

LISSOM Orientation Maps

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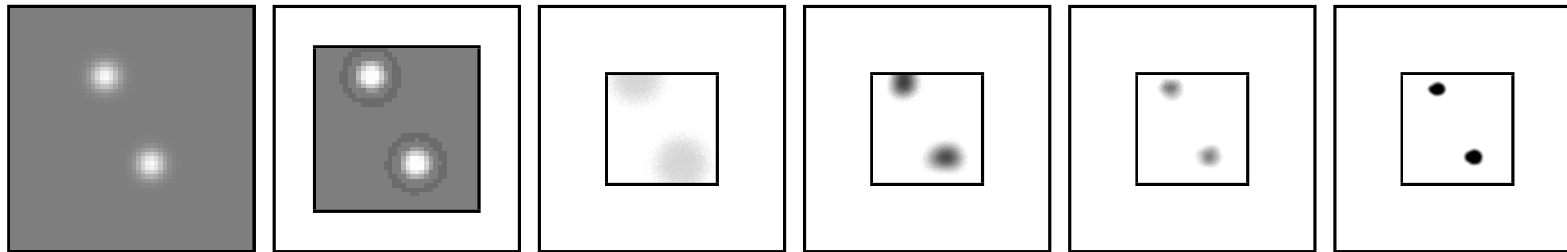
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<http://homepages.inf.ed.ac.uk/jbednar>

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

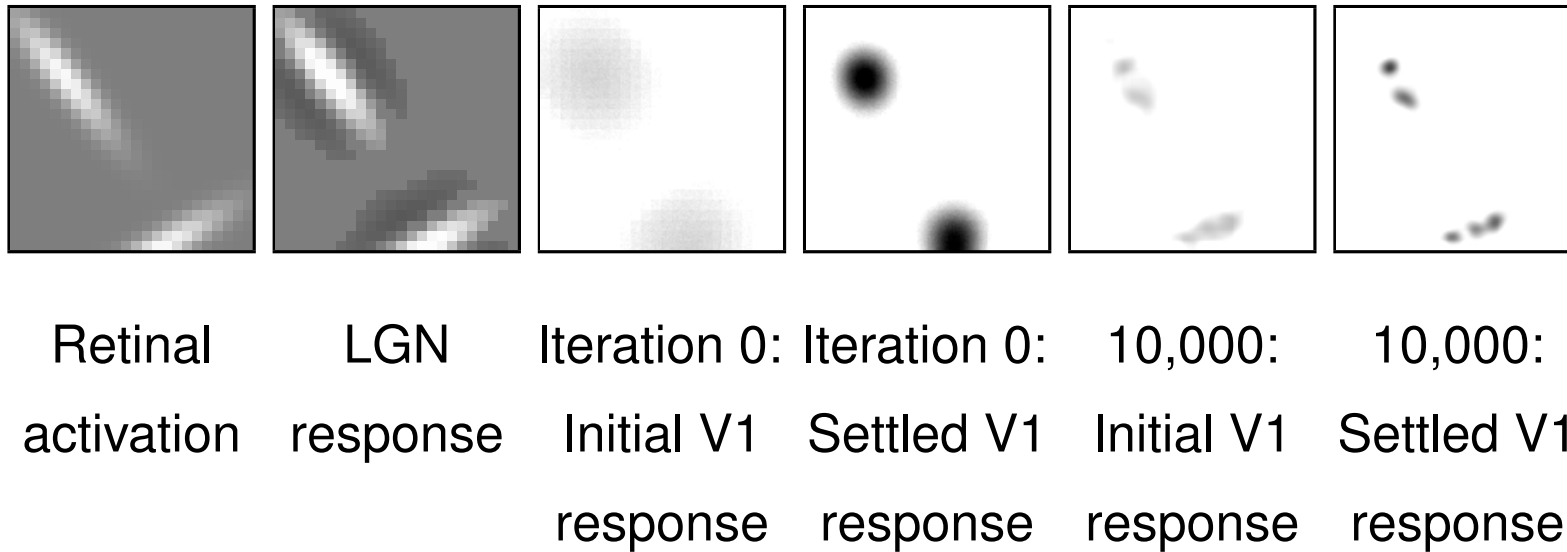


Retinal activation LGN response Iteration 0: Initial V1 response Iteration 0: Settled V1 response 10,000: Initial V1 response 10,000: Settled V1 response

CMVC figure 4.4

(Reminder from last time)

