

LISSOM Orientation Maps

Dr. James A. Bednar

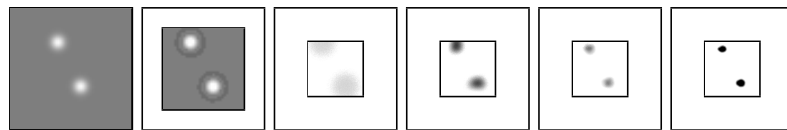
jbednar@inf.ed.ac.uk

<http://homepages.inf.ed.ac.uk/jbednar>

Modeling Orientation

- Starting point: Retinotopy model
- Same architecture, different input pattern
- Three dimensions of variance: x, y, orientation
- How will that fit into a 2D map?

Retinotopy input and response

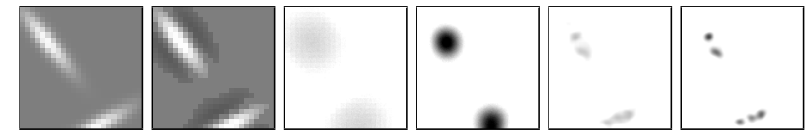


Retinal activation LGN response Iteration 0: Initial V1 response Iteration 0: Settled V1 response 10,000: Initial V1 response 10,000: Settled V1 response

CMVC figure 4.4

(Reminder from last time)

Orientation input and response

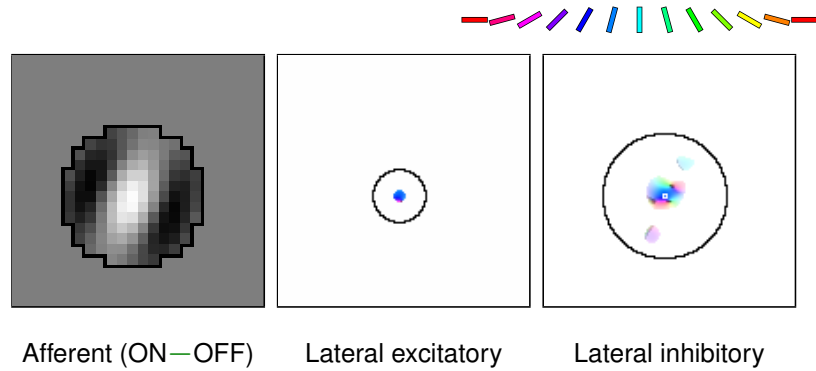


Retinal activation LGN response Iteration 0: Initial V1 response Iteration 0: Settled V1 response 10,000: Initial V1 response 10,000: Settled V1 response

CMVC figure 5.6

- Response before training similar to retinotopy case
- Response after training has multiple activity blobs per input pattern
- Blobs are orientation-specific

Self-organized V1 weights

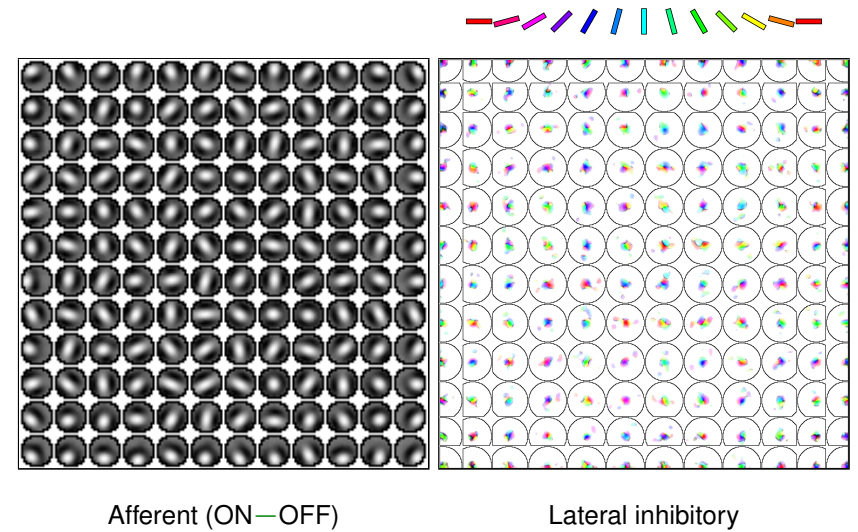


CMVC figure 5.7

Typical:

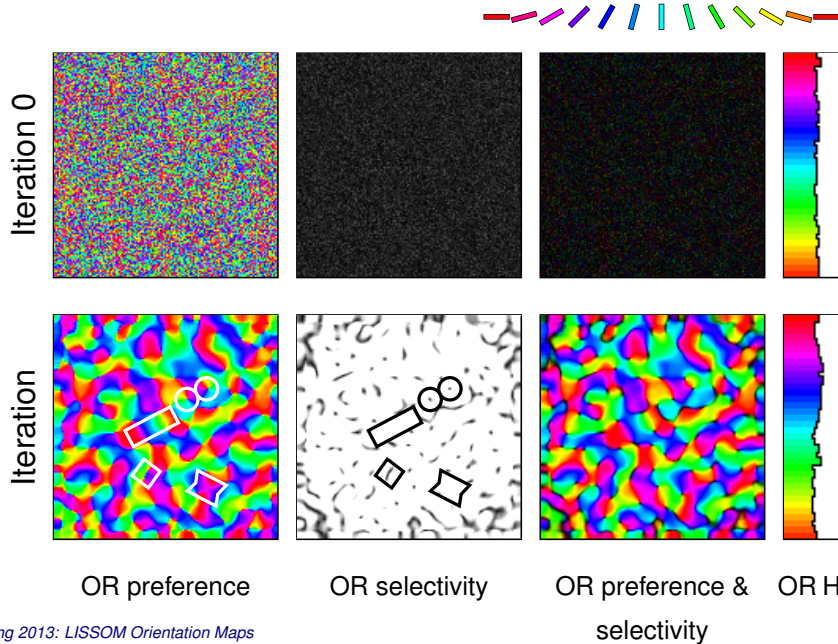
- Gabor-like afferent CF
- Nearly uniform short-range lateral excitatory
- Patchy, orientation-specific long-range lateral inhibitory

