WP5 - Demo 1.3 : Spiking model of motion-based prediction

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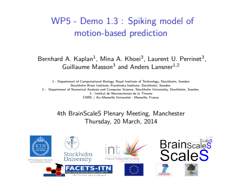
CNRS / Aix-Marseille Université - Marseille, France

4th BrainScaleS Plenary Meeting, Manchester
Thursday, 20 March, 2014



(hello) Hi, I am Bernhard A. Kaplan and I am Laurent U. Perrinet . Today we will speak about the role of predictive coding in neural computations and demonstrate an application at different levels from theory to biology and hardware simulations.

(akcno) This is joint work between INT and KTH. Thanks to FACETS-ITN and the BrainScaleS project for funding this project.

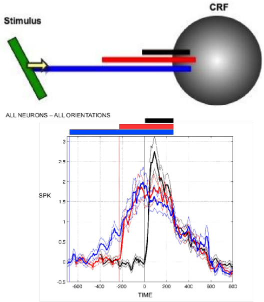
Outline: WP5 - Demo 1.3 : Spiking model of motion-based prediction

1. first, Laurent U. Perrinet will present the biological motivation and a theoretical formulation
2. then, Bernhard A. Kaplan will present an existing implementation on the ESS
3. Finally, Bernhard A. Kaplan will present ongoing work on the BCPNN rule.

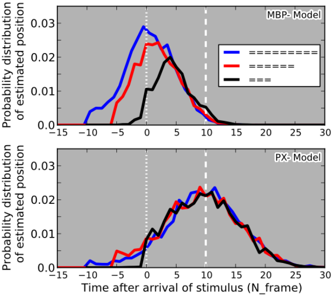
Outline: WP5 - Demo 1.3 : Spiking model of motion-based prediction

