Radical neural vision for autonomous intelligence: the neuromorphic prospective

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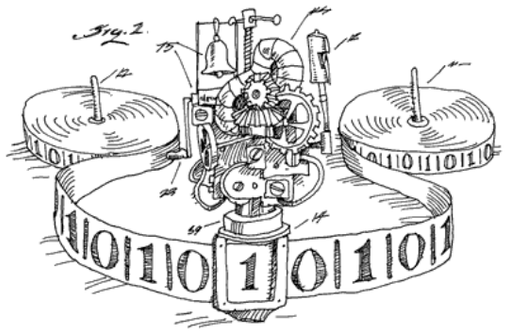
Computing substrate shapes our models

➡Turing machine

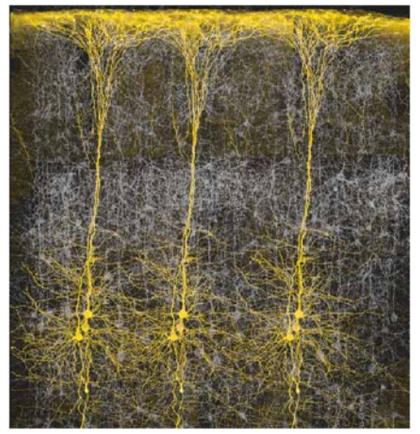


➡Todays computers

- sequential processing
- clocked
- separation of memory and processor
- digital representations
- running algorithms
- clear input and output

"Turing complete"

➡Neural systems



- massively parallel
- event-driven
- asynchronous
- memory and processor same
- adaptive
- not running programs
- not implementing algorithms
- dynamical system

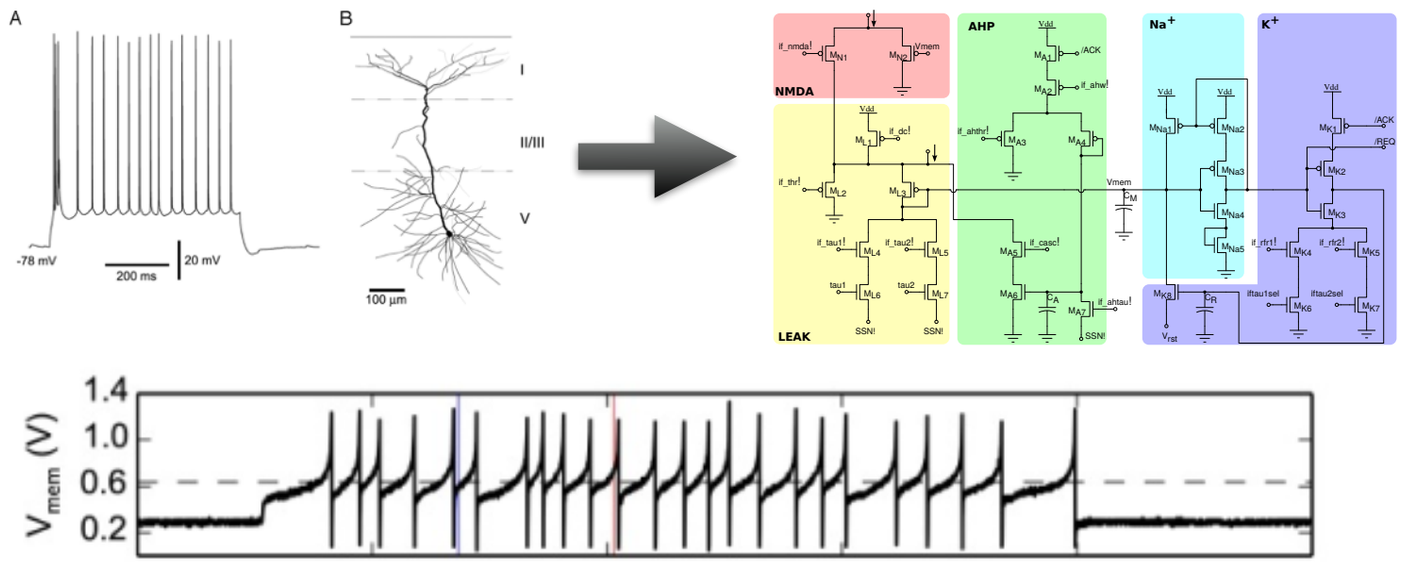
Beyond Turing?

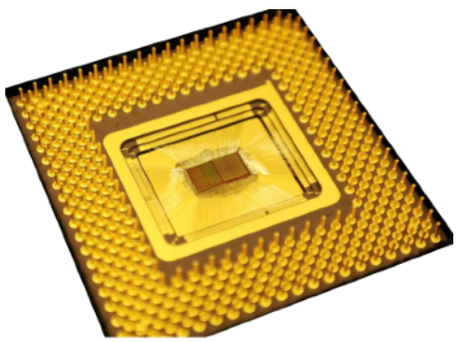
➡Different things are simple and hard

➡There is a cost for the hardware / process mismatch

Neuromorphic hardware

➡ Emulate activation dynamics of biological neurons



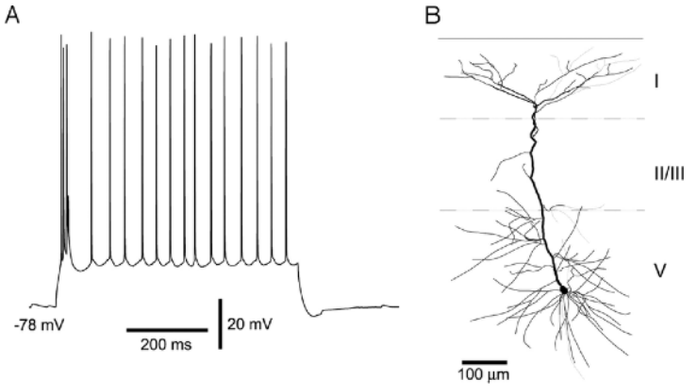


- using analogue physics of transistors in subthreshold regime
- to realise the leaky integrate-and-fire model

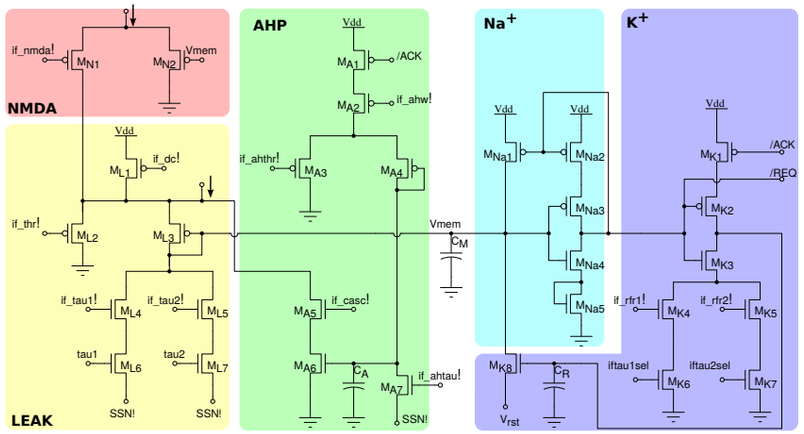
Inherit some of the properties of neural systems

➡ inherently parallel
➡ event-based, asynchronous
➡ co-location of memory and processing
➡ adaptive
➡ mismatch and variability
➡ do not run algorithms and programs

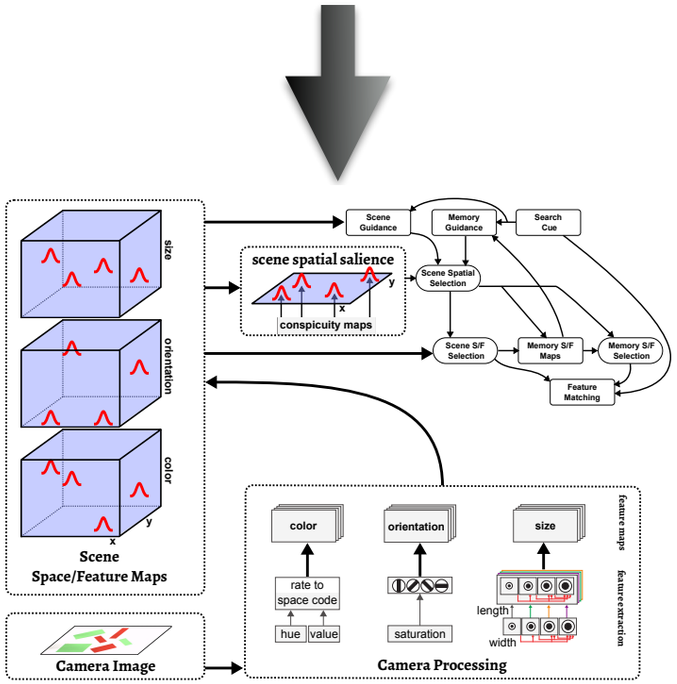
“Programming” neuromorphic hardware



neuron

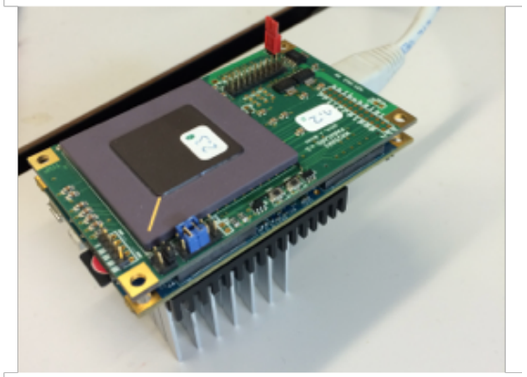


circuit of a neuron

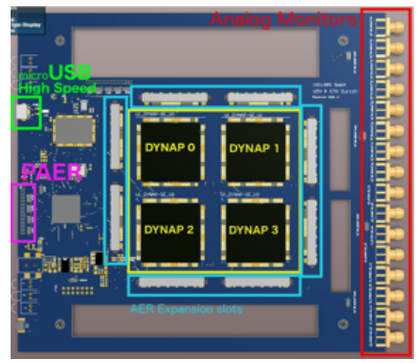


neural dynamics

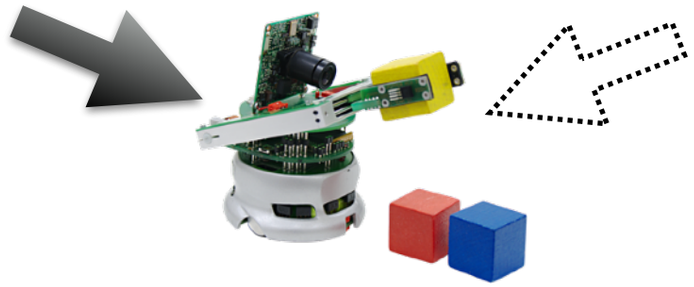
ROLLS



Dynap-se



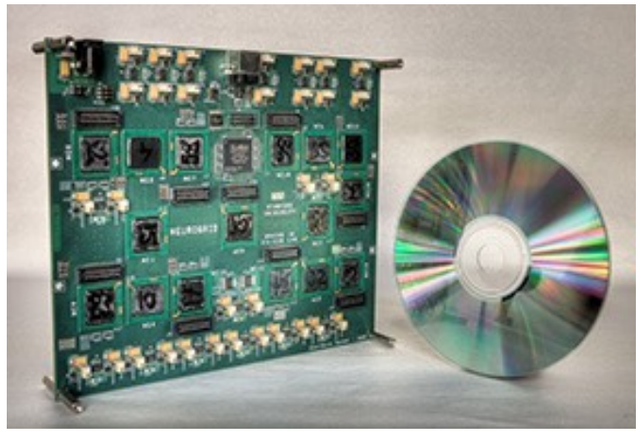
VLSI device



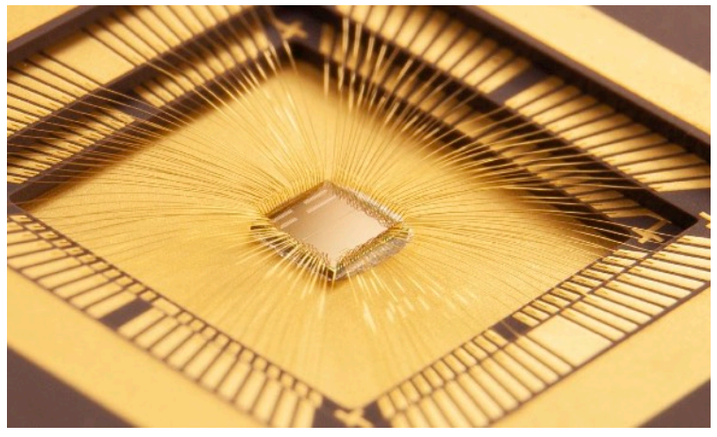
Diverse Neuromorphic Hardware devices

Analog

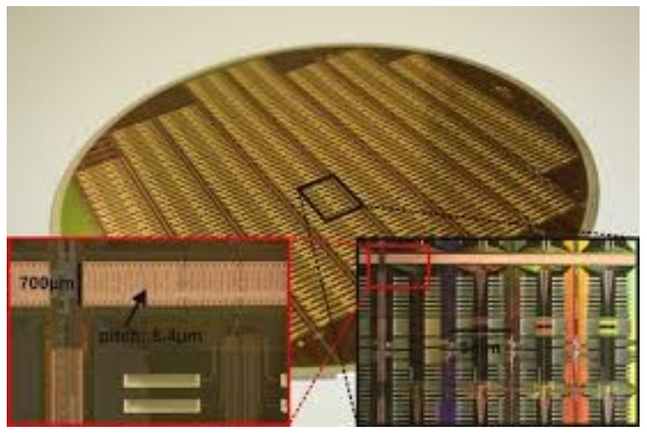
“BrainDrop” (Stanford)



DYNAP (Zurich)

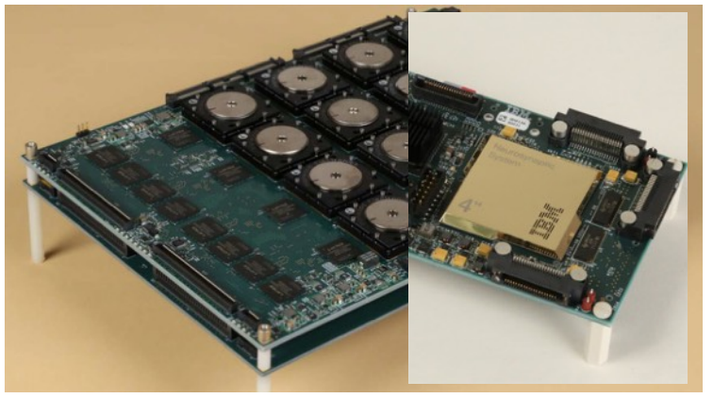


BrainScaleS (Heidelberg)

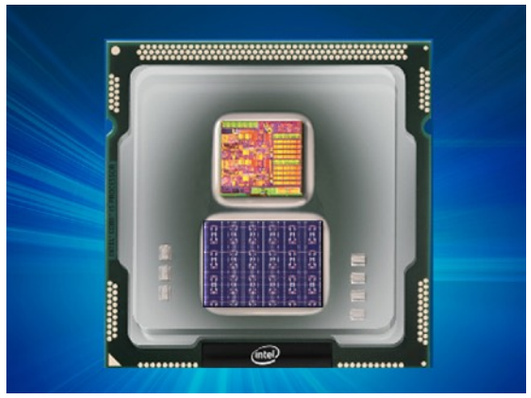


Digital

“TrueNorth” (IBM)



Loihi (Intel)