Self-organized weights across V1



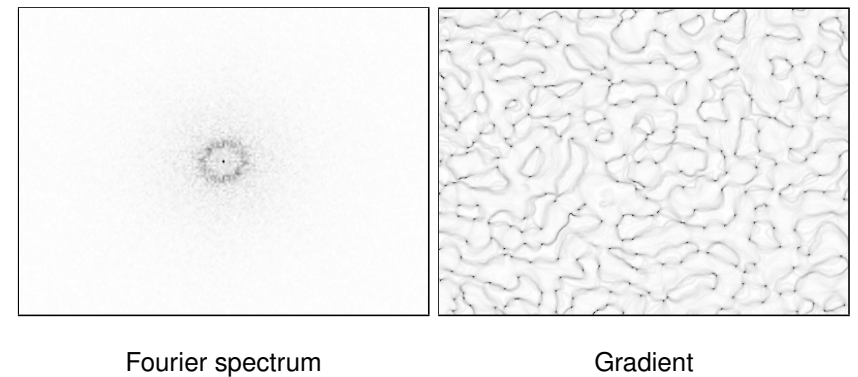
CMVC figure 5.8

OR map self-organization



CMVC figure 5.9

Macaque ORmap: Fourier, gradient

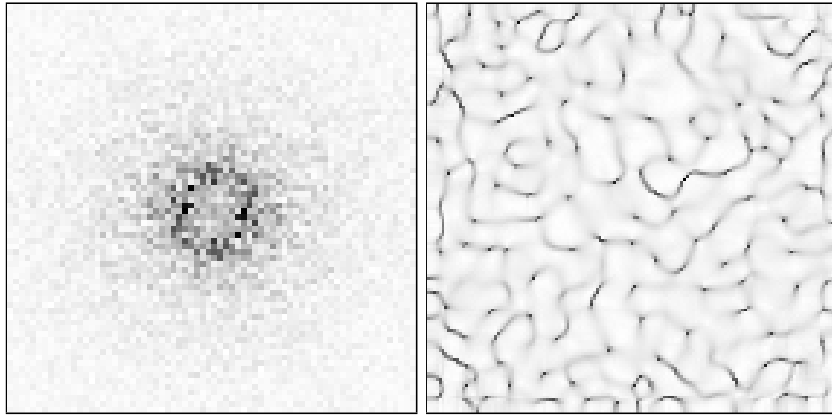


CMVC figure 5.1

In monkeys:

- Ring-shaped spectrum: repeats regularly in all directions
- High gradient at fractures, pinwheels.

OR Map: Fourier, gradient



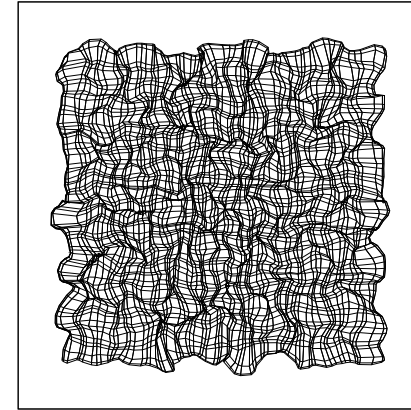
CMVC figure 5.10

Fourier spectrum

Gradient

LISSOM model has similar spectrum, gradient

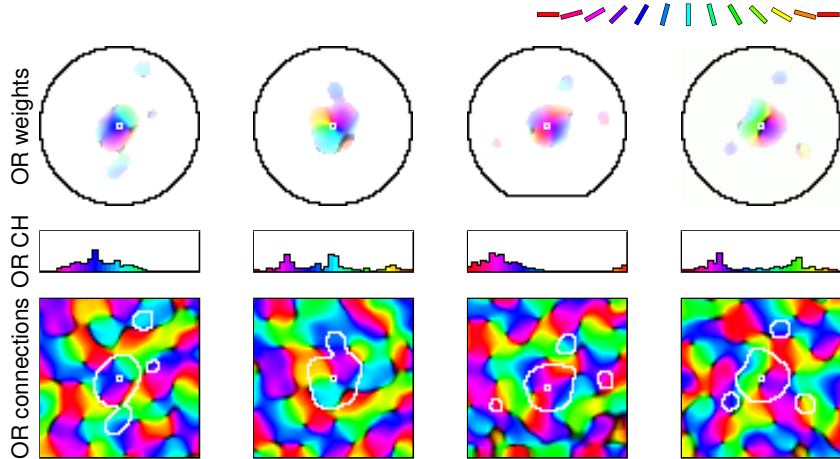
OR Map: Retinotopic organization



CMVC figure 5.11

- Retinotopy is distorted locally by orientation prefs
- Matches distortions found in animal maps?

