LISSOM Orientation Maps

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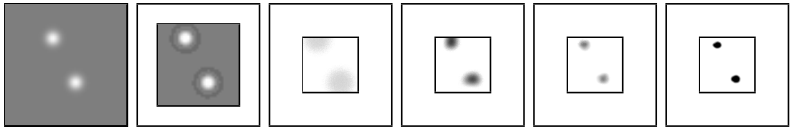
Modeling Orientation

- 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

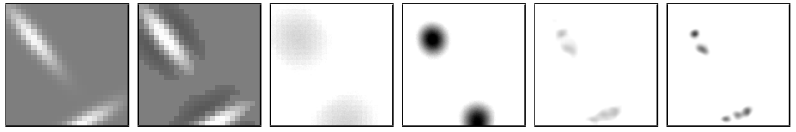


Retinal activation | LGN response | Iteration 0: Initial V1 response | Iteration 0: Settled V1 response | 10,000: Initial V1 response | 10,000: Settled V1 response

CMVC figure 4.4

(Reminder from last time)

Orientation input and response

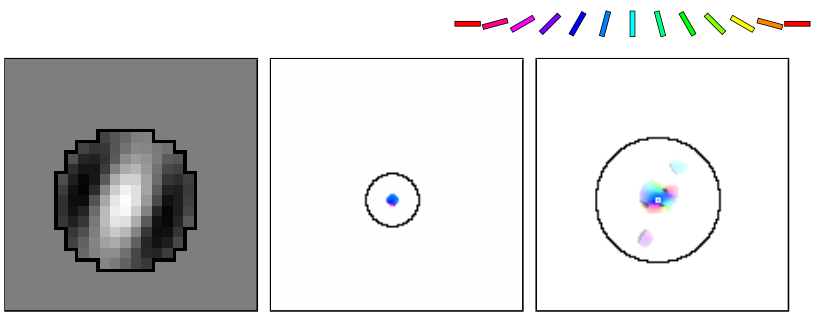


Retinal activation | LGN response | Iteration 0: Initial V1 response | Iteration 0: Settled V1 response | 10,000: Initial V1 response | 10,000: Settled V1 response

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



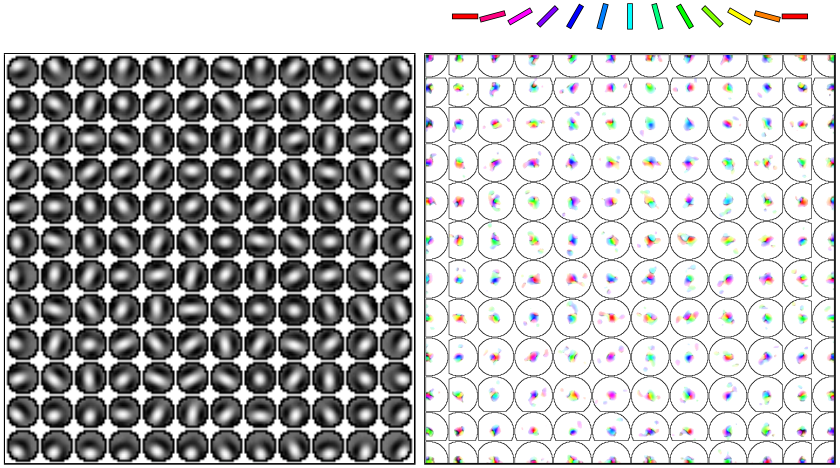
CMVC figure 5.7

Afferent (ON—OFF) Lateral excitatory Lateral inhibitory

Typical:

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

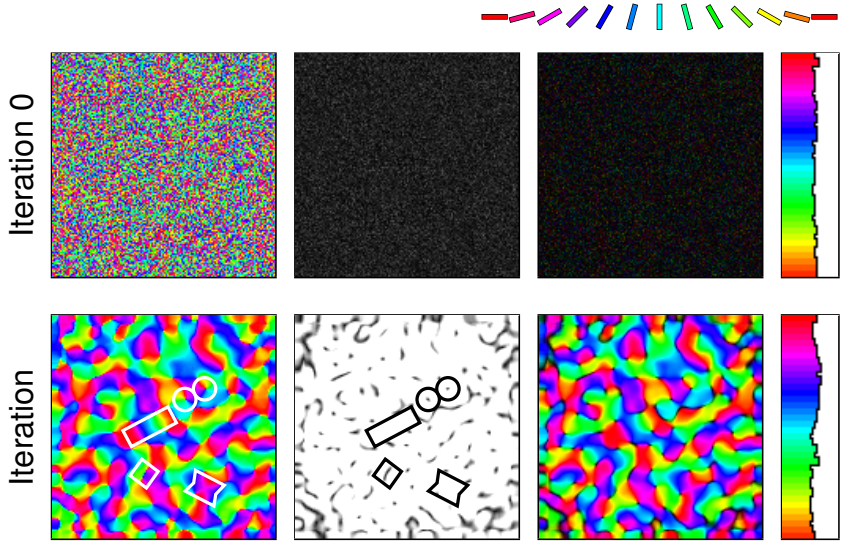
Self-organized weights across V1



CMVC figure 5.8

Afferent (ON—OFF) Lateral inhibitory

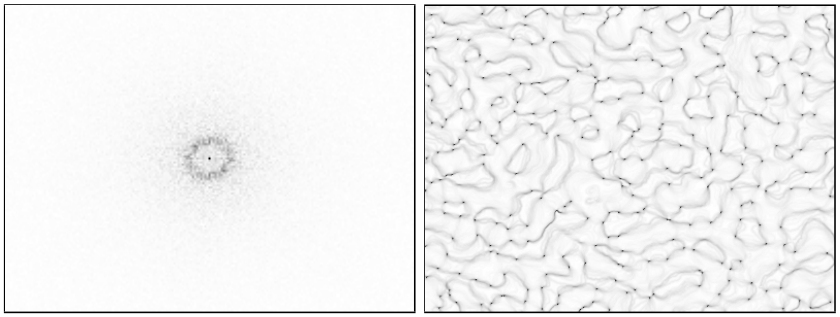
OR map self-organization



CMVC figure 5.9

OR preference OR selectivity OR preference & selectivity OR H

Macaque ORmap: Fourier,gradient



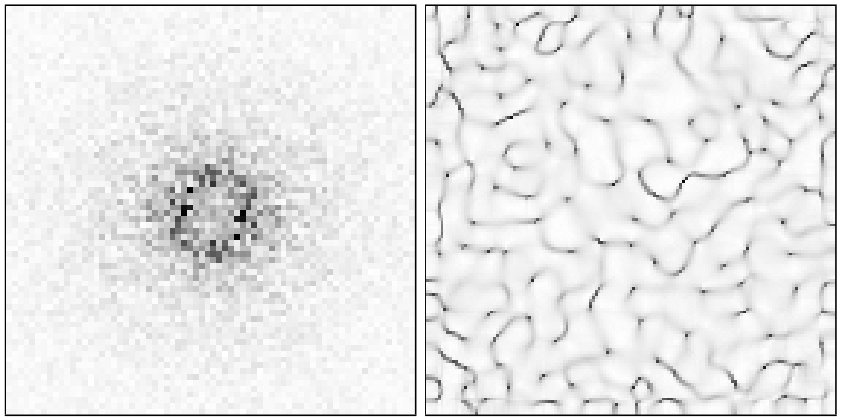
CMVC figure 5.1

Fourier spectrum Gradient

In monkeys:

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

OR Map: Fourier, gradient

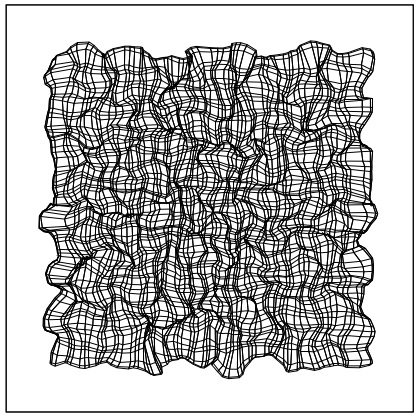


Fourier spectrum Gradient

CMVC figure 5.10

LISSOM model has similar spectrum, gradient

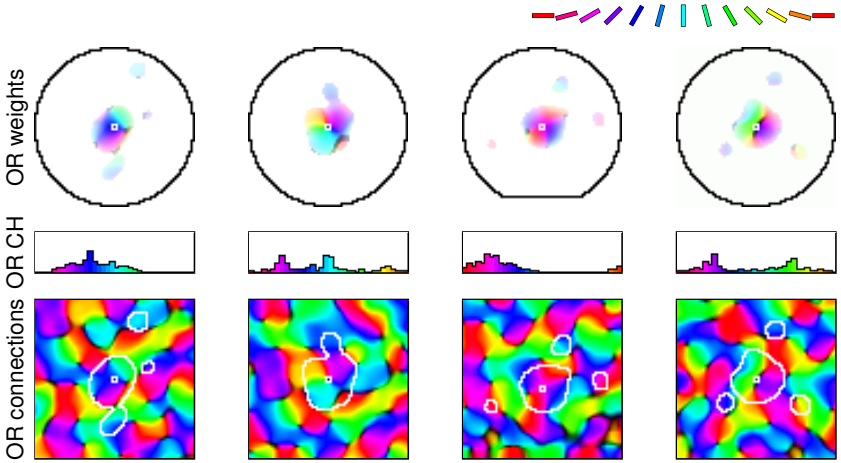
OR Map: Retinotopic organization



CMVC figure 5.11

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

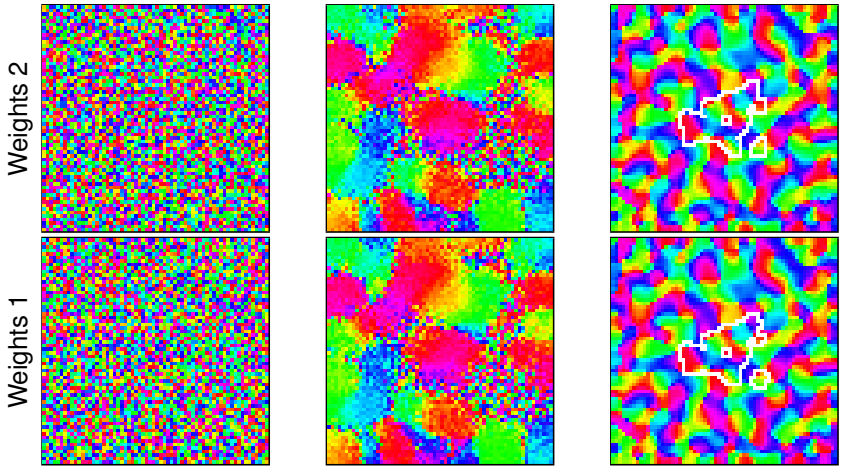
OR Map: Lateral connections



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

CMVC figure 5.12

Effect of initial weights

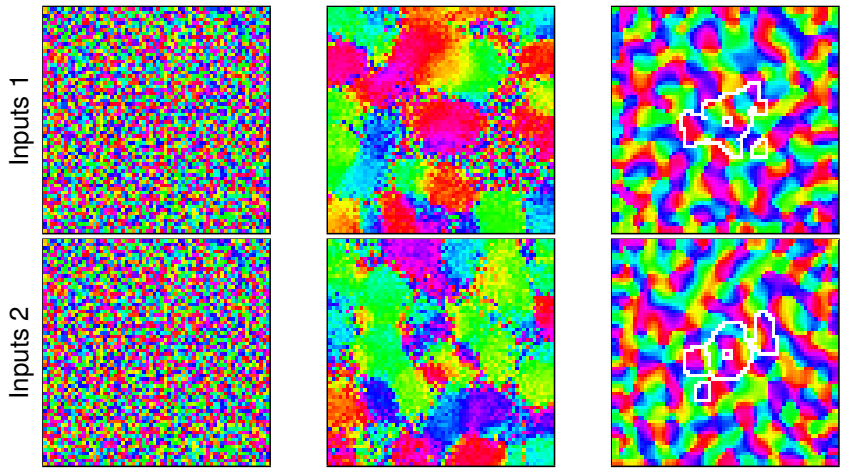


(*a*) Iteration 0 (*b*) Iteration 50 (*c*) Iteration 10,000

CMVC figure 8.5

Changing weights doesn't change map folding pattern.

Effect of input streams

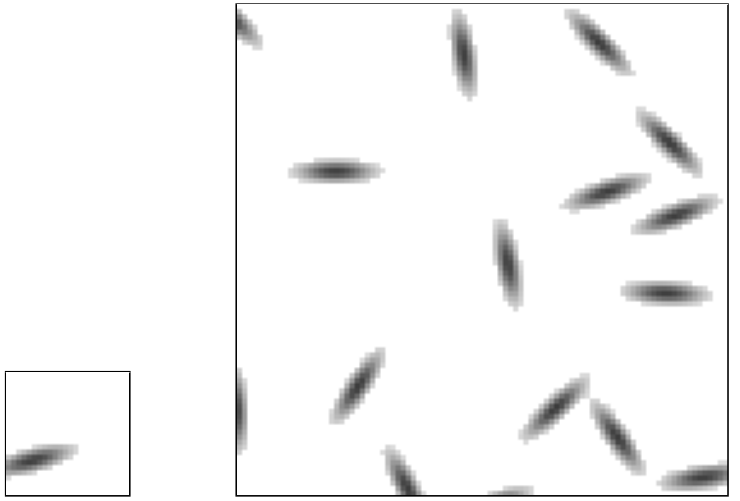


CMVC figure 8.5

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

Changing inputs changes entire pattern.

