Motion-based prediction with neuromorphic hardware

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October 7th, 2015

First GDR BioComp workshop, Saint-Paul de Vence

Coherence detection in a spiking neuron via Hebbian learning

Perrinet L. [a] Samuelides M. [a]

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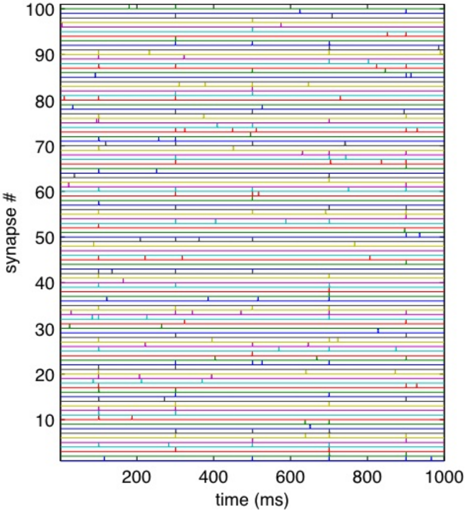

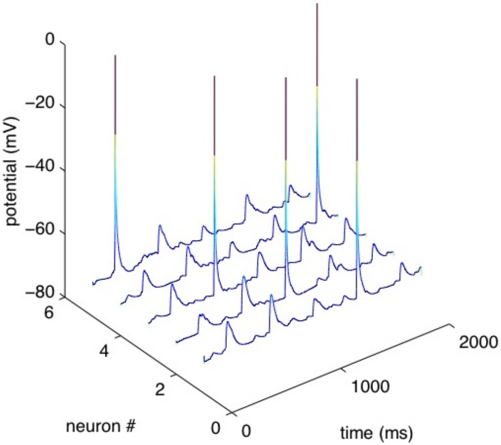

Coding static natural images using spiking event times : do neurons cooperate?

Laurent Perrinet, Manuel Samuelides,Simon Thorpe

See http://blog.invibe.net/posts/2015-05-22-a-hitchhiker-guide-to-matching-pursuit.html

LETTER Communicated by Aapo Hyvarinen

Role of Homeostasis in Learning Sparse Representations

Laurent U. Perrinet
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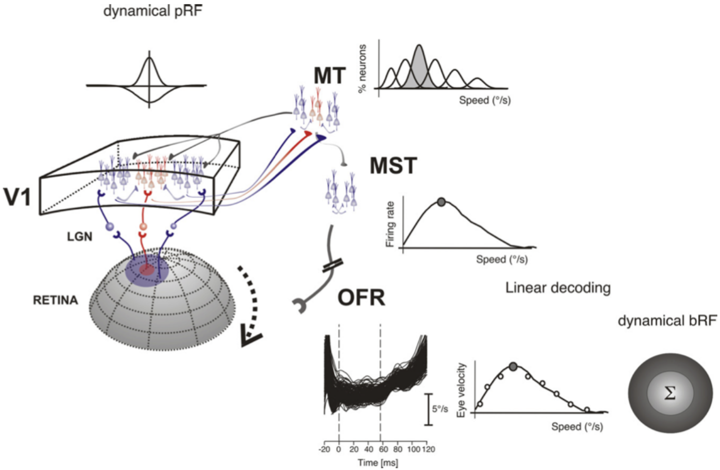
Review

The behavioral receptive field underlying motion integration for primate tracking eye movements

Guillaume S. Masson*, Laurent U. Perrinet

Team Dynamics of Visual Perception and Action (DyVA), Institut de Neurosciences Cognitives de la Méditerranée (INCM), CNRS & Aix-Marseille Université, 13402 Marseille Cedex 20, France



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Available online at www.sciencedirect.com
ScienceDirect
Journal of Physiology - Paris 101 (2007) 46–55

Journal of
Physiology
Paris

www.elsevier.com/locate/jphysparis

Modeling spatial integration in the ocular following response using a probabilistic framework