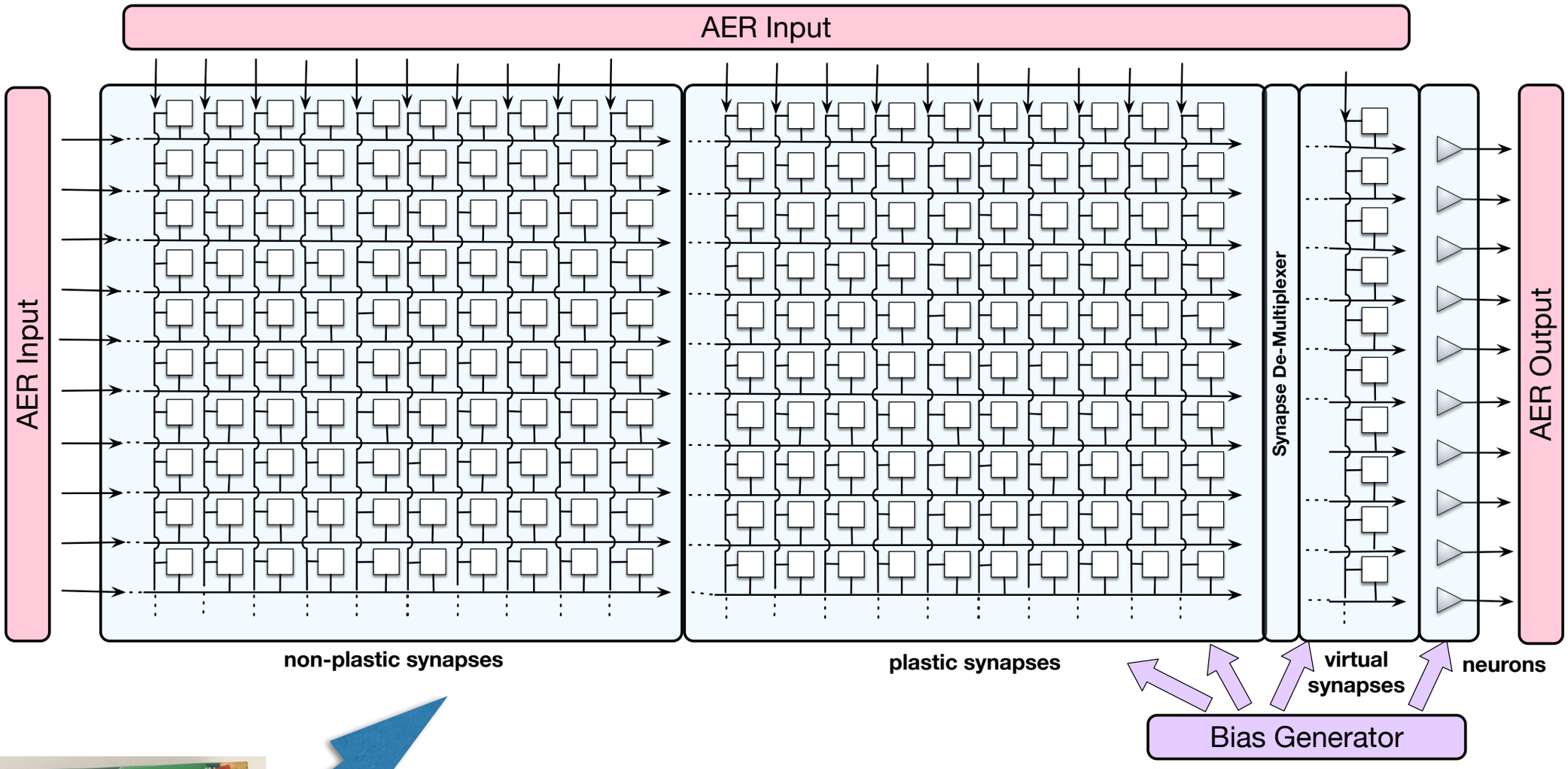
SpiNNaker (Manchester)

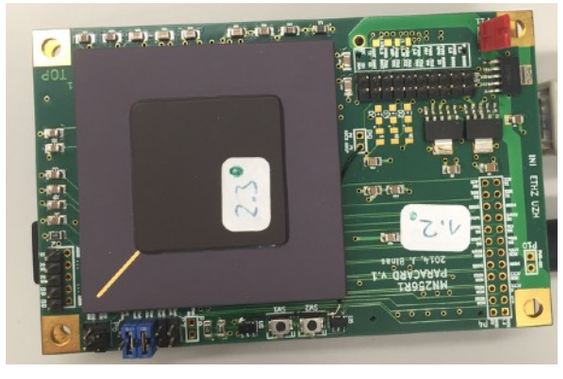
NEUROTECH

NEUROMORPHIC COMPUTING TECHNOLOGY LEADING TO AI REVOLUTION

Create and promote neuromorphic community in Europe: www.neurotechai.eu

Schematics of a neuromorphic chip



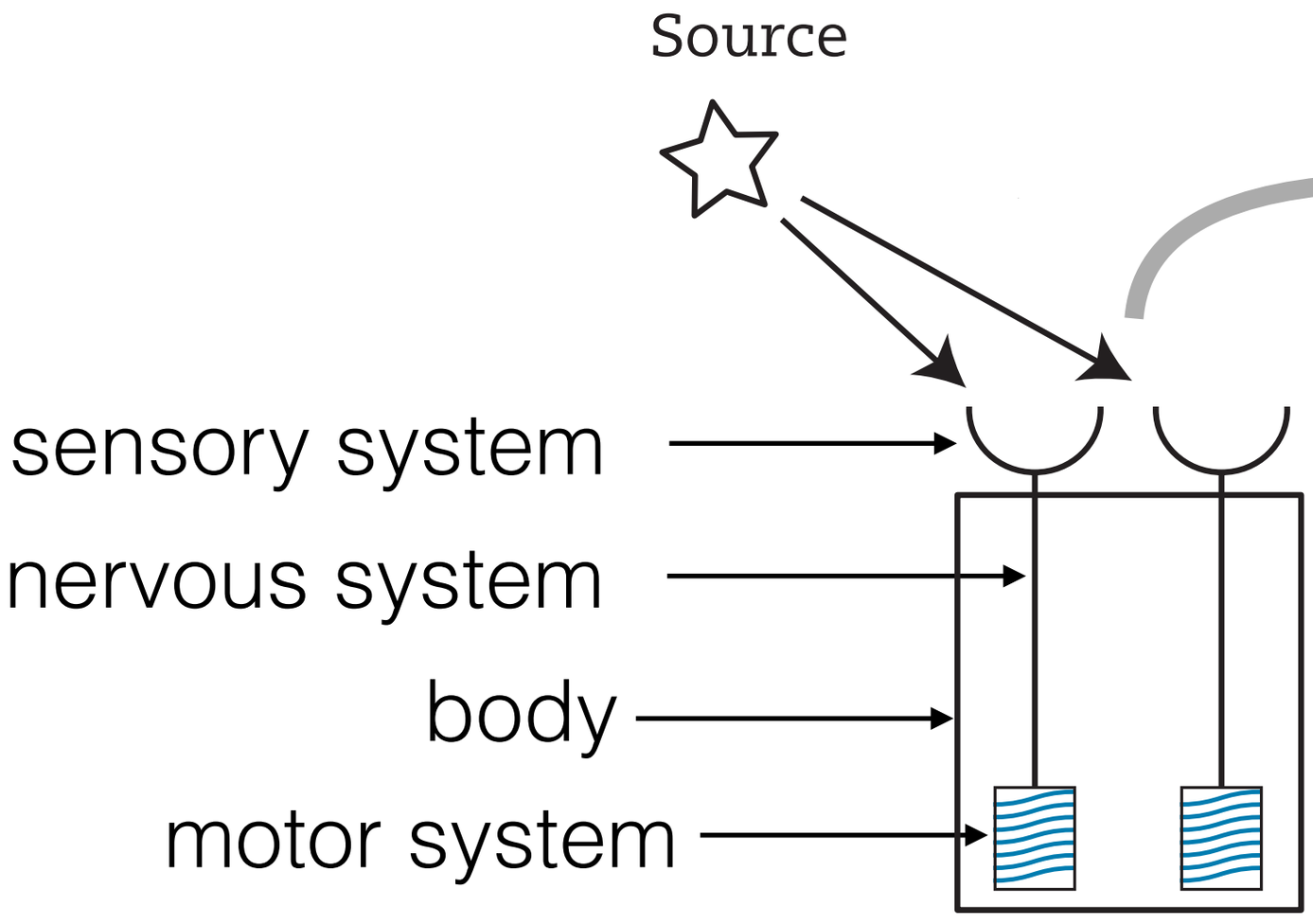


- analog circuits for neurons and synapses
- digital communication of spikes

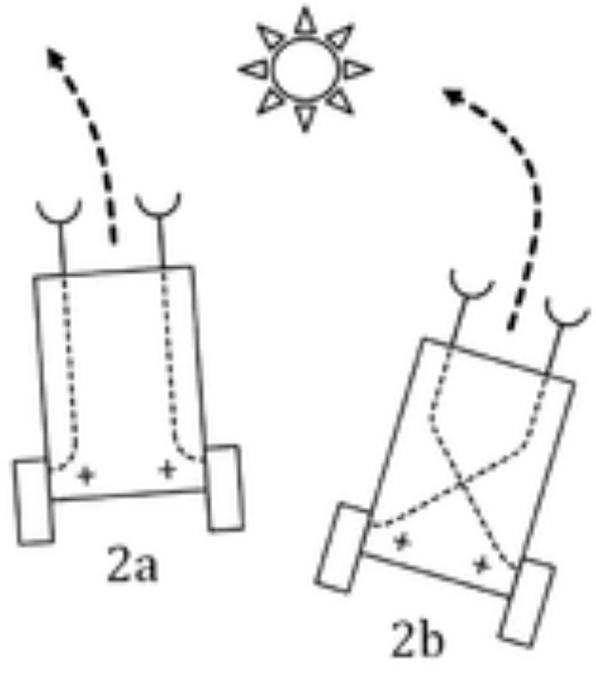
➡“programming” = wiring-up and setting parameters

Qiao et al, 2015

1. Reactive controller

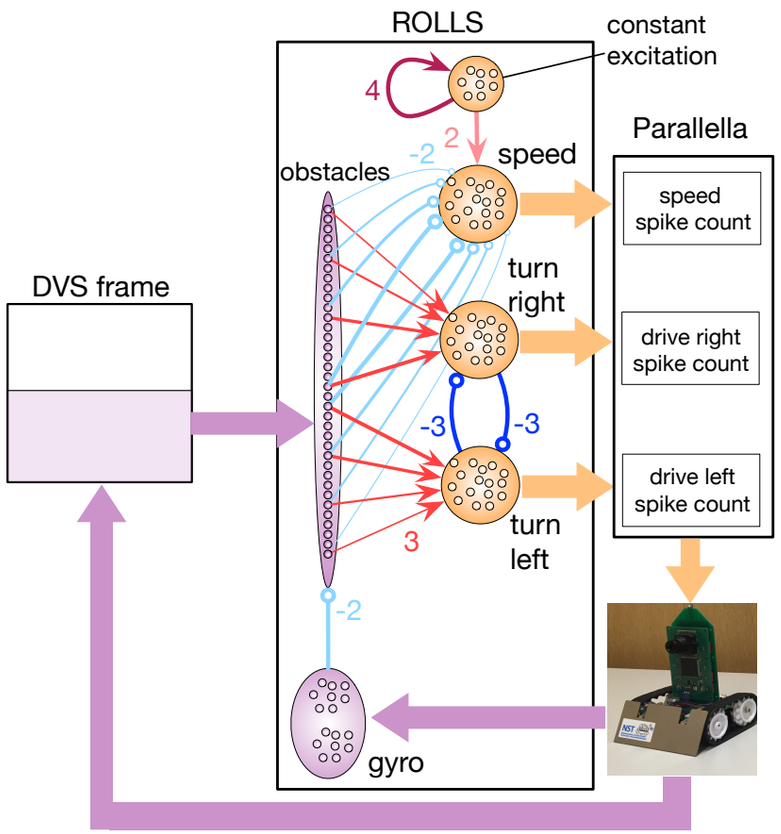


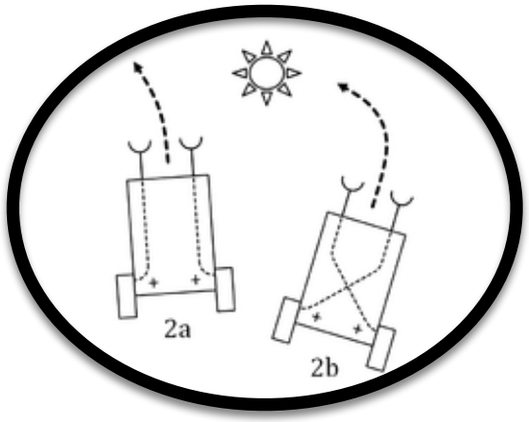
Different behaviours:



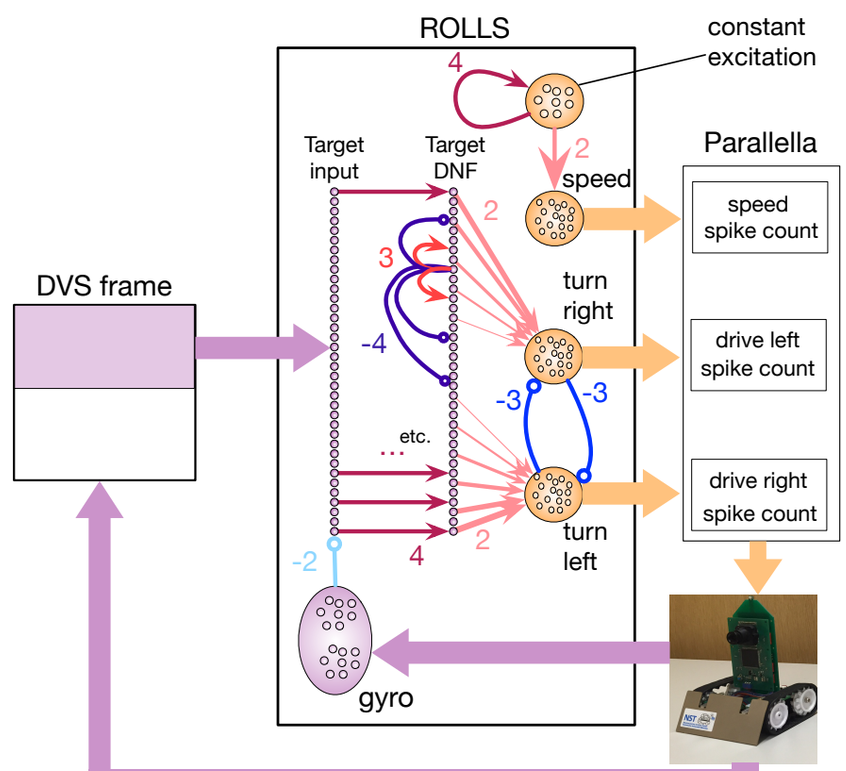
Braitenberg “de luxe”