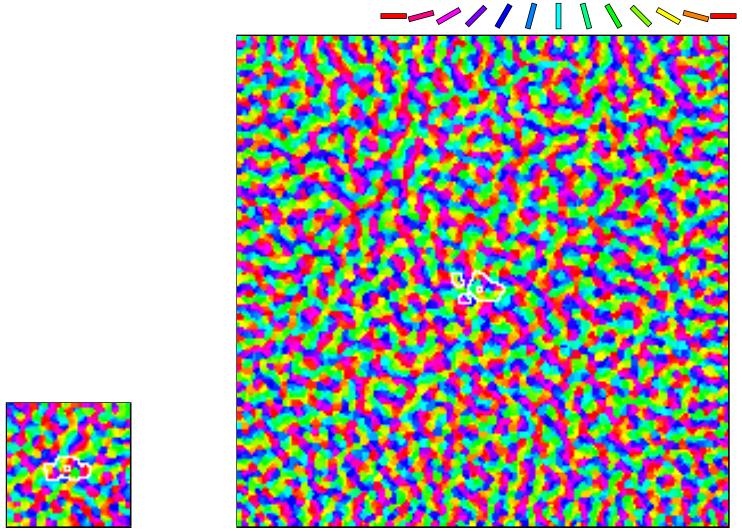
Scaling retinal and cortical area



CMVC figure 15.1a,b

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

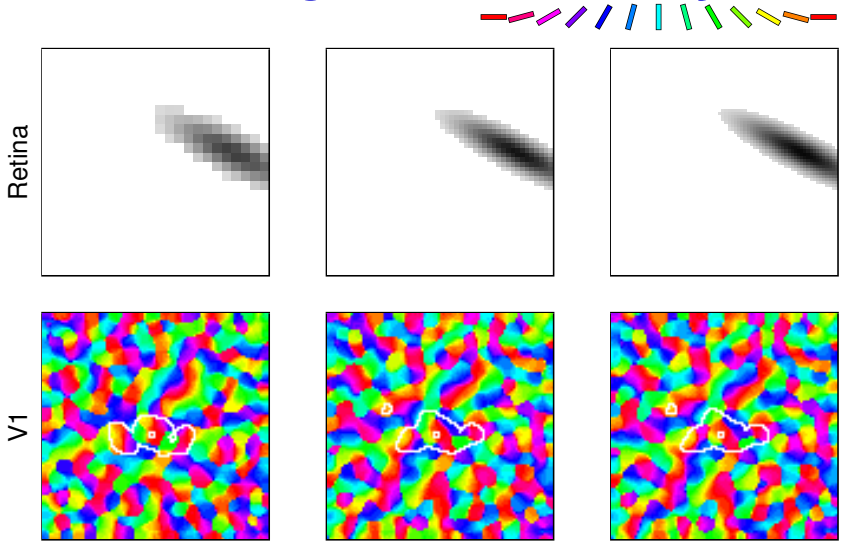
Scaling retinal and cortical area



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

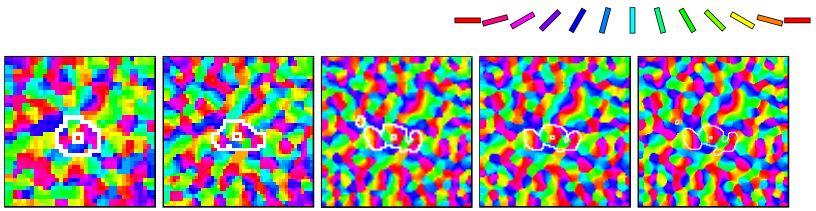
Scaling retinal density



CMVC figure 15.2

Original retina Retina scaled by 2 Retina scaled by 3

Scaling cortical density

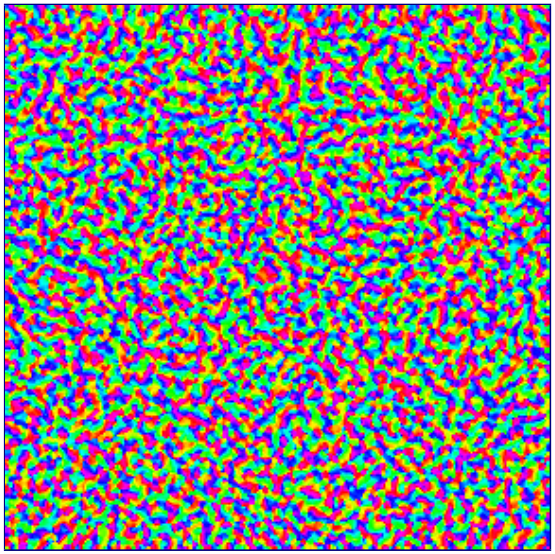


CMVC figure 15.3

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

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

Full-size V1 Map

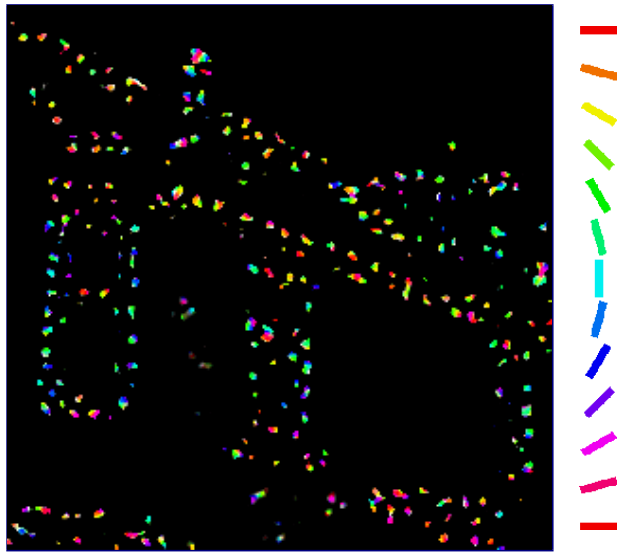


- Map scaled to cover most of visual field