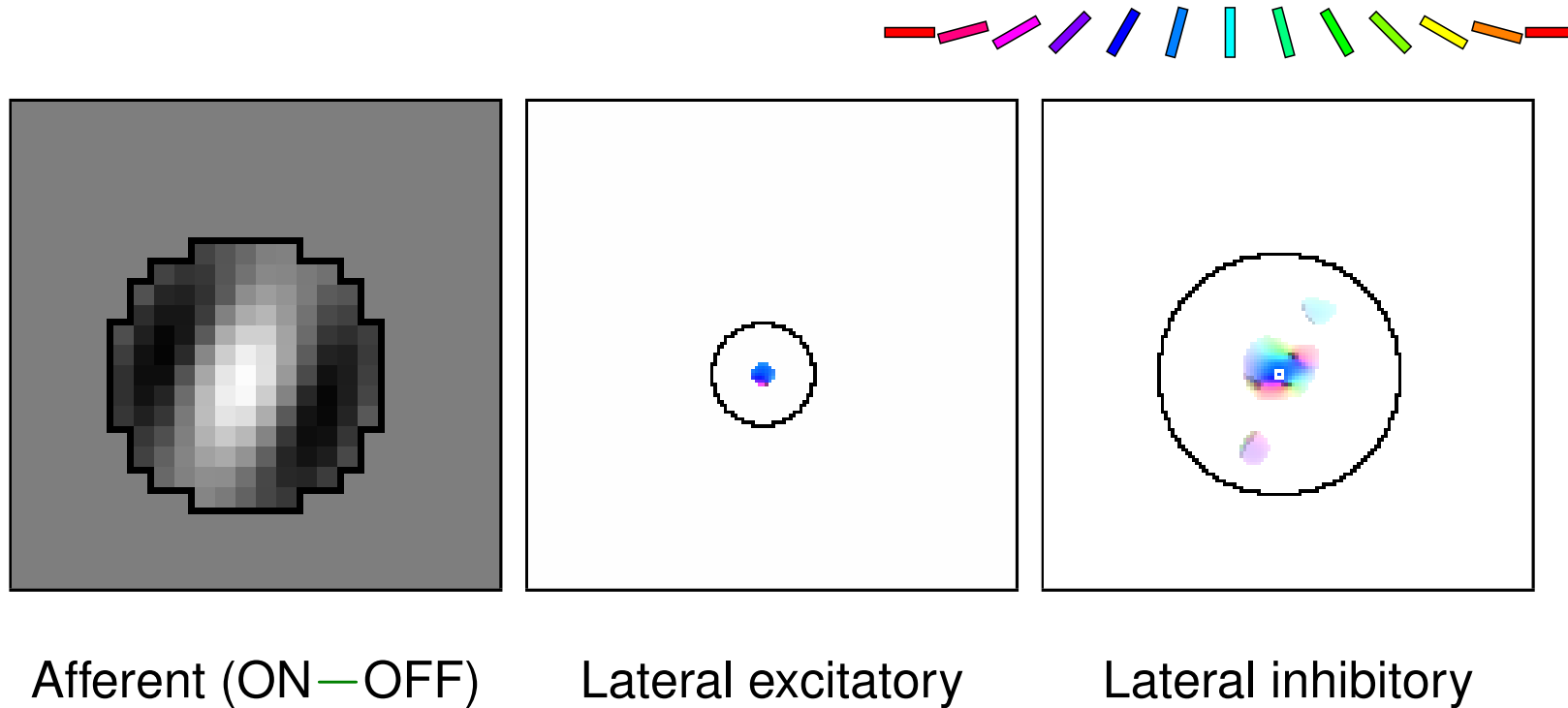
Orientation input and response



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

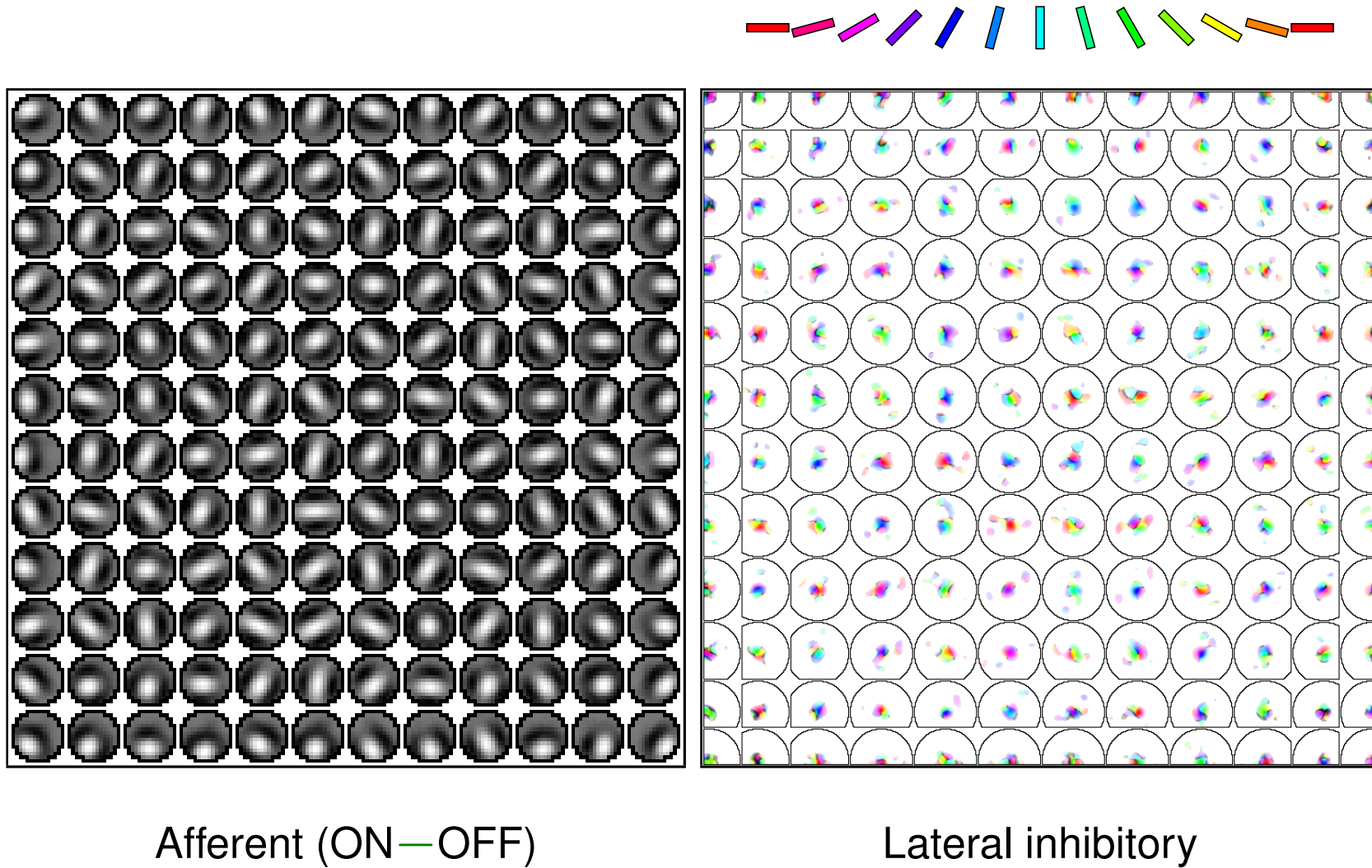


CMVC figure 5.7

Typical:

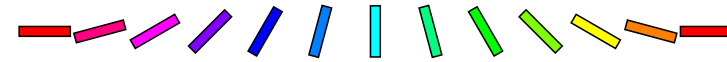
- Gabor-like afferent CF
- Nearly uniform short-range lateral excitatory
- Patchy, orientation-specific long-range lateral inhibitory

Self-organized weights across V1

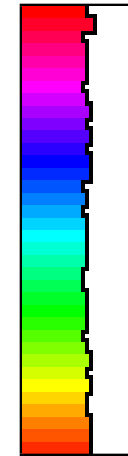
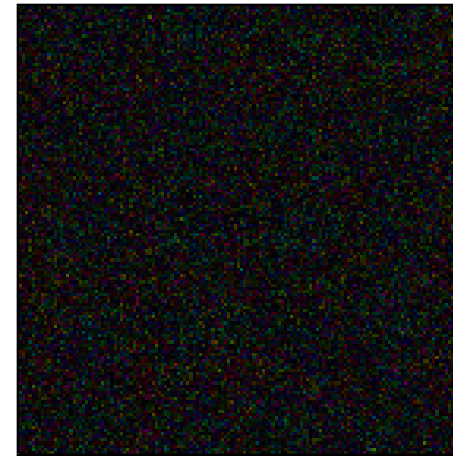
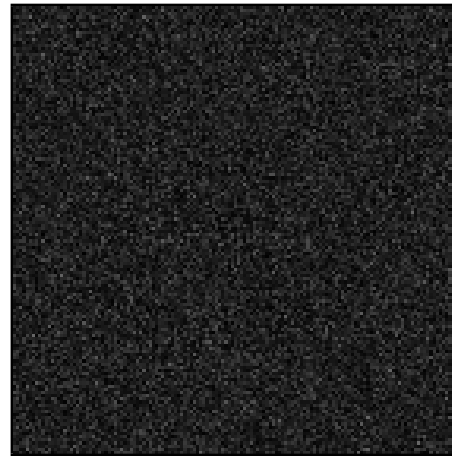
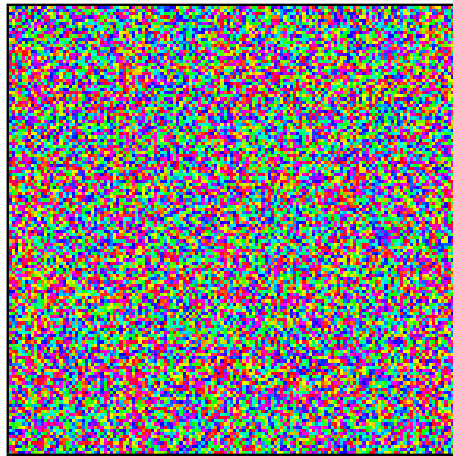


CMVC figure 5.8

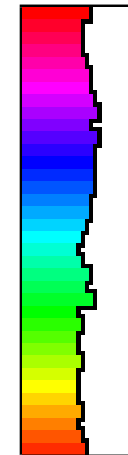
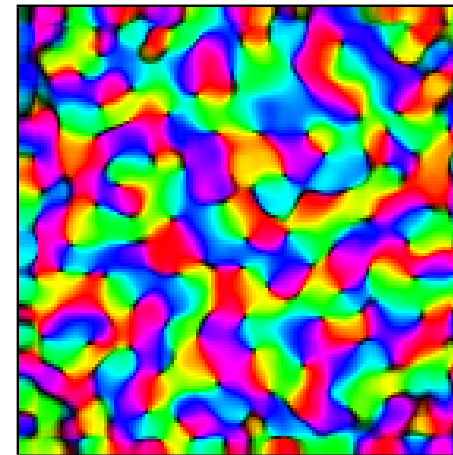
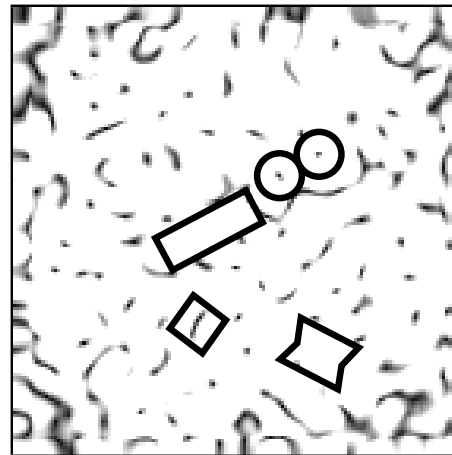
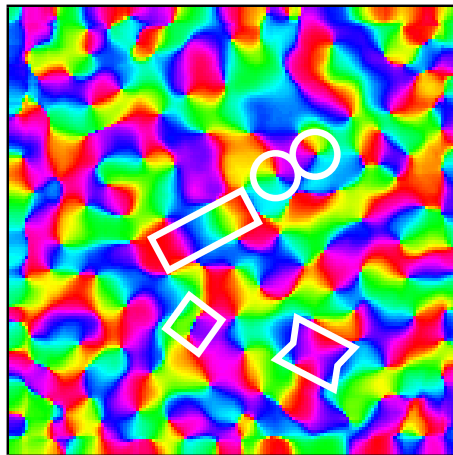
OR map self-organization



