell
&
Place cell generation
Guanella et al (2006; 2007) ICANN; J. Integ. Neurosci.
Reno Costa et al (2010;2013) Neuron, PLoS Comp Biol
– IROS 2013 –
Speed generalization capabilities of a cerebellar model on a rapid navigation task
Ivan Herreros, Giovanni Maffei, Santiago Brandi, Marti Sanchez-Fibla and Paul F.M.J. Verschure
SPECS, Technology Department, Universitat Pompeu Fabra, Carrer de Roc Boronat 138, 08018 Barcelona, Spain.
ICREA, Institucio Catalana de Recerca i Estudis Avancats, Passeig Lluis Companys 23, 08010 Barcelona
Herreros et al 2012 Neur. Netw.
A Day in the Life of Ada
Eng et al 2003 IROS.
Sanchez et al (2010/2011) IROS
NAIVE AGENT: random choice
Maffei et al (2015) Neur Netw
Foraging
- chemosearch
- landmark recognition
- path integration
Mathews et al (2009) IROS
Reactive control:
PID feedback controller rejects the disturbance within a wide time window
6 sec (± 35 cm range)
Verschure et al (1996) RAS
Maffei et al (2017) PTRS B

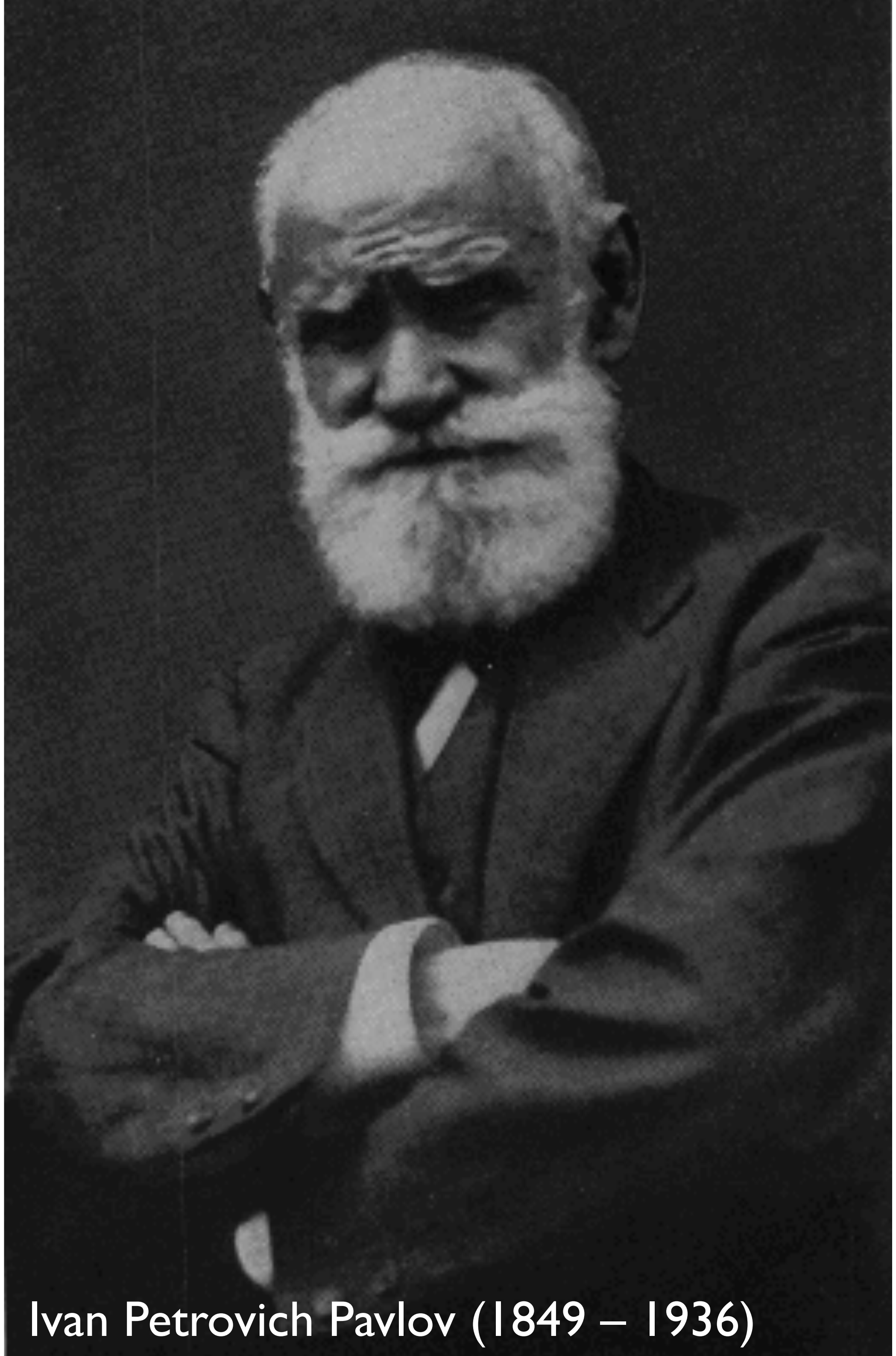
Constraint: Error processing



Paul Verschure

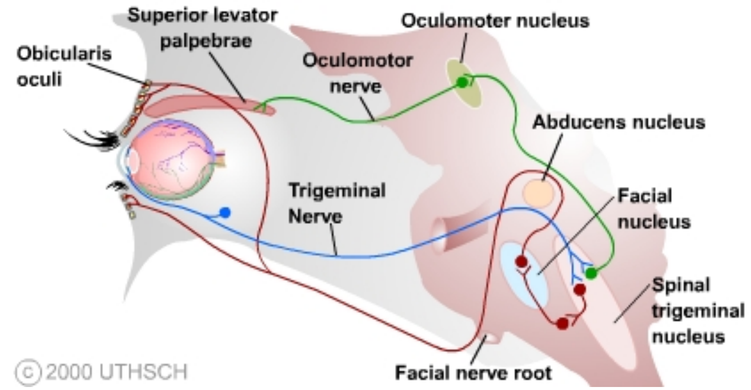
Classical/ Pavlovian Conditioning



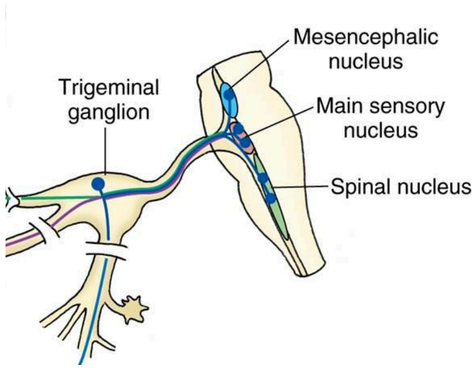


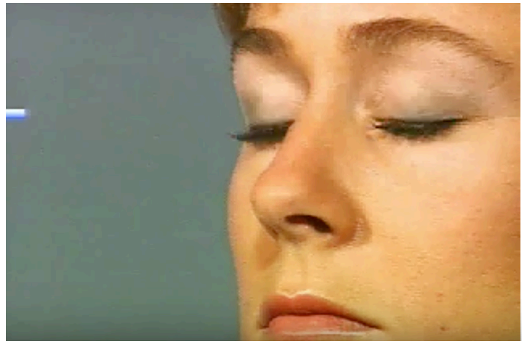
Ivan Petrovich Pavlov (1849 – 1936)

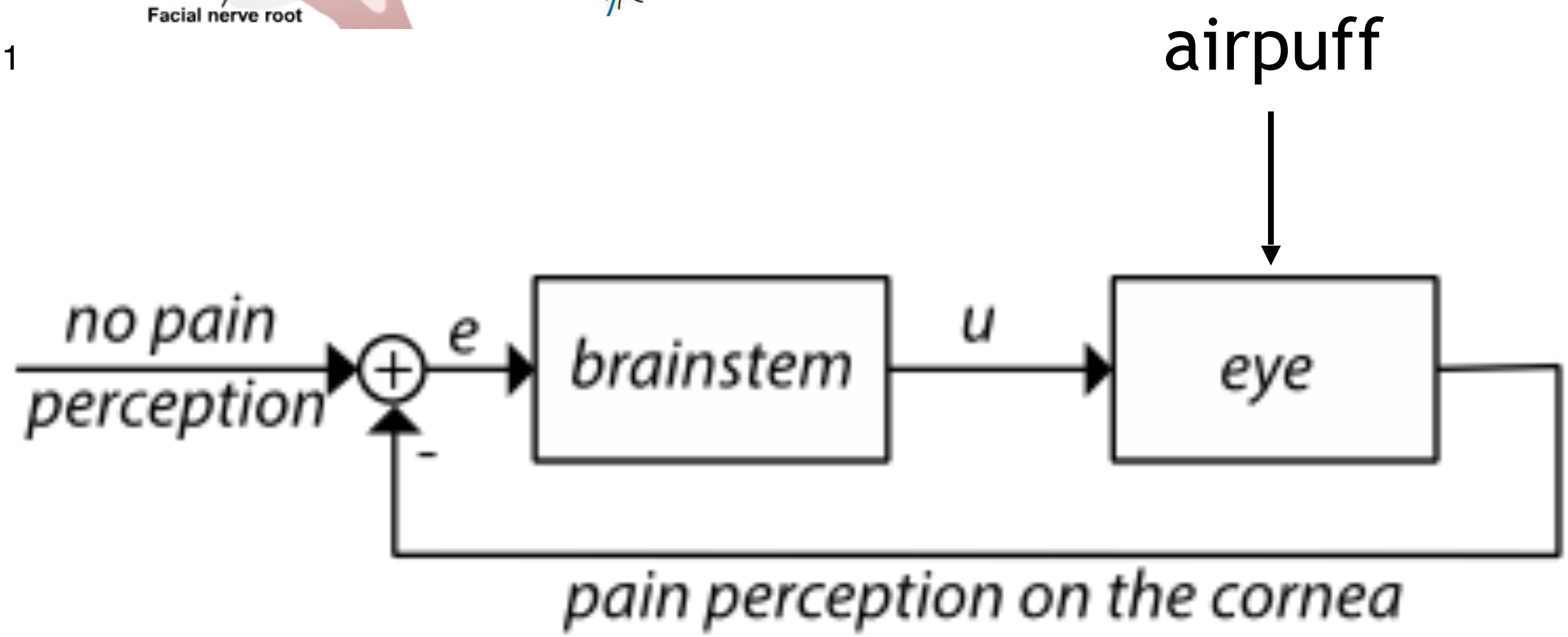
Reactive layer: Feedback control in the brainstem

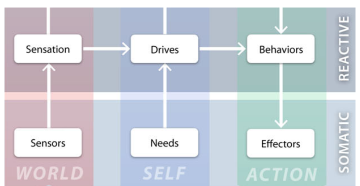


Kuypers 1981





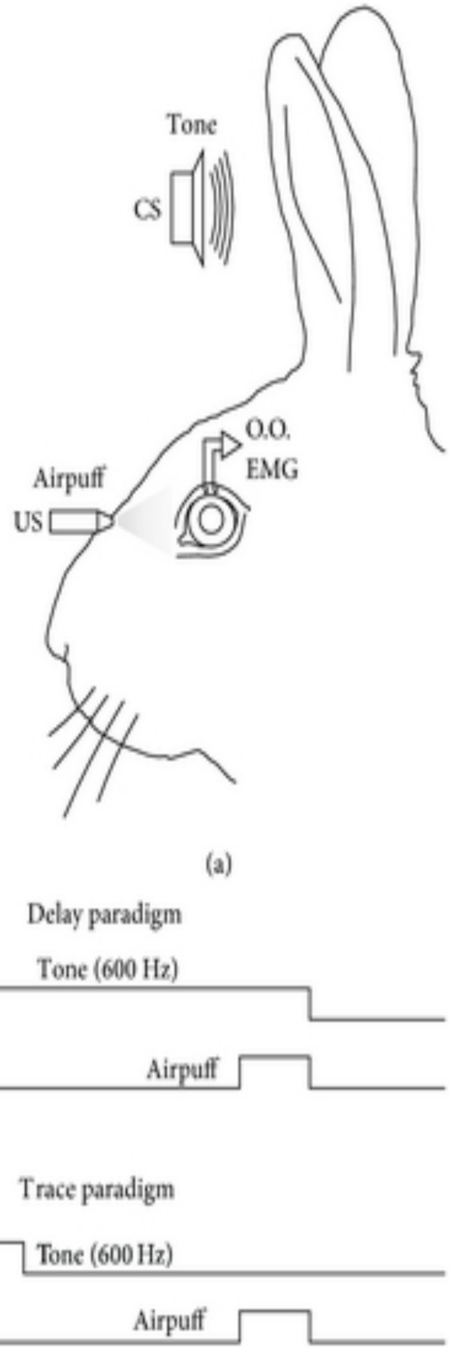




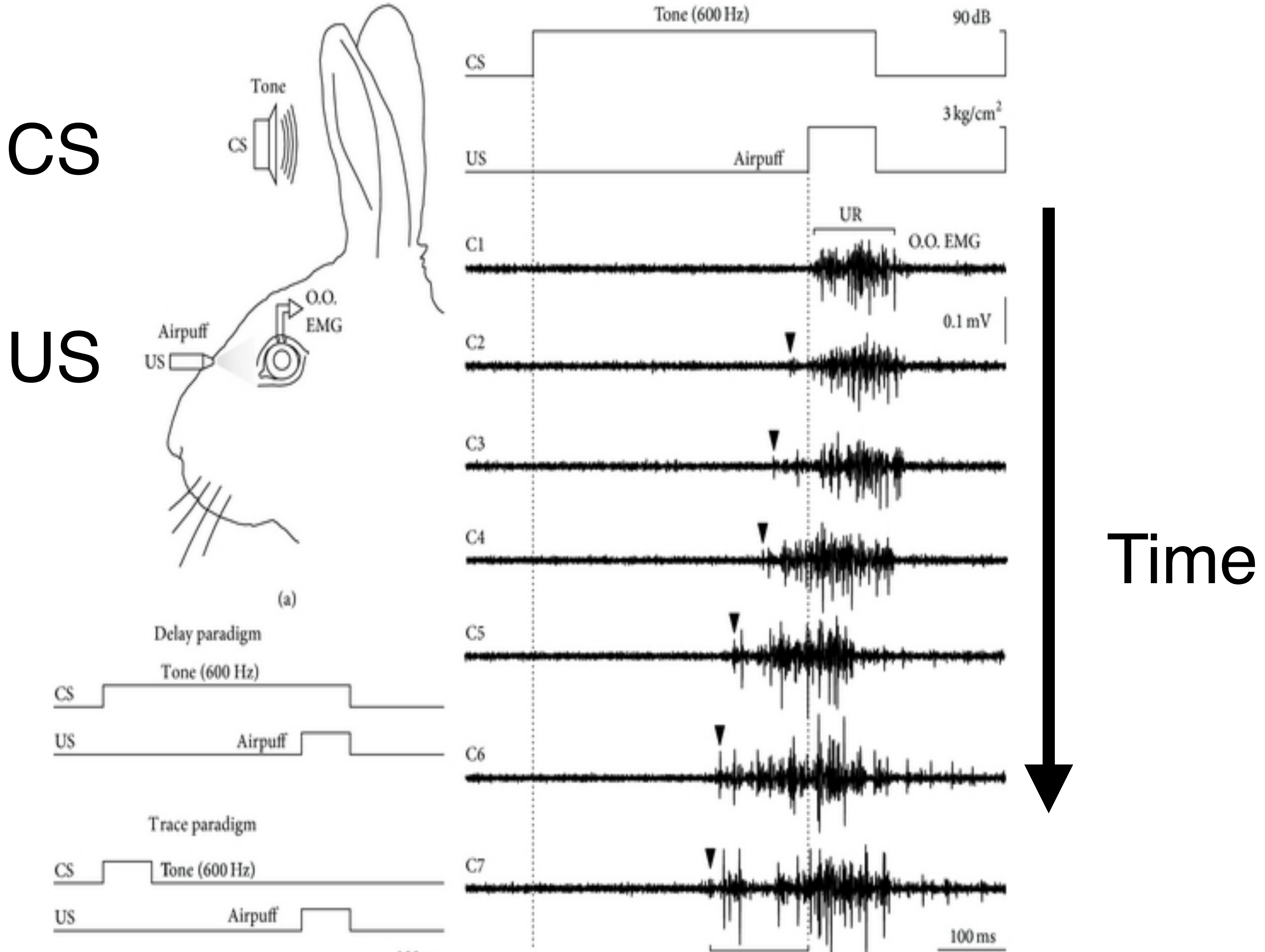
Classical Eyeblink Conditioning

CS

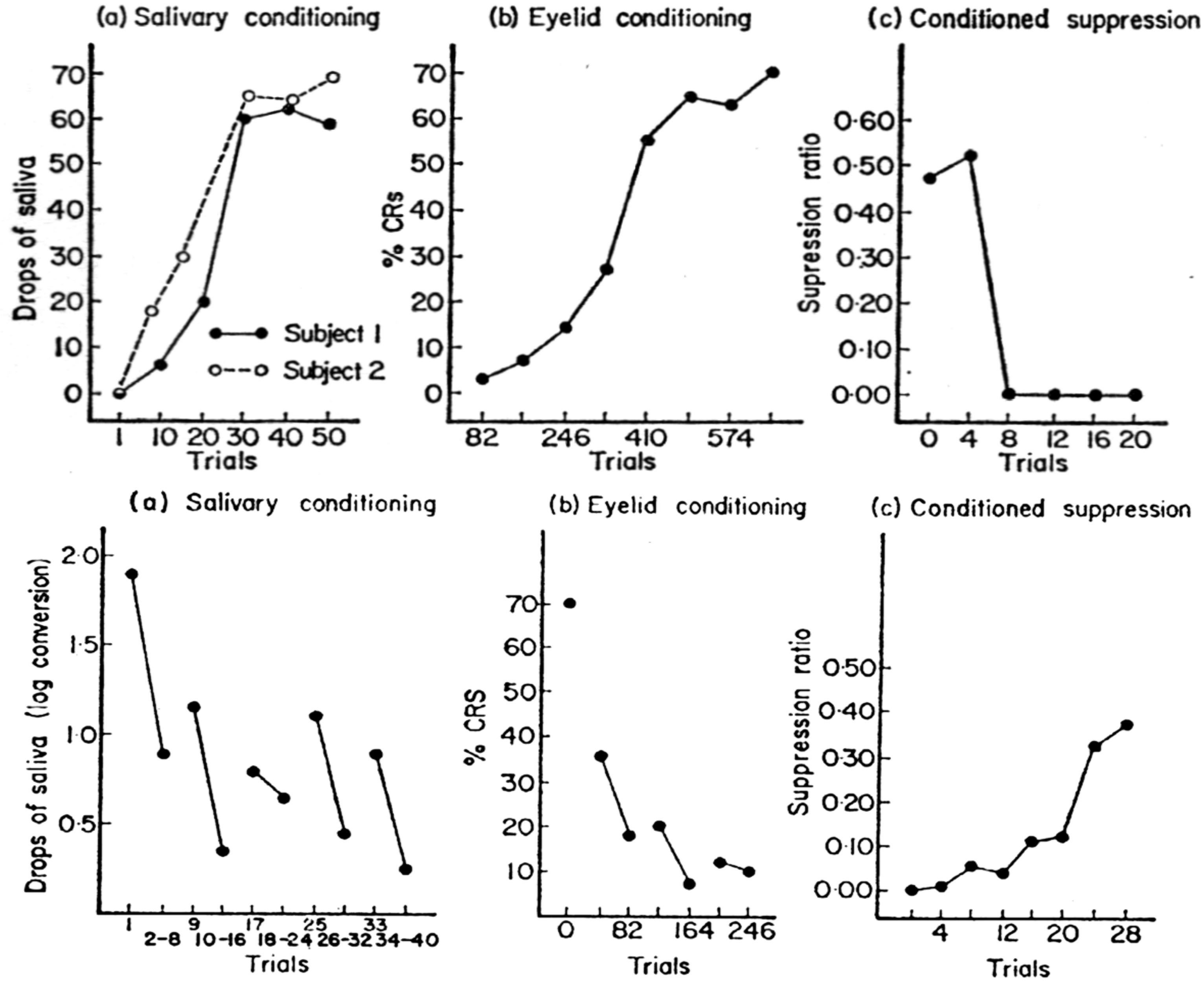
US



Classical Eyeblink Conditioning

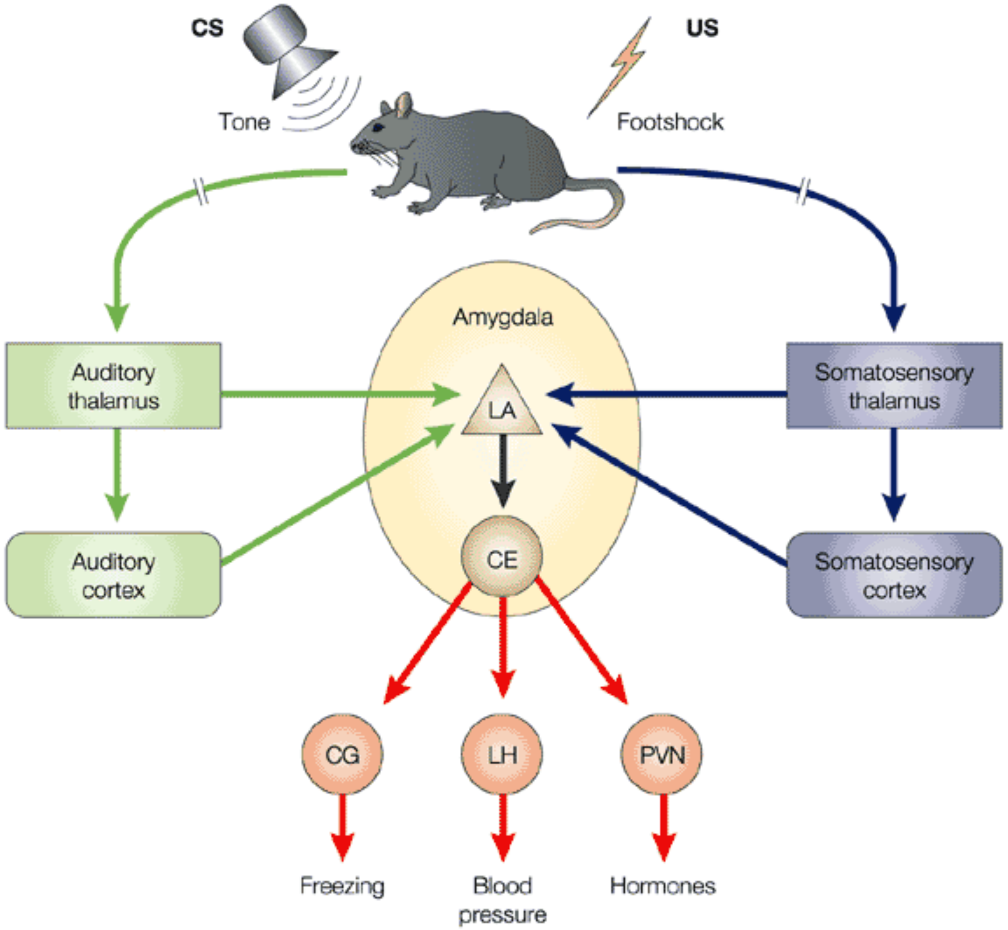


Specific Non-specific

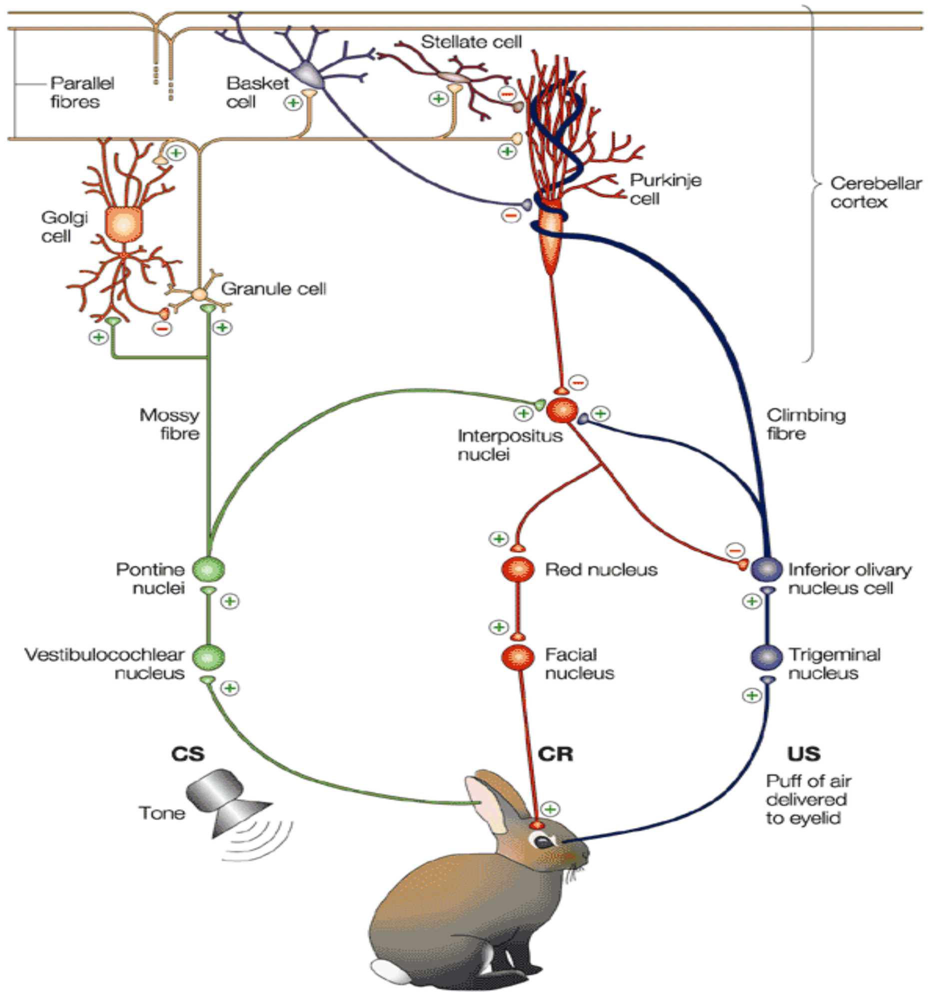


Konorski: 2 learning systems

Non-specific

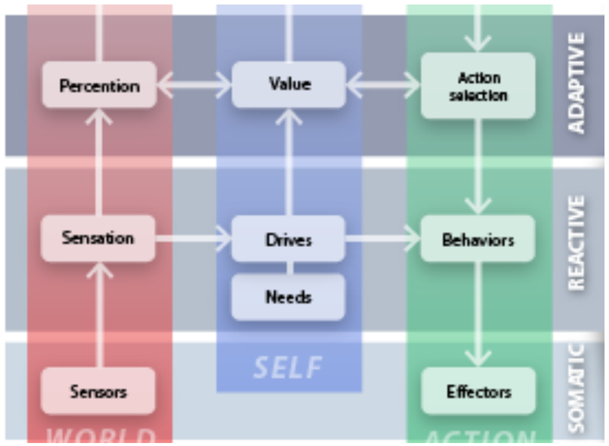


Specific



Medina et al, Nat Rev Neurosci, 2001

2 Phase model optimization objective: Correlation, Perceptual and Behavioral prediction



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

correlation

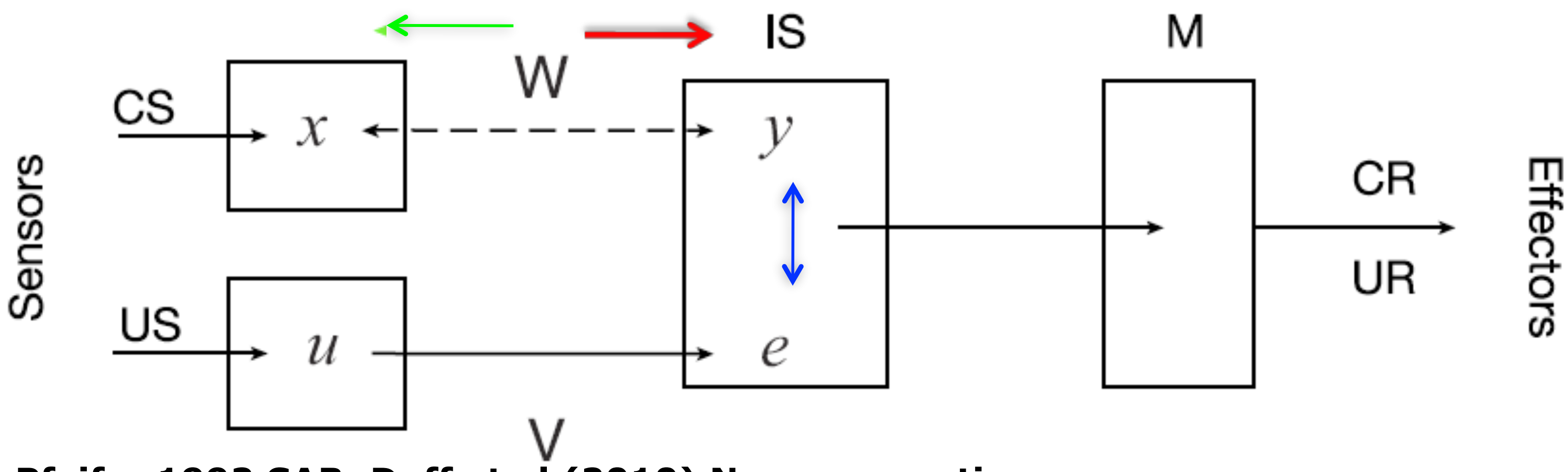
$$J_C(W) = E[trace(ye^{\mathsf{T}})|W] \qquad WW^{\mathsf{T}} = I \qquad y = W^{\mathsf{T}} x$$

