

LISSOM Orientation Maps

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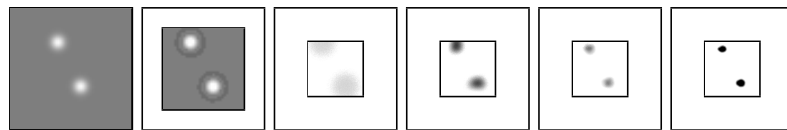
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Modeling Orientation

- Starting point: LISSOM retinotopy model
- Exactly the same architecture, different input pattern
- Three dimensions of variance: x, y, orientation
- How will that fit into a 2D map?

Retinotopy input and response

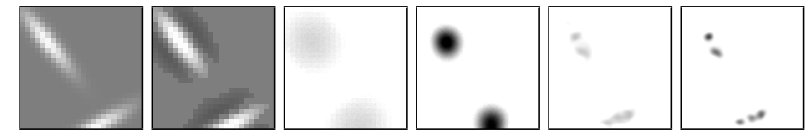


Retinal activation LGN response Iteration 0: Initial V1 response Iteration 0: Settled V1 response 10,000: Initial V1 response 10,000: Settled V1 response

CMVC figure 4.4

(Reminder from previous slides)

Orientation input and response

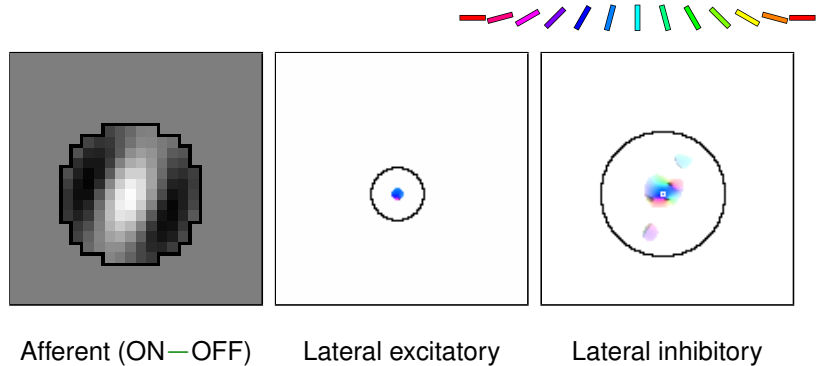


Retinal activation LGN response Iteration 0: Initial V1 response Iteration 0: Settled V1 response 10,000: Initial V1 response 10,000: Settled V1 response

CMVC figure 5.6

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

Self-organized V1 weights

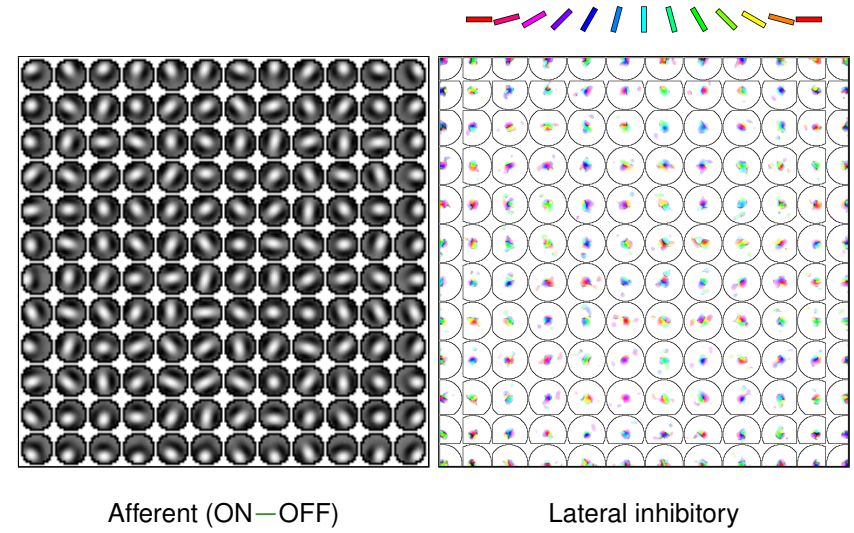


CMVC figure 5.7

Typical:

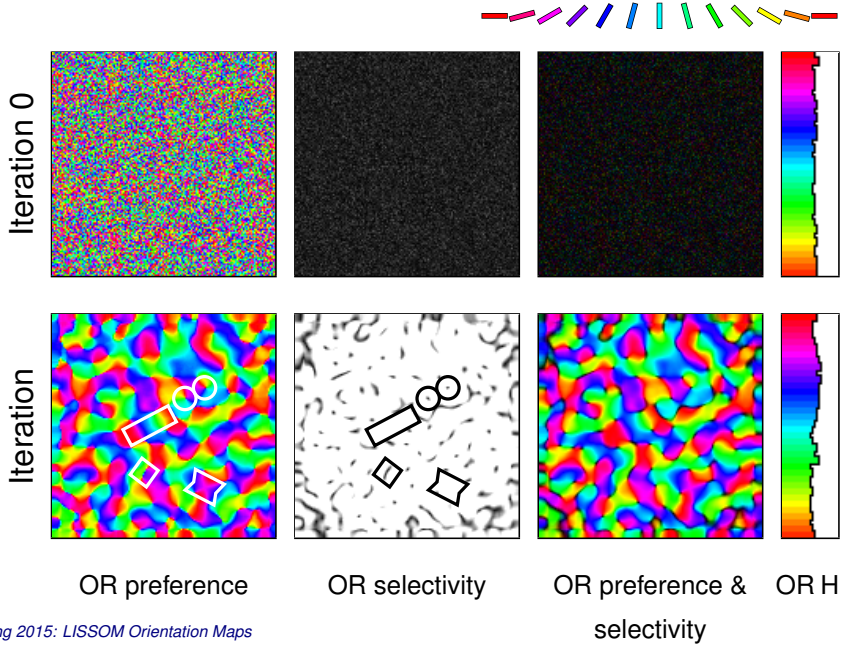
- Gabor-like afferent CF
- Nearly uniform short-range lateral excitatory
- Patchy, orientation-specific long-range lateral inhibitory