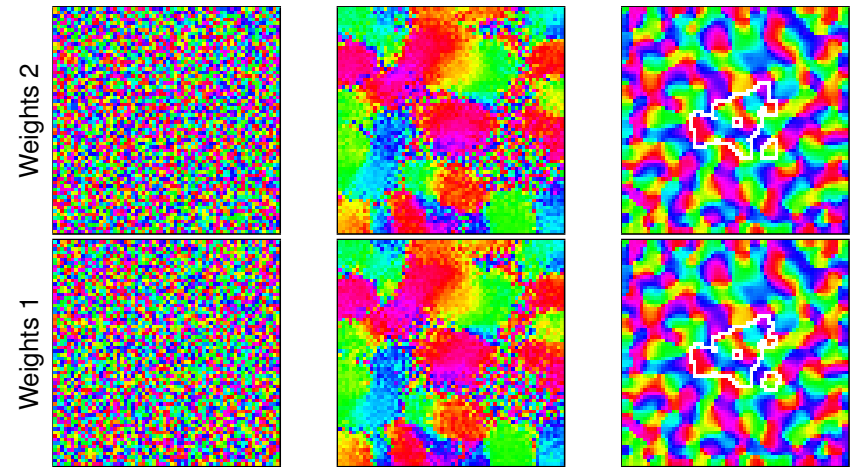
OR Map: Lateral connections



CMVC figure 5.12

Connections in iso-OR patches Connections in OR pinwheels Connections in OR saddles Connections in OR fractures

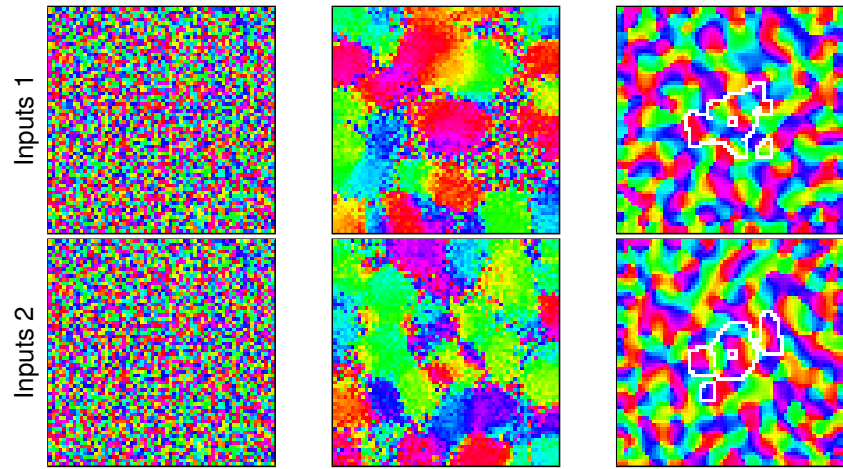
Effect of initial weights



CMVC figure 8.5

(a) Iteration 0 (b) Iteration 50 (c) Iteration 10,000
Changing weights doesn't change map folding pattern.

Effect of input streams

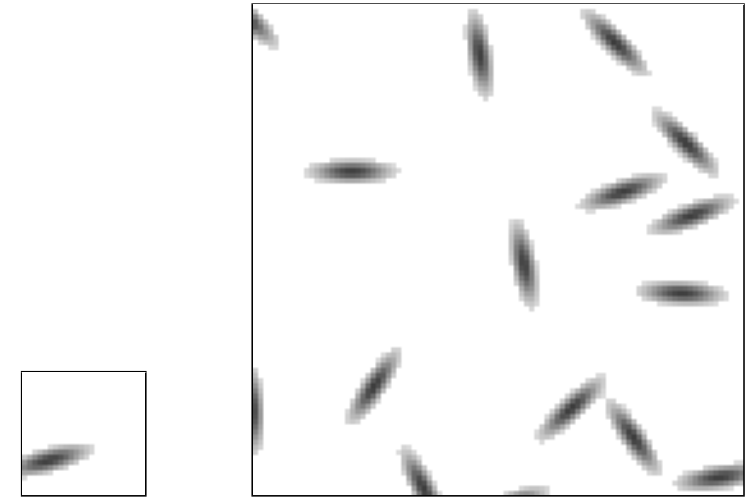


CMVC figure 8.5

(a) Iteration 0 (b) Iteration 50 (c) Iteration 10,000

Changing inputs changes entire pattern.

