

# **LISSOM Orientation Maps**

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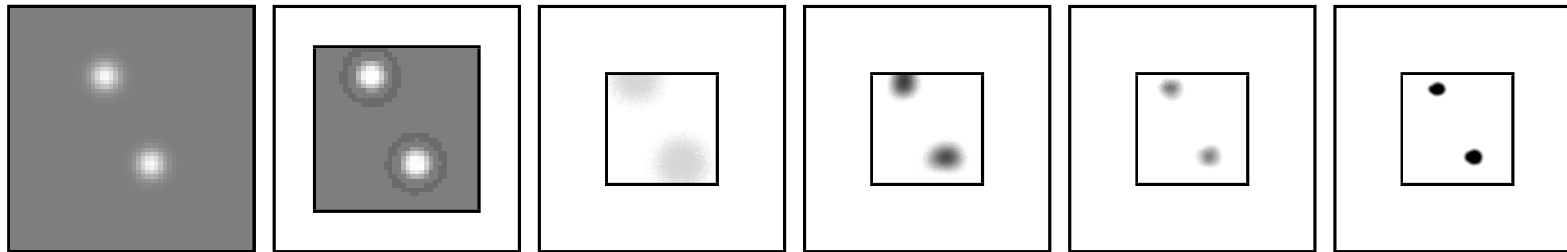
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# Modeling Orientation

- 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

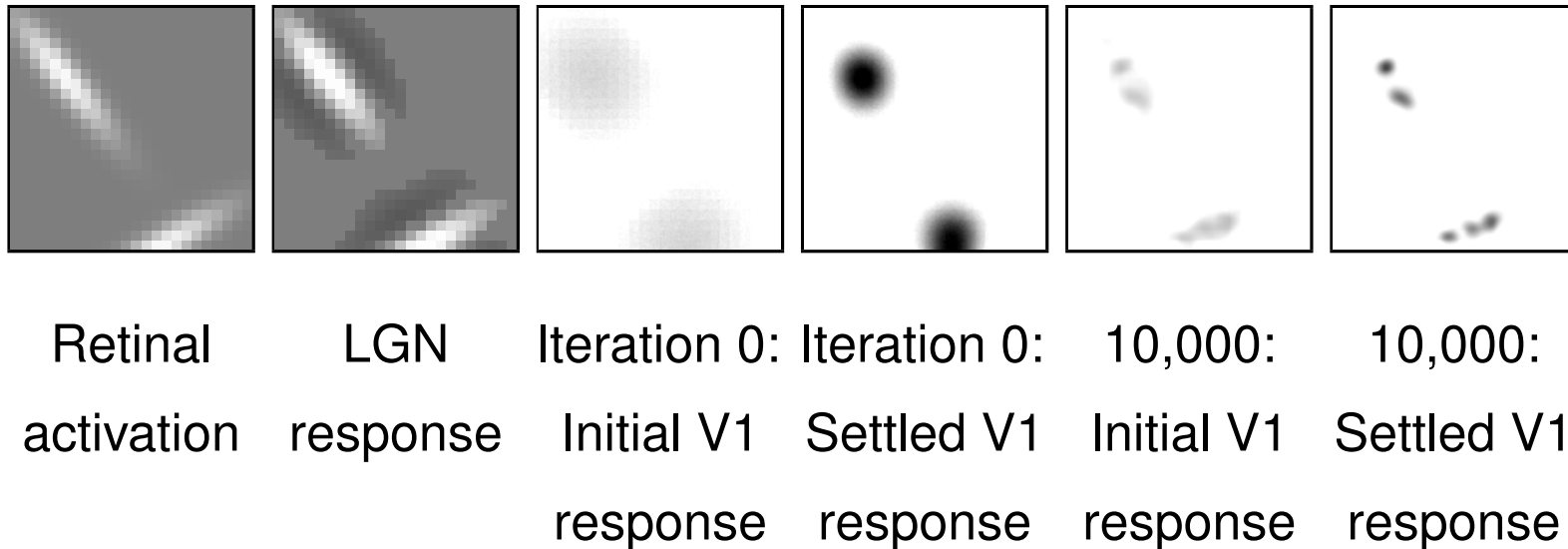


|            |          |              |              |            |            |
|------------|----------|--------------|--------------|------------|------------|
| Retinal    | LGN      | Iteration 0: | Iteration 0: | 10,000:    | 10,000:    |
| activation | response | Initial V1   | Settled V1   |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

CMVC figure 4.4

(Reminder from last time)

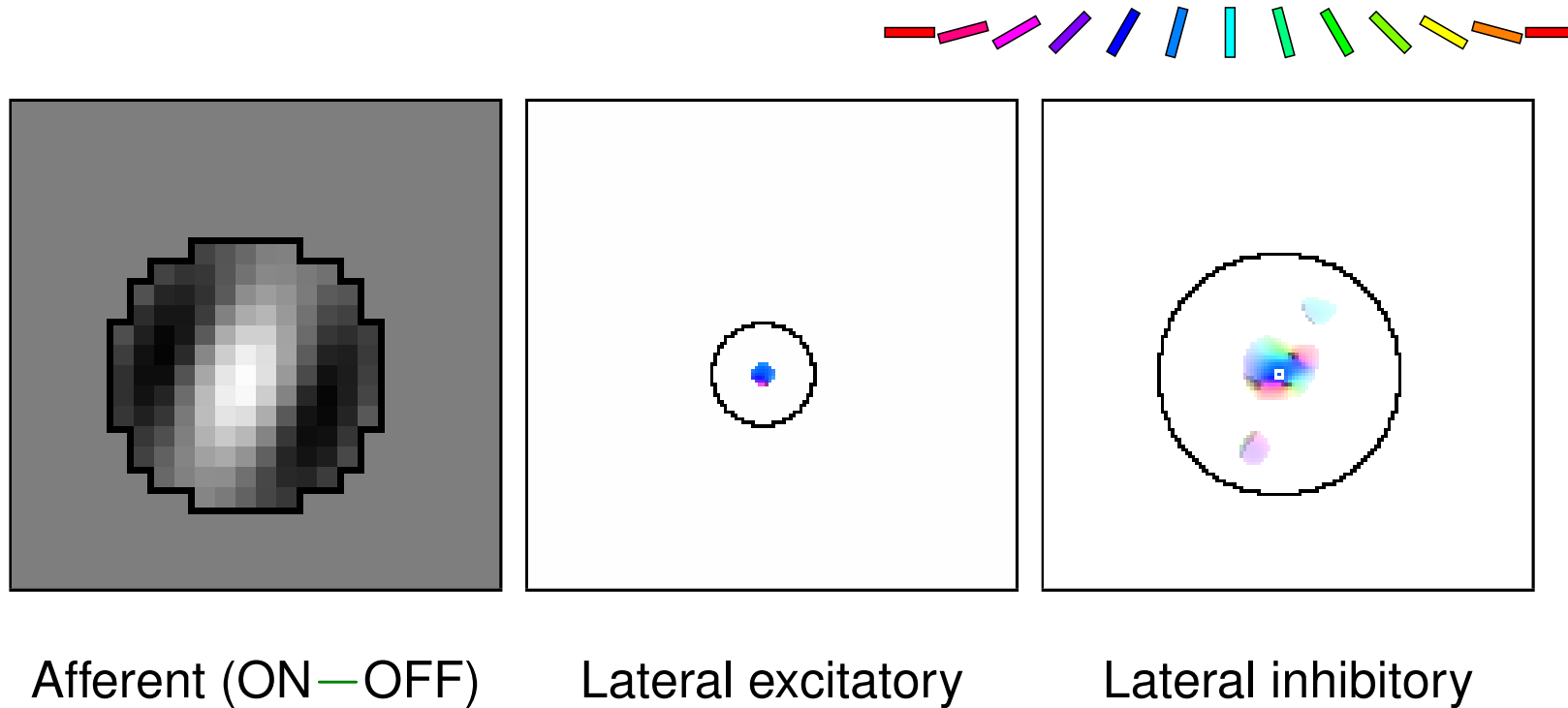
# Orientation input and response



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

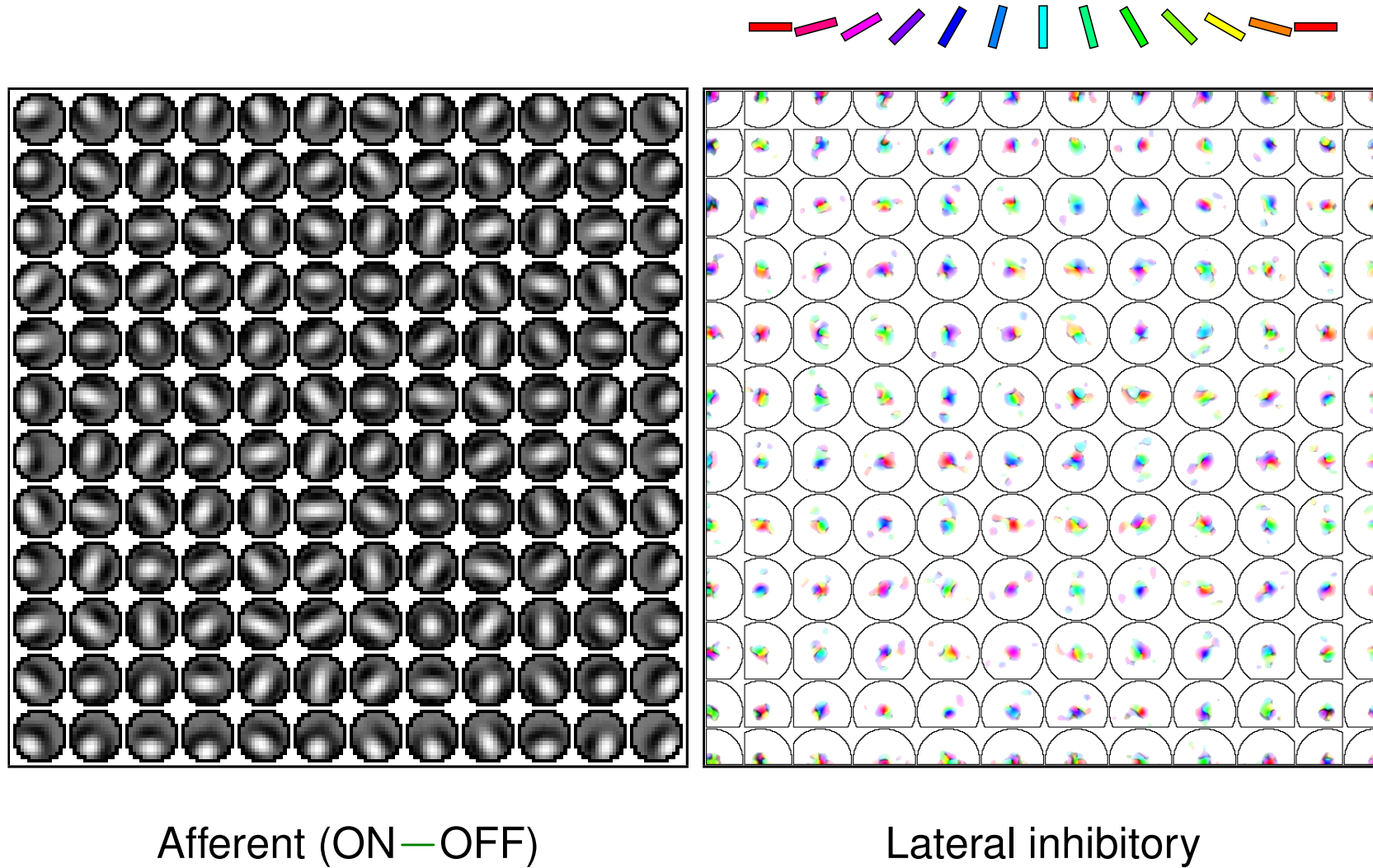


CMVC figure 5.7

Typical:

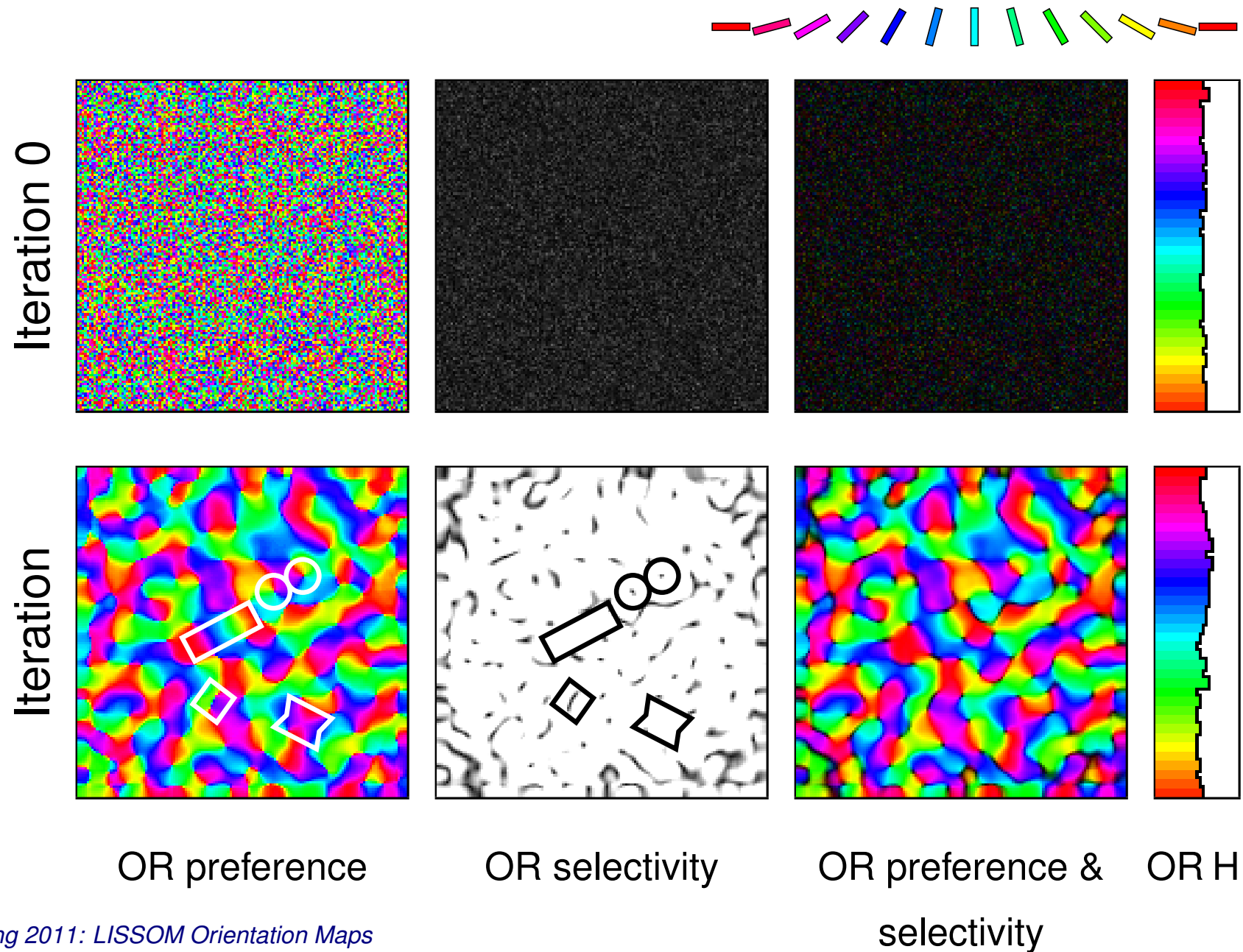
- Gabor-like afferent CF
- Nearly uniform short-range lateral excitatory
- Patchy, orientation-specific long-range lateral inhibitory