Motion-based anticipation

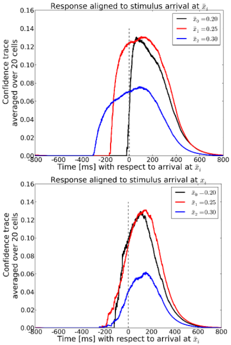
Experiment

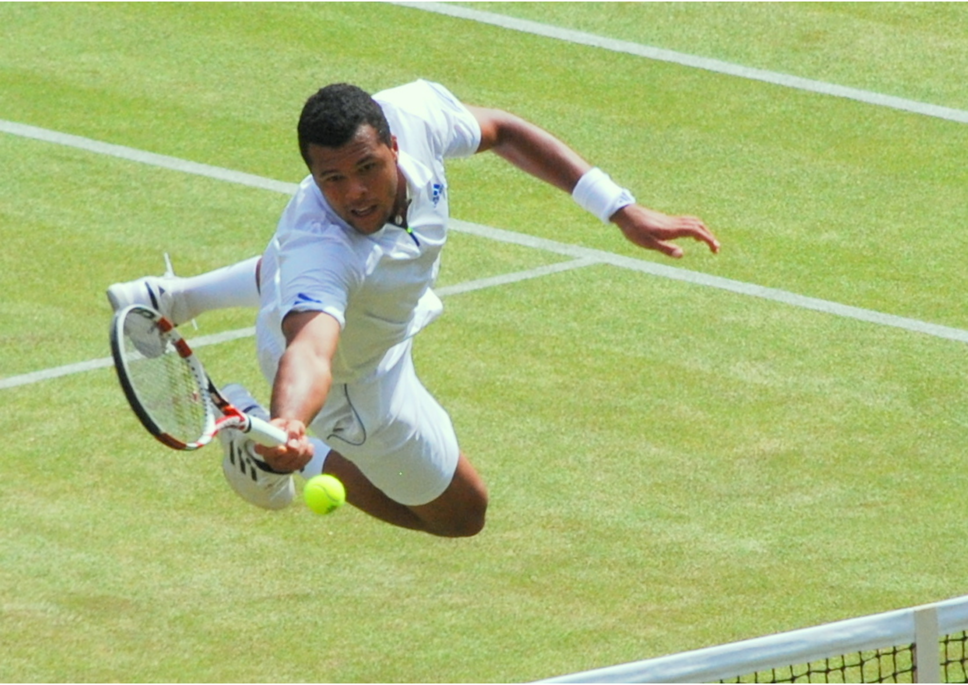


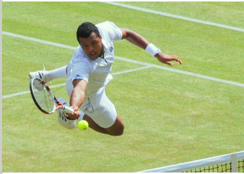
Abstract, probabilistic model



Spiking neural network

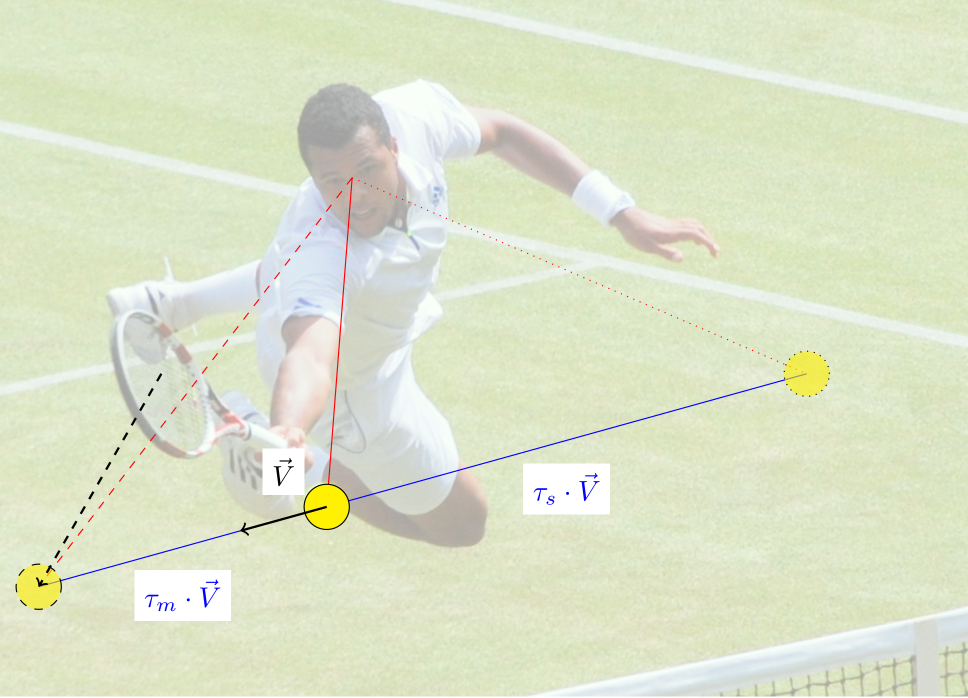




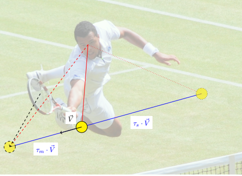


(x) Problem statement: optimal motor control under axonal delays. The central nervous system has to contend with axonal delays, both at the sensory and the motor levels.