Laurent U. Perrinet *, Guillaume S. Masson

Institut de Neurosciences Cognitives de la Méditerranée (INCM-UMR 6193, CNRS) 31, ch. Joseph Aiguier, 13402 Marseille Cedex 20, France

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Journal of Physiology - Paris 101 (2007) 64–77

Journal of
Physiology
Paris

www.elsevier.com/locate/jphysparis


Bayesian modeling of dynamic motion integration

Anna Montagnini [a,*], Pascal Mamassian [b], Laurent Perrinet [a], Eric Castet [a], Guillaume S. Masson [a]

Vision Research 51 (2011) 867–880

ELSEVIER

Contents lists available at ScienceDirect

Vision Research

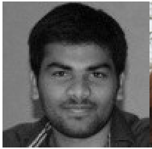
journal homepage: www.elsevier.com/locate/visres

VISION RESEARCH

Pursuing motion illusions: A realistic oculomotor framework for Bayesian inference

Amarender R. Bogadhi [a], Anna Montagnini [a], Pascal Mamassian [b], Laurent U. Perrinet [a], Guillaume S. Masson [a,*]

[a] *Team DyVA, INCM, CNRS & Aix-Marseille Université, Marseille, France*
[b] *LPP, CNRS & Paris Descartes, Paris, France*




J Neurophysiol 107: 3217–3226, 2012.
First published March 14, 2012; doi:10.1152/jn.00737.2011.

Innovative Methodology

Motion clouds: model-based stimulus synthesis of natural-like random textures for the study of motion perception

Paula Sanz Leon, Ivo Vanzetta, Guillaume S. Masson, and Laurent U. Perrinet
Institut de Neurosciences de la Timone, Centre National de la Recherche Scientifique/Aix-Marseille University, Marseille, France

nature neuroscience

More is not always better: adaptive gain control explains dissociation between perception and action

Claudio Simoncini[1], Laurent U Perrinet[1], Anna Montagnini[1], Pascal Mamassian[2] & Guillaume S Masson[1]

Moving objects generate motion information at different scales, which are processed in the visual system with a bank of spatiotemporal frequency channels. It is not known how the brain pools this information to reconstruct object speed and whether this pooling is generic or adaptive; that is, dependent on the behavioral task. We used rich textured motion stimuli of varying bandwidths to decipher how the human visual motion system computes object speed in different behavioral contexts. We found that, although a simple visuomotor behavior such as short-latency ocular following responses takes advantage of the full distribution of motion signals, perceptual speed discrimination is impaired for stimuli with large bandwidths. Such opposite dependencies can be explained by an adaptive gain control mechanism in which the divisive normalization pool is adjusted to meet the different constraints of perception and action.

Motion-based prediction with neuromorphic hardware

Beliefs

- From sparse coding...
- ...to probabilities

Trajectories

- Detecting motion coherence
- Motion extrapolation
- Neuromorphic hardware

Directions

- The Free-energy principle
- Active inference, eye movements & oculomotor delays
- Motion-based anticipation

Perspectives

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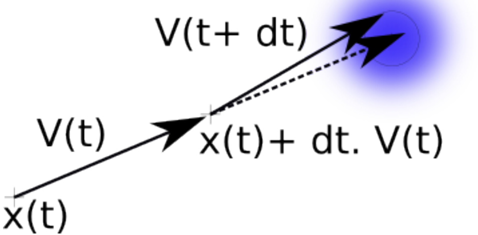
Detecting motion coherence



