Edge statistics in natural versus laboratory images

Implications for understanding lateral connectivity in primary visual cortex with respect to animal environments

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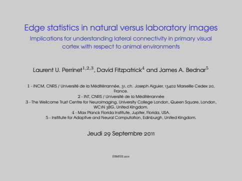
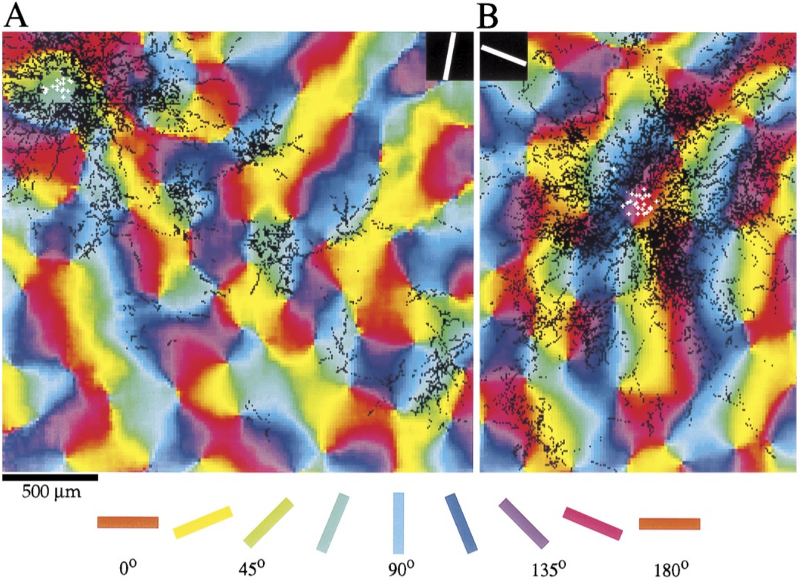
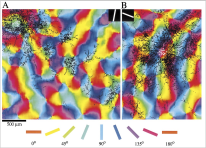


(hello) Hello, I am Laurent U. Perrinet . I work at the team “Vision & Behavior” supervised by Guillaume Masson in Marseille and I am currently on visit in Karl Friston’s team in London at the UCL. My interests are in computational neuroscience, in discovering the code used to efficiently represent images in the early visual system and the application to novel computational paradigms (sparsity, probabilities, prediction, hierarchical models). We now “compile” such models as neural networks and as parallel wafer systems in the BrainscaleS project.

(today) Today, I will talk about the potential role of environment of animals as measured by edge statistics in understanding lateral connectivity in the primary visual cortex. This will illustrate an application of techniques familiar to you, such as sparse coding, to a neuroscience problem. Using these results, I will give some predictions on neurophysiological observations. This is joint work with James Bednar who is an expert in topographical models of cortical areas and David Fitzpatrick who is a leading neuroscientist, in particular in deciphering the pattern of lateral connectivity ...



(Bosking et al, 1997, Journal of Neuroscience)



(Bosking et al, 1997, Journal of Neuroscience)

- (neural) if one looks at the primary visual area in the occipital lobe of the cortex using a technique called optical imaging as here in the treeshew by Bosking and colleagues under the supervision of DF, one could represent the distributed, topographical representation of orientation. OS is represented by hue, and typical structures are magnified right: stripes (on the periphery) and pinwheels. You can understand this as a packing of a 3D feature space on the 2D surface of the cortex (see Petitot for instance).
- (lateral) using a tracer injected in some group of neurons with similar orientations and position, they could map the network of lateral connectivity. There is a structure in this connectivity towards locality (B) + connecting iso orientations even on long ranges (A),
- (colin) ... that is to colinearities. This is a typical assumption that the role of lateral interactions is to enhance the activity of neurons which are collinear : it is the so-called *association field* formalized in Field 93,
- (model) knowing the structure of this connectivity is important for our understanding of the neural computations operating in the primary visual cortex as is captured by models such as the topographically-based LISSOM from Miikulainen and Bednar

(link) there is therefore a dependency between the co-linearity of the input to the primary visual cortex, the connectivity pattern of lateral interactions and our understanding of this machinery underlying early vision. This is quite general and present in the somatosensory and auditory systems.

(natural) but this connection between natural scene statistics and neurophysiology is based on some definition of what is a natural image, which could be something like this (imagine the treeshew sitting on a tree and seeing this scene),

(lab) However, what is observed in a laboratory environment is quite different. Here I show a picture taken from inside a typical cage as it would be seen from the animal. It is qualitatively quite different and it seems that there are more collinear edges. Our goal here is to quantitatively measure this difference and to give some predictions as to how this may play a role in neurophysiolocal experiments compared to what would be observed in wild animals (plasticity?).