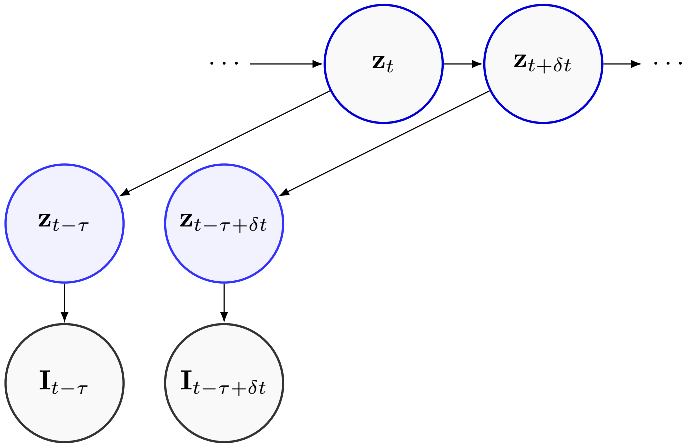
(xxx) ... For instance, in the human visuo-oculomotor system, it takes approximately $\tau_s = 50$ *ms* for the retinal image to reach the visual areas implicated in motion detection, and a further $\tau_m = 40$ *ms* to reach the oculomotor muscles. As a consequence, for a tennis player trying to intercept a ball at a speed of $20\ m.s^{-1}$, the sensed physical position is 1 *m* behind the true position (as represented here by $\tau_s \cdot \vec{V}$), while the position at the moment of emitting the motor command will be .8 *m* ahead of its execution ($\tau_m \cdot \vec{V}$).

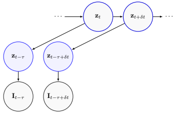


$\vec{V}$
$\tau_s \cdot \vec{V}$
$\tau_m \cdot \vec{V}$



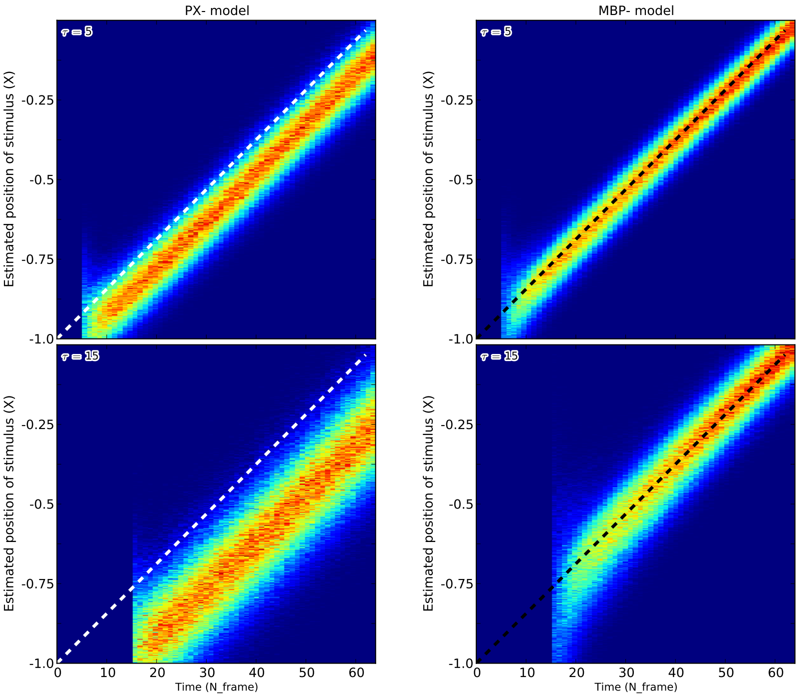
(xxx) Note that while the actual position of the ball when its image formed on the photoreceptors of the retina hits visual read is approximately at 45 degrees of eccentricity (red dotted line), the player's gaze is directed to the ball at its *present* position (red line), in anticipatory fashion. Optimal control directs action (future motion of the eye) to the expected position (red dashed line) of the ball in the future — and the racket (black dashed line) to the expected position of the ball when motor commands reach the periphery (muscles).


$\cdots$
$\mathbf{z}_t$
$\mathbf{z}_{t+\delta t}$
$\cdots$
$\mathbf{z}_{t-\tau}$
$\mathbf{z}_{t-\tau+\delta t}$
$\mathbf{I}_{t-\tau}$
$\mathbf{I}_{t-\tau+\delta t}$

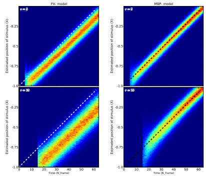


So, how do we handle that?

