Sparse Coding Of Natural Images
Using A Prior On Edge Co-Occurences
Applications of Edge co-occurrences in computer vision

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(hello) ⊙Hi, I am Laurent U. Perrinet and I work at the team ”inference in Vision & Behavior” at the INT. My research interest is to put in relation visual functions and the statistics of natural images. I am therefore a computational neuroscientist, 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).

(today) Today I will present a work done during a visit in Karl Friston’s team in London at the UCL: I will talk about the potential role of the co-occurrence of edges in building efficient codes to represent images. This is joint work with James Bednar who is an expert in topographical models of cortical areas now at Continuum Analytics, Austin TX.

akno Thanks to the BrainScaleS project for funding this project.
A major challenge in neuroscience is to understand how images are represented in the neural activity, which mainly consists of asynchronous events, called spikes. We have developed such a framework based on the hypothesis that these spikes represent sparse features in images. To illustrate how one may encode an image using spikes in a fast and efficient manner, let’s show a movie the reconstruction as a function of the number of spikes.

- on the bottom left, N gives the number of spikes
- at the first step, we can see one filter with a specific orientation, scale, amplitude and phase
- when we continue, one can recognize the image after a few hundreds steps

SparseLets framework: event-based representation of images

N=2048
This framework is based on a modified Matching Pursuit algorithm:

- on the left, I show the residual image, that is the part of the image not yet encoded in the pattern of spike
- on the right, one can see the reconstruction

quickly one sees that the residual is unstructured noise, confirming that all information was correctly passed. More on http://blog.invibe.net/posts/2015-05-22-a-hitchhiker-guide-to-matching-pursuit.html
SparseLets framework: event-based representation of images

http://github.com/meduz/SparseEdges
Sparse Coding Of Natural Images Using A Prior On Edge Co-Occurrences

- Introduction: efficient event-based coding of natural scenes
  - SparseLets framework: event-based representation of images
    - SparseLets framework: event-based representation of images

  - on the left, ...
  - at the first step...

All the code is documented in the following papers and in a recent review paper and the source code is available on github at http://github.com/meduz/SparseEdges
SparseLets framework: event-based representation of images

the step from the PHRs to the scale pyramid uses a linear transformation via a log-gabor representation

(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. we show here on the top left that these filters tile evenly the Fourier space, but also that these correspond to a good model of edges at different orientation, scale and phase compared to other dictionaries like the Daubechies wavelet base Db4 in (e) and the steerable pyramid by Eero Simoncelli,

(they) obviously, this dictionary is over-complete, but their correlation is easy to compute and allow for a relative translation-rotation-scale invariance. we proved that this was better adapted to the extraction of edges than gabor filters (Fischer, 07).
SparseLets framework: event-based representation of images

Natural

Laboratory
Sparse Coding Of Natural Images Using A Prior On Edge Co-Occurrences

Introduction: efficient event-based coding of natural scenes

SparseLets framework: event-based representation of images

SparseLets framework: event-based representation of images

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(edges) We show here the results of the edge extraction on a set of patches extracted from 2 databases. Parameters for each edge are the scalar amplitude, position, phase, orientation and scale. The hue gives the orientation, the length represents the size (scale) of the edge. This shows that edges are qualitatively well extracted.

(efficient) This method is rather general and proves to be efficiently grabbing most edges. In particular we can reconstruct the image from them and we achieved a performance measured by the RMSE of $\approx 5 - 10\%$

(natural) Oriented edges that constitute images of natural scenes tend to be aligned in co-linear or co-circular arrangements, such as when you follow the contours of these boulders: lines and smooth curves are more common than other possible arrangements of edges. See for example the work of Mariano Sigman on co-circularity in natural images (see Sigman, 2001).
Second-order statistics: edge co-occurrences in natural images

As can be seen in Fig. 3D, edge elements that are co-circular (i.e. consistent with a smooth continuous contour) are more likely to belong to the same physical contour. These results support our interpretation of the absolute statistics in Fig. 3C, and provide further evidence that the Gestalt principle of good continuation has a physical basis in the statistics of the natural world. Most importantly, these results allow us to determine a maximum likelihood (optimal) local grouping function for contour grouping in natural scenes. Given the fundamental importance of contour grouping for useful vision, it is possible that the human local grouping function is near this optimum.

[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) in this study, they defined second-order statistics to compare an edge as a function of a central reference edge as a pdf on 3 parameters: the distance $d$ between their centers, the angle $\psi$ between the central edge sand the center of the second and $\theta$ the difference between the orientation of both edges. Probability is represented by this colormap and to represent on the 2D of the screen this 3d function, they represent in (B) the most probable difference of orientation at each distance and angle, showing the tendency of having collinear, parallel structures in natural images and (C) the most probable angle for each difference of angle and distance, showing a prior bias in natural image for cocircular edges.

One possible candidate substrate for implementing such an association field in mammals is the set of long-range lateral connections between neurons in the primary visual cortex (V1), which could act to facilitate detection of contours matching the association field, and/or inhibit detection of other contours. To fill this role, the lateral connections would need to be orientation specific and aligned along contours,
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(neural) if one looks at the primary visual area in the occipital lobe of the cortex using optical imaging as here in the treeshrew by Bosking and colleagues under the supervision of DF, one could represent the distributed, topographical representation of orientation selectivity. In (A) and (B) the orientation giving the most response at each cortical position is represented by hue using the code below from orange for horizontal to blue for verticals,

(method) Tree shrew orientation preference maps were obtained using optical imaging. Additionally, 540 nm light was used to map surface blood vessels used for alignment. Biocytin was then injected into a specific site in V1 and the animal was sacrificed 16 hours later. Slices of V1 were imaged to locate the biocytin bouton and the surface blood vessels.

