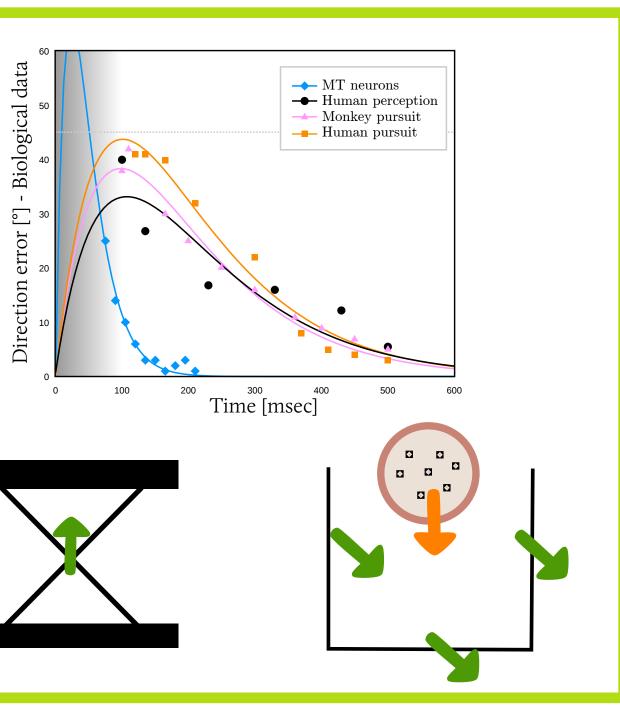


We propose a dynamical model of 2D motion integration where diffusion is modulated by luminance information. It incorporates feedforward, feedback, and inhibitive lateral connections and is inspired by the neural architecture and dynamics of motion processing cortical areas in the primate (V1, V2, and MT). The first aspect of our contribution is to propose a new anisotropic integration model, offering a competitive alternative to less parsimonious models based on a large set of cortical layers. A second aspect that is often ignored is that biological computation of global motion is highly dynamical. Our model can also explain several properties of MT neurons regarding the dynamics of selective motion integration, a fundamental property of object motion disambiguation and segmentation.

## Goals

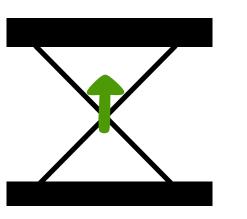
#### $\sim$ Integrate 2D motion

→ Reproduce perception Berzhanskaya et al. (2007) → Reproduce dynamics



## $\sim$ With a bio-inspired model

 $\rightarrow$  Cortical layers, feedback, . . . Bayerl & Neumann (2004)



# Model overview

#### $\sim$ Cortical areas

- → Activity model
- → Retinotopic neurons
- → Distributed velocity

 $p_i(t, x, v)$ 

## $\sim$ Multiple interactions

→ Integration via feedforward from VI to MT

 $p_1$ 

(V1)

- $\rightarrow$  Selection via local inhibitive connections
- → Propagation via feedback from MT to VI

#### $\sim$ Luminance-gated diffusion

- → Feedforward integration is anisotropic
- $\rightarrow$  Luminance (form) information modulates integration

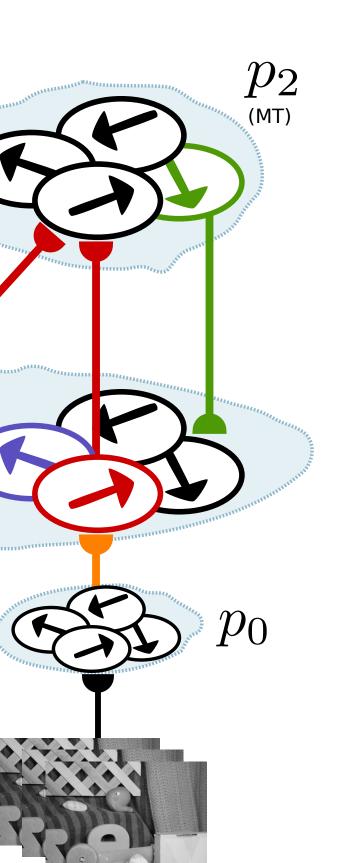
Bibliography **Baeck & Sajda (2005)** Neural Computation, 5(8) Bayerl & Neumann (2004) Neural Computation, 16

Berzhanskaya (2007) Spatial Vision, 20(4) Bowns (1996) Vision Research, 36 Huang et al. (2007) Neuron, 53



# A dynamical neural model of motion integration É. Tlapale<sup>†</sup>, P. Kornprobst<sup>†</sup>, G.S. Masson<sup>‡</sup>

