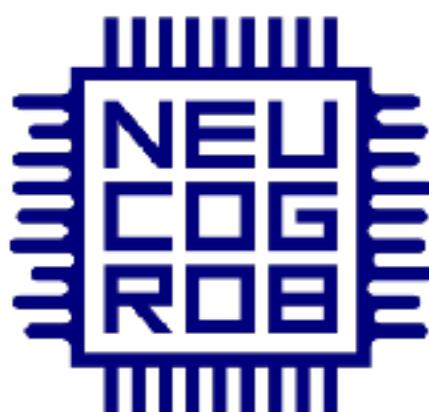


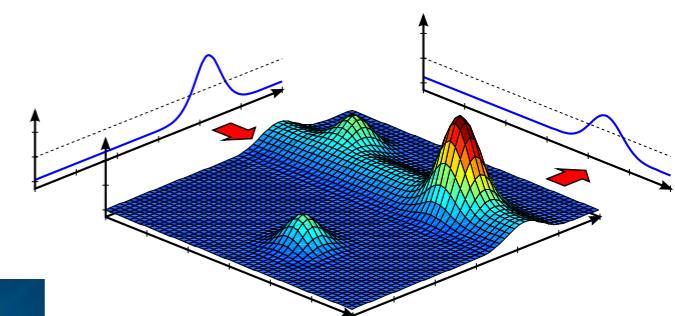
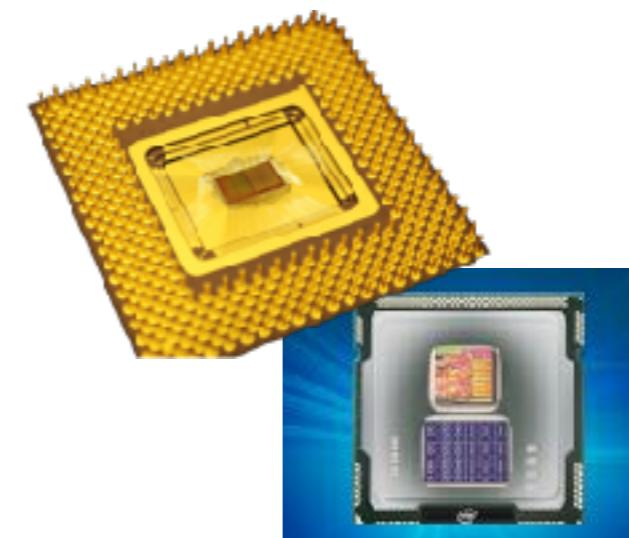
Reliable computation in recurrent, spiking, and plastic networks: from proof of concept to real-world applications

Yulia Sandamirskaya

Institute of Neuroinformatics
University of Zurich and ETH Zurich

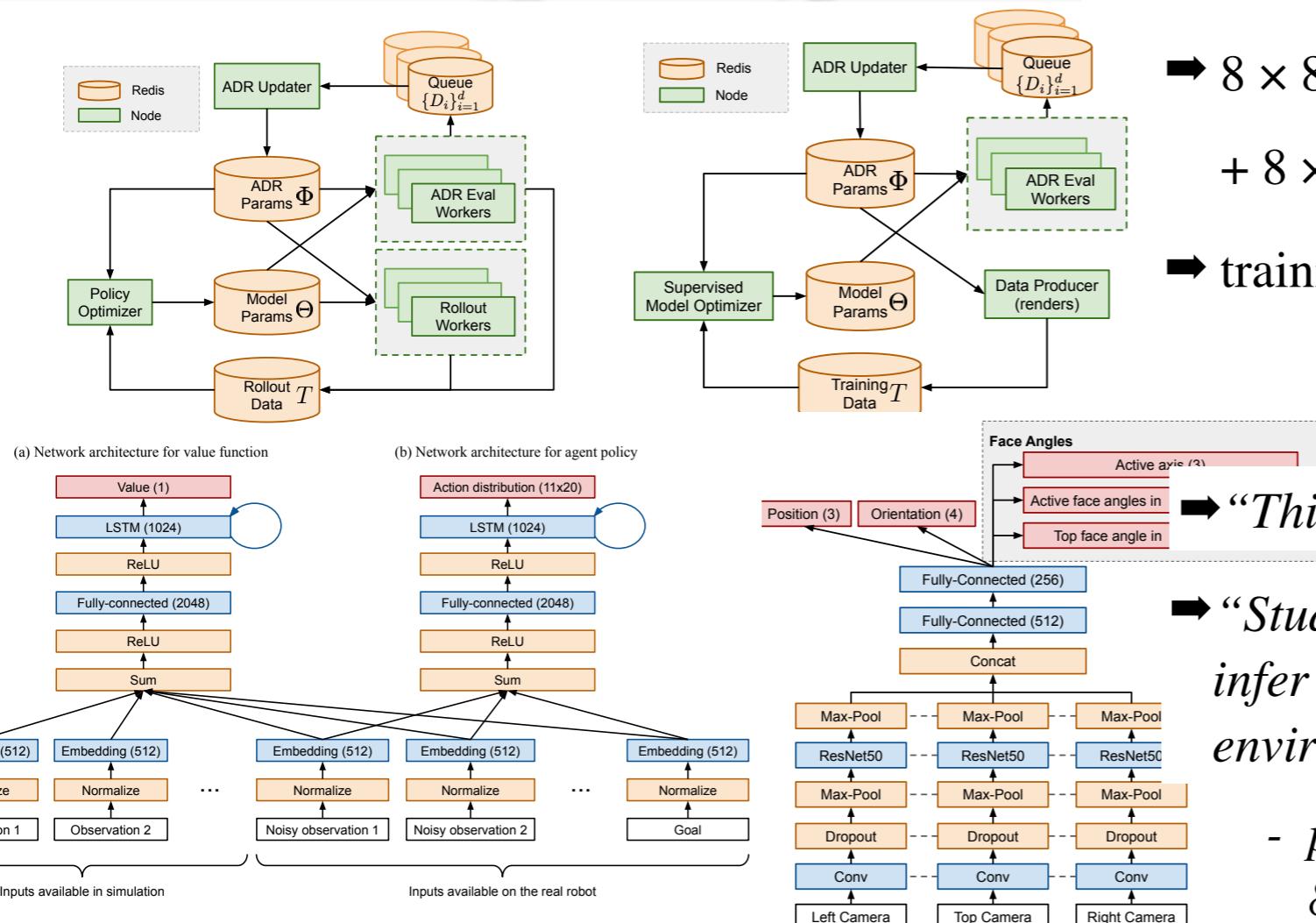
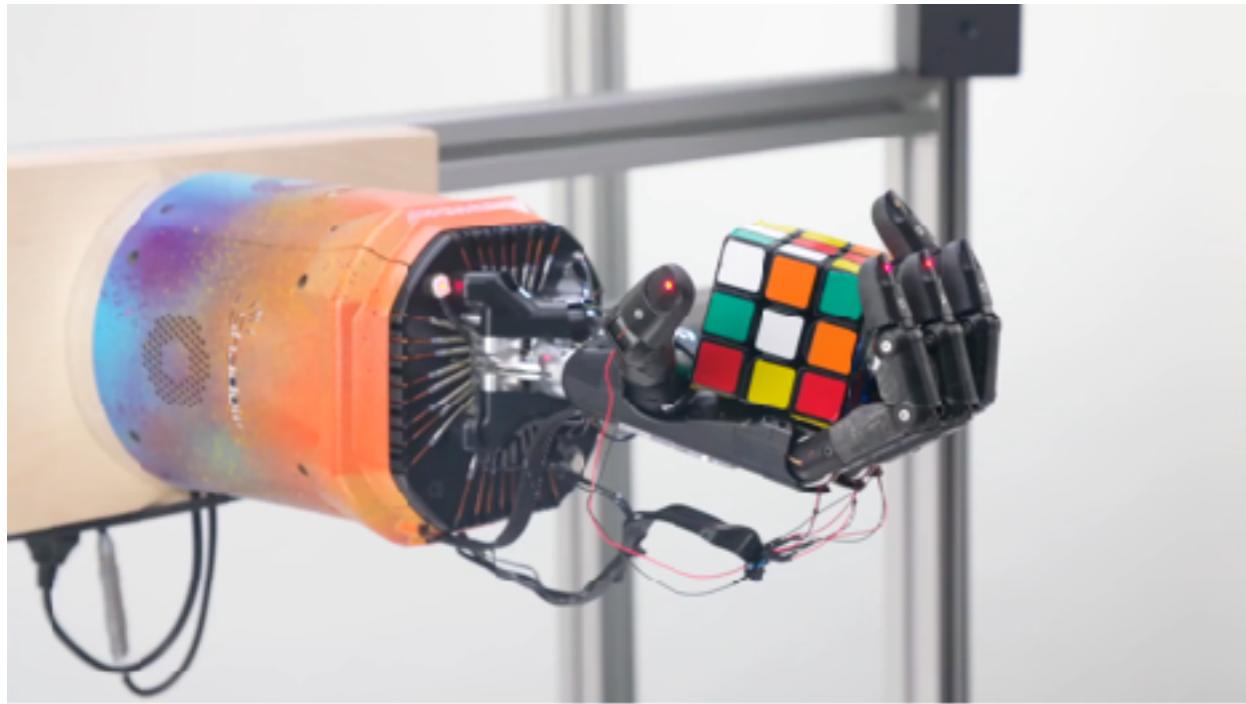


Research group
“Neuromorphic Cognitive Robots”



Intelligent systems: Artificial vs Biological

Intelligent systems: Artificial vs Biological



- $8 \times 8 = 64$ NVIDIA V100 GPUs
- + $8 \times 115 = 920$ worker machines with 32 CPU
- training the policy continuously for several month
 - = 13 thousand years
 - 13,863,132 trainable parameters per network

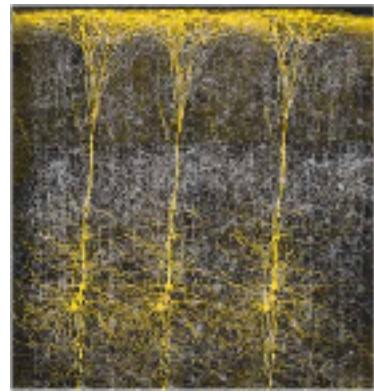
→ “This has worked surprisingly well (policy cloning)”

- “Study whether the policy has learned to infer and store useful information about the environment in its recurrent state”

- *prediction accuracy rapidly improves to over 80% for certain parameters....*

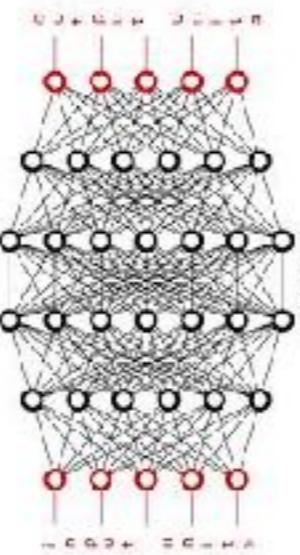
What do we know about biological neuronal systems?

Biological neural networks



- Massively parallel
- Massively recurrent
 - filtering
 - stable states
- Event-based
 - save power
 - be fast
- Plastic
 - can learn on the fly

Artificial neural networks



- GPU, parallel computing
- Recurrence is difficult:
leads to loops; non-Markovian; no clear input and output
- Processing is clocked,
asynchrony is hard to deal with; no gradients to learn
- “Training”. Plasticity is difficult: Convergence? Testing?