LETTER **Communicated by Linda Bowns**

Motion-Based Prediction Is Sufficient to Solve the Aperture Problem

Laurent U. Perrinet
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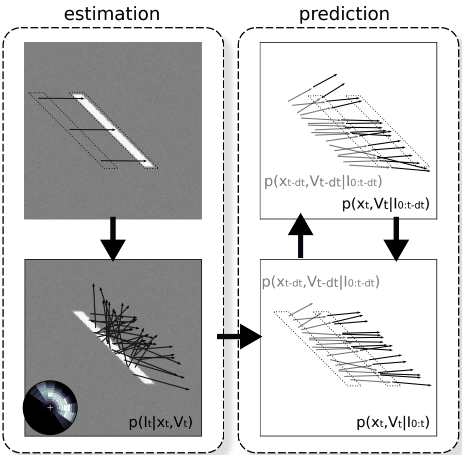
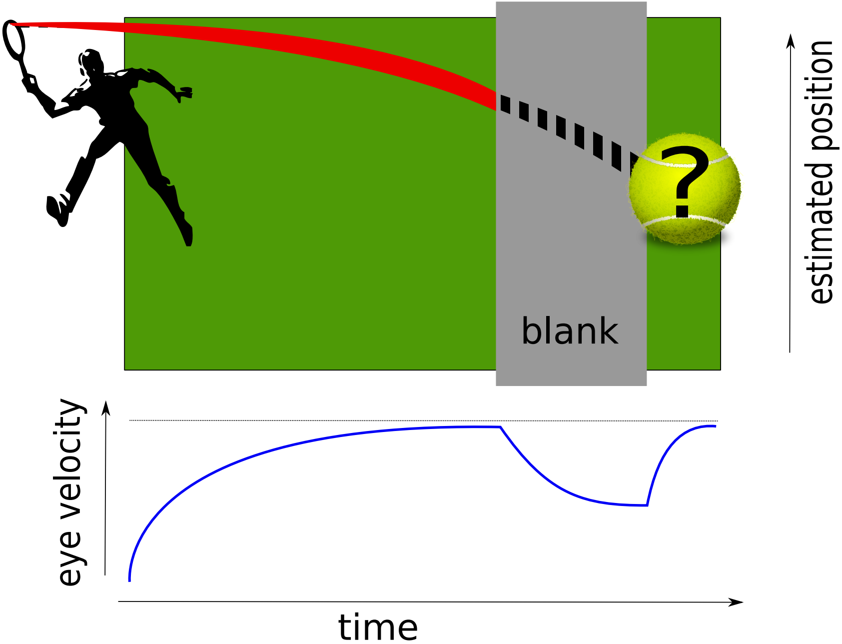
Guillaume S. Masson
guillaume.masson@univ-amu.fr
Institut de Neurosciences de la Timone, CNRS/Aix-Marseille University 13385 Marseille Cedex 5, France