Self-organized weights across V1



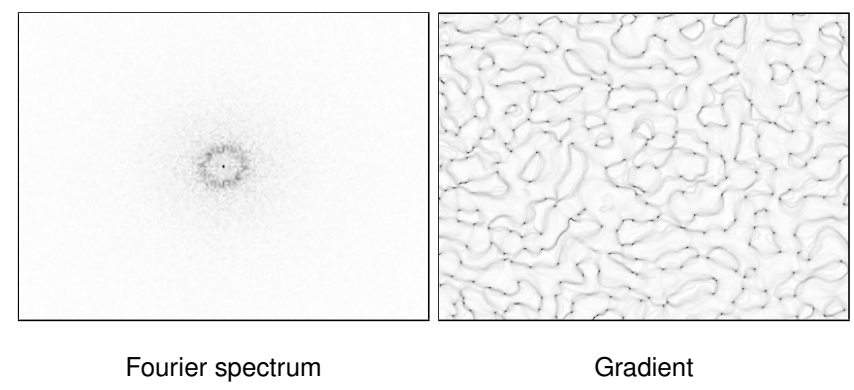
CMVC figure 5.8

OR map self-organization



CMVC figure 5.9

Macaque ORmap: Fourier, gradient

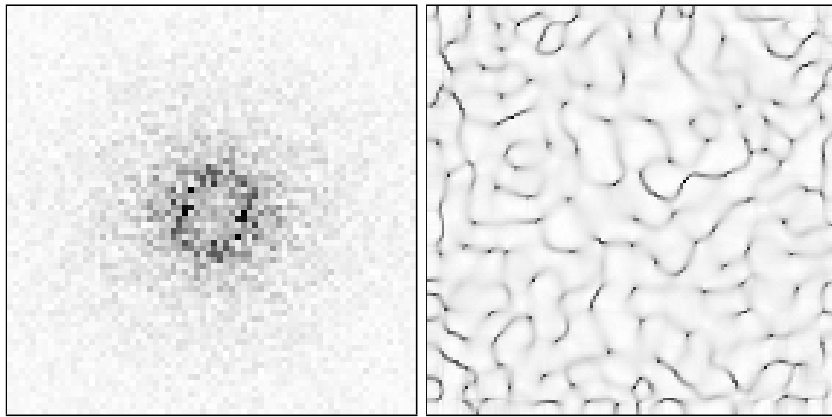


CMVC figure 5.1

In monkeys:

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

OR Map: Fourier, gradient



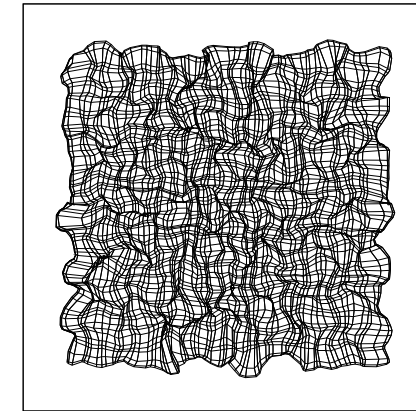
CMVC figure 5.10

Fourier spectrum

Gradient

LISSOM model has similar spectrum, gradient

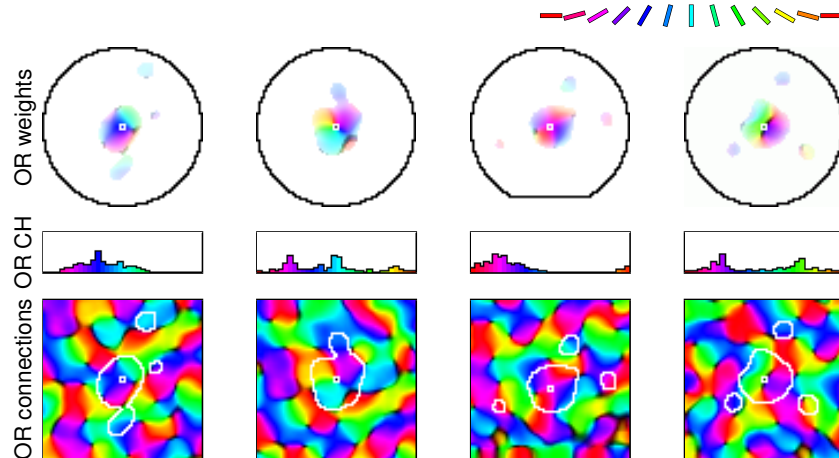
OR Map: Retinotopic organization



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

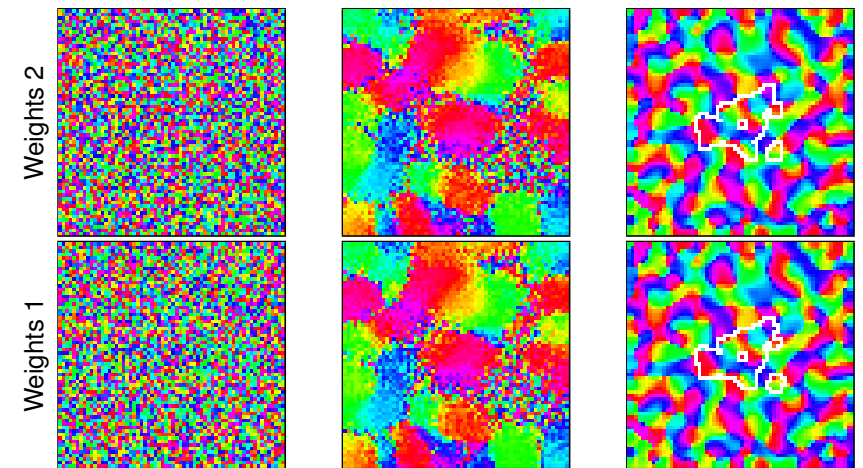
Connections in iso-OR patches

Connections in OR pinwheels

Connections in OR saddles

Connections in OR fractures

Effect of initial weights



CMVC figure 8.5

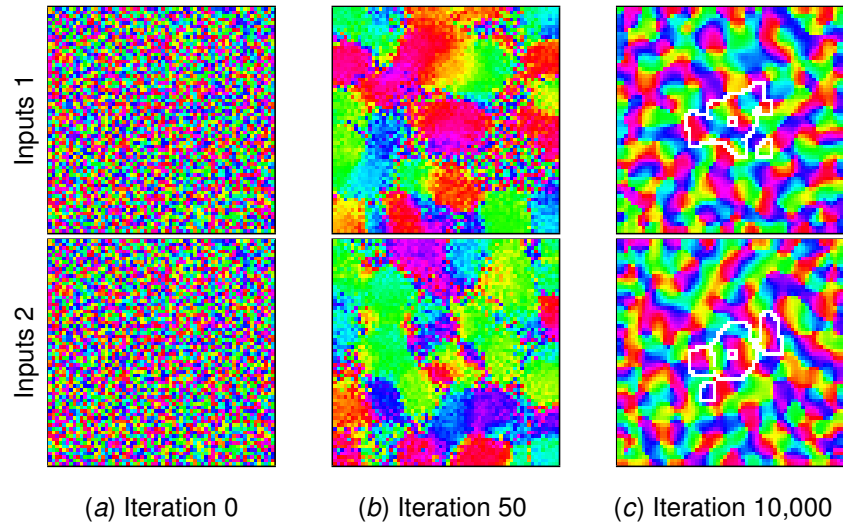
(a) Iteration 0

(b) Iteration 50

(c) Iteration 10,000

Changing weights doesn't change map folding pattern.

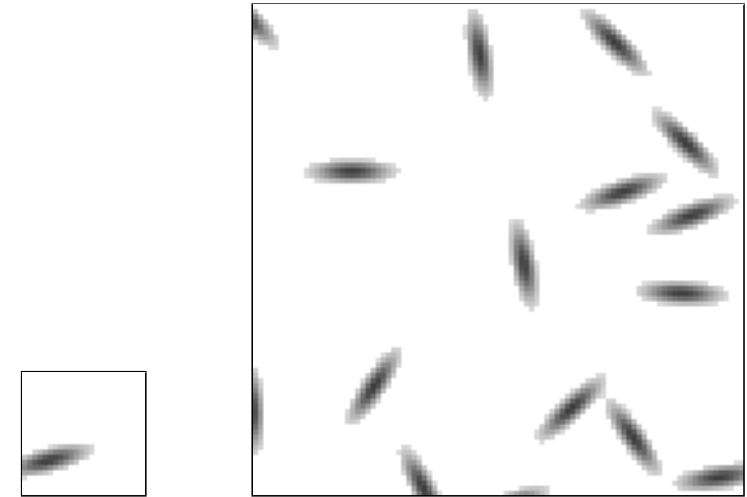
Effect of input streams



CMVC figure 8.5

(a) Iteration 0 (b) Iteration 50 (c) Iteration 10,000
Changing inputs changes entire pattern.