# Self-organized weights across V1

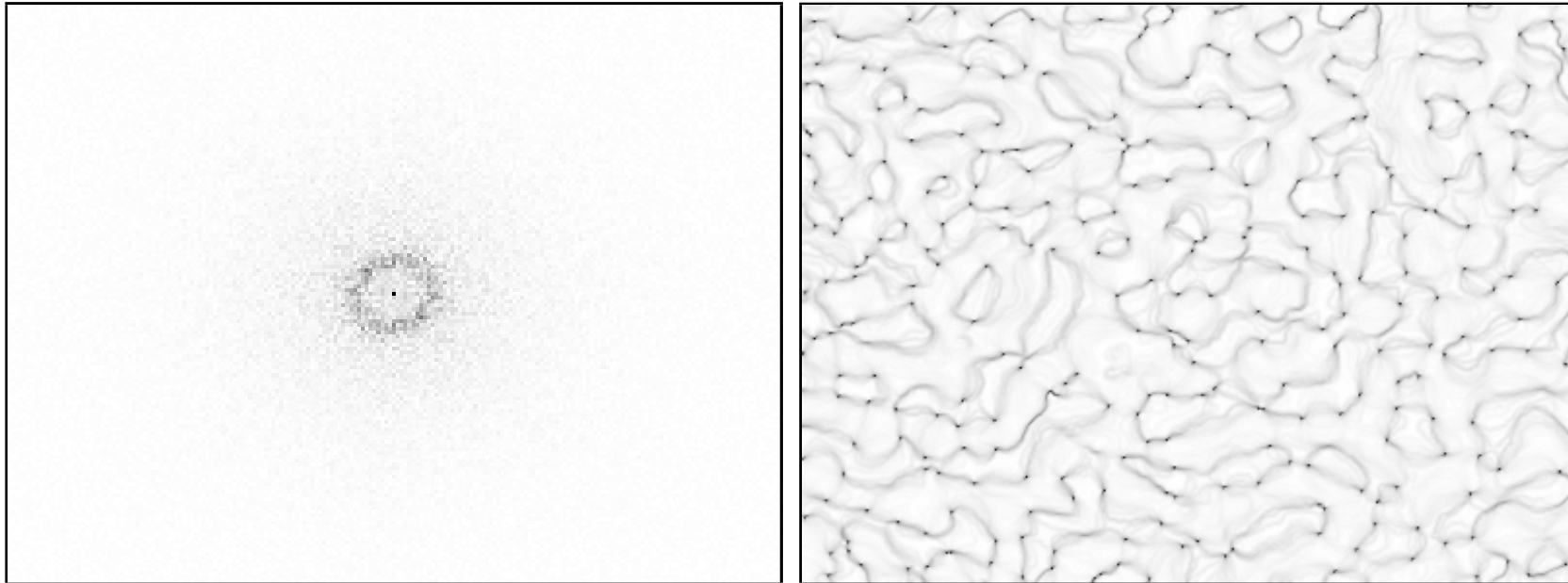


CMVC figure 5.8

# OR map self-organization



# Macaque ORmap: Fourier, gradient



CMVC figure 5.1

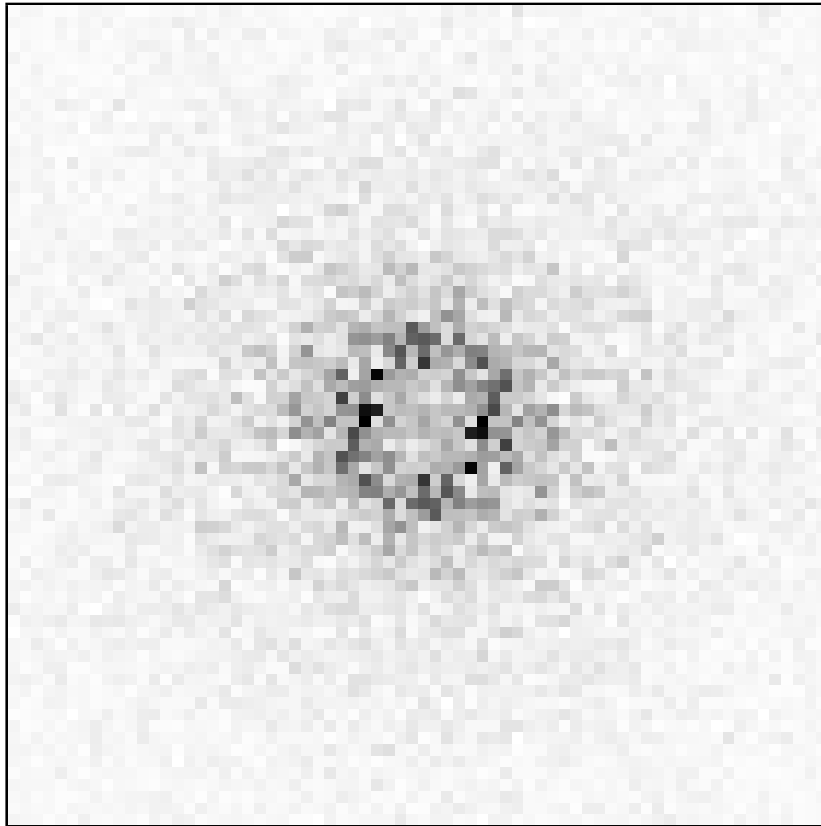
Fourier spectrum

Gradient

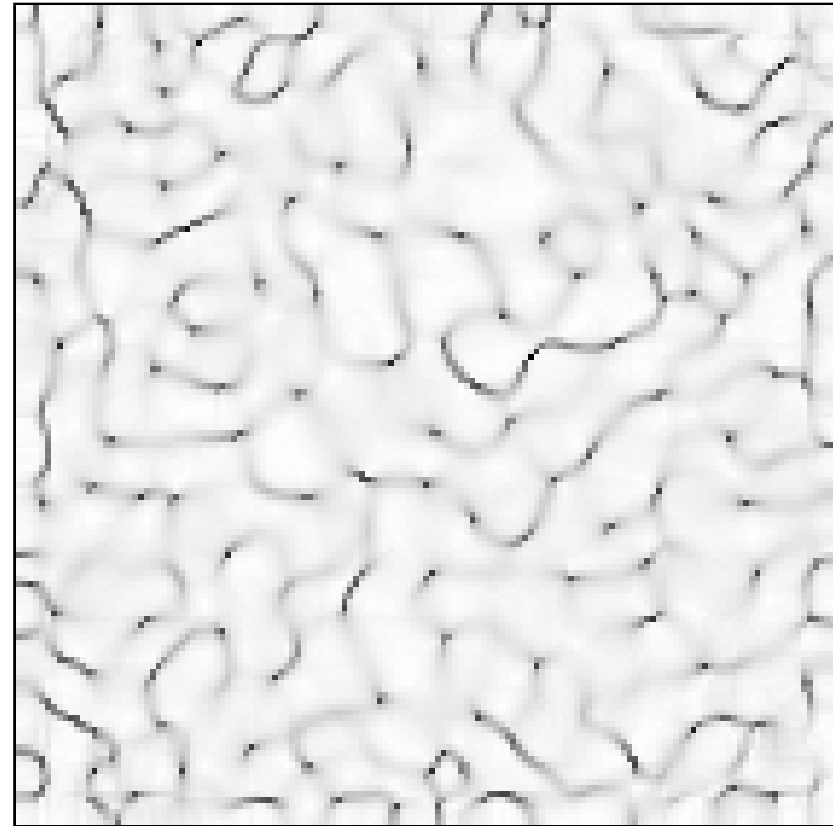
In monkeys:

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

# OR Map: Fourier, gradient



Fourier spectrum

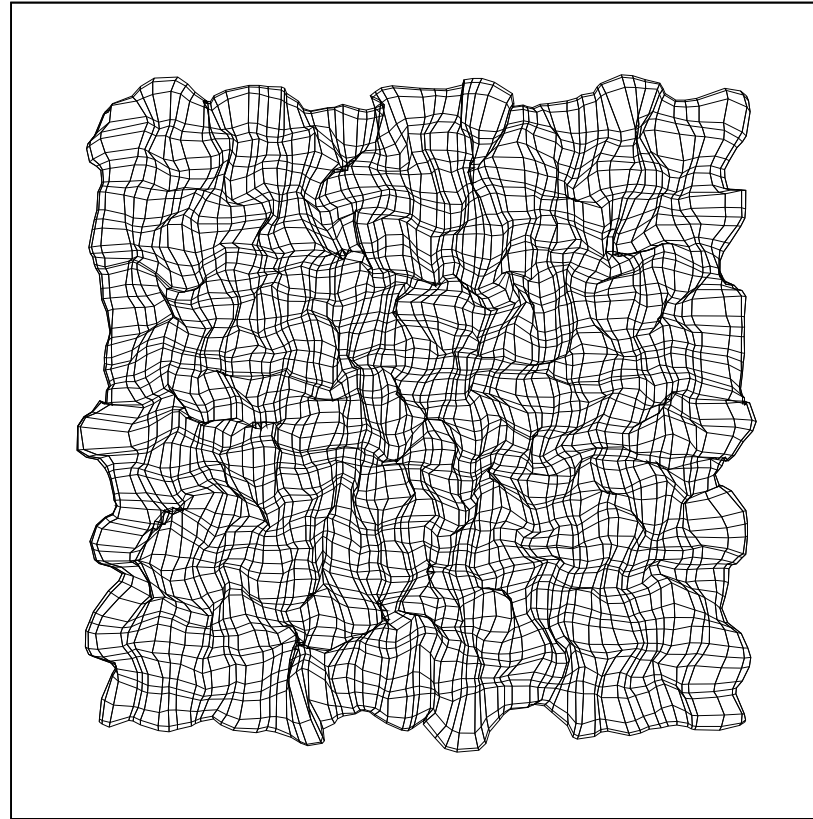


Gradient

CMVC figure 5.10

LISSOM model has similar spectrum, gradient

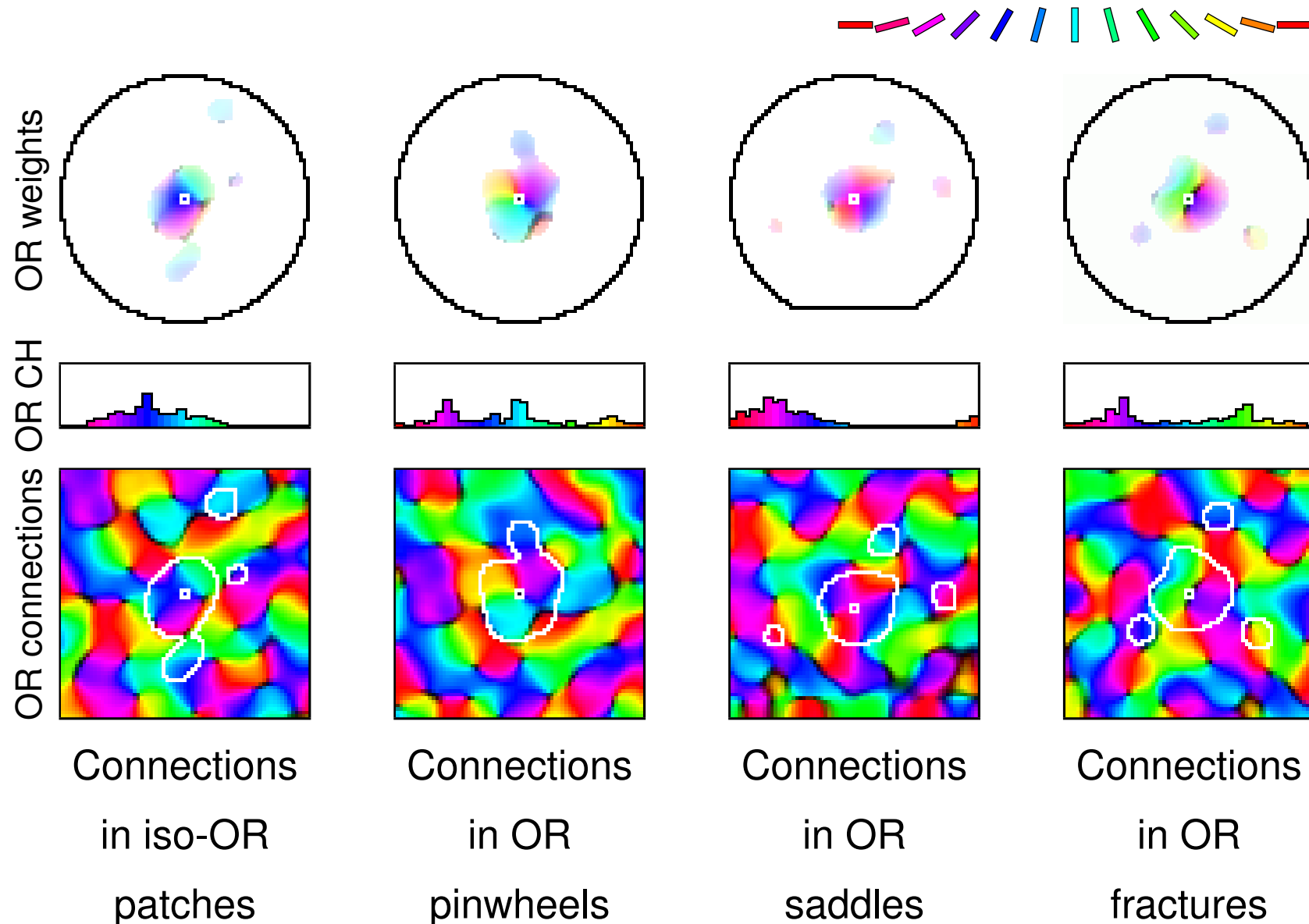
# OR Map: Retinotopic organization



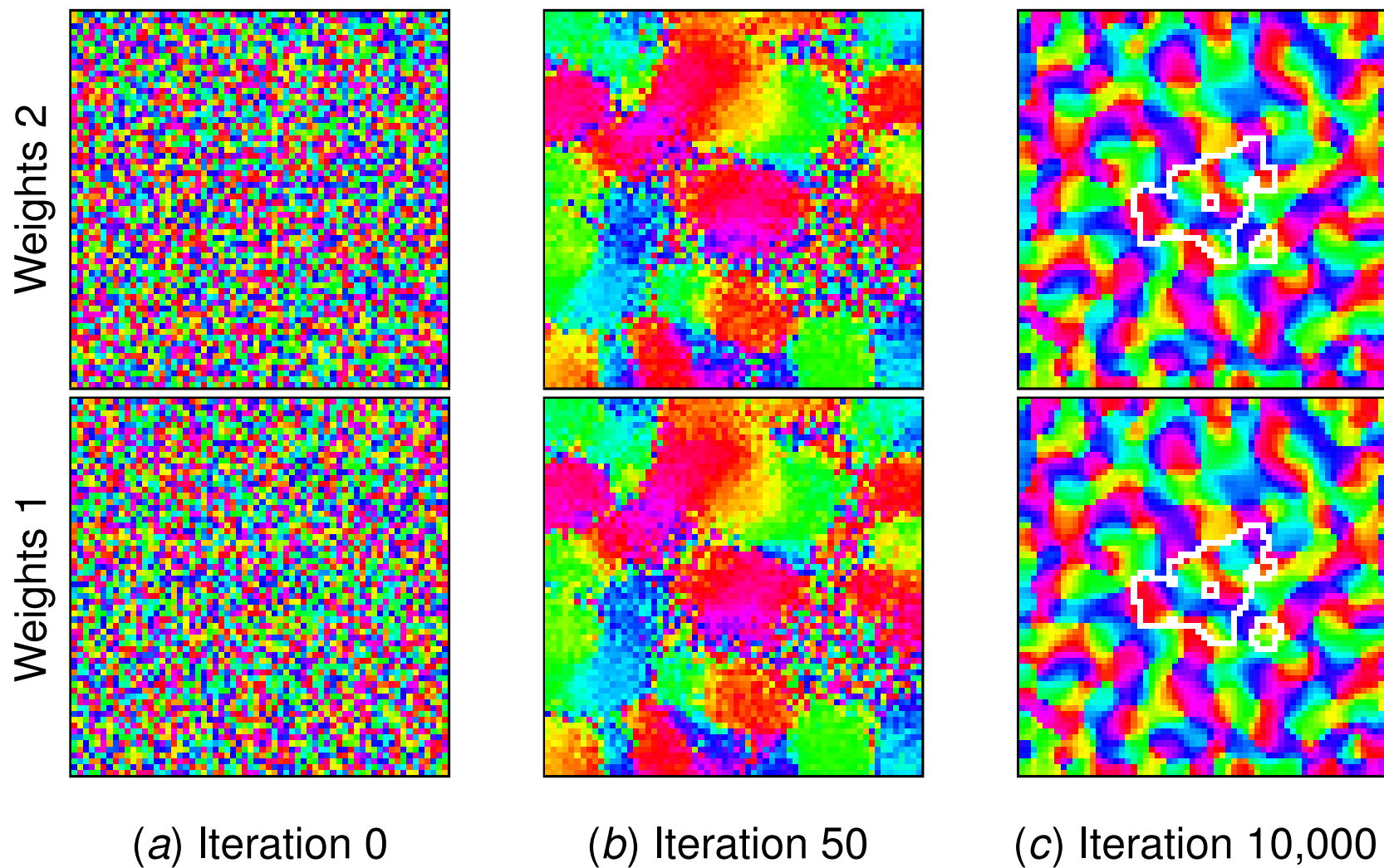
CMVC figure 5.11

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

# OR Map: Lateral connections



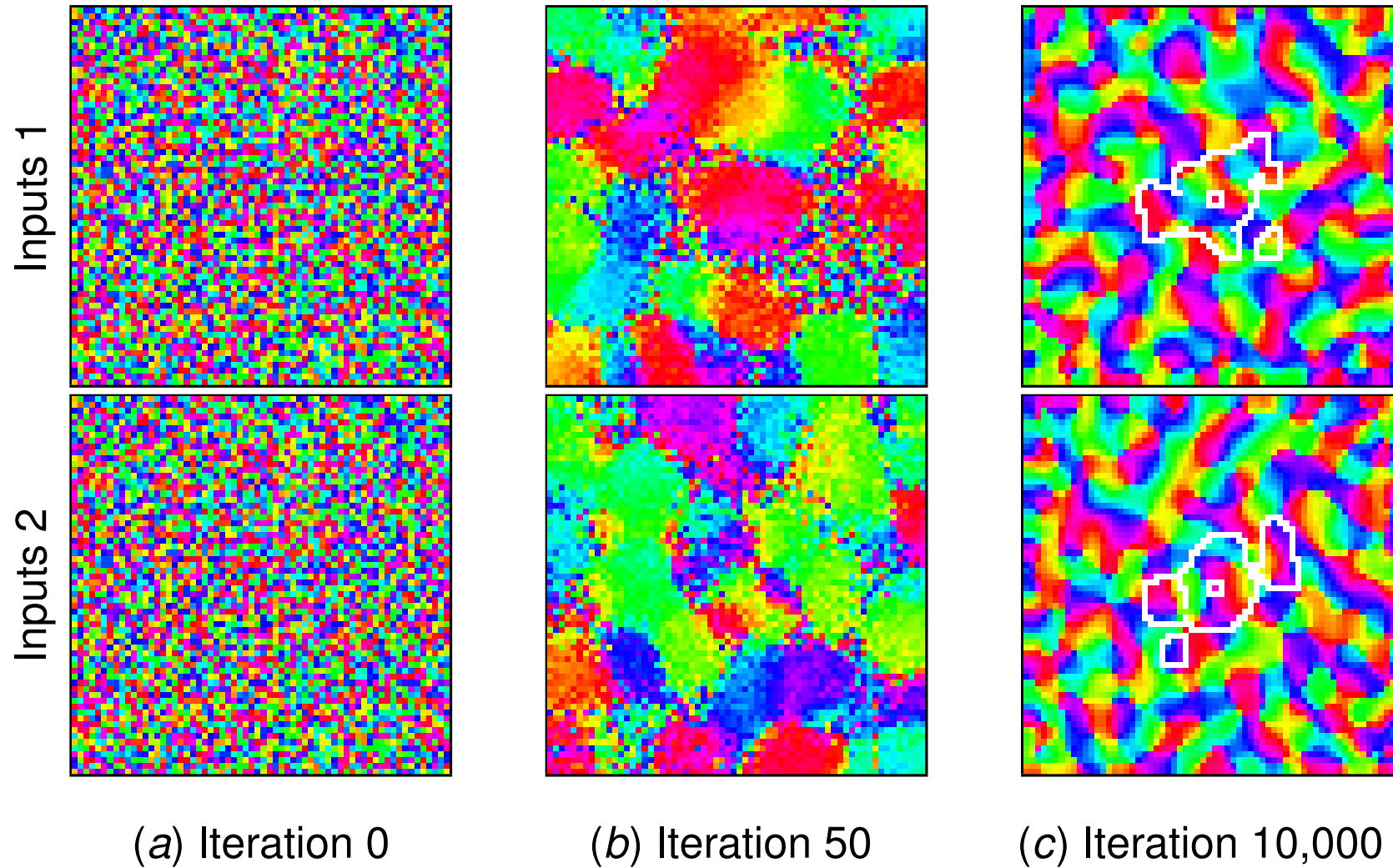
# Effect of initial weights



CMVC figure 8.5

Changing weights doesn't change map folding pattern.

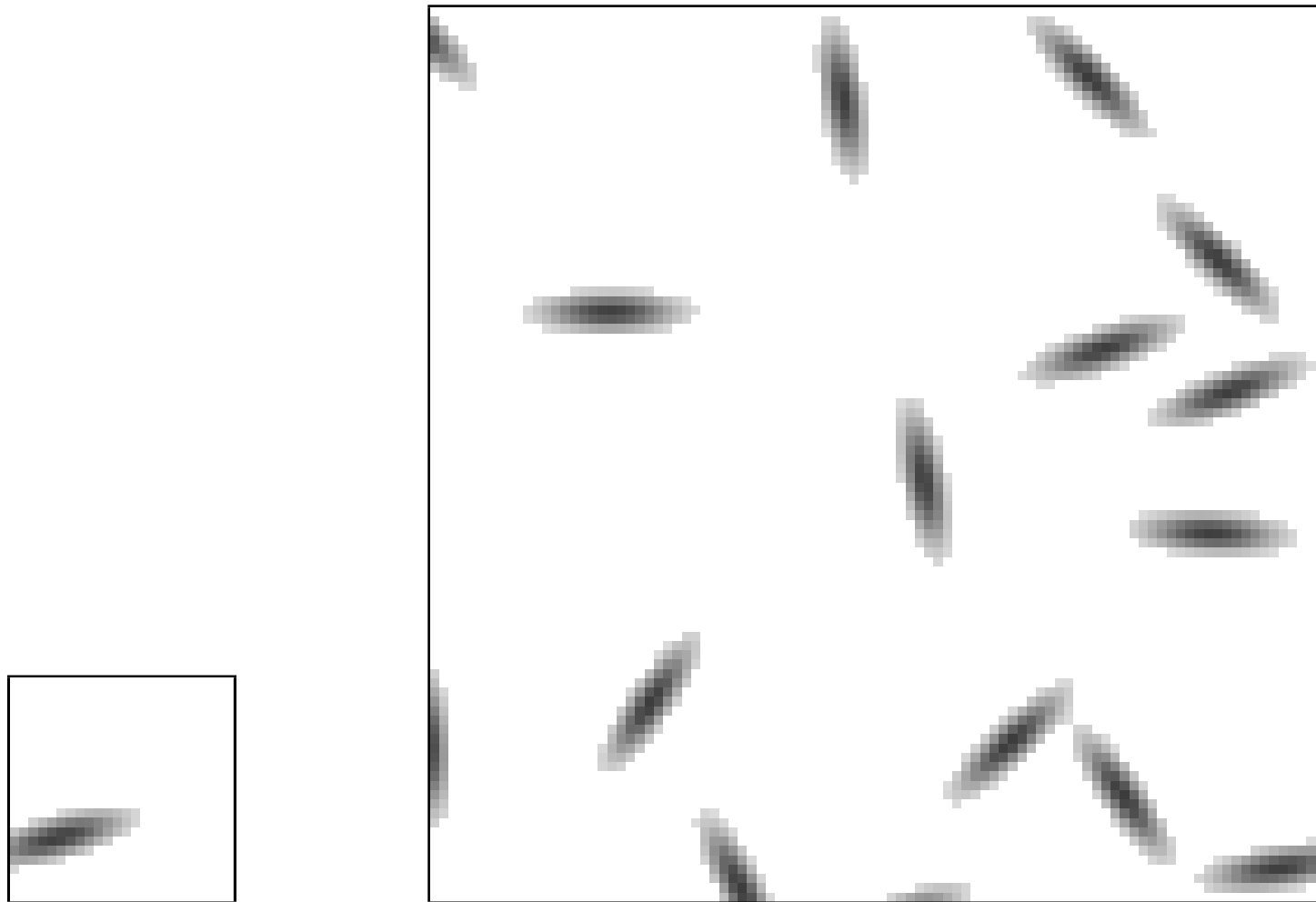
# Effect of input streams



CMVC figure 8.5

Changing inputs changes entire pattern.