→ Dynamical NS, “Type B”

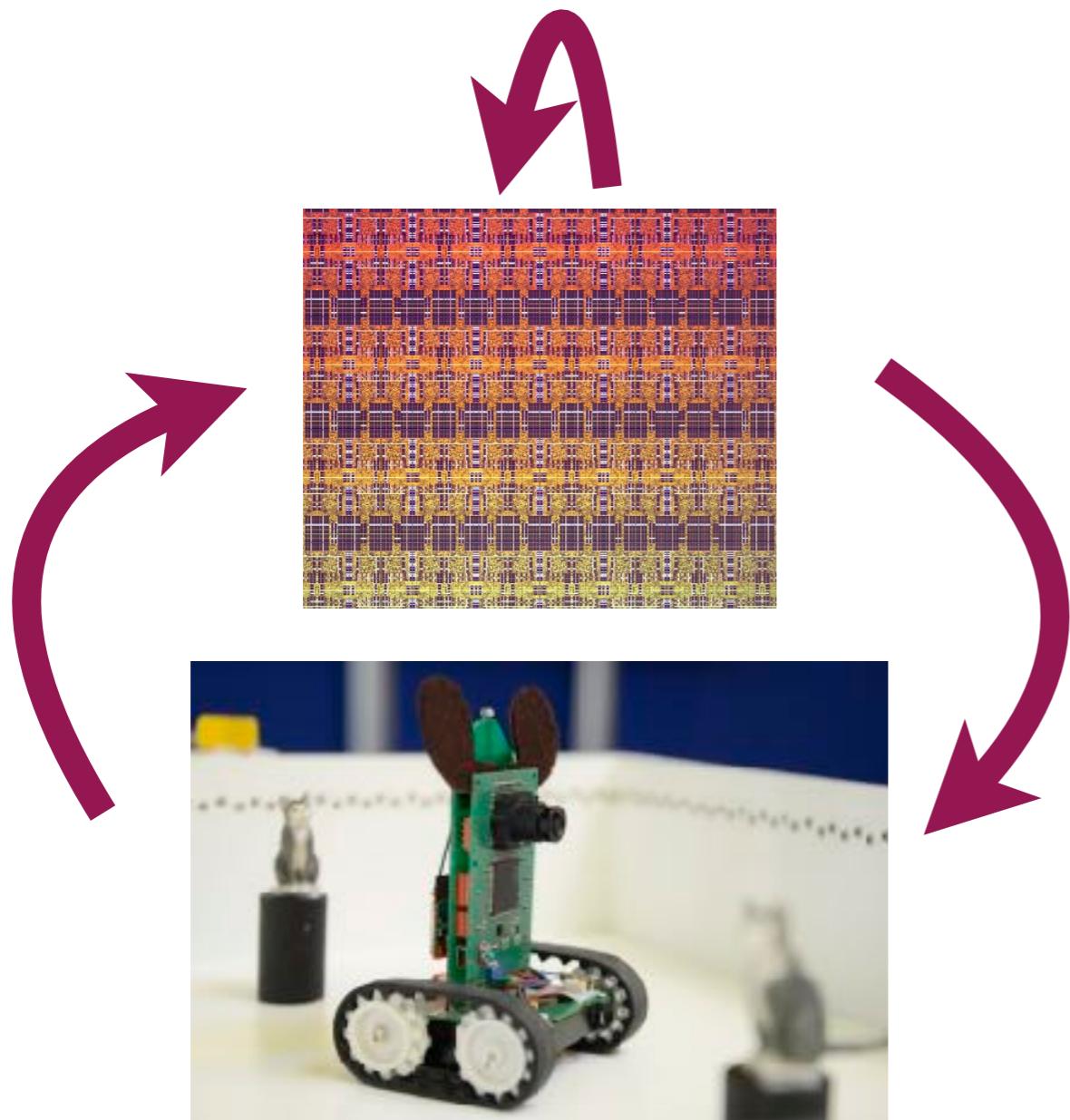
- “Computing” with the substrate
- Control

→ Turing-compliant NS, “Type A”

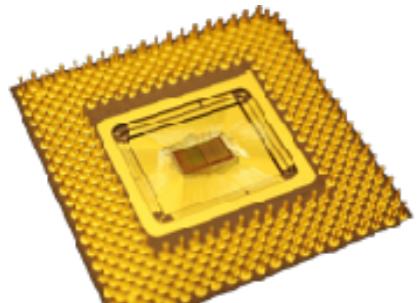
- Turing Machine: the computing substrate doesn’t matter
- Information processing

Can we build, control, and use neuronal systems of Type B?

Neuromorphic controllers



ROLLS

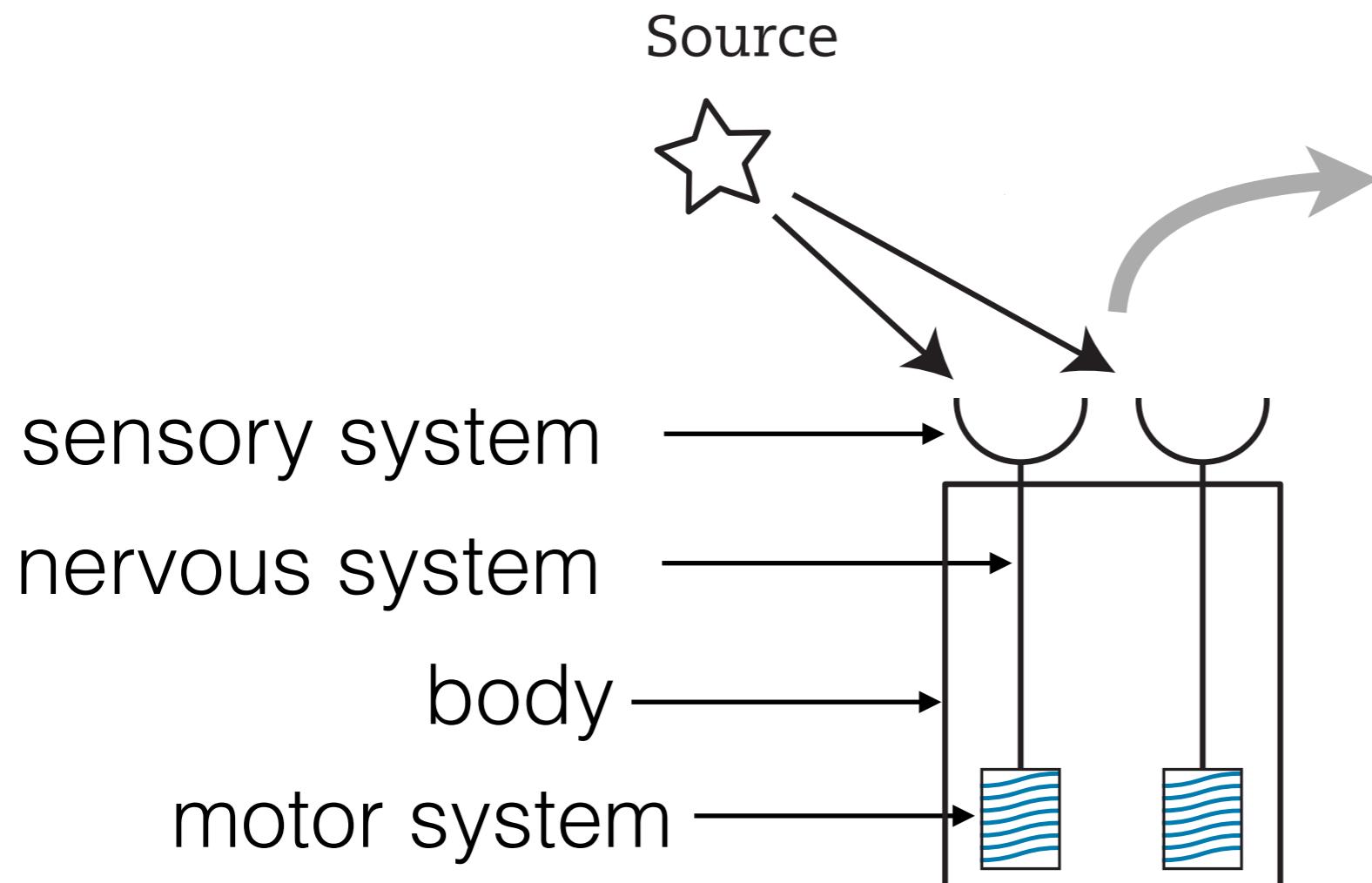


Loihi

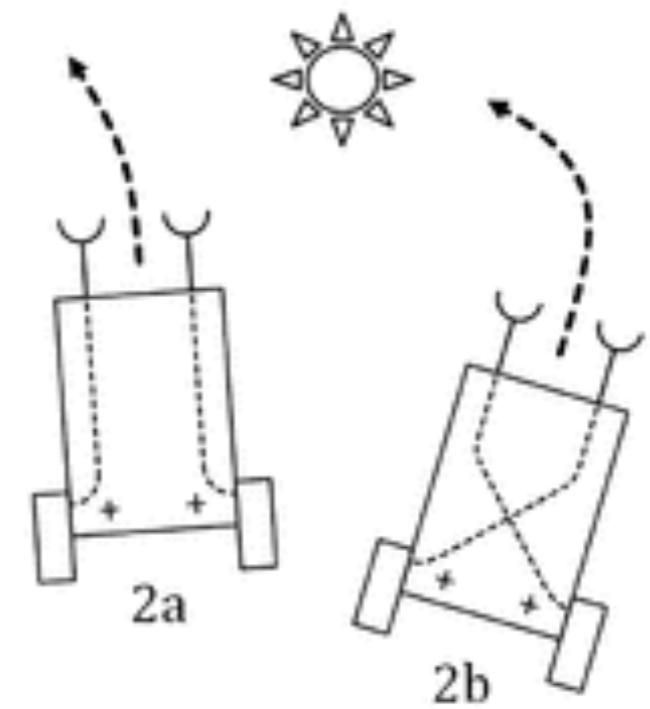


- Massive concurrency
 - I/O interfaces
 - “encoding”
 - rate, timing, place
- Massive recurrence
 - flexible connectivity
 - attractor dynamics
- Event-based
 - spiking
 - and analogue
- Plastic
 - on-chip local learning
 - “memory trace”

Reactive behaviour in navigation (Braitenberg)

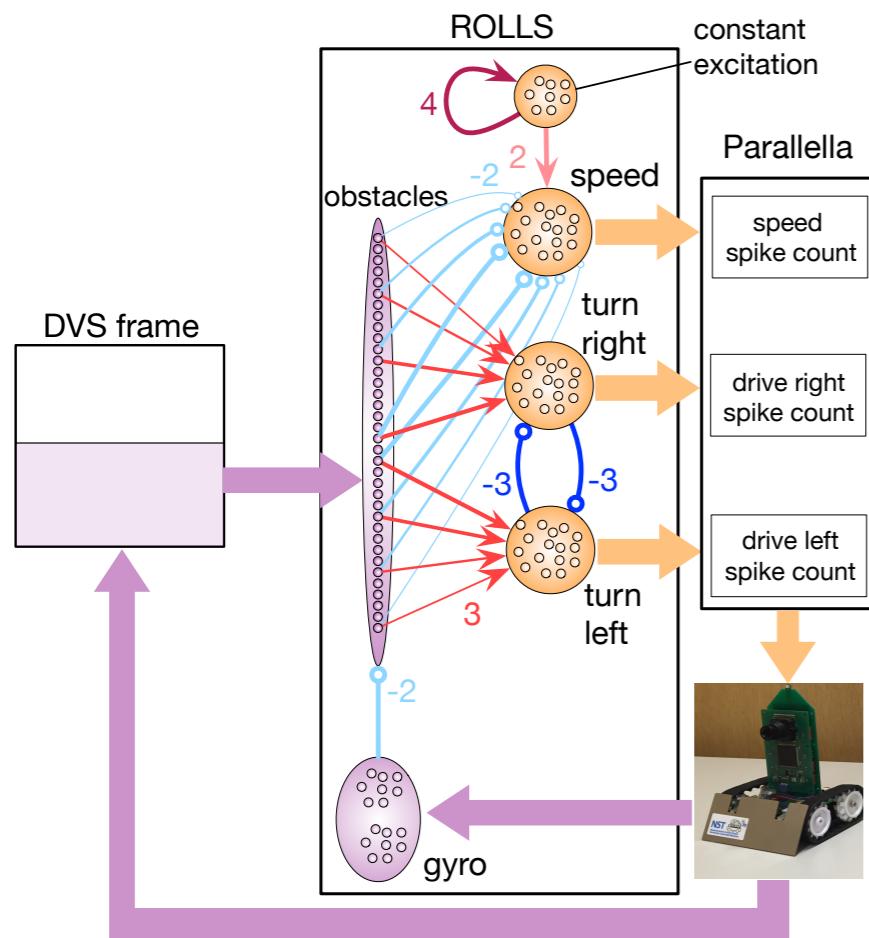


Different behaviours:

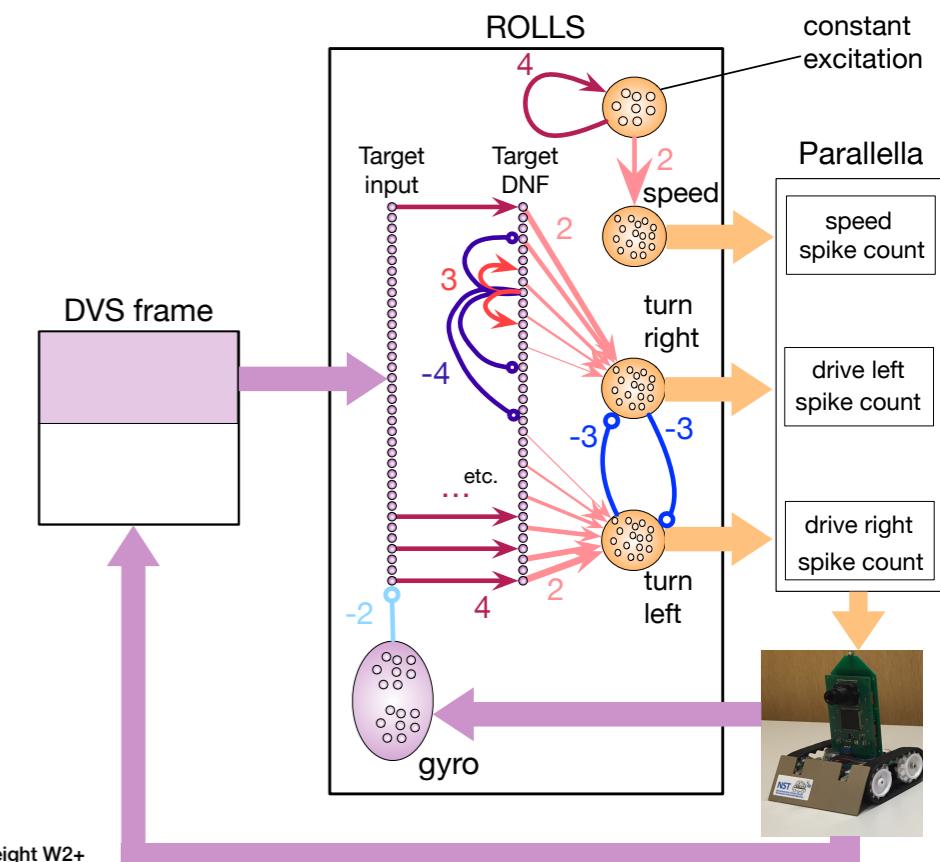


Braitenberg “de luxe” on a neuromorphic chip

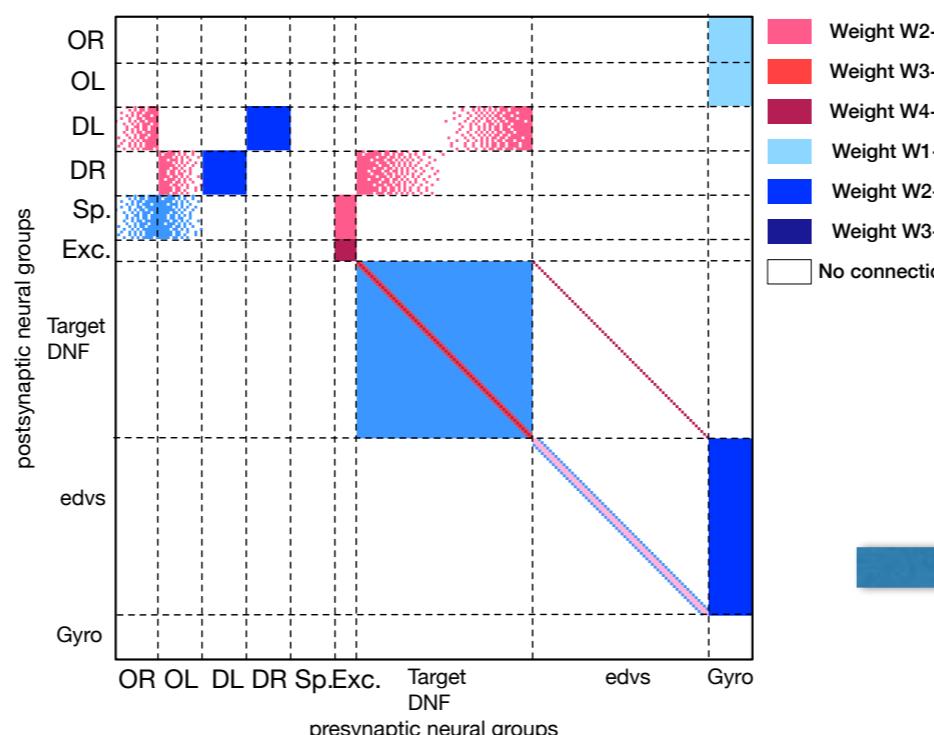
Obstacle avoidance



Target acquisition



Connectivity

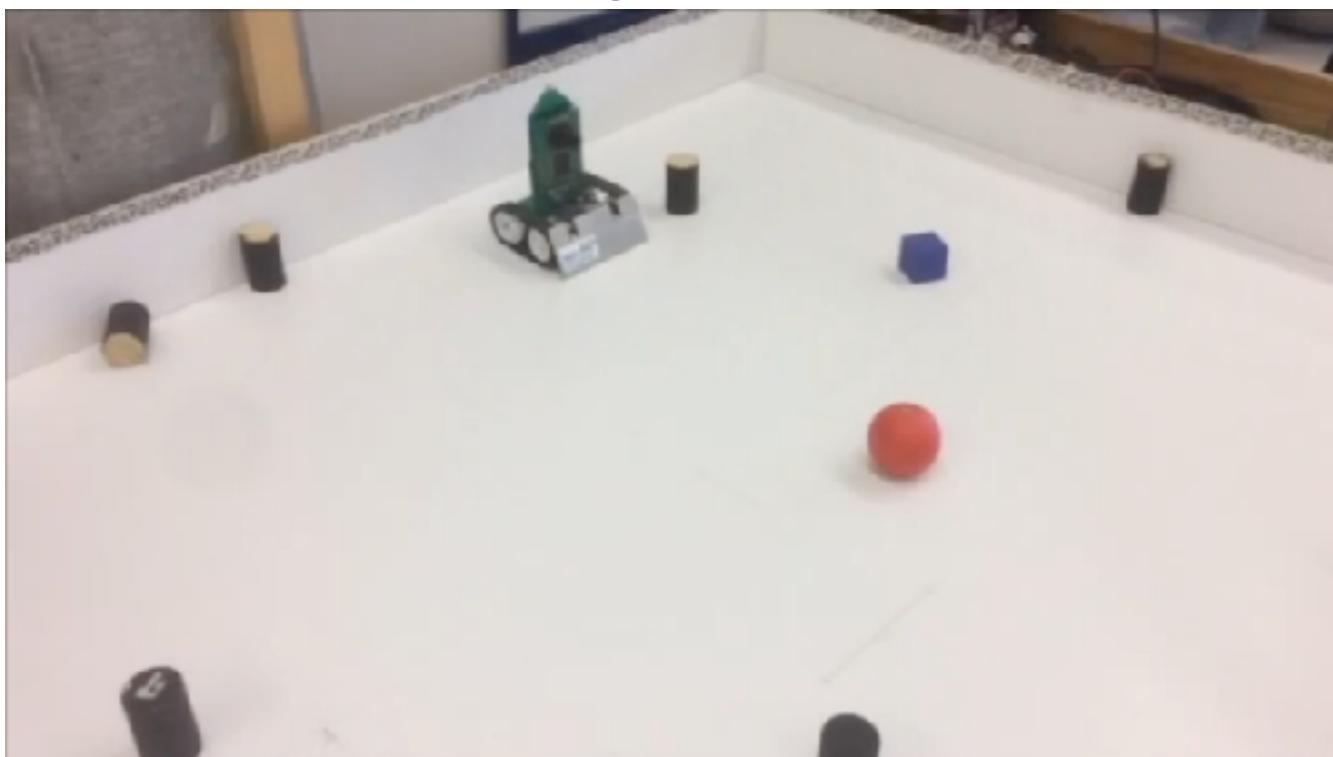


ROLLS

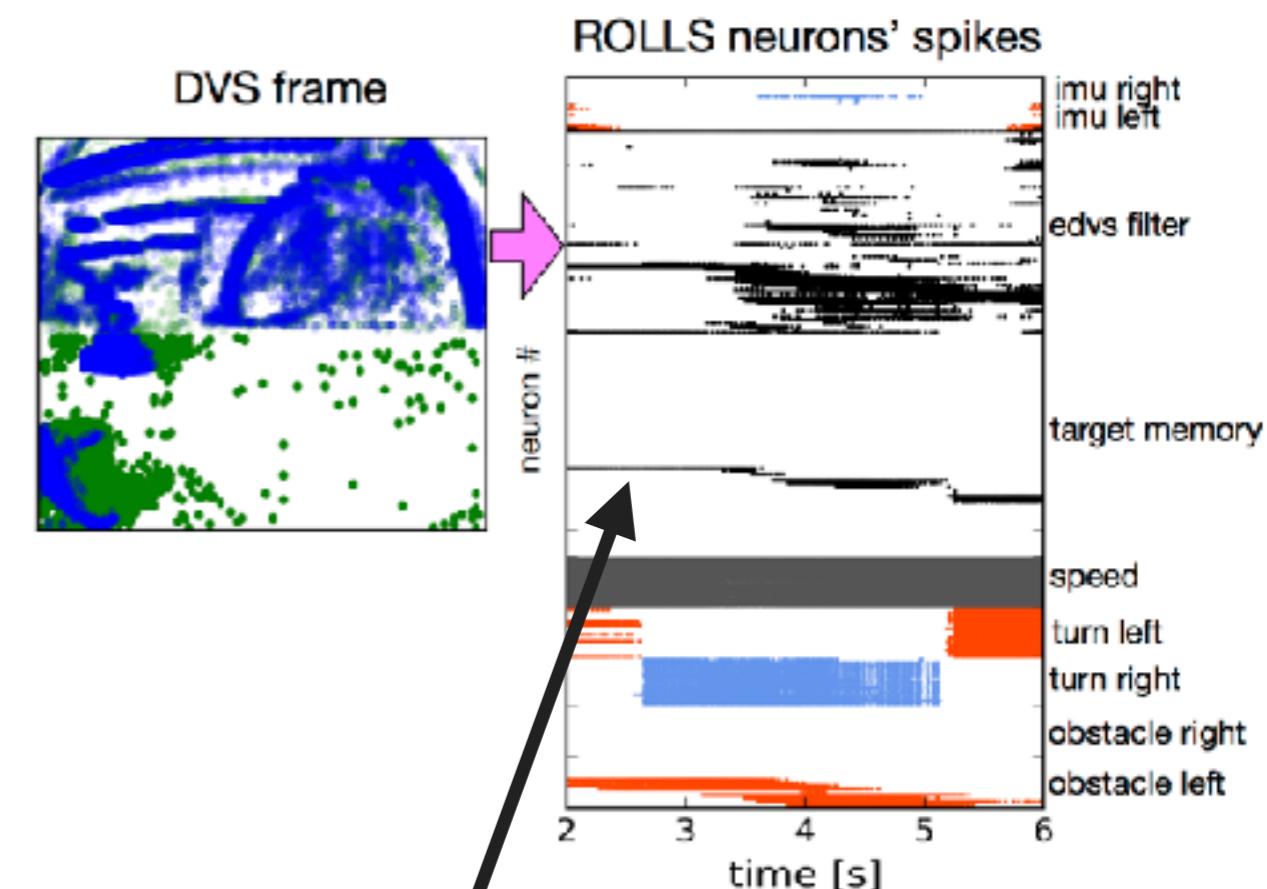


Navigation with a neuromorphic device

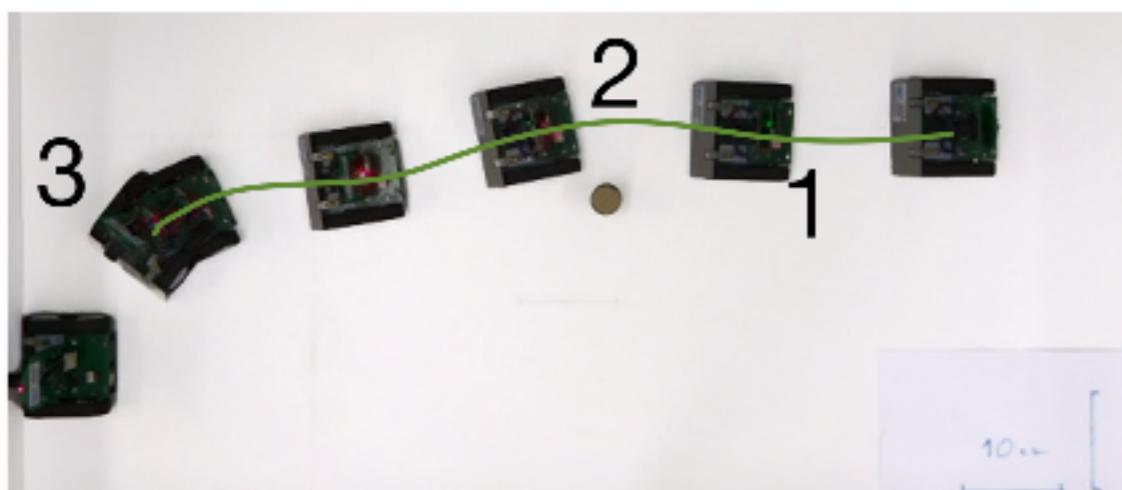
Avoiding obstacles



Output of the sensor and the chip



Target acquisition



WTA / DNF
(recurrence, filtering)