Outline: Edge statistics in natural versus laboratory images

Introduction: linking neural structure to natural scenes

Method: detection of edges

- Geisler, 2001
- Log Gabor representation
- Competition-Optimized Matching Pursuit

Results: natural vs. laboratory images

- Some examples of edge extraction
- Second-order statistics
- Quantitative difference using classification

Take-home message

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1. first, we will define a framework adapted to the computation of second-order edge statistics, using the detection of edges in natural images and laboratory images
2. then, we will show the results of simulations on both classes of images and show the observed statistics
3. Finally, we will summarize results and present some predictions and perspectives

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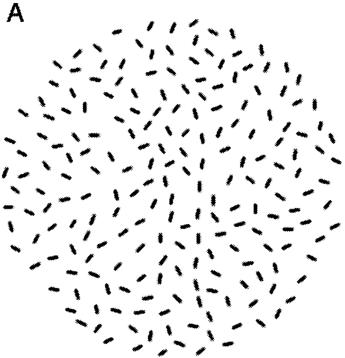
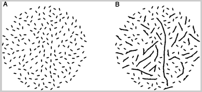
Take-home message

Geisler, 2001



(Geisler et al., 2001, Vision Research)

Geisler, 2001



(Geisler et al., 2001, Vision Research)

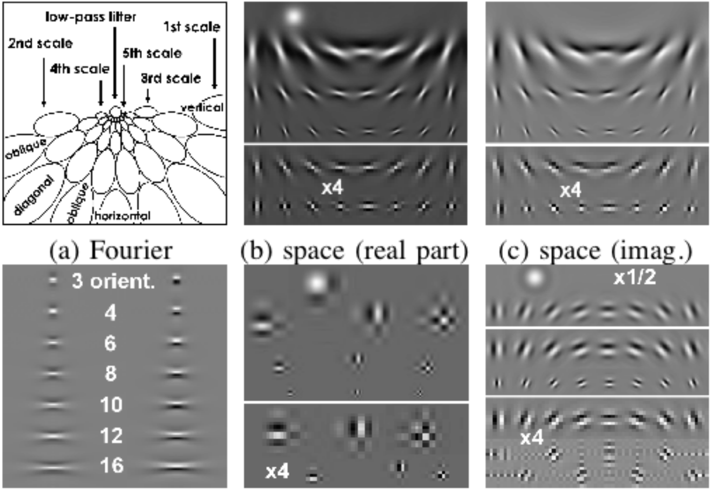
A successful method to measure the statics of second order was shown by (Geisler et al., 2001, Vision Research) on a set of natural images

(definition) this shows, aligned on a central edge (Left) the most probable difference of orientation at each distance and angle, showing the tendency of having collinear, parallel structures in natural images and (Right) the most probable angle for each difference of difference of angle and distance, showing a prior bias in natural image for cocircular edges

(Gestalt) using this measure of second-order statistics combined with an iterative grouping rule, they could reproduce diverse behavioral results at a global level. This thus gives a link between this local dependence and the emergence of some global, Gestalt rules

(neural) however this was done using an heuristic and on a limited number of images and that’s why I collaborated with James Bednar to validate the results on natural images and extend on a quantitative comparison with laboratory environment

Log Gabor representation

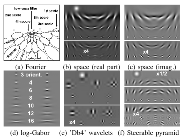


(a) Fourier (b) space (real part) (c) space (imag.)

(d) log-Gabor (e) 'Db4' wavelets (f) Steerable pyramid

(Fischer et al, 2007, International Journal of Computer Vision)

Log Gabor representation



(a) Fourier (b) space (real part) (c) space (imag.)
(d) log-Gabor (e) 'Db4' wavelets (f) Steerable pyramid

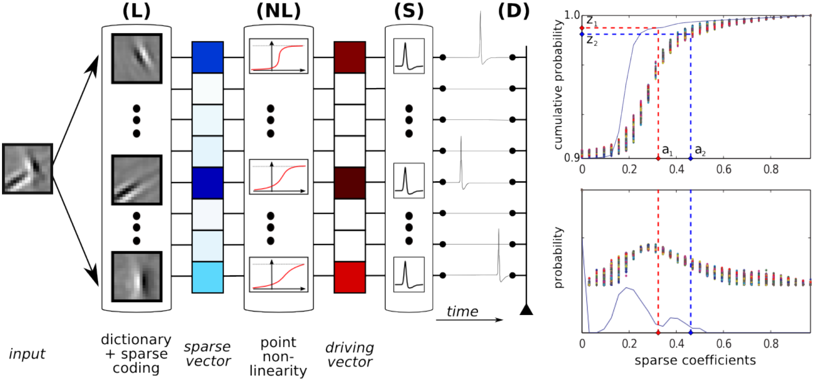
(Fischer et al, 2007, International Journal of Computer Vision)

in order to do that, we first used a linear transformation using a log-gabor representation

(definition) this representation is a good and generic model of edges as defined by their shape, orientation and scale. It matches what is well described for the response of simple cells' response in area V1. obviously, these are over-complete, but their correlation is easy to compute and allow for a relative translation-rotation-scale invariance

(fischer) we proved that this was better adapted to the extraction of edges than gabors.