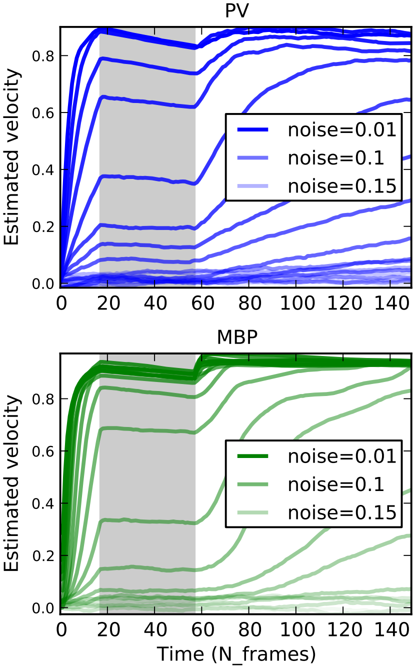


Detecting motion coherence

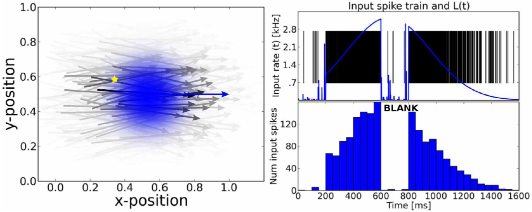
Motion extrapolation

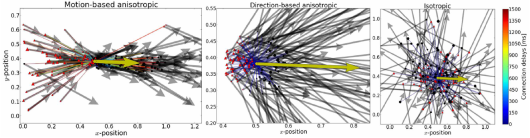


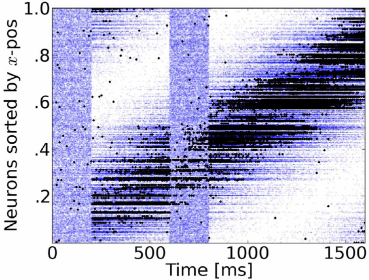
Motion extrapolation

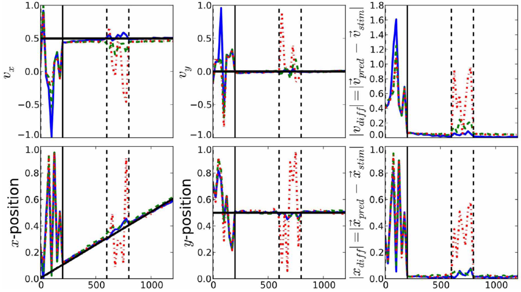


Neuromorphic hardware









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

PyNN: A common language for SNNs

neuralensemble.org/PyNN/

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PyNN

A Python package for simulator-independent specification of neuronal network models.

- Documentation
- Download
- Source code
- Mailing list
- Issue tracker

Licence: CeCILL

PyNN (*pronounced 'pine'*) is a simulator-independent language for building neuronal network models.

In other words, you can write the code for a model once, using the PyNN API and the Python programming language, and then run it without modification on any simulator that PyNN supports (currently NEURON, NEST, PCSIM and Brian).

The PyNN API aims to support modelling at a high-level of abstraction (populations of neurons, layers, columns and the connections between them) while still allowing access to the details of individual neurons and synapses when required. PyNN provides a library of standard neuron, synapse and synaptic plasticity models, which have been verified to work the same on the different supported simulators. PyNN also provides a set of commonly-used connectivity algorithms (e.g. all-to-all, random, distance-dependent, small-world) but makes it easy to provide your own connectivity in a simulator-independent way, either using the Connection Set Algebra (Djurfeldt, 2010) or by writing your own Python code.

The low-level API is good for small networks, and perhaps gives more flexibility. The high-level API is good for hiding the details and the book-keeping, allowing you to concentrate on the overall structure of your model.

The other thing that is required to write a model once and run it on multiple simulators is standard cell models. PyNN translates standard cell-model names and parameter names into simulator-specific names, e.g. standard model `IF_curr_alpha` is `iaf_neuron` in NEST and `StandardIF` in NEURON, while `SpikeSourcePoisson` is a `poisson_generator` in NEST and a `NetStim` in NEURON.

Even if you don't wish to run simulations on multiple simulators, you may benefit from writing your simulation code using PyNN's powerful, high-level interface. In this case, you can use any neuron or synapse model supported by your simulator, and are not restricted to the standard models.

PyNN is a work in progress, but is already being used for several large-scale simulation projects.

Citing PyNN

If you publish work using or mentioning PyNN, we would appreciate it if you would cite the following paper:

Davison AP, Brüderle D, Eppler JM, Kremkow J, Muller E, Pecevski DA, Perrinet L and Yger P (2008) PyNN: a common interface for neuronal network simulators. *Front. Neuroinform.* **2**:11 doi:10.3389/neuro.11.011.2008 [pdf]