Iteration 0



Iteration



OR preference

OR selectivity

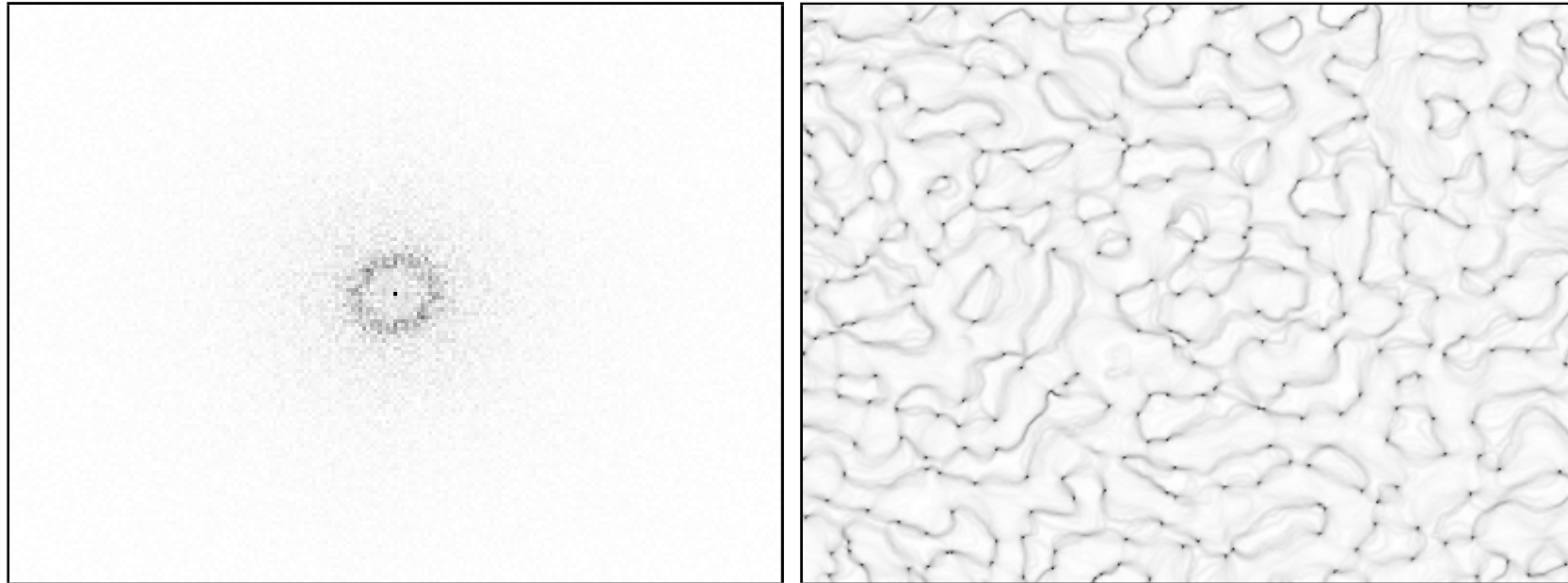
OR preference &

OR H

selectivity

CMVC figure 5.9

Macaque ORmap: Fourier, gradient



CMVC figure 5.1

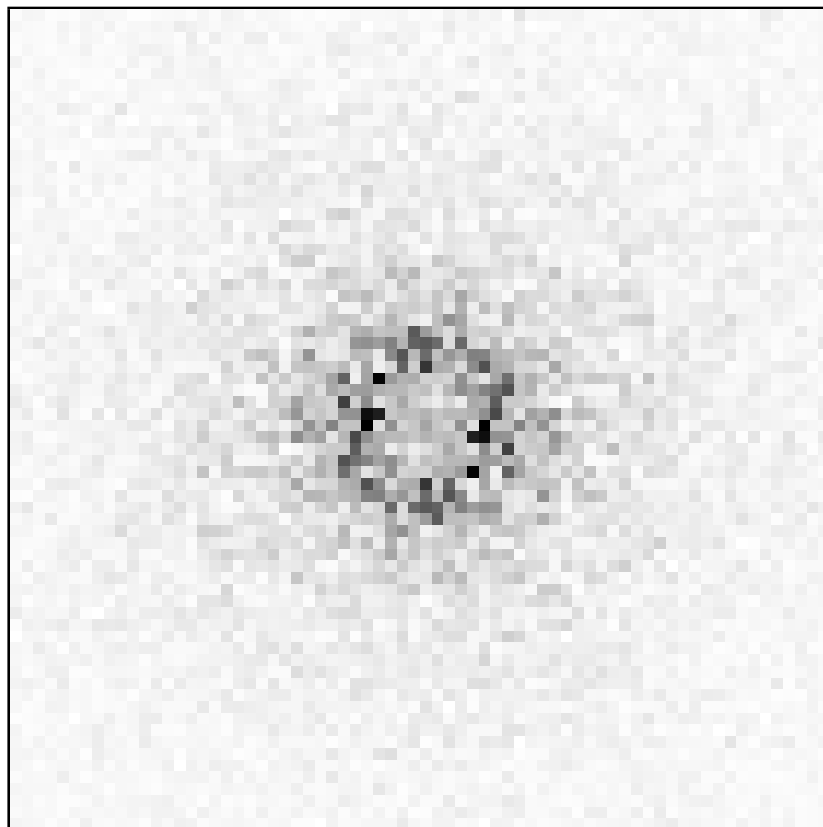
Fourier spectrum

Gradient

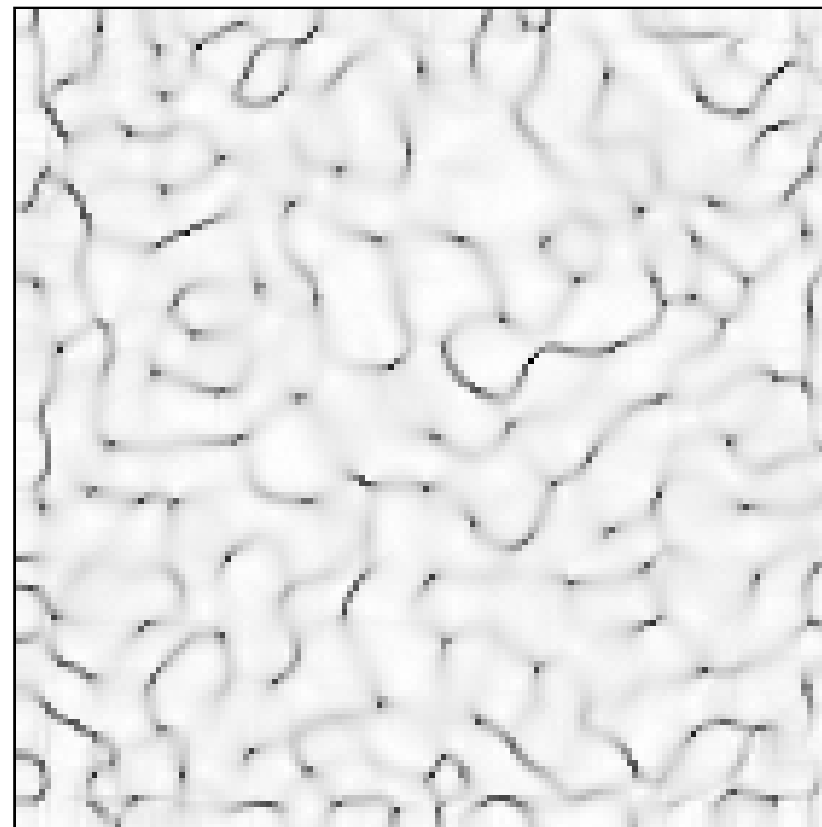
In monkeys:

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

OR Map: Fourier, gradient



Fourier spectrum

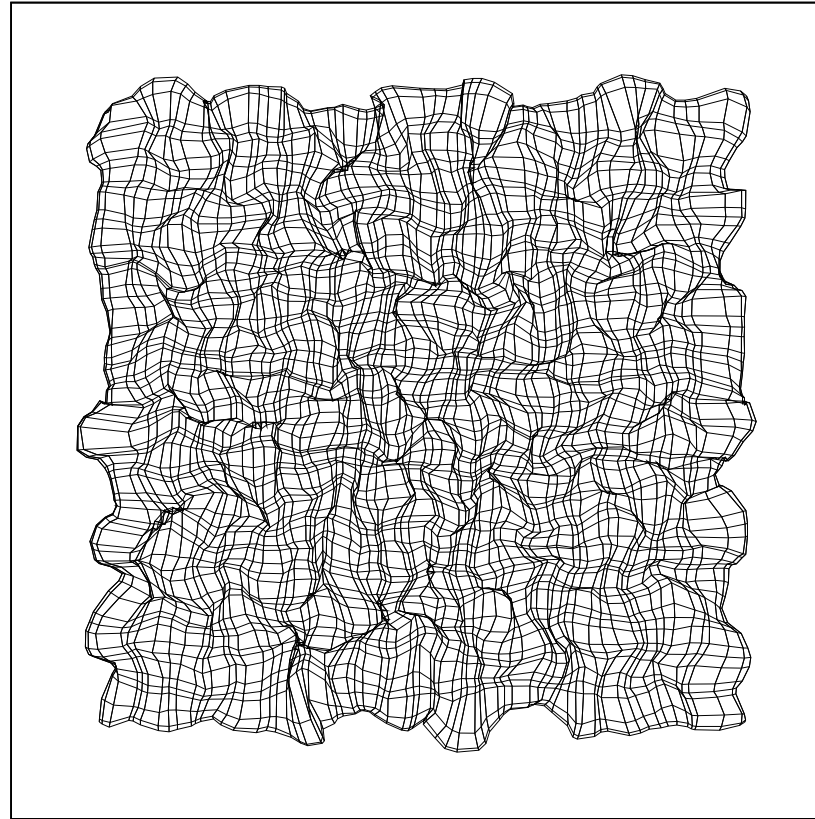


Gradient

LISSOM model has similar spectrum, gradient

CMVC figure 5.10

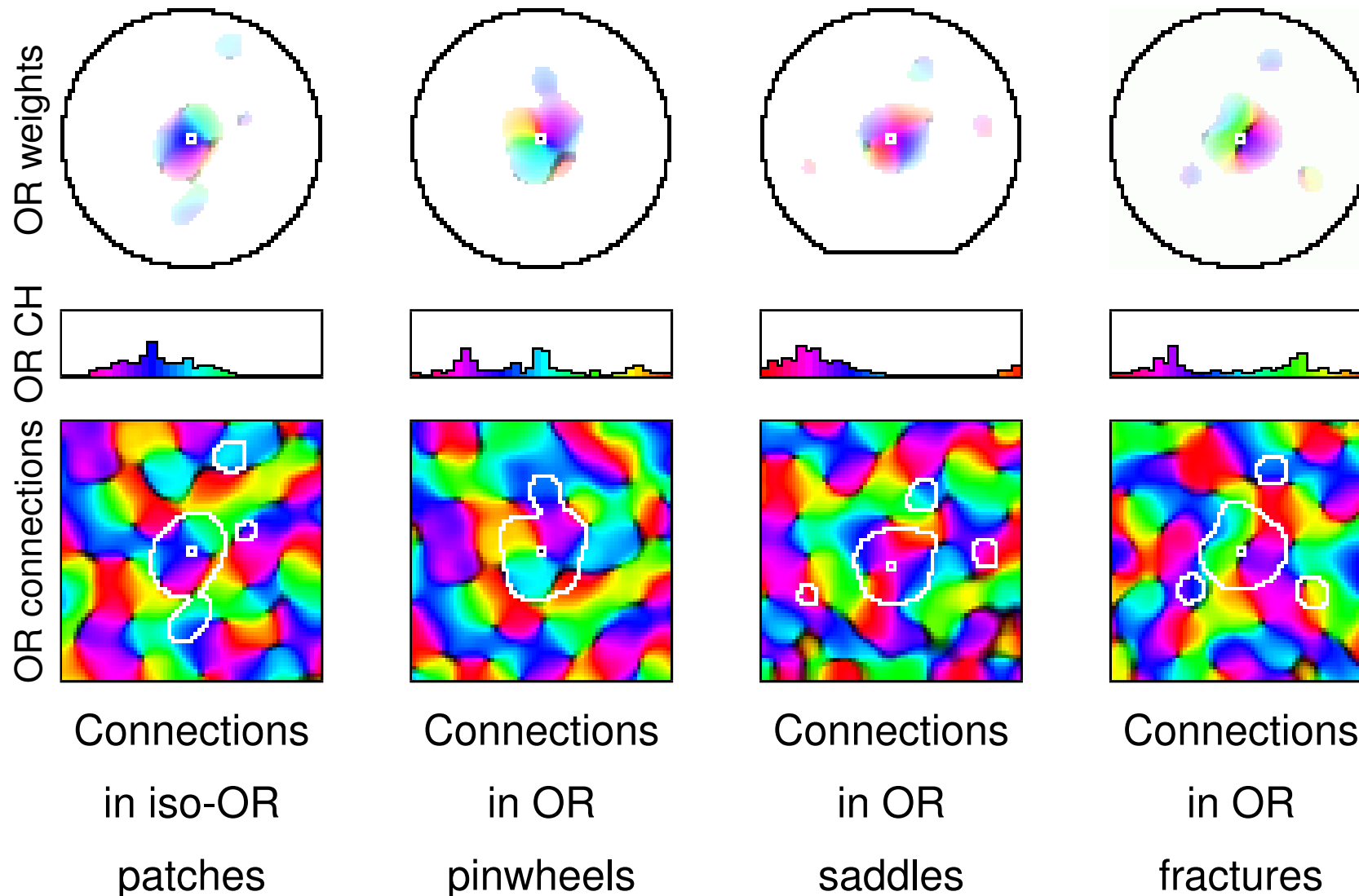
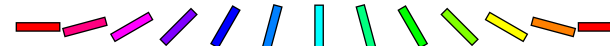
OR Map: Retinotopic organization



CMVC figure 5.11

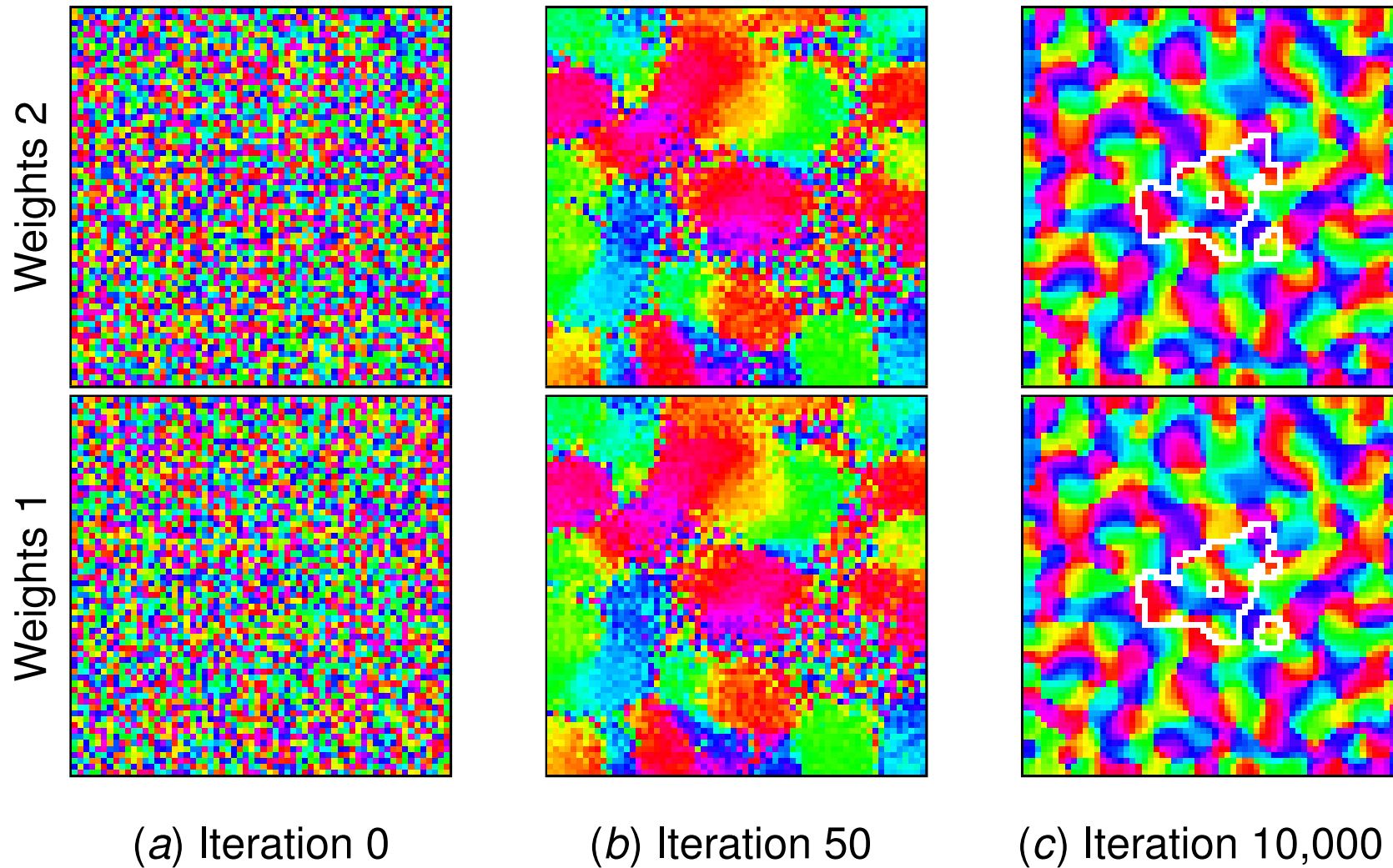
- Retinotopy is distorted locally by orientation prefs
- Matches distortions found in animal maps?