- markov chain: dynamical system
- diagonal model from Nihjawan: pushing to the future present
- equivalent formulation pulling from the past

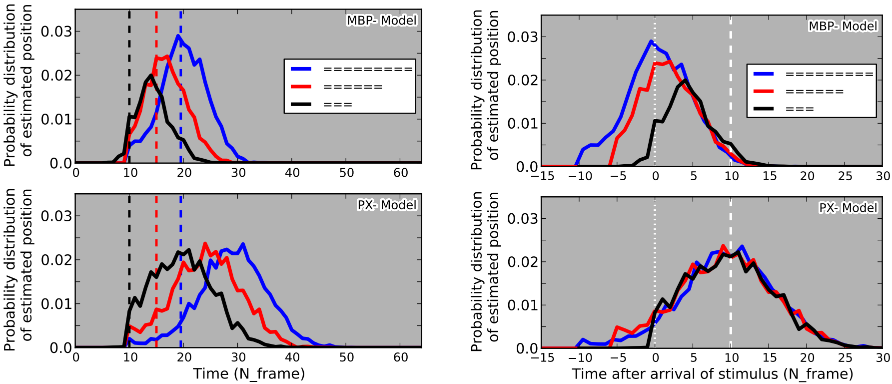


PX- model
MBP- model
$\tau = 5$
$\tau = 15$
Estimated position of stimulus (X)
-0.25
-0.5
-0.75
-1.0
0
10
20
30
40
50
60
Time (N_frame)

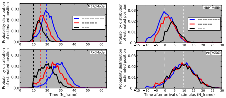


So, how do we handle that?

- results for a delayed dot with simple trajectory: PX vs MBP
- catching up the real trajectory
- time travel

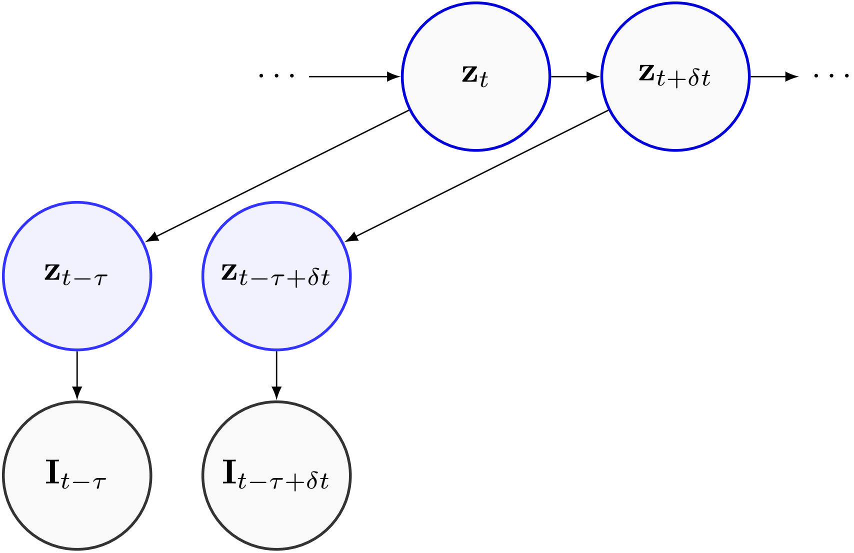


MBP- Model
PX- Model
MBP- Model
PX- Model
=========
======
===
Probability distribution of estimated position
Time (N_frame)
Time after arrival of stimulus (N_frame)



So, how do we handle that?