Obstacle avoidance

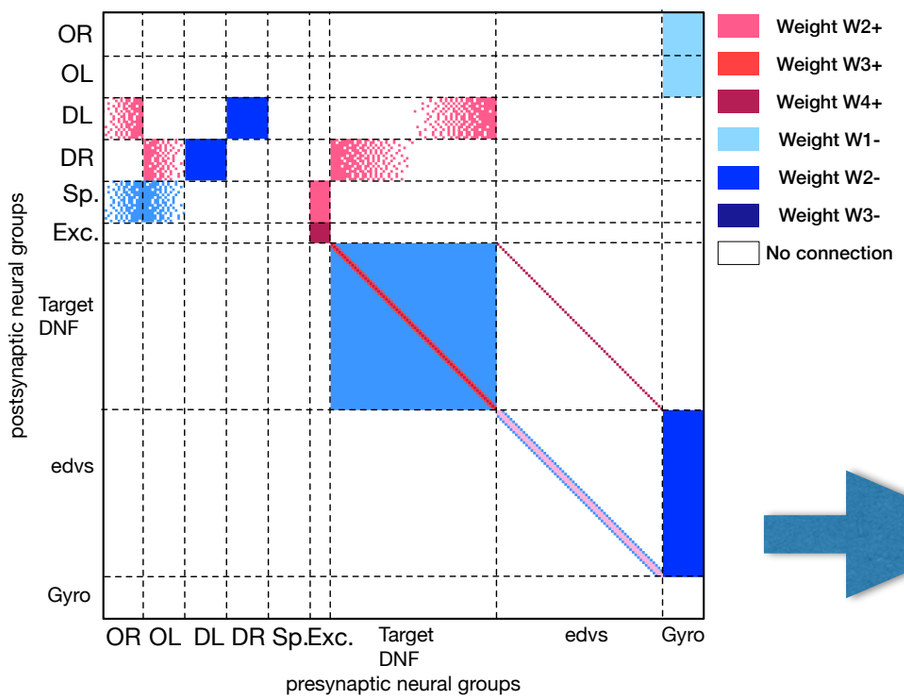




Target acquisition



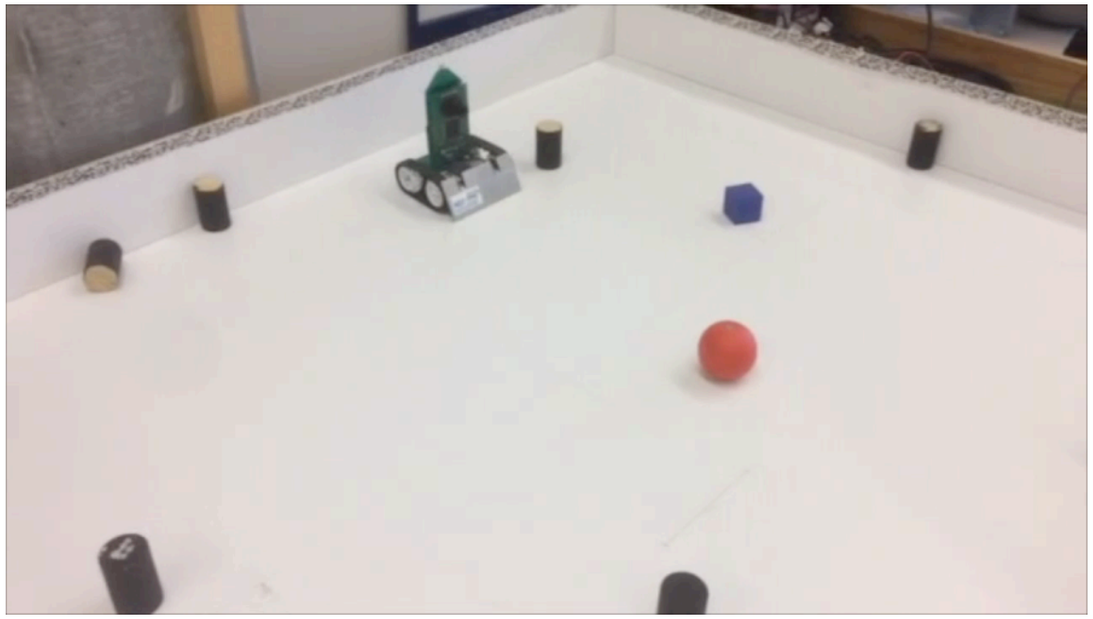
Connectivity



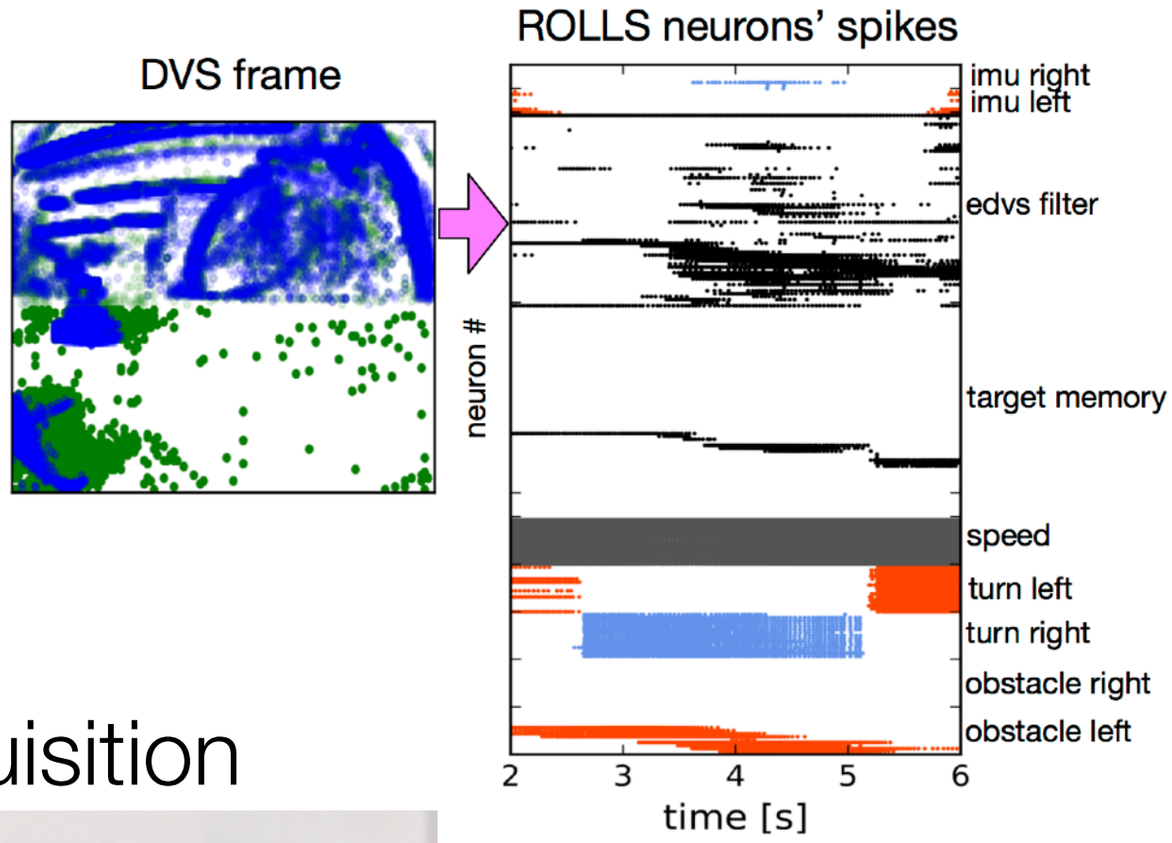
ROLLS

Navigation with a neuromorphic device

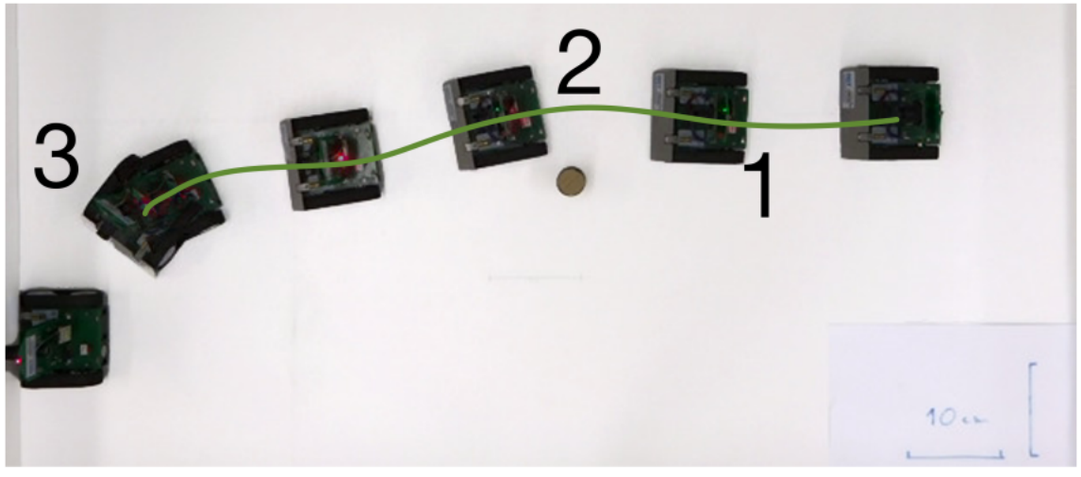
Avoiding obstacles



Output of the sensor and the chip



Target acquisition



Milde, M.; Blum, H.; Dietmüller, A; Sumislawska, D.; Conradt, J.; Indiveri, G. & Sandamirskaya, Y. Obstacle avoidance and target acquisition for robot navigation using a mixed signal analog/digital neuromorphic processing system Frontiers in Neurorobotics, 2017.

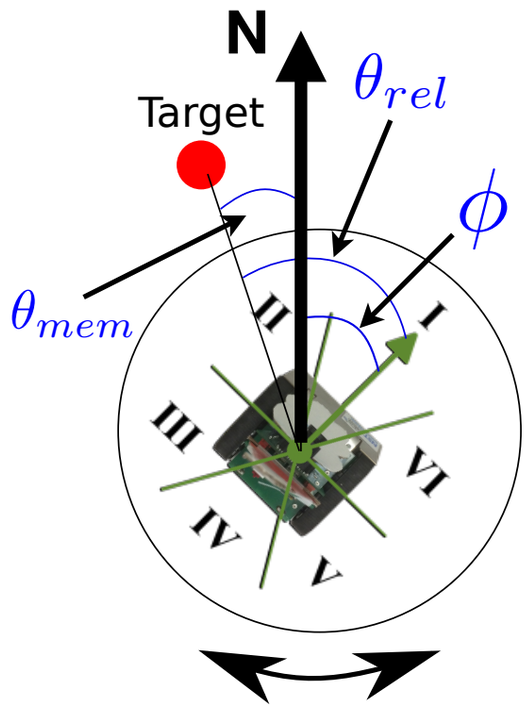
2. Memory and reference frames

View-based target representation:

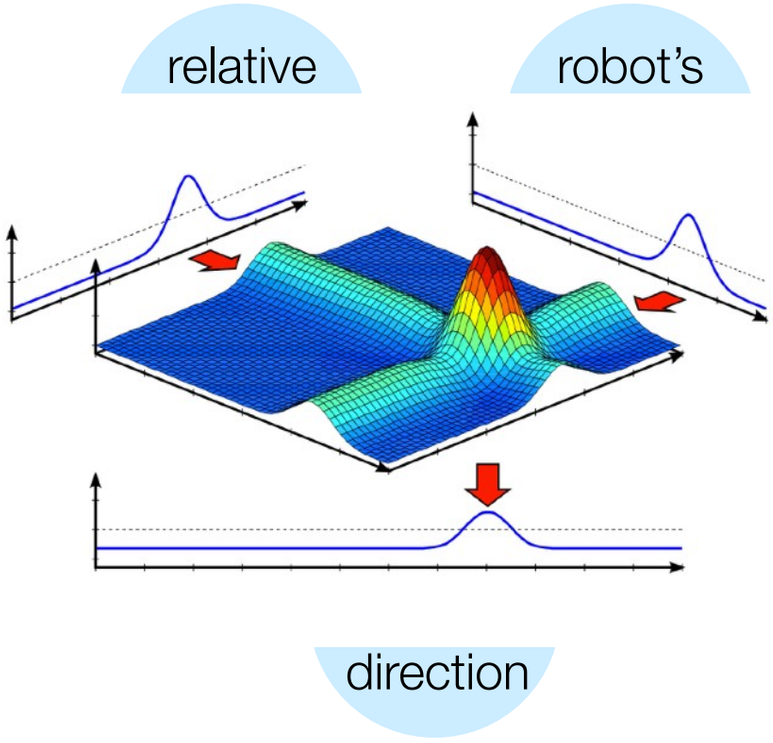
- target in view

- target lost from view

Allocentric target representation:

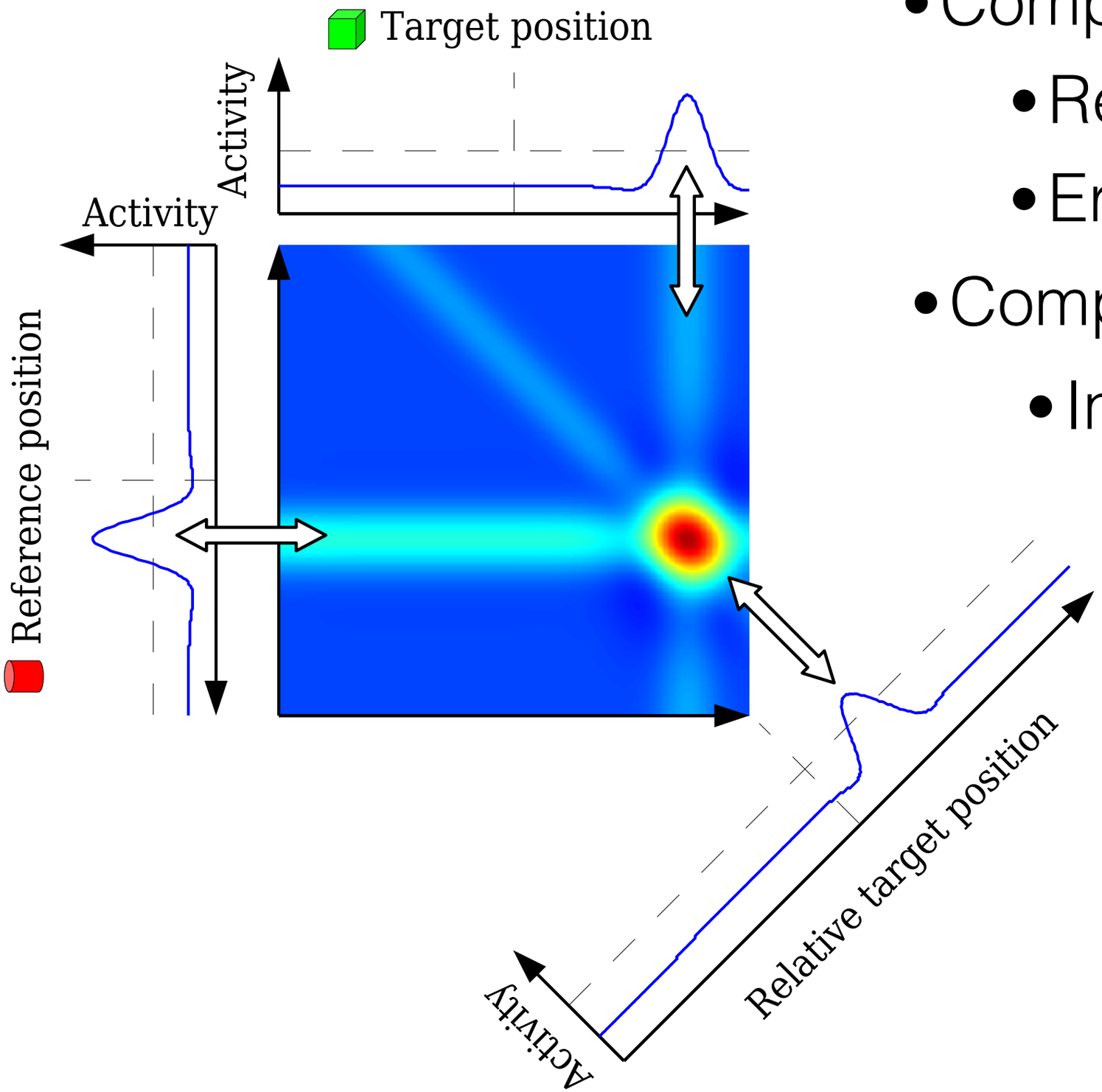


Neural ref. frame transformation:



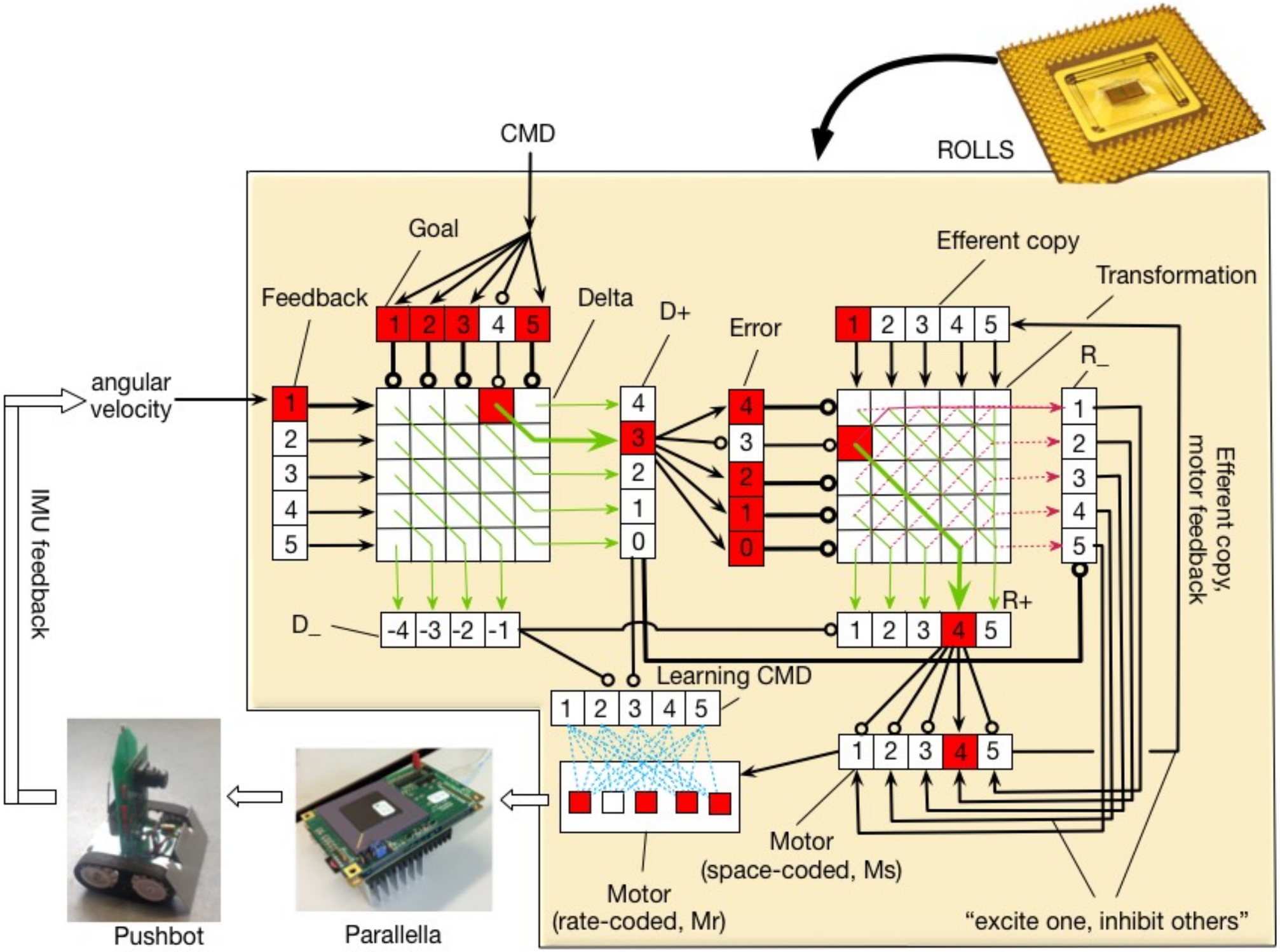
ROLLS device

“Relational” architecture



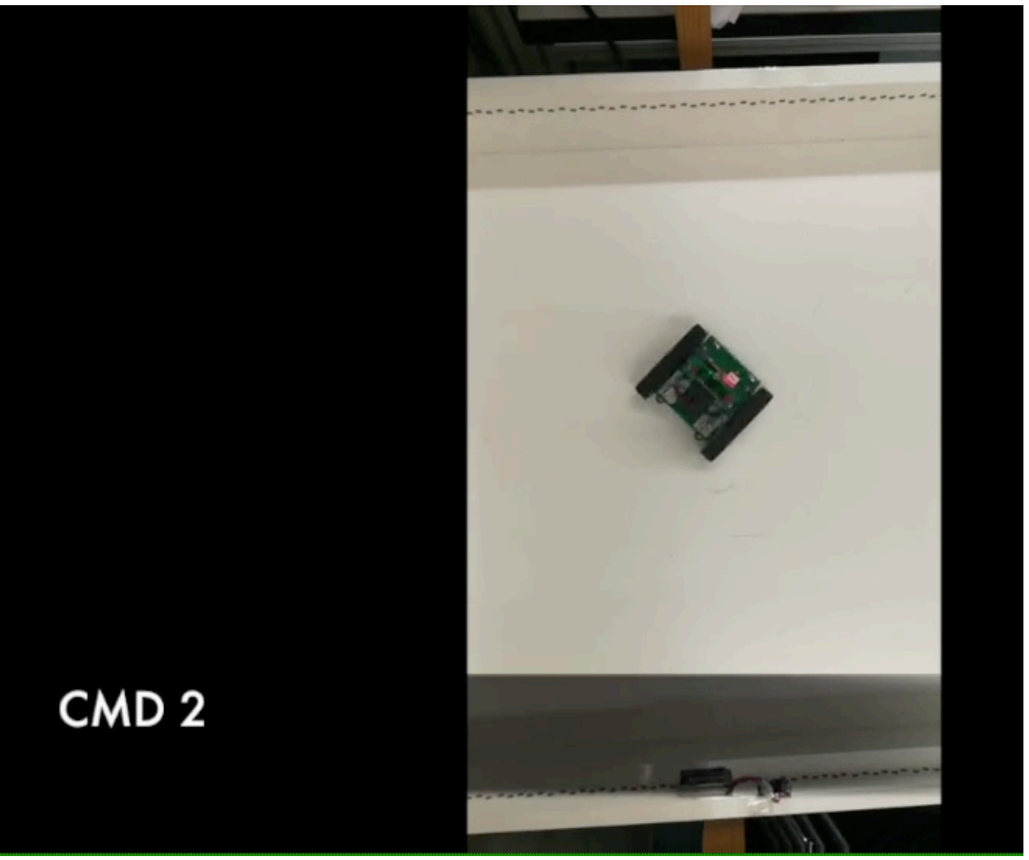
- Computing differences
  - Reference frame transform
  - Error estimation
- Computing sums
  - Integration

3. Neuromorphic motor controller

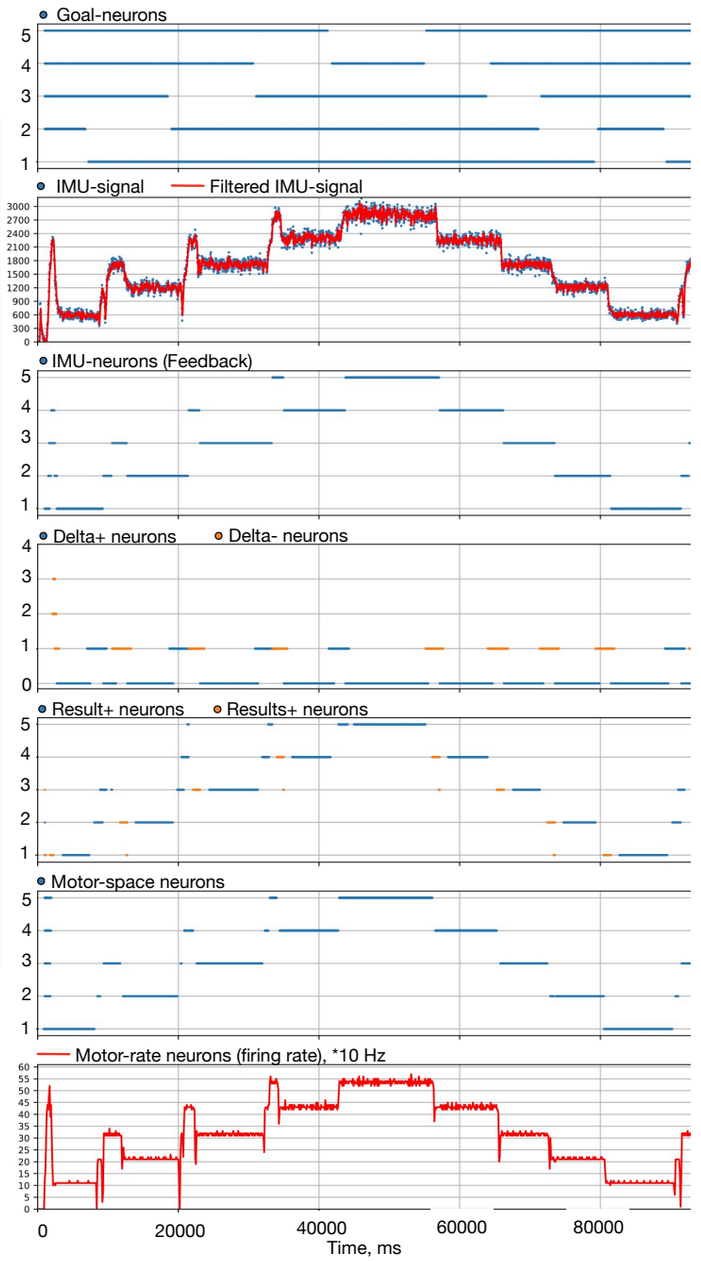


Glatz, S.; Kreiser, R.; Martel, J. N. P.; Qiao, N. & Sandamirskaya, Y. Adaptive motor control and learning in a spiking neural network, fully realised on a mixed-signal analog/digital neuromorphic processor. ICRA, arxiv, **2019**