# Scaling retinal and cortical area



CMVC figure 15.1a,b

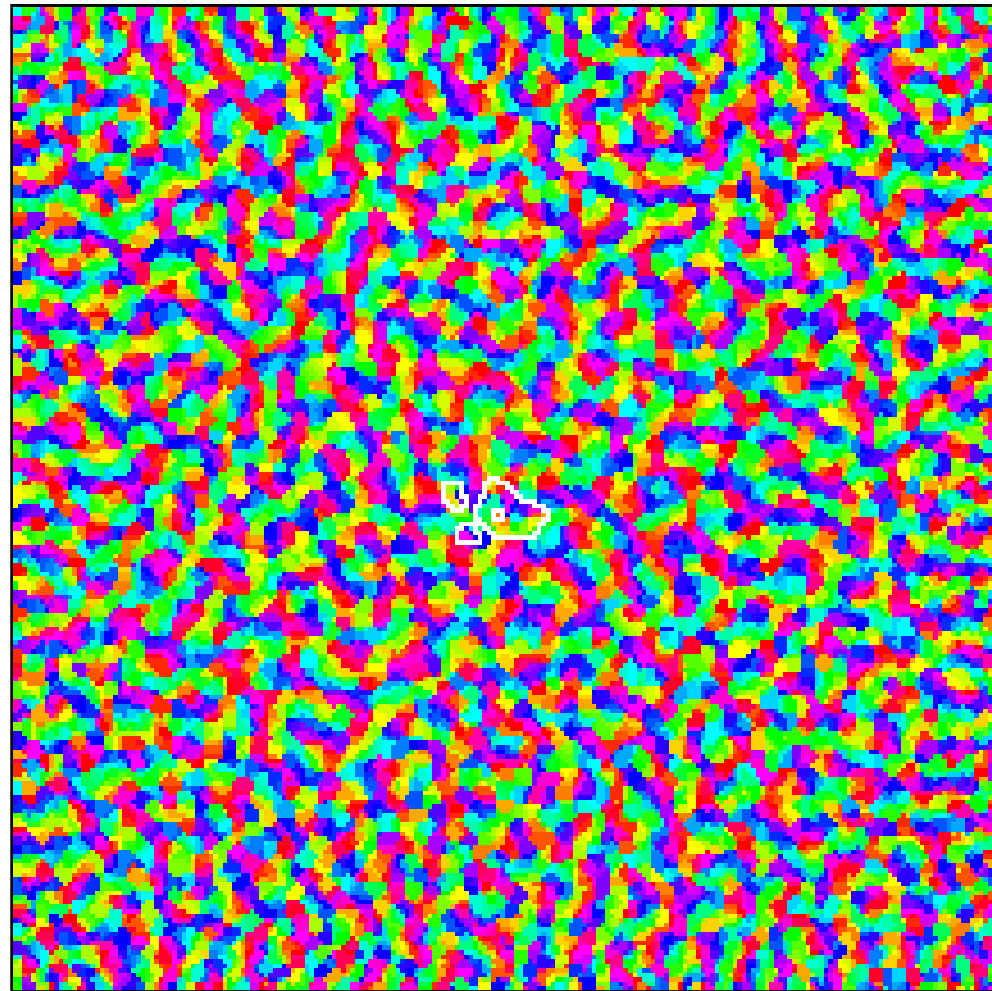
(a) Original retina:  $R = 24$     (b) Retinal area scaled by 4.0:  
 $R = 96$

# Scaling retinal and cortical area



(c) Original V1:

$N = 54$ , 0.4 hours, 8 MB

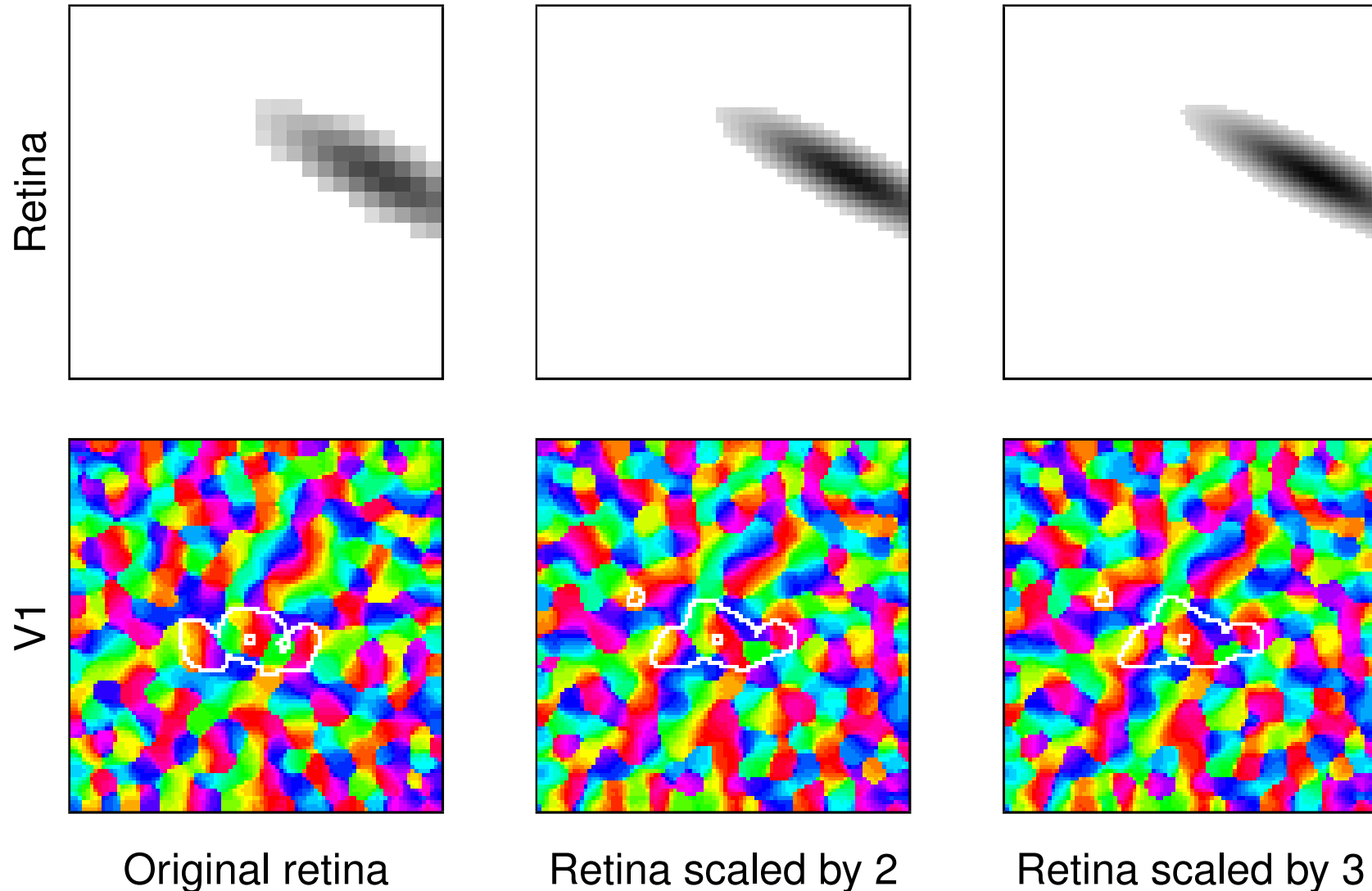


(d) V1 area scaled by 4.0:

$N = 216$ , 9 hours, 148 MB

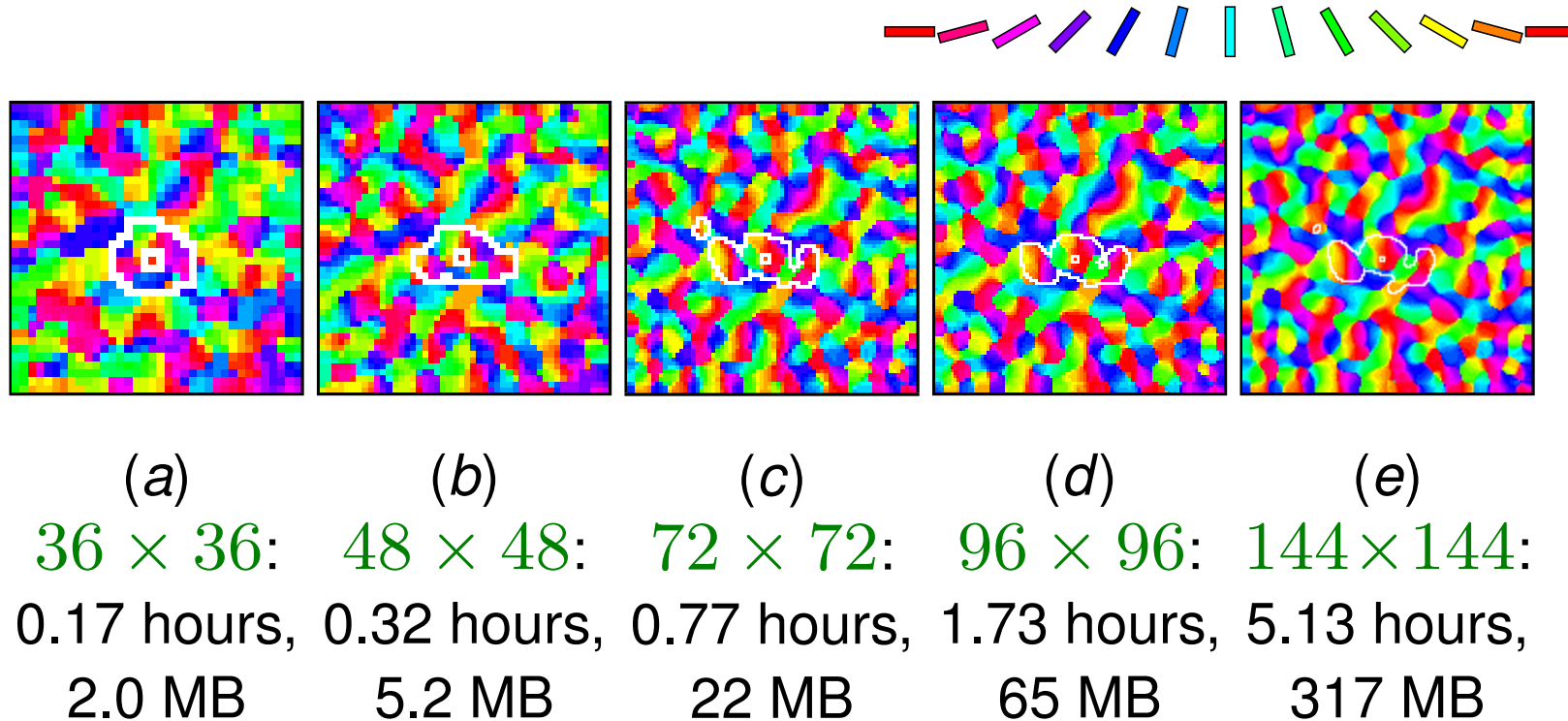
CMVC figure 15.1c,d

# Scaling retinal density



CMVC figure 15.2

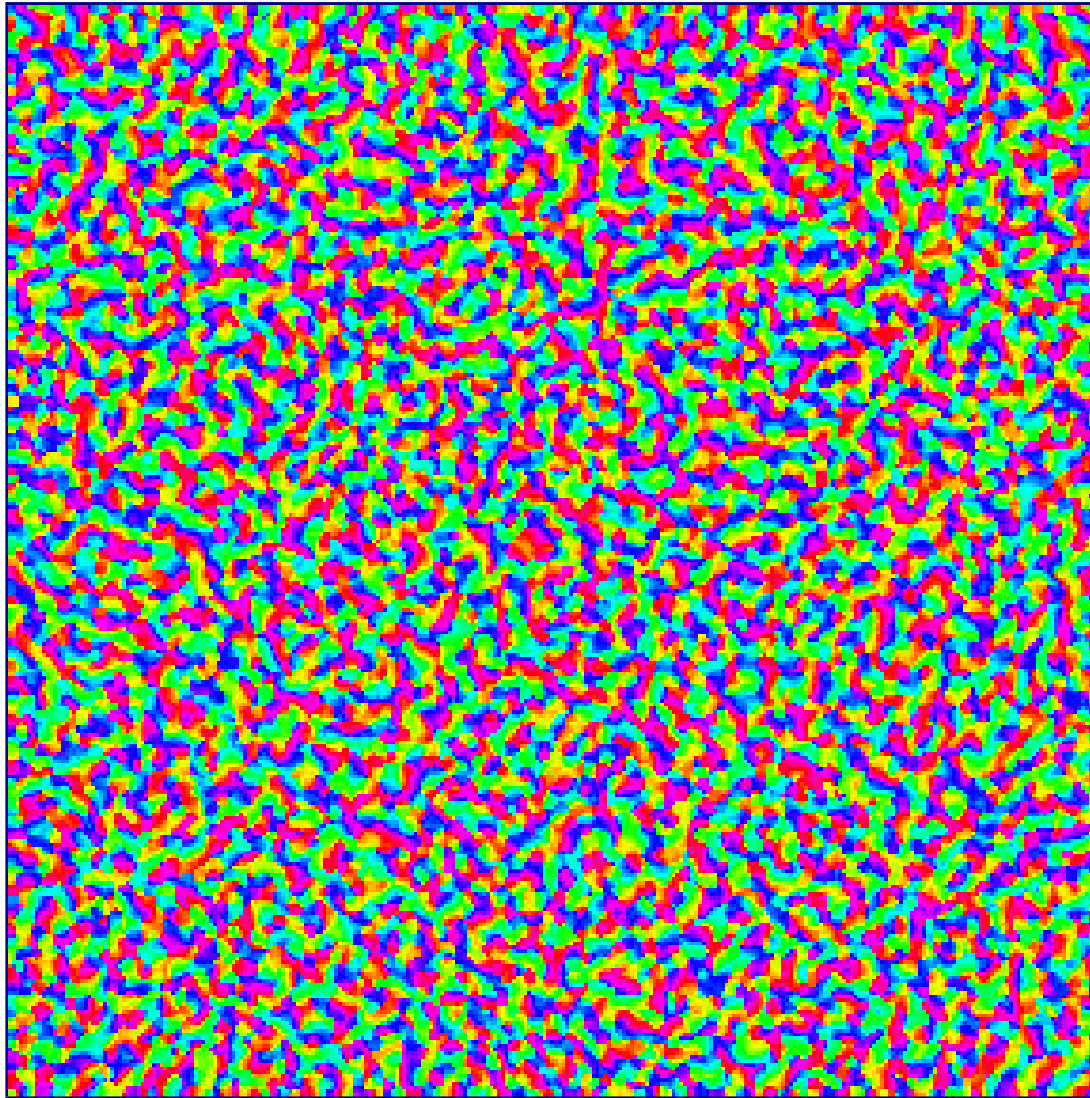
# Scaling cortical density



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

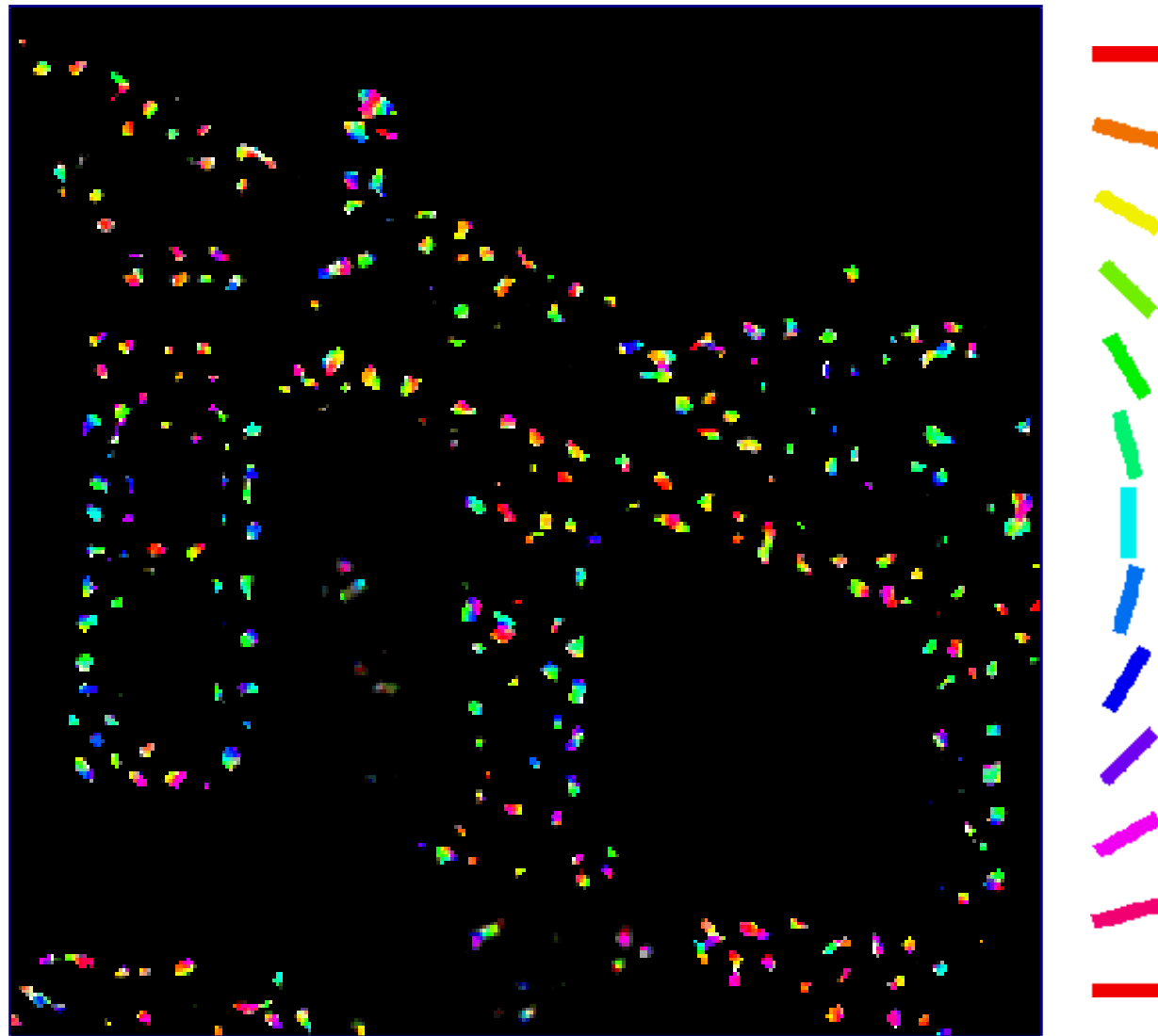
# Sample Image



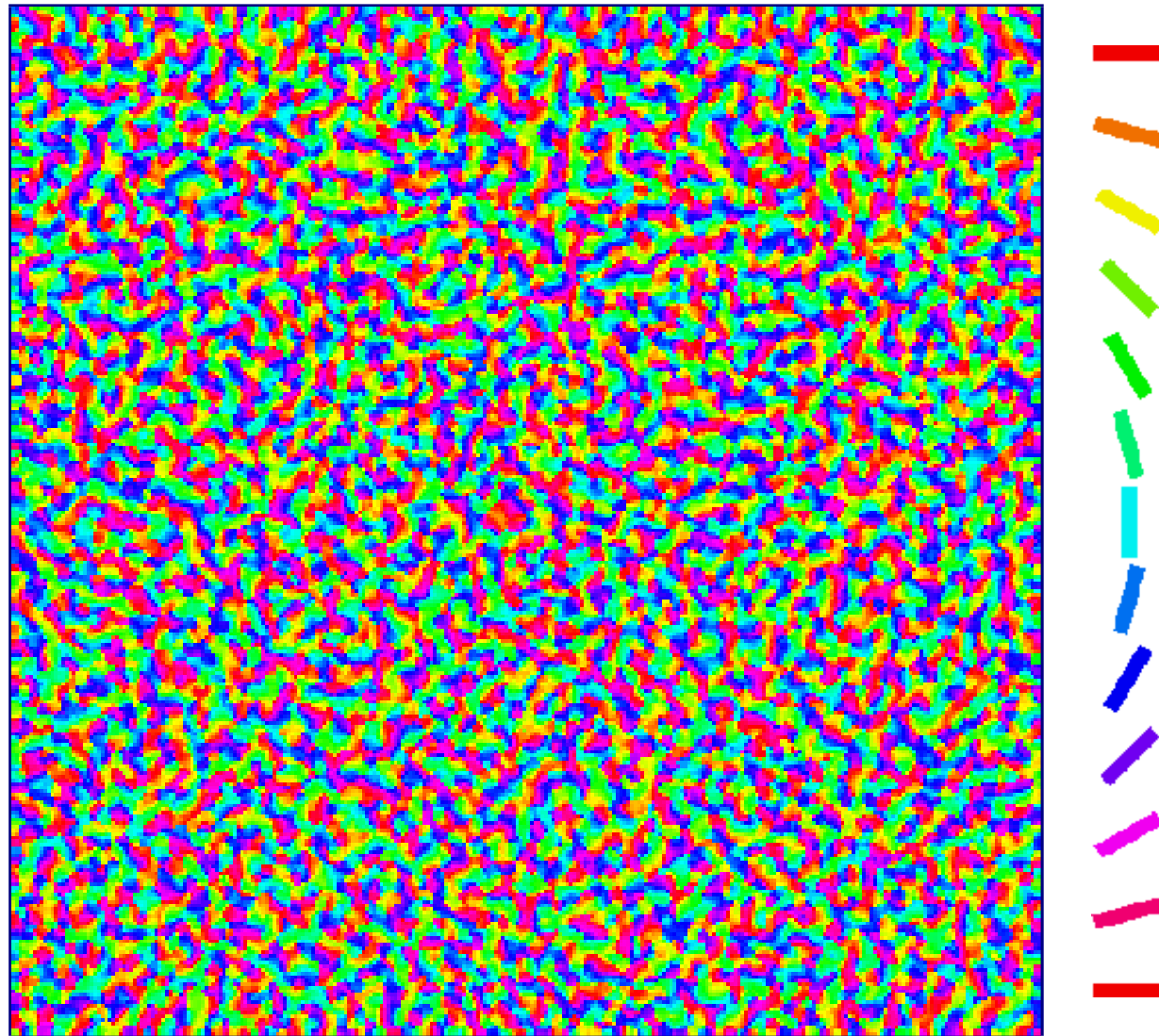
# RGC/LGN Response



# V1 Response with $\gamma_n$



# 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  $\rho$  of neuron  $(i, j)$

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

$\gamma_A, \gamma_n$  are constant scaling factors

# RGC/LGN response to large image



Retinal activation

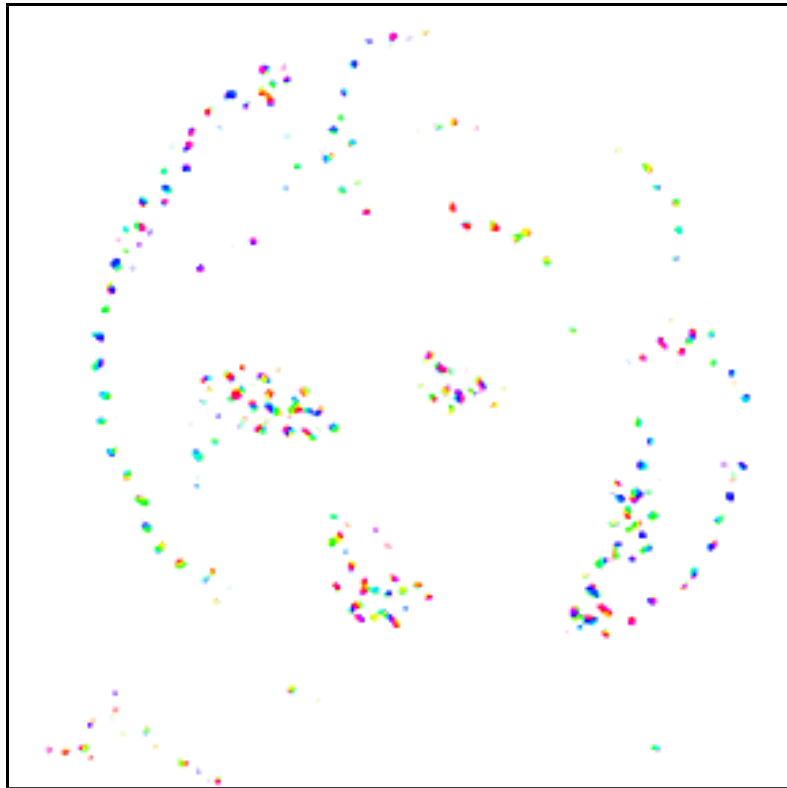


LGN response

CMVC figure 8.2a,b

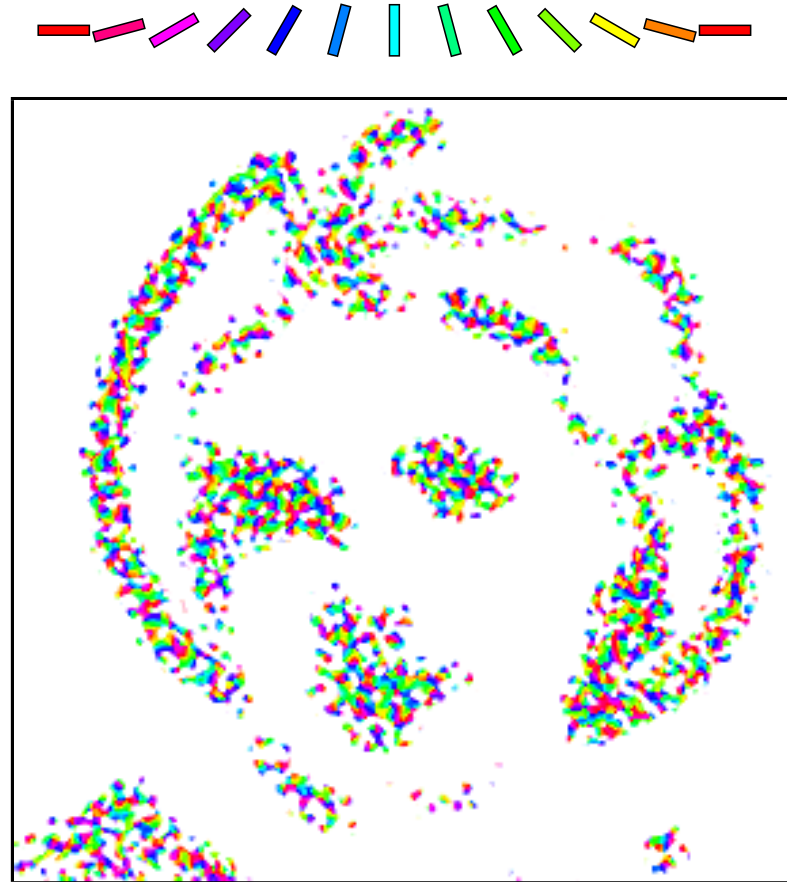
RGC/LGN responds to most of the visible contours

# V1 without afferent normalization



V1 response:

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



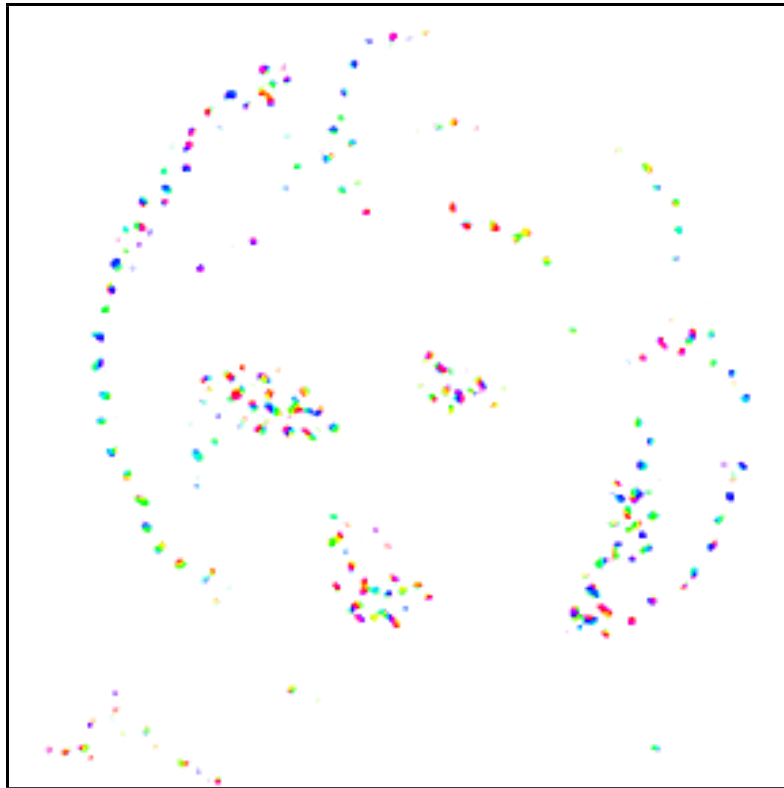
V1 response:

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

Cannot get selective response to all contours

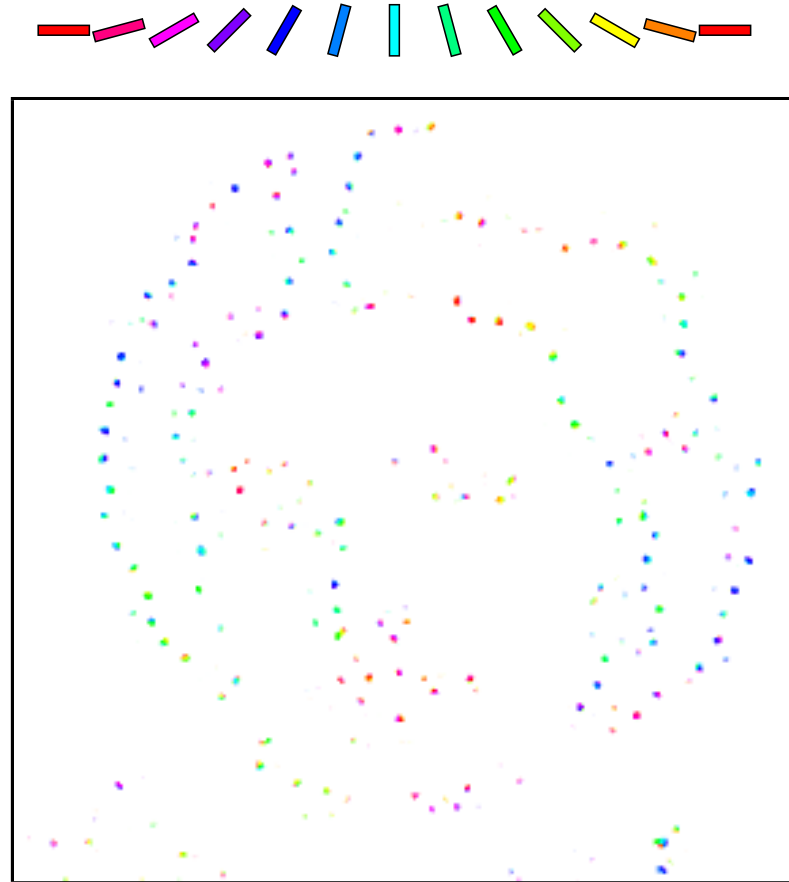
CMVC figure 8.2c-e

# V1 with afferent normalization



V1 response:

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



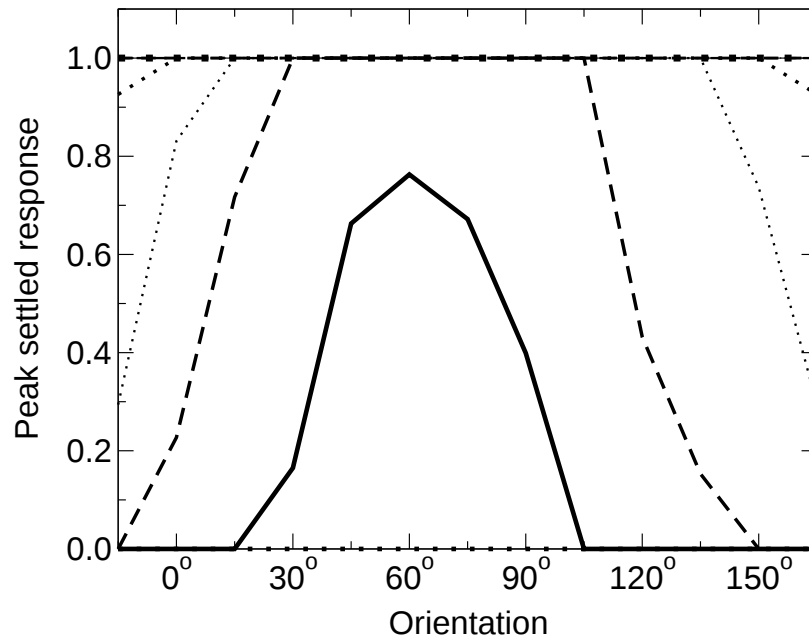
V1 response:

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

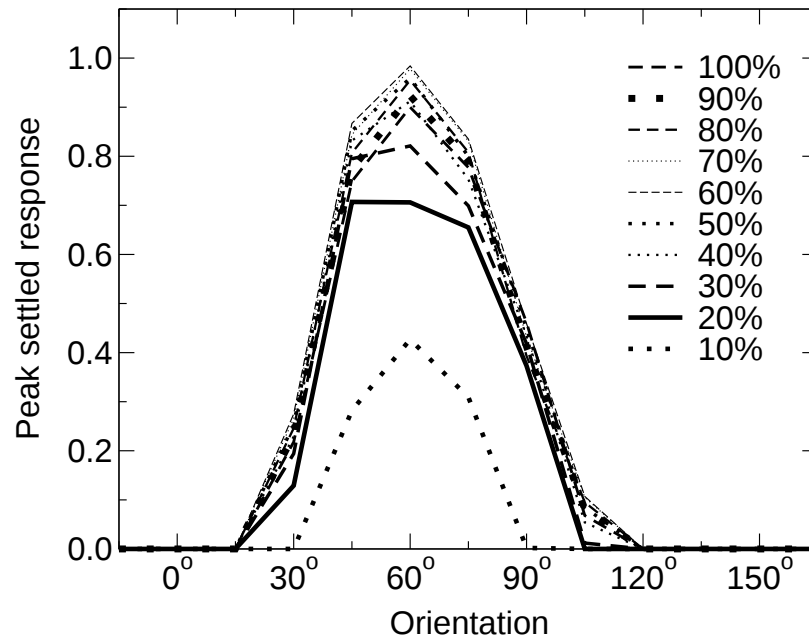
Responds based on contour, not contrast

CMVC figure 8.2c-e

# Tuning with afferent normalization



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



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

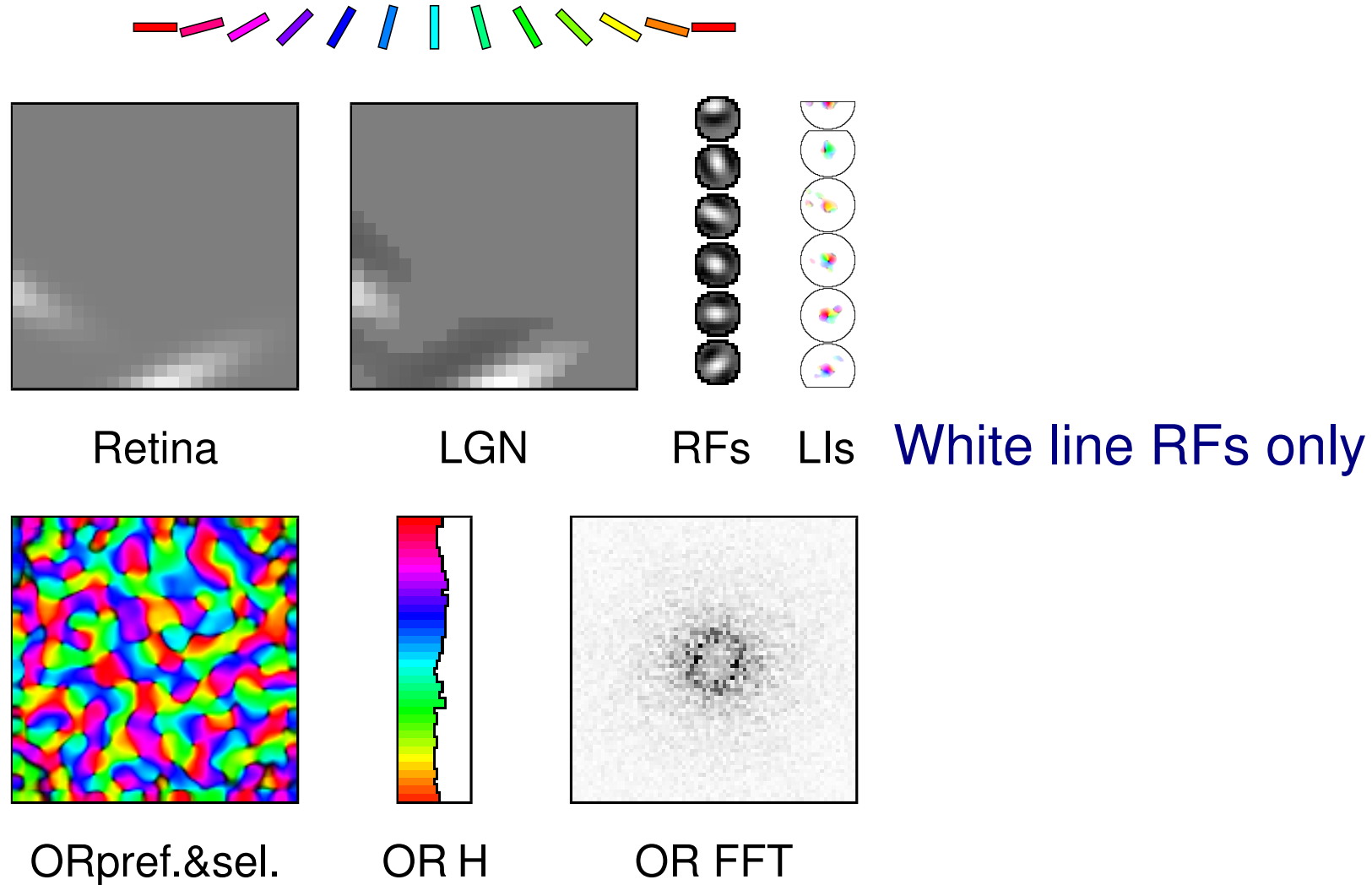
CMVC figure 8.3

Sine grating tuning curve:

- Without  $\gamma_n$ : selectivity lost as contrast increases
- With  $\gamma_n$ : always orientation-specific