- let's look at one neuron as a function of time
- PX vs MBP
- Flash-lag effect


$\cdots$
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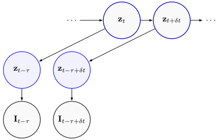
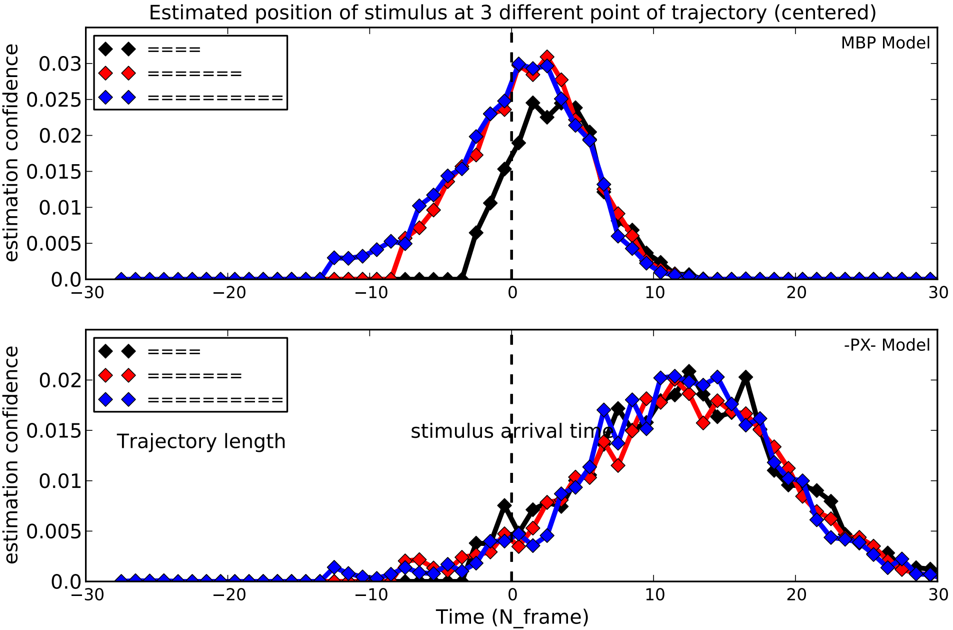


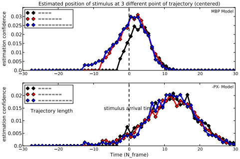
So, how do we handle that?

- diagonal pull model
- Neurobiologically, the application of delay operators just means changing synaptic connection strengths to take different mixtures of generalized sensations and their prediction errors.
- application to a SNN?

Connectivity for motion-based anticipation



Connectivity for motion-based anticipation

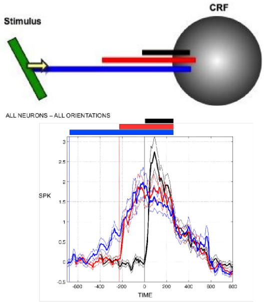


Intermediate summary

- biology
- theory
- ESS

Motion-based anticipation

Experiment



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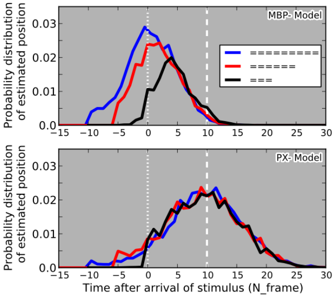
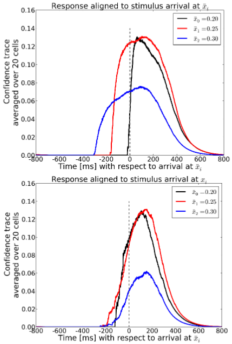


Spiking neural network



This work has been accepted for presentation at the International Joint Conference on Neural Networks 2014:
"Signature of an anticipatory response in area V1 as modelled by a probabilistic model and a spiking neural network" B.Kaplan* M.Khoei* A.Lansner L.Perrinet; * BK & MK contributed equally

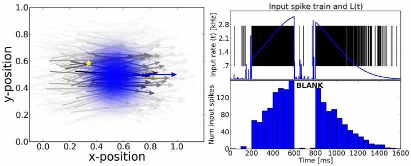
Outline: WP5 - Demo 1.3 : Spiking model of motion-based prediction