- Allows testing with full-size images
- 30 million connections

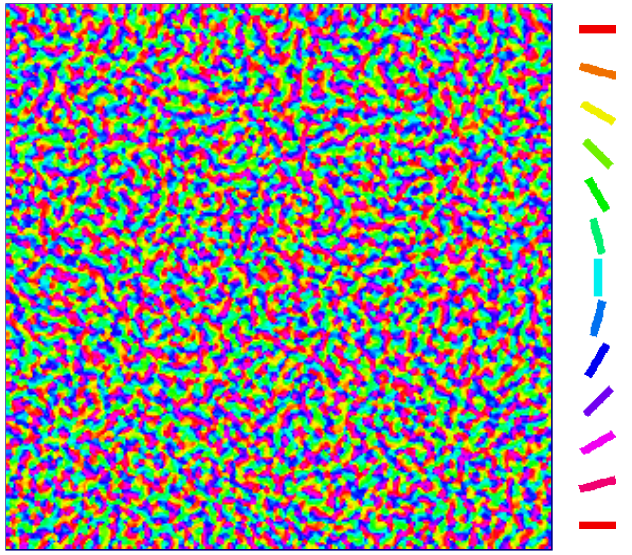
Sample Image

RGC/LGN Response

V1 Response with γ_{n}



V1 Orientation Map



Afferent normalization

Mechanism for contrast invariant tuning:

$$s_{ij} = \frac{\gamma_{\mathrm{A}} \left(\sum_{\rho ab} \xi_{\rho ab} A_{\rho ab,ij} \right)}{1 + \gamma_{\mathrm{n}} \left(\sum_{\rho ab} \xi_{\rho ab} \right)}, \qquad (1)$$

$\xi_{\rho ab}$: 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

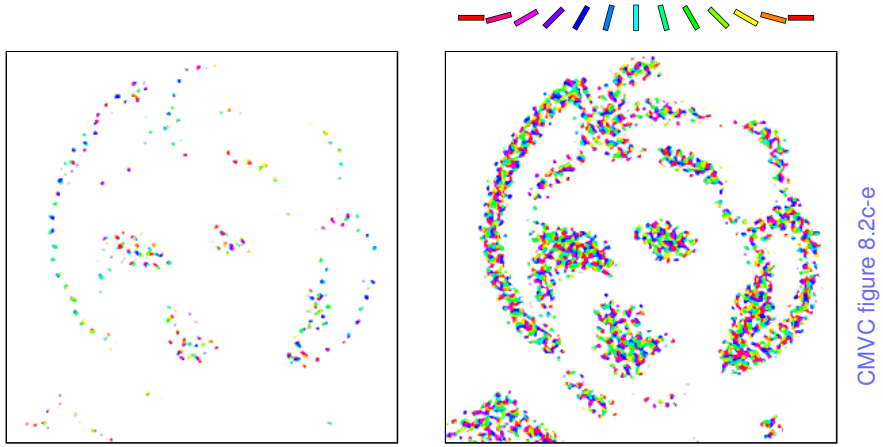
RGC/LGN response to large image

Retinal activation LGN response

CMVC figure 8.2a,b

RGC/LGN responds to most of the visible contours

V1 without afferent normalization



CMVC figure 8.2c-e

V1 response:

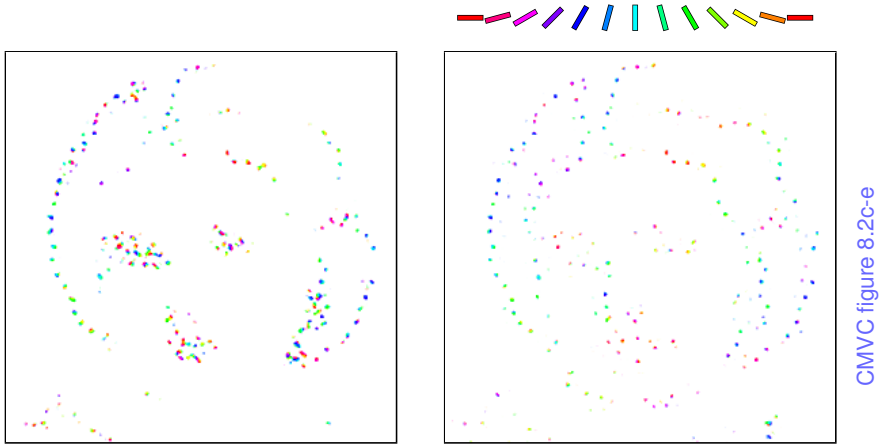
$\gamma_n = 0, \gamma_A = 3.25$

V1 response:

$\gamma_n = 0, \gamma_A = 7.5$

Cannot get selective response to all contours

V1 with afferent normalization



CMVC figure 8.2c-e

V1 response:

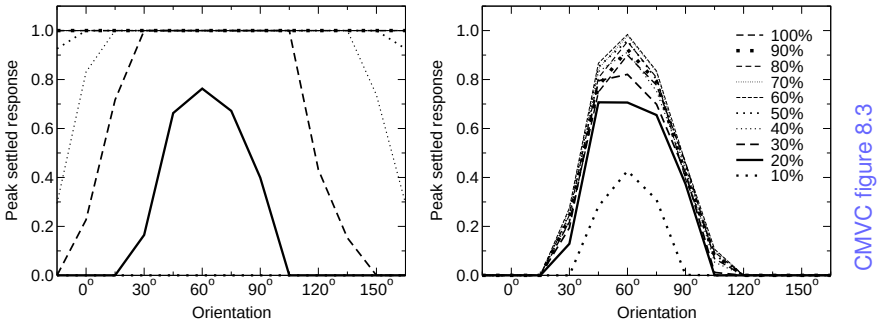
$\gamma_n = 0, \gamma_A = 3.25$

V1 response:

$\gamma_n = 80, \gamma_A = 30$

Responds based on contour, not contrast

Tuning with afferent normalization



CMVC figure 8.3

$\gamma_n = 0, \gamma_A = 3.25$

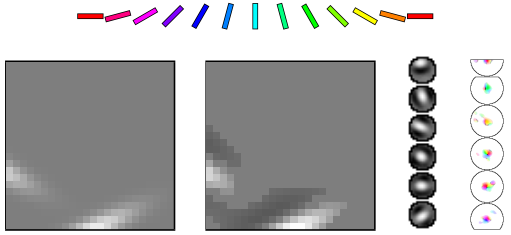
$\gamma_n = 80, \gamma_A = 30$

Sine grating tuning curve:

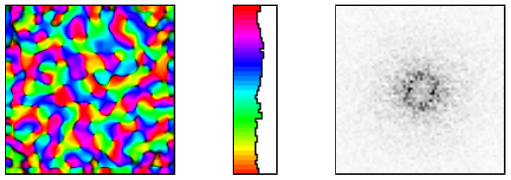
- Without γ_n: selectivity lost as contrast increases
- With γ_n: always orientation-specific