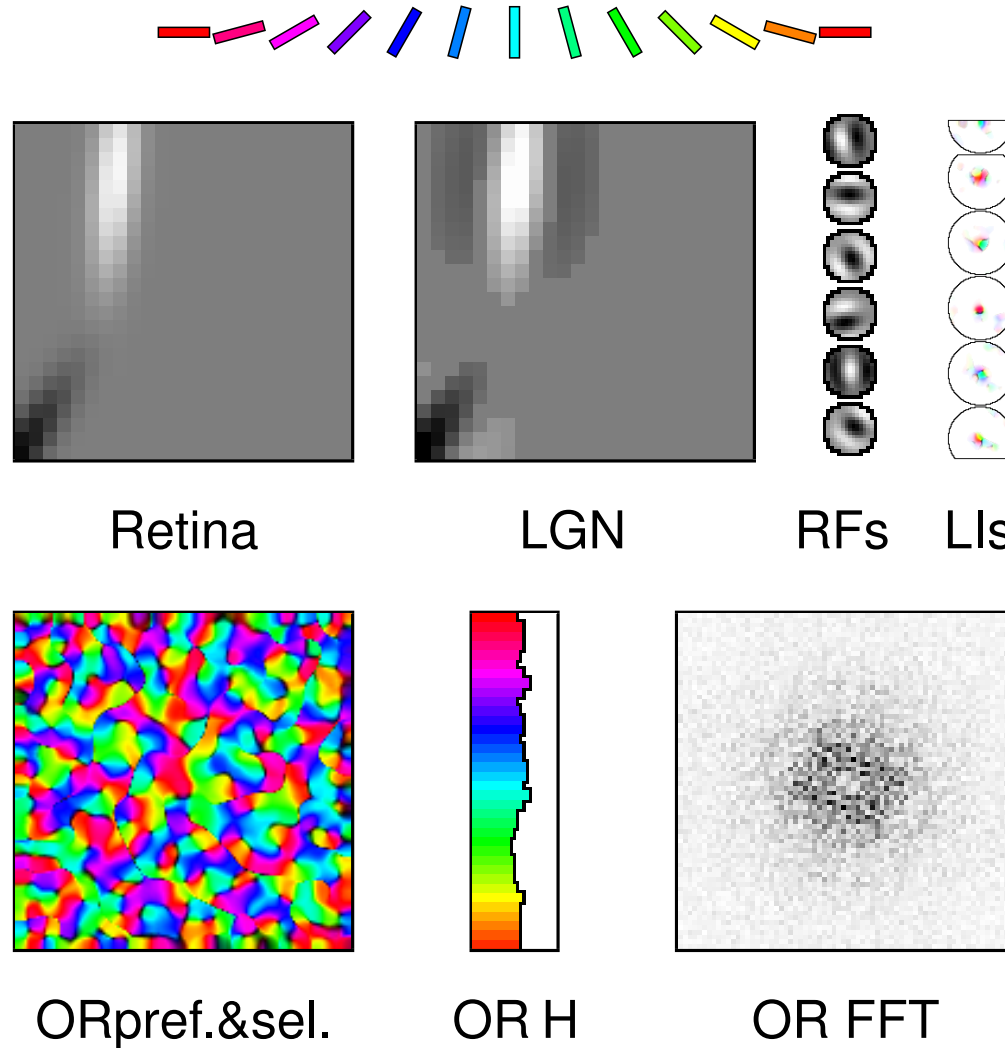
# OR Map: Gaussian

CMVC figure 5.13



# OR Map: +/- Gaussian

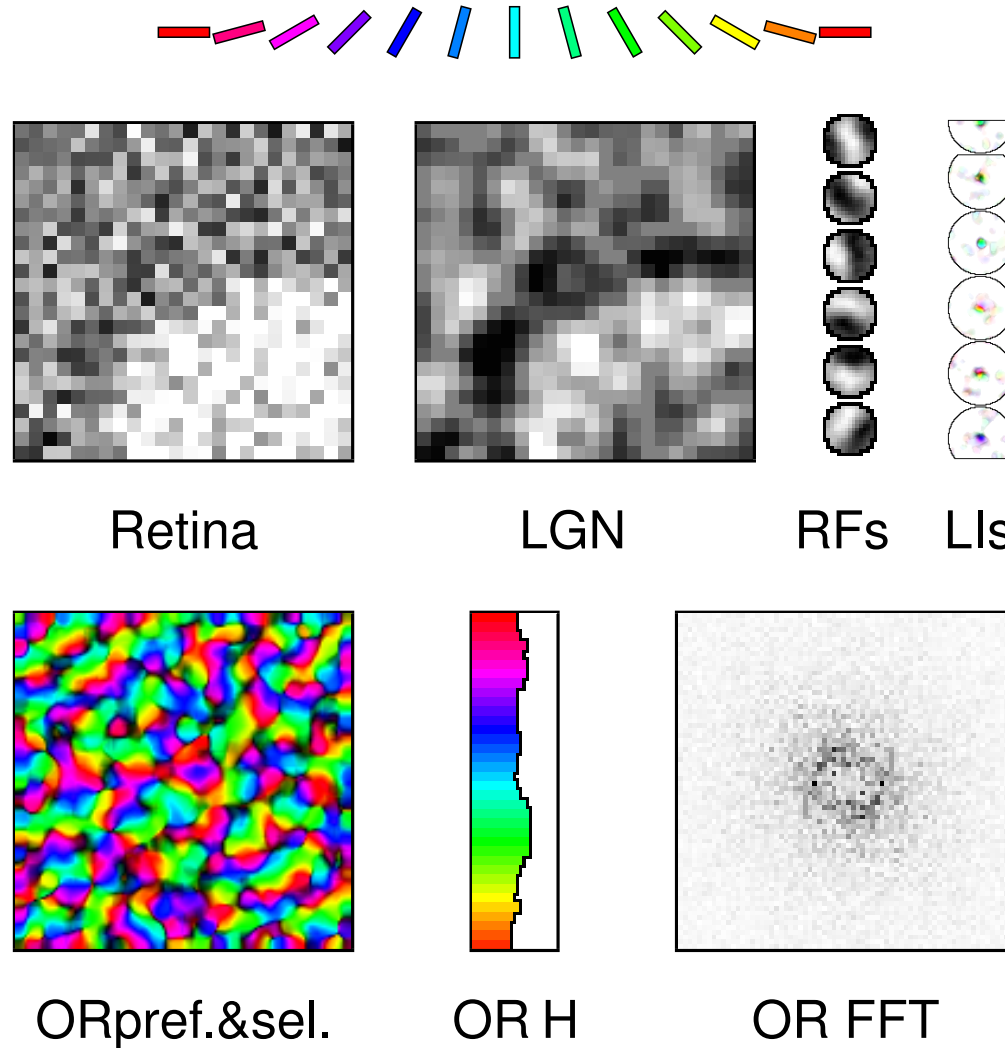
CMVC figure 5.13



White or black line  
RFs

# OR Map: Retinal wave model

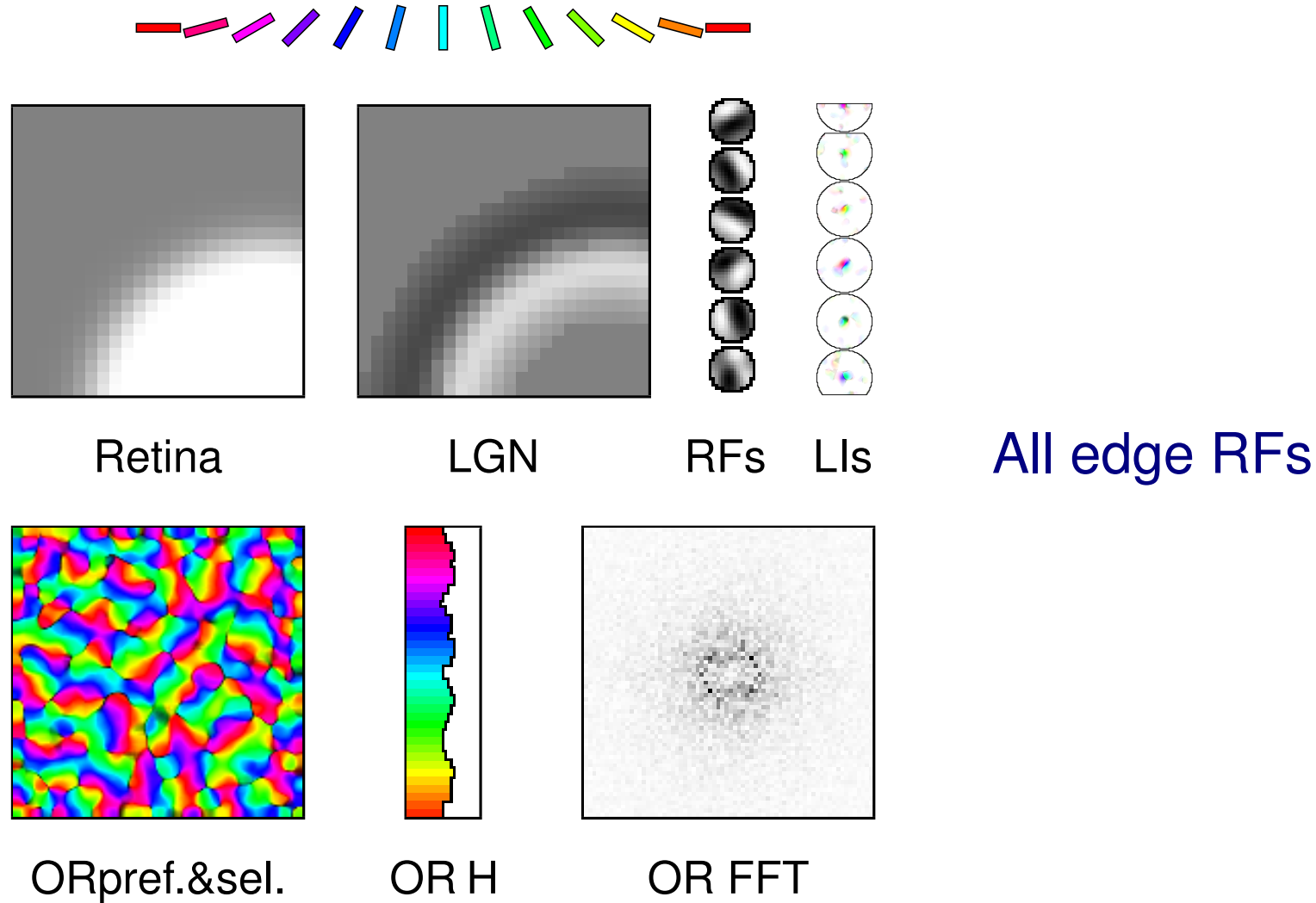
CMVC figure 5.13



Some line, mostly  
edge RFs

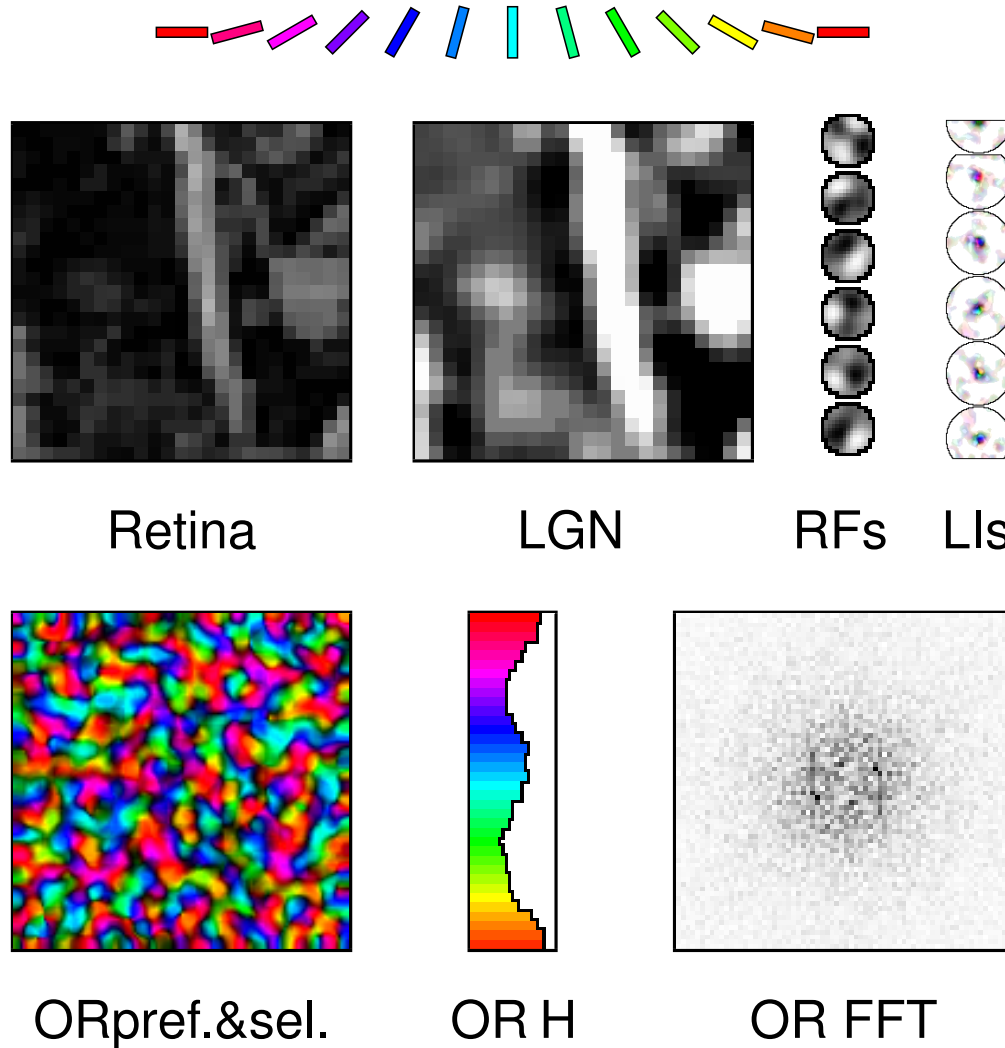
# OR Map: Smooth disks

CMVC figure 5.13



# OR Map: Natural images

CMVC figure 5.13

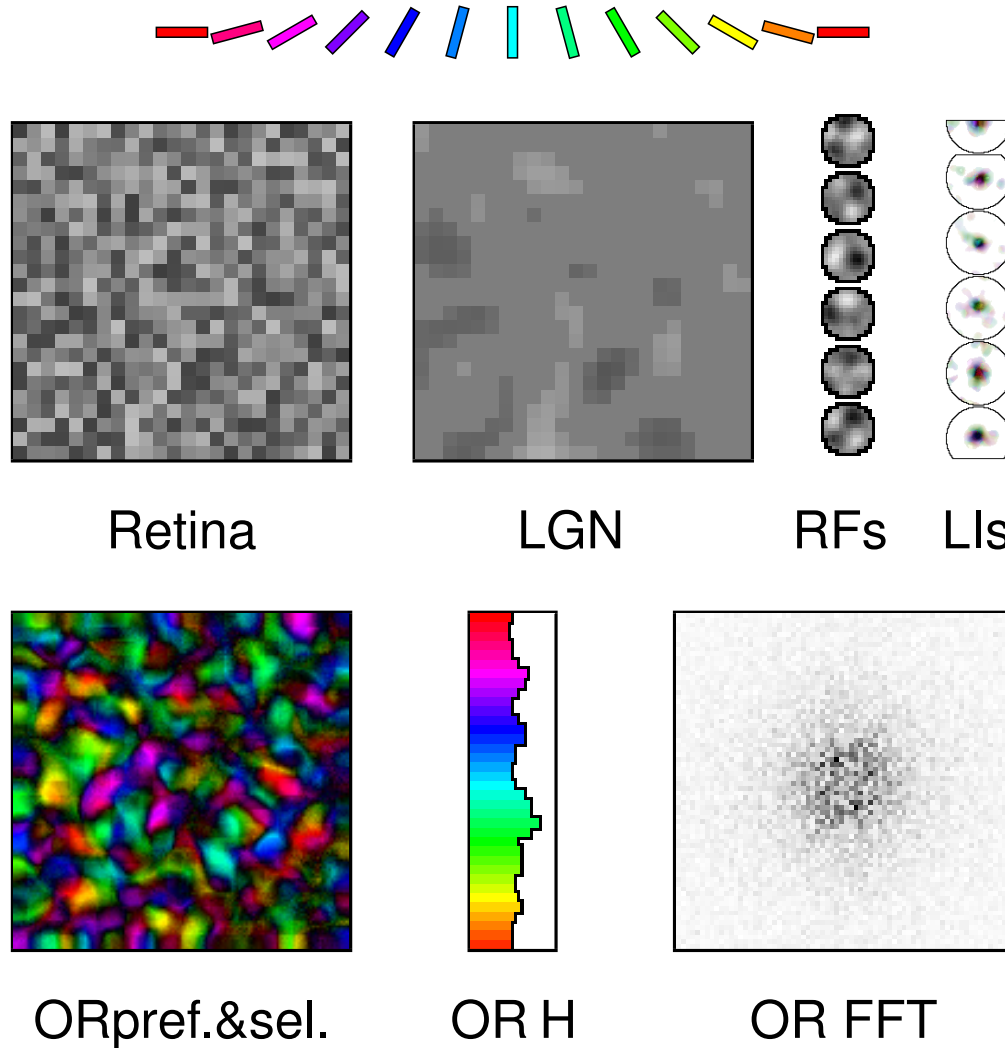


All types of RFs  
Longer range lateral  
weights

Histogram:  
horizontal, vertical  
bias

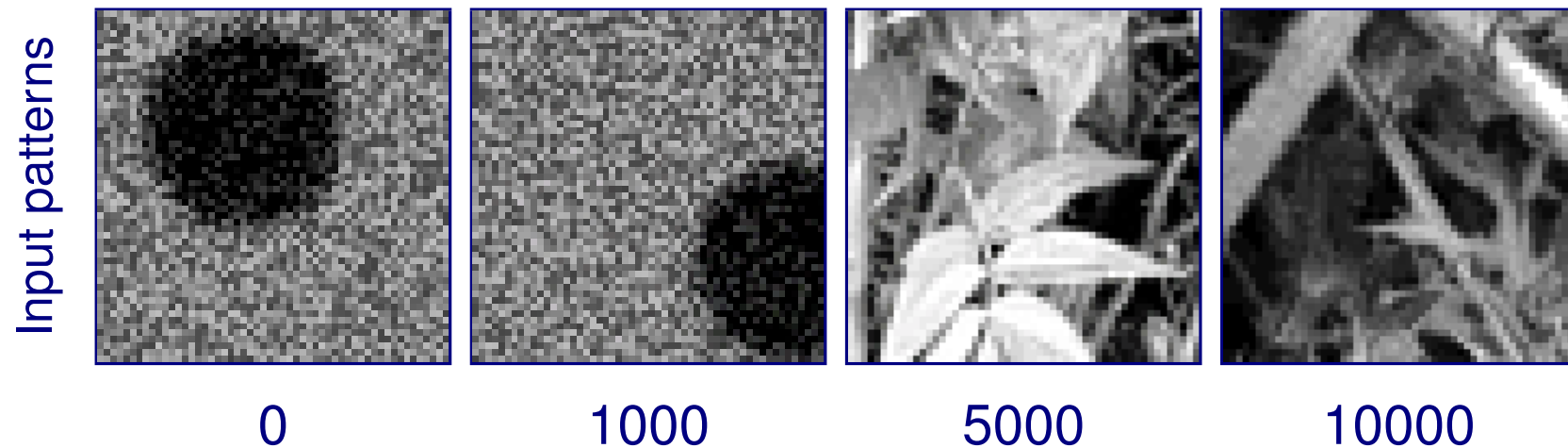
# OR Map: Uniform noise

CMVC figure 5.13



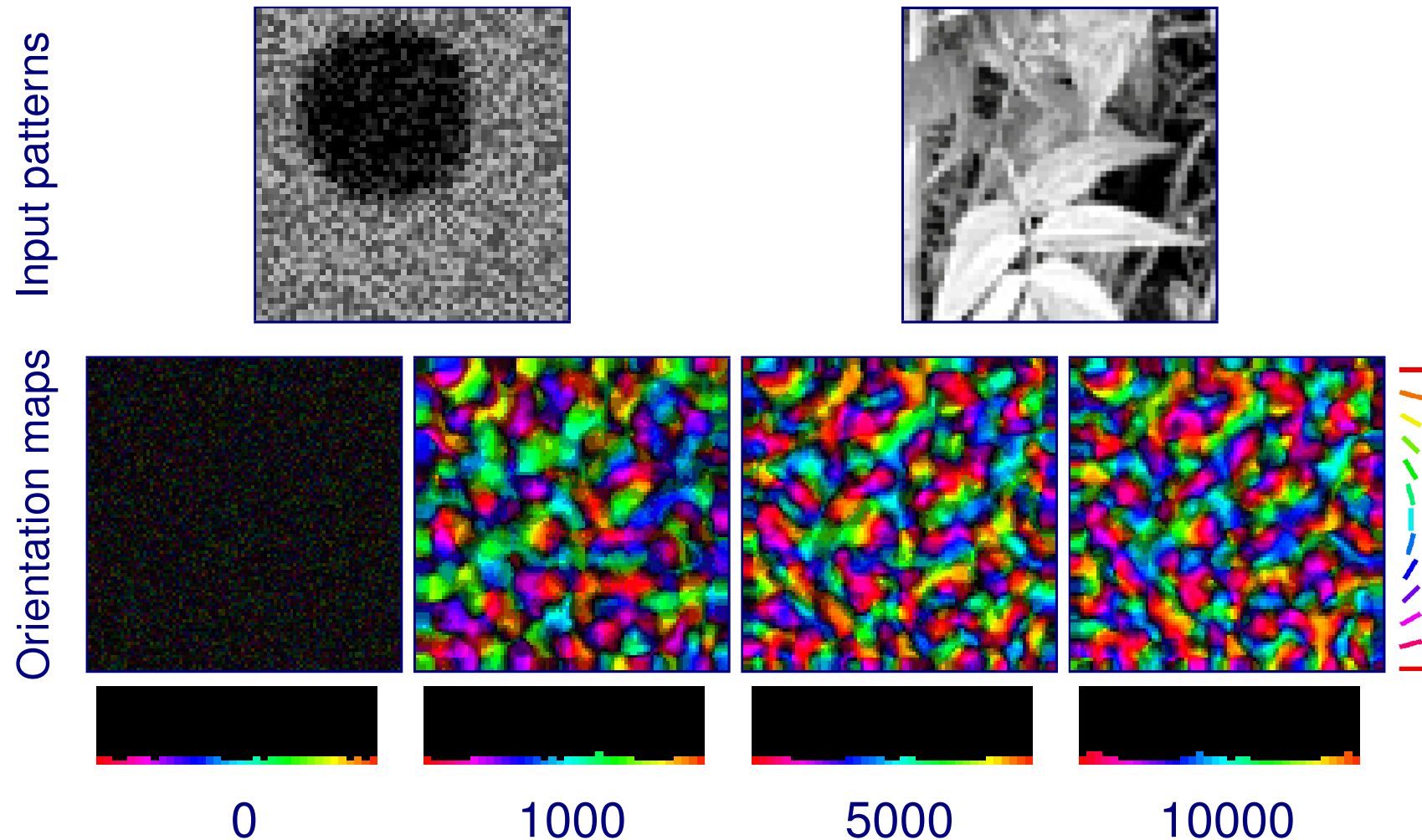
Relatively  