Reference frames

View-based target representation:

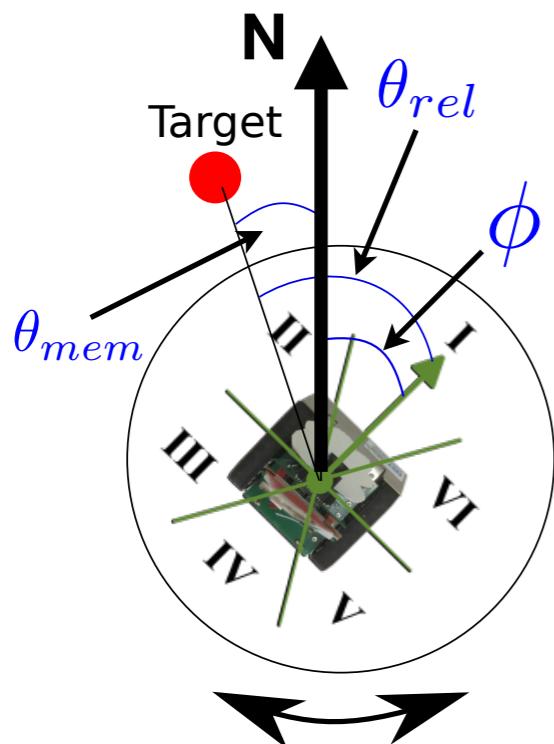
- target in view



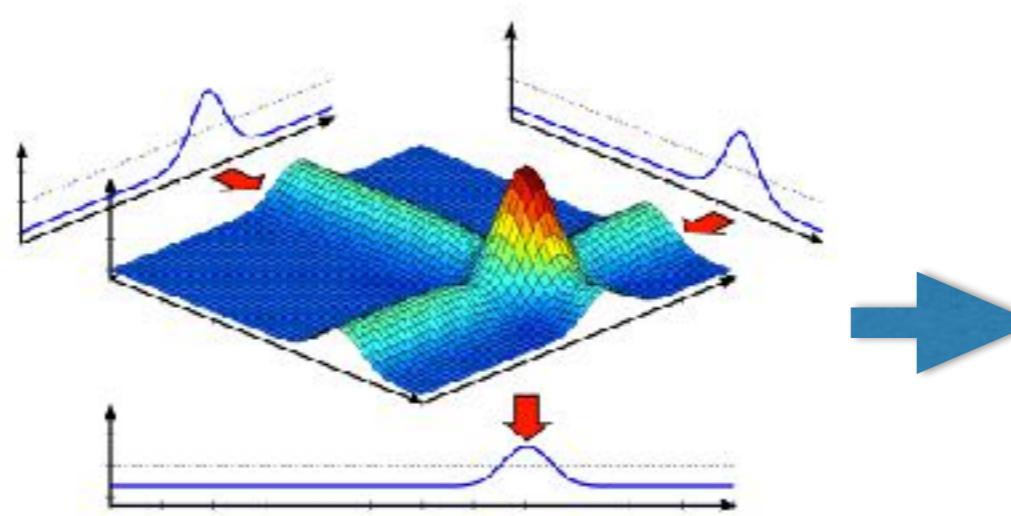
- target lost from view



Allocentric target representation:



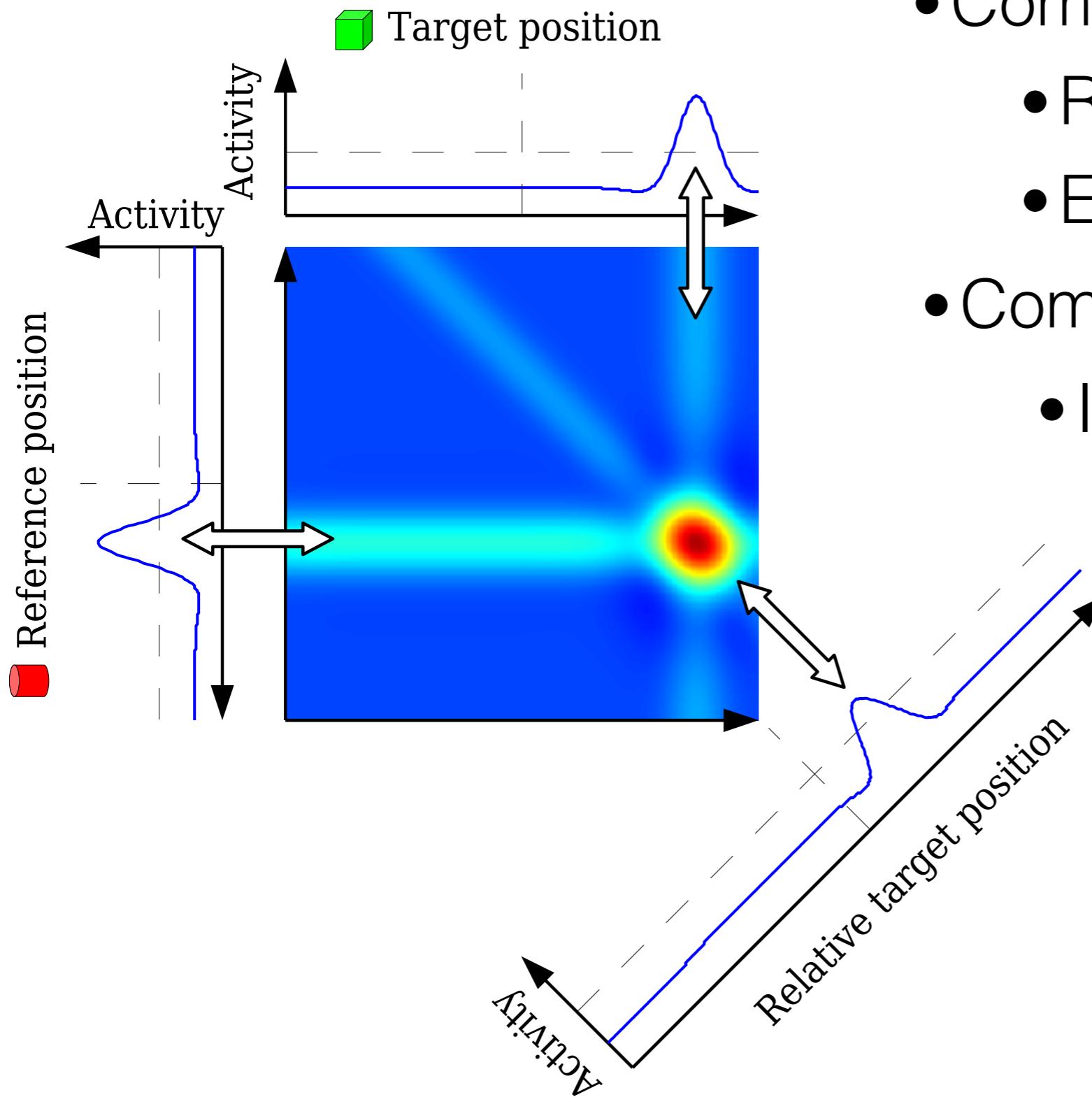
Neural ref. frame transformation:



ROLLS device

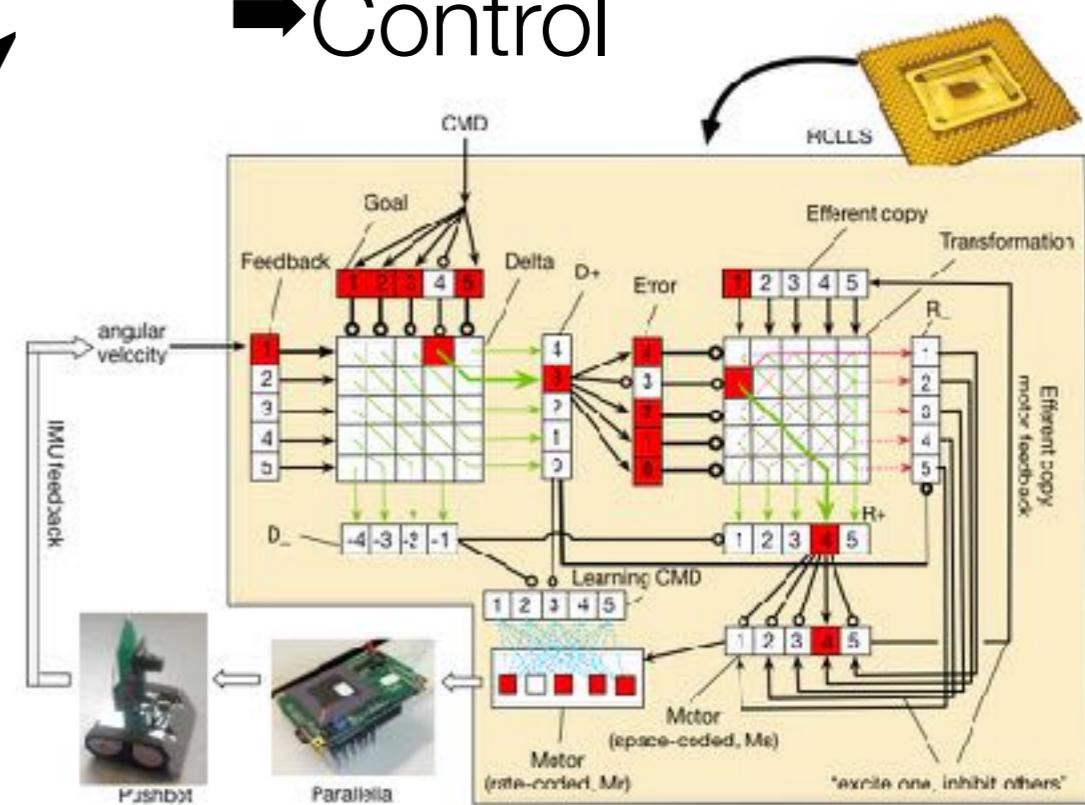


Neuronal coding of 3-way relations

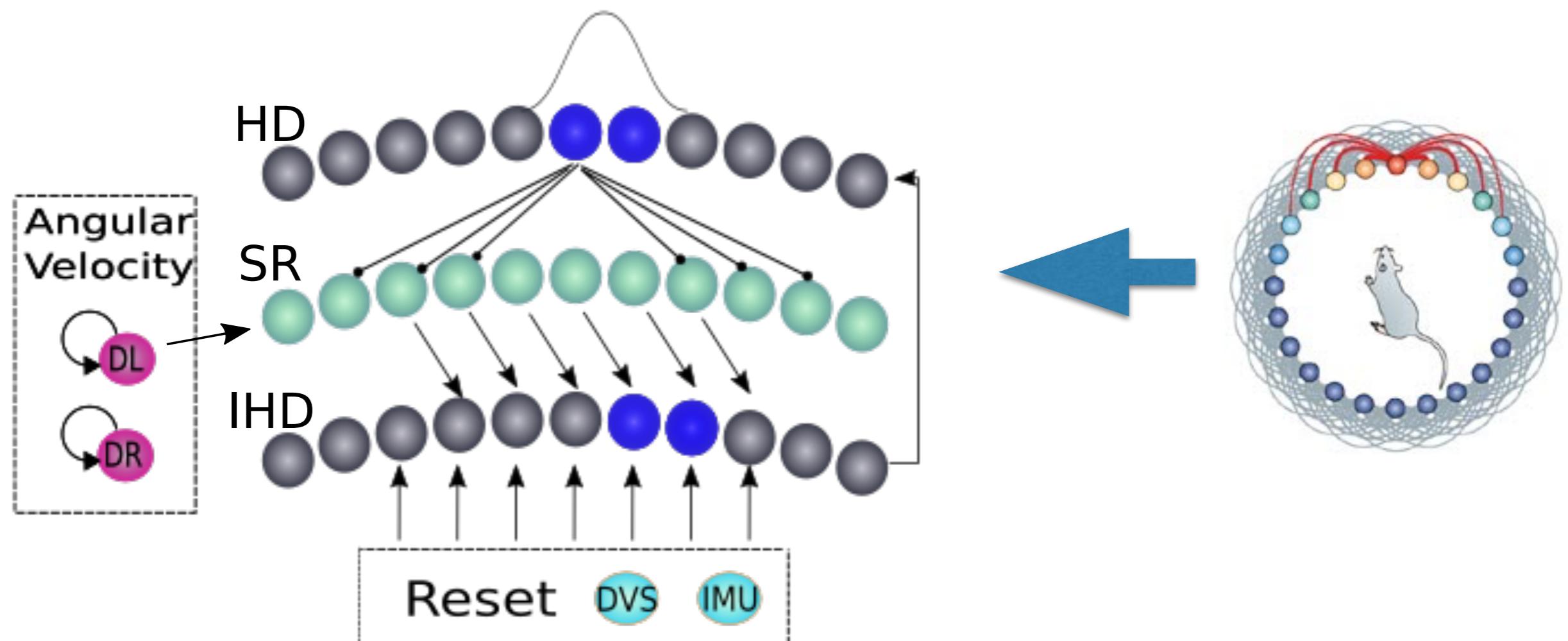


- Computing differences
 - Reference frame transform
 - Error estimation
- Computing sums
 - Integration