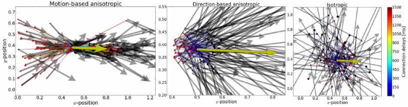
Introduction: Motion-anticipation

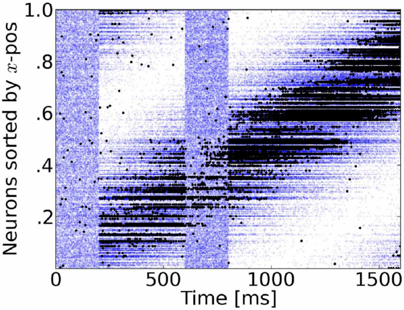
Motion extrapolation - Towards the ESS

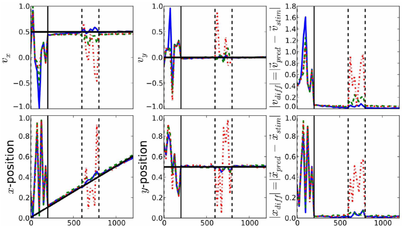
Self-organized connectivity for motion-extrapolation

Motion-based extrapolation



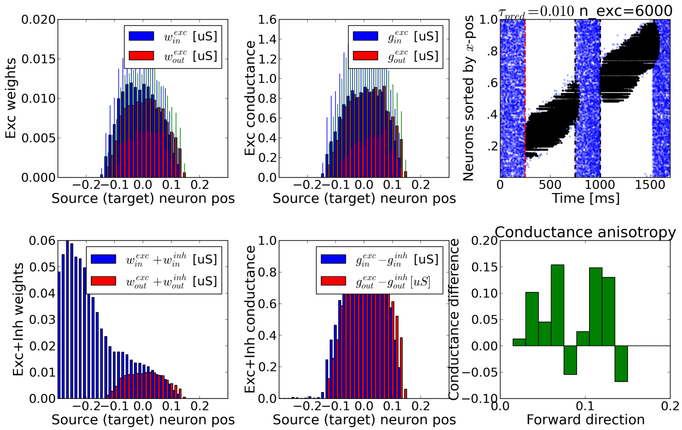






Published in: Kaplan Lansner Masson Perrinet "Anisotropic connectivity implements motion-based prediction in a spiking neural network", Front Comput Neurosci 2013

Net conductance analysis: Towards the ESS



Towards the ESS: Conclusions

- HMF requires specific model changes
- Parameter changes towards ESS regimes $\rightarrow$ qualitative changes in behavior
- Model requires fine tuning
- Unlikely to function on the HMF under given constraints
- $\rightarrow$ Learning instead of hard-wiring connectivity!

