Implementation of models showing emergence of cortical fields and maps

BrainScaleS's Demos 1, Task 4

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Using the ESS + Neuromorphic hardware Workshop

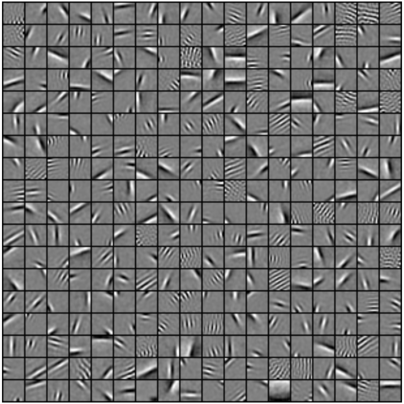
Outline: BrainScaleS's Demos 1, Task 4

Example 1: Unsupervised learning of natural images

Example 2: Topographic models and association fields

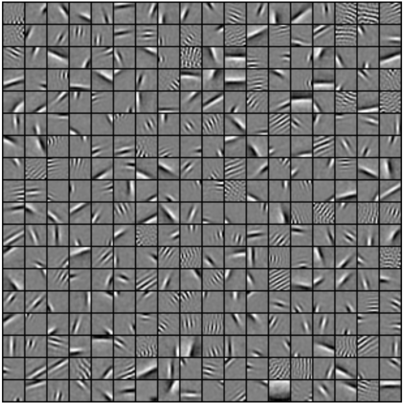
Example 3: Motion-based prediction

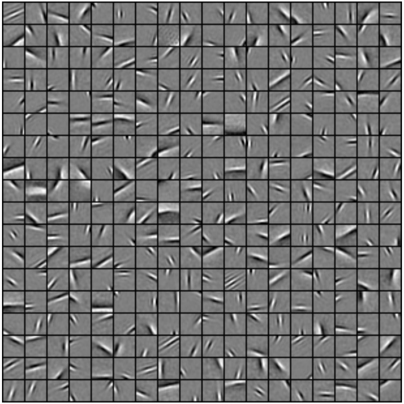
Example 1: Unsupervised learning of natural images



$$\mathcal{C}(\mathbf{s}|\mathbf{x}, \mathbf{A}) = \frac{1}{2.\sigma^2}.\|\mathbf{x} - \sum_j s_j.\mathbf{A}_j\|^2 + \lambda.\|\mathbf{s}\|_0$$

Example 1: Unsupervised learning of natural images

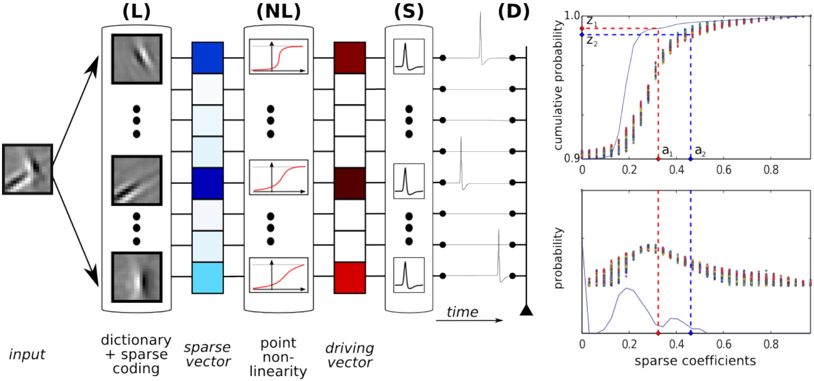




$\mathcal{C}(\mathbf{s}|\mathbf{x}, \mathbf{A}) = \frac{1}{2.\sigma^2}.\|\mathbf{x} - \sum_j s_j.\mathbf{A}_j\|^2 + \lambda.\|\mathbf{s}\|_0$

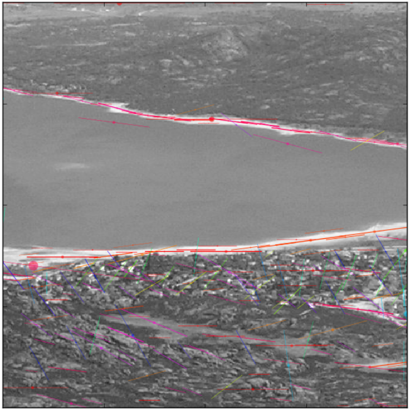
(Perrinet, 2010, Neural Computation)