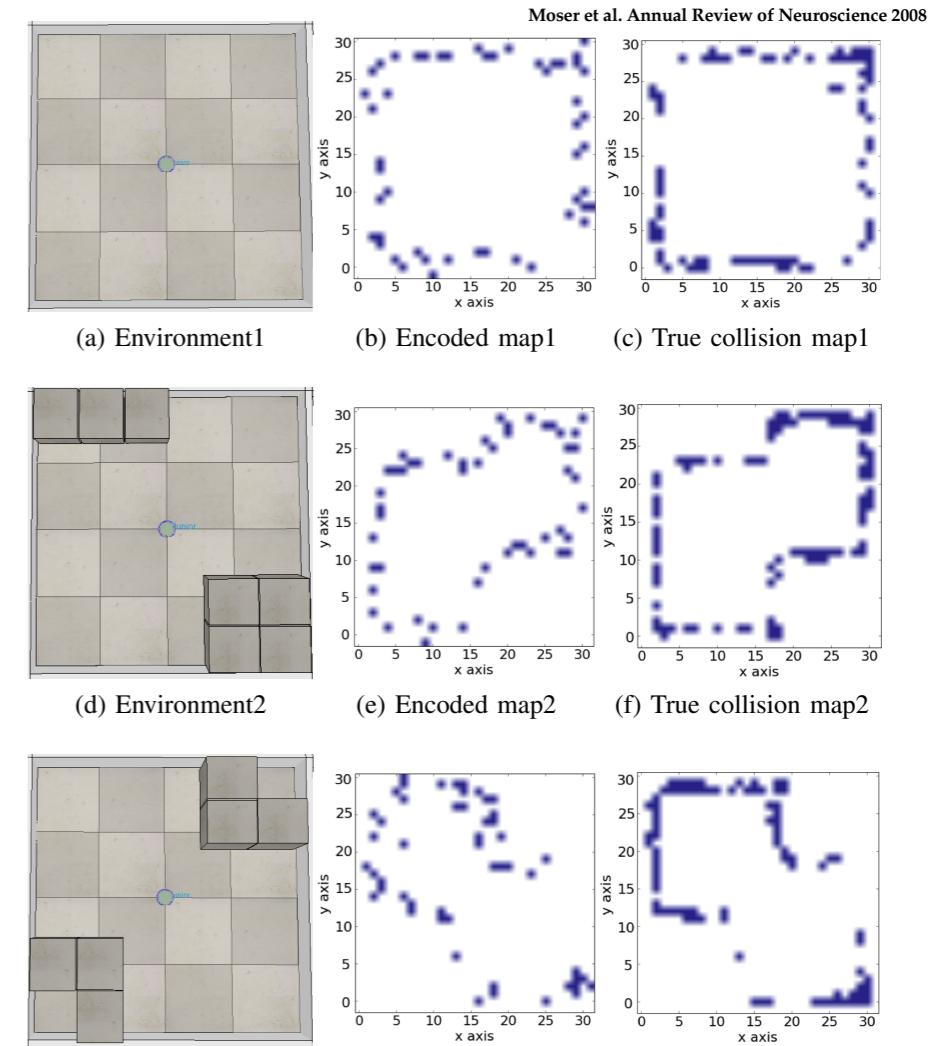
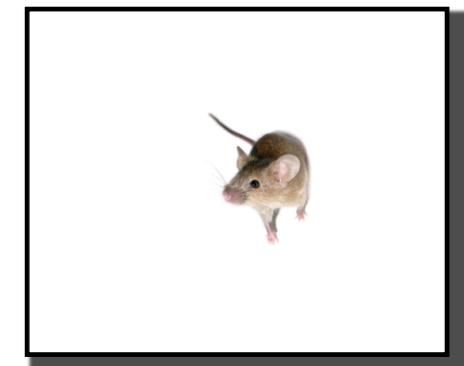
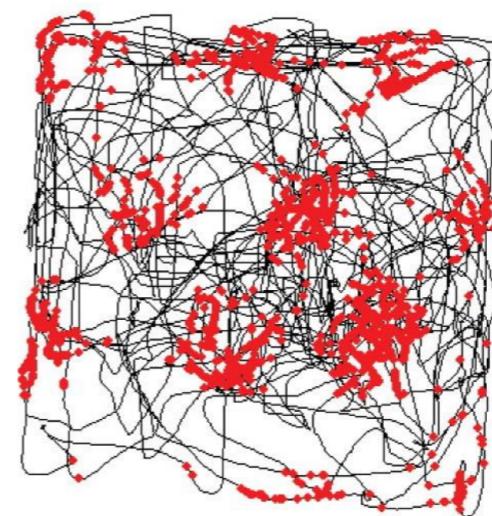
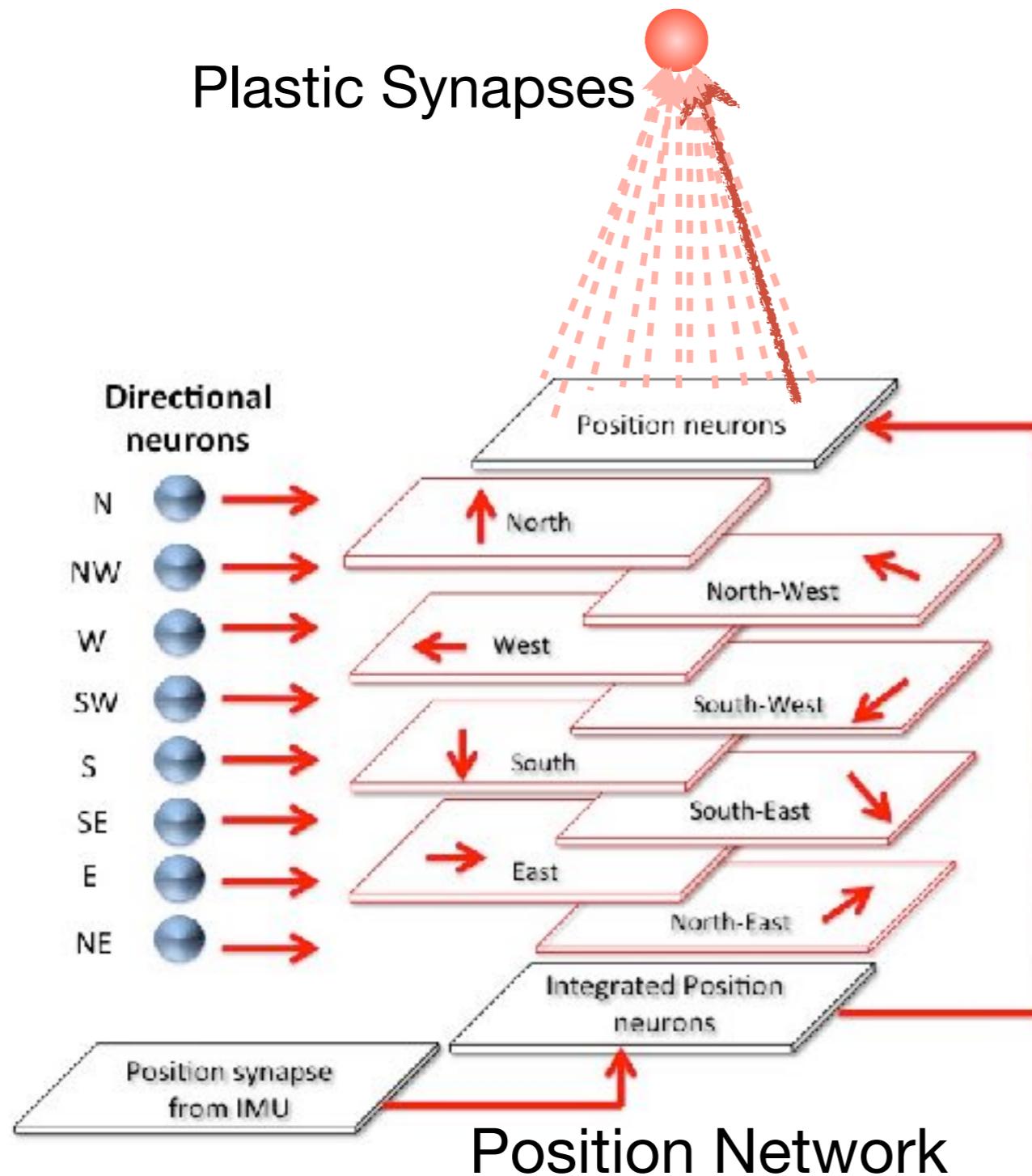
→ Control