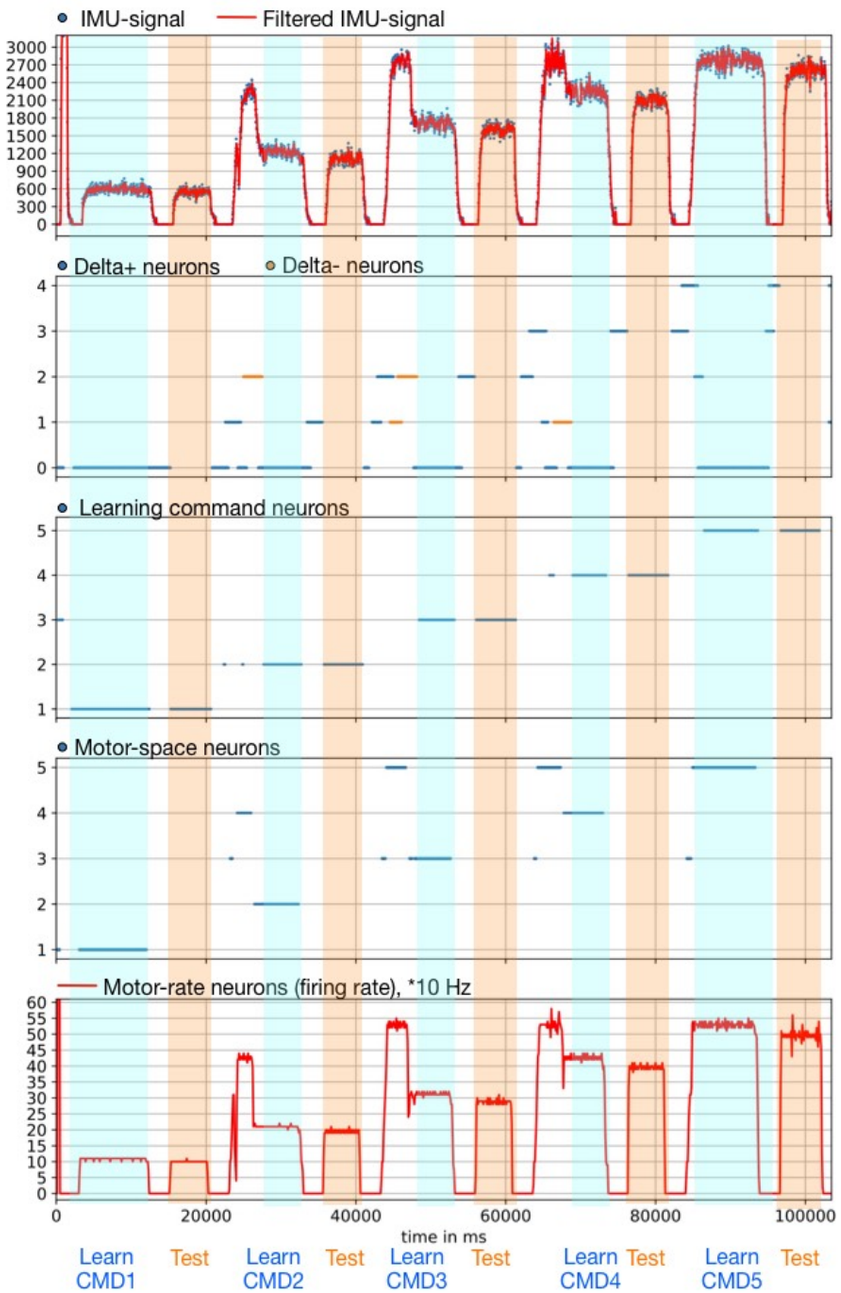
Experiments with a robot



Controller

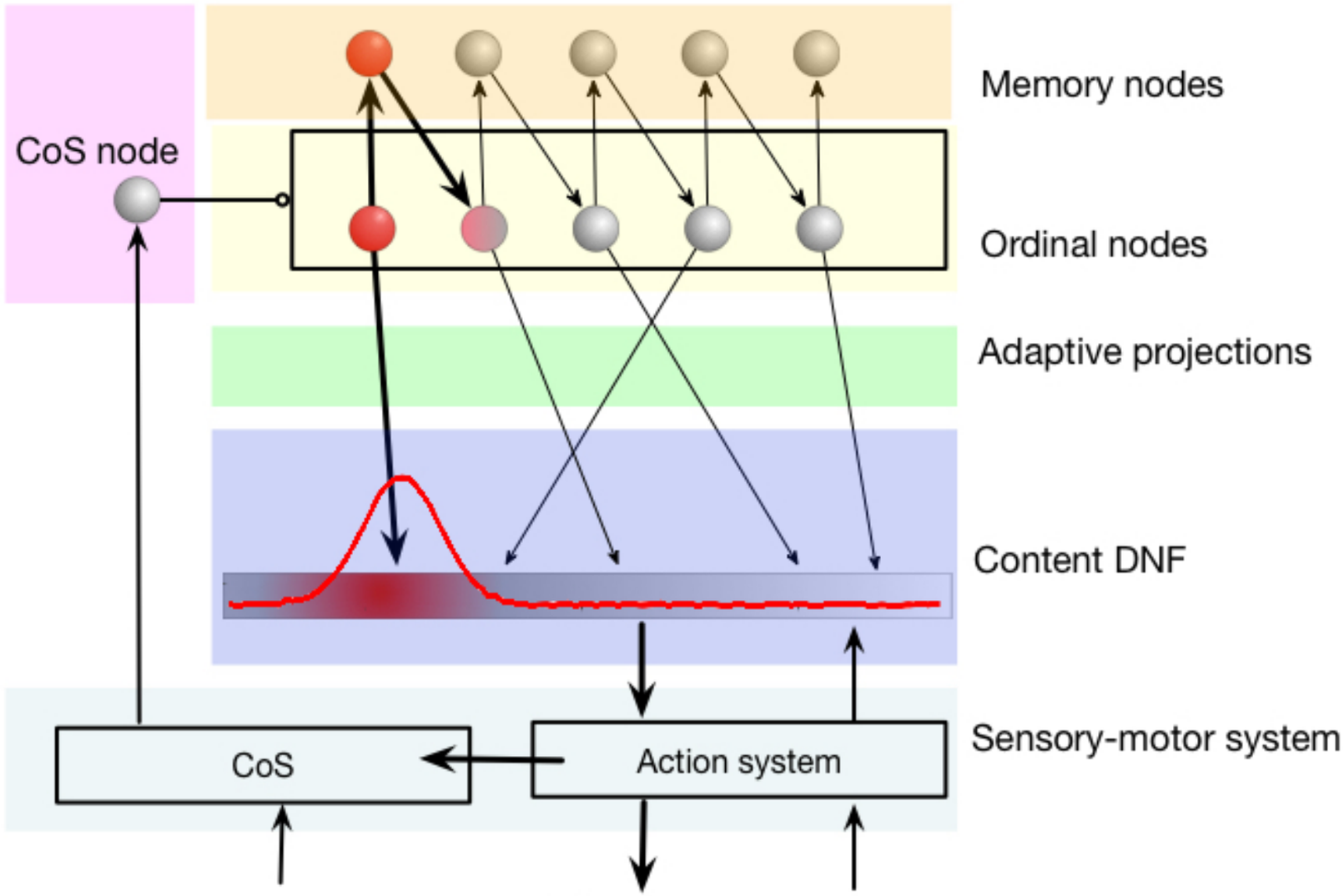


Learning the inverse

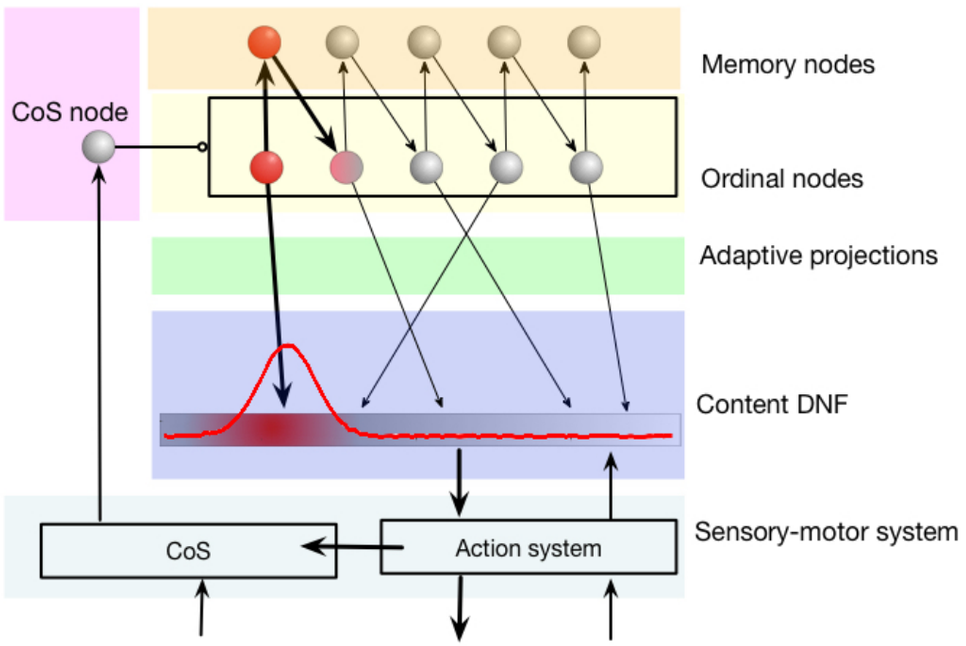


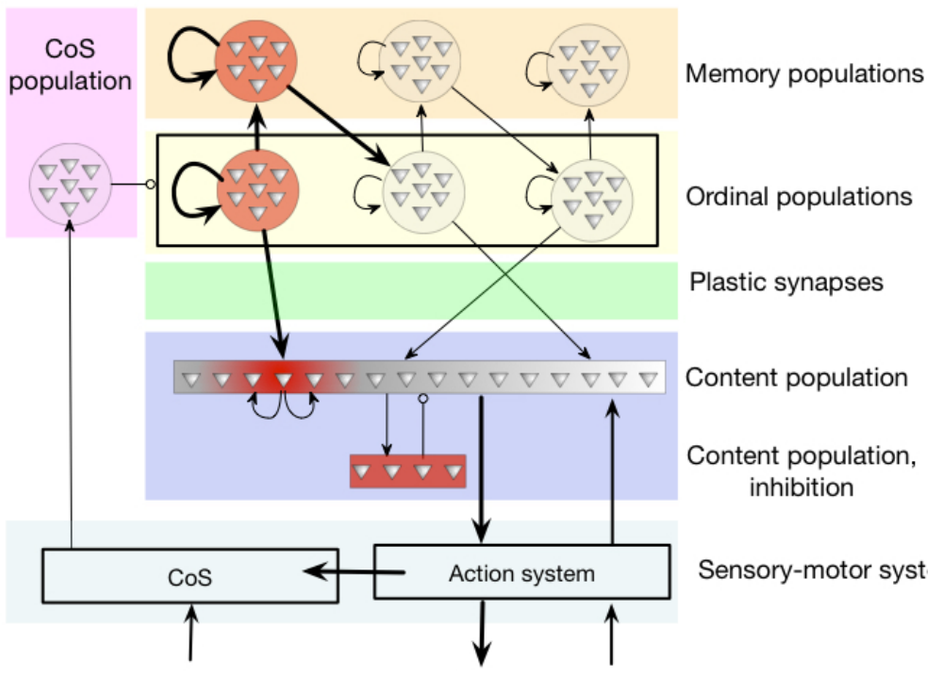
Glatz, S.; Kreiser, R.; Martel, J. N. P.; Qiao, N. & Sandamirskaya, Y. Adaptive motor control and learning in a spiking neural network, fully realised on a mixed-signal analog/digital neuromorphic processor. ICRA, **2019**

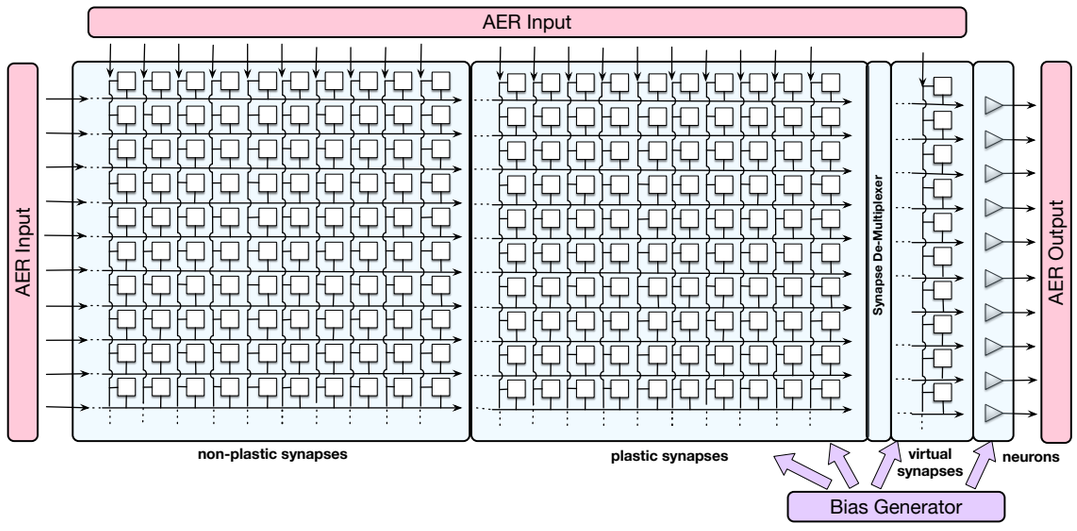
4. Sequences: serial order



Sequence learning “program”

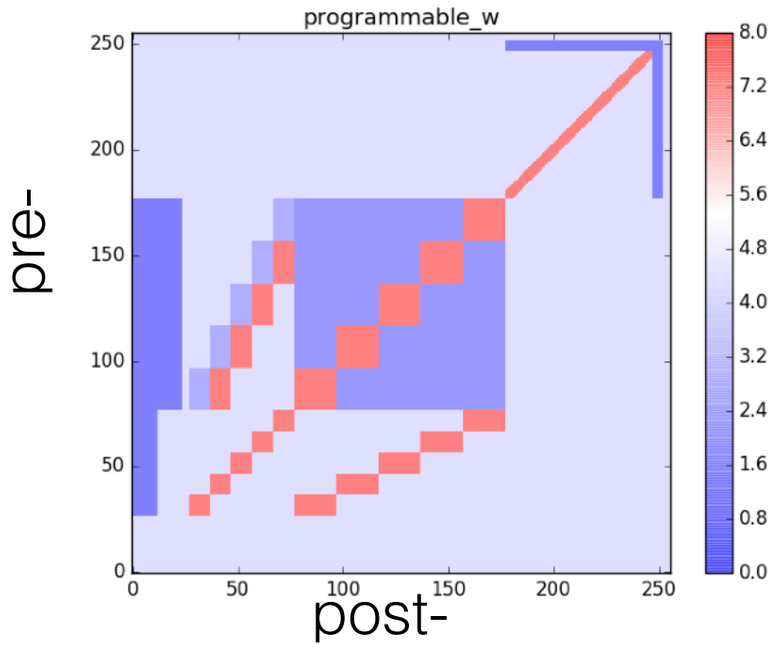






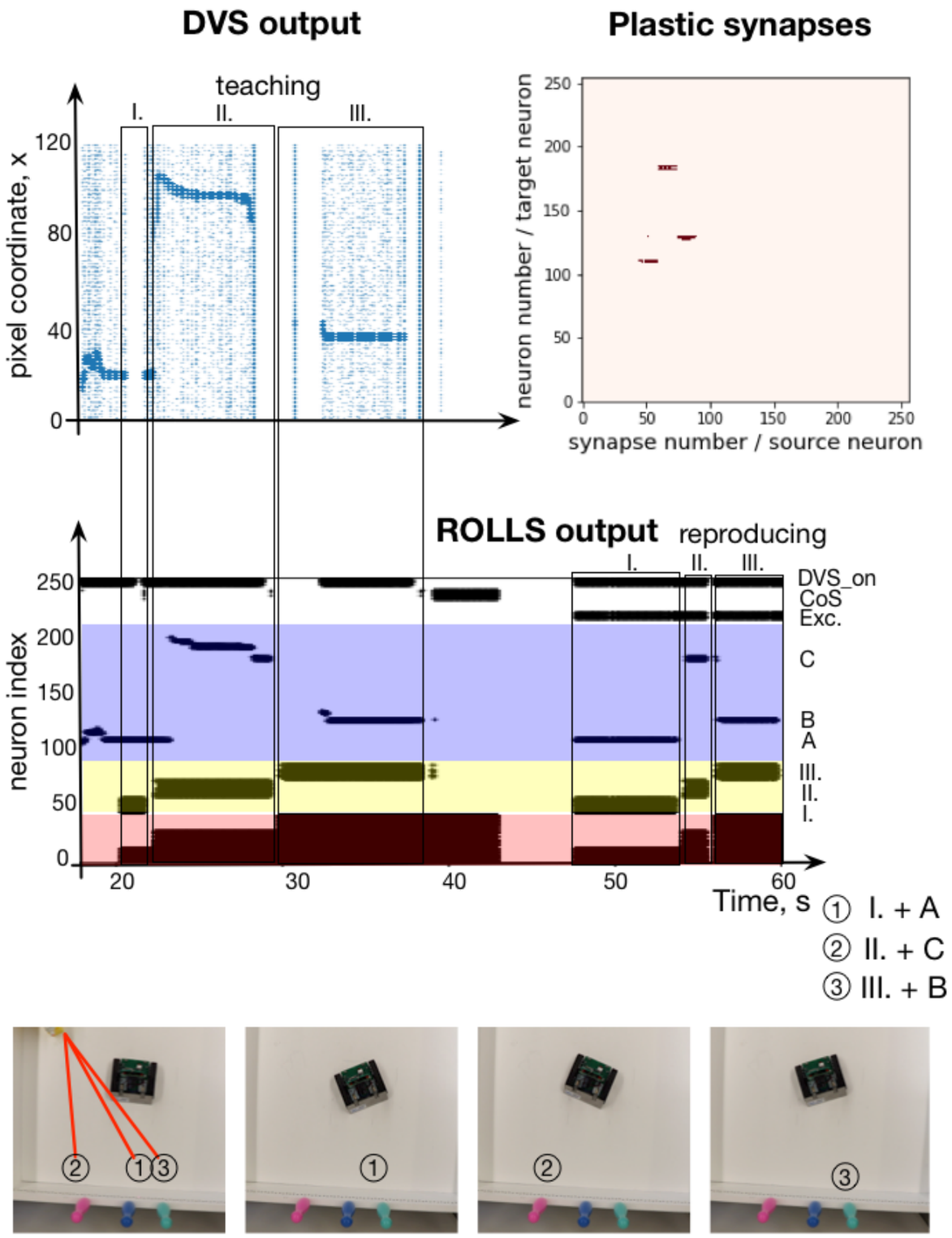
“Programm”

Connectivity matrix



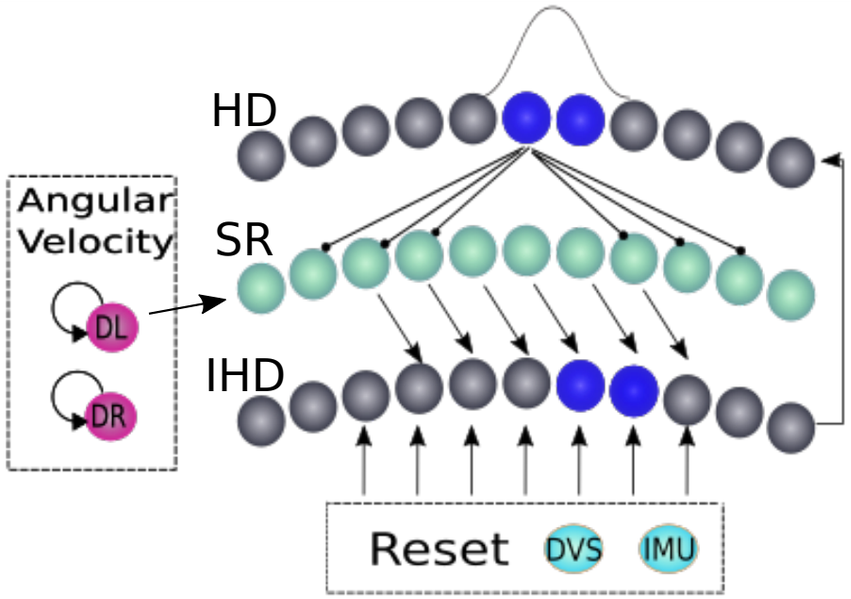
Kreiser, R.; Aathmani, D.; Qiao, N.; Indiveri, G. & Sandamirskaya, Y. Organising Sequential Memory in a Neuromorphic Device Using Dynamic Neural Fields. Frontiers in Neuromorphic Engineering, **2018**