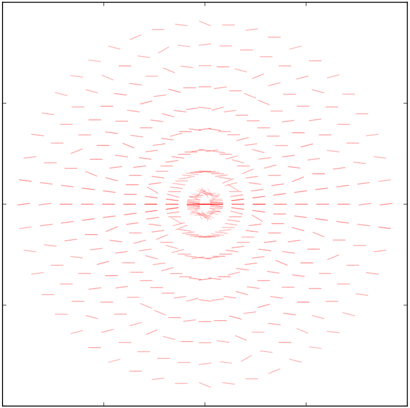
Example 1: Unsupervised learning of natural images



(Perrinet, 2010, Neural Computation)

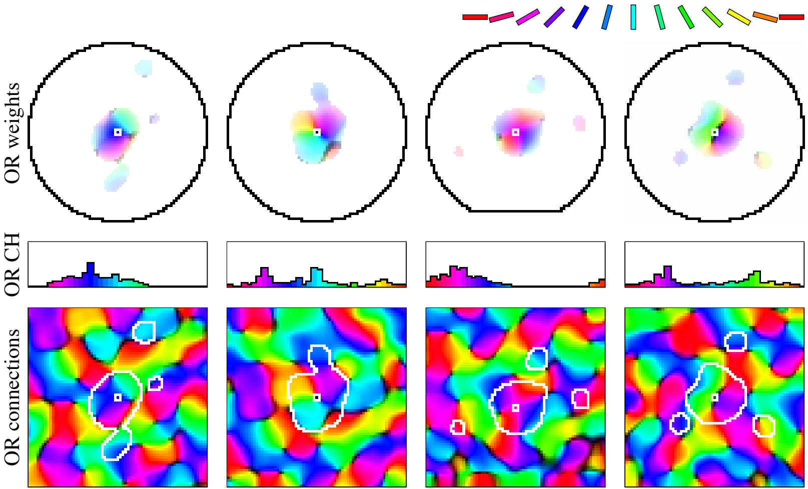
Example 2: Topographic models and association fields





(Perrinet, Bednar & Fitzpatrick, 2011, SfN)

Example 2: Topographic models and association fields



(*a*) Connections in iso-OR patches

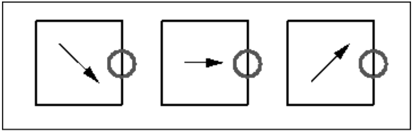
(*b*) Connections in OR pinwheels

(*c*) Connections in OR saddles

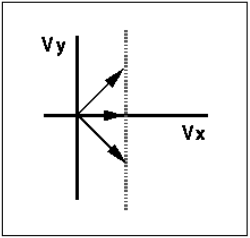
(*d*) Connections in OR fractures

(Miikkulainen et al., 2005, Computational Maps in the Visual Cortex)

Example 3: Motion-based prediction

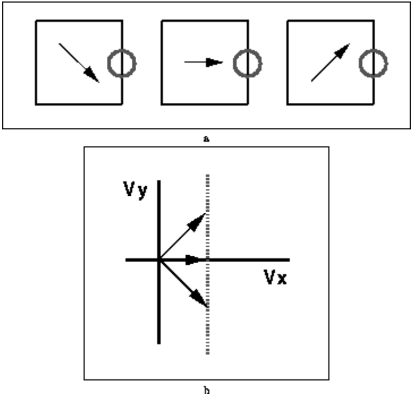


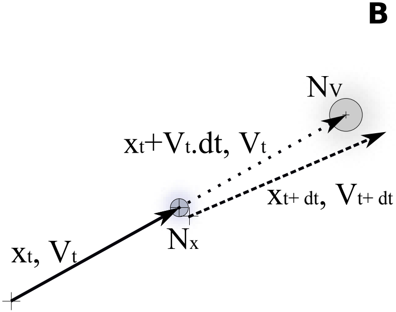
a



b

Example 3: Motion-based prediction





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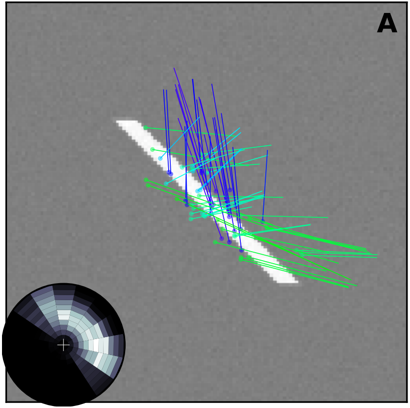