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BELIEFS

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...to probabilities

TRAJECTORIES

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DIRECTIONS

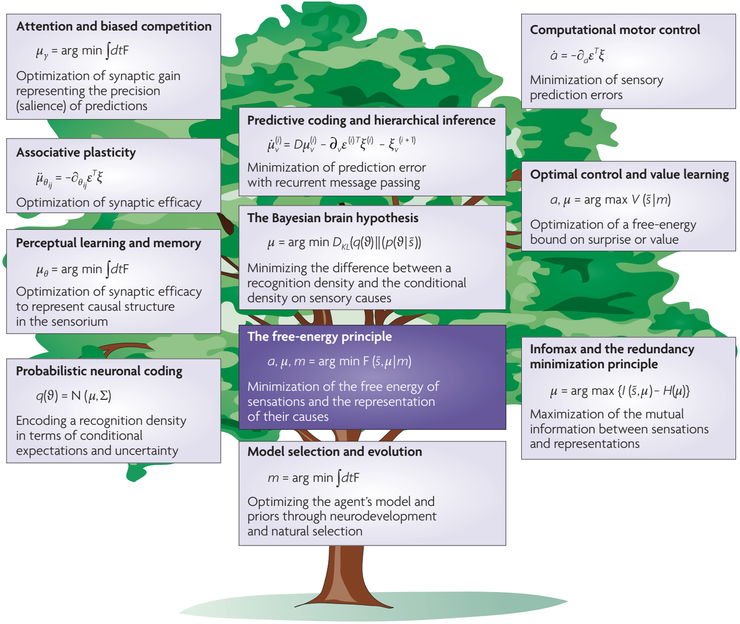
The Free-energy principle

Active inference, eye movements & oculomotor delays

Motion-based anticipation

Perspectives

The Free-energy principle



The Free-energy principle

frontiers in
PSYCHOLOGY

ORIGINAL RESEARCH ARTICLE
published: 28 May 2012
doi: 10.3389/fpsyg.2012.00151

Perceptions as hypotheses: saccades as experiments

Karl Friston[1]*, Rick A. Adams[1], Laurent Perrinet[1,2] and Michael Breakspear[3]

[1] *The Wellcome Trust Centre for Neuroimaging, University College London, London, UK*
[2] *Institut de Neurosciences de la Timone, CNRS - Aix-Marseille University, Marseille, France*
[3] *Queensland Institute of Medical Research, Royal Brisbane Hospital, Brisbane, QLD, Australia*