perceptual prediction

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

behavioral prediction

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

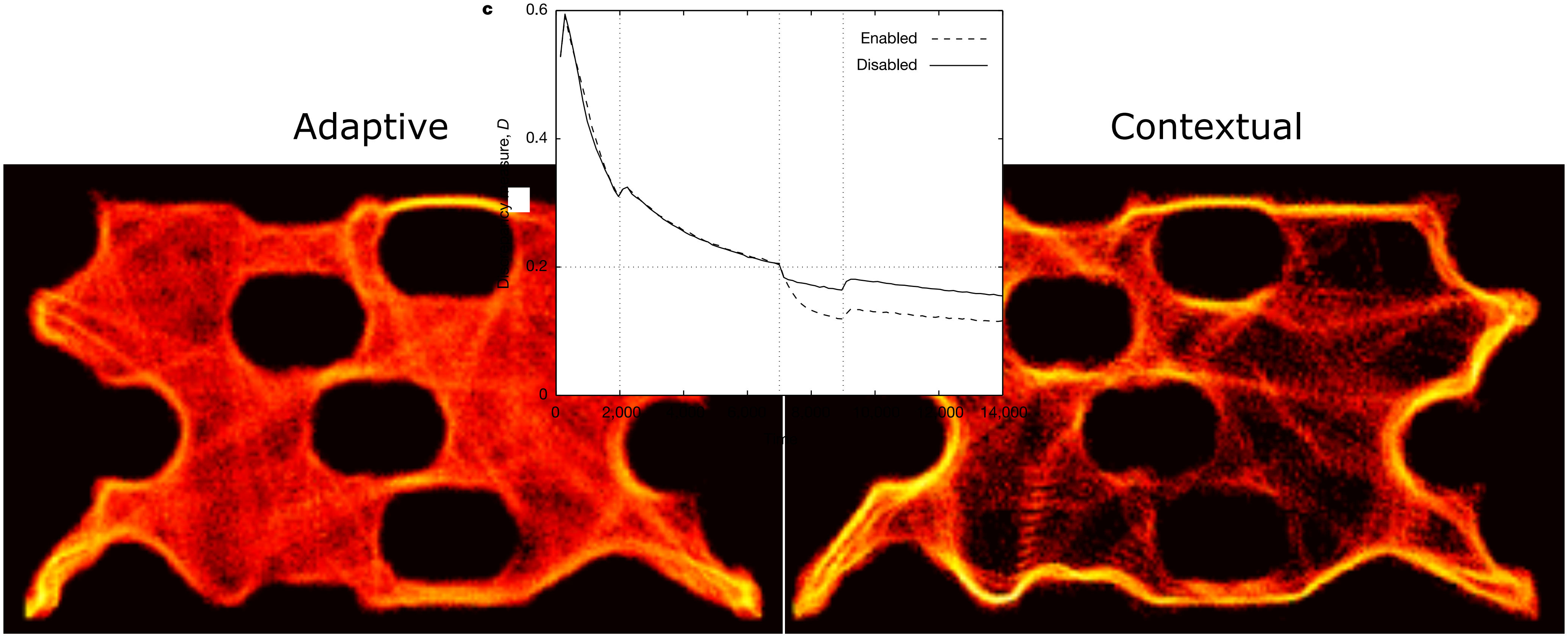


Verschure & Pfeifer 1992 SAB; Duff et al (2010) Neurocomputing

Behavioral feedback, effective environments and perceptual learning

Adaptive

Contextual



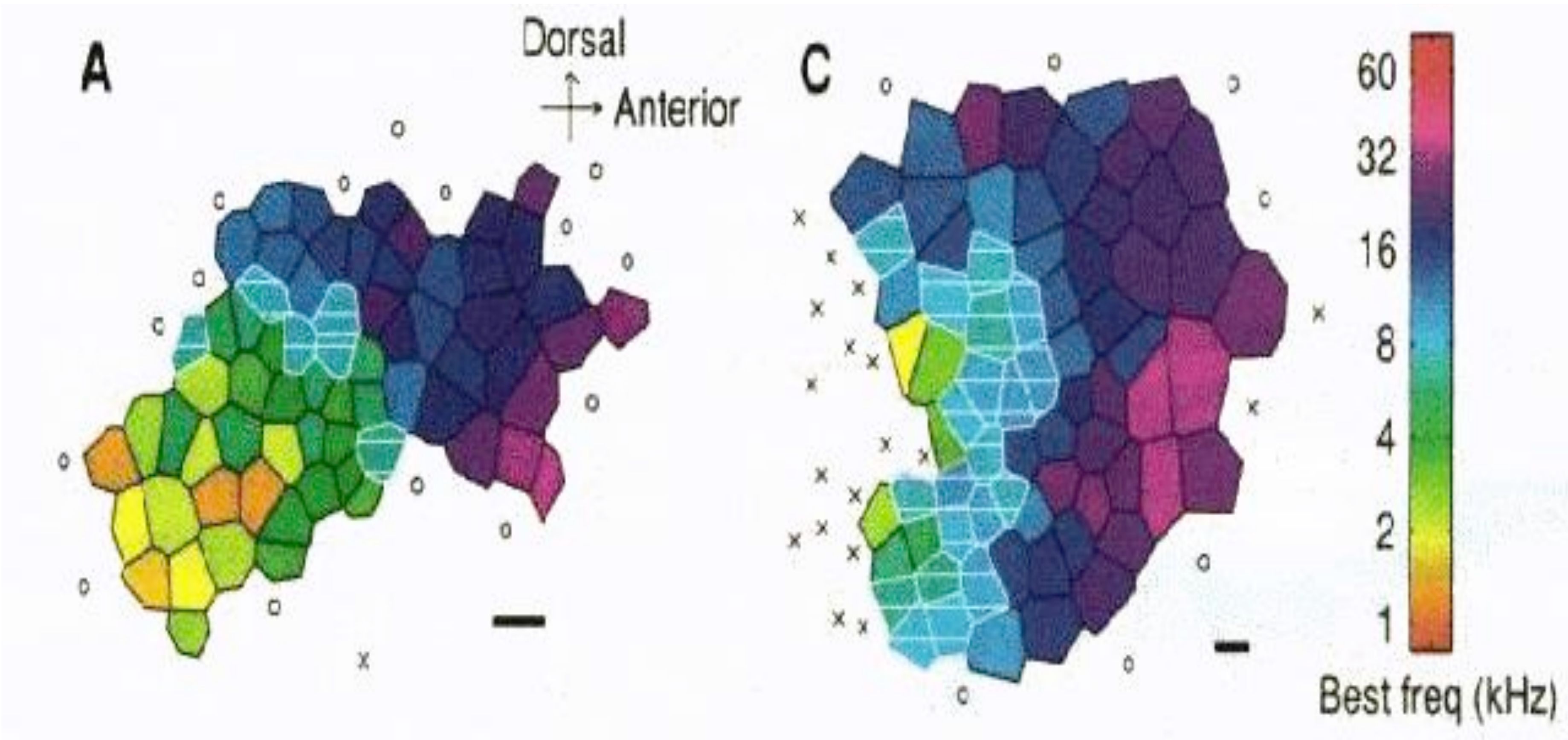
Simulation: 10^6 timesteps

$$H = -\sum_{a \in E} p(a) \log_2 p(a) \text{ with } \sum_{a \in E} p(a) = 1$$

Hb = 15.1	Behavioral Entropy	Hb = 14.2
Hs = 7.95	Sensor Sampling Entropy	Hs = 6.8

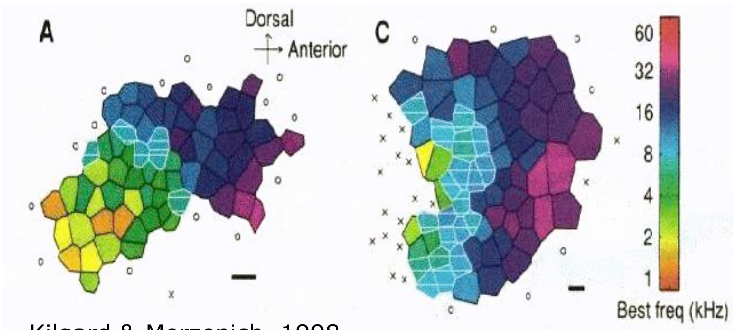
Verschure et al (2003) Nature, 425:620-24

Non-specific: CS Identification

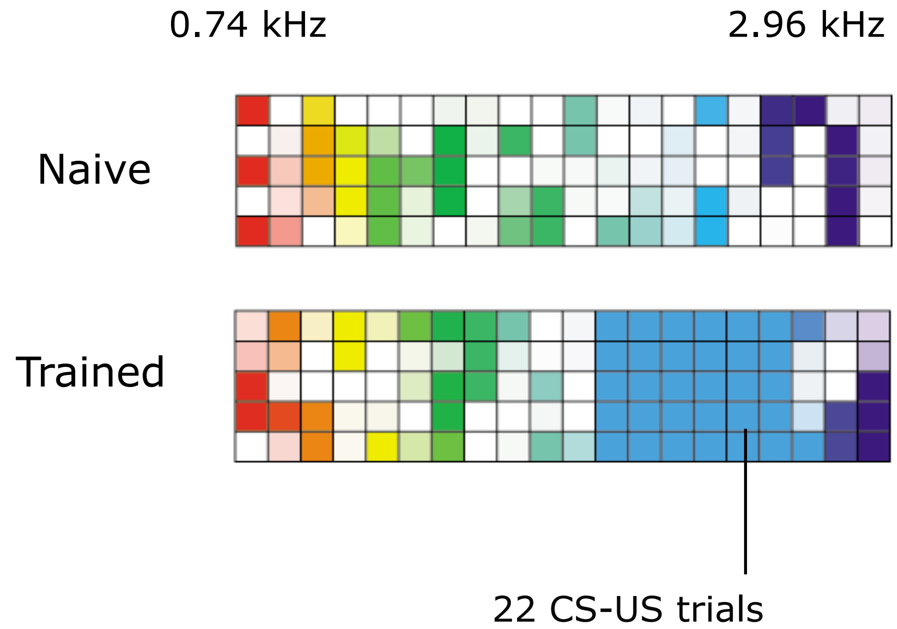


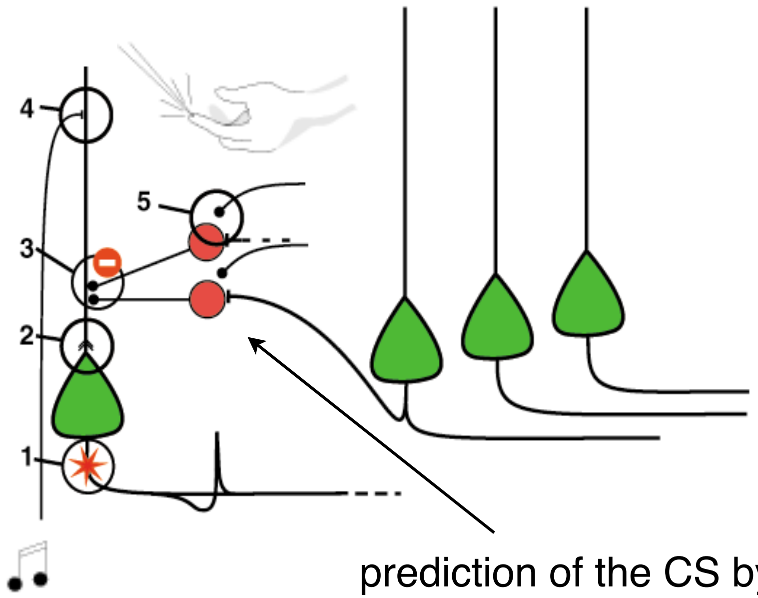
Kilgard & Merzenich, 1998

Non-specific: CS Identification



Kilgard & Merzenich, 1998



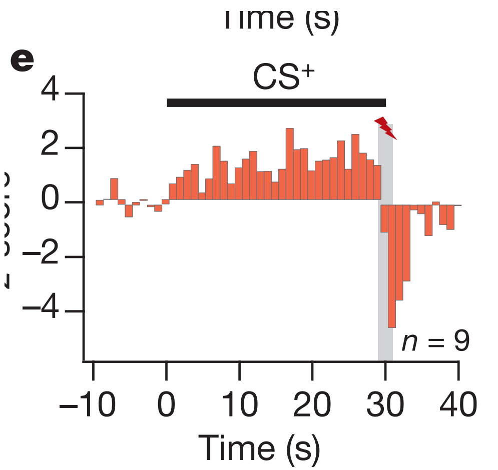


prediction of the CS by the excitatory population

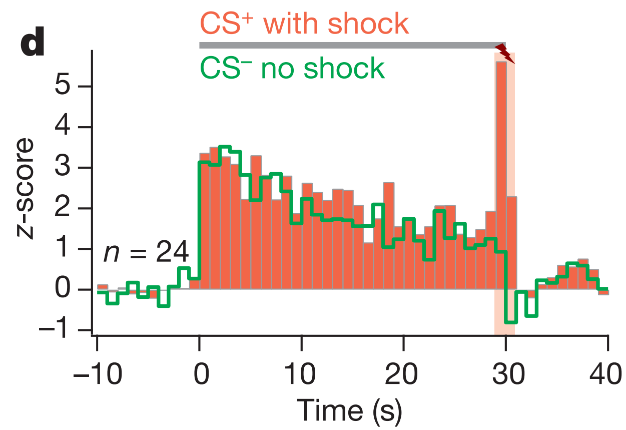
Sanchez-Montanes et al (2000/2002)

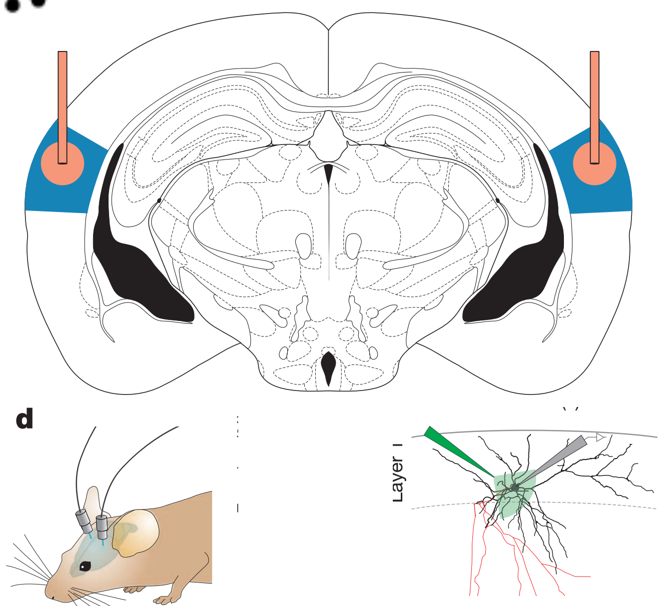
Empirical evidence: Interneurons modulate learning in auditory

Interneuron response

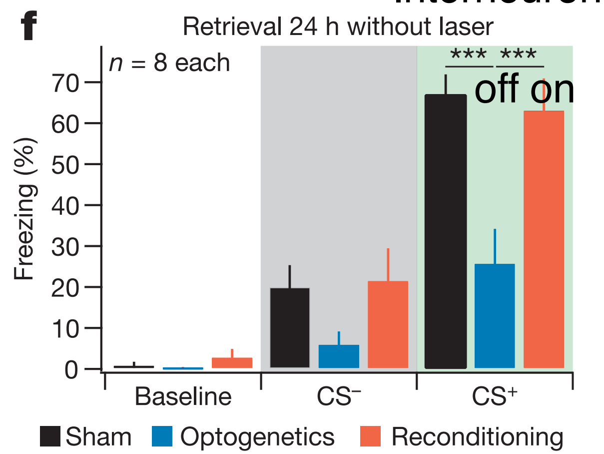


Pyramidal cell response





Interneuron

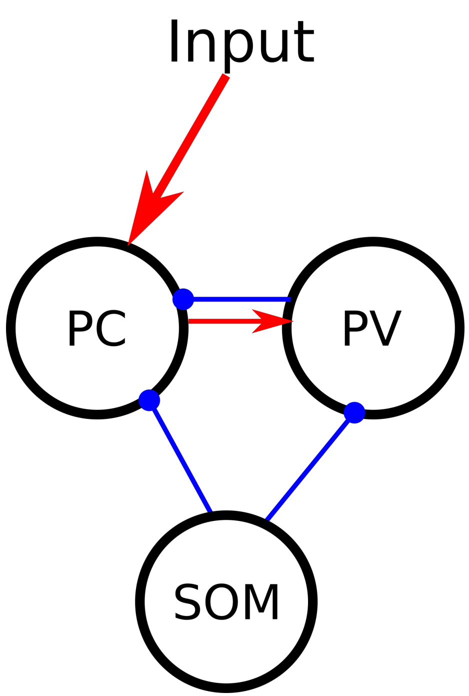


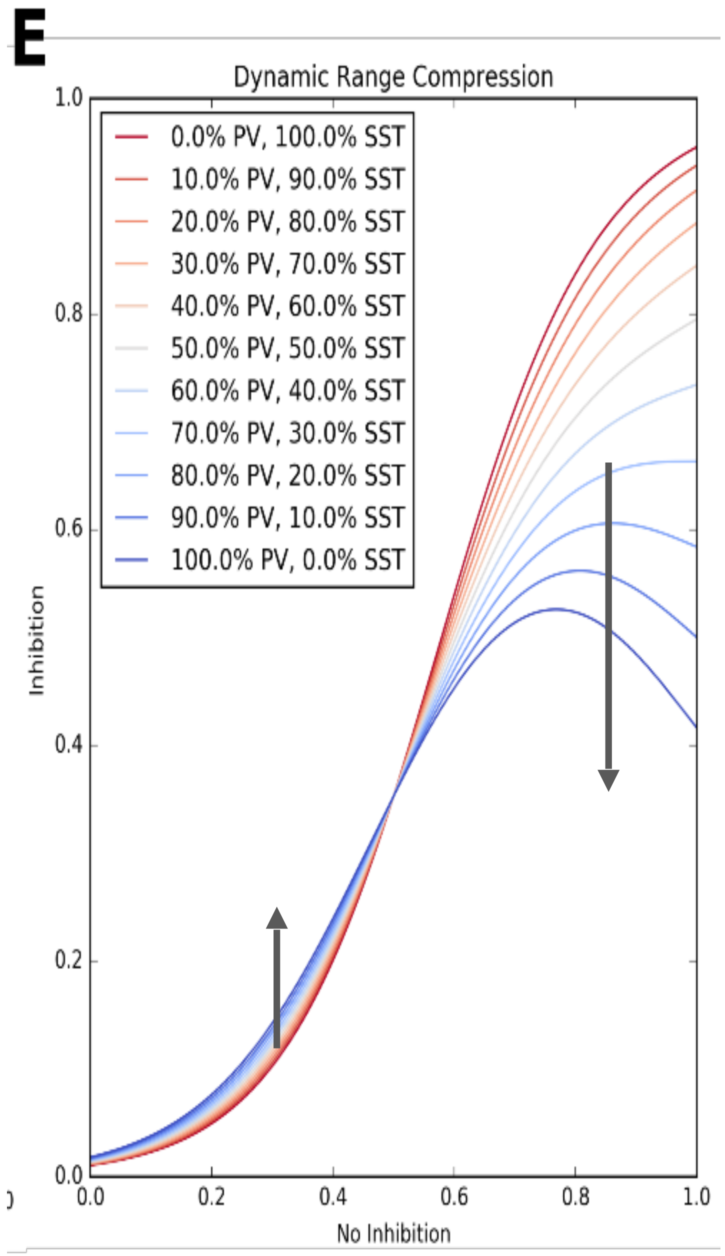
Letzkus et al 2011, Nature

Cholinergic Modulation of Dynamic Range Compression

Gain control of one signal excitatory unit with and without the effects of inhibition. Color modulates balance in inhibitory activity for different inh. Populations

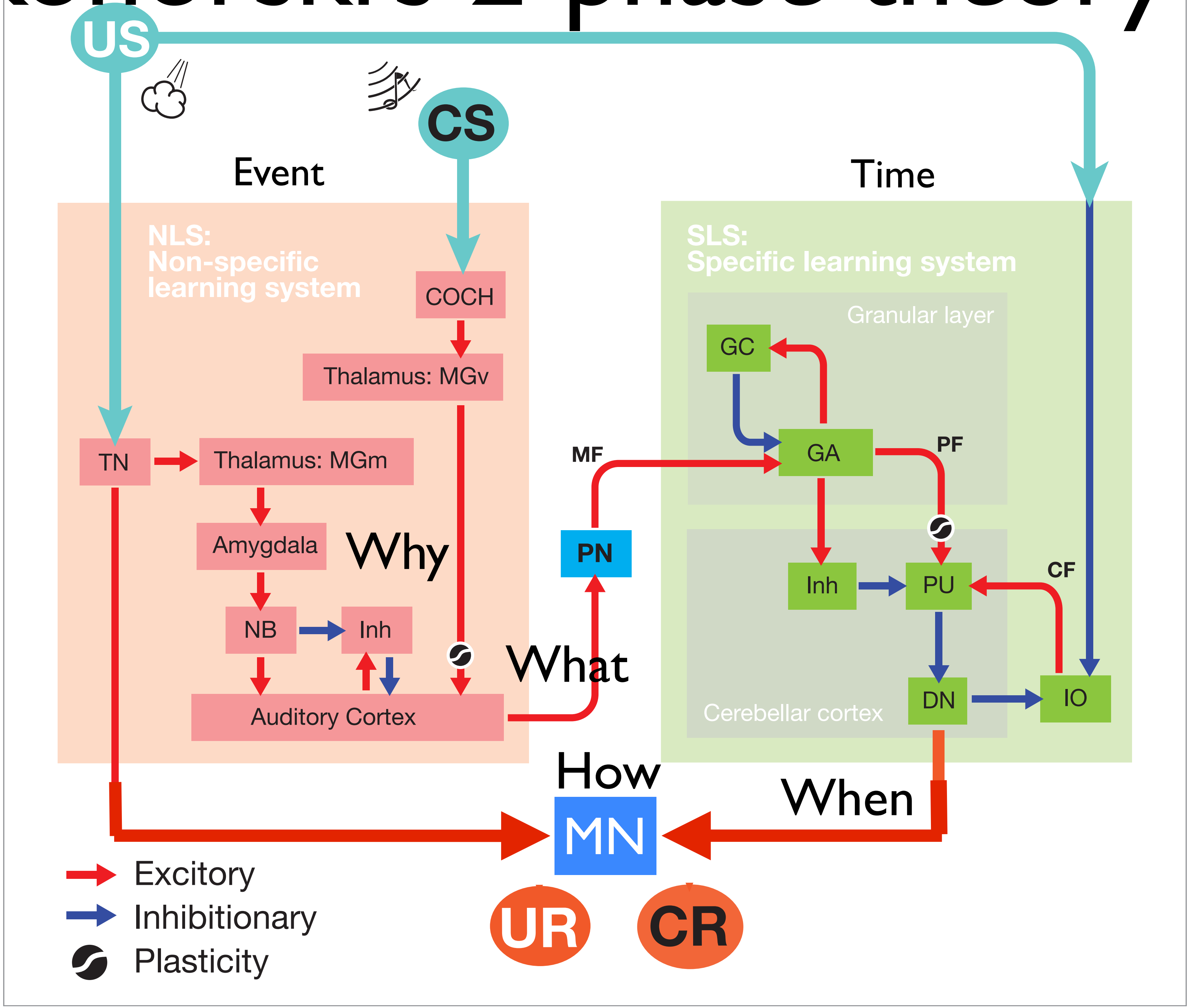
ACh could foster sensory exploration (global disinhibition + stronger local inhibition)