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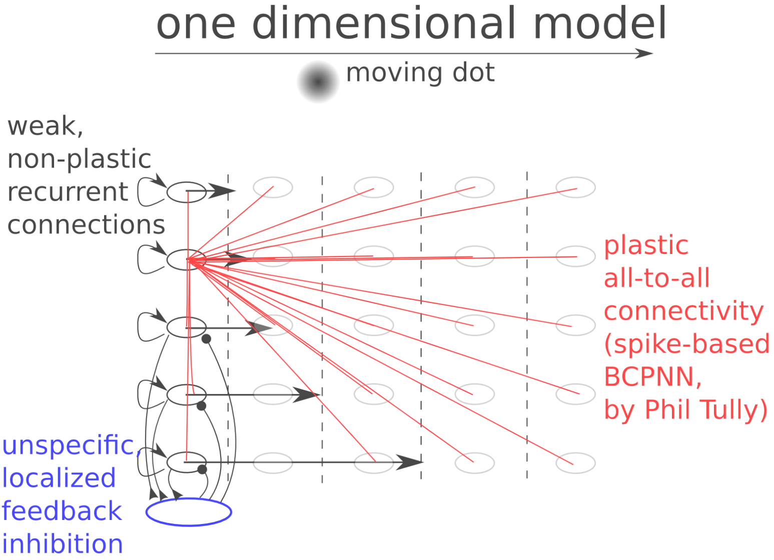
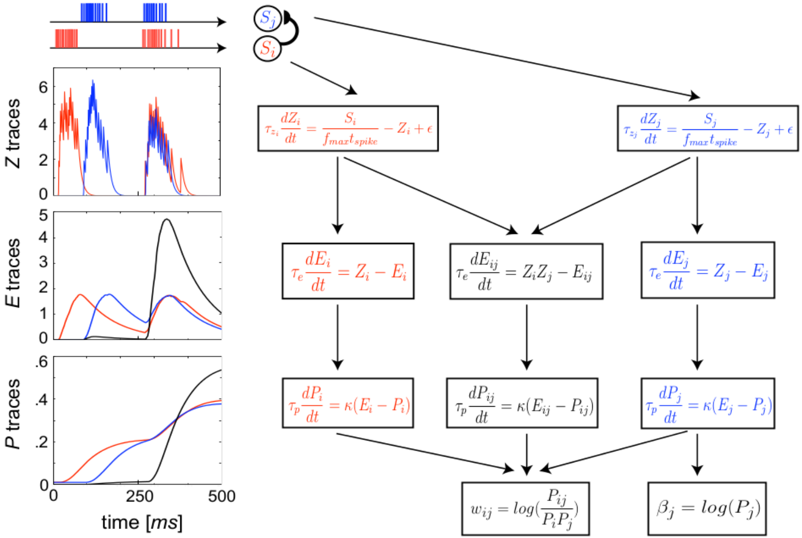
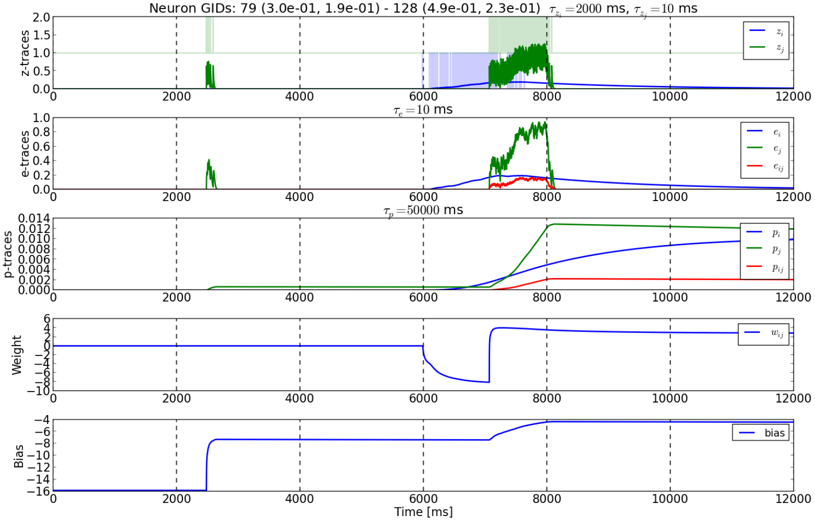