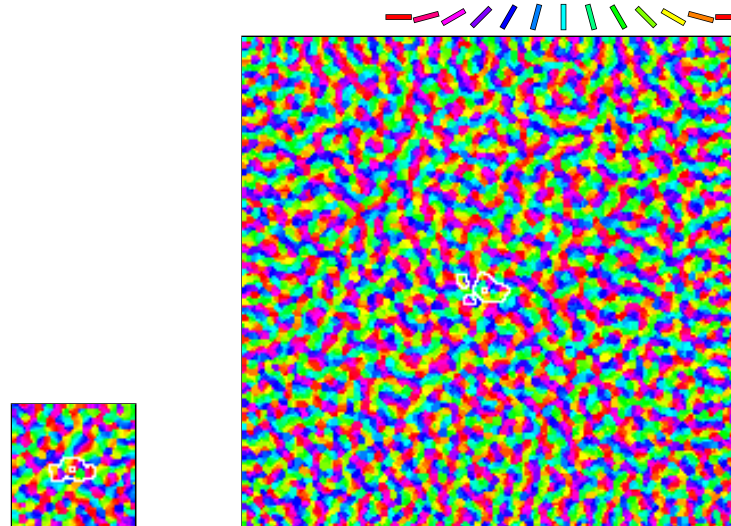
Scaling retinal and cortical area



CMVC figure 15.1a,b

(a) Original retina: $R = 24$ (b) Retinal area scaled by 4.0:
 $R = 96$

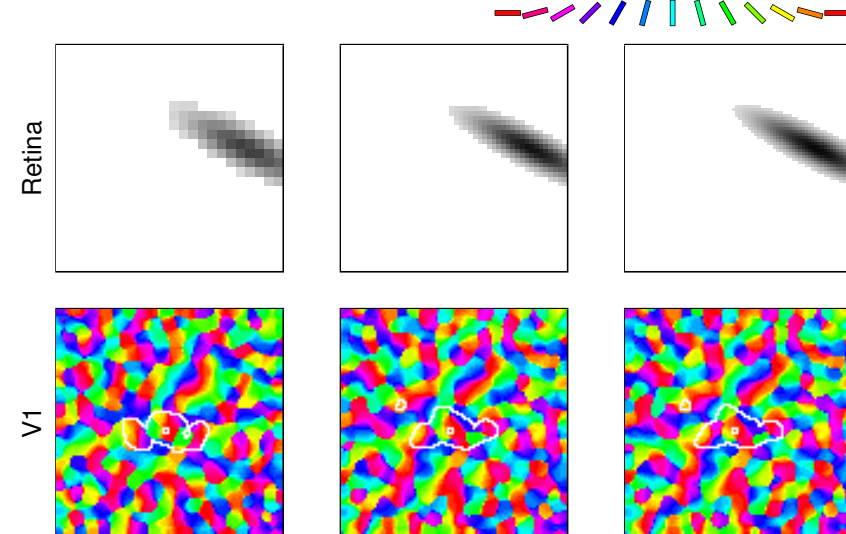
Scaling retinal and cortical area



CMVC figure 15.1c,d

(c) Original V1: $N = 54$, 0.4 hours, 8 MB (d) V1 area scaled by 4.0:
 $N = 216$, 9 hours, 148 MB

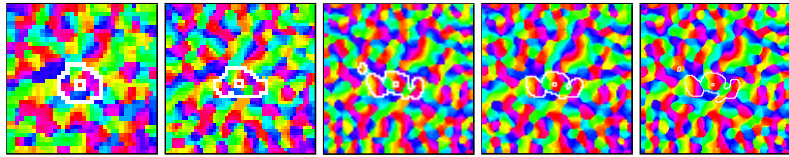
Scaling retinal density



CMVC figure 15.2

Original retina Retina scaled by 2 Retina scaled by 3

Scaling cortical density

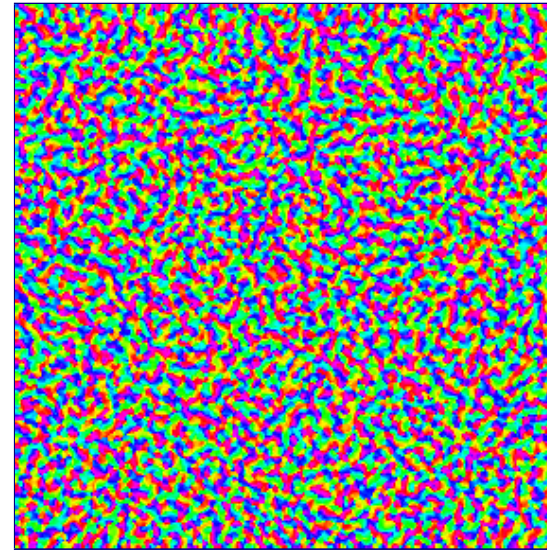


CMVC figure 15.3

(a)	(b)	(c)	(d)	(e)
36×36 :	48×48 :	72×72 :	96×96 :	144×144 :
0.17 hours,	0.32 hours,	0.77 hours,	1.73 hours,	5.13 hours,
2.0 MB	5.2 MB	22 MB	65 MB	317 MB

Above minimum density (due to lateral radii),
density not crucial for organization

Full-size V1 Map



- Map scaled to cover most of visual field
- Allows testing with full-size images
- 30 million connections