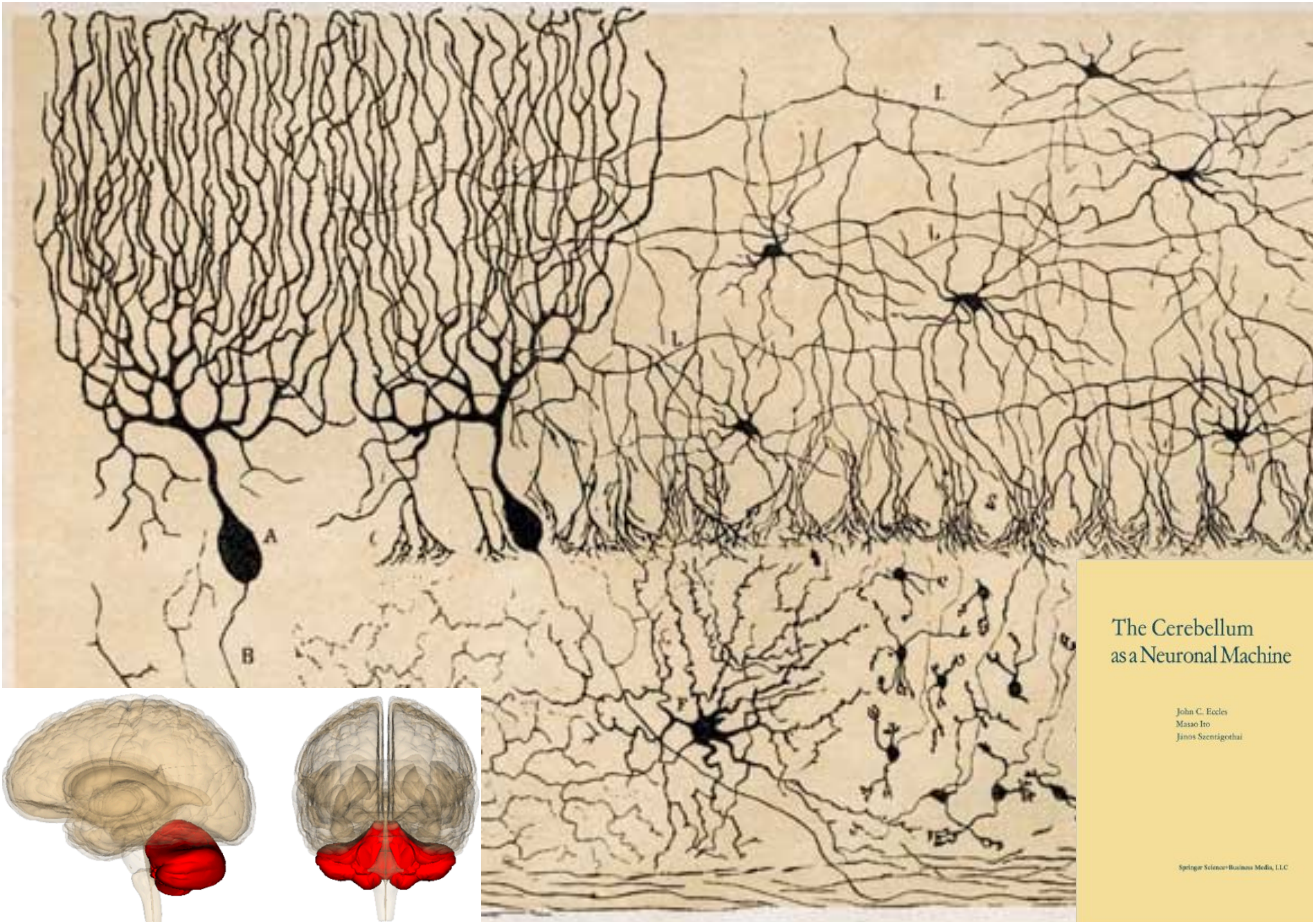


Puigbo et al 2017 IBM J Res

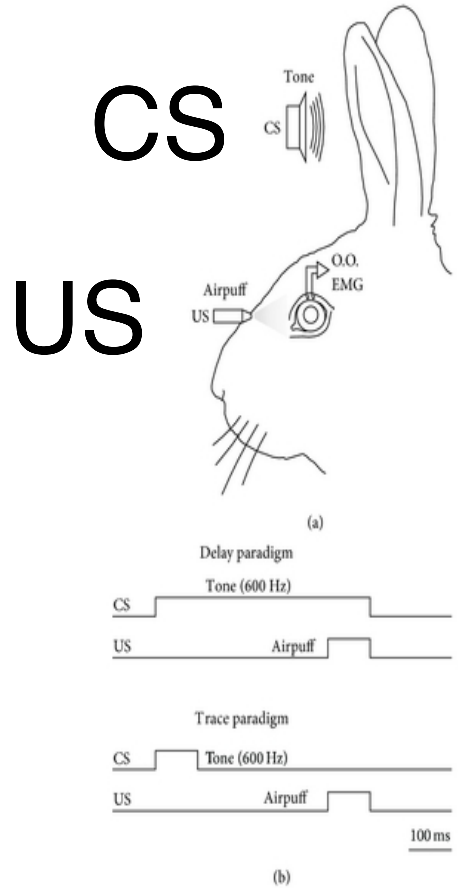
Konorski's 2-phase theory

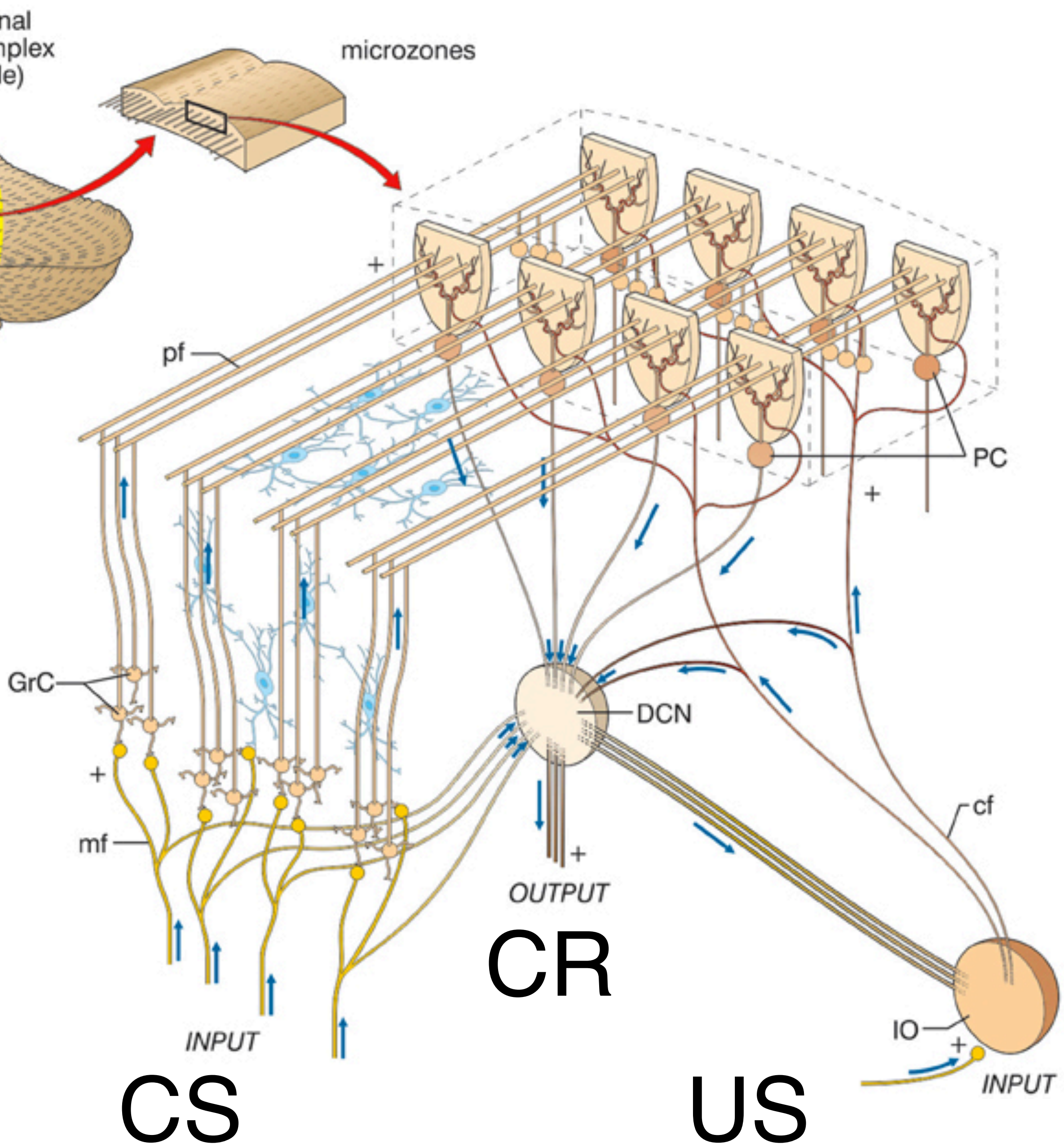


Learning anticipatory actions in the cerebellum



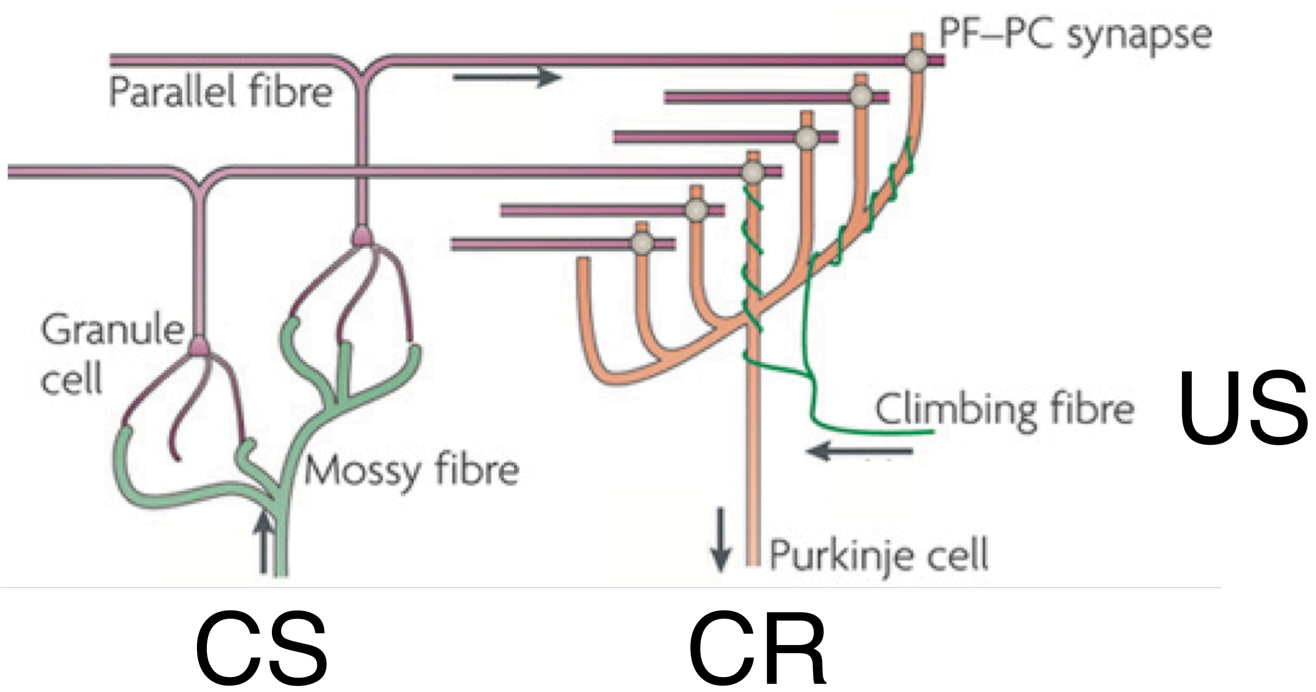
Learning anticipatory actions in the cerebellum





Learning anticipatory actions in the cerebellum

The cerebellum associates predictive signals with adaptive motor responses

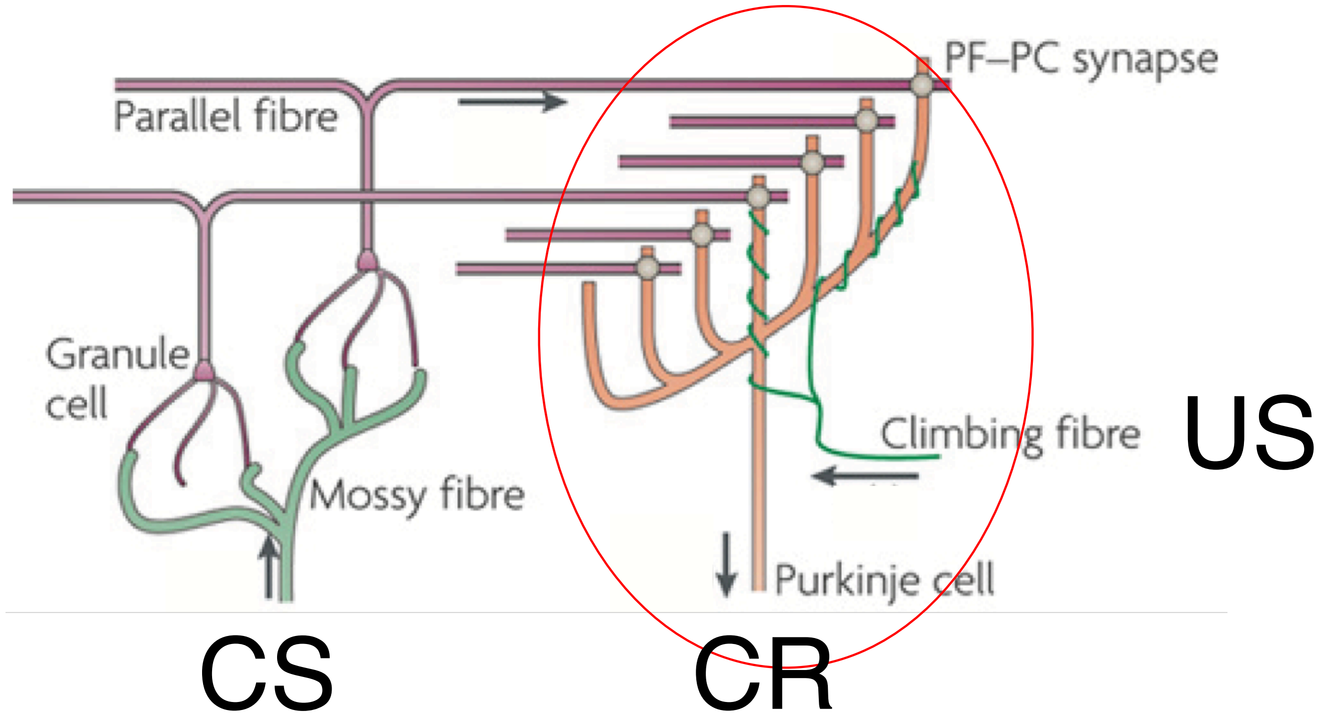


Adapted from: Dean et al, 2009

Learning anticipatory actions in the cerebellum

The cerebellum associates predictive signals (CS) with adaptive motor responses (CR)

- Anticipatory action: Purkinje Cell – Deep Cerebellar Nucleus



Adapted from: Dean et al, 2009

Learning anticipatory actions in the cerebellum

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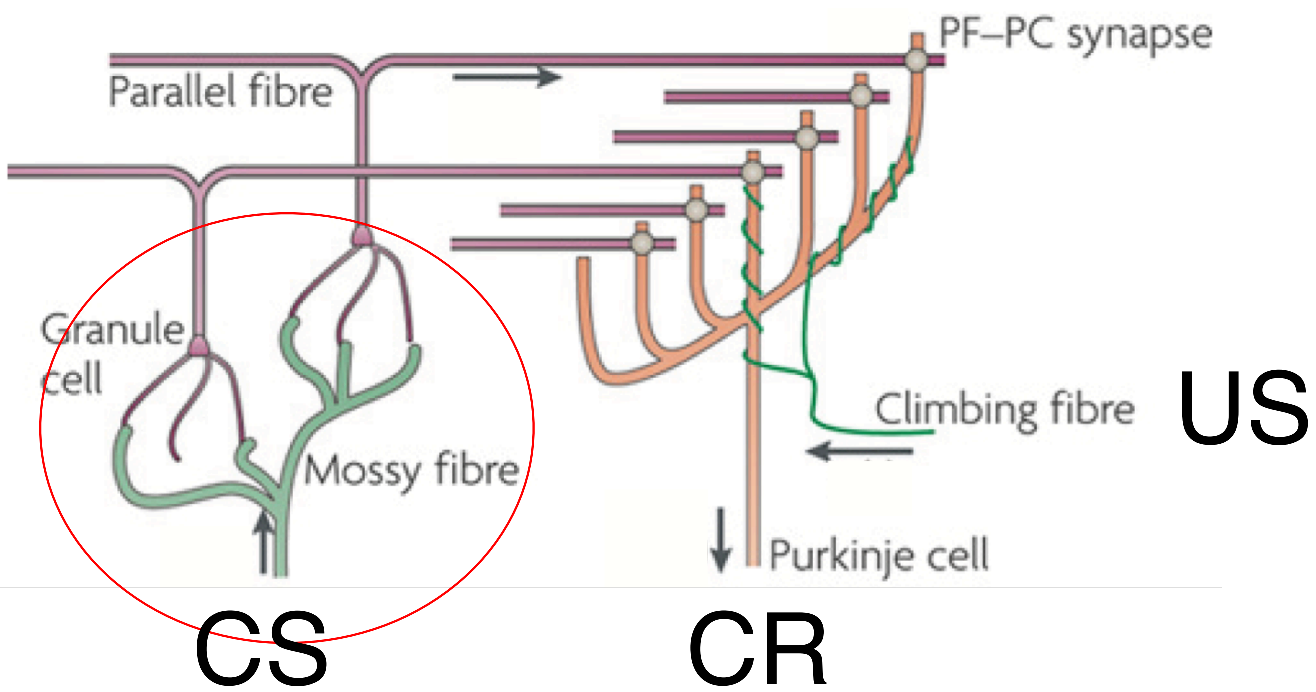

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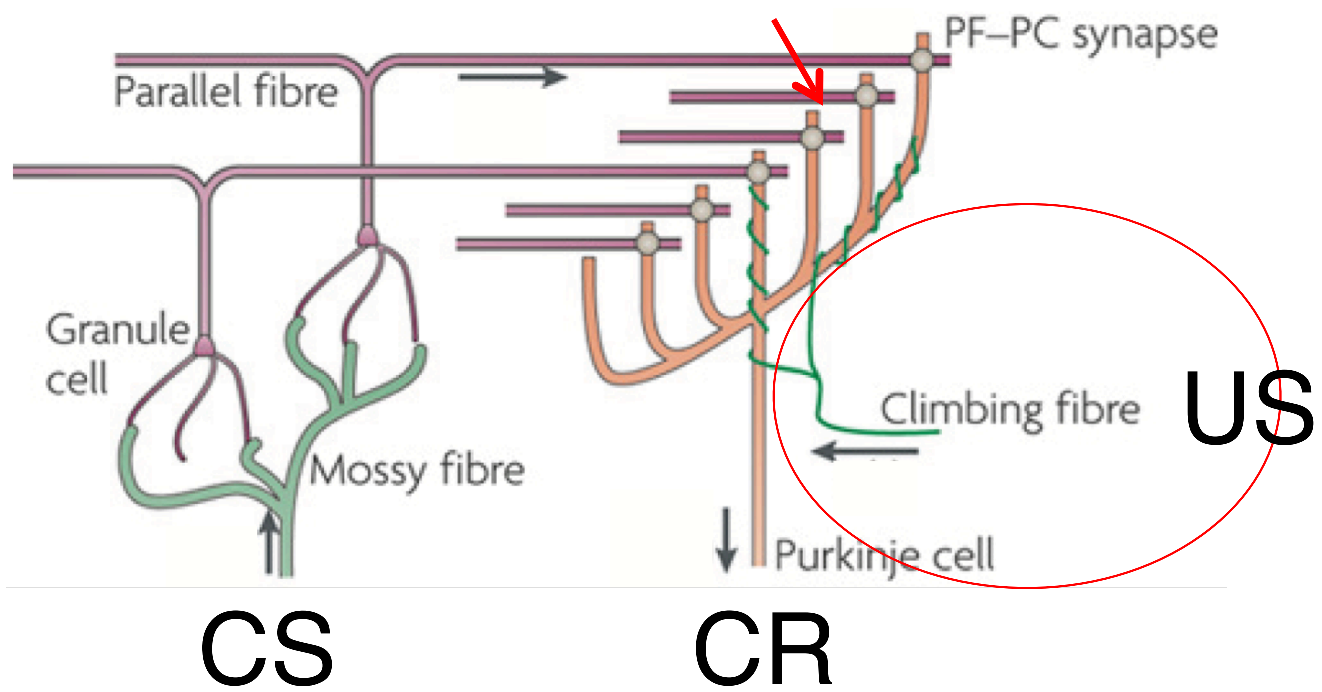

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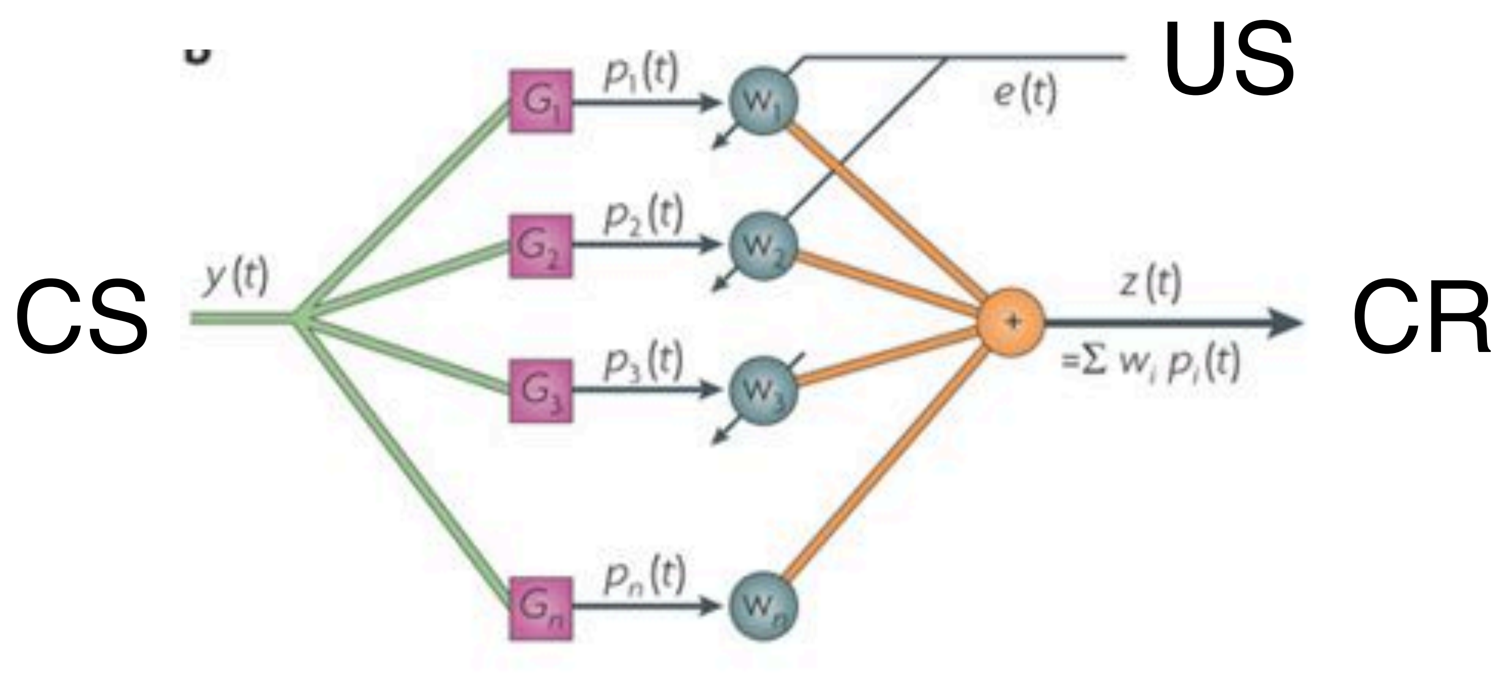

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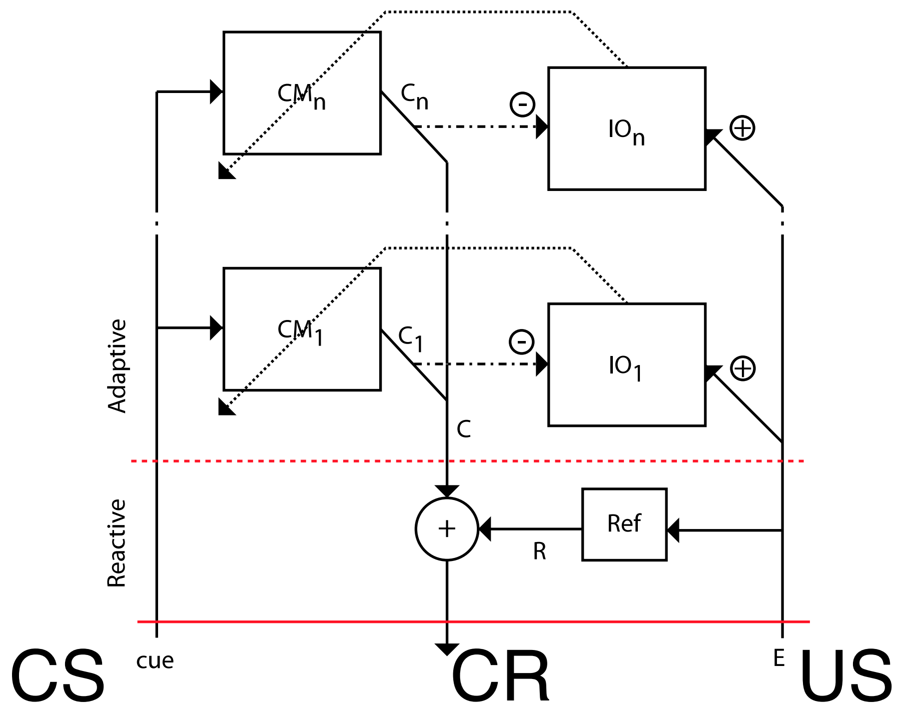
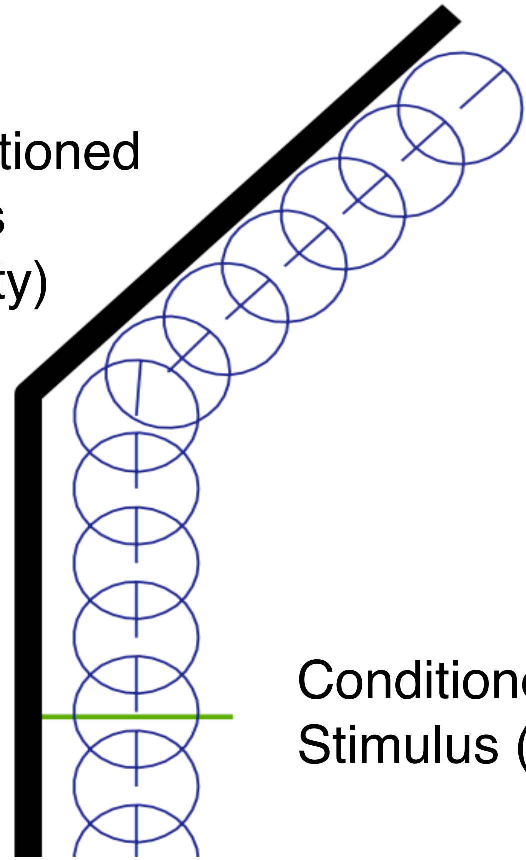
Anticipatory actions in robots



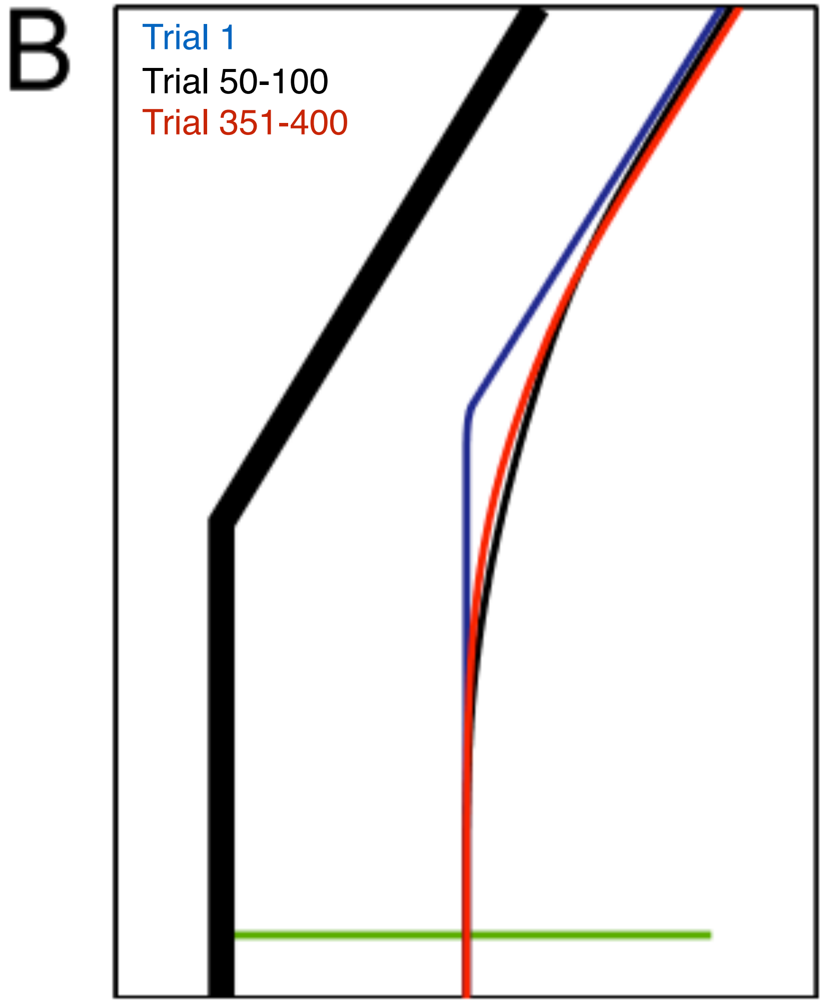


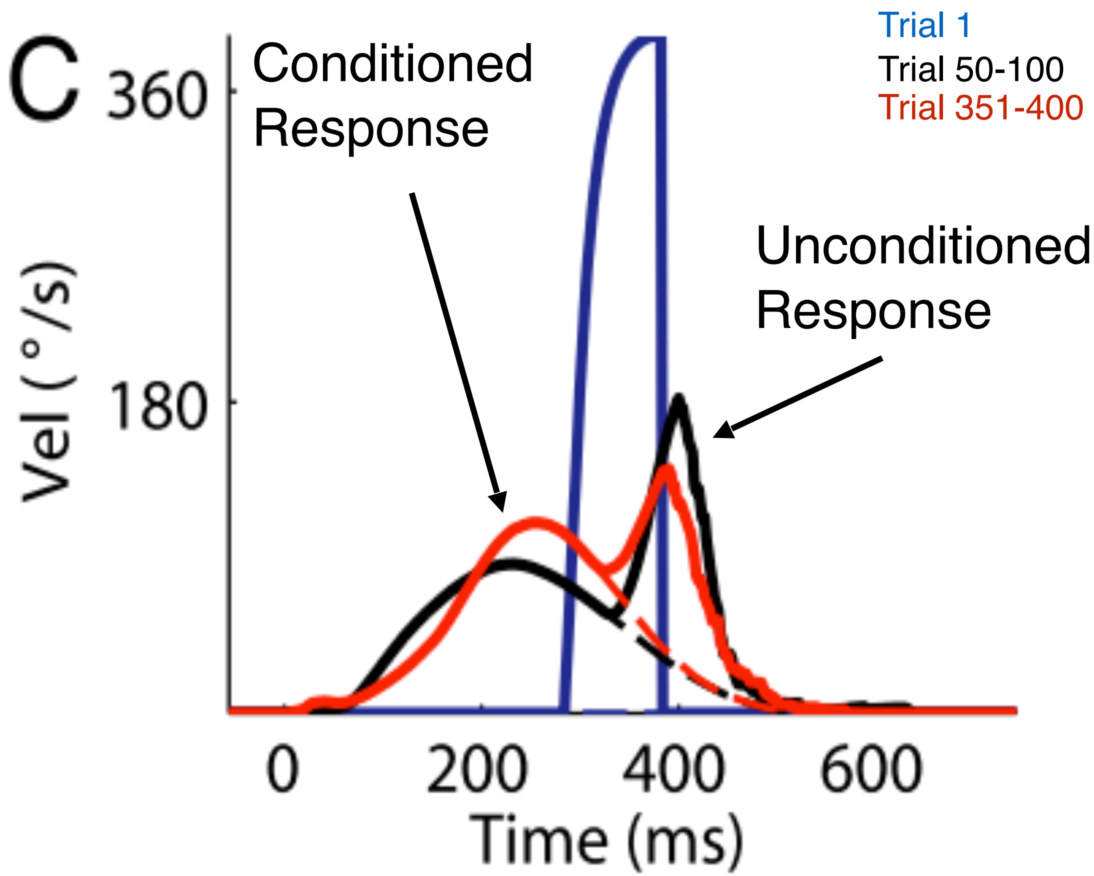
Herreros & Verschure, Neural Networks, 2013