(lateral) we show here one result of (Bosking et al., J Neurosci 17:2112-27, 1997) which overlay over a map or orientation selectivity the network of lateral connectivity originating from a group of neurons with similar orientations and position. There is a structure in this connectivity towards locality (more pronounced for site B) connecting iso orientations even on long ranges (A). This type of structure tends to wire together those neurons that have similar orientations, indicating a prior to colinearities.
[Fischer et al., 2007]
Introduction: efficient event-based coding of natural scenes

Second-order statistics: edge co-occurrences in natural images

(physio) is there a match of these structures with the statistics of natural images? 1: Hunt & Goodhill have reinterpreted above data and shown that there is more diversity than that - 2) Some authors (Kisvarday, 1997, Chavane and Monier) even say it is weak or inexistent on a the scale of the area...

(colin) 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, as was for instance modeled neurally in the work from P. Series or in this version for computer vision: todo=describe...

(neural) The visual system appears to take advantage of this prior information, and human contour detection and grouping performance is well predicted by what is coined an "association field" (Field et al., 1993)...

(Gestalt) ... this has been measured and quantified by Geisler in 2001 and using a measure of second-order statistics combined with an iterative grouping rule, they could reproduce diverse behavioral results at a global level, for instance here the link that is reported from a display of artificial edges (A) to what is reported as perceived (B). This thus gives a link between this local dependence present in natural images and the emergence in neural computations of some global Gestalt-like rules as implemented in the brain.
Problem statement: Use of this prior in Computer Vision

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(MP) from this linear representation, we searched for the most sparse representation using a $\ell_0$ norm approach for which Matching Pursuit proved to be a good approximation. I refer to this paper that appeared in IEEE TIP for more details (BICV) and that i reviewed in a recent book chapter (Perrinet, 2015 bicv), including a model of complex cells’ response (Fischer, 2007). It is generic and efficient.

Specifically, we analyzed the co-occurrence statistics of edge elements in images of natural scenes, and explore how this may be included in the Sparselets framework
Problem statement: Use of this prior in Computer Vision

(A) Diagram showing the relationship between $\phi$, $\theta$, and $\psi$.

(B) Heatmap illustrating the probability ratio for azimuth and orientation differences.
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 extraction on both classes of images and show the observed statistics

3. Finally, we will summarize results and present some predictions and perspectives
Outline: Sparse Coding Of Natural Images Using A Prior On Edge Co-Occurrences

Introduction: efficient event-based coding of natural scenes
   SparseLets framework: event-based representation of images
   Second-order statistics: edge co-occurrences in natural images
   Problem statement: Use of this prior in Computer Vision

Results: event-based contour completion
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Results: event-based contour completion
let’s now see the results of using such a method by

- defining a toy model image
- computing second-order statistics
- observe the sequence of extracted edges
Results: event-based contour completion

(A) Diagram showing angles $\phi$, $\theta$, $\psi$.

(B) Heatmap showing orientation difference $\theta$ and azimuth difference $\psi$, with probability ratio colors.
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Results: event-based contour completion

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This resulted in the possibility to include this prior in the event-based sparselet scheme. We illustrate that in this toy example consisting of a background iid noise and a circle without (left in blue) or with (right in red) this prior consistent with neurophysiological and psychophysical (Kovacs) results, one see that the circle is first extracted when using this prior.
Summary

Photoreceptors

Edge & scale map

Sparse edge image
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Results: event-based contour completion

Summary

We have shown here

1. first, we can define an event-based framework adapted to the detection of edges in natural images
2. then, that this can be used for the computation of second-order edge statistics
3. Finally, we that this may be used in a variant of the sparselet framework

Thank you for your attention.
Summary

(A) and (B) illustrate the relationship between azimuth difference $\psi$, orientation difference $\theta$, and probability ratio. The diagrams show how changes in $\psi$ and $\theta$ affect the probability ratio, with $\psi$ ranging from $-\pi/2$ to $\pi/2$ and $\theta$ ranging from $0$ to $\pi$. The color scale on the right indicates the probability ratio, ranging from 0.5 to 4.0.
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Thank you for your attention.
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Contour integration by the human visual system: evidence for a local "association field".

W. Geisler, J. Perry, B. Super, D. Gallogly
Edge co-occurrence in natural images predicts contour grouping performance.

W. Bosking, Y. Zhang, B. Schofield, and D. Fitzpatrick
Orientation selectivity and the arrangement of horizontal connections in tree shrew striate cortex

L. U. Perrinet
Sparse models.

Self-Invertible 2D Log-Gabor Wavelets.

L. U. Perrinet.
Role of homeostasis in learning sparse representations.

L. U. Perrinet, and J. Bednar
Edge co-occurrences can account for rapid categorization of natural versus animal images.
Scientific Reports, 2015.
URL http://invibe.net/LaurentPerrinet/Publications/Perrinet15eusipco