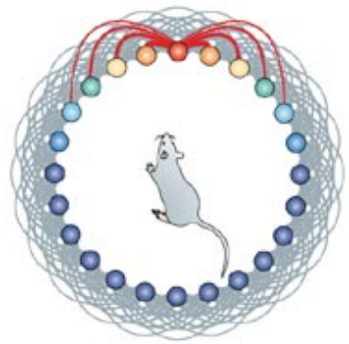
Robotic experiment

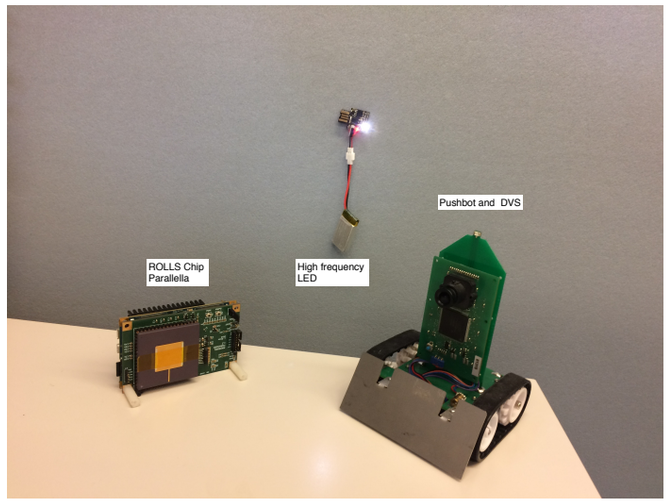


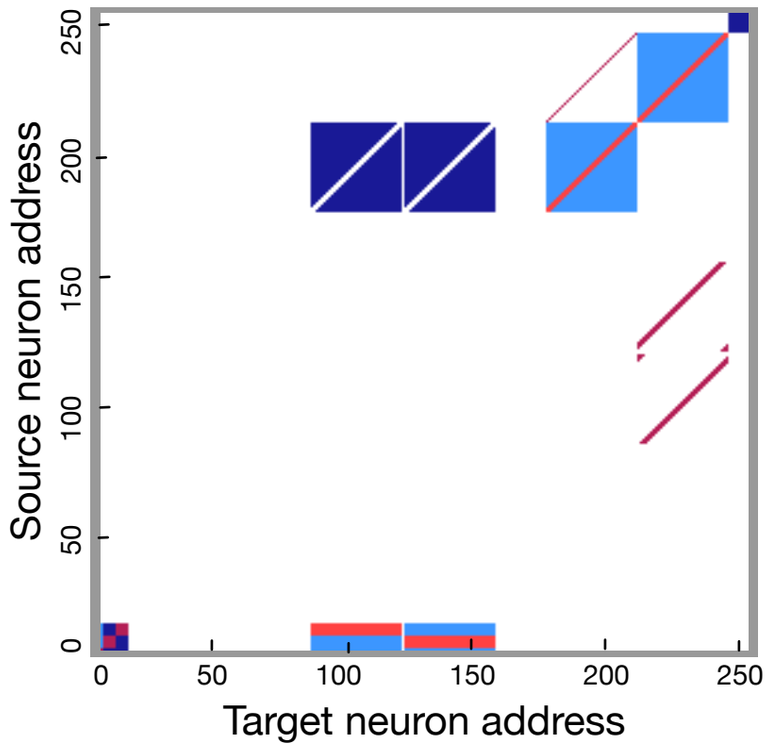
Kreiser, R.; Aathmani, D.; Qiao, N.; Indiveri, G. & Sandamirskaya, Y. Organising Sequential Memory in a Neuromorphic Device Using Dynamic Neural Fields. Frontiers in Neuromorphic Engineering, **2018**

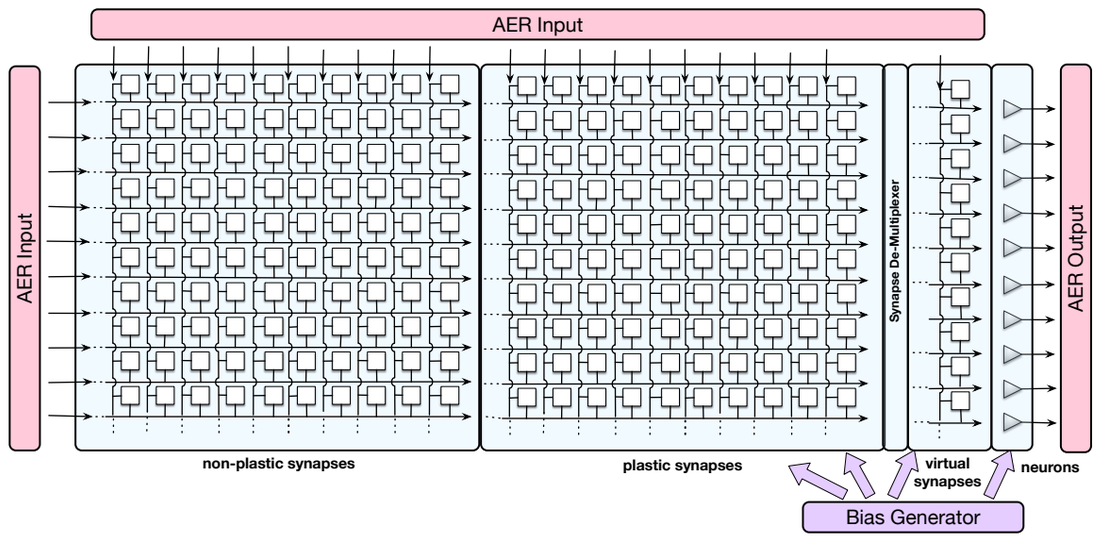
5. Long-term memory: SLAM







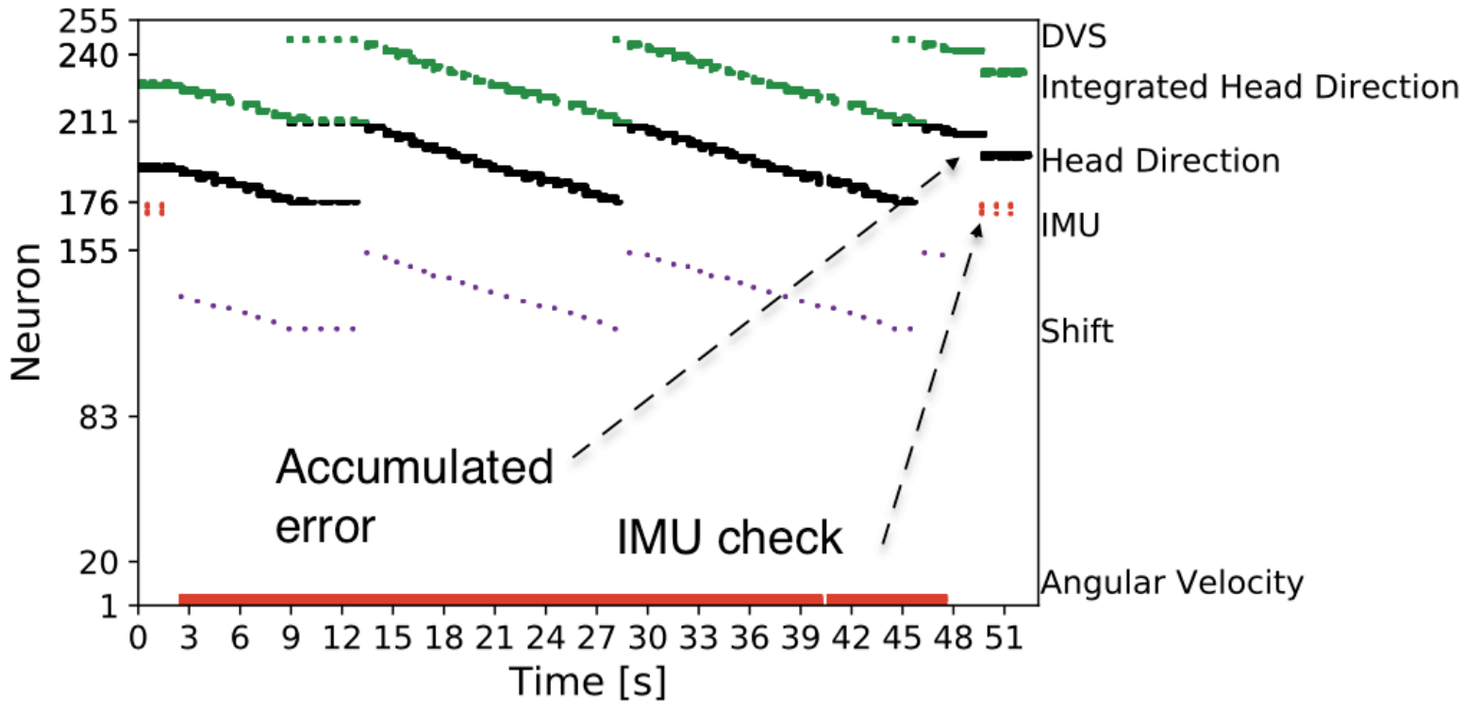




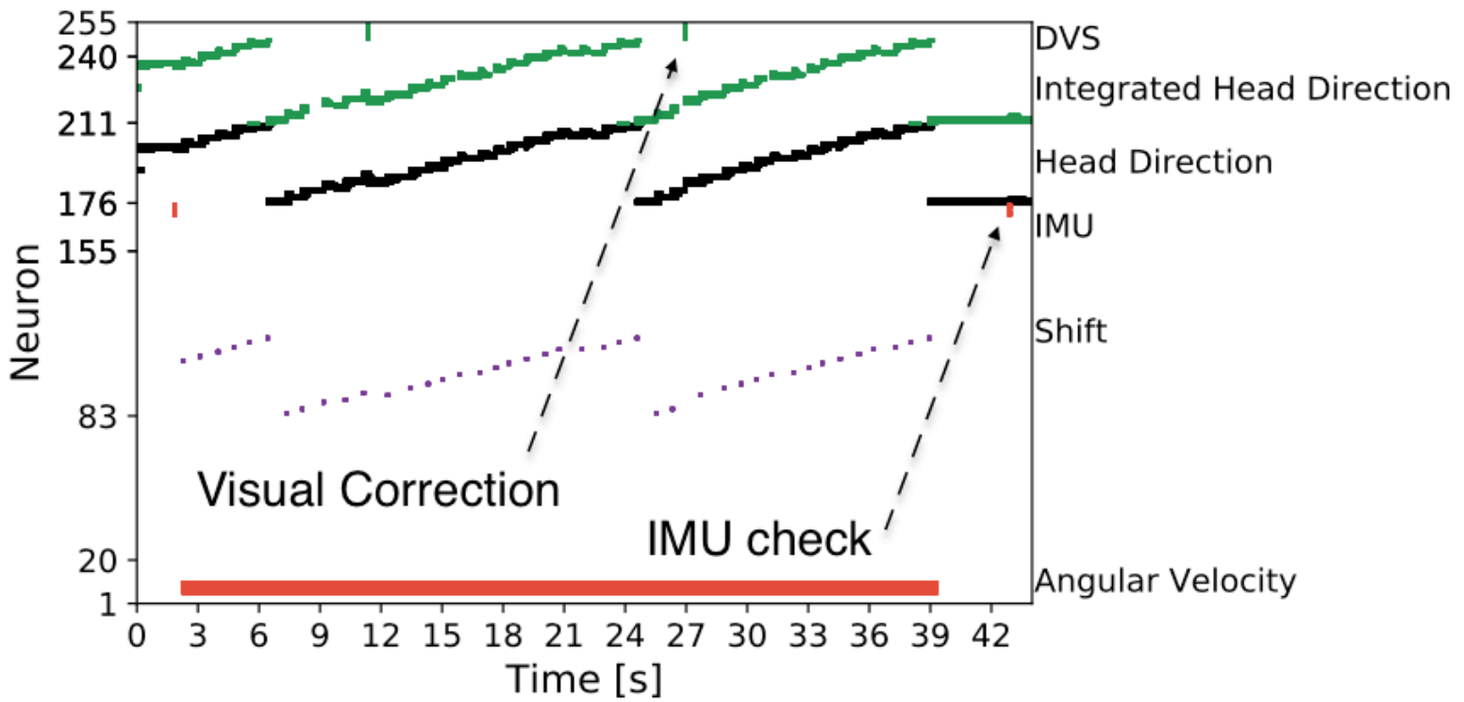
Kreiser, R.; Cartiglia, M. & Sandamirskaya, Y. A Neuromorphic approach to path integration: a head direction spiking neural network with visually-driven reset. IEEE Symposium for Circuits and Systems, ISCAS, **2018**