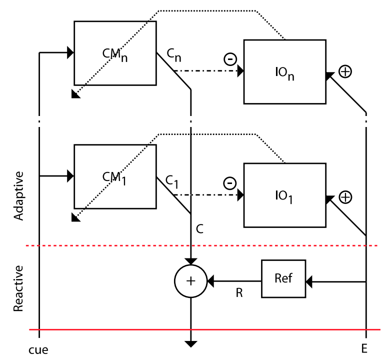
Anticipatory actions in robots

Herreros & al., Intelligent Robots and Systems, 2013

Anticipatory actions in robots





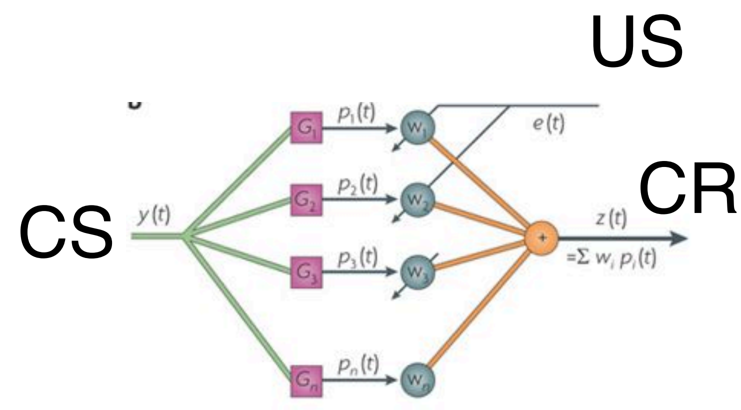


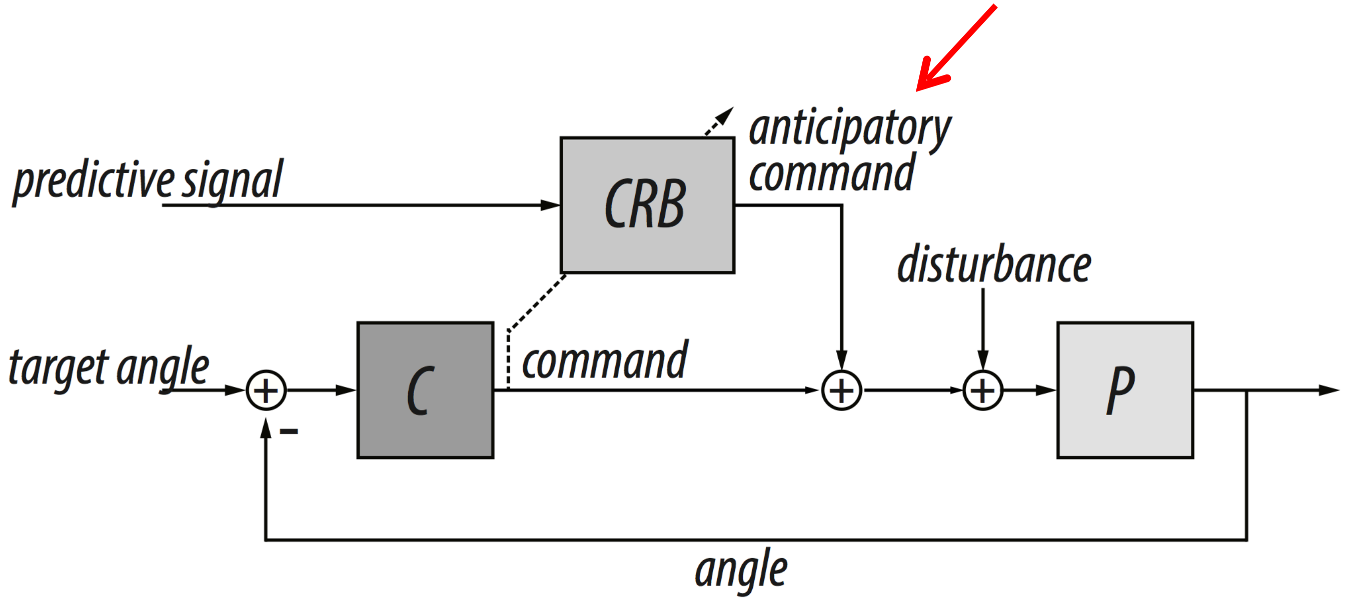
Herreros & Verschure, Neural Networks, 2013

Cerebellum as a inverse model (Kawato, 1987)

Advancing a corrective action to achieve a desired state of the body

- Anticipatory motor command





Adapted from: Kawato and Gomi,1992

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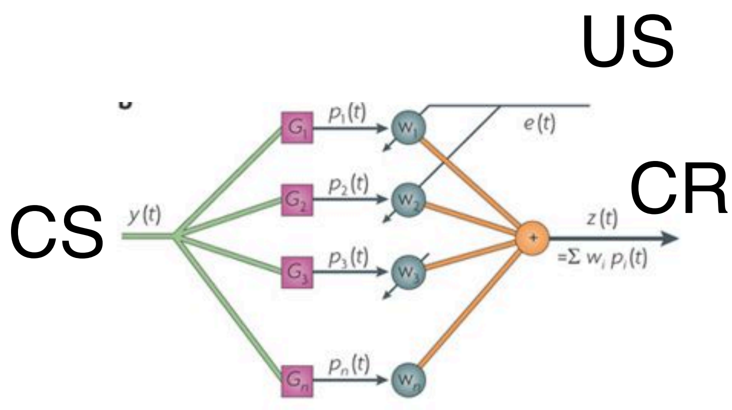
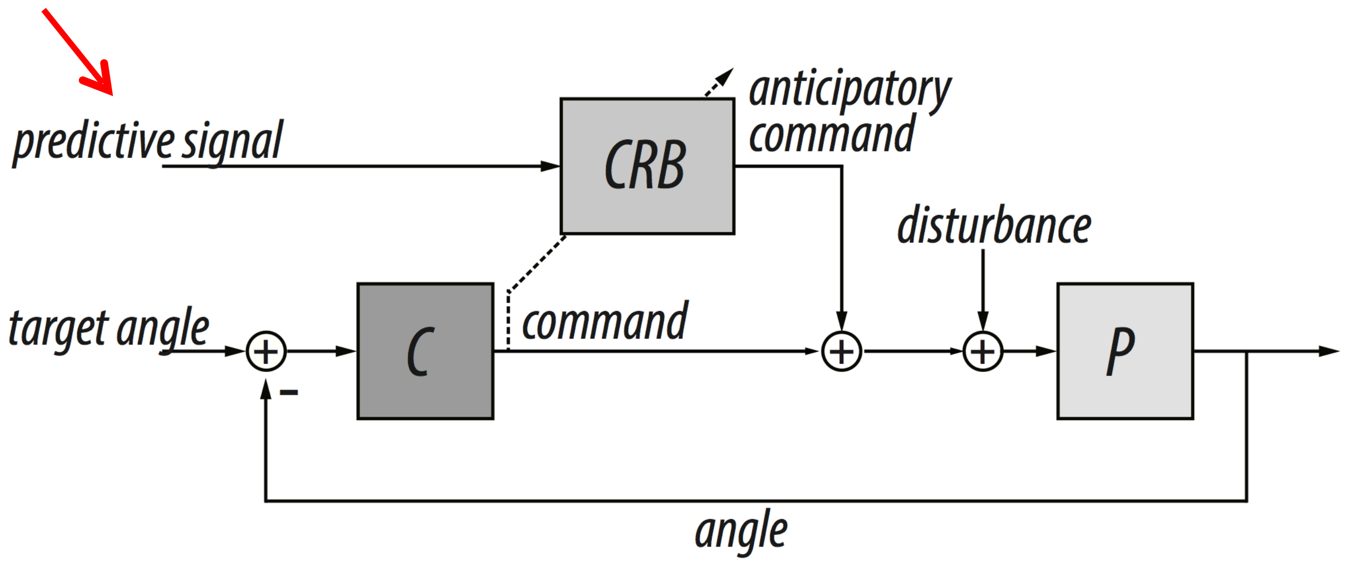
Advancing a corrective action to achieve a desired state of the body

- Anticipatory motor command
- Trigger: predictive signal



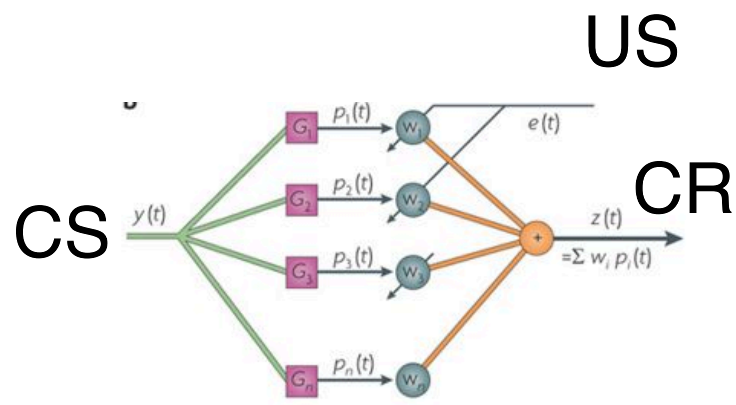


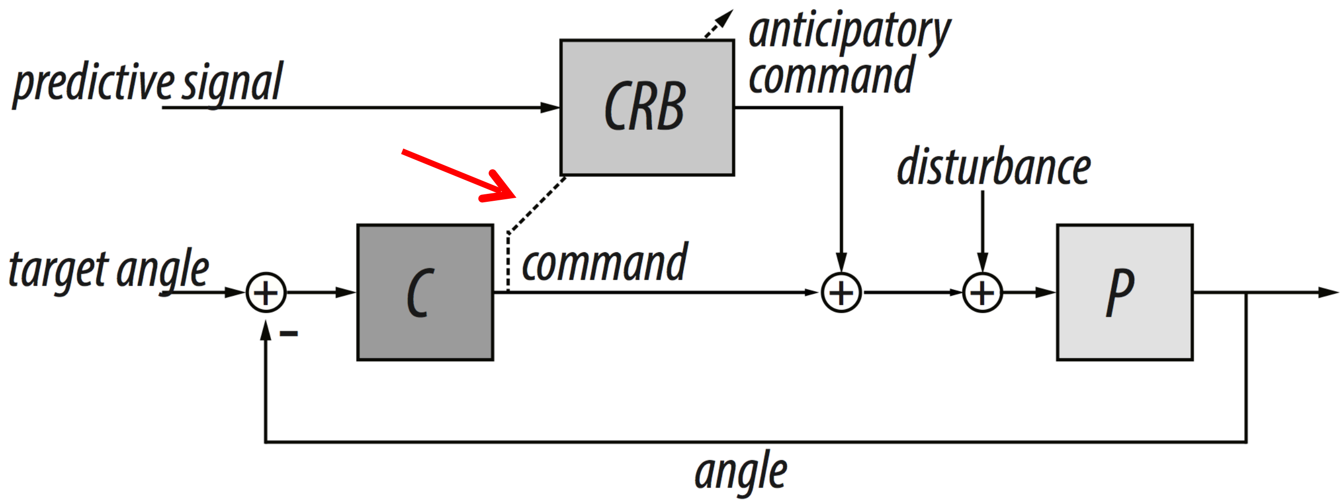
Adapted from: Kawato and Gomi,1992

Cerebellum as a inverse model (Kawato, 1987)

Advancing a corrective action to achieve a desired state of the body

- Anticipatory motor command
- Trigger: predictive signal
- Teaching signal: output of the feedback controller





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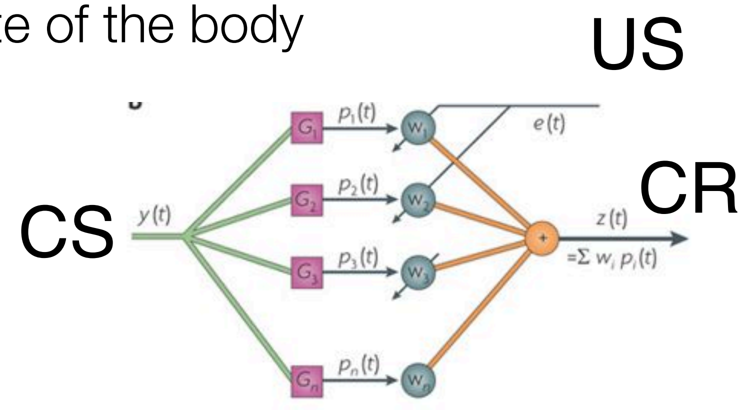
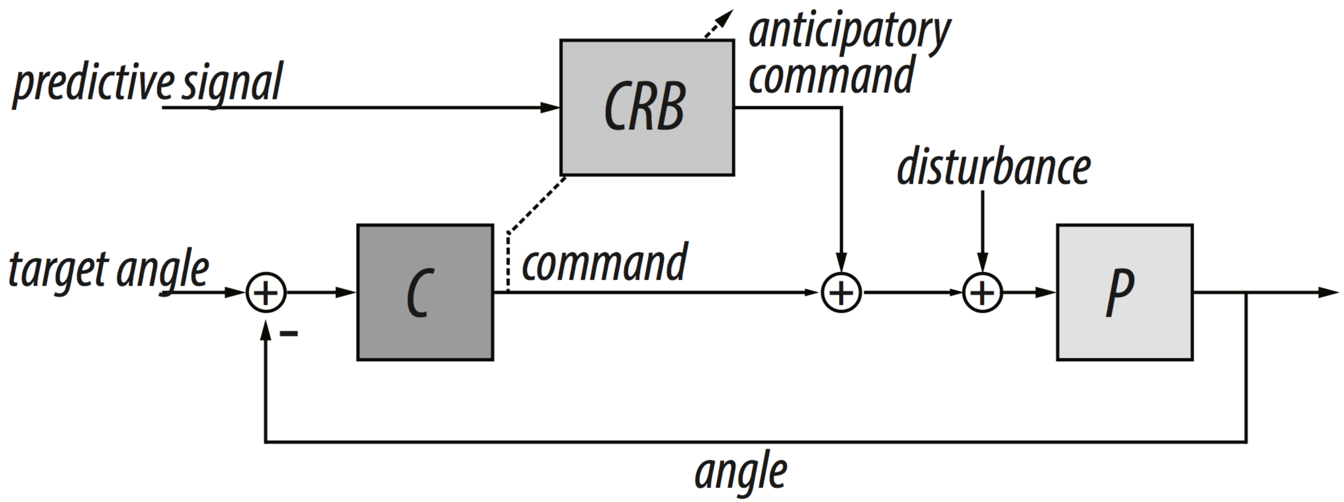


Feedback Error Learning (FEL)
(Kawato, 1987; Kawato and Gomi, 1992)



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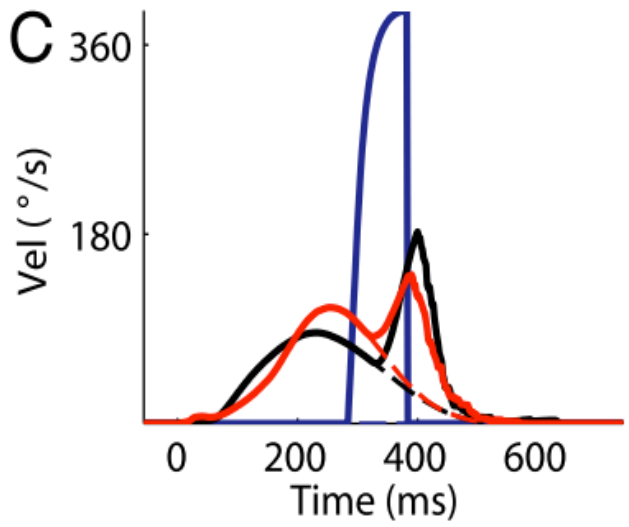

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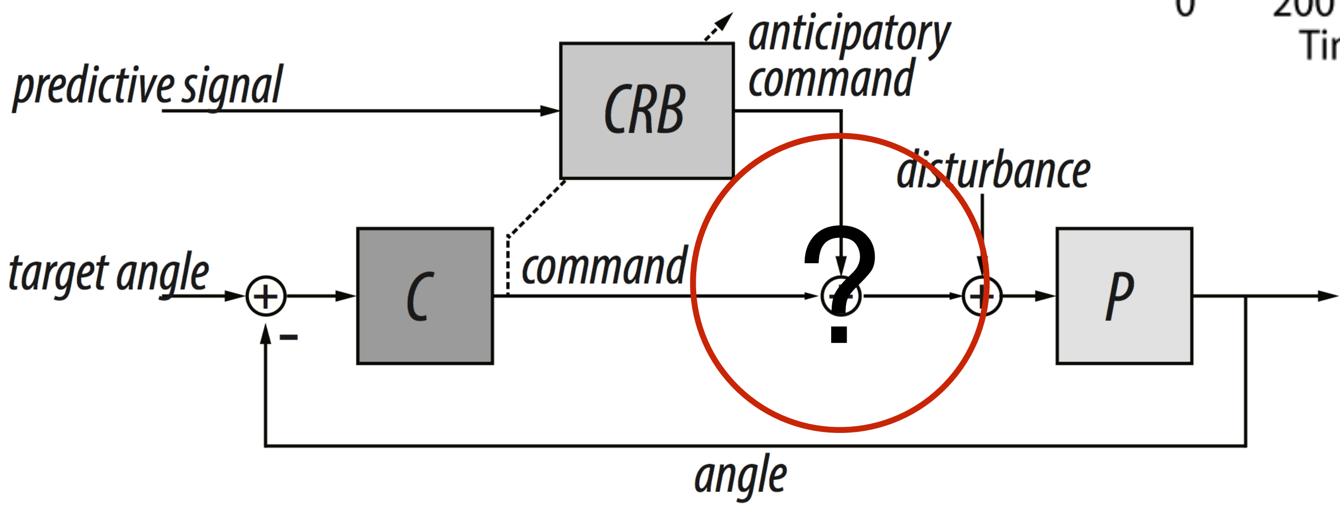
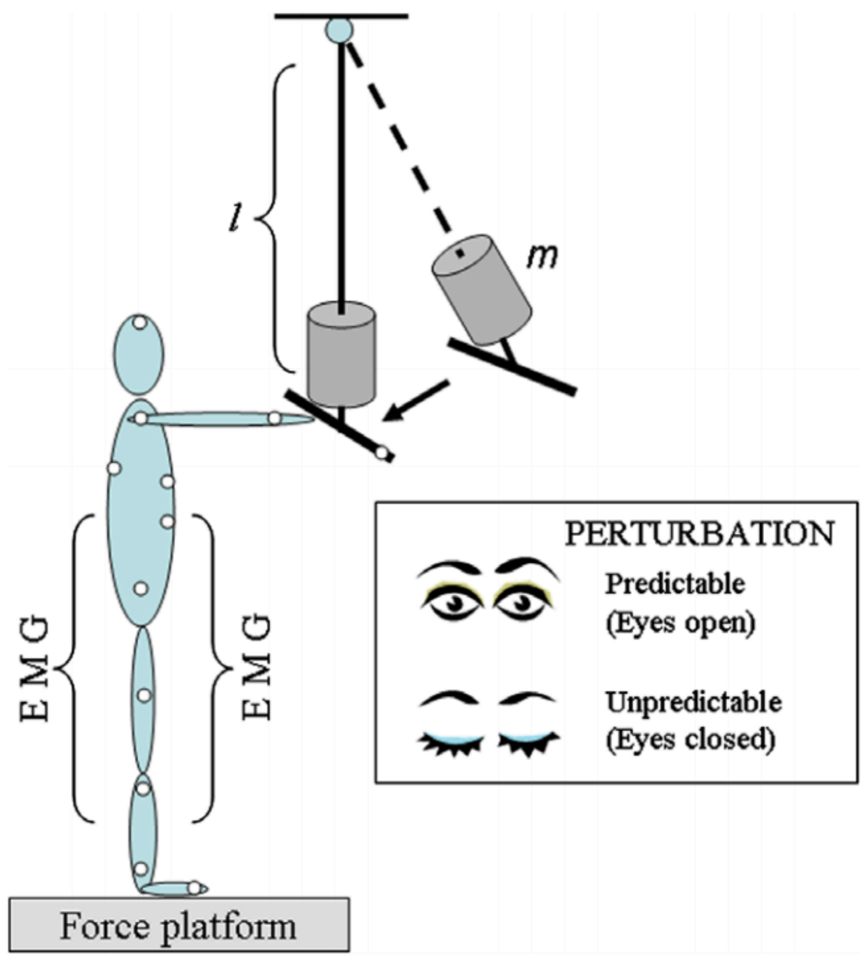
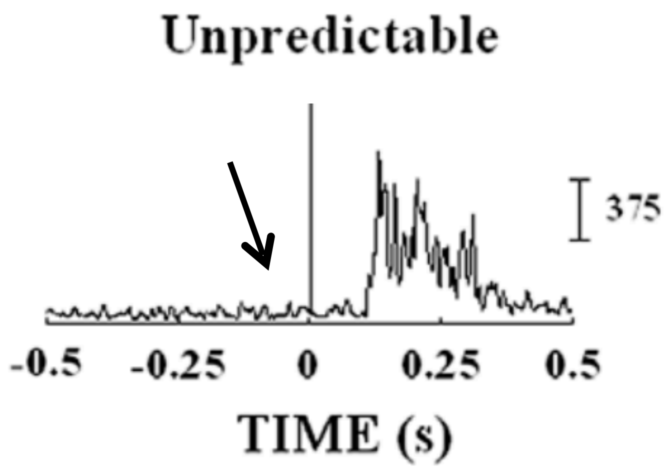


Adapted from: Kawato and Gomi,1992

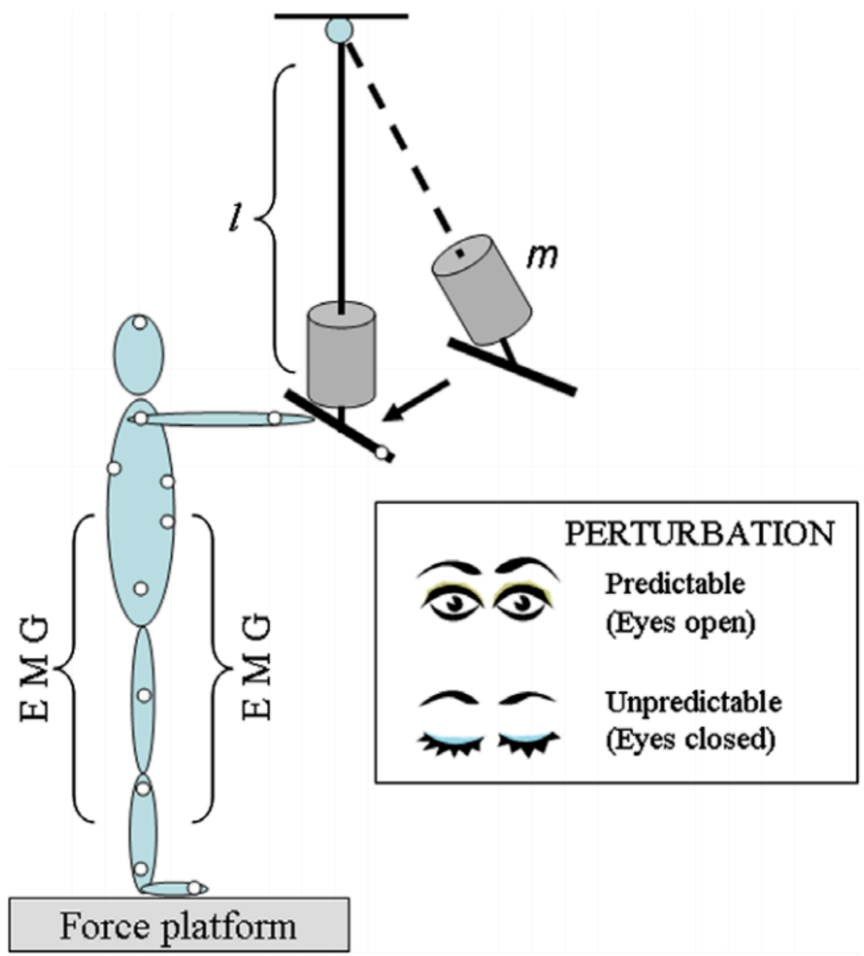
Anticipatory postural adjustments

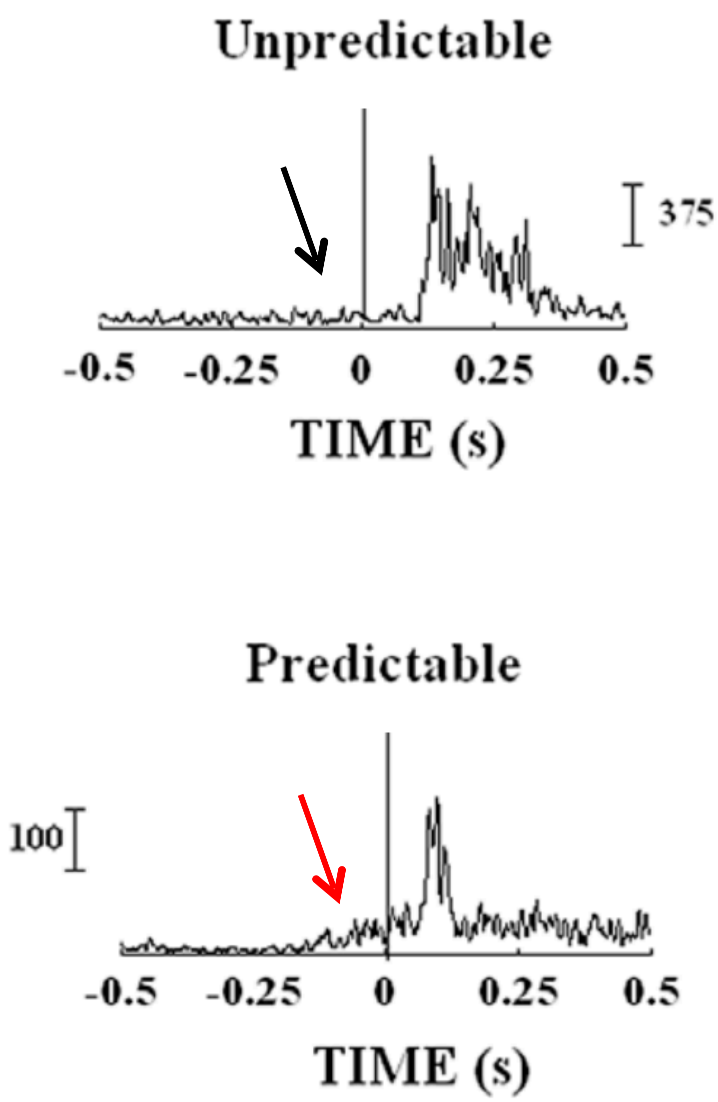




Santos et al. 2010

Anticipatory postural adjustments



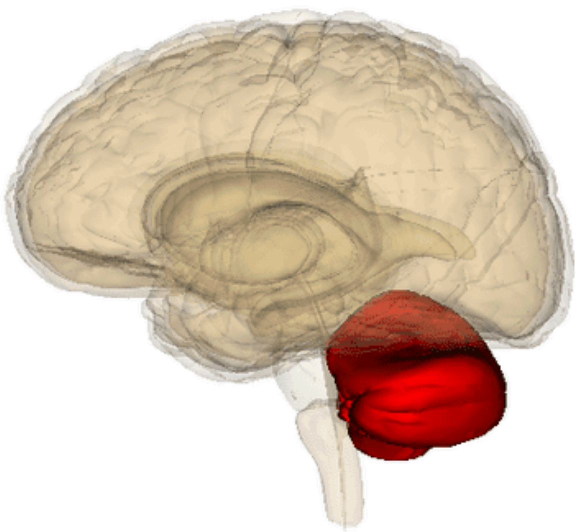


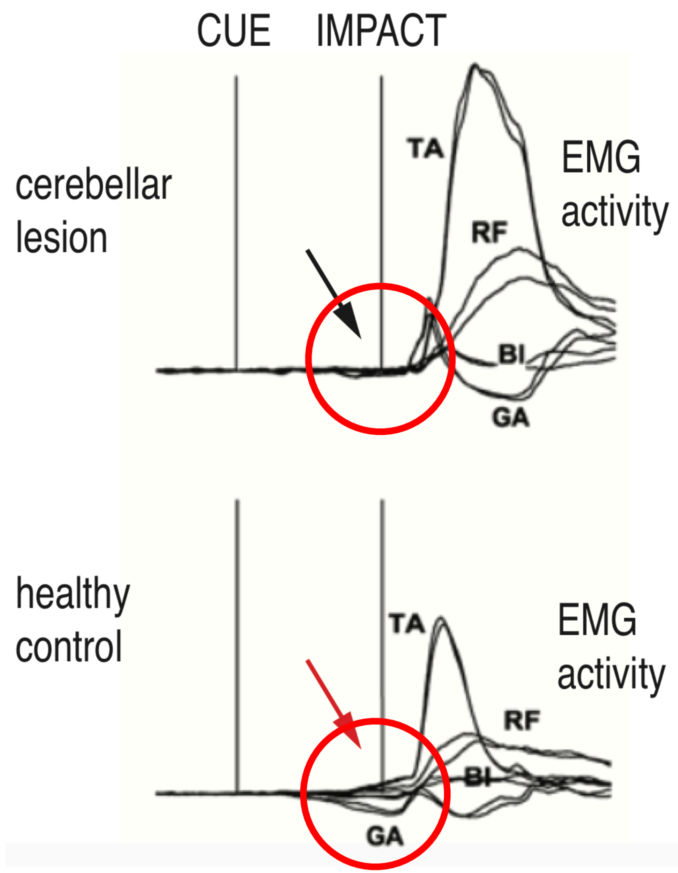
Santos et al. 2010

Anticipatory behaviors

Anticipatory postural adjustments depend on the cerebellum (Massion, 1994)