Neuromorphic SLAM: 1) Heading direction / orientation

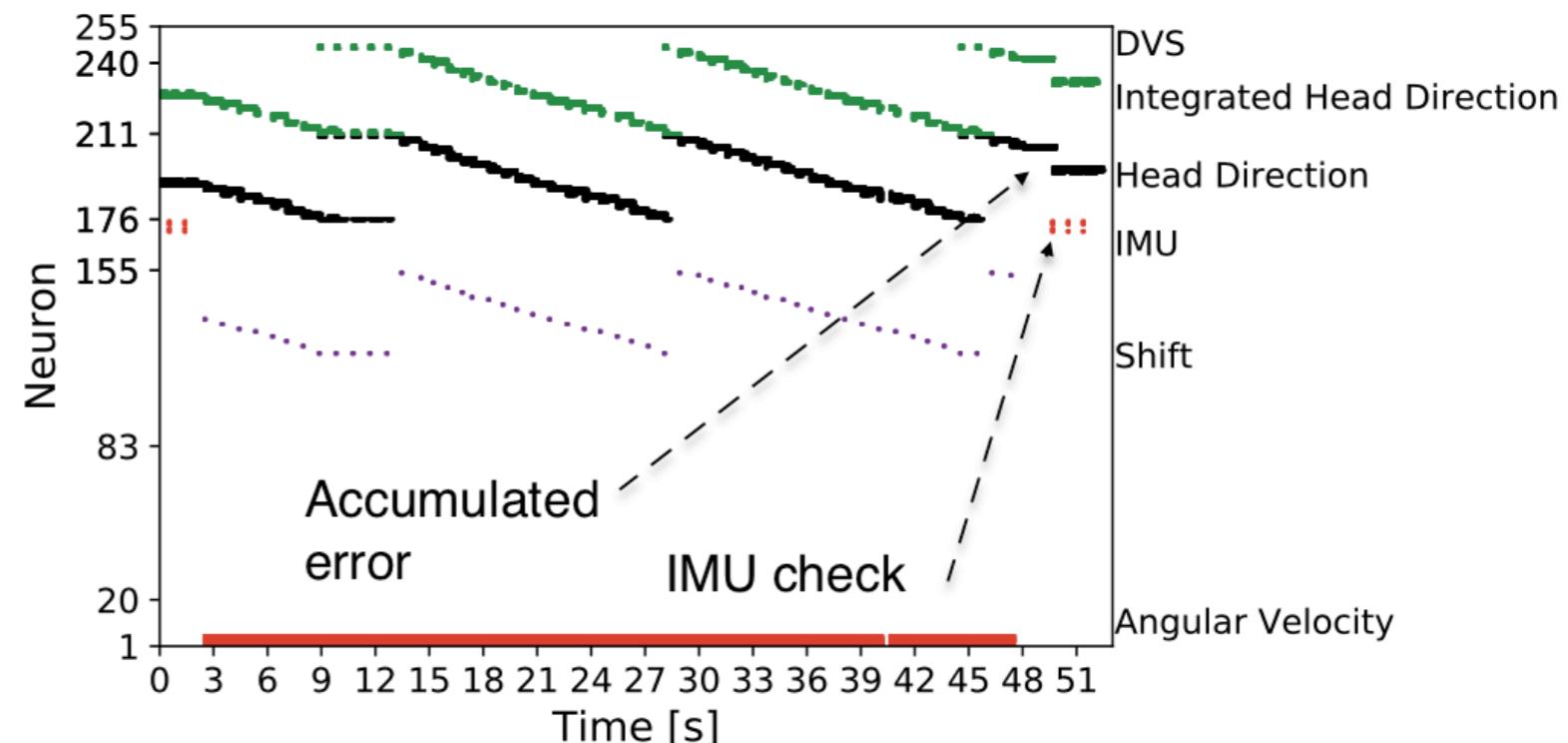


Neuromorphic SLAM: 2) Position, 2D map

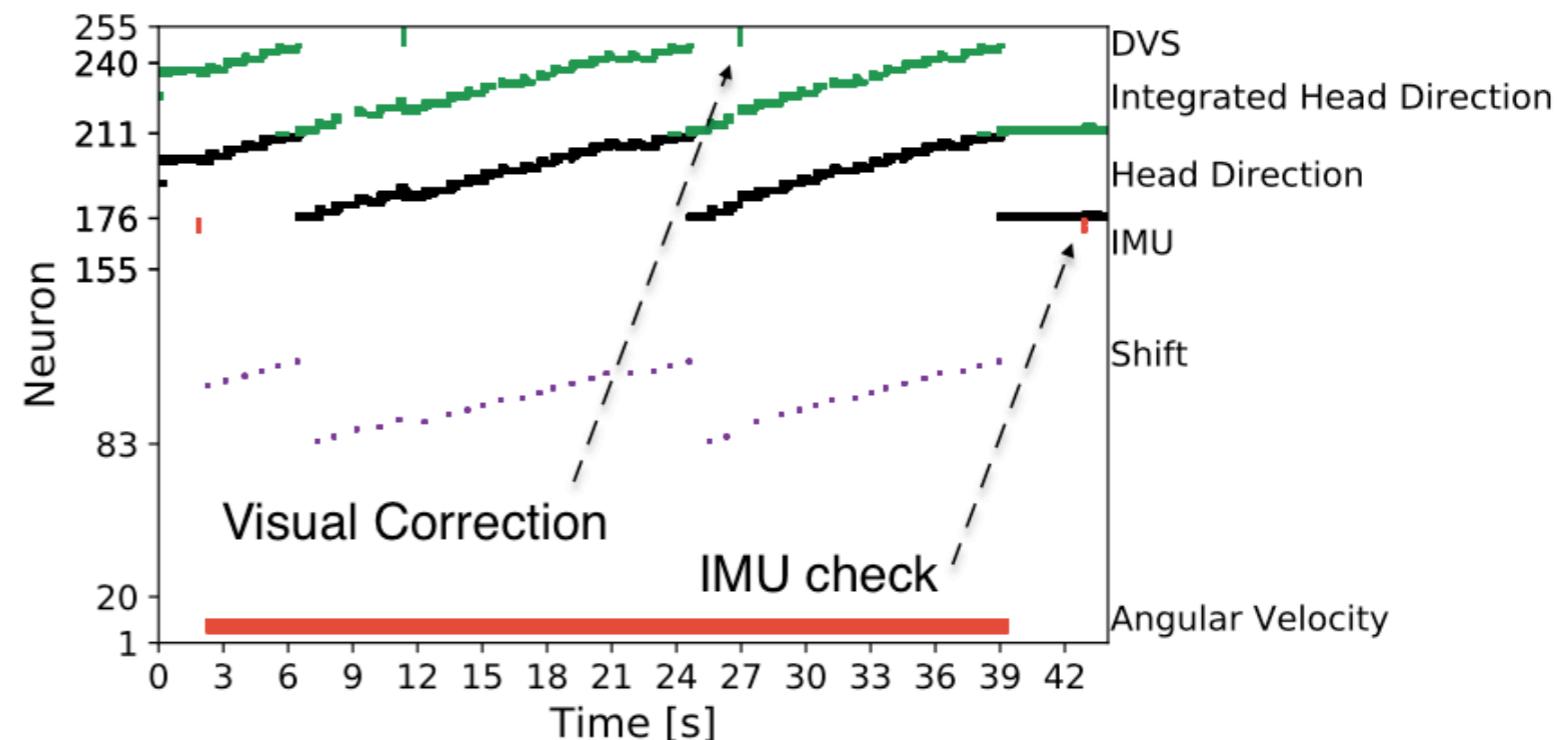


Neuromorphic SLAM: 3) Errors, sensor fusion

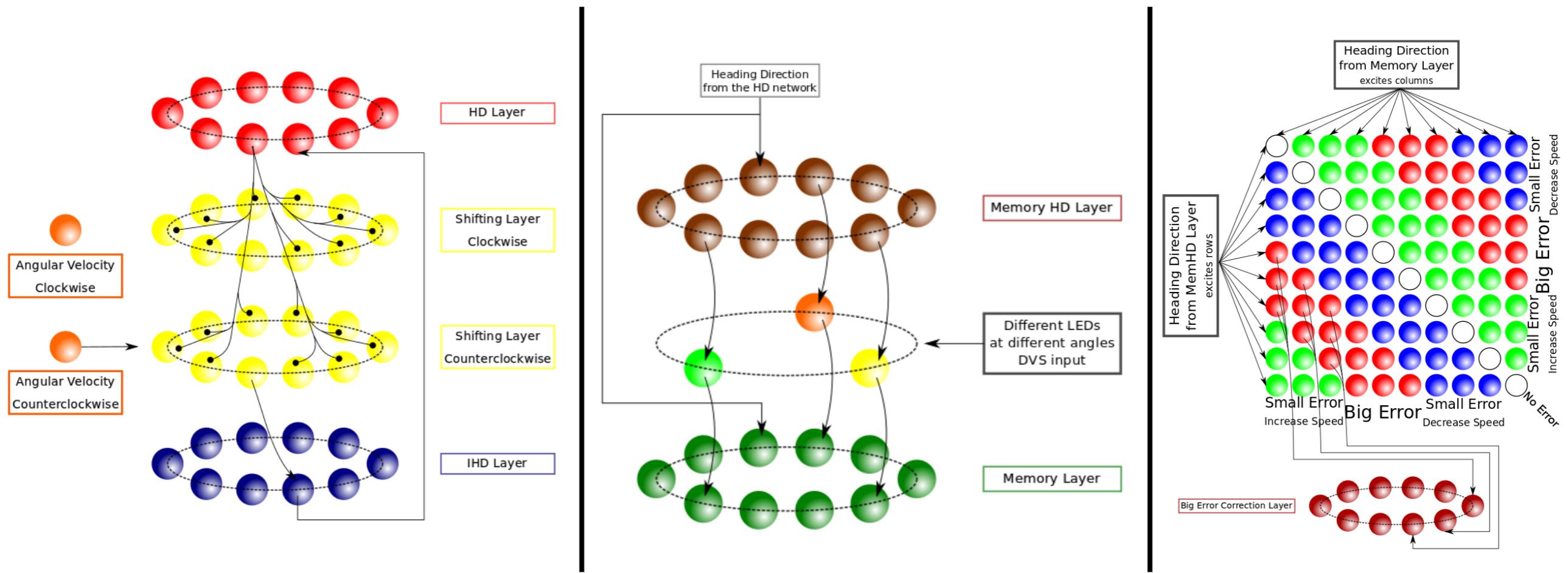
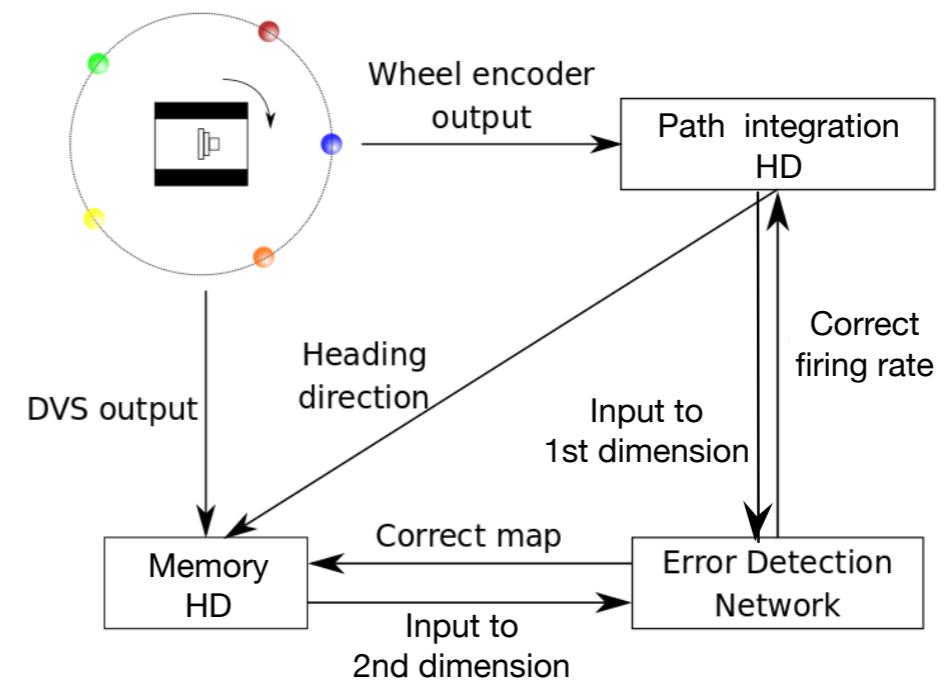
“Proprioception” only