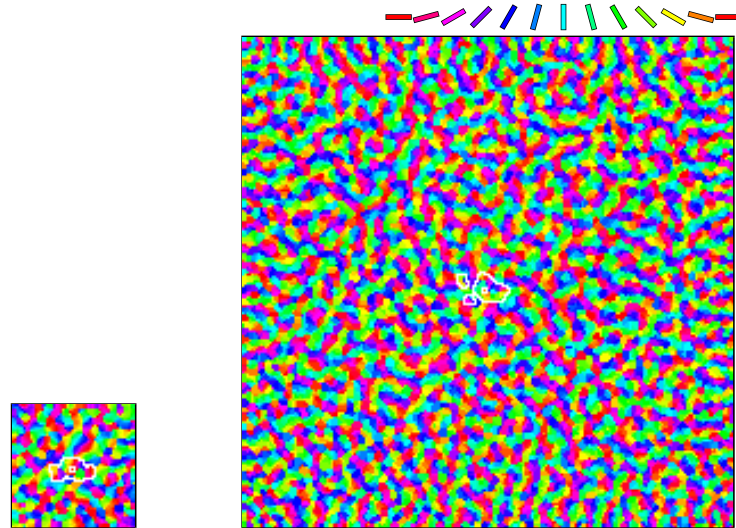
Scaling retinal and cortical area



CMVC figure 15.1a,b

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

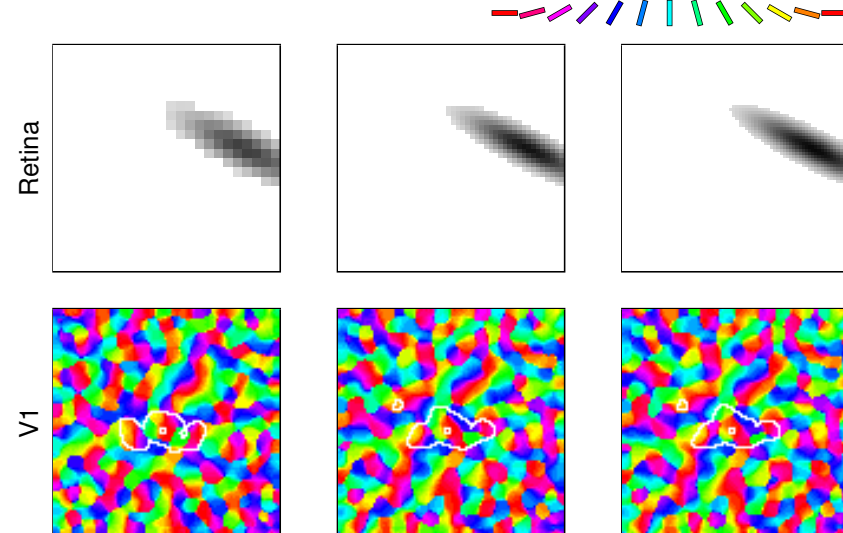
Scaling retinal and cortical area



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

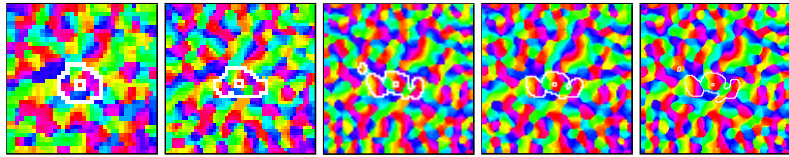
Scaling retinal density



CMVC figure 15.2

Original retina Retina scaled by 2 Retina scaled by 3

Scaling cortical density

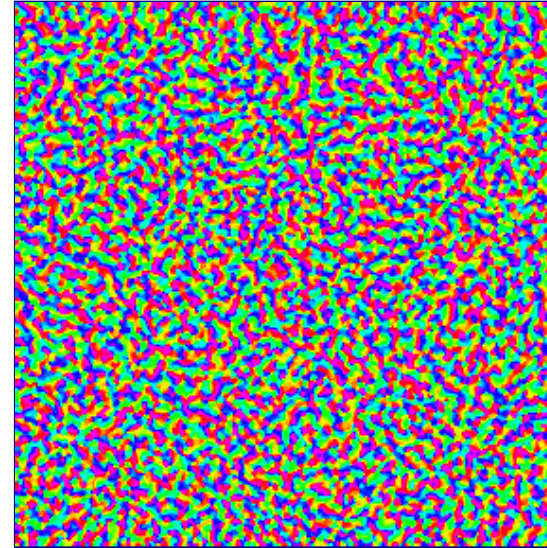


(a) 36×36 : 0.17 hours, 2.0 MB
 (b) 48×48 : 0.32 hours, 5.2 MB
 (c) 72×72 : 0.77 hours, 22 MB
 (d) 96×96 : 1.73 hours, 65 MB
 (e) 144×144 : 5.13 hours, 317 MB