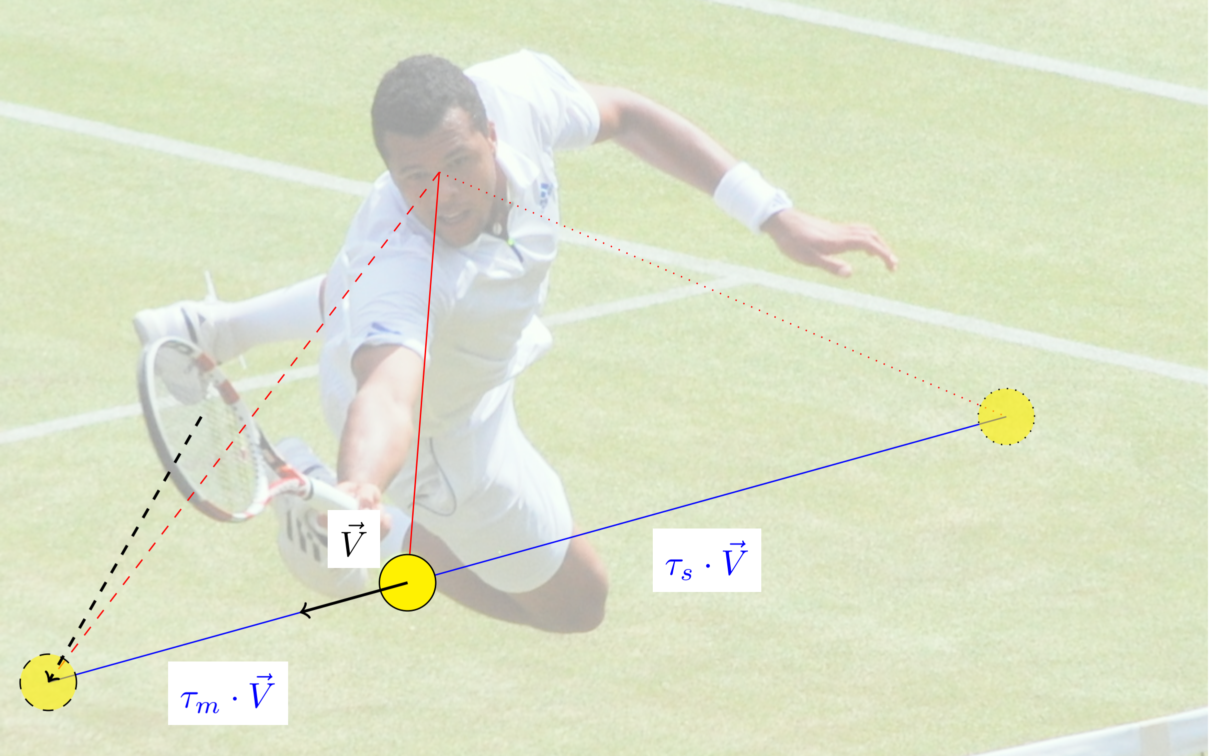
OPEN ACCESS Freely available online

PLOS | ONE

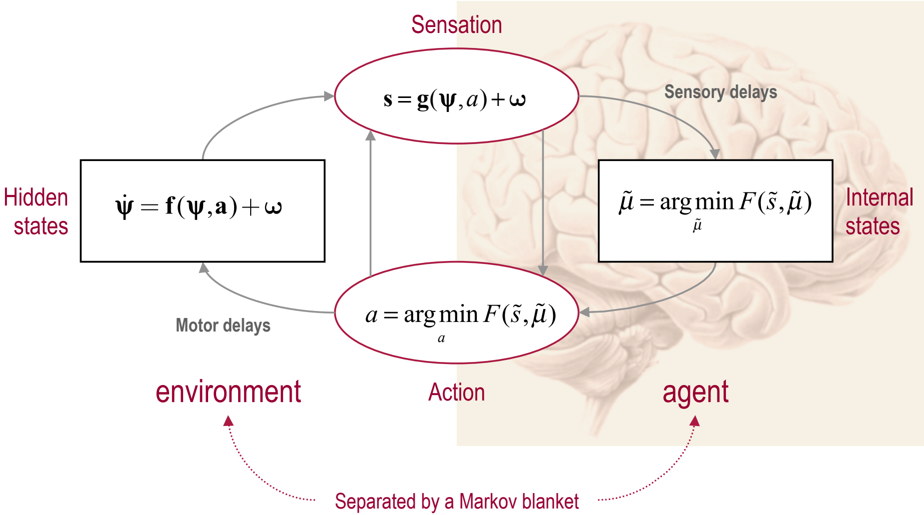
Smooth Pursuit and Visual Occlusion: Active Inference and Oculomotor Control in Schizophrenia

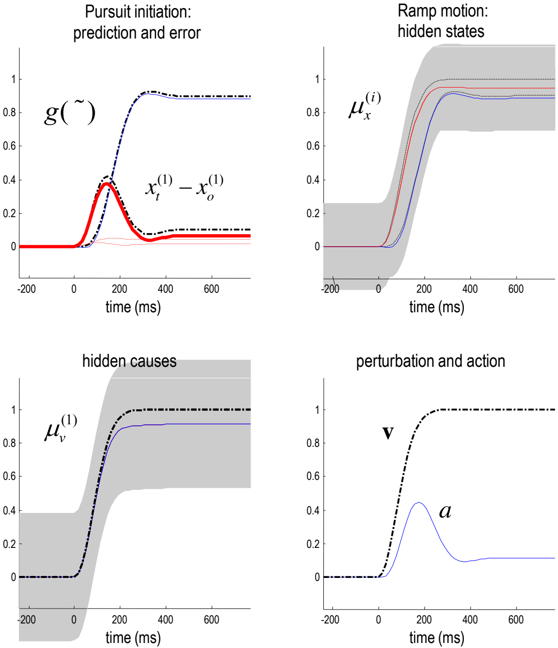
Rick A. Adams[1]*, Laurent U. Perrinet[1,2], Karl Friston[1]