Navigation: Head-direction network

Without visual reset

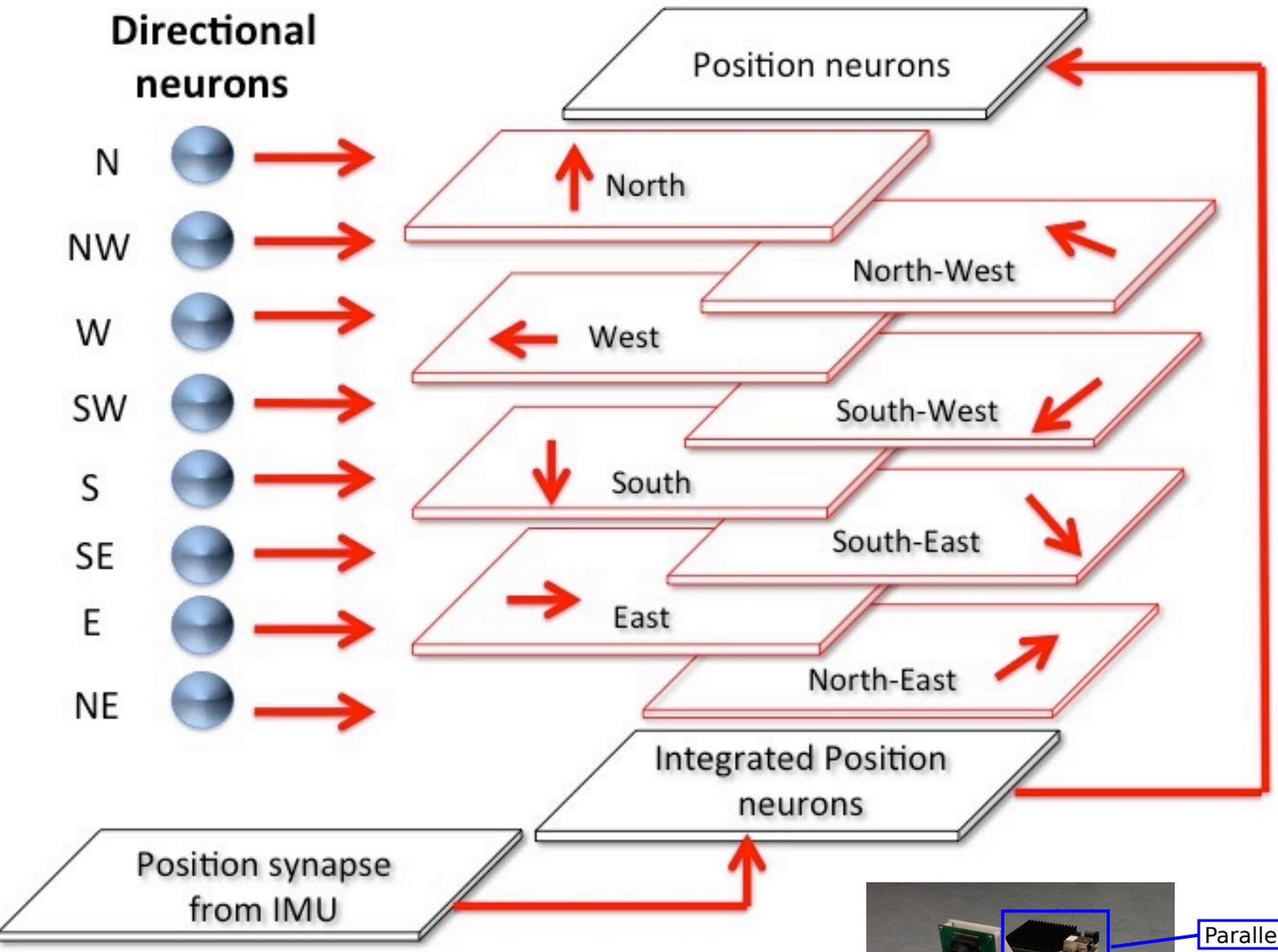


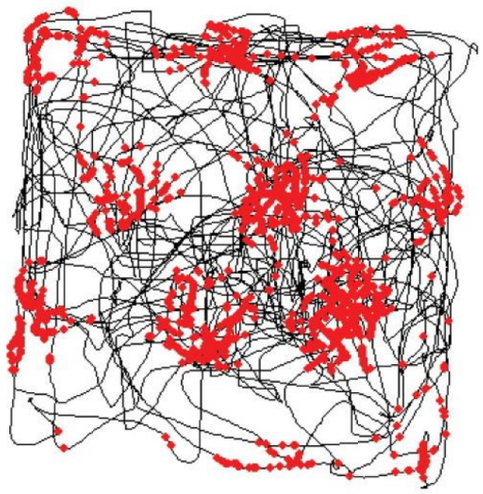
With visual reset

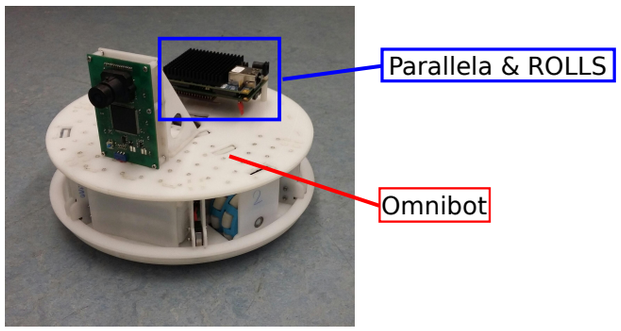


Map formation: Path integration in 2D

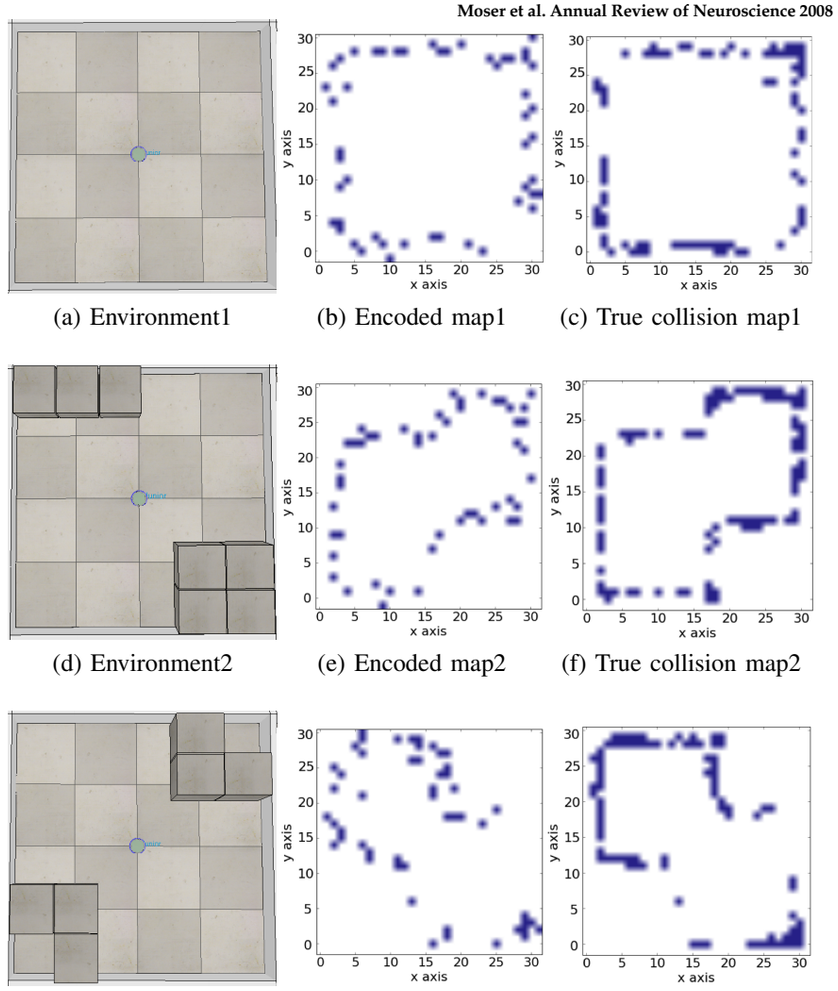
“Grid cells”







Moser et al. Annual Review of Neuroscience 2008

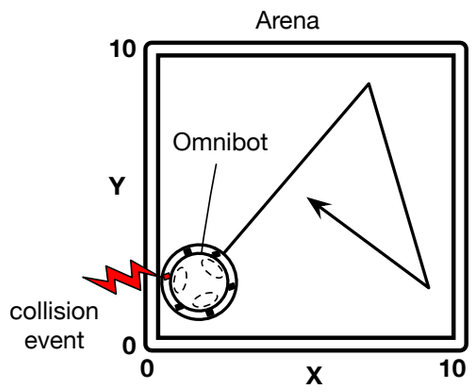


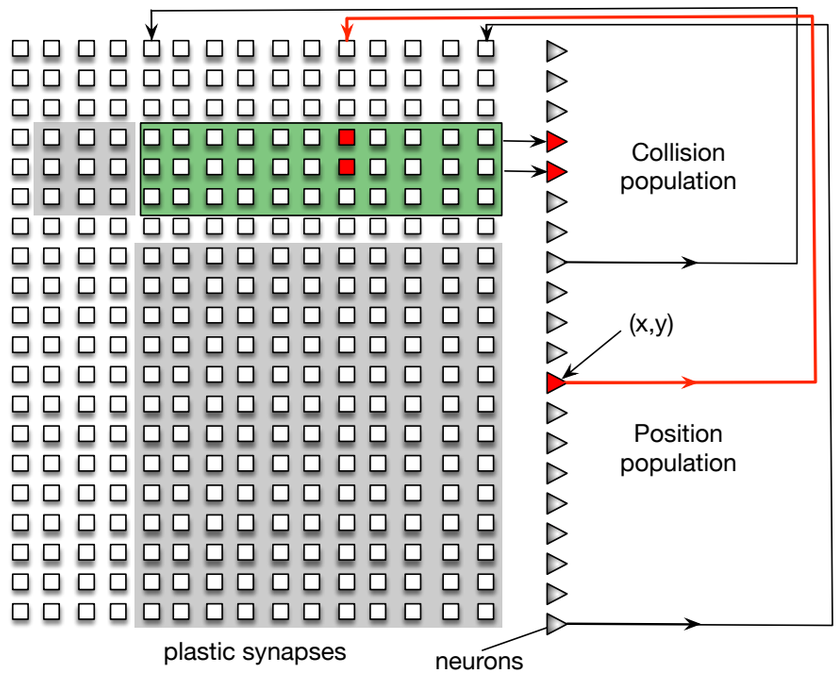
(a) Environment1 (b) Encoded map1 (c) True collision map1

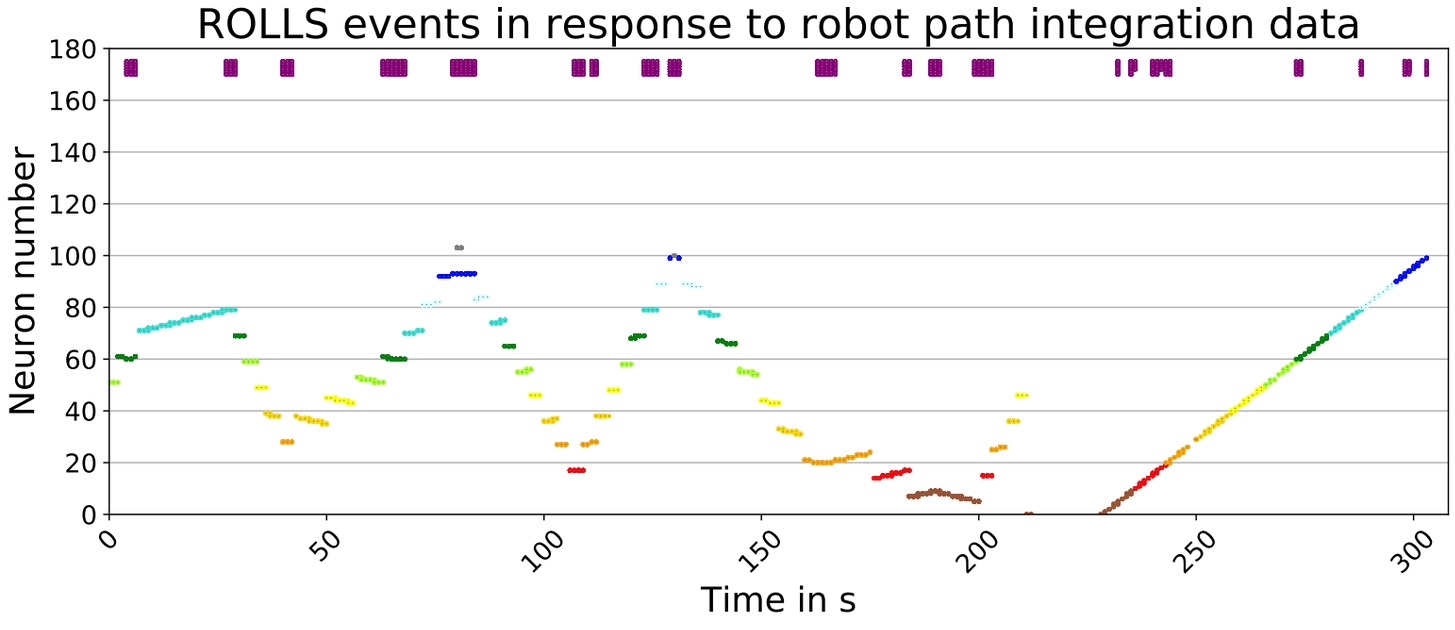
(d) Environment2 (e) Encoded map2 (f) True collision map2

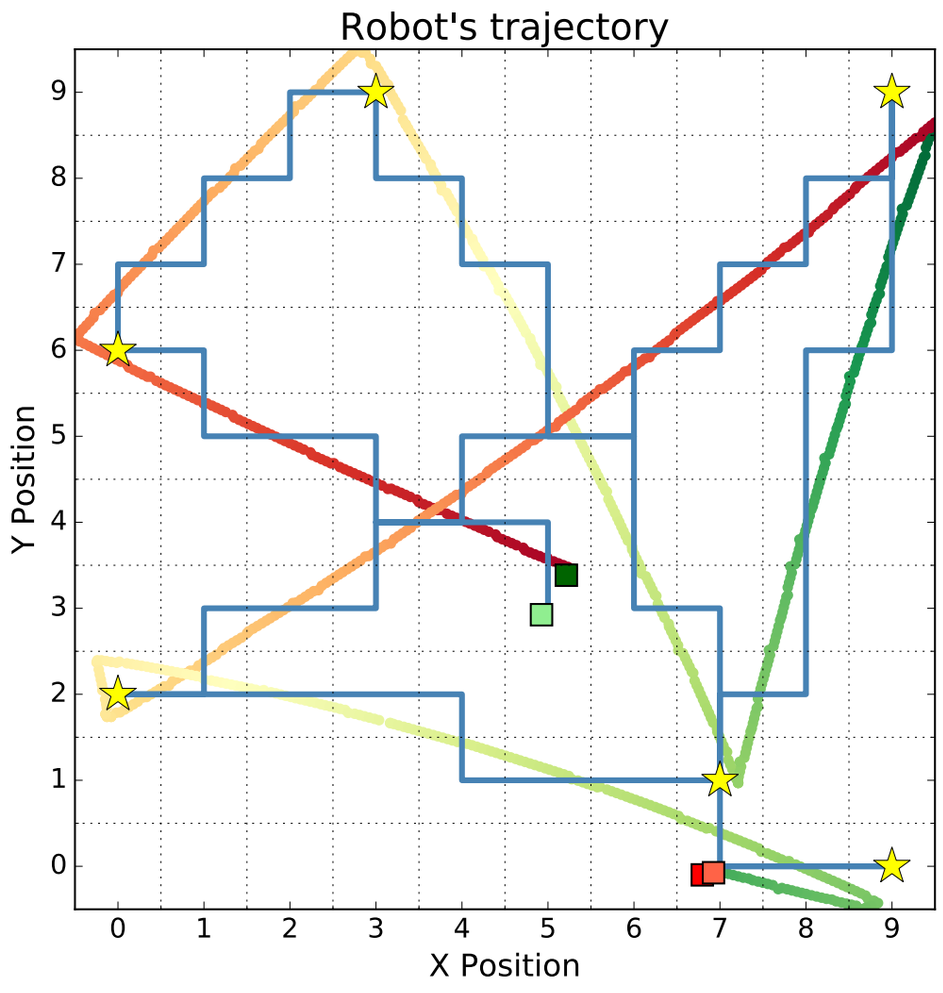
Kreiser, R.; Pienroj, P.; Renner, A. & Sandamirskaya, Y. Pose Estimation and Map Formation with Spiking Neural Networks: towards Neuromorphic SLAM. 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, **2018**