CMVC figure 15.3

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

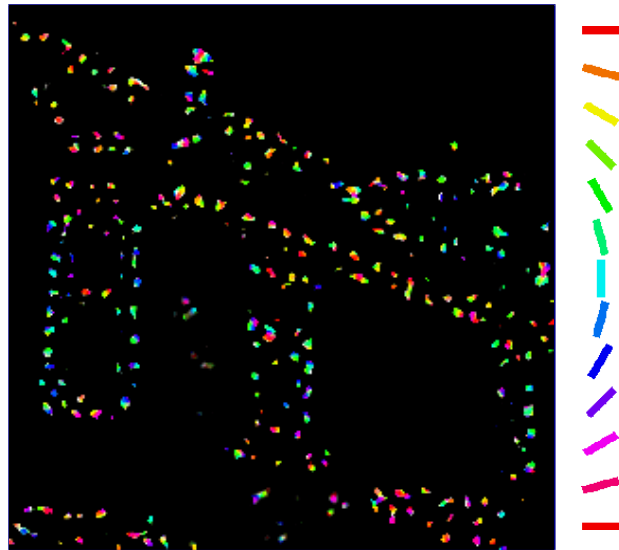
Sample Image



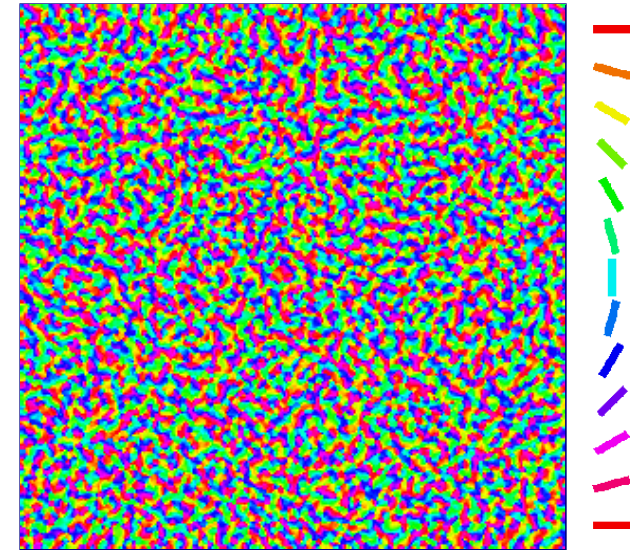
RGC/LGN Response



V1 Response with γ_n



V1 Orientation Map



Afferent normalization

LISSOM 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 CF ρ of neuron (i, j)

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

γ_A, γ_n are constant scaling factors

GCAL achieves similar results with lateral inhibition in RGC/LGN

RGC/LGN response to large image

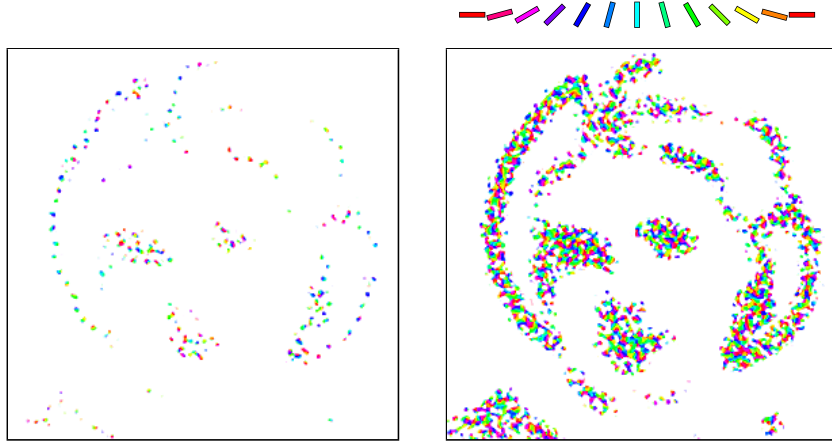


Retinal activation

LGN response

RGC/LGN responds to most of the visible contours

V1 without afferent normalization



CMVC figure 8.2c-e

V1 response:

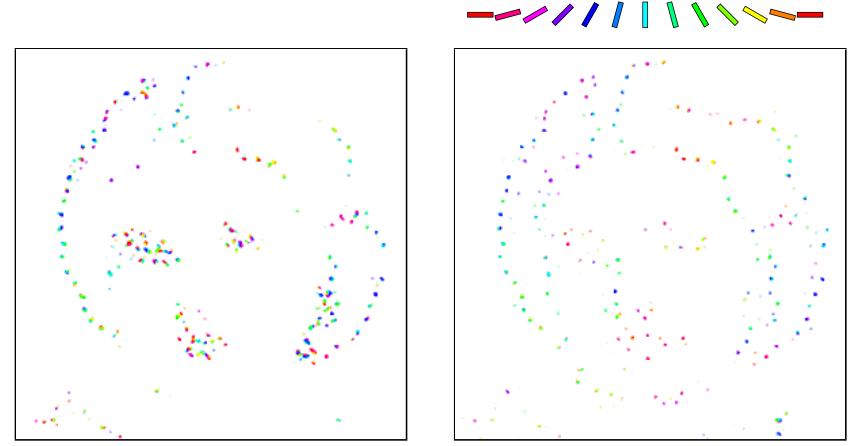
$$\gamma_n = 0, \gamma_A = 3.25$$

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:

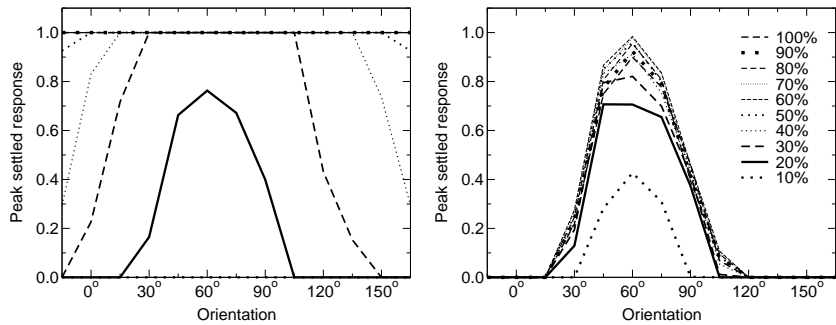
$$\gamma_n = 0, \gamma_A = 3.25$$

Responds based on contour, not contrast

V1 response:

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

Tuning with afferent normalization



CMVC figure 8.3

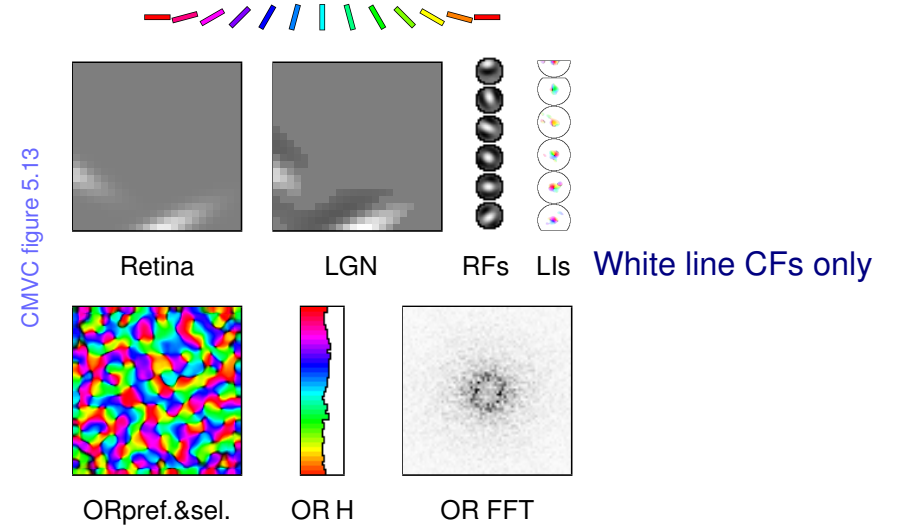
$$\gamma_n = 0, \gamma_A = 3.25$$

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

Sine grating tuning curve:

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

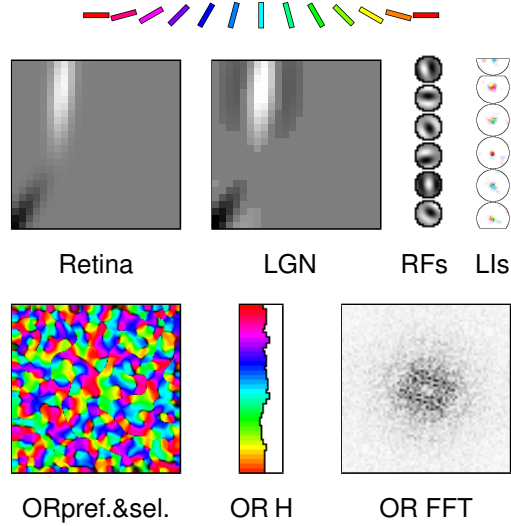
OR Map: Gaussian



CMVC figure 5.13

OR Map: +/- Gaussian

CMVC figure 5.13

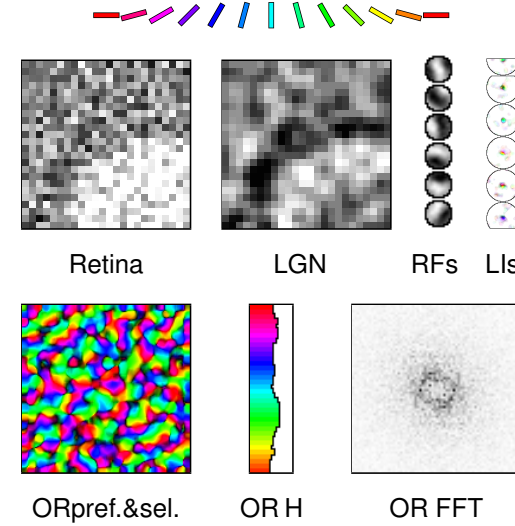


White or black
line CFs

OR map disrupted
due to phase
columns

OR Map: Retinal wave model

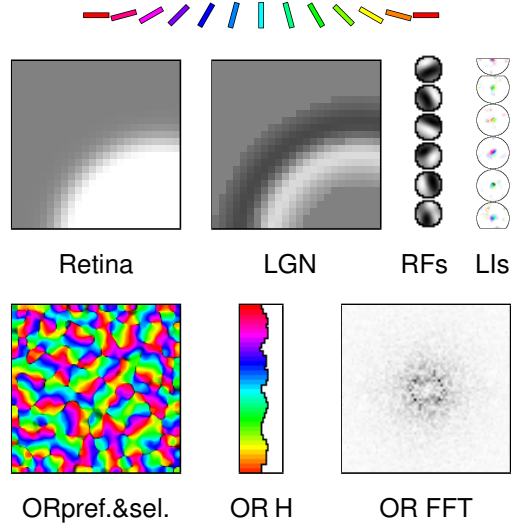
CMVC figure 5.13



Some line, mostly
edge CFs

OR Map: Smooth disks

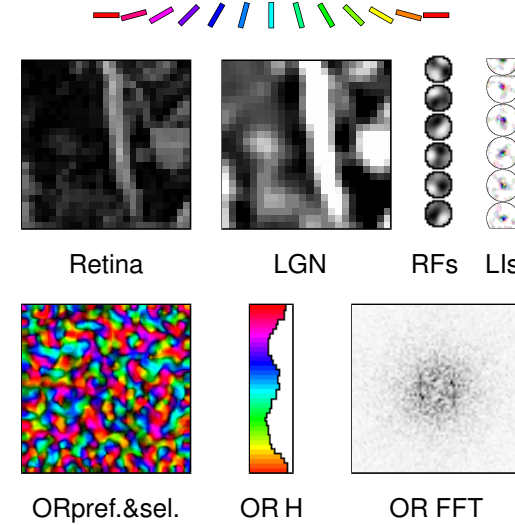
CMVC figure 5.13



All edge CFs

OR Map: Natural images

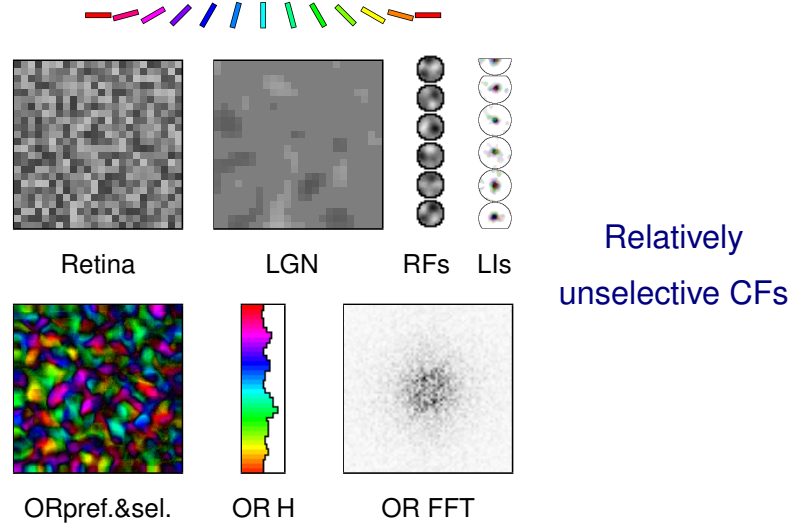
CMVC figure 5.13



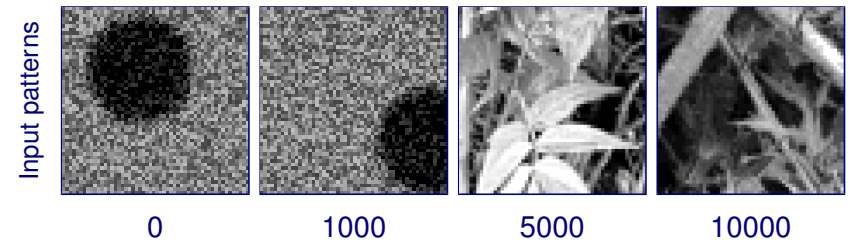
All types of CFs
Longer range lateral
weights
Histogram:
horizontal, vertical
bias