- Cerebellar ataxic subjects do not display APAs
- Muscle activity follows the displacement even if predictable

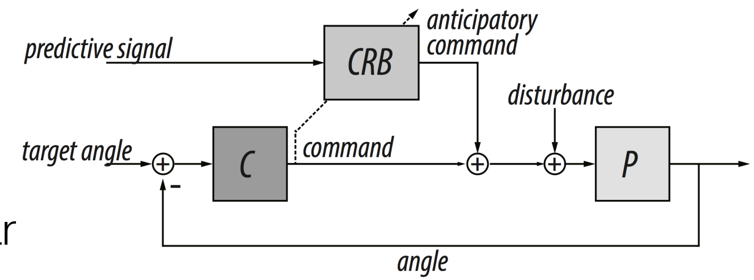




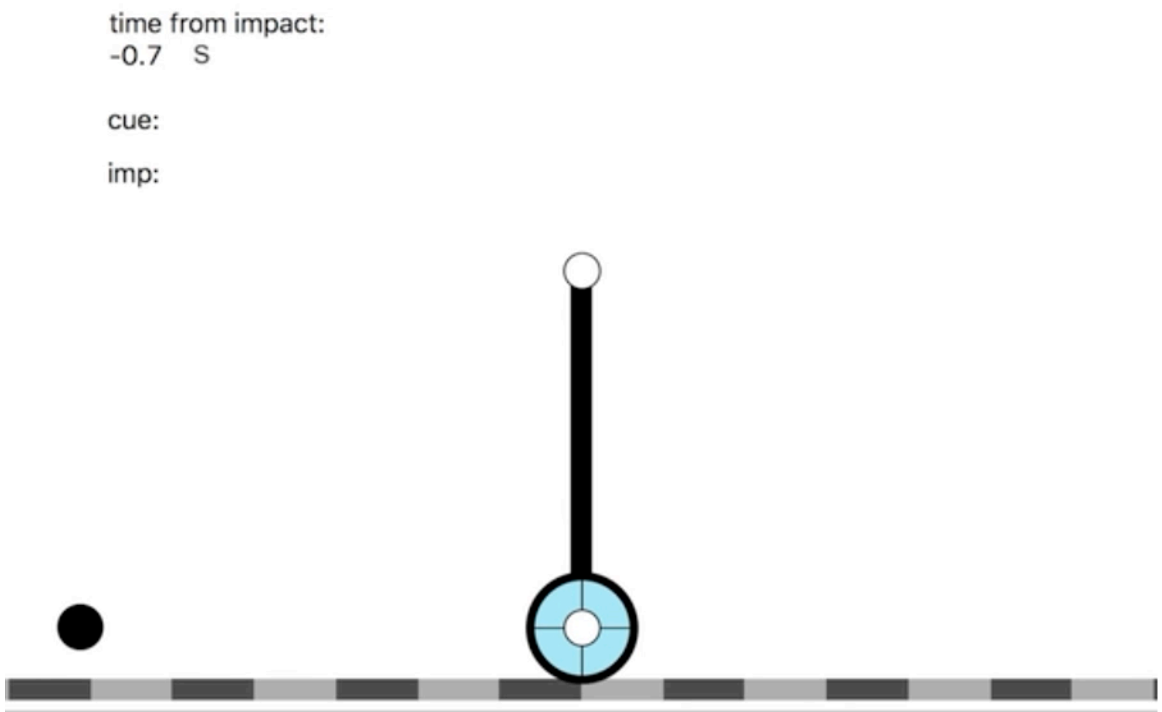
Kolb et al. 2004

Testing FEL in a postural task

Anticipatory postural control in a mobile robot



- An agent has to minimize the effect of a predictable disturbar
- Disturbance provokes a vestibular error: angle
- Disturbance is preceded by distal cue (vision) and proximal cue (proprioception)



Maffei et al., 2014

Testing FEL in a postural task

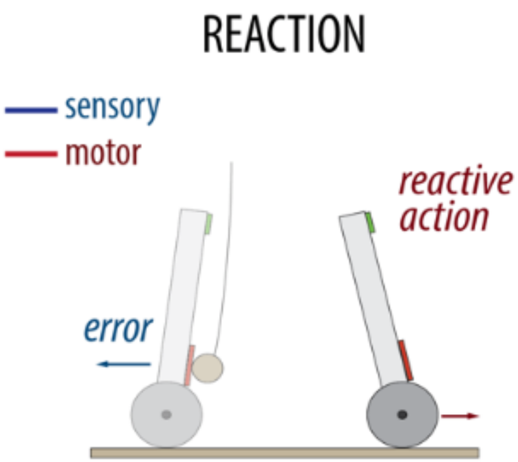
Three phases of postural control (Latash, 2008)

Maffei et al., 2014

Testing FEL in a postural task

Three phases of postural control (Latash, 2008)

- Reaction: corrective action triggered by vestibular error



Maffei et al., 2014

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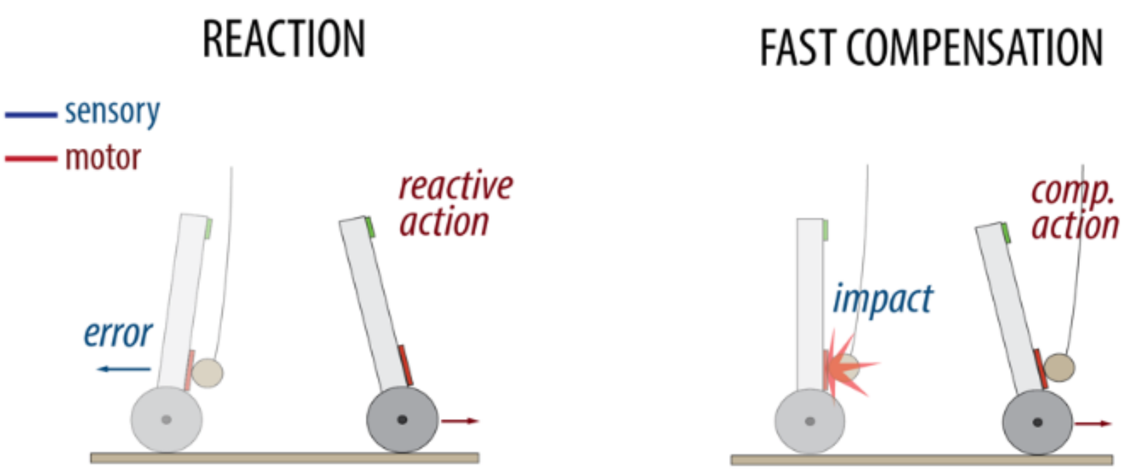
Three phases of postural control (Latash, 2008)

- Reaction: corrective action triggered by vestibular error
- Fast compensation: corrective action triggered by the impact



Maffei et al., 2014

Testing FEL in a postural task

Three phases of postural control (Latash, 2008)

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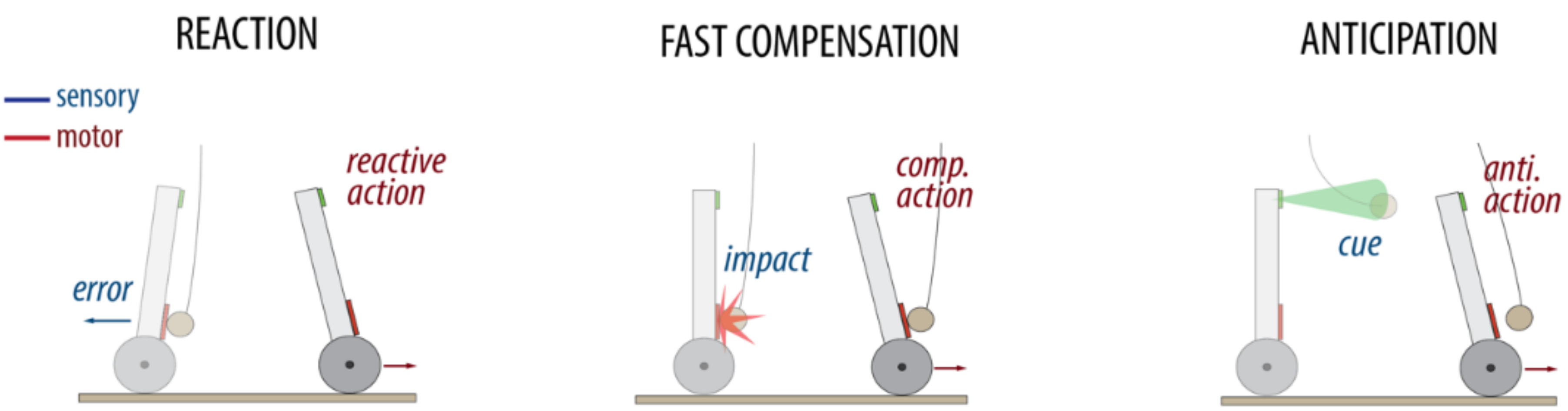
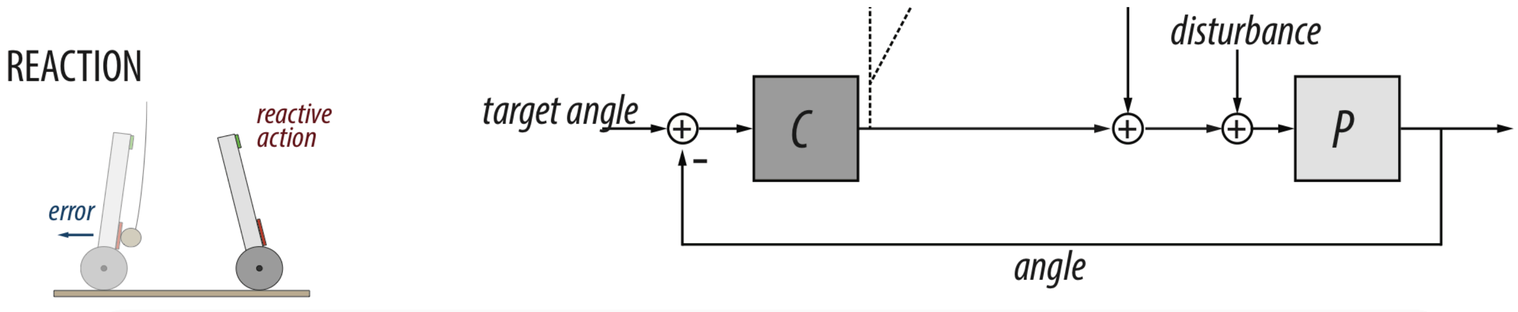
- Anticipation: corrective action triggered by the the cue



Maffei et al., 2014

Testing FEL in a postural task

Postural control architecture based on Feedback Error Learning (Kawato,1987)



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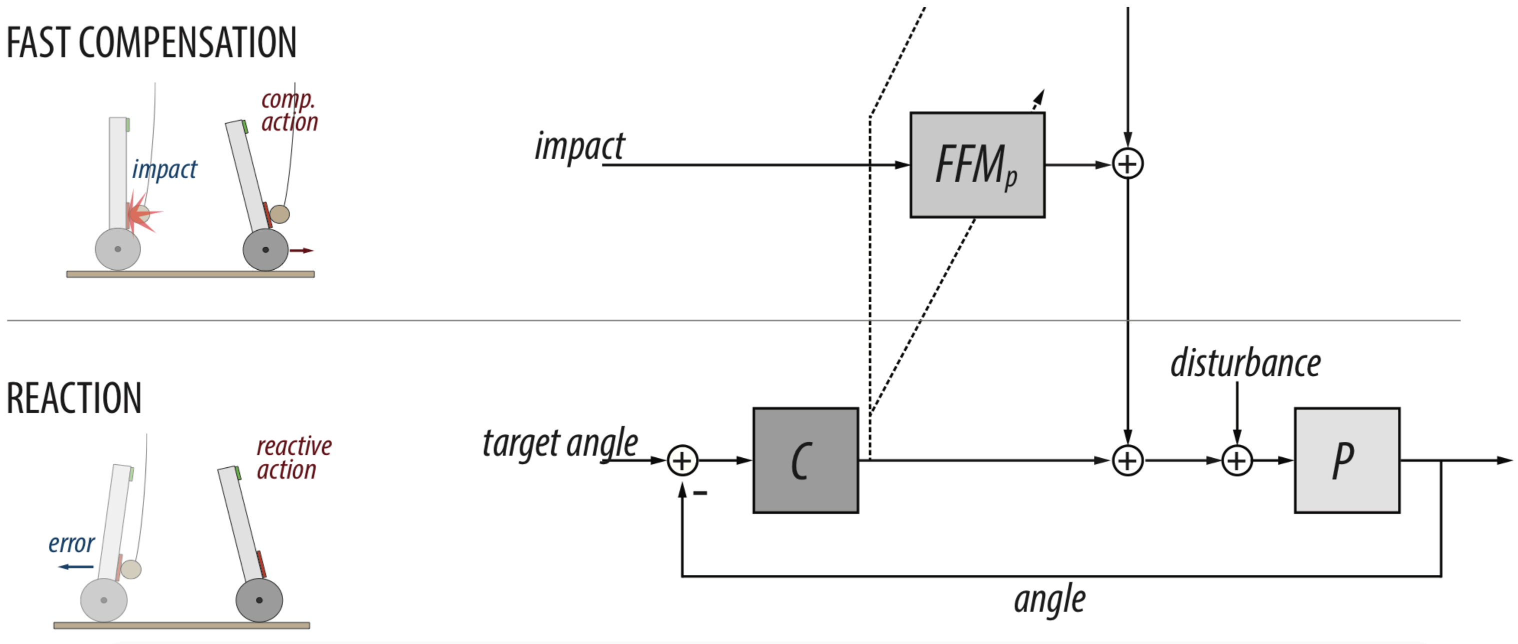

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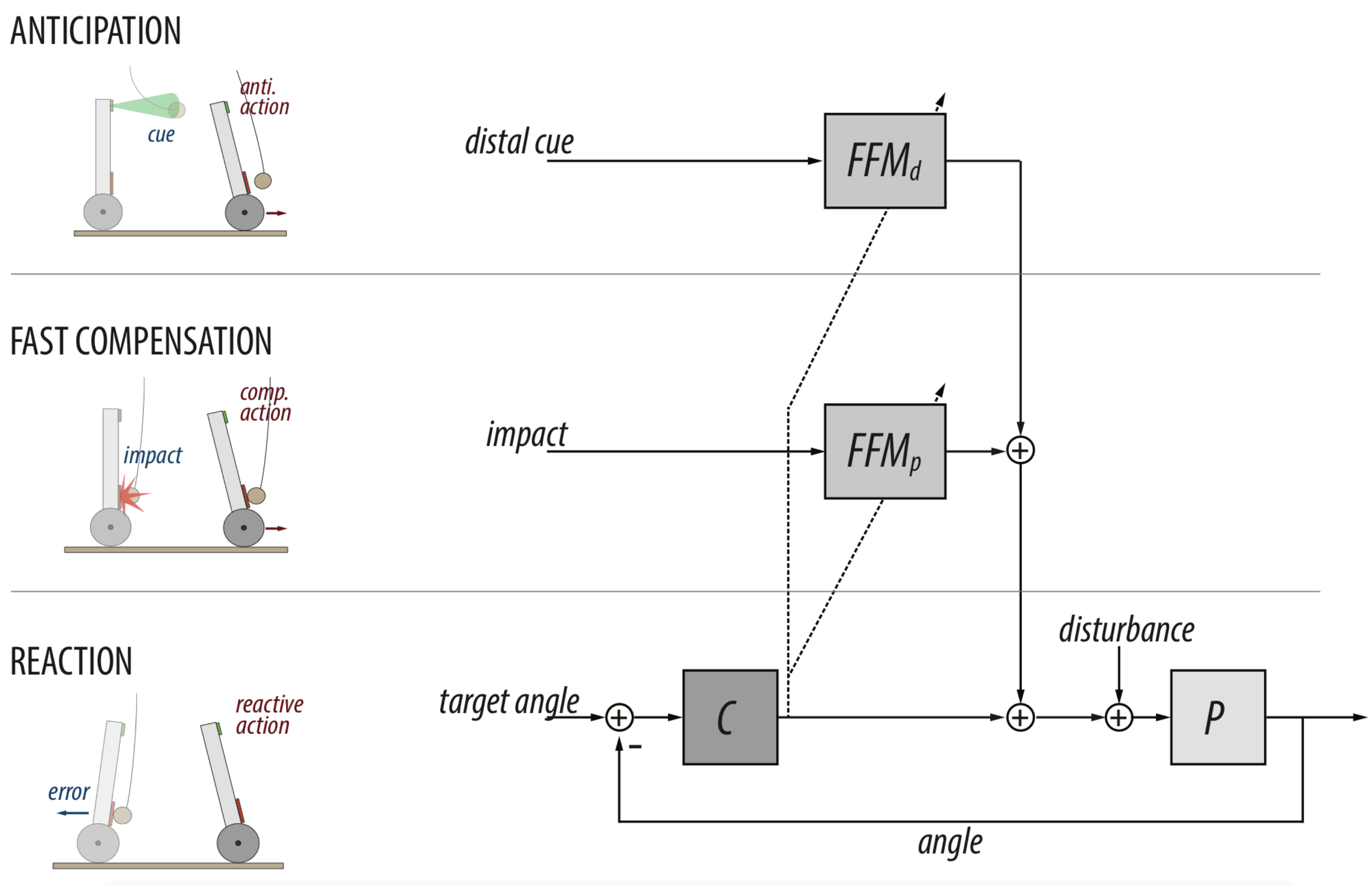
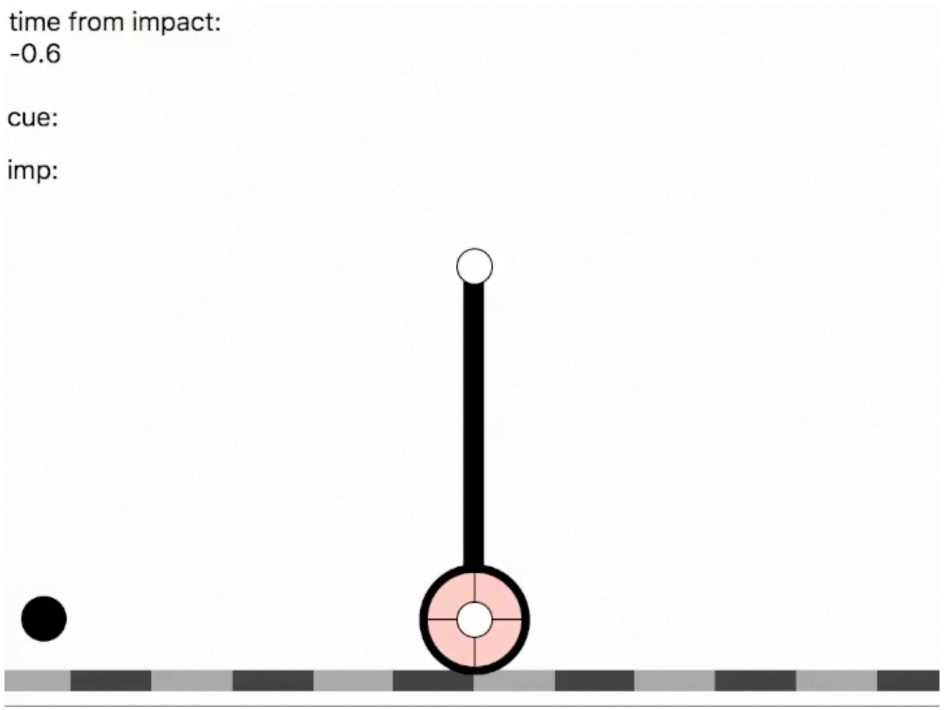


Maffei et al., 2014

Testing FEL in a postural task

Fast compensatory and anticipatory responses minimize postural error

- In early trials action follows the displacement
- In late trials action precedes the displacement



Maffei et al., 2014

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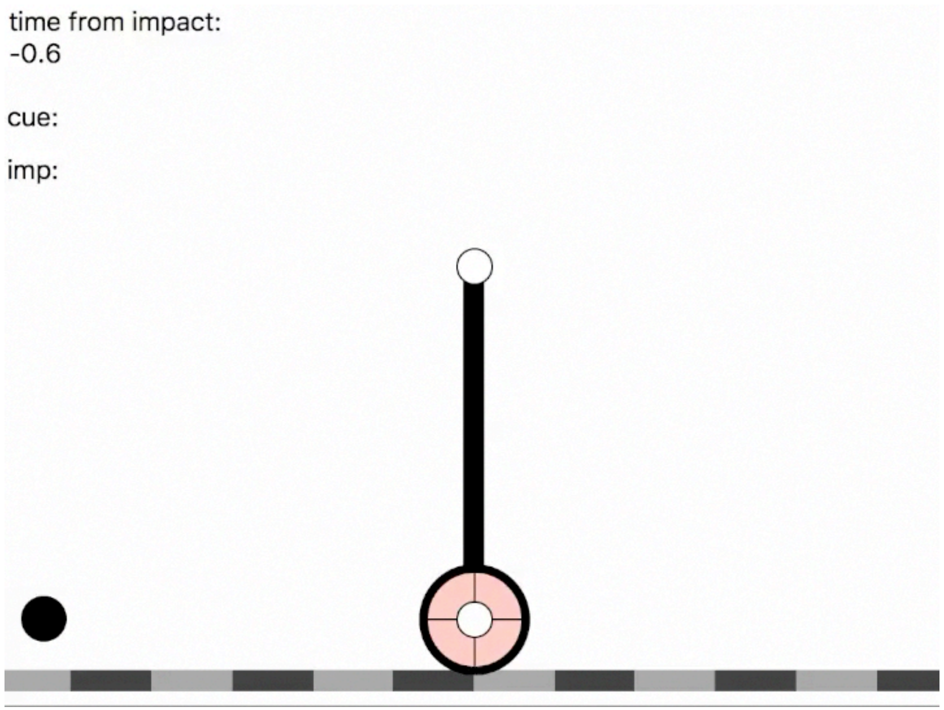
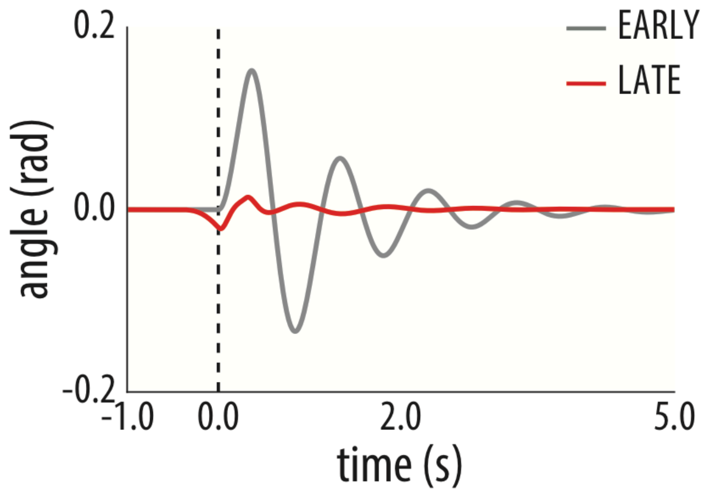
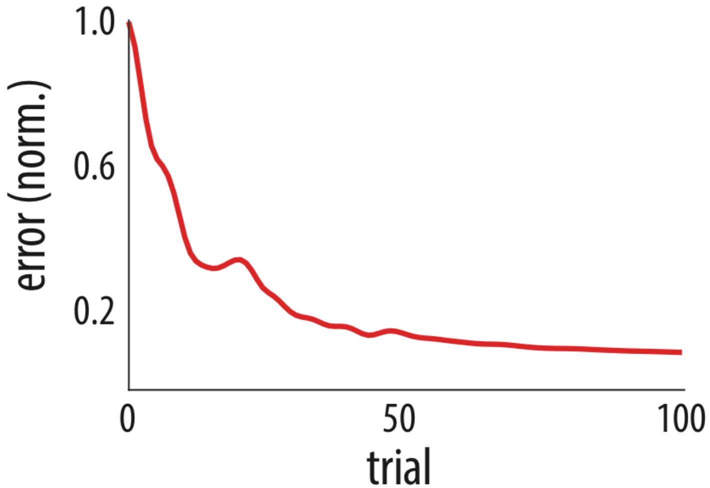




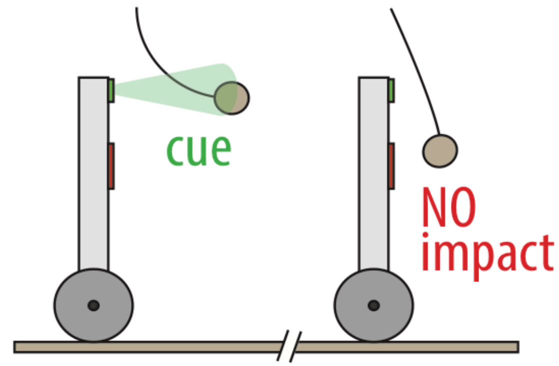


Maffei et al., 2014

Testing FEL during postural prediction errors

Catch trials induce prediction errors:

- Predictive cue is presented
- No disturbance is delivered



Maffei et al., 2014

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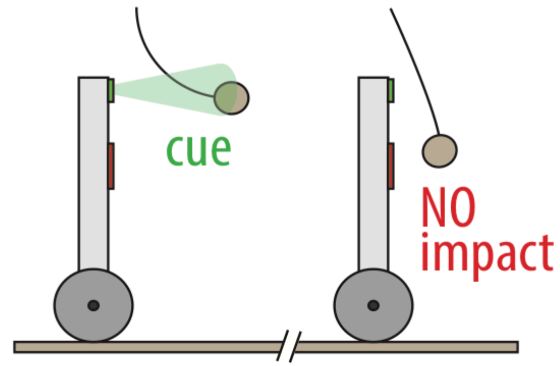
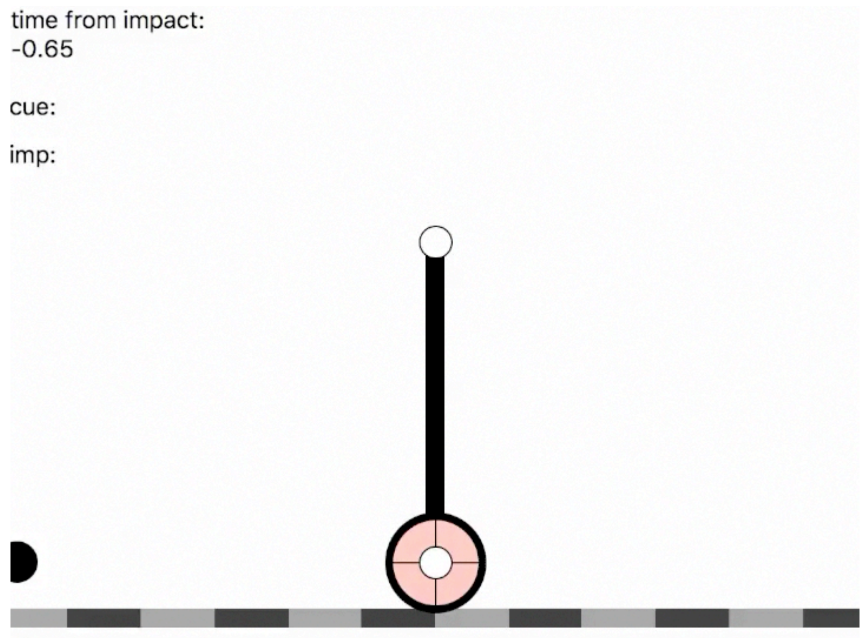


FEL fails to correct for prediction errors

- Anticipatory actions cannot be retracted
- Self-induced instability
- Lack of robustness

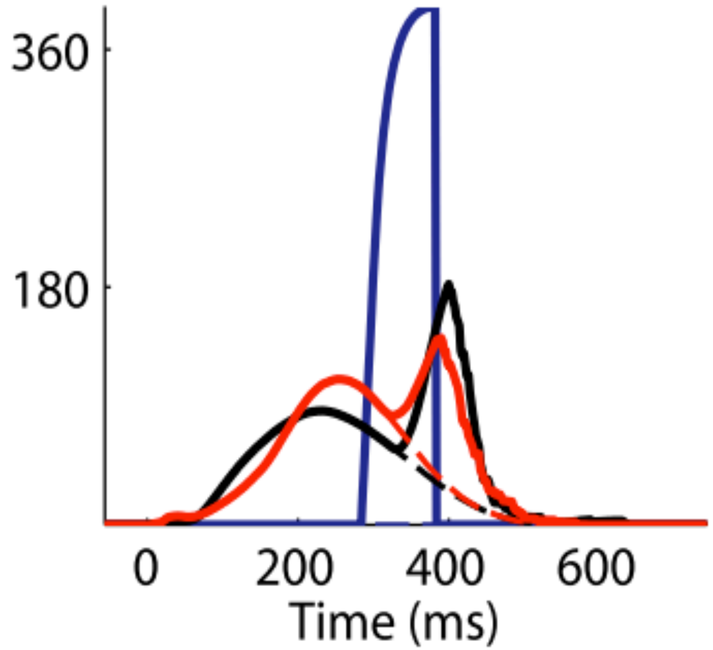


Maffei et al., 2014

How could the brain control anticipatory actions that are robust to uncertainty?