Correction using vision

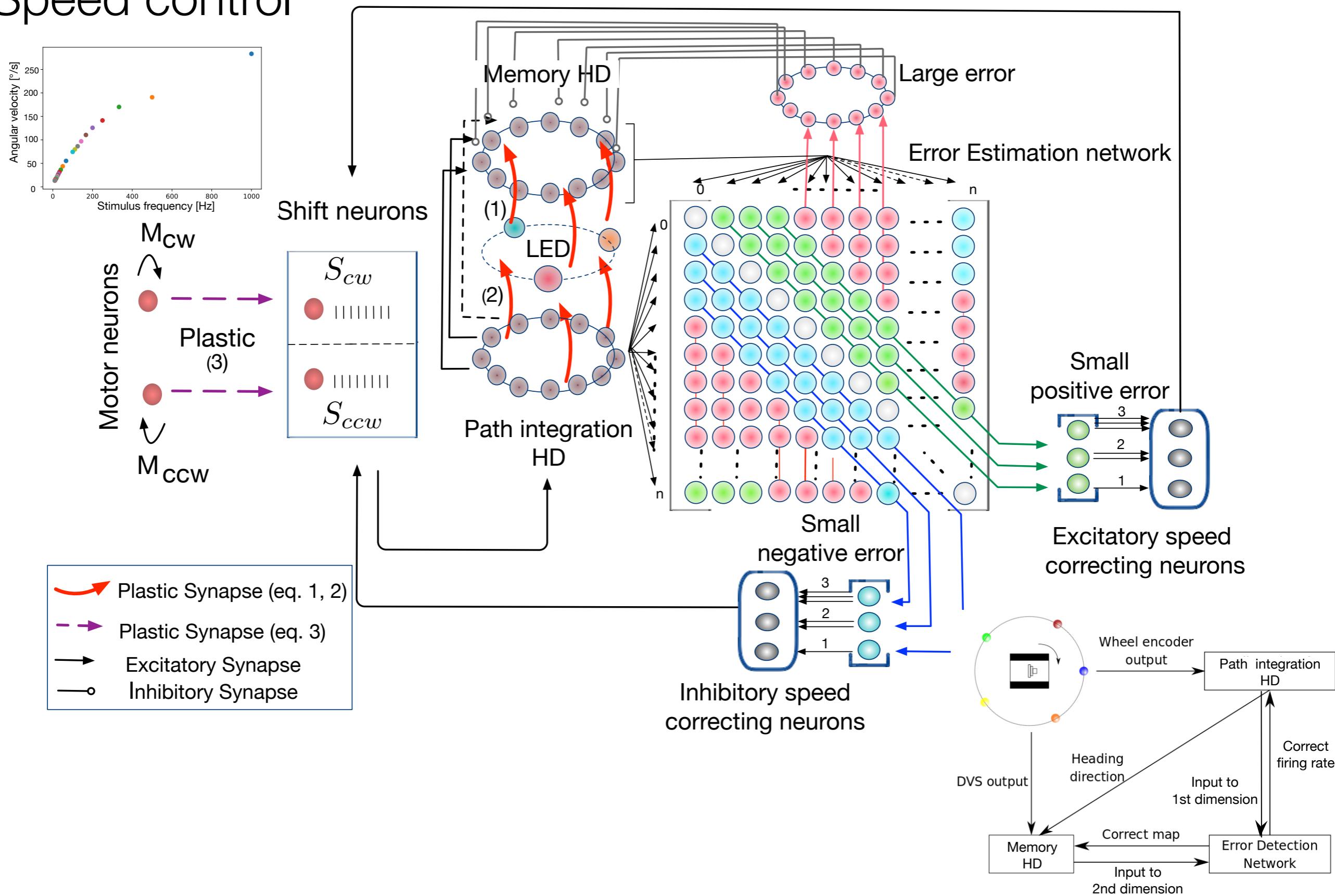


Neuromorphic SLAM: 4) Loop closure

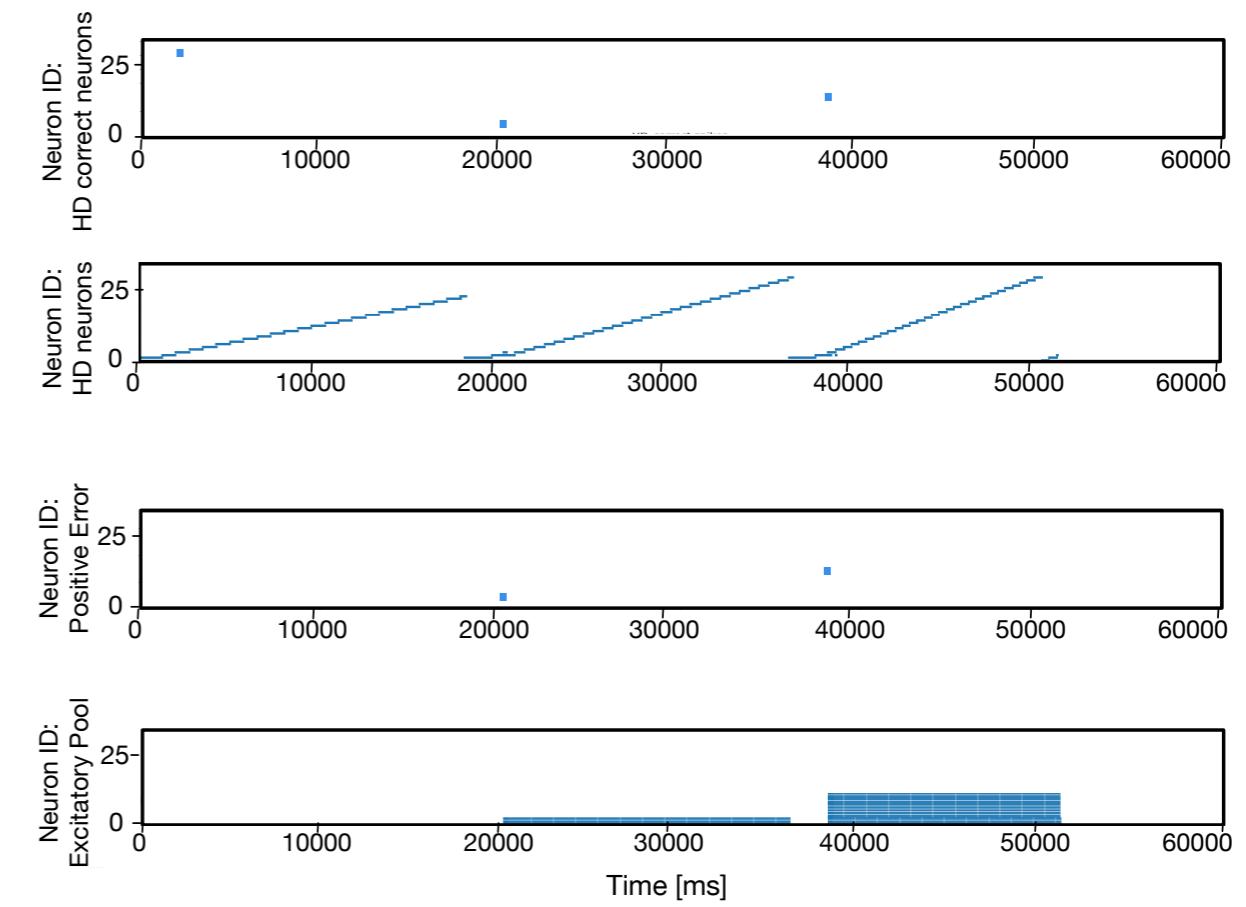
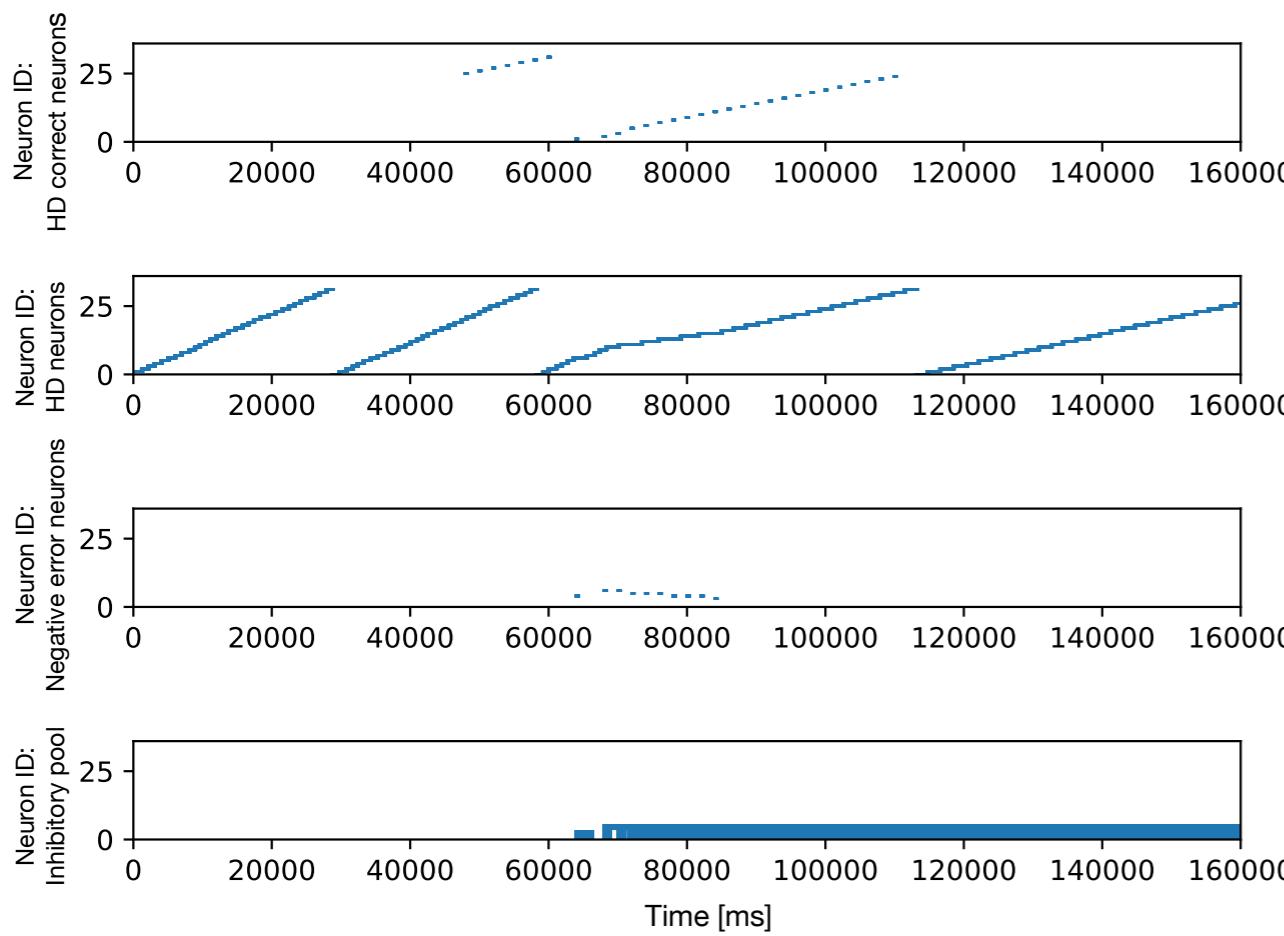
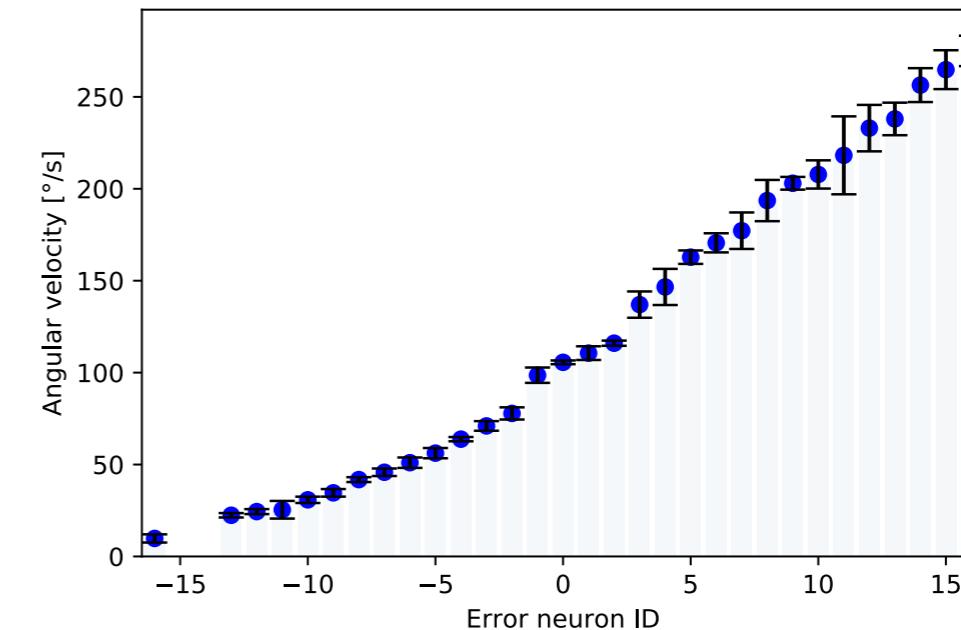
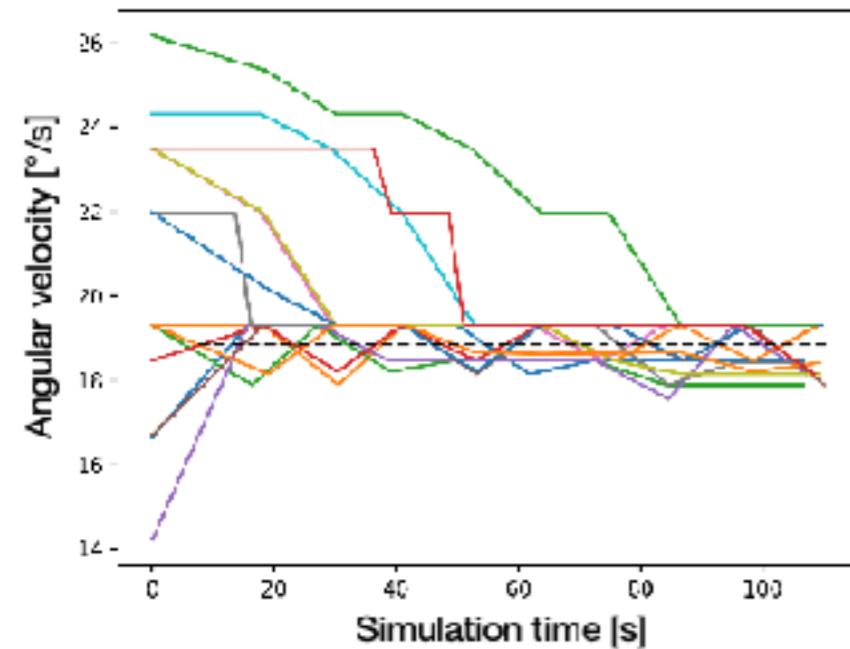