1 The Wellcome Trust Centre for Neuroimaging, University College London, Queen Square, London, United Kingdom, **2** Institut de Neurosciences de la Timone, CNRS – Aix-Marseille University, Marseille, France

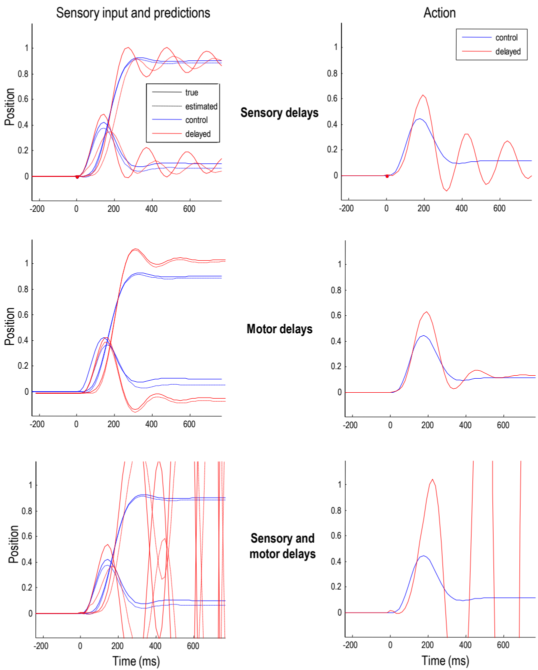

$\vec{V}$
$\tau_s \cdot \vec{V}$
$\tau_m \cdot \vec{V}$

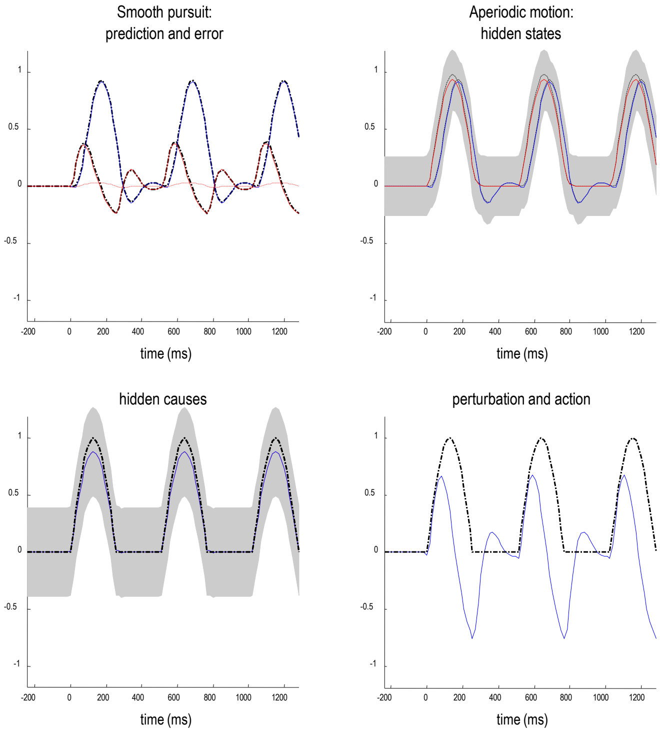
Active inference, eye movements & oculomotor delays