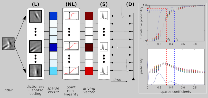
Competition-Optimized Matching Pursuit



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

(Perrinet, 2010, Neural Computation)

Competition-Optimized Matching Pursuit



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

(Perrinet, 2010, Neural Computation)

(MP) from this linear representation, we seemed for the most sparse representation using a ℓ_0 norm approach for which Matching Pursuit which we proved to be mappable to some neural mechanisms, including a model of complex cells' response.

(COMP) most importantly, we have proven that is well adapted to natural images when we optimized the gain of each filter so that the atom that is chosen at every matching step is *a priori* equiprobable. in practice, this tunes the gain of different frequency bands and orientations. I refer to this paper for more details.

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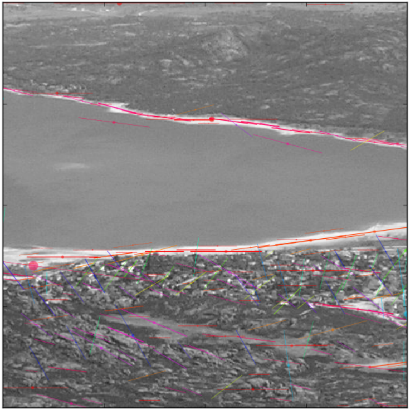
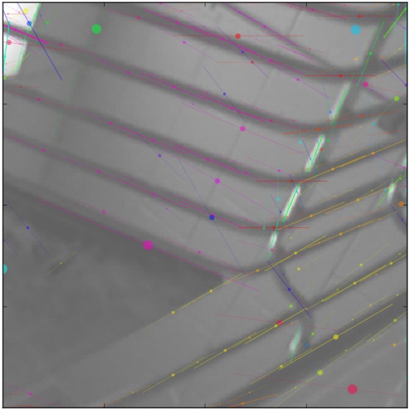
Some examples of edge extraction

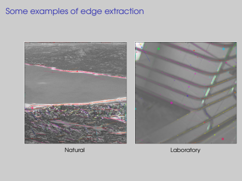


Natural



Laboratory

2011-11-09



(edges) We show here the results of the edge extraction on a set of patches extracted from both database. The hue gives the orientation, the length represents the scale.

(stats) This shows that edges are qualitatively well extracted. This was confirmed by the reconstruction of the images from the edges (not shown)

(qual) Both images classes appear qualitatively different...

Second-order statistics

../figures/edgestats_big_proba-edgefield_colin_Yelan.pdf

Natural

../figures/edgestats_big_proba-e

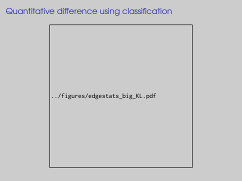
Laboratory

(colin) When we compute the second-order statistics from these edges, one reproduces the results from Geisler. Here I show for each distance and angle the most probable difference of angle, showing that collinear and parallel edges predominate.

(lab) when using the images from the laboratory environment, one finds a different pattern where the colinearity clearly dominates: this quantitatively shows the difference between the edges's second-order statistics. Obviously, this should have a consequence on

Quantitative difference using classification

../figures/edgestats_big_KL.pdf



... by using a simple criteria (the KL distance between the histogram of one image to the average histogram go each class), one gets a simple, translation, orientation and scale invariant classifier which can efficiently differentiate between one natural image and a lab image. it comes as a big surprise as this is only based on some local characteristic, but it sufficient to get good classification. this gives also a quantitative method (measuring the area under the ROC curve) to rate different methods and databases. The result as computed by the Area Under the Curve is of 99.3% accuracy.

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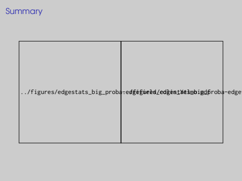
Summary

../figures/edgestats_big_proba-edgefield_clinYelmo.pdf	../figures/edgestats_big_proba-edgef



To summarize, during this talk I hope I convinced you that

- using Matching Pursuit may be efficiently used to extract edges on natural images using an optimization of the matching step,
- the second-order statistics of edges are very different in different environments and this may have consequences on the pattern of lateral interactions that is learned by the primary visual cortex due to plasticity and therefore on the results of Bosking and therefore on our understanding through models
- these results may have some repercussions on edge extraction and we could use this prior knowledge to enhance the detection of edges (particles filtering)

Thank you for your attention.

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