SLAM 4: Loop closure architecture

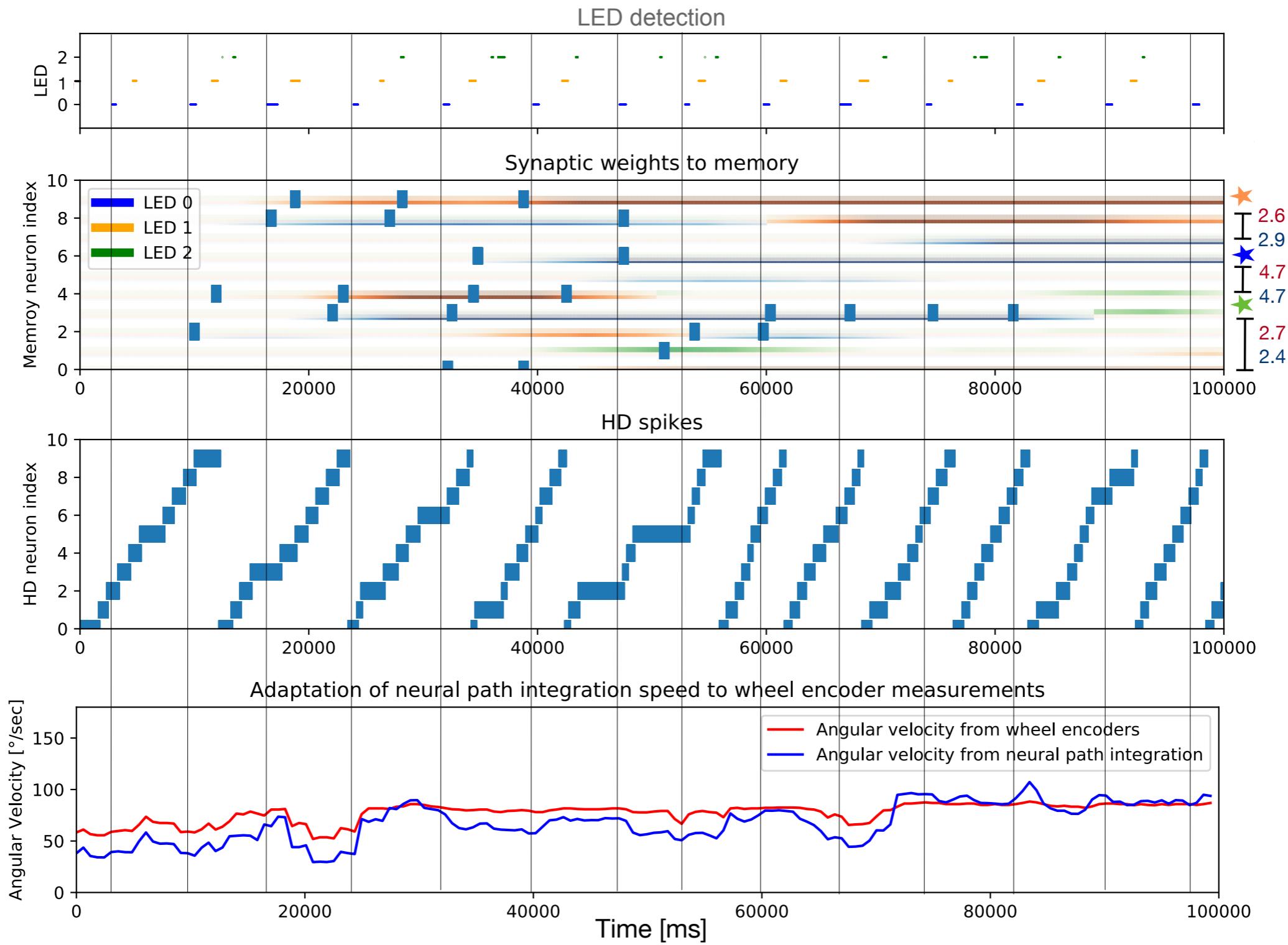
Speed control



Neuromorphic SLAM: Results (calibration)



Neuromorphic SLAM: Results (+map formation)

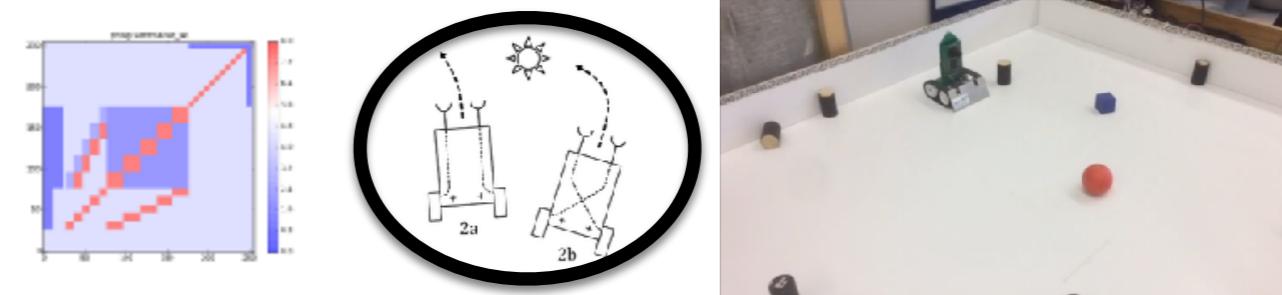


Overview of Neuromorphic building blocks

→ Reactive loops

- attractors in a sensory-motor loop

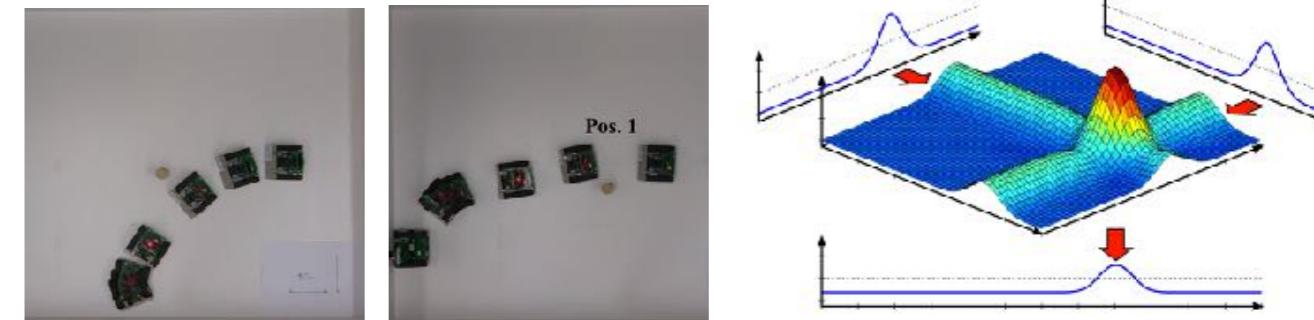
Milde et al 2017a,b; Kreiser et al 2018



→ Reference frame transformations

- key for linking modalities

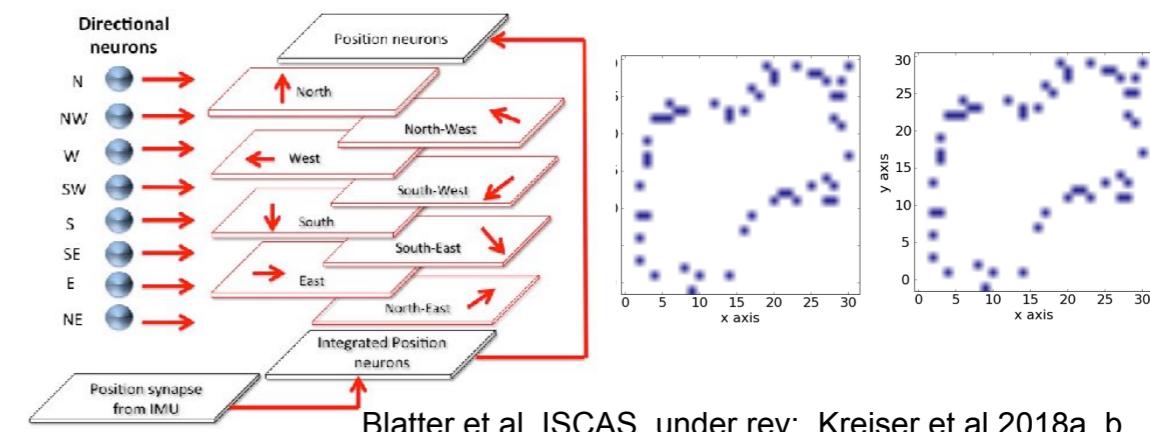
Blum et al 2017



→ Pose estimation and map formation

- state estimation, building representations

Kreiser et al 2018, 2019a, b

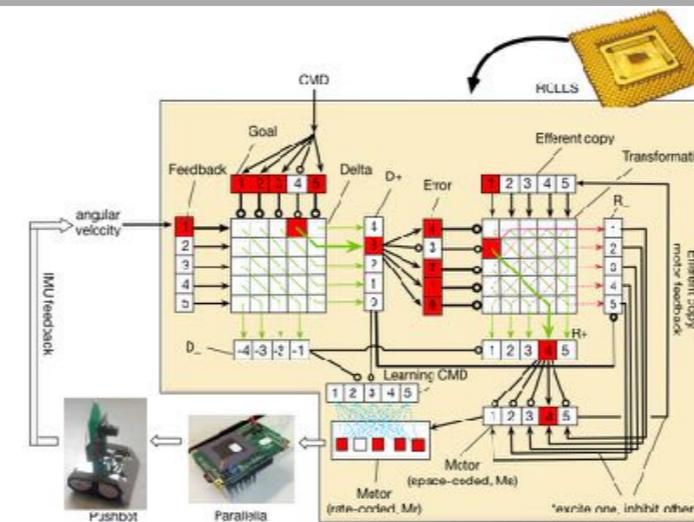


Blatter et al, ISCAS, under rev; Kreiser et al 2018a, b

→ Adaptive motor control

- key element for adaptive behavior

Glatz et al, ICRA2019



Conclusion: We need to **redefine computing** to use neuromorphic hardware

variable

- neuronal population
 - high-/low-dimensional, continuous or discrete (symbolic)
 - adjustable resolution
 - sensory, motor, abstract

To enable neuronally-inspired computing we need to work out its theory, framework, and tools

- can be adaptive

input/output

- interfaces to sensors and motors

Operating System

- a hierarchy of neuronal structures for particular task

Thank you!



Universität
Zürich^{UZH}

ZNZ
Zentrum für
Neurowissenschaften Zürich

- Marie Curie IF
- FET PROACT
- Ambizione
- Project coordination
- Forschungskredit
- GRC Grant
- Junior Group fellowship



MSc, BSc theses

Gwendolyn English
Eloy Barrero
Llewyn Salt
Mathis Richter
Tobias Storck
Christian Bell
Claudia Rudolph
Jianlin Lu
Ammar Bitar
Jonathan Müller
Kay Müller
Sebastian Glatz
Valery Metry
Alpha Renner
David Niederberger
Raphaela Kreiser

PhD Students

Julien Martel
Alpha Renner*
Raphaela Kreiser*
Claudius Strub*
Moritz Milder
Dora Sumislawska

Semester theses

Alexander Dietmüller Héctor Vazquez
Mario Blatter Sebastian Glatz
Frédéric Debraine Herman Blum
Lukas Blässig Matteo Cartiglia
Lennard de Graf Lin Jin
Michel Frising David Niederberger
Zahra Farsijani Nicolas Käenzig
Michael Purcell Panin Pienroj
Viviane Yang Paul Joseph
Davide Plozza Nuria Armengol
Damiano Steger Jozef Bucko
Nuria Balduim Dettling
...



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