unselective RFs

# Modeling pre/post-natal phases



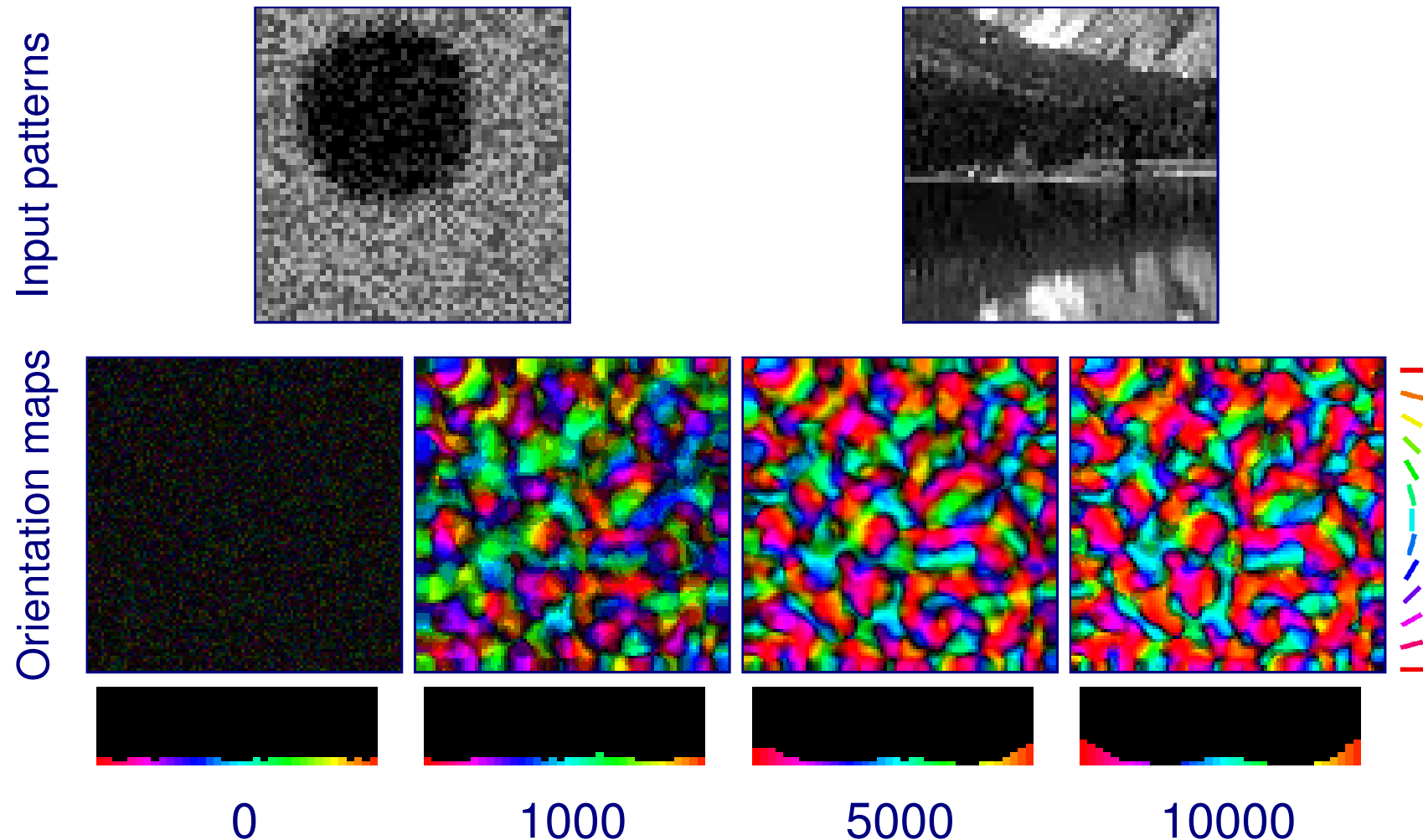
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

# Pre/post-natal V1 development



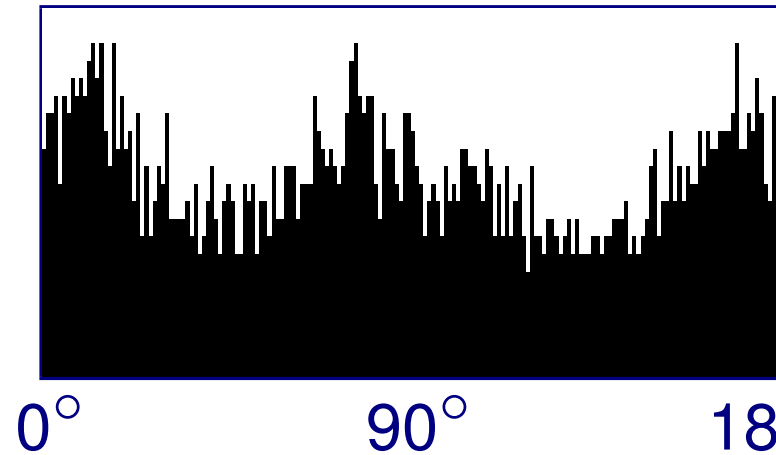
- Neonatal map smoothly becomes more selective

# Statistics drive development

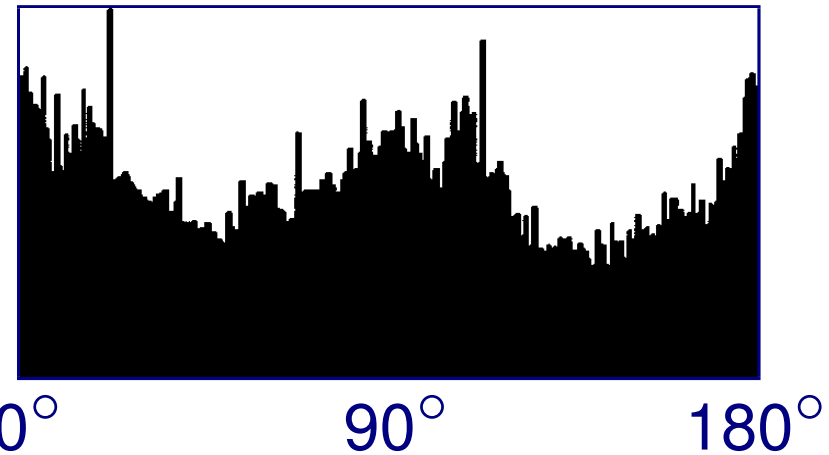


- Biased image dataset: mostly landscapes
- Smoothly changes into horizontal-dominated map

# OR Histograms



HLISSOM model

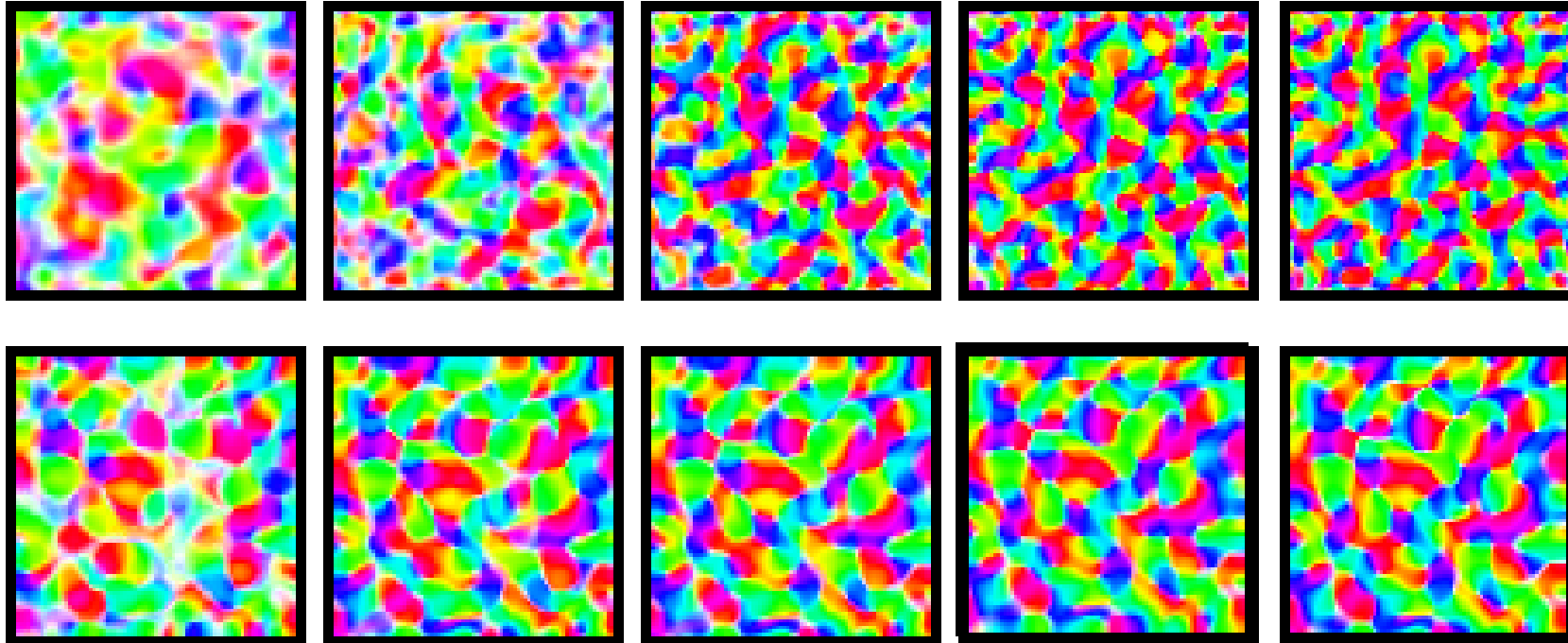


Adult ferret V1  
(Coppola et al. 1998)

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

# Stable development

## Standard LISSOM



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.