Sensory prediction hypothesis

Anticipatory behavior as a cascade of sensory predictions

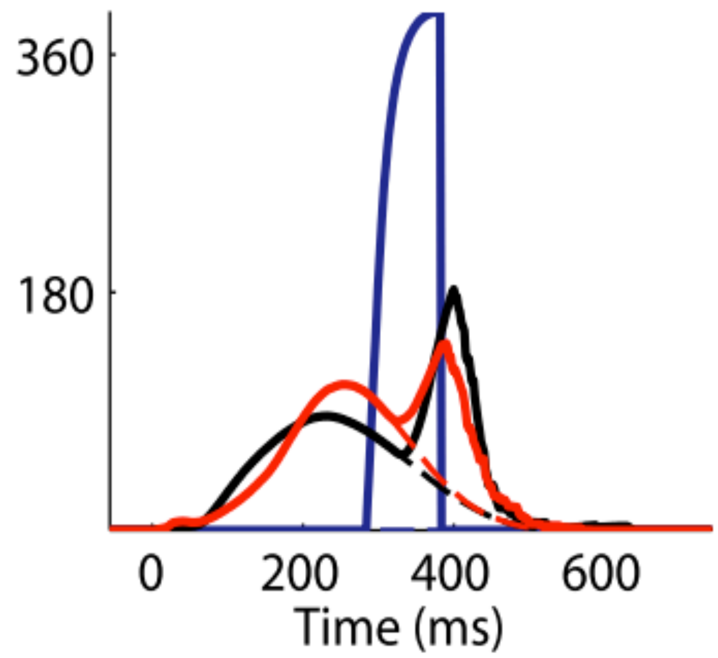


Maffei, Herreros et al., 2017

Sensory prediction hypothesis

Anticipatory behavior as a cascade of sensory predictions

- Cerebellum could advance predictions of future perceptual events (Roth, 2013)
- Sensory predictions could follow a hierarchical scheme (Apps & Garwicz, 2005)
- Predicted events could drive the motor system anticipatorily (Friston, 2011)



Maffei, Herreros et al., 2017

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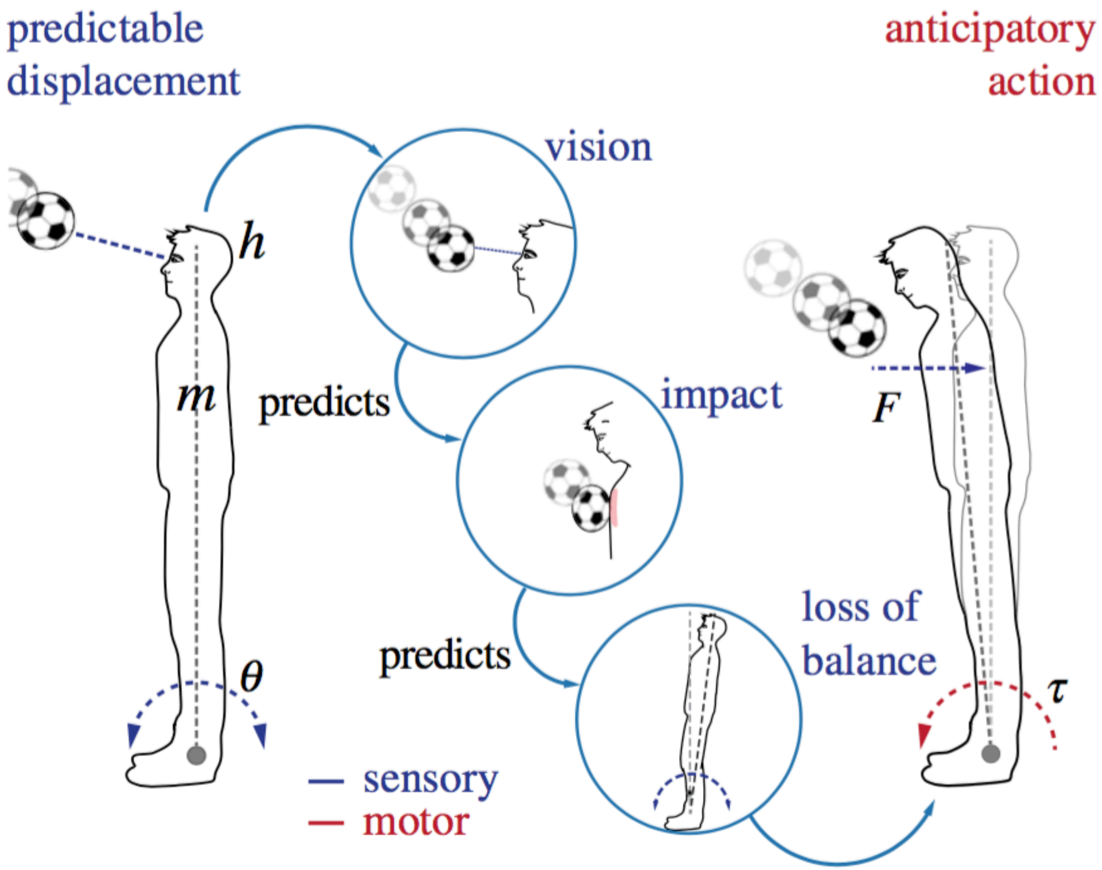
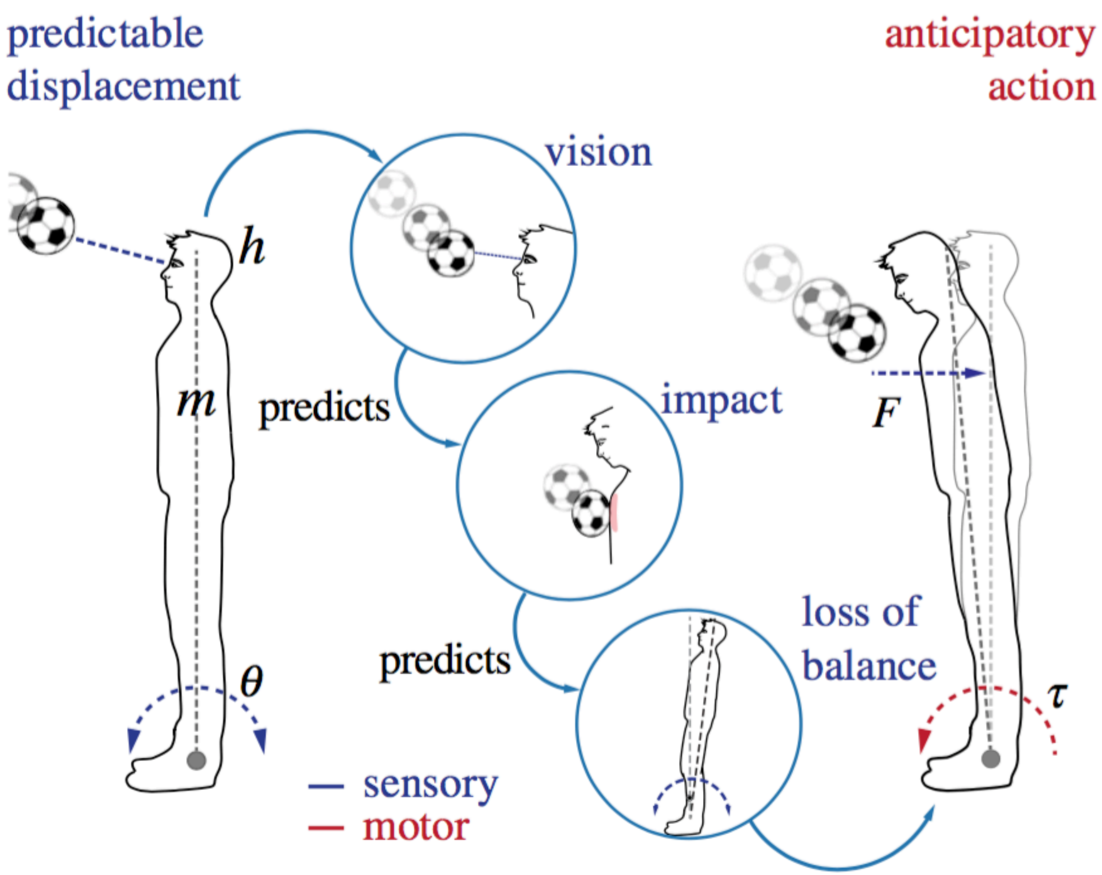


Maffei, Herreros et al., 2017

Sensory prediction hypothesis

Hierarchical sensory predictive control (HSPC)

(Maffei, Herreros et al., 2017, Phil Roy Soc B)



Herreros et al., NIPS 2016

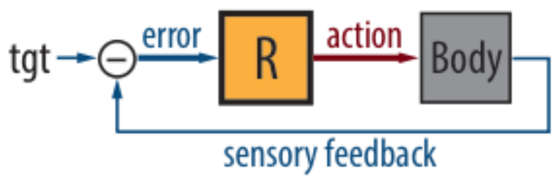
Maffei, Herreros et al., 2017

Motor anticipation (FEL) vs Sensory prediction (HSPC)

Reaction

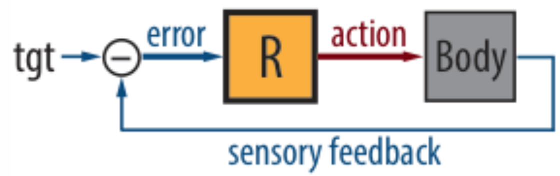
MOTOR ANTICIPATION (FEL)

Corrective action driven by sensory feedback



SENSORY PREDICTION (HSPC)

Corrective action driven by sensory feedback



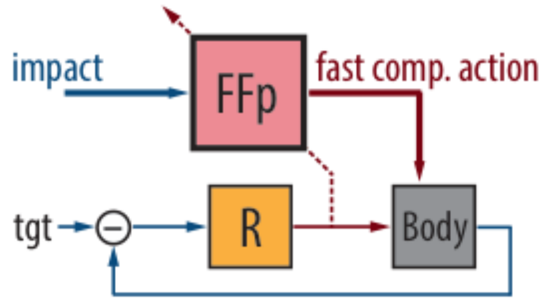
Maffei, Herreros et al., 2017

Motor anticipation (FEL) vs Sensory prediction (HSPC)

Fast compensation

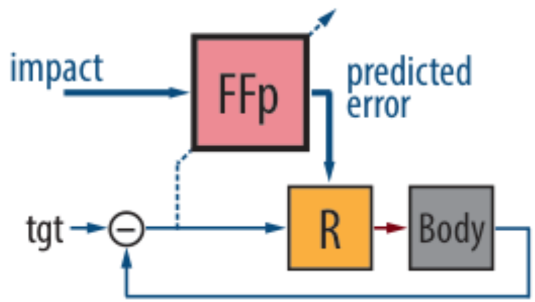
MOTOR ANTICIPATION (FEL)

Motor command triggered by the impact



SENSORY PREDICTION (HSPC)

Predicted error triggered by the impact



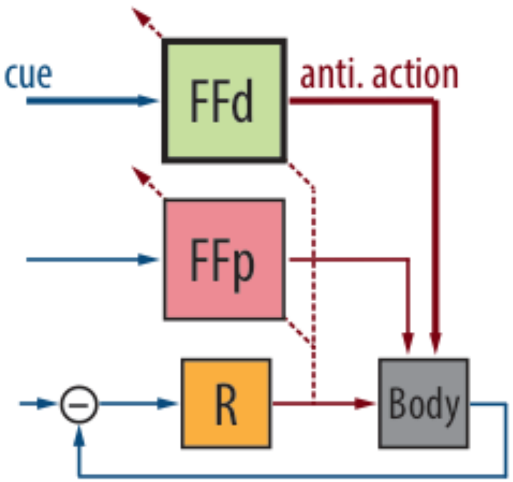
Maffei, Herreros et al., 2017

Motor anticipation (FEL) vs Sensory prediction (HSPC)

Anticipation

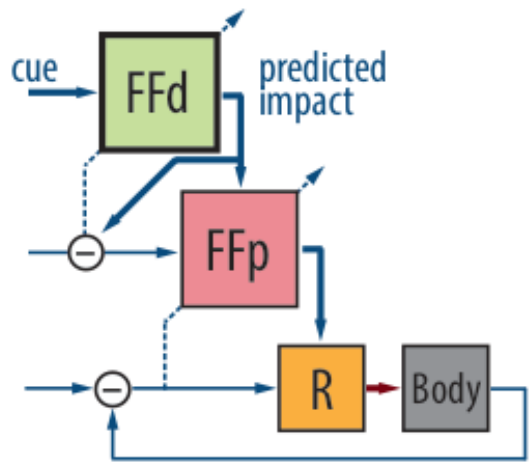
MOTOR ANTICIPATION (FEL)

Motor command triggered by the cue



SENSORY PREDICTION (HSPC)

Predicted impact triggered by the cue



Maffei, Herreros et al., 2017

Acquisition paradigm

Comparing the acquisition of APAs in FEL and HSPC

- Regular trial: disturbance is preceded by distal and proximal cues

Learning

Setup

Maffei, Herreros et al., 2017

Acquisition paradigm

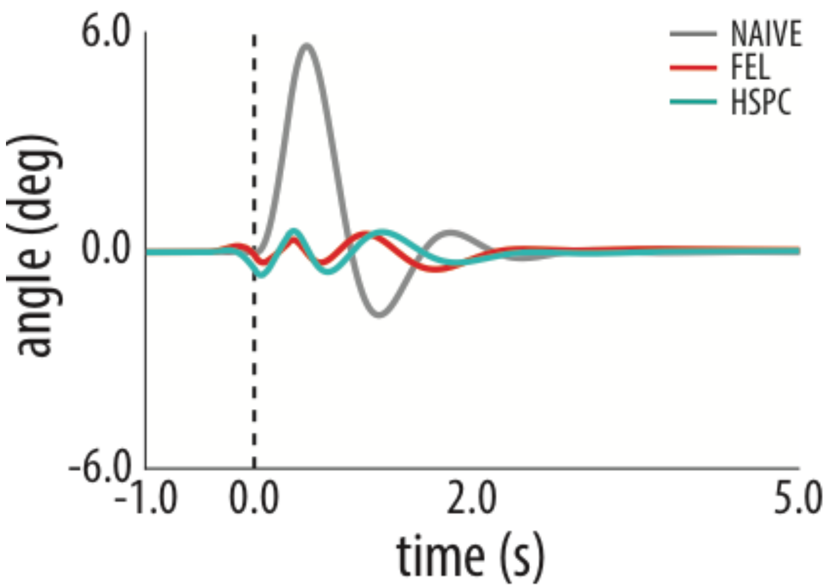
Comparing the acquisition of APAs in FEL and HSPC

- Regular trial: disturbance is preceded by distal and proximal cues

Learning

Setup

FEL and HSPC behave equally

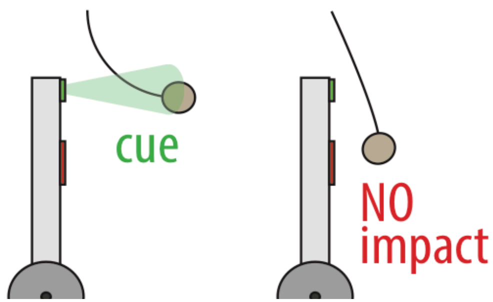


Maffei, Herreros et al., 2017

Robustness paradigm

Comparing FEL and HSPC during catch trials

- Catch trials: cue is presented but disturbance is NOT delivered



2.2

Catch trial, HSPC vs. FEL

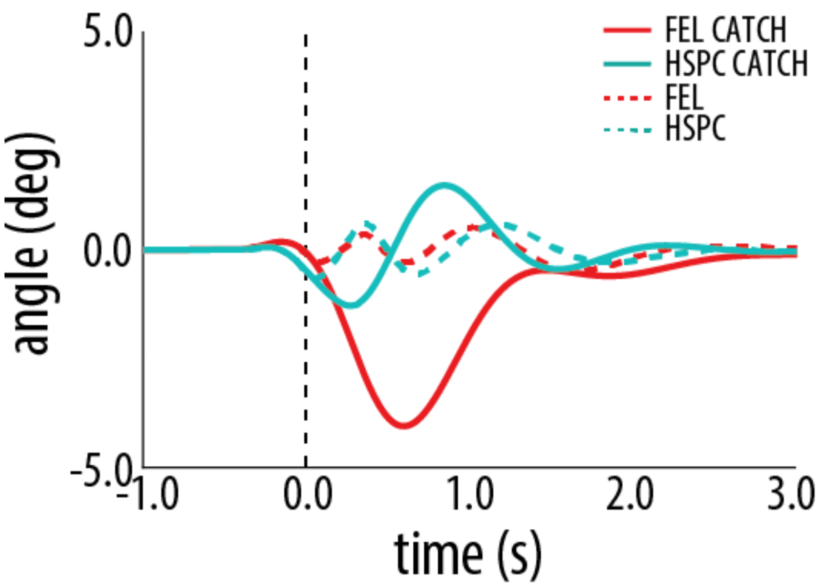
In the trained robot, the omitted impact is rapidly corrected by HSPC but introduces a greater disturbance in FEL.

Maffei, Herreros et al., 2017

Comparing FEL and HSPC during catch trials

- Catch trials: cue is presented but disturbance is NOT delivered

HSPC outperforms FEL



Maffei, Herreros et al., 2017

2.2

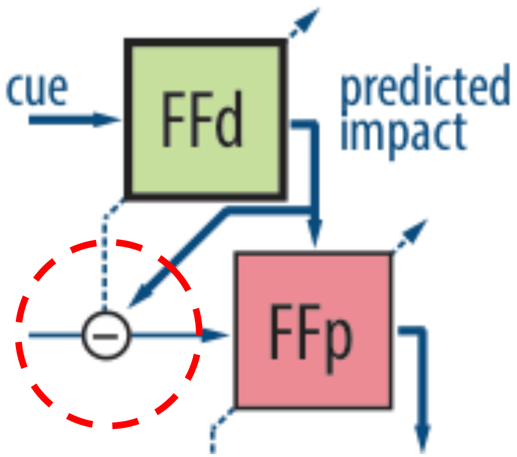
Catch trial, HSPC vs. FEL

In the trained robot, the omitted impact is rapidly corrected by HSPC but introduces a greater disturbance in FEL.

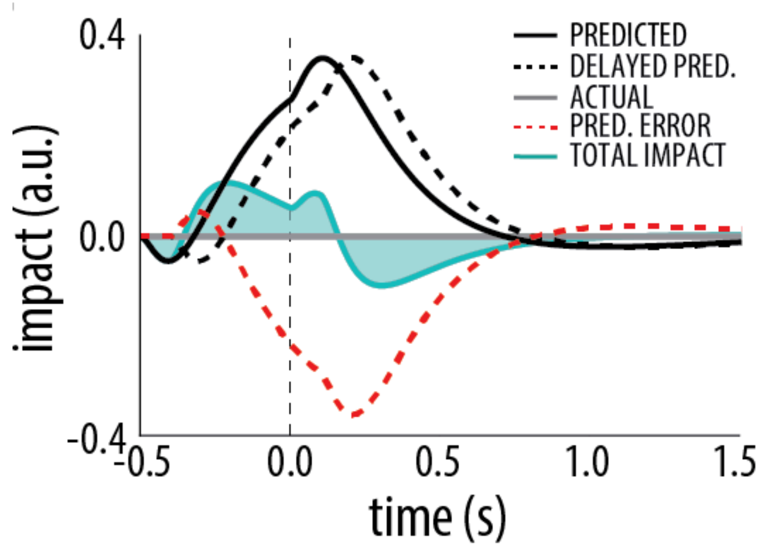
Robustness paradigm

A sensory prediction can be rapidly retracted

- SPEs drive perceptual learning
- SPEs correct for errors in real time



Sensory prediction error (SPE)

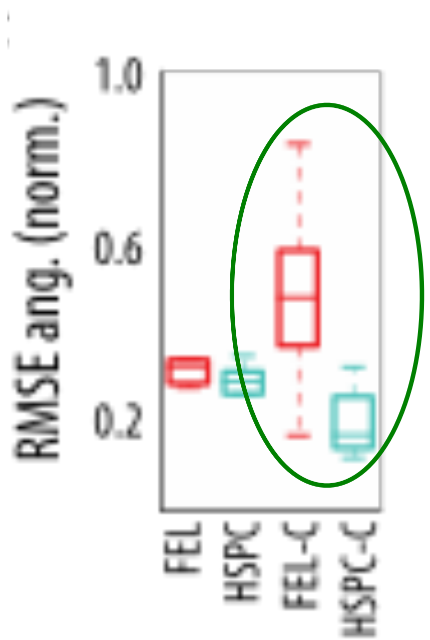


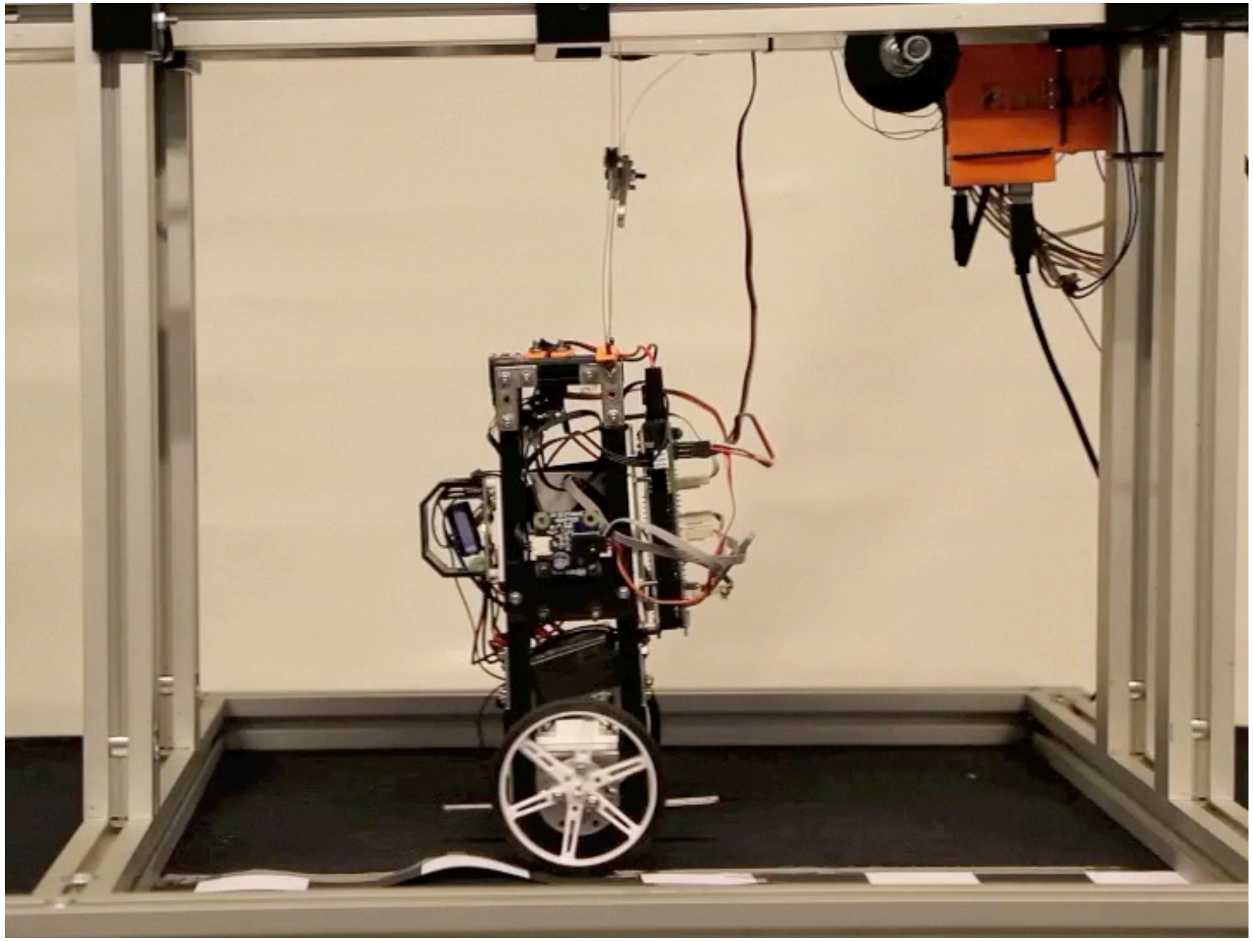
Maffei, Herreros et al., 2017

Robotic setup: the Perturbator

Comparing acquisition and catch trials in a balancing robot

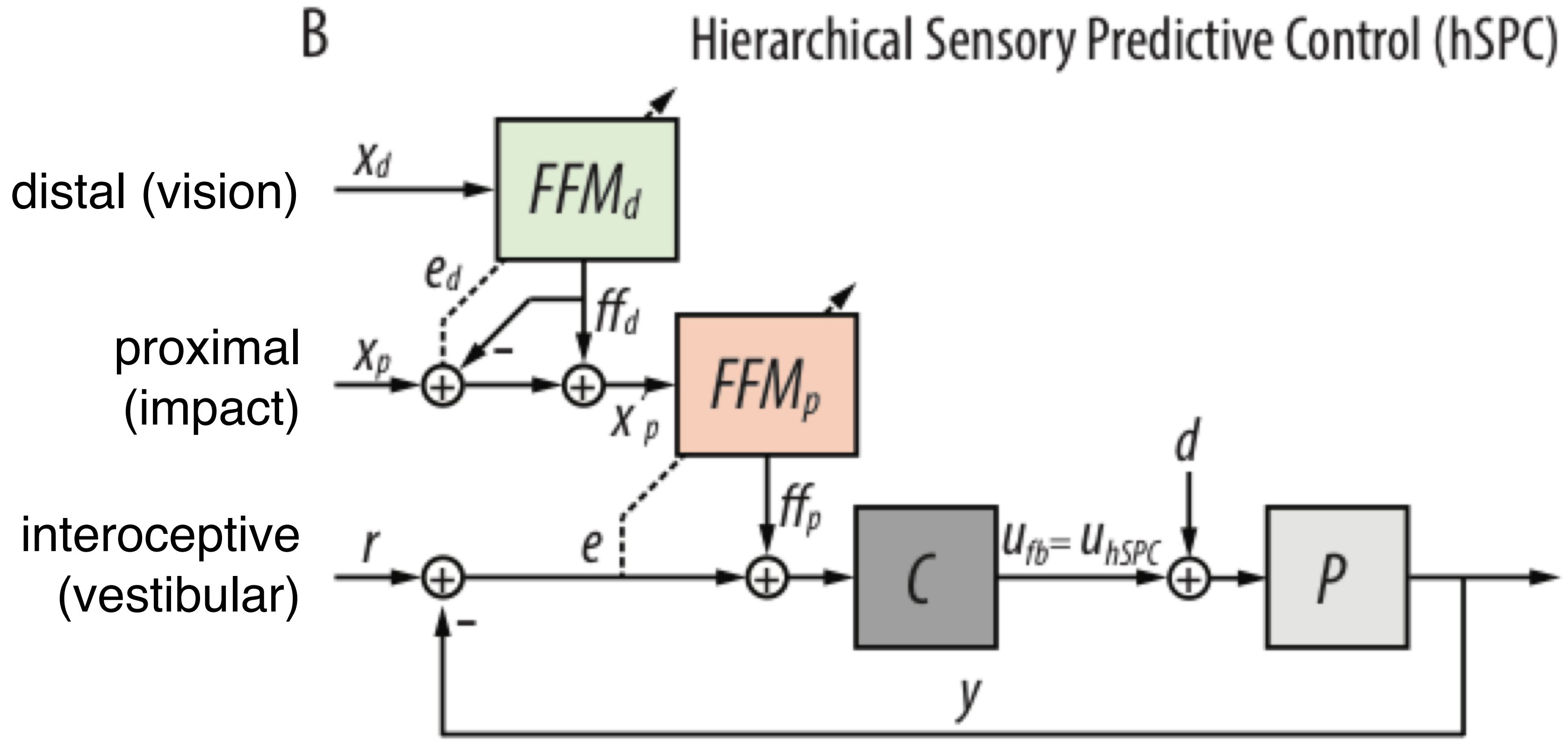
HSPC outperforms FEL during catch trials