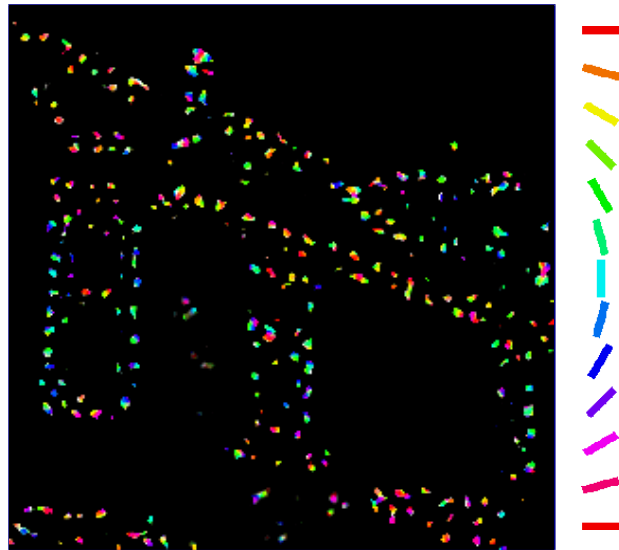
Sample Image



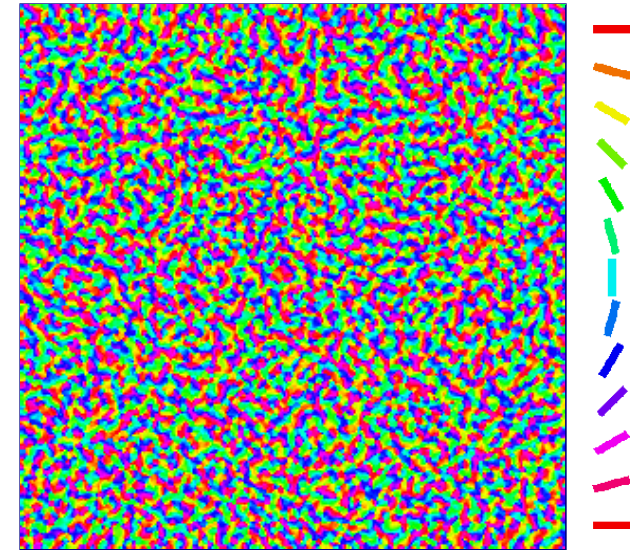
RGC/LGN Response



V1 Response with γ_n



V1 Orientation Map



Afferent normalization

Mechanism for contrast invariant tuning:

$$s_{ij} = \frac{\gamma_A \left(\sum_{\rho ab} \xi_{\rho ab} A_{\rho ab, ij} \right)}{1 + \gamma_n \left(\sum_{\rho ab} \xi_{\rho ab} \right)}, \quad (1)$$

$\xi_{\rho ab}$: activation of unit (a, b) in afferent RF ρ of neuron (i, j)

$A_{ab, ij}$ is the corresponding afferent weight

γ_A, γ_n are constant scaling factors

RGC/LGN response to large image

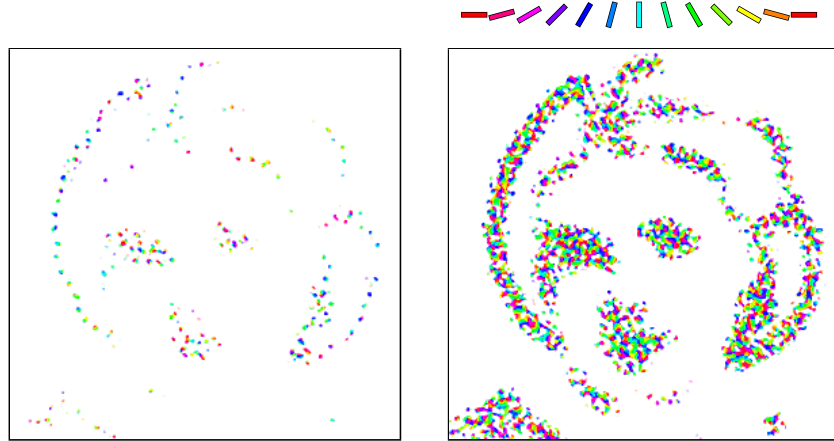


Retinal activation

LGN response

RGC/LGN responds to most of the visible contours

V1 without afferent normalization



CMVC figure 8.2c-e

V1 response:

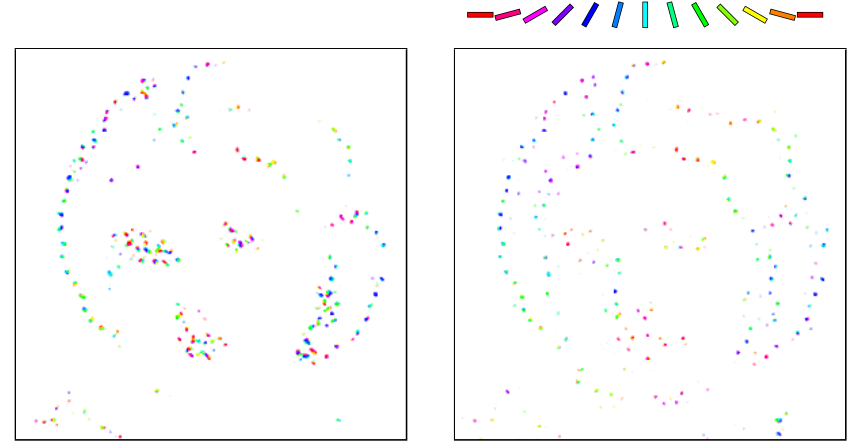
$$\gamma_n = 0, \gamma_A = 3.25$$

Cannot get selective response to all contours

V1 response:

$$\gamma_n = 0, \gamma_A = 7.5$$

V1 with afferent normalization



CMVC figure 8.2c-e

V1 response:

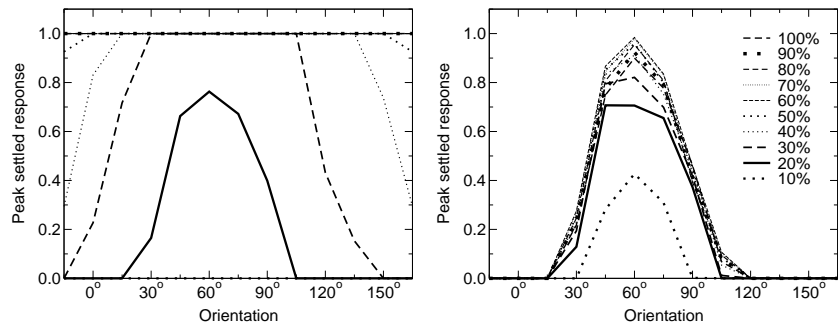
$$\gamma_n = 0, \gamma_A = 3.25$$

Responses based on contour, not contrast

V1 response:

$$\gamma_n = 80, \gamma_A = 30$$

Tuning with afferent normalization



CMVC figure 8.3

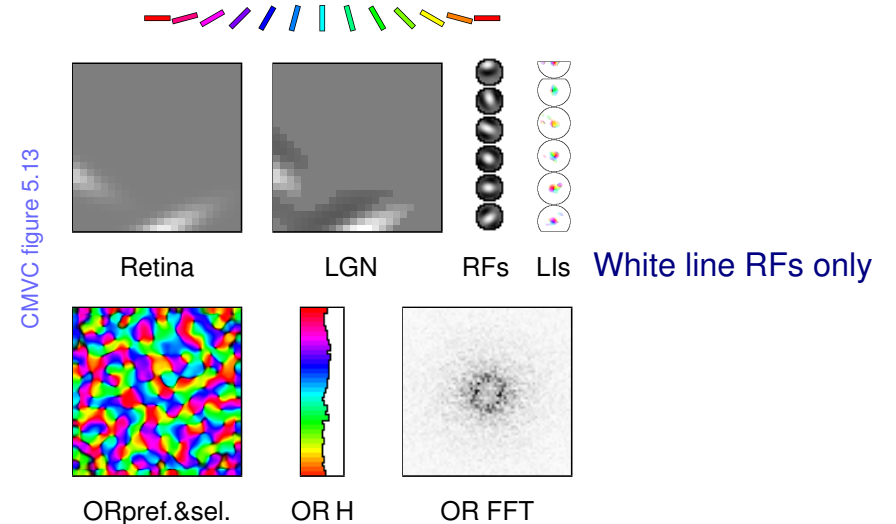
$$\gamma_n = 0, \gamma_A = 3.25$$

$$\gamma_n = 80, \gamma_A = 30$$

Sine grating tuning curve:

- Without γ_n : selectivity lost as contrast increases
- With γ_n : always orientation-specific