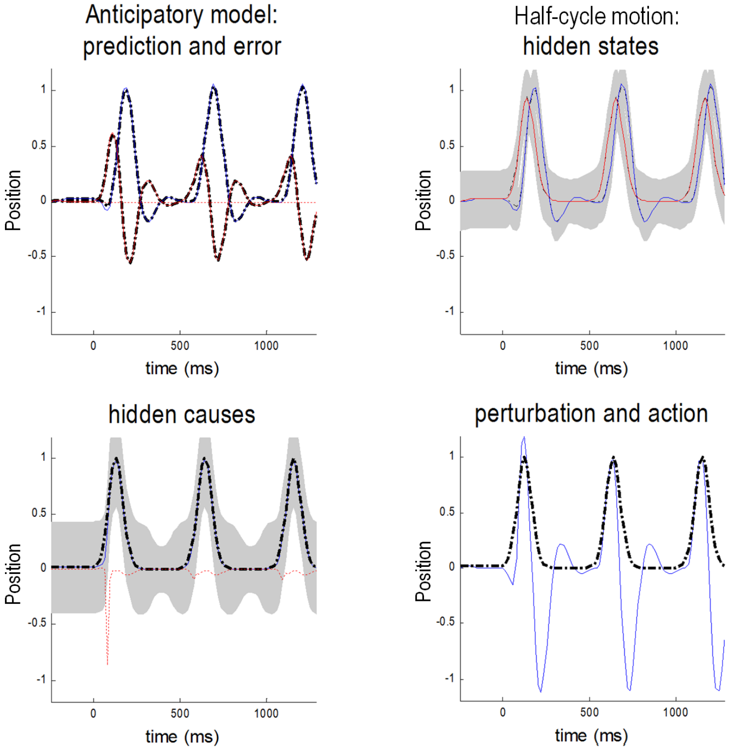


Pursuit initiation: prediction and error
$g(\tilde{\ })$
$x_t^{(1)} - x_o^{(1)}$
time (ms)
Ramp motion: hidden states
$\mu_x^{(i)}$
time (ms)
hidden causes
$\mu_v^{(1)}$
time (ms)
perturbation and action
$\mathbf{v}$
a
time (ms)


Sensory input and predictions
Action
Position
true
estimated
control
delayed
Sensory delays
Motor delays
Sensory and motor delays
-200
0
200
400
600
0
0.2
0.4
0.6
0.8
1
Time (ms)



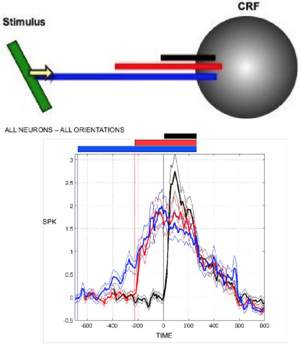
Smooth pursuit:
prediction and error
Aperiodic motion:
hidden states
hidden causes
perturbation and action
time (ms)
time (ms)
time (ms)
time (ms)


Anticipatory model:
prediction and error
Half-cycle motion:
hidden states
hidden causes
perturbation and action
Position
time (ms)
1
0.5
0
-0.5
-1
0
500
1000

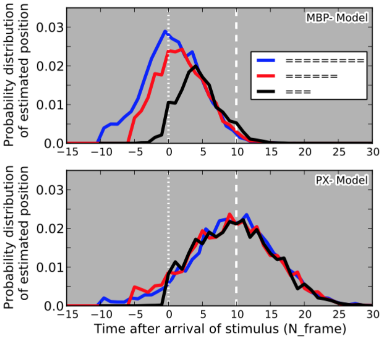
Motion-based anticipation

Motion-based anticipation

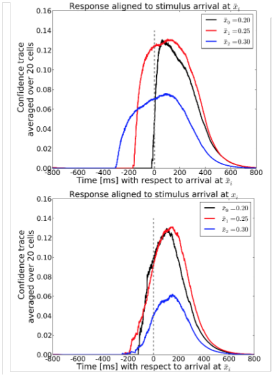
Experiment



Abstract, probabilistic model



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 modeled by a probabilistic model and a spiking neural network" B. Kaplan* M. Khoei* A. Lansner L. Perrinet (* BK & MK contributed equally)

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