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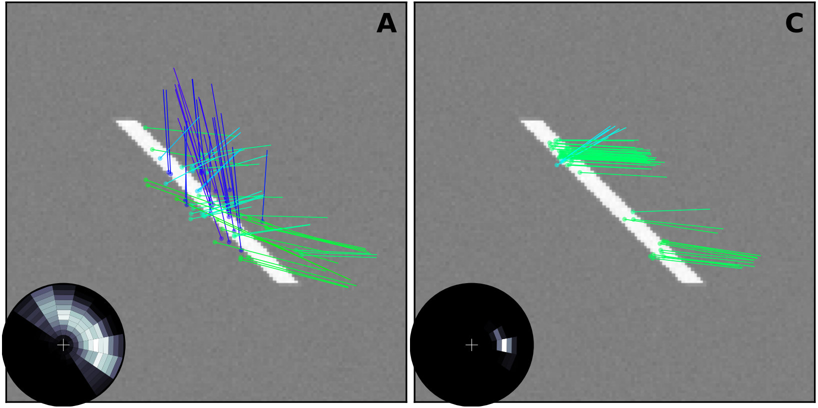
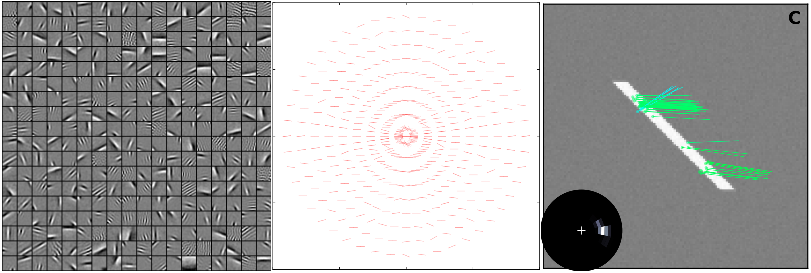


Summary



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Task 4. Emerging properties of large-scale networks

In connection with WP1 and WP2, we will link dynamics of spiking networks and neural fields with probabilistic computations for early sensory processing. Emphasis will be put onto the role of diffusion, in particular within a cortical area through lateral interactions. In addition, such diffusion is modulated in a context-dependent manner through re-entrant signals from higher stages along the cortical hierarchy. We have previously elaborated probabilistic (Perrinet & Masson, 2010) or dynamical (Tlapale et al., 2010; Grimbert et al., 2006) models of motion information diffusion along cortical retinotopic trajectories. Probabilistic models give a complete representation of the information that is represented by populations of neurons. Particle filtering methods will be used to investigate how this propagation can solve low-level computational problems such as motion integration, extrapolation or prediction in visual (Mason & Ilg, 2010) or somatosensory (Shulz et al. 2006) cortices. Partner TUG will test his new model for emulating such particle filters in networks of spiking neurons. With Partner INRIA, neural-mass models will describe this diffusion using analogue values representing the activity at a given point in the field, for instance by using a tensor representation of texture elements (Chossat & Faugeras, 2009). This will be confronted with an exploration of the neural activity and behavior using specific stochastic stimuli with controlled complexity as defined in WP4 --- Task 1. Comparison between these probabilistic and neural-mass approaches will enable us to build local population-based models and explore their computational properties. We will investigate how the theoretical link between these two classes of models allows to bridge micro and mesoscopic descriptions of the same neuronal dynamics as observed in a few dedicated tasks such as contour and motion integrations and extrapolation (see WP1). Using the existing integration of these implementations within PyNN, we will next implement these models in the networks developed in Task 2 in order to test them in HPC and HMF. Using this architecture, we will build models testing the emergence of maps of cortical receptive fields optimally tuned to elaborate sparse, multi-scale representations of the visual or tactile world. The challenging question is whether functional models of self-organization can be translated in large-scale networks of spiking neurons (Perrinet, 2010). We will investigate how spatio-temporal receptive fields and higher-order feature detectors (such as curve contours) can emerge through learning of statistical regularities in the images and study how hierarchic structures can arise as a self-organized emerging property.

- Deliverable D5-4.1: Implementation of models showing emergence of cortical fields and maps
- Due in month 48, 2014/09/30 `https://brainscales.kip.uni-heidelberg.de/jss/Deliverables?m=showDeliverable&bk_deliverableID=25`
- link with WP 5 Task 5: Multi-scale and hierarchical neural representation and Gestalt processing in modular cortical networks