OR Map: Gaussian

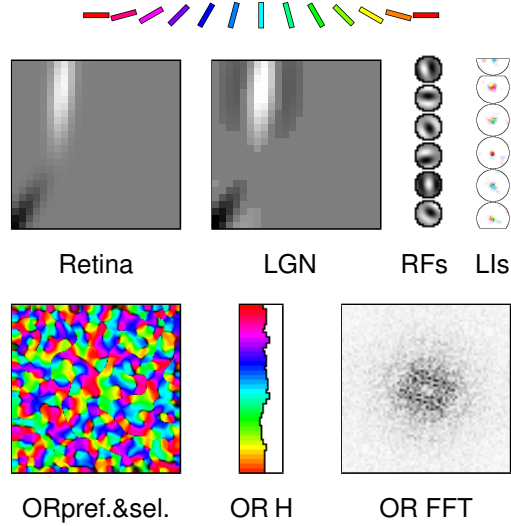


CMVC figure 5.13

White line RFs only

OR Map: +/- Gaussian

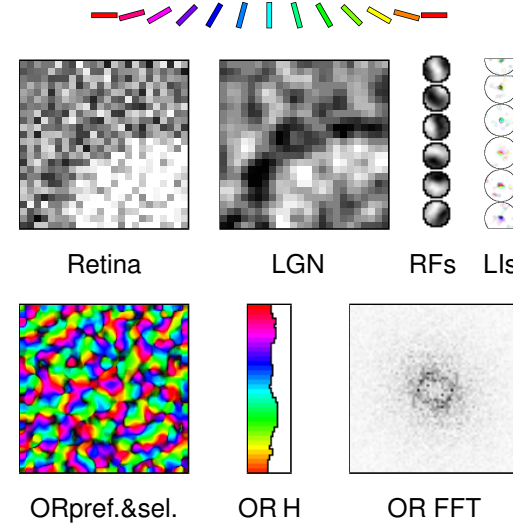
CMVC figure 5.13



White or black line
RFs

OR Map: Retinal wave model

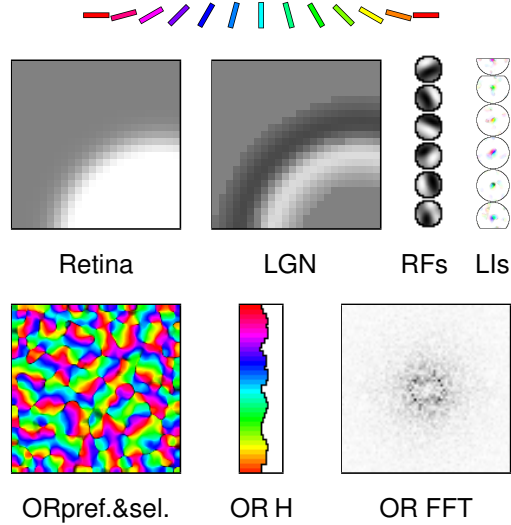
CMVC figure 5.13



Some line, mostly
edge RFs

OR Map: Smooth disks

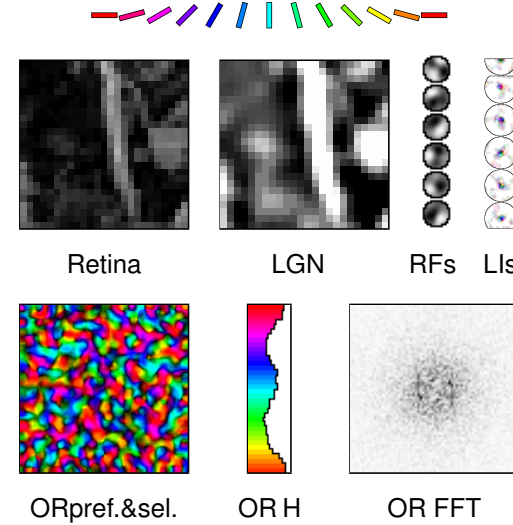
CMVC figure 5.13



All edge RFs

OR Map: Natural images

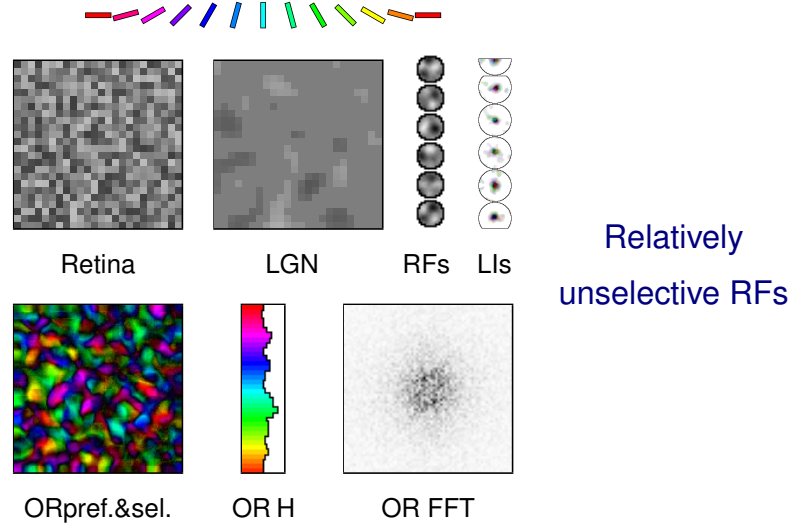
CMVC figure 5.13



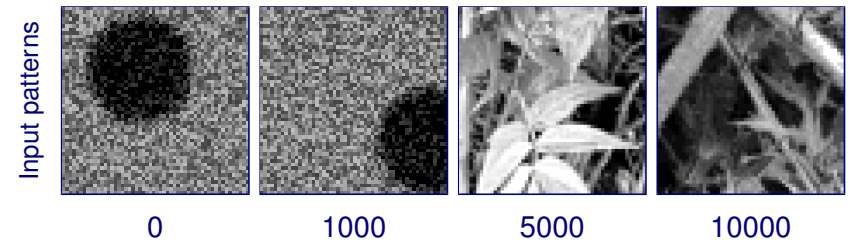
All types of RFs
Longer range lateral
weights
Histogram:
horizontal, vertical
bias