OR Map: Uniform noise

CMVC figure 5.13

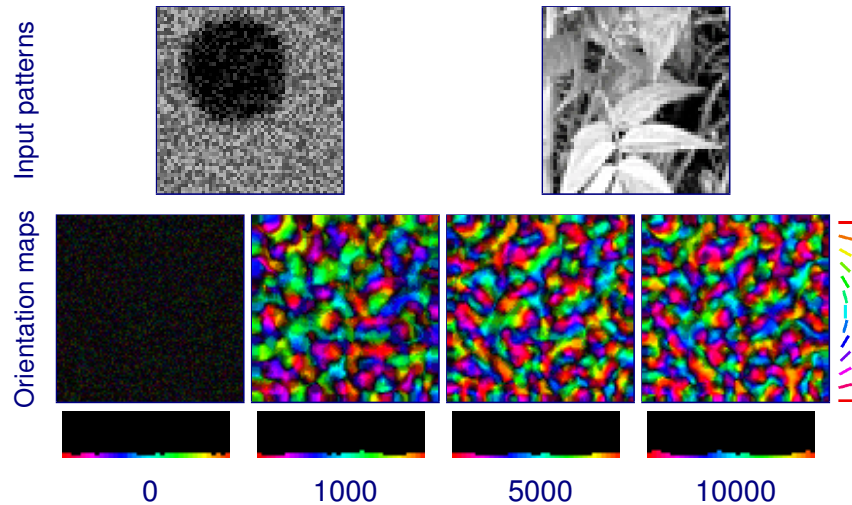


Modeling pre/post-natal phases



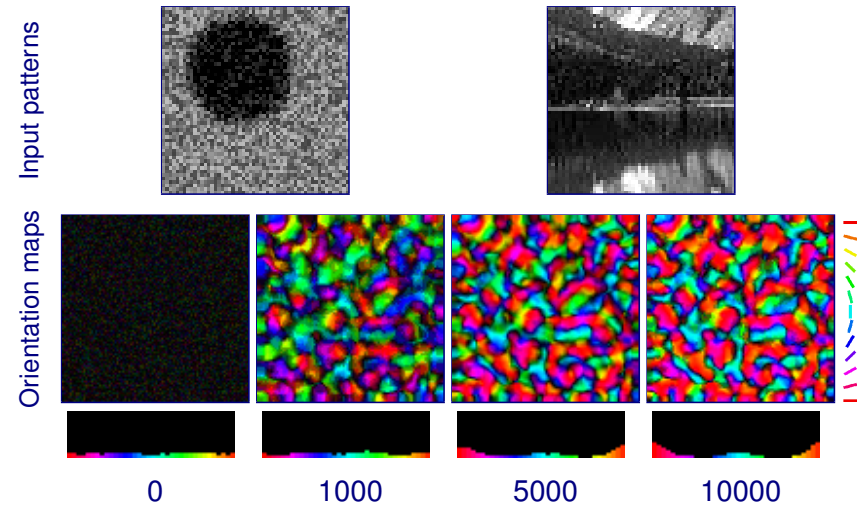
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

Pre/post-natal V1 development



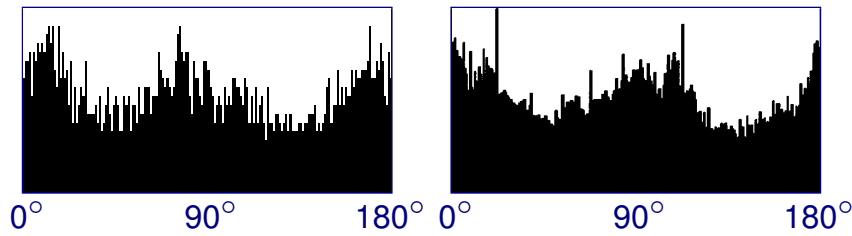
- Neonatal map smoothly becomes more selective

Statistics drive development



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

OR Histograms

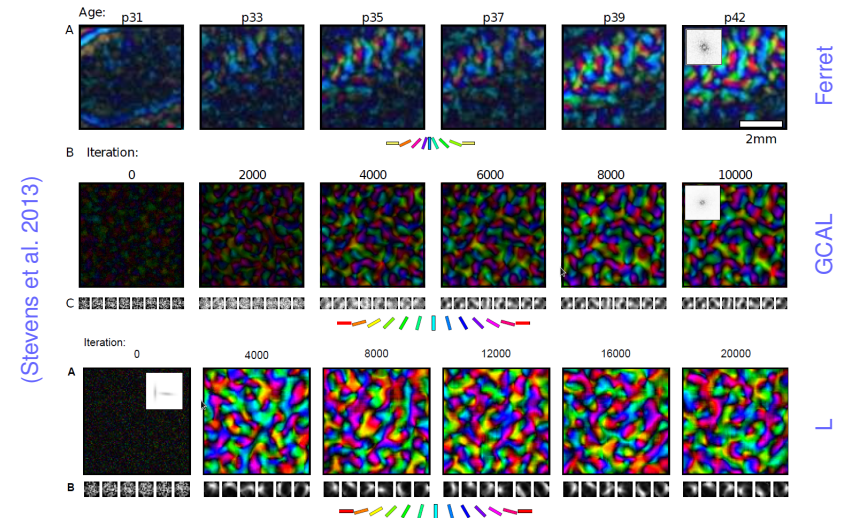


HLISSOM model

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

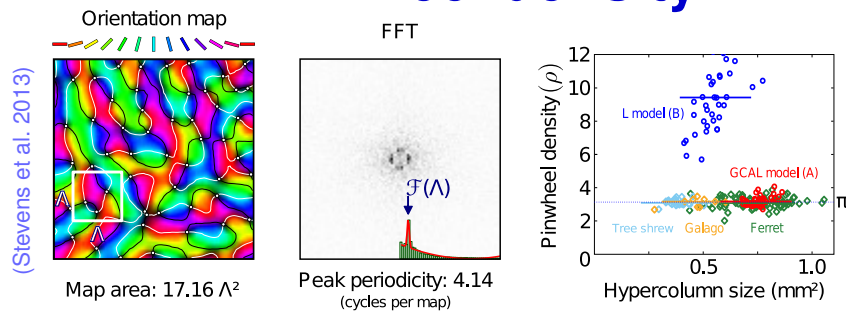
Stable development



(Stevens et al. 2013)

GCAL map development is stable like ferret V1; LISSOM is unstable even w/o threshold changes, radius shrinking (L)

Pinwheel density



(Stevens et al. 2013)

- Animal orientation maps have an average of π pinwheels per hypercolumn (Kaschube et al. 2010)
- GCAL is so far the only mechanistic model shown to have this property
- LISSOM probably would as well, but requires unrealistic mechanisms to do so, since L does not

Summary

- Development depends on features of input pattern
- Orientation maps develop with many different patterns
- Develops Gabor-type CFs 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

- 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.
- Kaschube, M., Schnabel, M., Löwel, S., Coppola, D. M., White, L. E., & Wolf, F. (2010). Universality in the evolution of orientation columns in the visual cortex. *Science*, 330 (6007), 1113–1116.
- 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.

- Stevens, J.-L. R., Law, J. S., Antolik, J., & Bednar, J. A. (2013). Mechanisms for stable, robust, and adaptive development of orientation maps in the primary visual cortex. *Journal of Neuroscience*, 33, 15747–15766.