Maffei et al., *In Prep*

Hierarchical Sensory Predictive Control



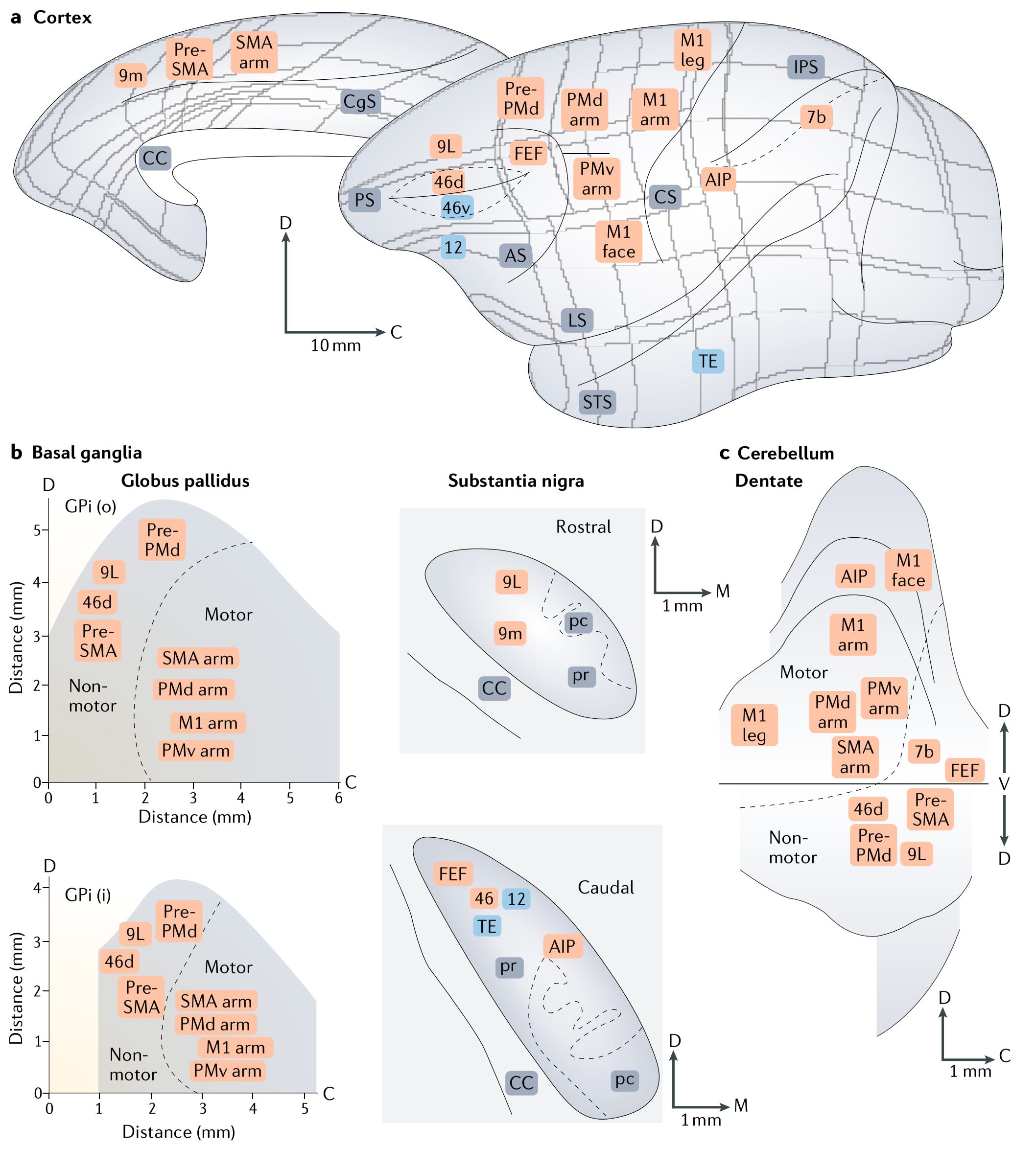
Where are the forward models stored?

Maffei, Herreros et al., *in preparation*

Interfacing procedural and executive control

CRX targets of BG & CRBLM

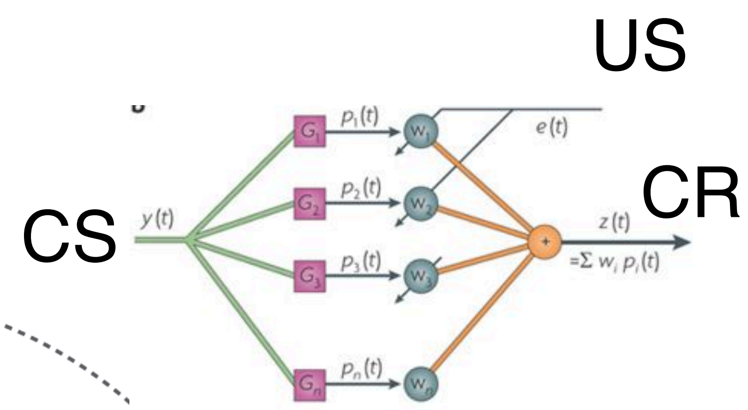
CRX targets of BG

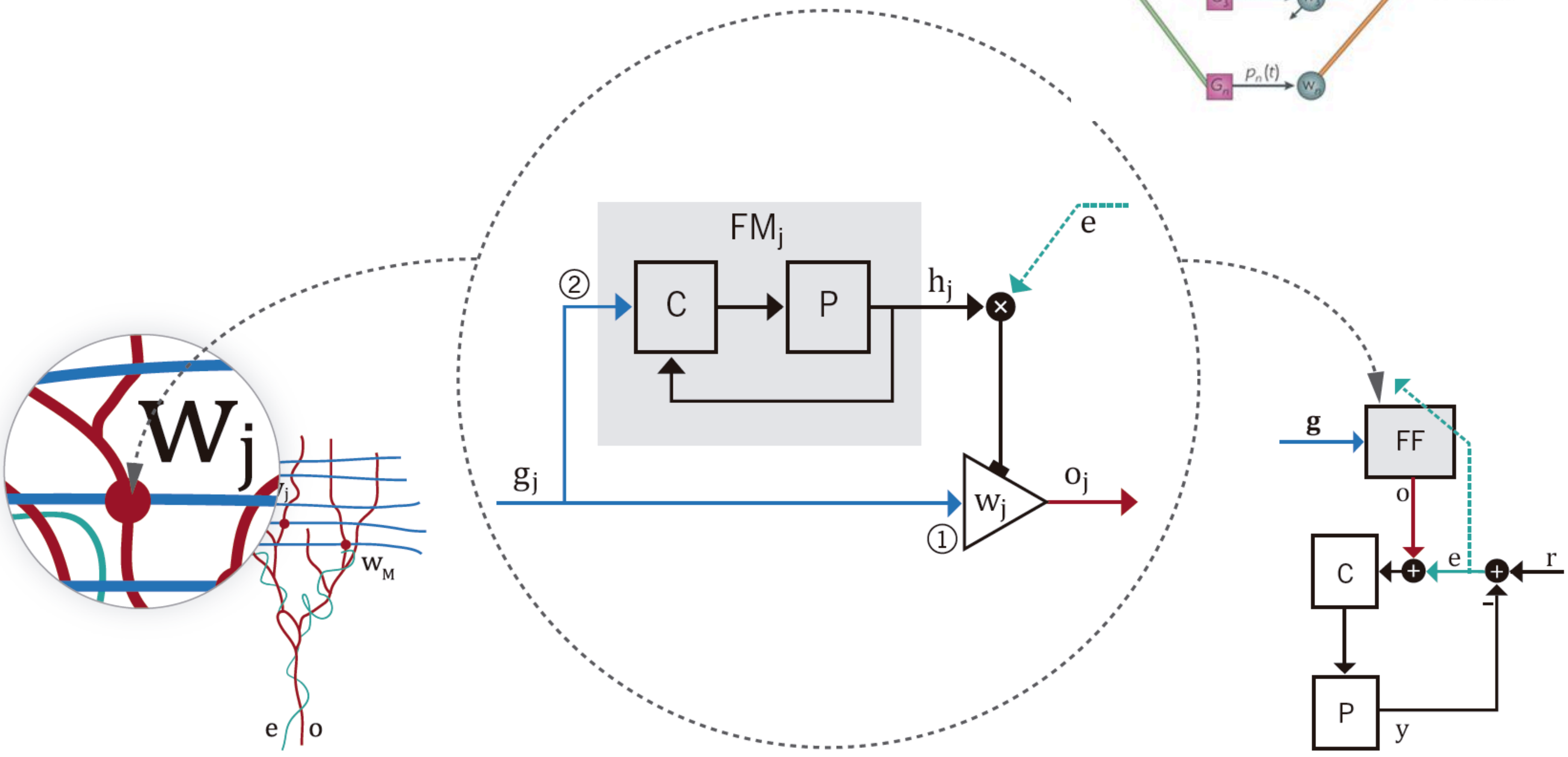


Bostan & Strick 2018 Nat Rev Neurosci

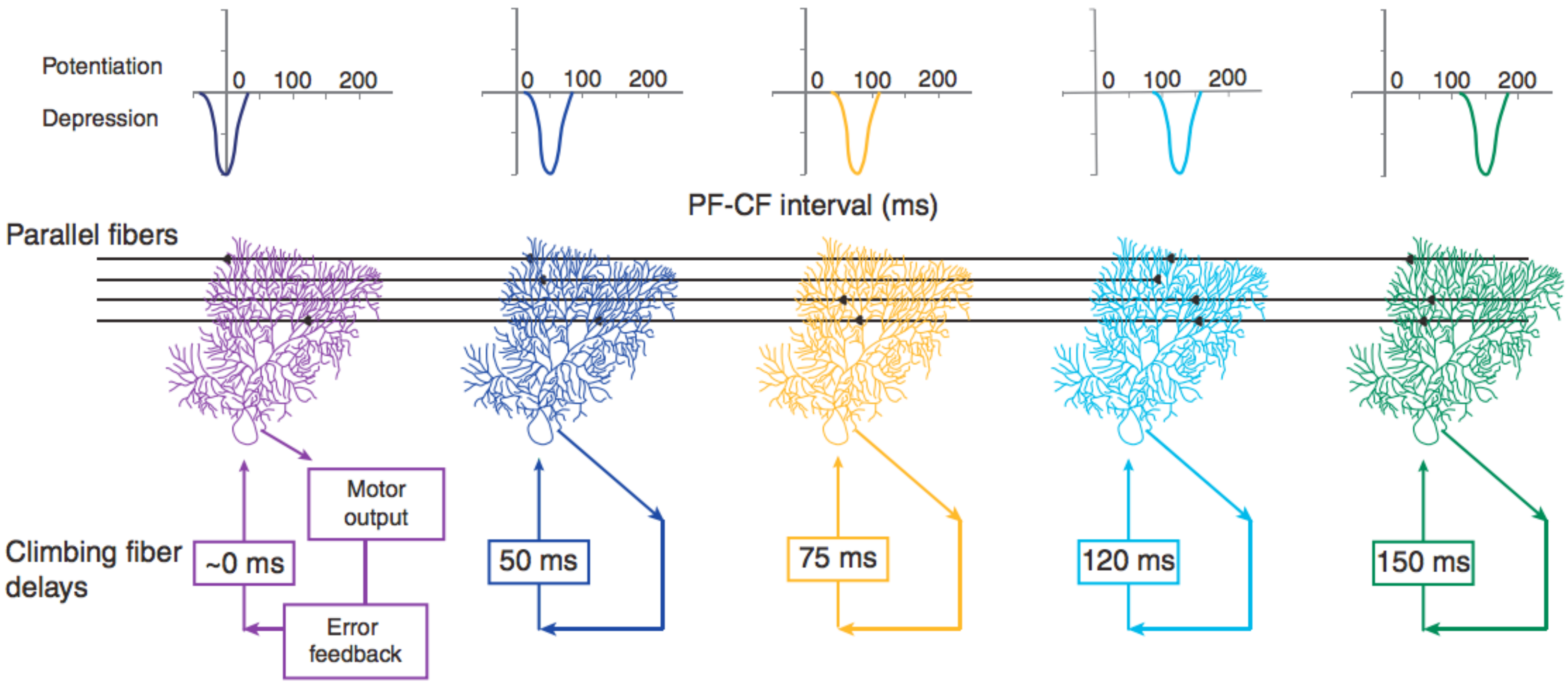
Hierarchical Sensory Predictive Control

COUNTER FACTUAL PREDICTIVE CONTROL





PF-Pu synapses have intrinsic time constants tuned to specific peripheral targets

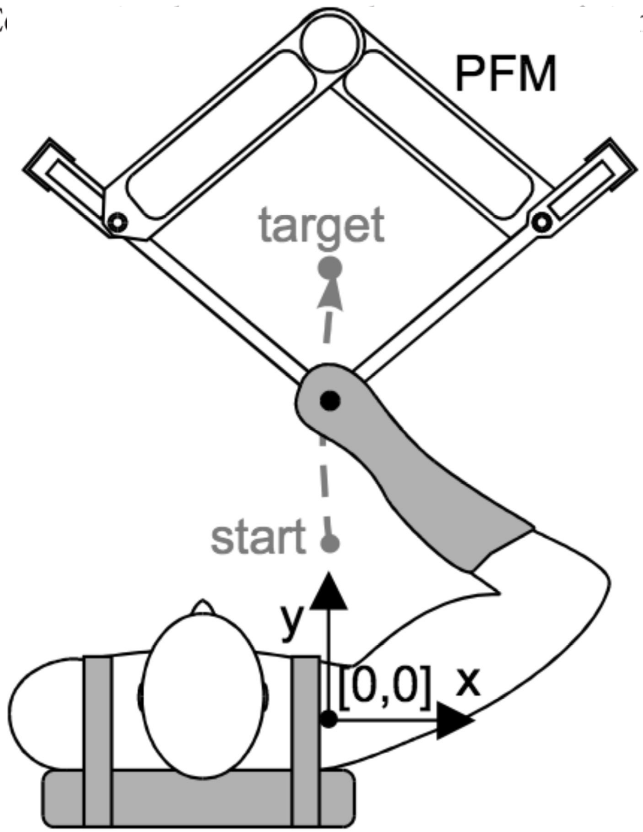


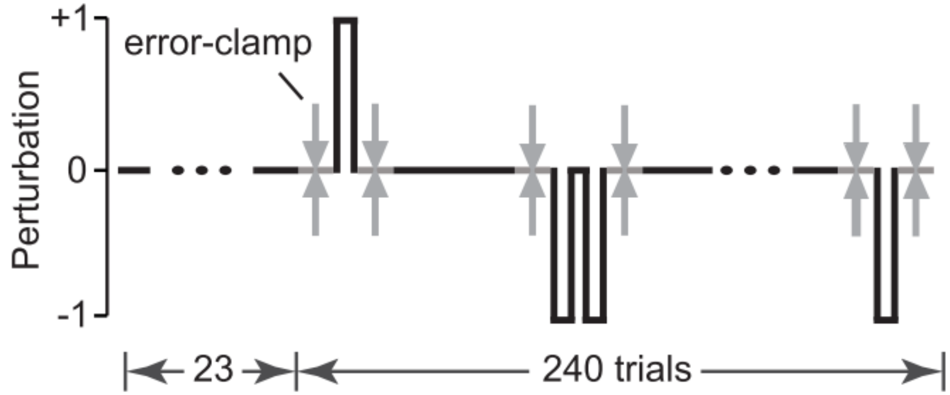
Suvrathan et al., Neuron, 2016

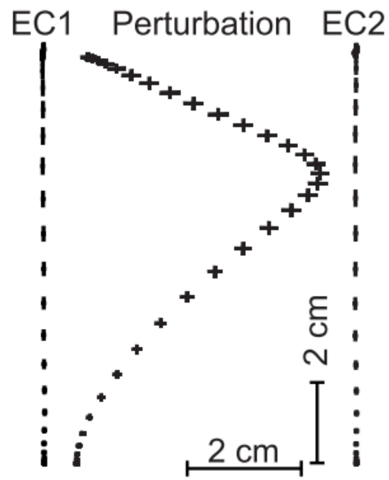
Behavioral/Cognitive

The Neural Feedback Response to Error As a Teaching Signal for the Motor Learning System

Scott T. Albert and Reza Shadmehr
Laboratory for C… nedical Enginee







The Neural Feedback Response to Error As a Teaching Signal for the Motor Learning System

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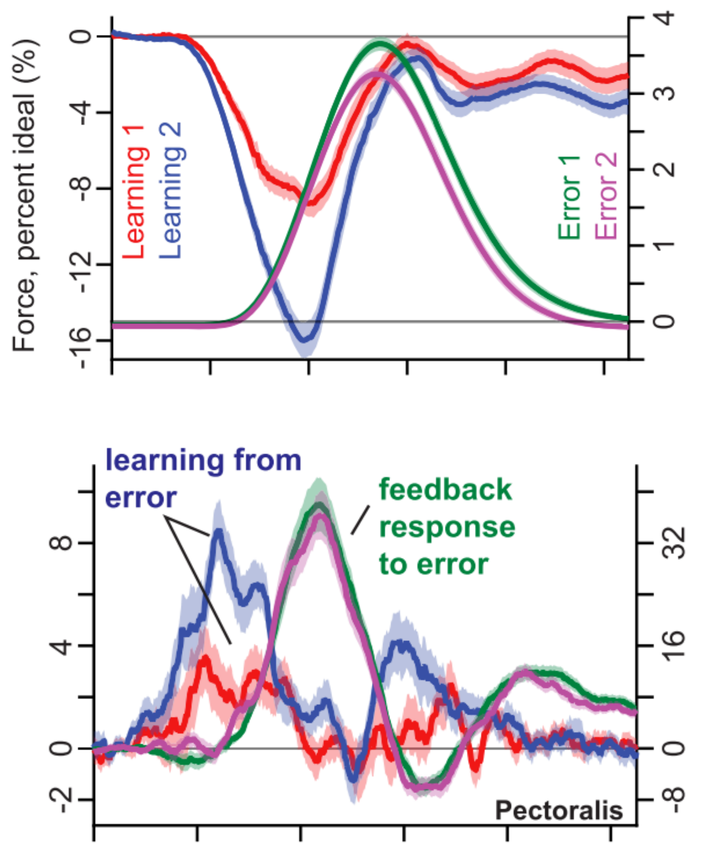
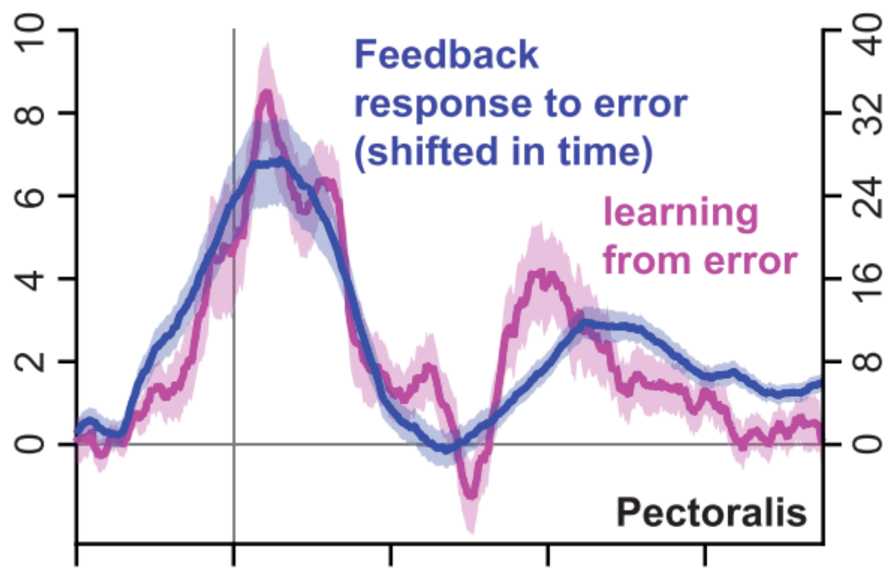
Laboratory for Computational Motor Control, Department of Biomedical Engineering, Johns Hopkins School of Medicine, Baltimore, Maryland 21205





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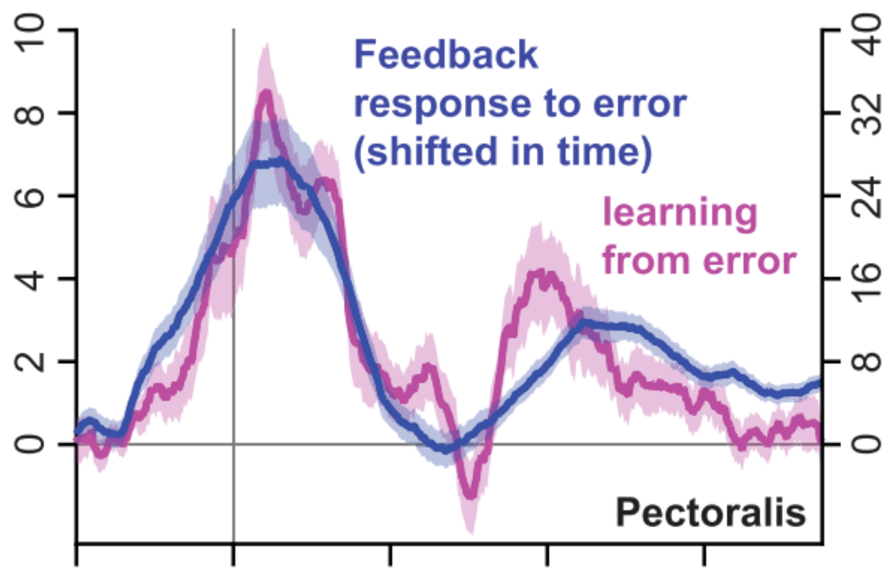
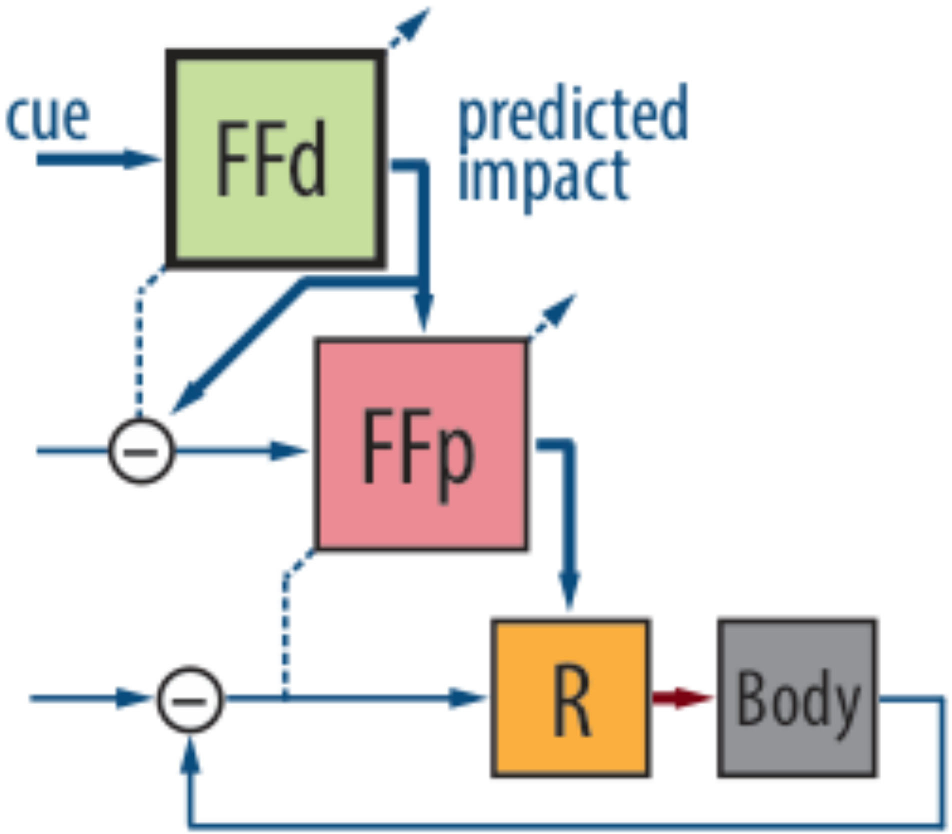
Results support the shift-and-scale learning strategy.

Can't tell whether the feedback response or the sensory error acted as the teaching signal *(despite the paper's title)*



Exploiting counterfactual errors in the clinic

Can we overcome learned non-use through counterfactual error manipulation?