OR Map: Uniform noise

CMVC figure 5.13

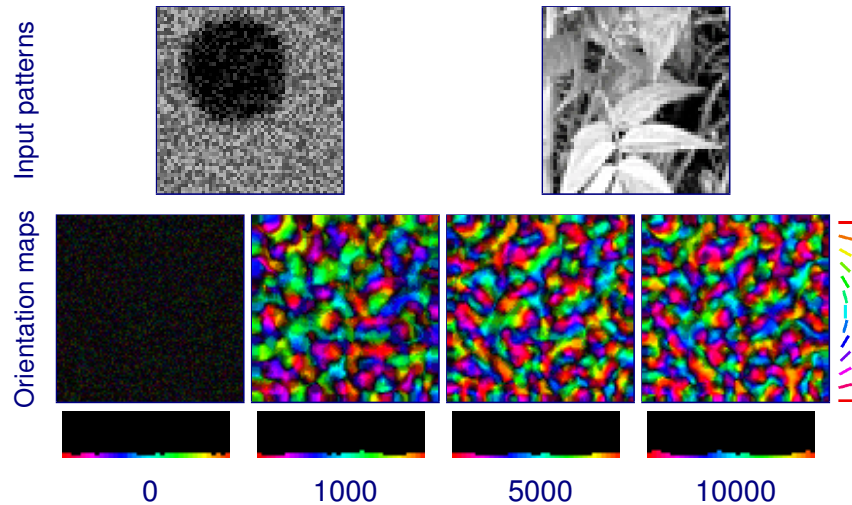


Modeling pre/post-natal phases



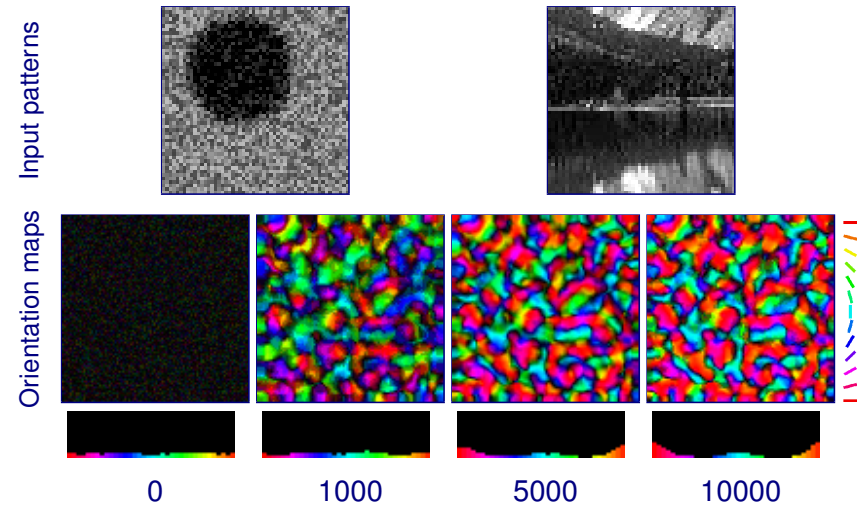
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

Pre/post-natal V1 development



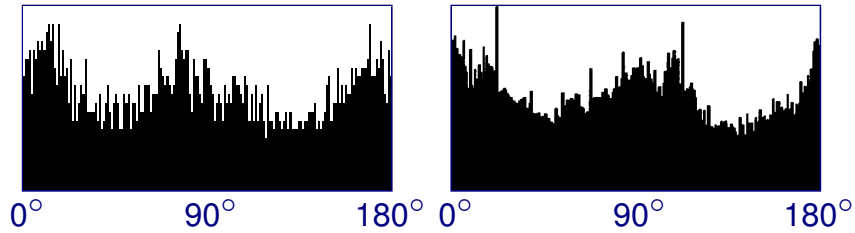
- Neonatal map smoothly becomes more selective

Statistics drive development



- Biased image dataset: mostly landscapes
- Smoothly changes into horizontal-dominated map

OR Histograms

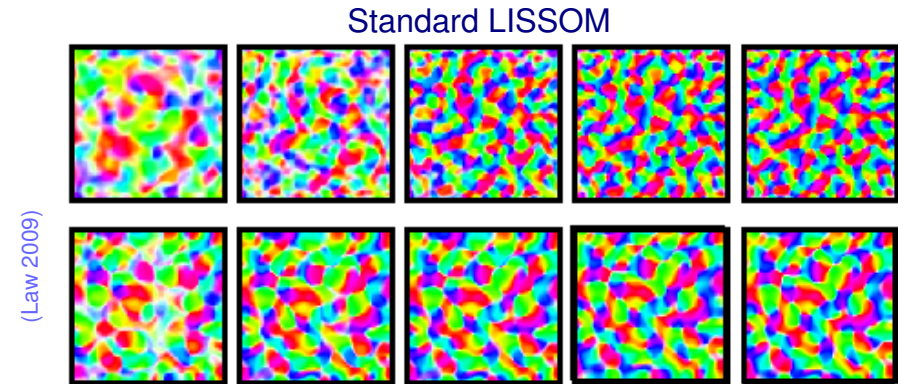


HLISSOM model

Adult ferret V1
(Coppola et al. 1998)

- After postnatal training on Shouval natural images, orientation histogram matches results from ferrets
- Model adapts to statistical structure of images

Stable development



Early GCAL version (see Bednar 2012; Law et al. 2011)

If the manual thresholds of standard LISSOM are replaced with homeostatic plasticity, excitatory radius shrinking can be eliminated. Result: map shape remains stable over time.

Summary

- Development depends on features of input pattern
- Orientation maps develop with many different patterns
- Develops Gabor-type RFs with most inputs
- Breaks up image into oriented patches
- Scale response by local contrast to work for large images
- Matching biology requires prenatal, postnatal phases
- Can get more elaborate: complex cells, multiple laminae/cell types, short-range inhibition, feedback, ...

References

- Bednar, J. A. (2012). Building a mechanistic model of the development and function of the primary visual cortex. *Journal of Physiology (Paris)*, 106, 194–211.
- Coppola, D. M., White, L. E., Fitzpatrick, D., & Purves, D. (1998). Unequal representation of cardinal and oblique contours in ferret visual cortex. *Proceedings of the National Academy of Sciences, USA*, 95 (5), 2621–2623.
- Law, J. S. (2009). *Modeling the Development of Organization for Orientation Preference in Primary Visual Cortex*. Doctoral Dissertation, School of Informatics, The University of Edinburgh, Edinburgh, UK.
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Miikkulainen, R., Bednar, J. A., Choe, Y., & Sirosh, J. (2005). *Computational Maps in the Visual Cortex*. Berlin: Springer.

Shouval, H. Z., Intrator, N., Law, C. C., & Cooper, L. N. (1996). Effect of binocular cortical misalignment on ocular dominance and orientation selectivity. *Neural Computation*, 8 (5), 1021–1040.