OR Map: Lateral connections



CMVC figure 5.12

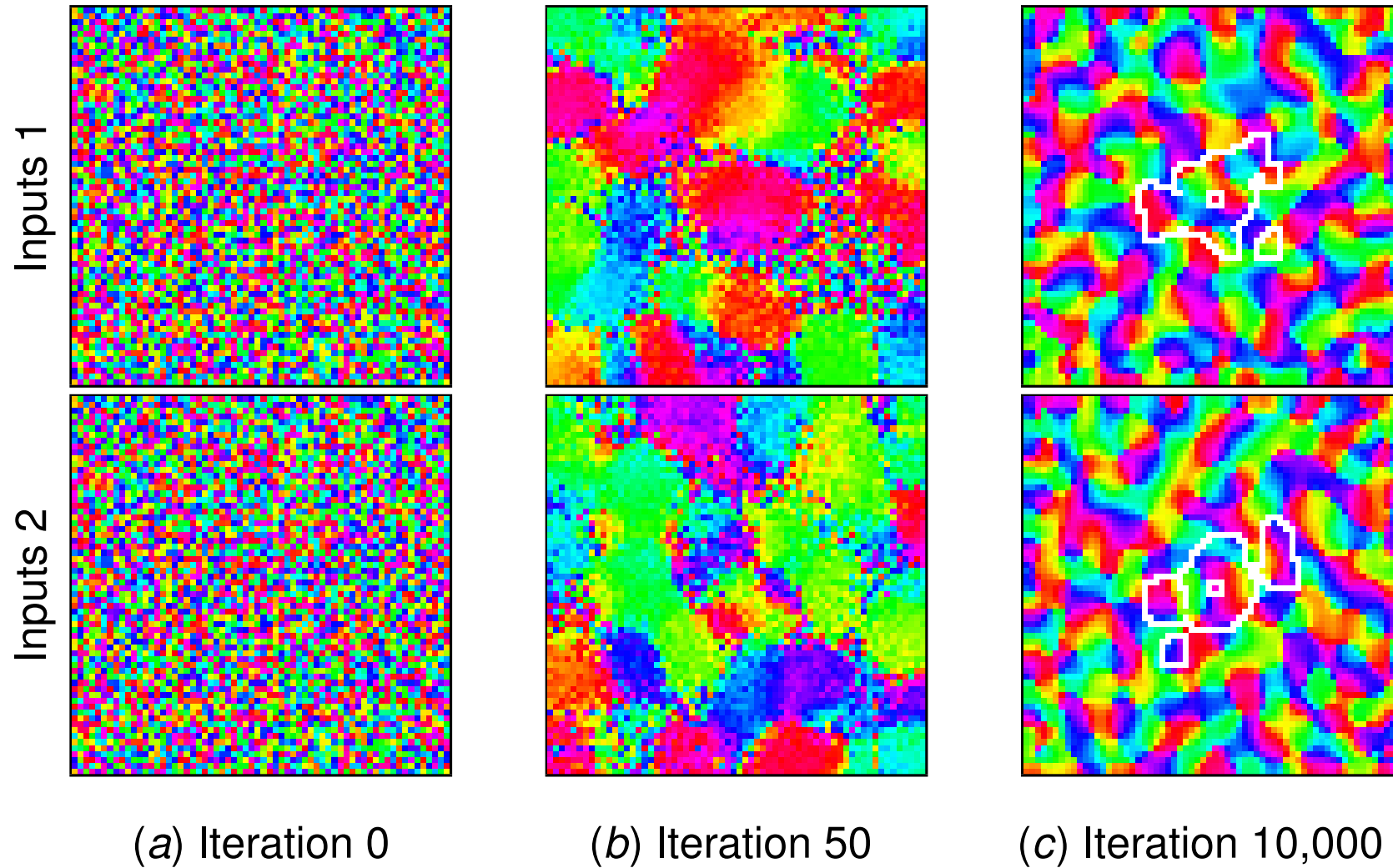
Effect of initial weights



CMVC figure 8.5

Changing weights doesn't change map folding pattern.

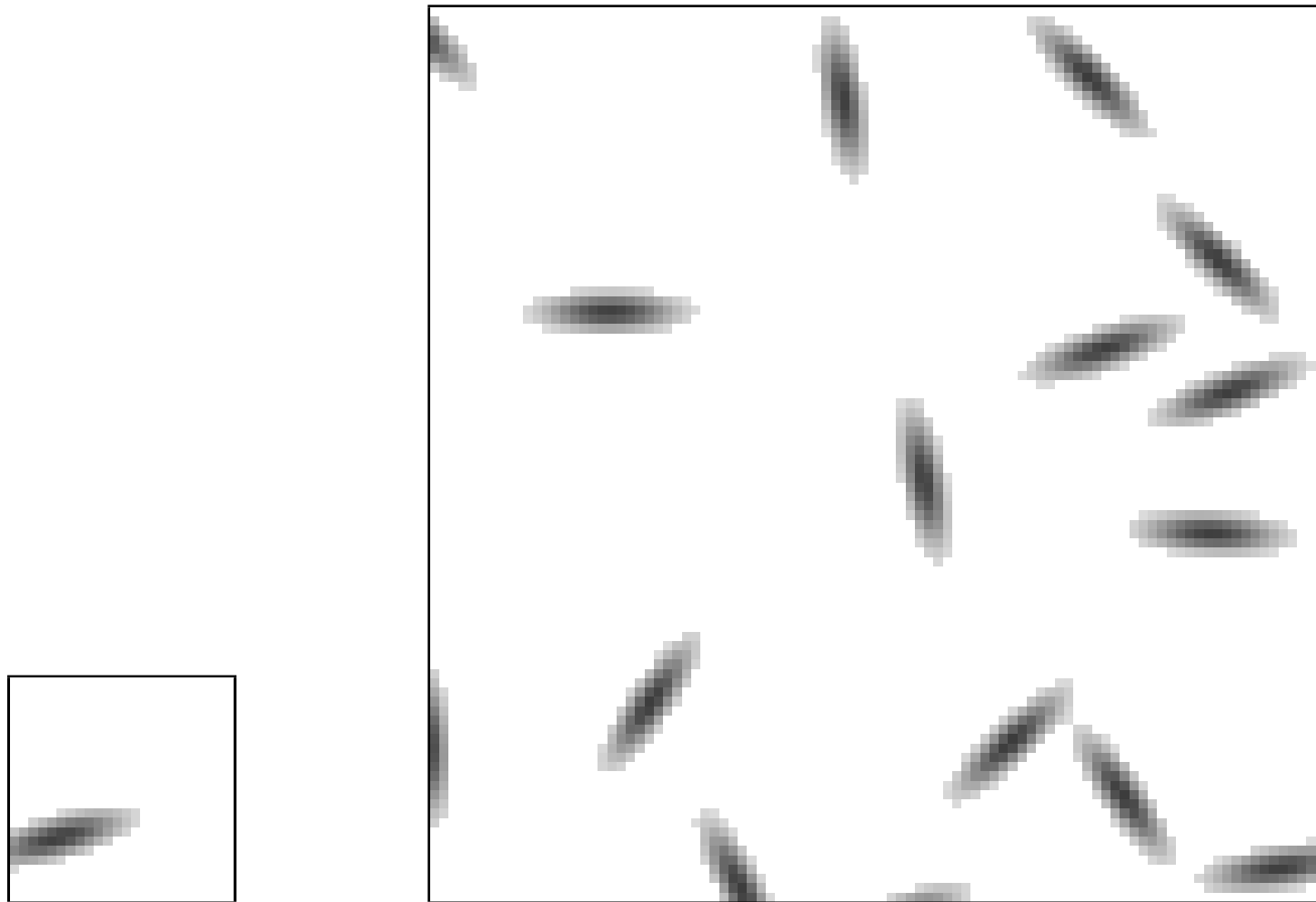
Effect of input streams



CMVC figure 8.5

Changing inputs changes entire pattern.