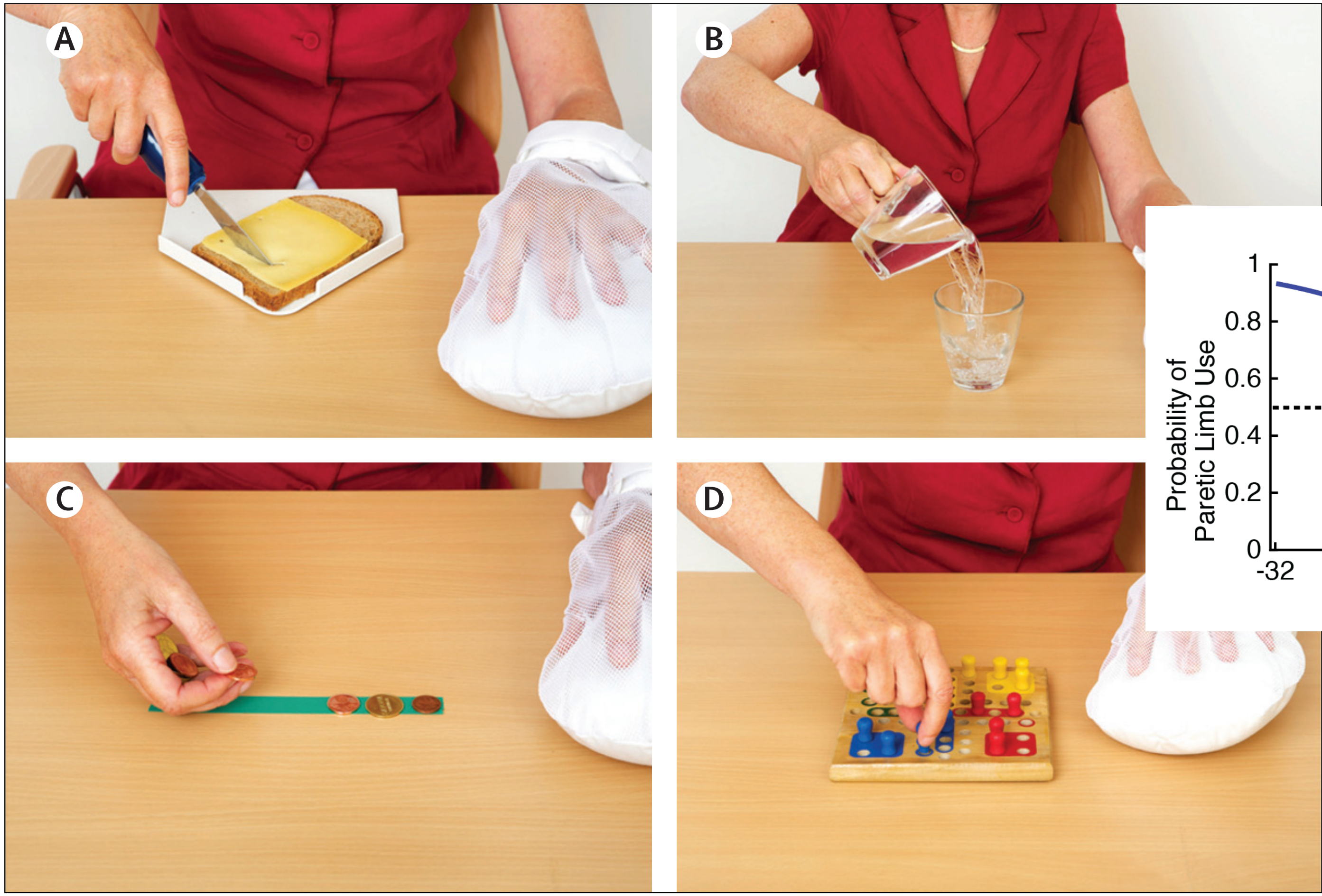


Maffei, Herreros et al., 2017

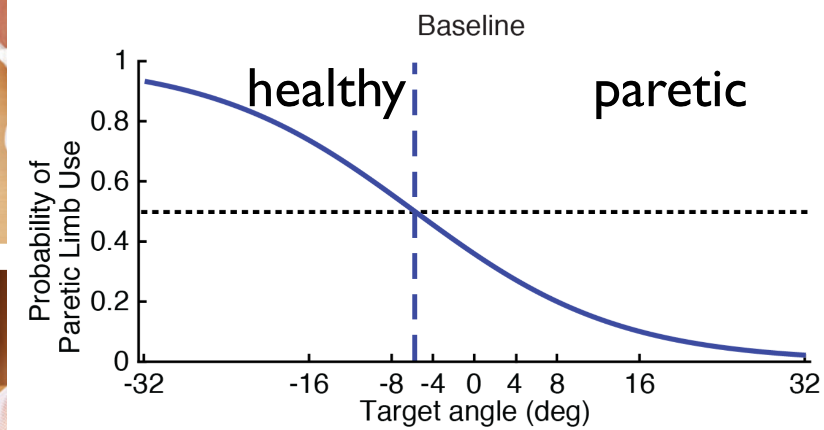
Verschure & Mintz (2000) Comp Neuro;

Herreros & Al. , Neur Net (2013)

Acquired non-use: A RGS alternative to Constrained Induced Movement Therapy

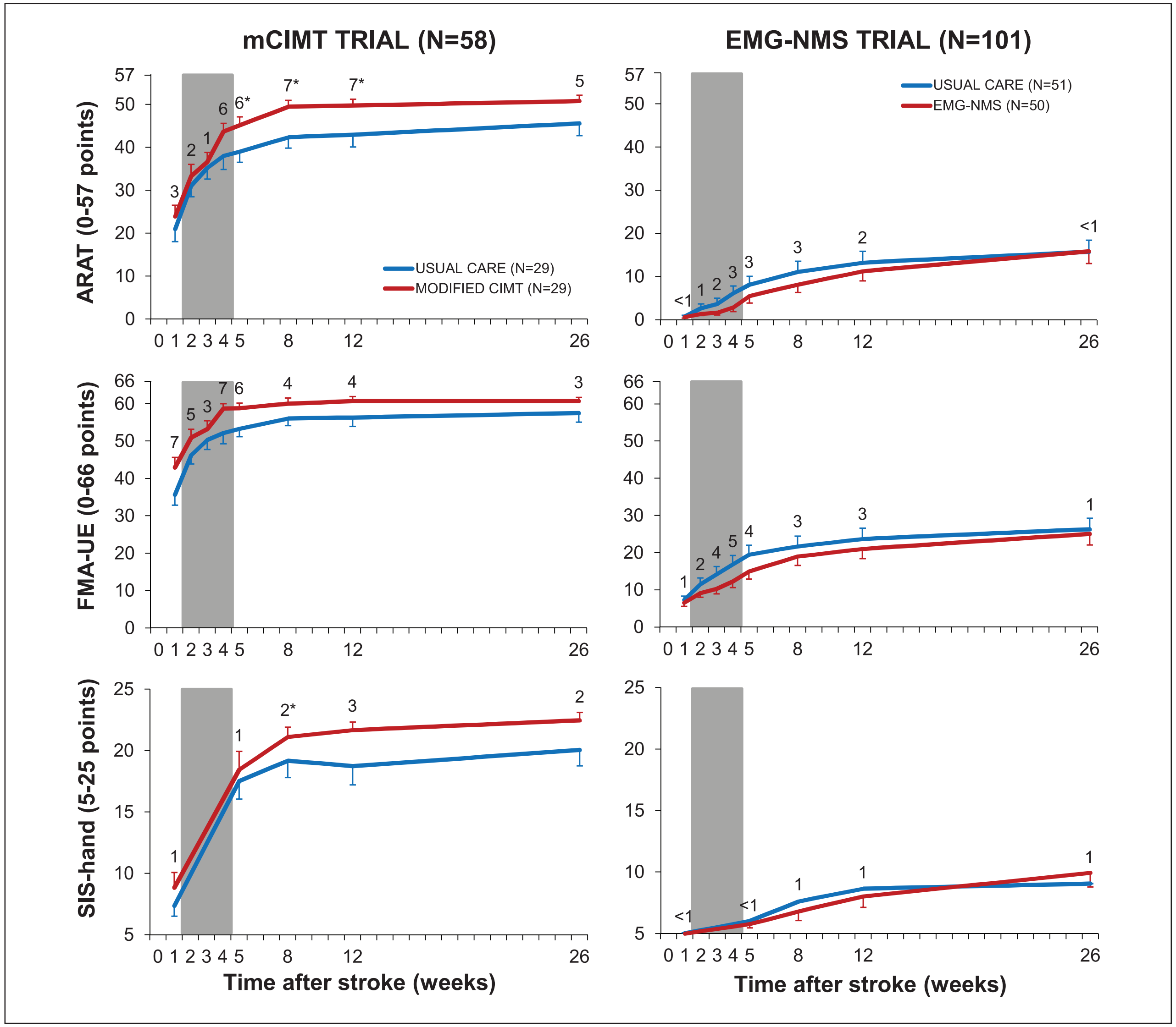


-6 deg



Taub E, et al (1994). *J Exp Anal Behav*

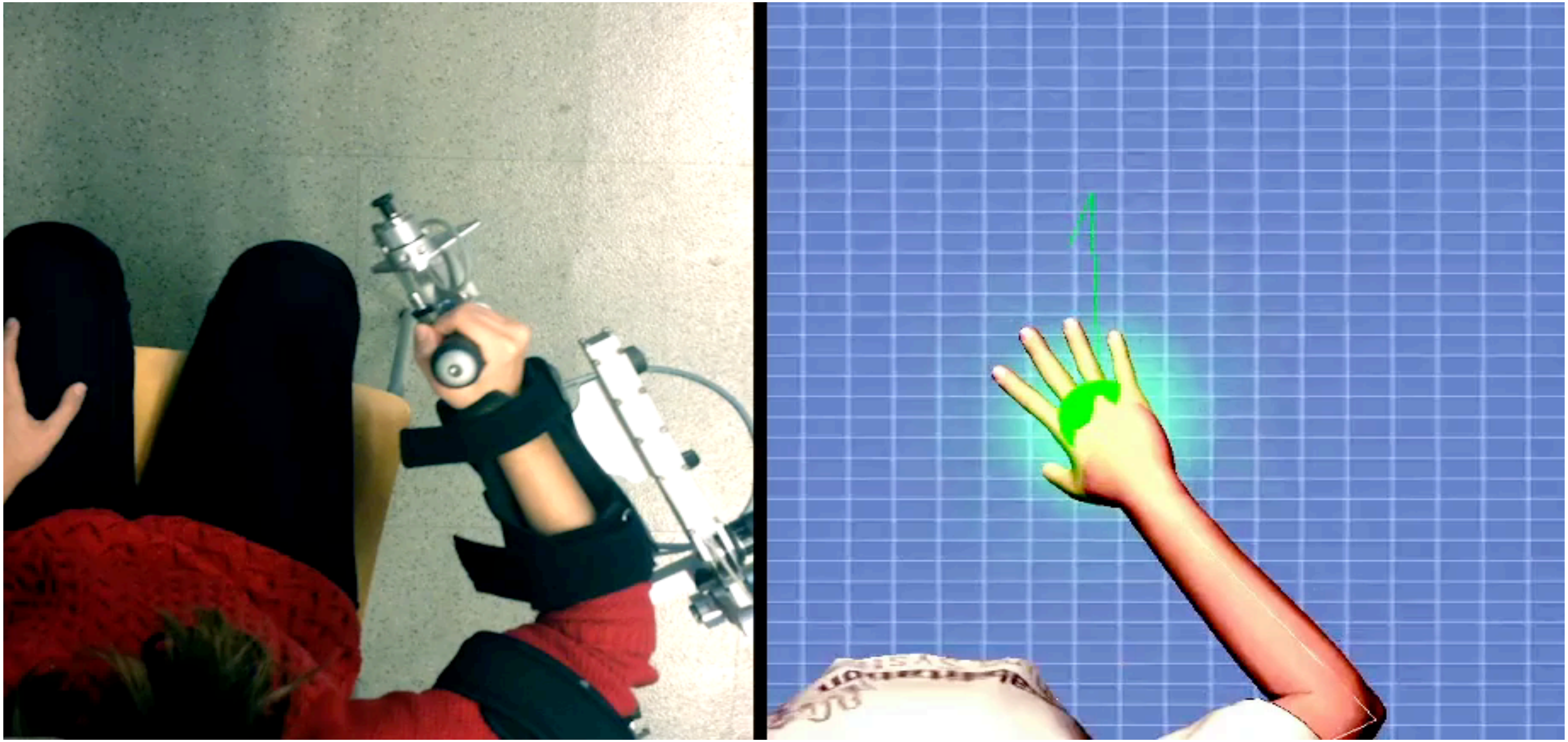
intense CIMT vs FES (EXPLICIT)



"Despite meaningful improvements in upper limb capacity, no evidence was found that the time-dependent neurological improvements early poststroke are significantly influenced by either mCIMT or EMG-NMS. "

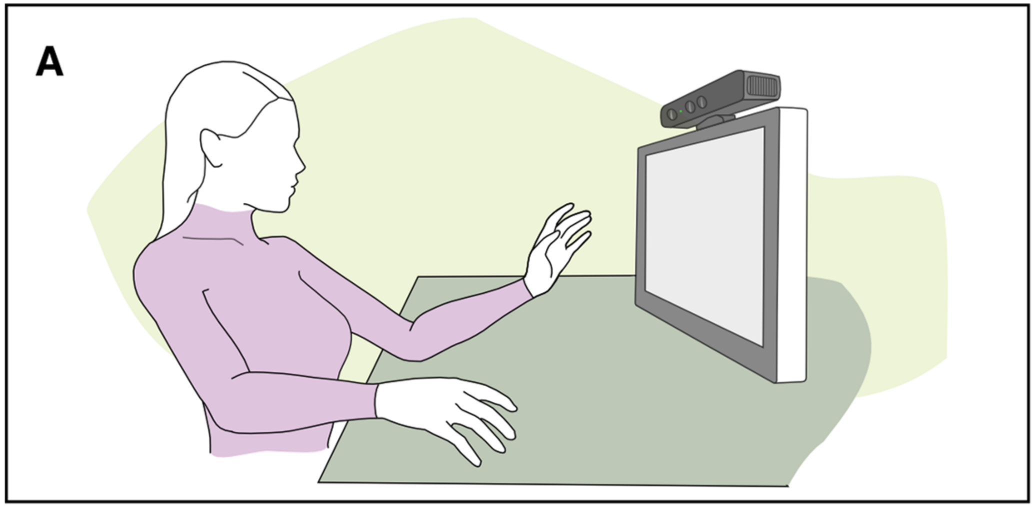
Kwakkel et al 2016 RNN

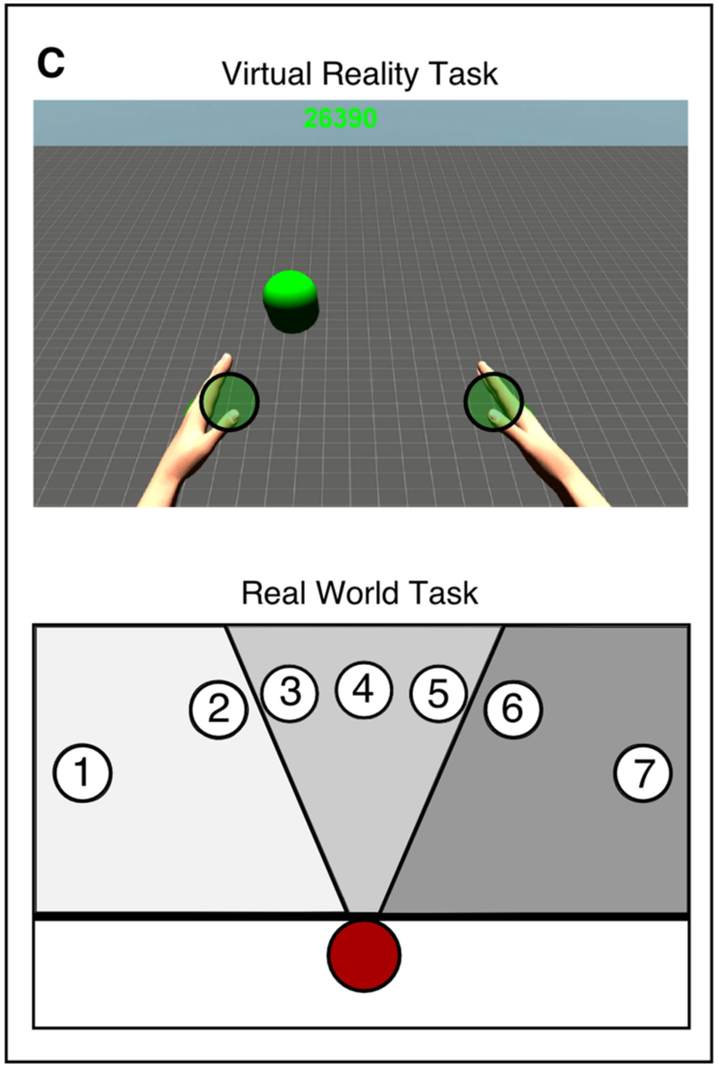
An alternative to CIMT



with the Rehabilitation Gaming System - RGS

A RGS alternative to CIMT

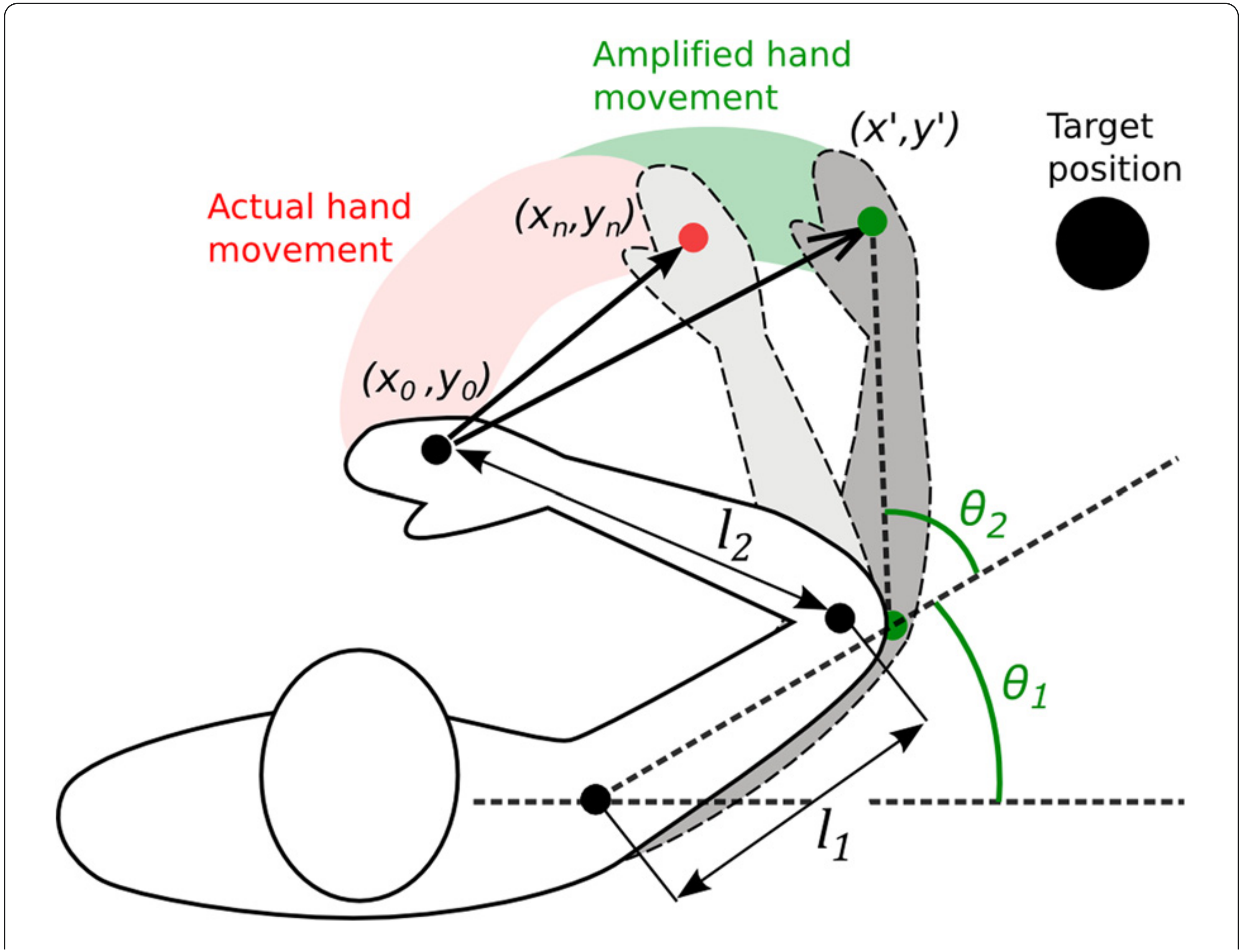




N=20 (chronic)   Paretic arm **error minimization**

Rubio et al (2015) JNER

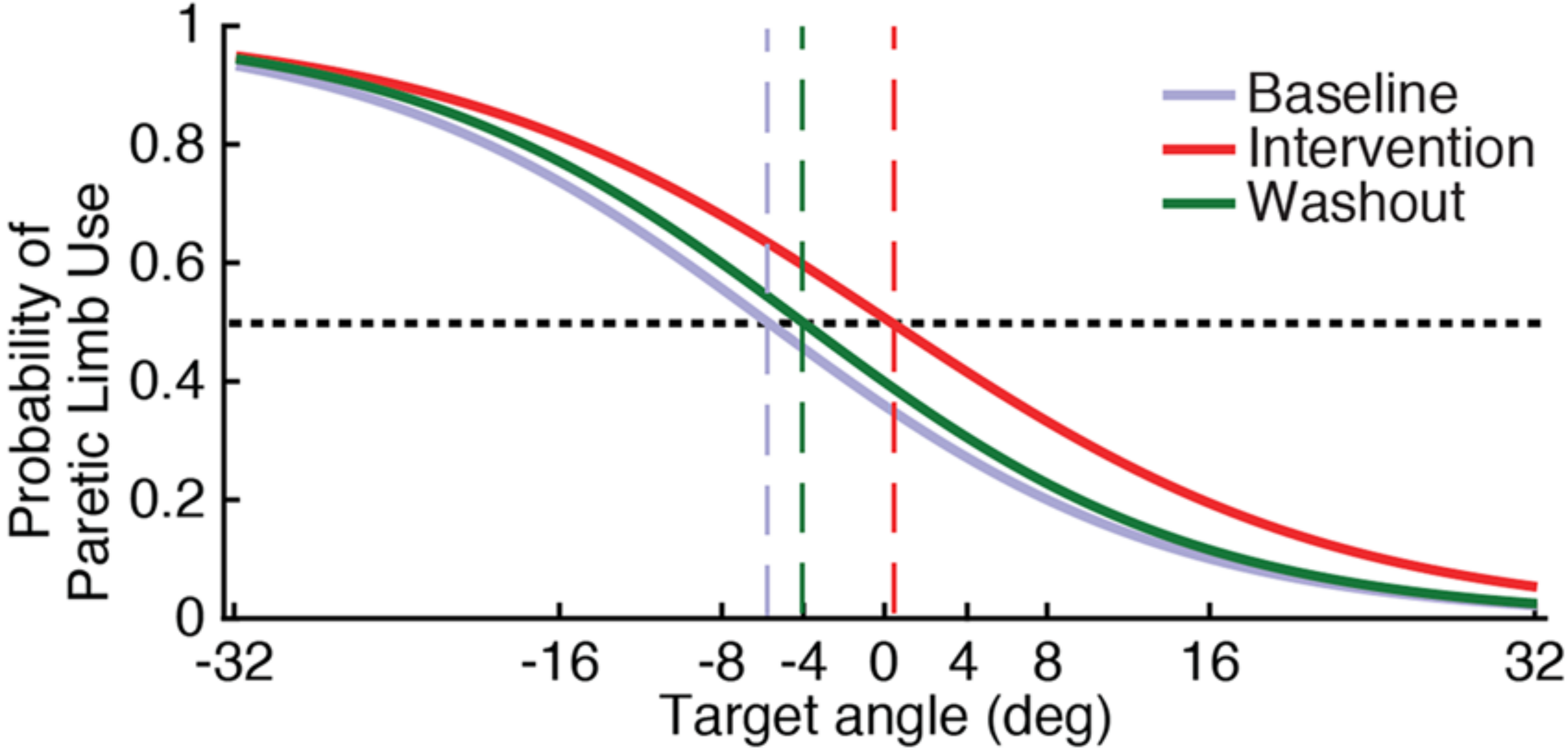
Intention compatible movement amplification



Rubio et al (2015) JNER

Paretic arm **visual error minimization**

A RGS alternative to CIMT

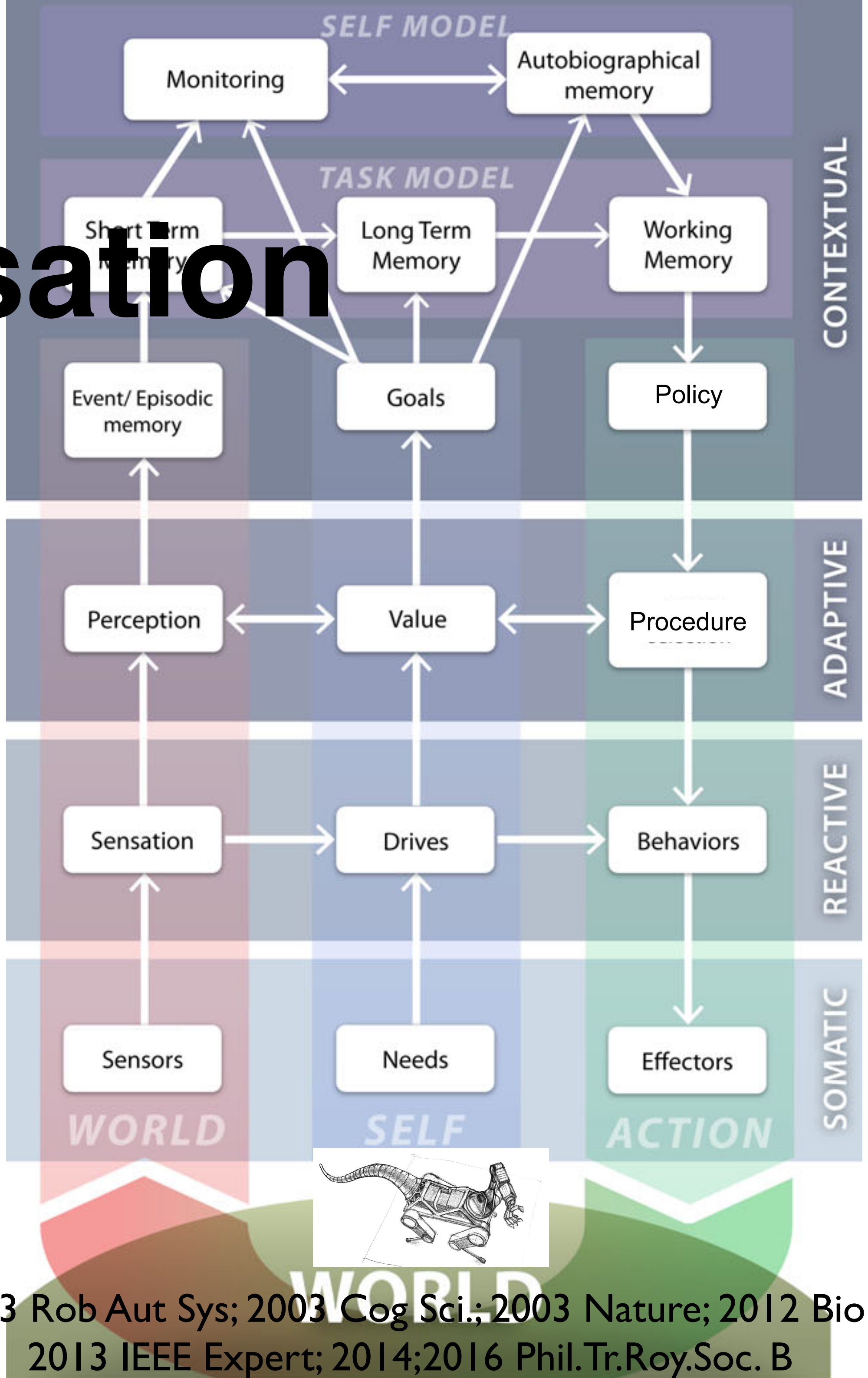


Rubio et al (2015) JNER

Sequential
Acquired
Flexible

Virtualisation

Distributed Adaptive Control



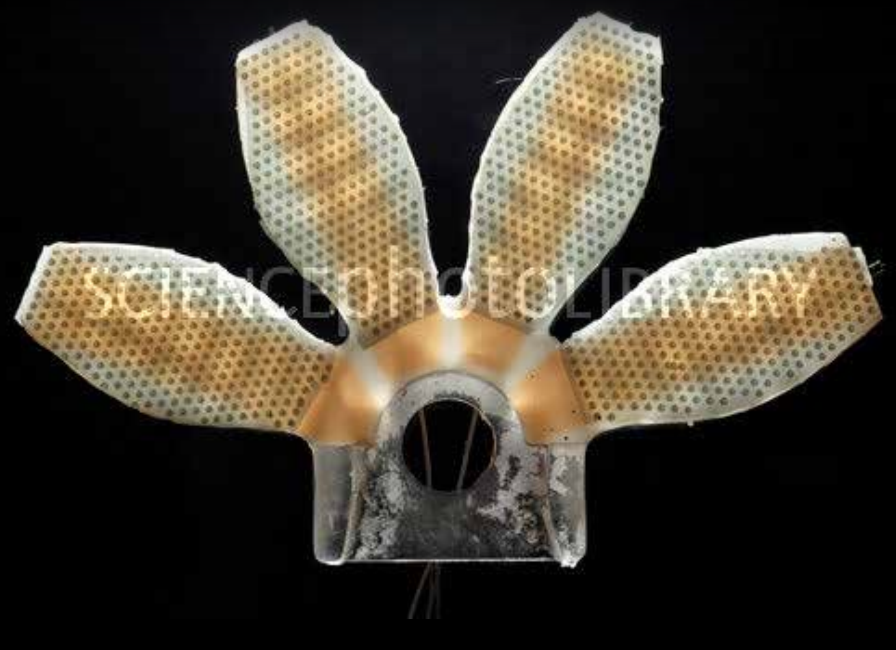
Rigid
Speed
Prior
Parallel

Verschure et al 1993 Rob Aut Sys; 2003 Cog Sci.; 2003 Nature; 2012 Biol. Insp.Cog.Arch.; 2013 IEEE Expert; 2014;2016 Phil.Tr.Roy.Soc. B

OXFORD

LIVING MACHINES

A handbook of research in bioimetic and biohybrid systems



EDITED BY

TONY J. PRESCOTT, NATHAN LEPORA, & PAUL F. M. J. VERSCHURE

Conclusions/Questions

- DAC describes the brain as a multi-layered control system
- Testing DACs predictions:
  - Error/Surprise processing
- Classical conditioning, 2 Phase model
- Cerebellum: synergy between FB and FF control
- FEL vs HSPC
  - HSPC has better explanatory power and control
  - Makes sense of dense Cerebellar-Cortical interaction
- DAC-HSPC tested in acquired non-use after stroke
- The brain is not only hallucination perception but also its errors