OR Map: Gaussian

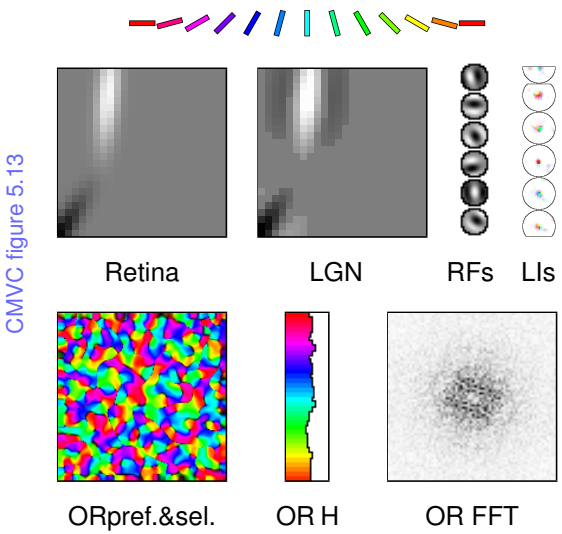
CMVC figure 5.13



White line RFs only

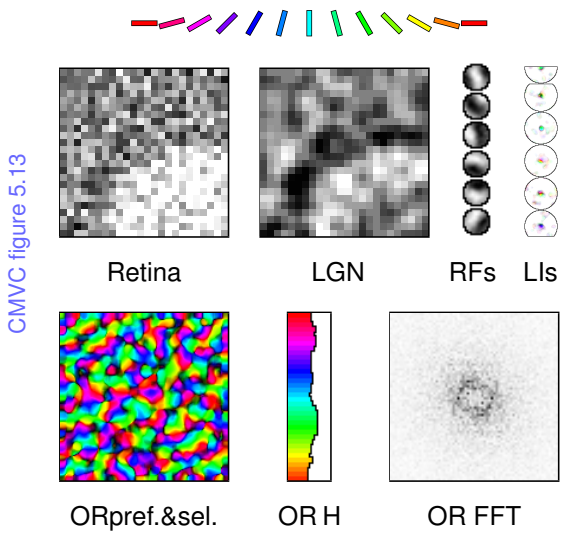


OR Map: +/- Gaussian



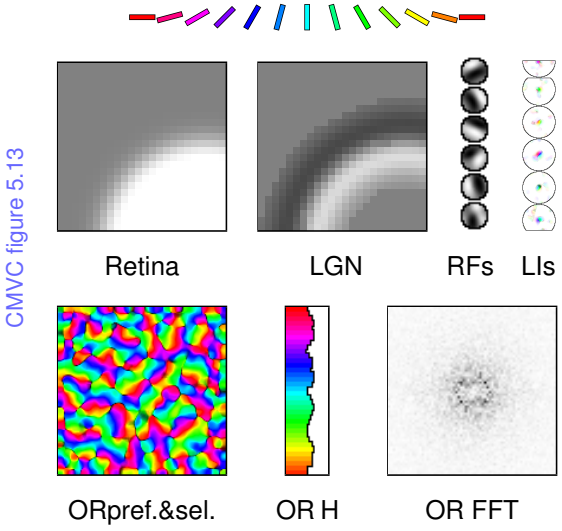
White or black line RFs

OR Map: Retinal wave model



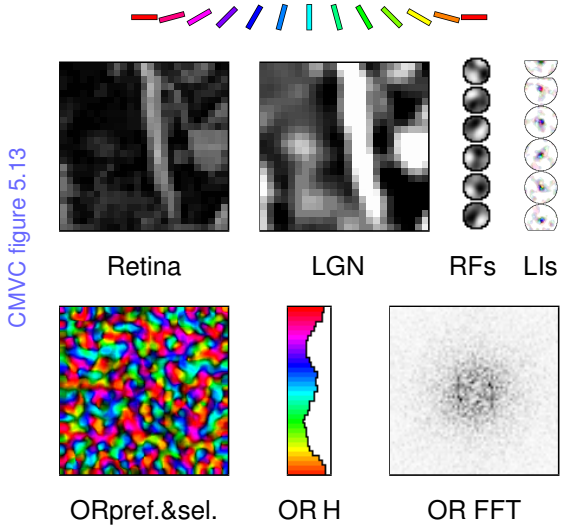
Some line, mostly edge RFs

OR Map: Smooth disks



All edge RFs

OR Map: Natural images

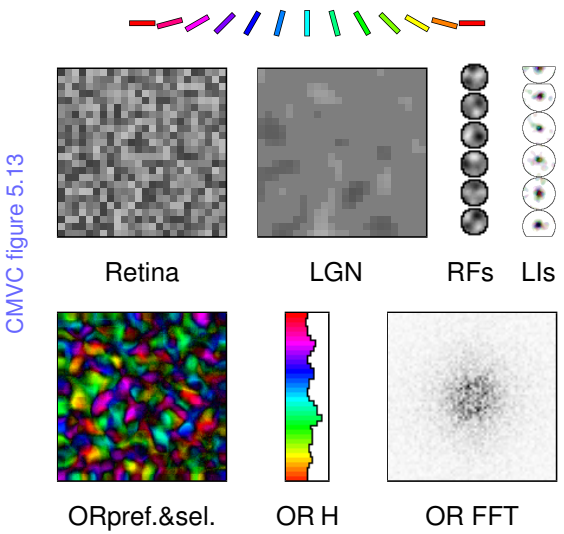


All types of RFs

Longer range lateral weights

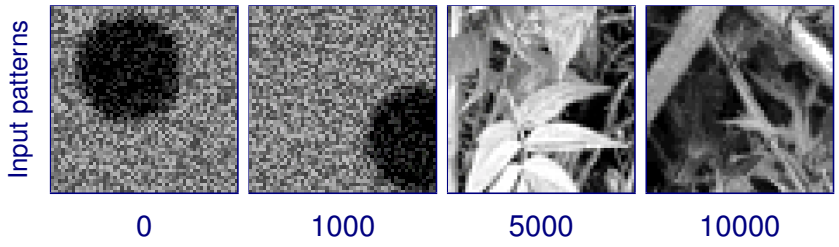
Histogram: horizontal, vertical bias

OR Map: Uniform noise



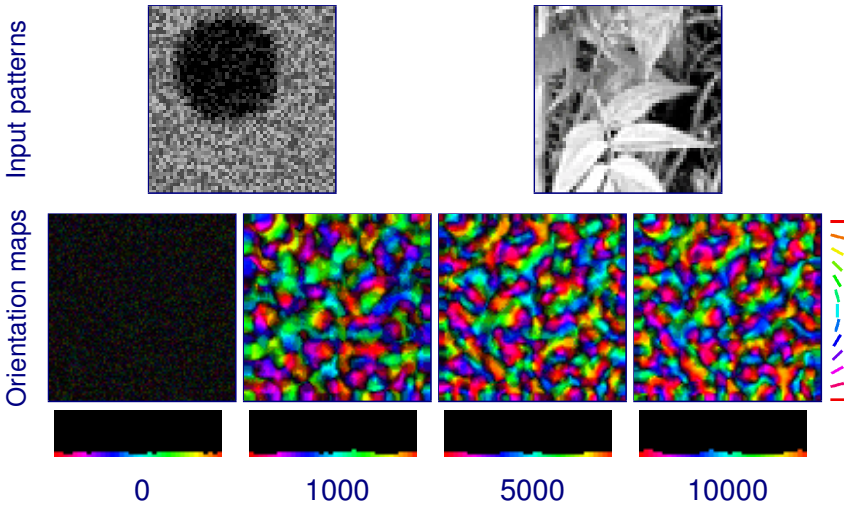
Relatively unselective RFs

Modeling pre/post-natal phases