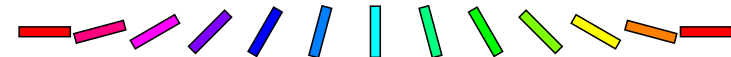
Scaling retinal and cortical area



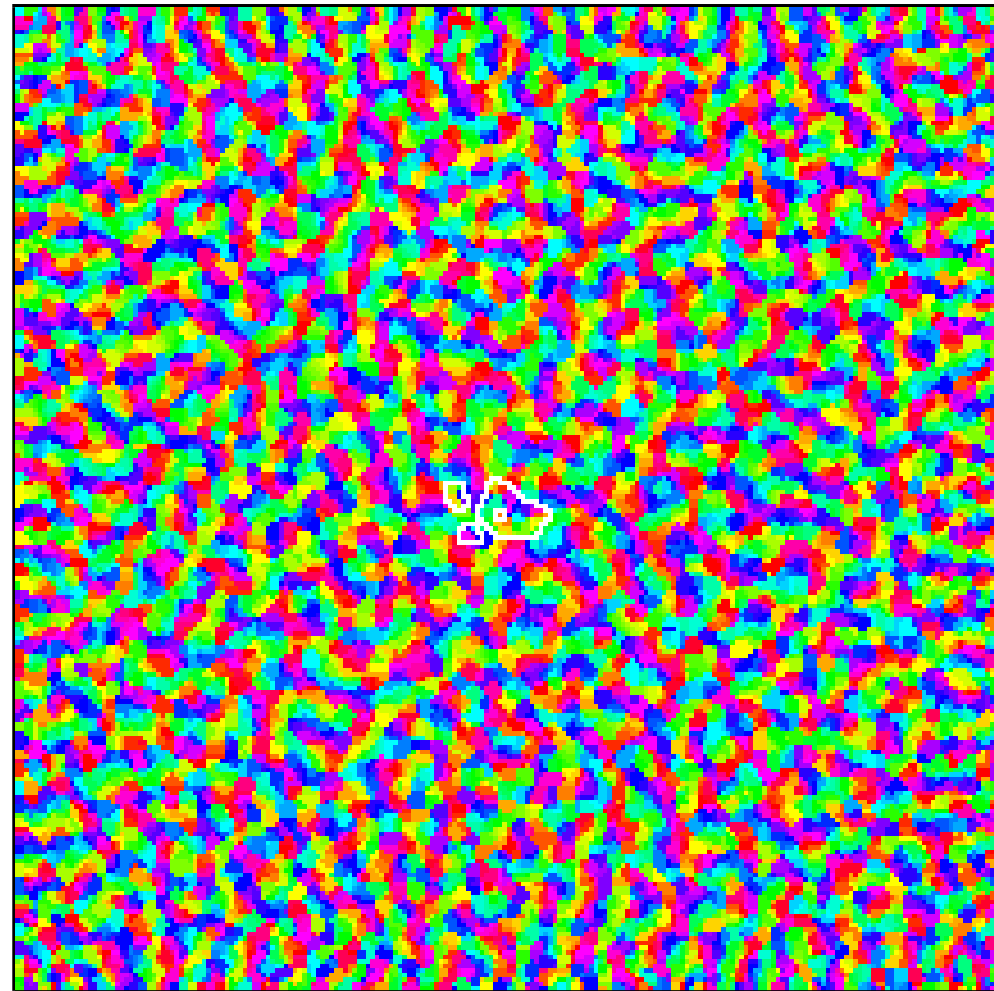
CMVC figure 15.1a,b

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

Scaling retinal and cortical area



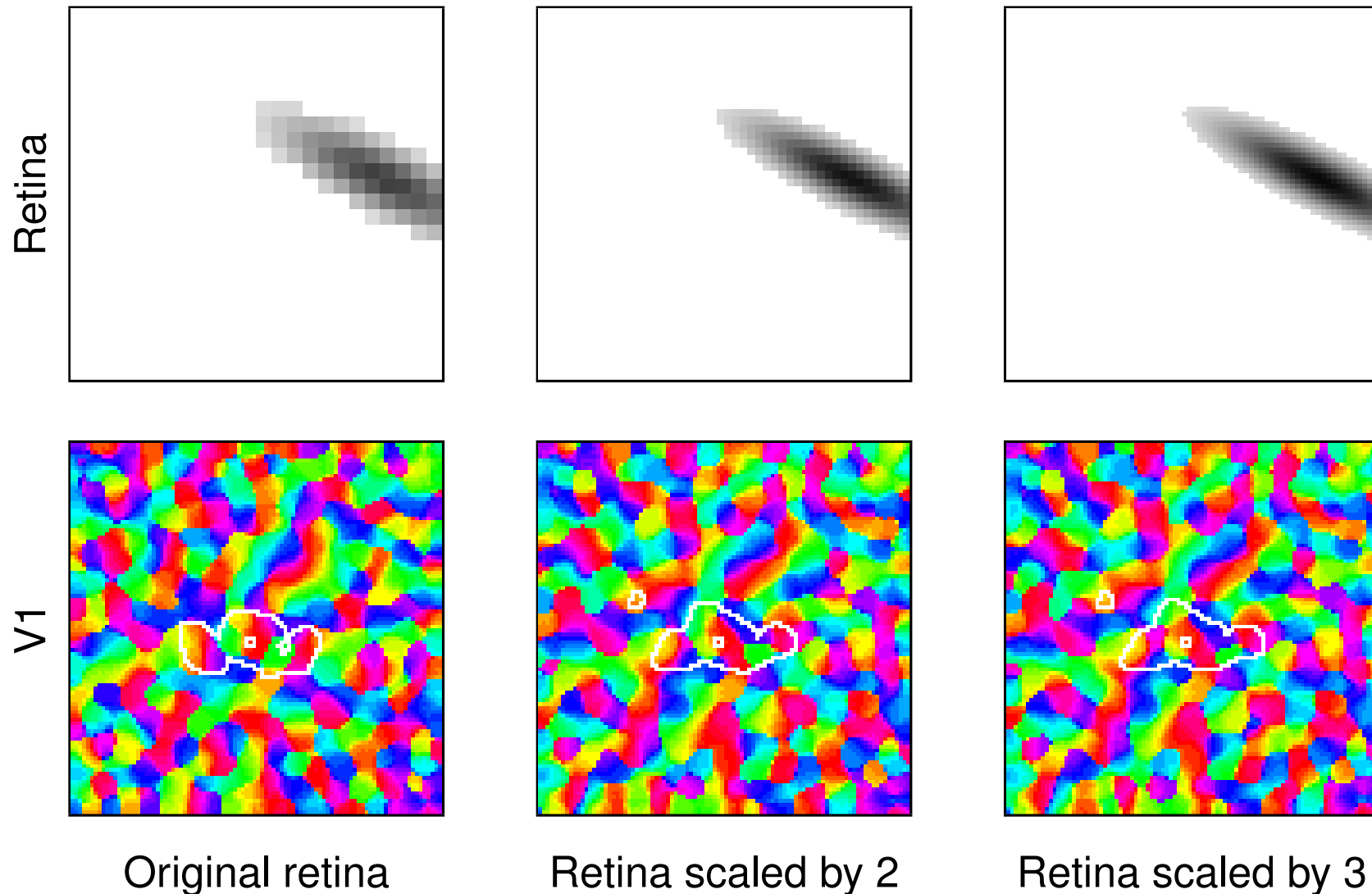
(c) Original V1:
 $N = 54$, 0.4 hours, 8 MB