Map formation on the ROLLS chip

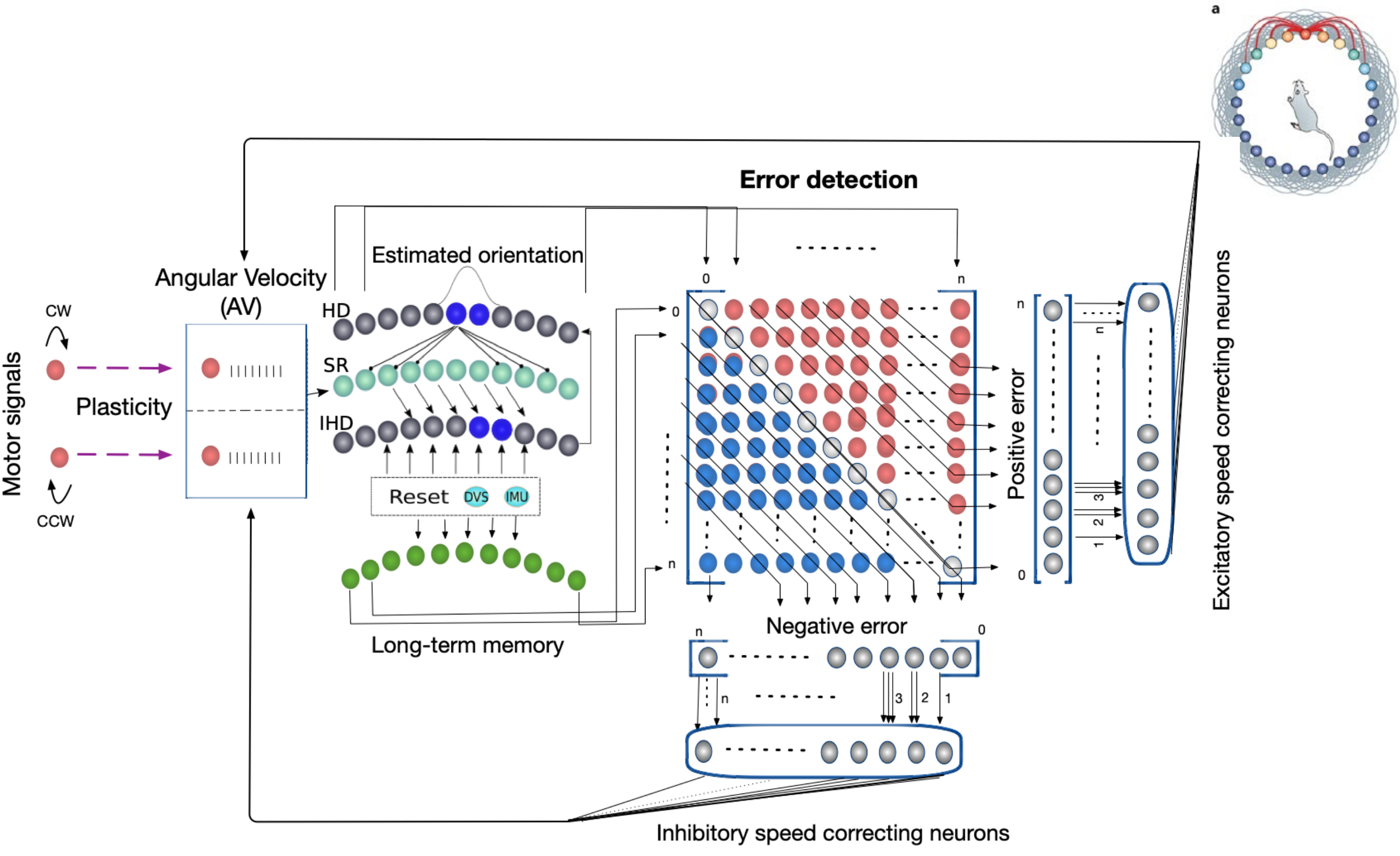






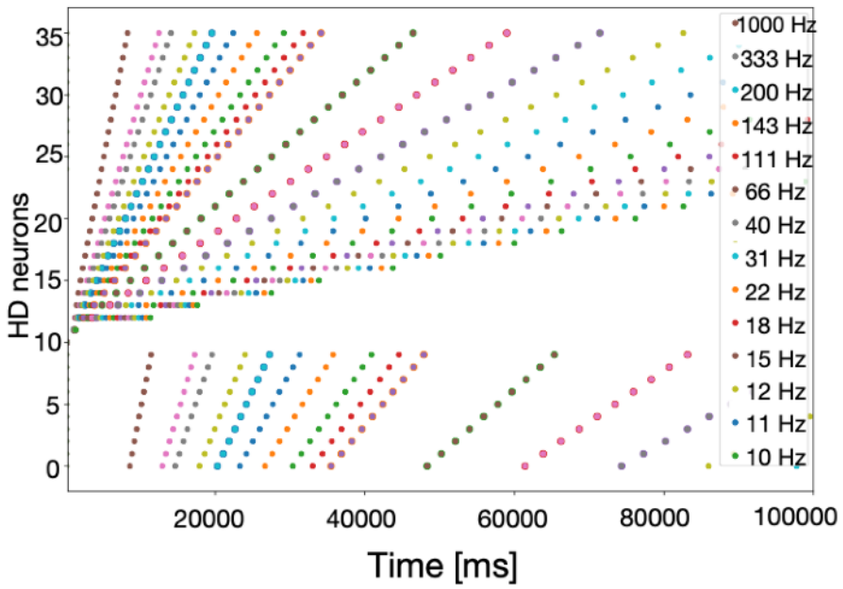


6. Autonomous learning: calibration of HD network

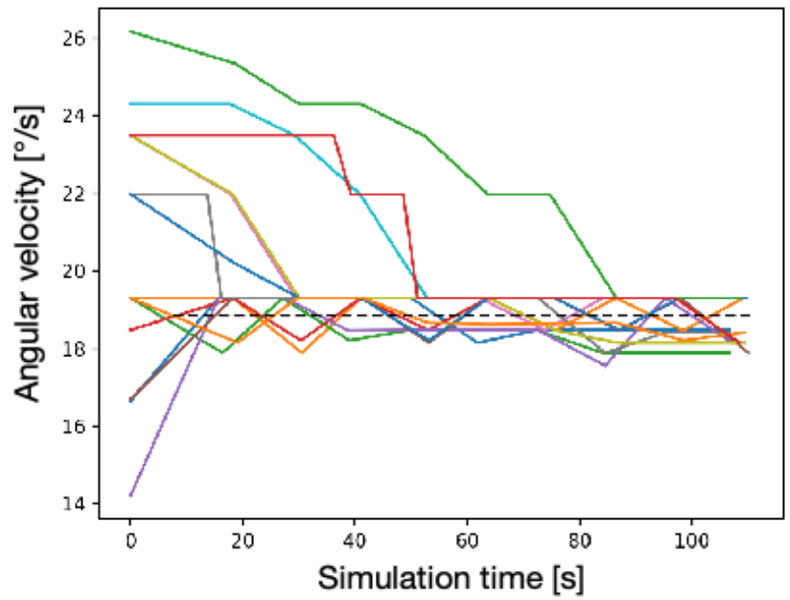


Autonomous adaption / calibration

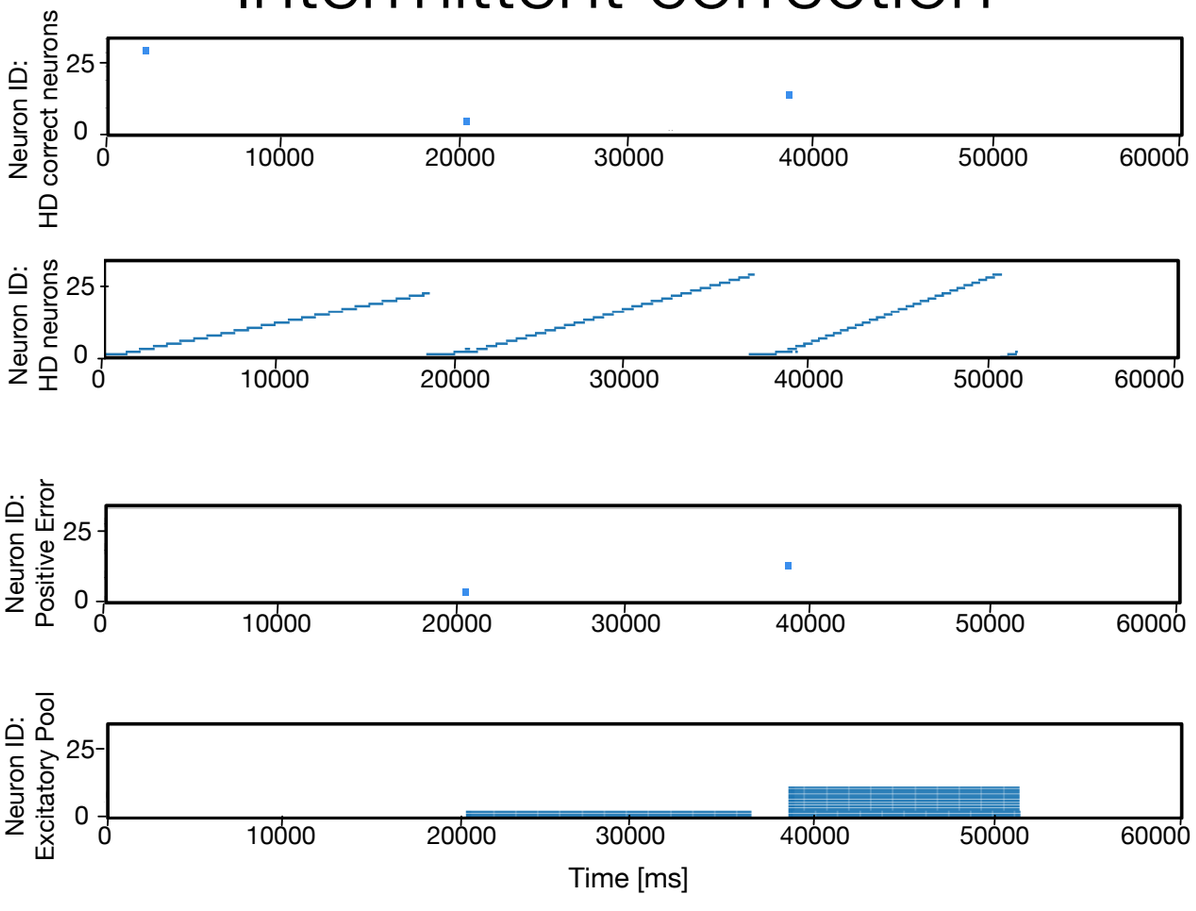
Controlling integration speed



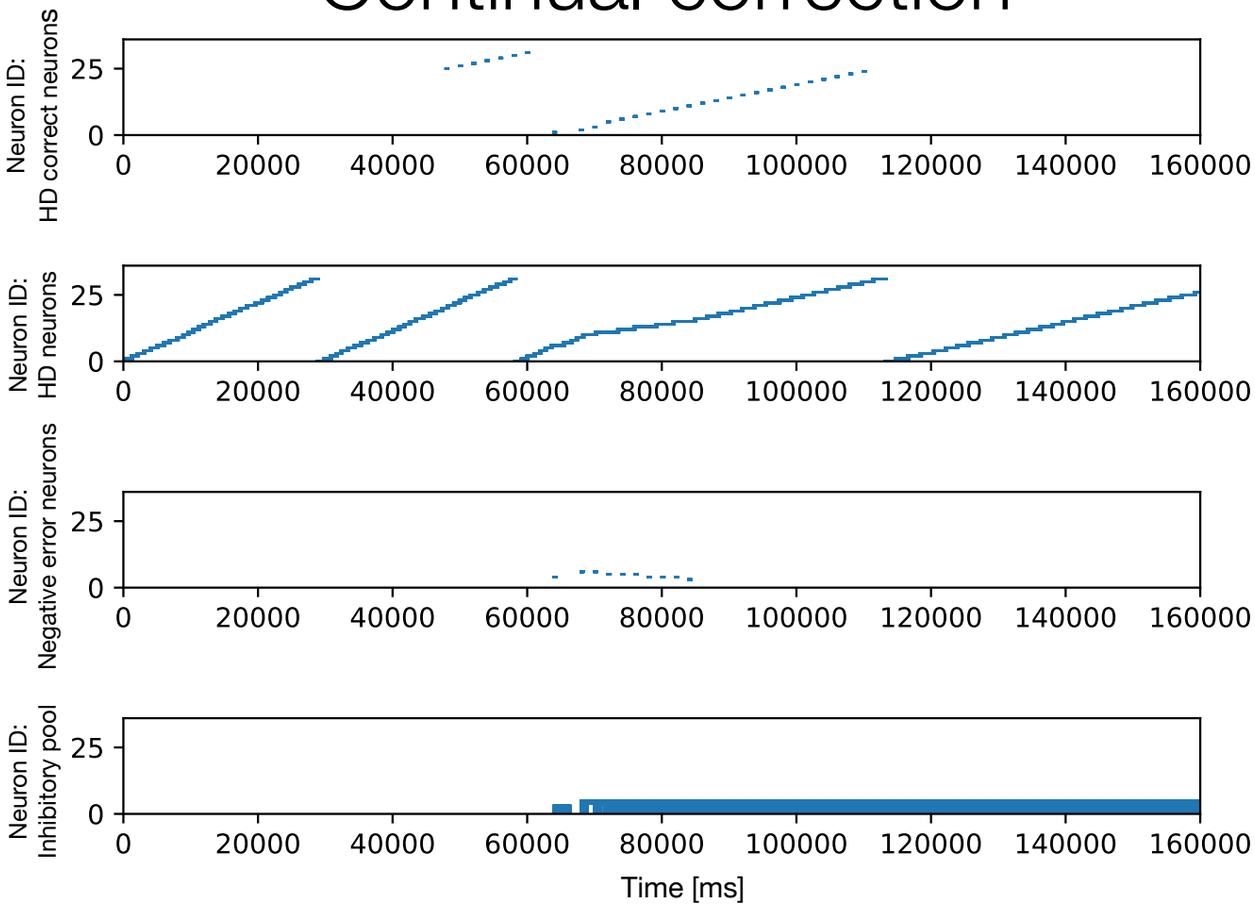
Convergence



Intermittent correction



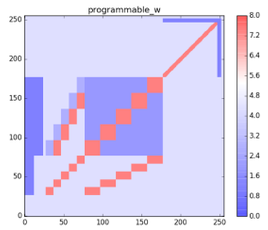
Continual correction

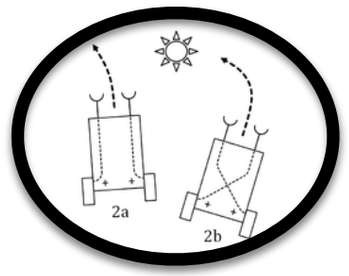


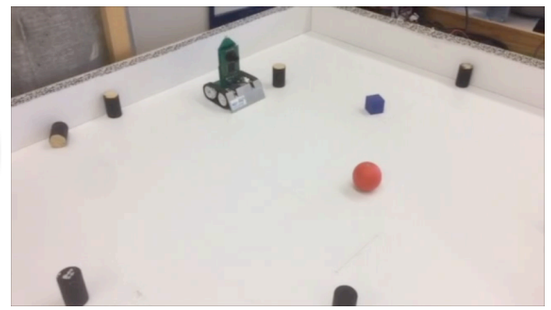
Neuromorphic architectures: building blocks

➡ **Braintenberg vehicle, sequences**

- attractors in a sensory-motor loop



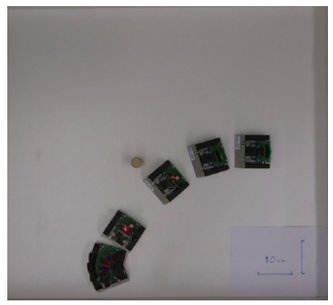


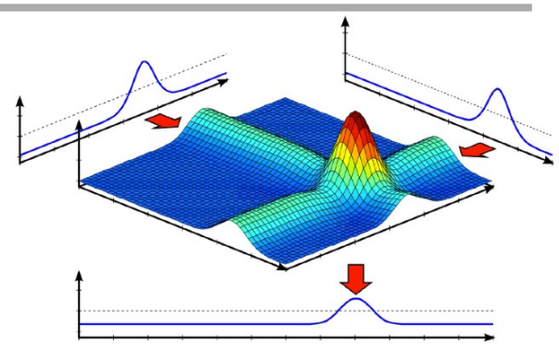


Milde et al 2017a,b; Kreiser et al 2018

➡ **Reference frame** transformations

- key for linking modalities

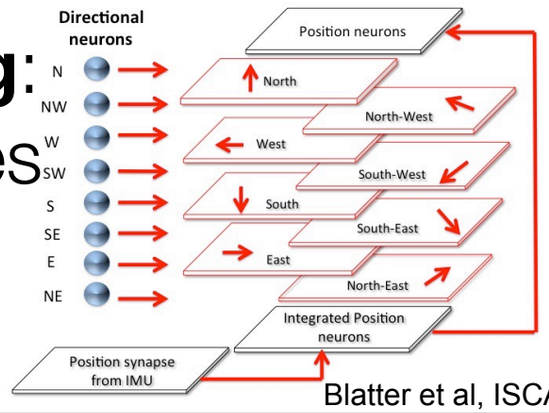


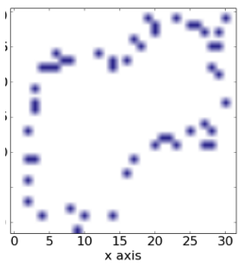


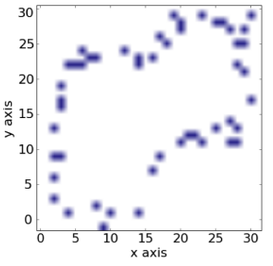
Blum et al 2017

➡ Simultaneous **localisation and mapping**: path integration, learning a map, sequences

- state estimation, building representations



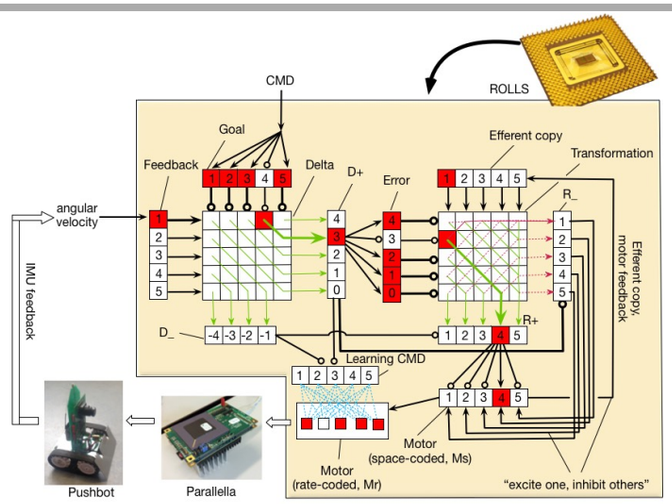




Blatter et al, ISCAS, under rev; Kreiser et al 2018a, b

➡ **Adaptive motor control**

- key element for adaptive behavior



Glatz et al, arxiv, 2018

Conclusions

➡ lots of structure is needed to control behavior with neurons

- represent state with neuronal populations (“place code”)
- stabilise states and decision with recurrent connections (DNF)
- disinhibition for robustness
- adaptive couplings between sensed quantities and states
- error estimation and correction

➡ object representation/recognition is a map-formation problem, not (just) pattern learning and recognition

➡ learning can then be very simple

- one-shot
- binary weight

➡ computing substrate sets additional constraints on models

- can lead to new inspiration and more efficient systems

Thanks!

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