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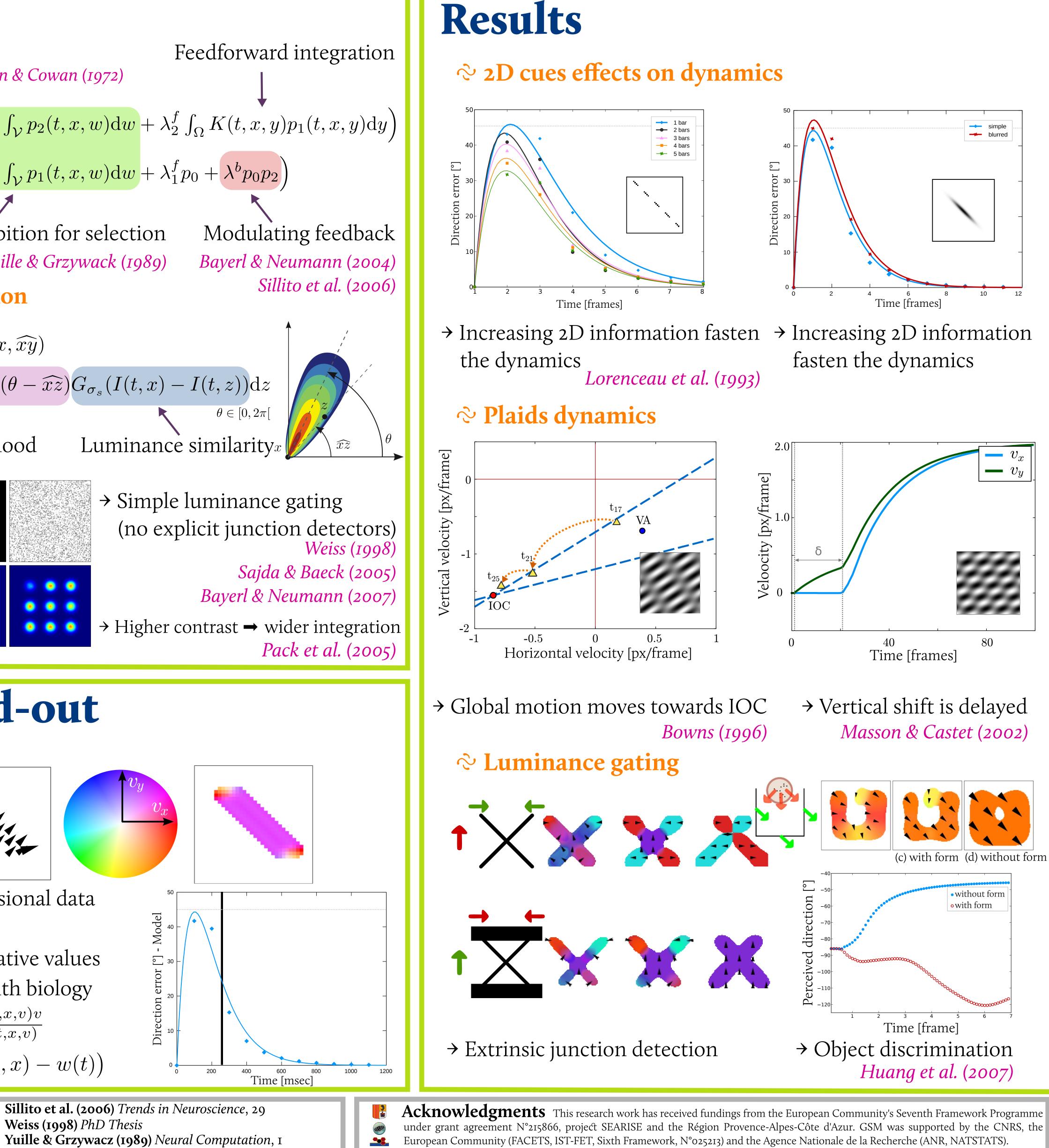
(r) → Simplify multi-dimensional data  $\sim$  Biological read-outs → Fetch simpler quantitative values  $\rightarrow$  Allows comparison with biology  $m_i(t,x) = \frac{\sum_{v \in \mathcal{V}} p_i(t,x,v)v}{\sum_{v \in \mathcal{V}} p_i(t,x,v)}$  $\frac{\mathrm{d}w}{\mathrm{d}t} = \lambda \left( \sum_{x \in \Omega} m_2(t, x) - w(t) \right)$ Lorenceau et al. (1993) Vision Research, 33 Masson & Castet (2002) J Neuroscience, 22 Pack et al. (2005) J Neurophysiol, 93

Formalism  $\sim$  Neural fields Wilson & Cowan (1972)  $\frac{\partial p_2}{\partial t} = -\lambda_2 p_2 + S_2 \left( -\lambda_2^l G_{\sigma_2^l} * \int_{\mathcal{V}} p_2(t, x, w) \mathrm{d}w + \lambda_2^f \int_{\Omega} K(t, x, y) p_1(t, x, y) \mathrm{d}y \right)$  $\frac{\partial p_1}{\partial t} = -\lambda_1 p_1 + S_1 \left( -\lambda_1^l G_{\sigma_1^l} * \int_{\mathcal{V}} p_1(t, x, w) \mathrm{d}w + \lambda_1^f p_0 + \lambda^b p_0 p_2 \right)$ Lateral inhibition for selection Decay Yuille & Grzywack (1989)  $\sim$  Luminance modulation  $K(t, x, y) = G_{\sigma_2^f}(|x - y|)\phi(t, x, \widehat{xy})$  $\phi(t, x, \theta) = \int_{\Omega} G_{\sigma_x}(x - z) G_{\sigma_\theta}(\theta - \widehat{xz}) G_{\sigma_s}(I(t, x) - I(t, z)) dz$ Directional neighborhood • • • • • • • • . . . . . . . . . . Defining read-out  $\sim$  Color-coded results





Weiss (1998) PhD Thesis



http://www-sop.inria.fr/neuromathcomp