Self-organized connectivity for motion-extrapolation

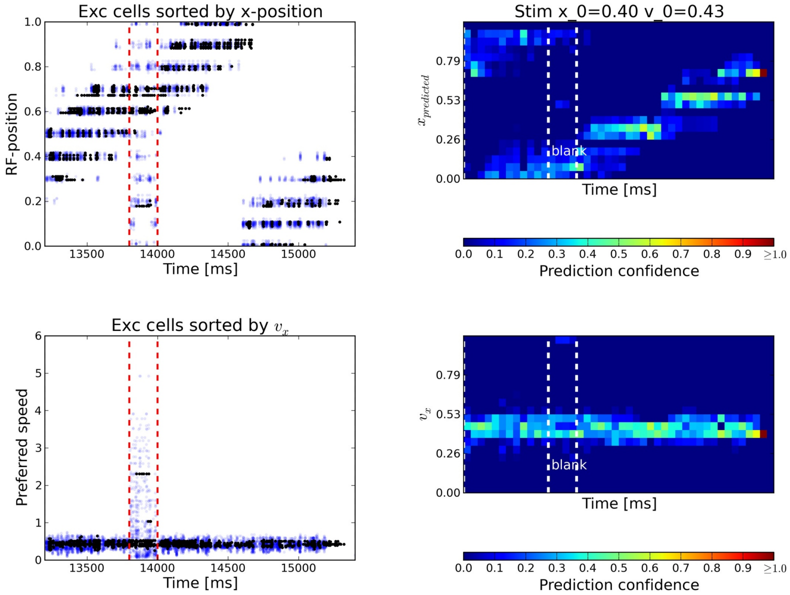


Figures & NEST implementation done by Phil Tully

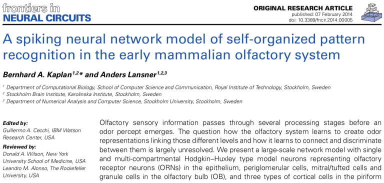
Self-organized connectivity for motion-extrapolation



Testing the system with blank phases



WP5 - Task 5: Multi-scale and hierarchical neural representation and Gestalt processing in modular cortical networks


frontiers in NEURAL CIRCUITS

ORIGINAL RESEARCH ARTICLE
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A spiking neural network model of self-organized pattern recognition in the early mammalian olfactory system

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[2] Stockholm Brain Institute, Karolinska Institute, Stockholm, Sweden
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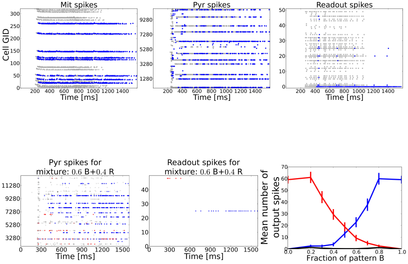
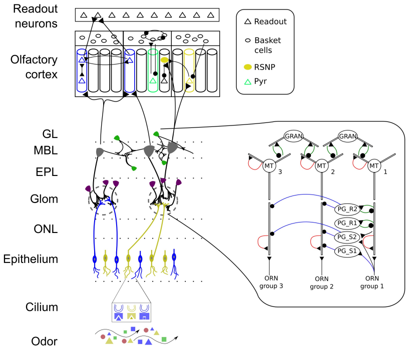
Olfactory sensory information passes through several processing stages before an odor percept emerges. The question how the olfactory system learns to create odor representations linking those different levels and how it learns to connect and discriminate between them is largely unresolved. We present a large-scale network model with single and multi-compartmental Hodgkin–Huxley type model neurons representing olfactory receptor neurons (ORNs) in the epithelium, periglomerular cells, mitral/tufted cells and granule cells in the olfactory bulb (OB), and three types of cortical cells in the piriform





→ Poster-session!

Summary & Plans for Year 4

	Simulation	HMF	SpiNNaker
Motion-anticipation	accepted	Will be done	Will be done
Motion-extrapolation (ME)	published	?	Will be done
Self-organized M.E	in progress	X	Will be done

Modelling:

- Publish the work on self-organized motion-extrapolation

Hardware:

- Work in progress, Continue parameter search to run motion-extrapolation on the HMF
- Verify that trajectory-dependent anticipation signature can be seen using the HMF
- Run motion extrapolation with BCPNN trained connectivity on SpiNNaker

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Training:

- Presentation of different stimuli (different start position, different speeds)
- Plastic all-to-all connectivity between excitatory cells (BCPNN) develops, but weights are updated after the training; no online training
- Testing: Can the learned connectivity implement motion-based prediction, when test stimuli contain a blank-phase?
- work in progress → learning important, because imposing the connectivity is very difficult