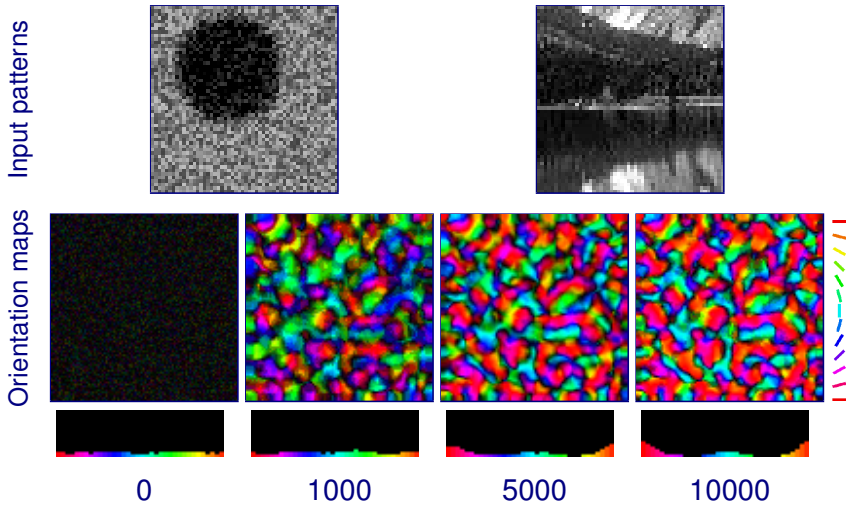
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

Pre/post-natal V1 development



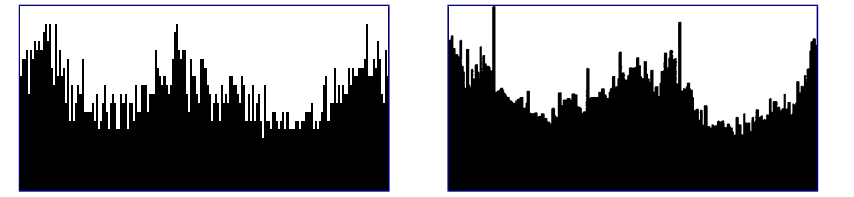
- Neonatal map smoothly becomes more selective

Statistics drive development



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

OR Histograms



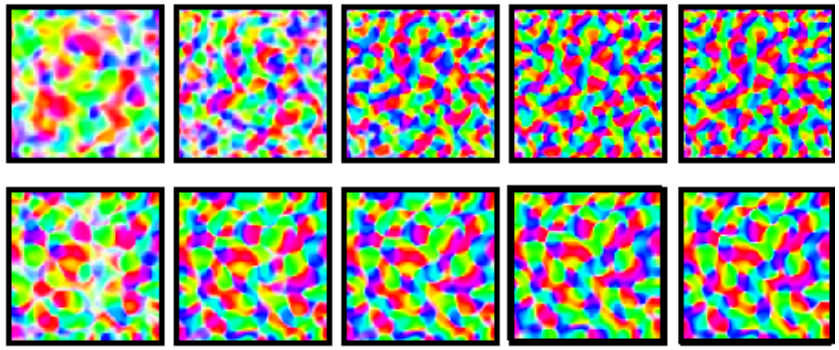
HLISSOM model

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

Standard LISSOM



(Law 2009)

Early GCAL version (see Topographica examples)

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

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.

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.