(d) V1 area scaled by 4.0:
 $N = 216$, 9 hours, 148 MB

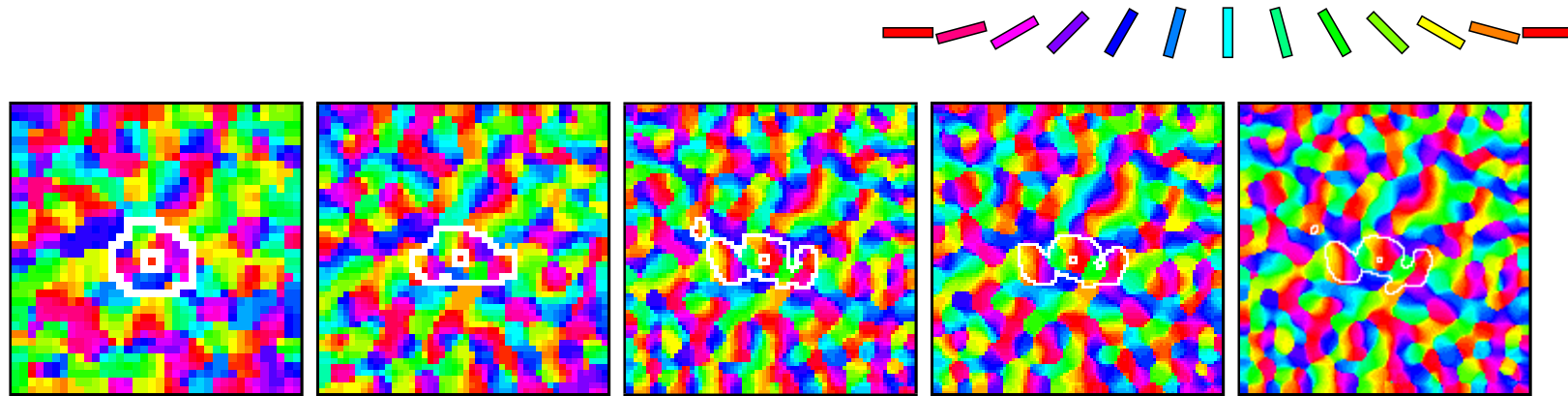
CMVC figure 15.1c,d

Scaling retinal density



CMVC figure 15.2

Scaling cortical density

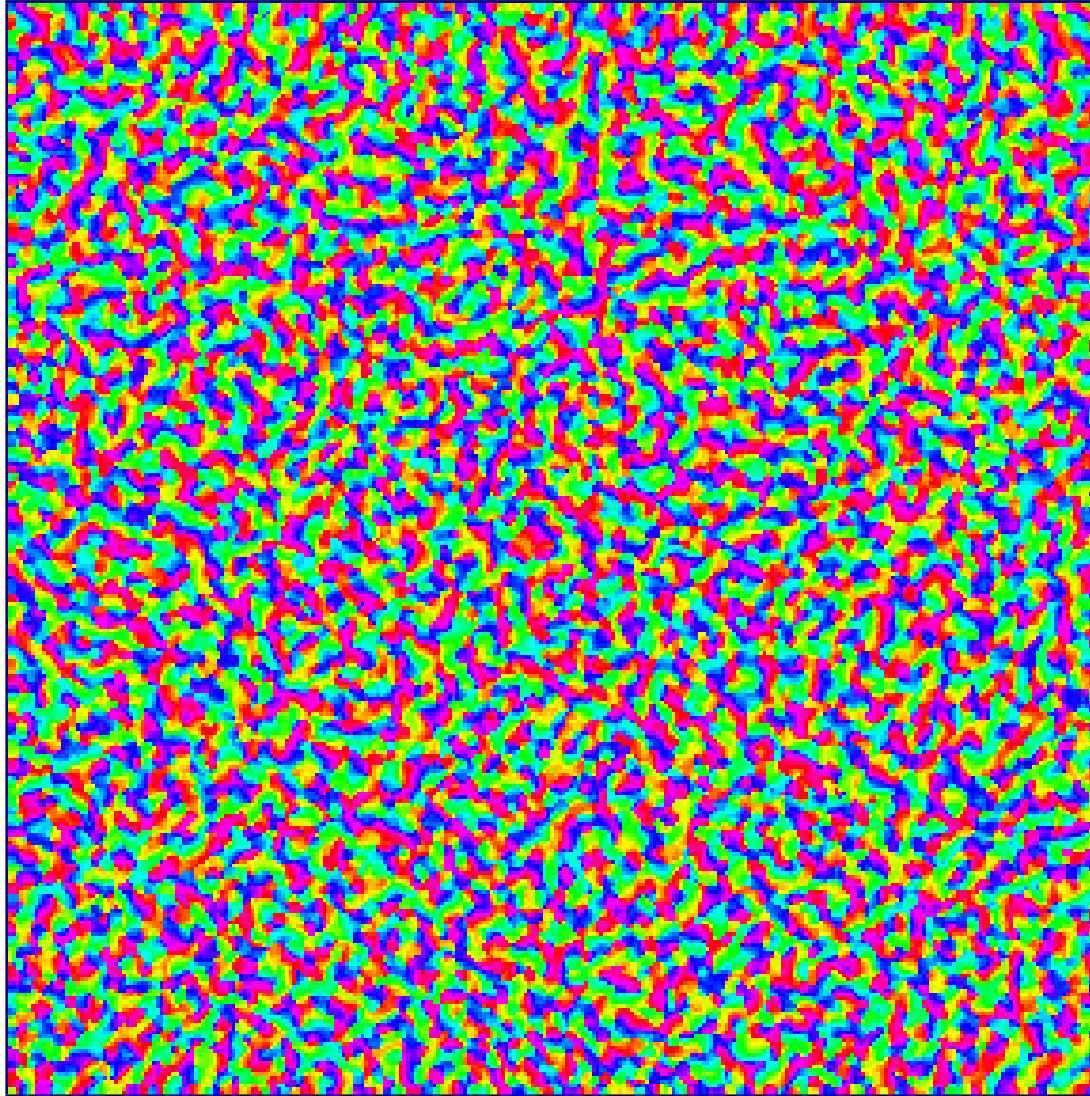


(a) 36×36 : 0.17 hours, 2.0 MB
(b) 48×48 : 0.32 hours, 5.2 MB
(c) 72×72 : 0.77 hours, 22 MB
(d) 96×96 : 1.73 hours, 65 MB
(e) 144×144 : 5.13 hours, 317 MB

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

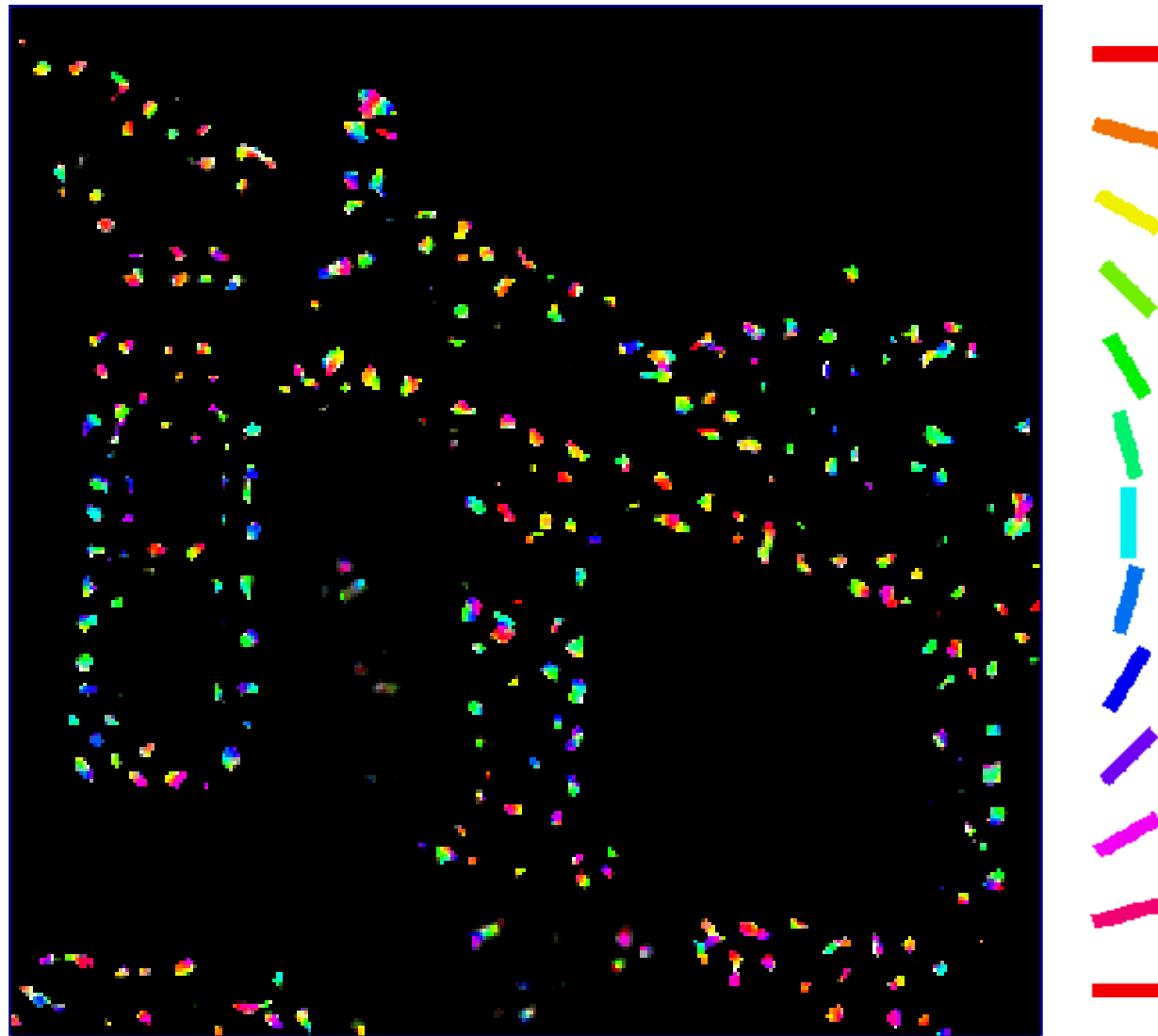
Sample Image



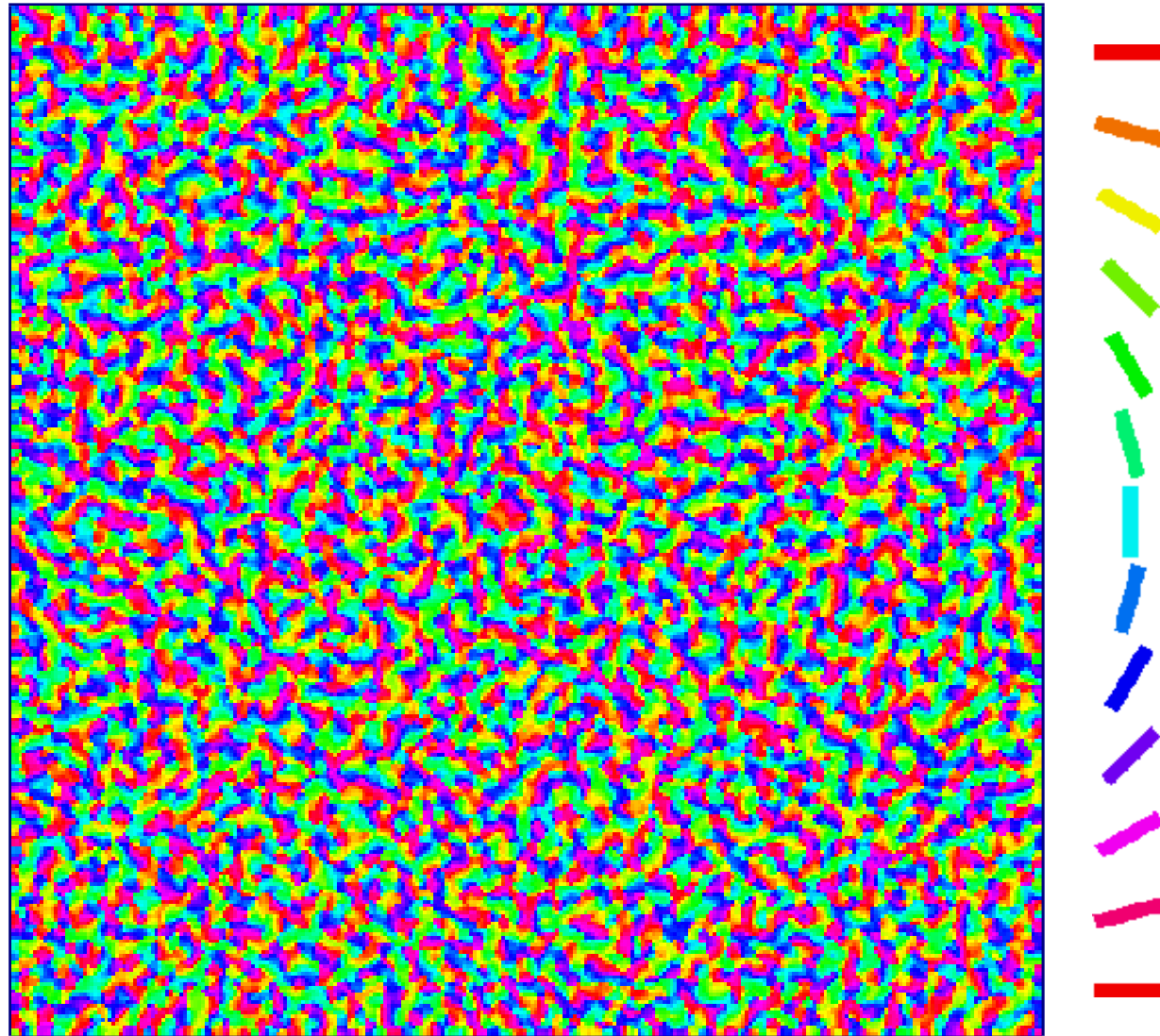
RGC/LGN Response



V1 Response with γ_n



V1 Orientation Map



Afferent normalization

Mechanism for contrast invariant tuning:

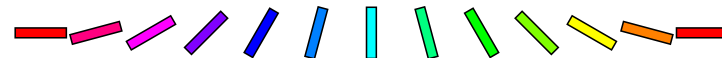
$$s_{ij} = \frac{\gamma_A \left(\sum_{\rho ab} \xi_{\rho ab} A_{\rho ab, ij} \right)}{1 + \gamma_n \left(\sum_{\rho ab} \xi_{\rho ab} \right)}, \quad (1)$$

$\xi_{\rho ab}$: 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

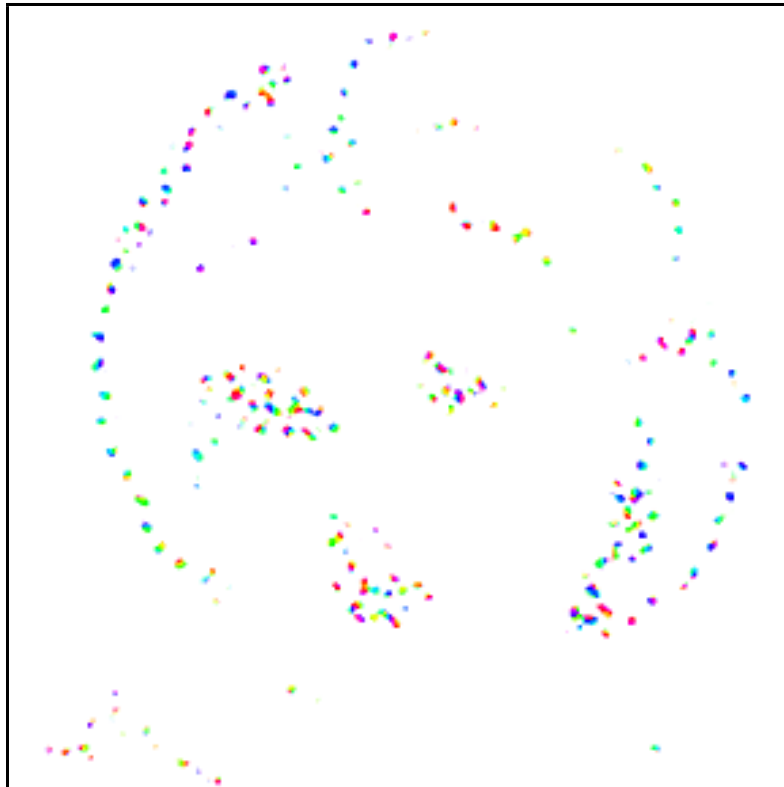


LGN response

RGC/LGN responds to most of the visible contours

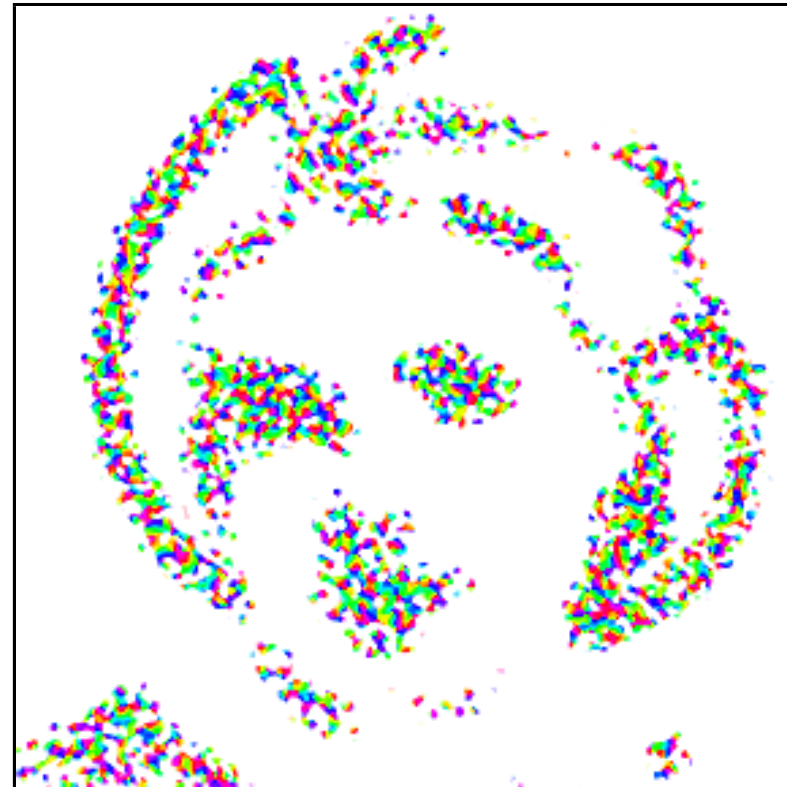
CMVC figure 8.2a,b

V1 without afferent normalization



V1 response:

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



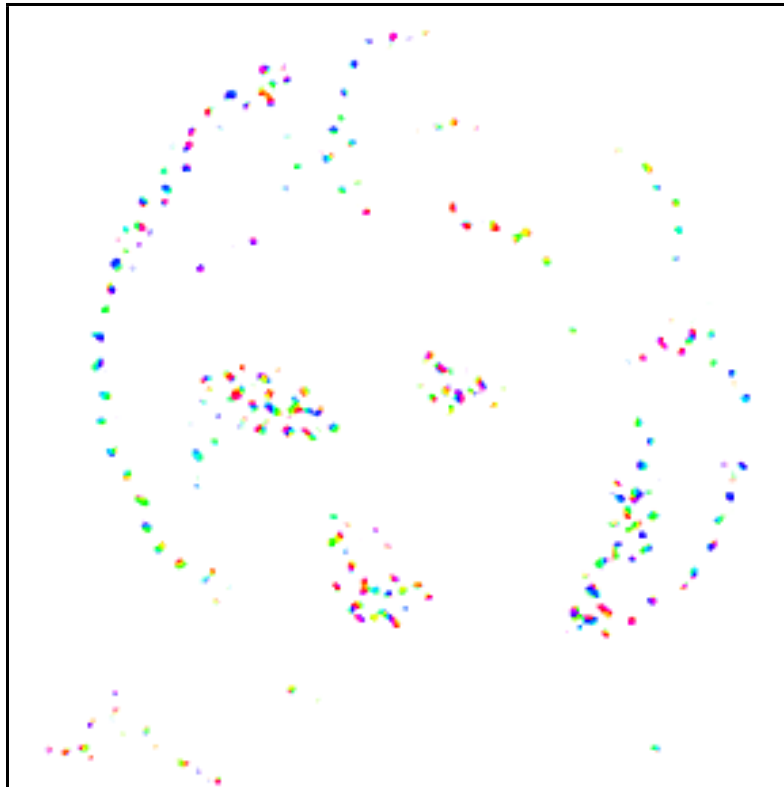
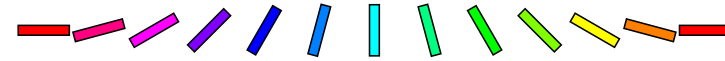
V1 response:

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

Cannot get selective response to all contours

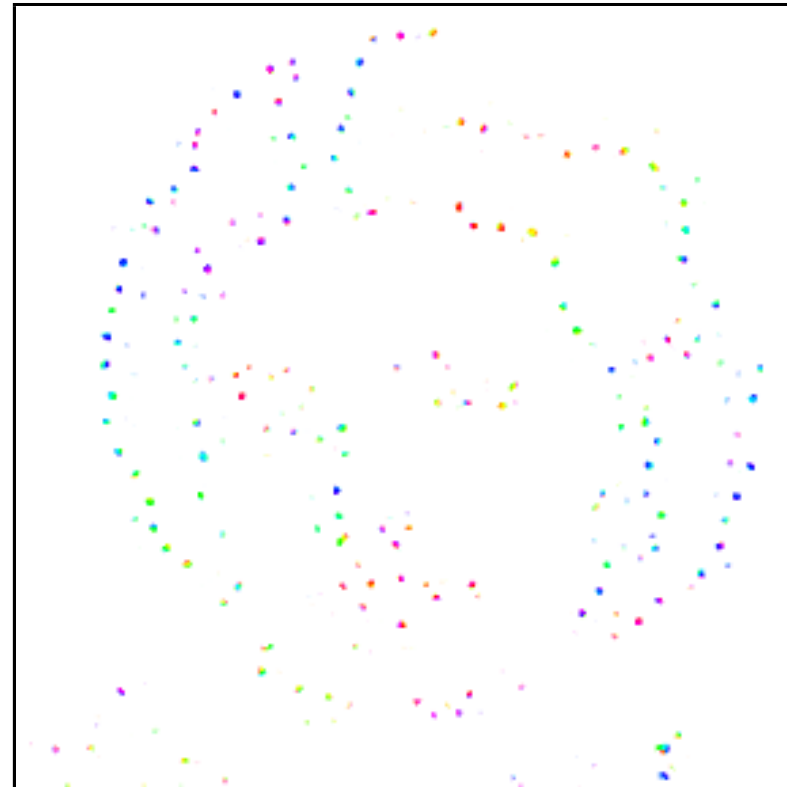
CMVC figure 8.2c-e

V1 with afferent normalization



V1 response:

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



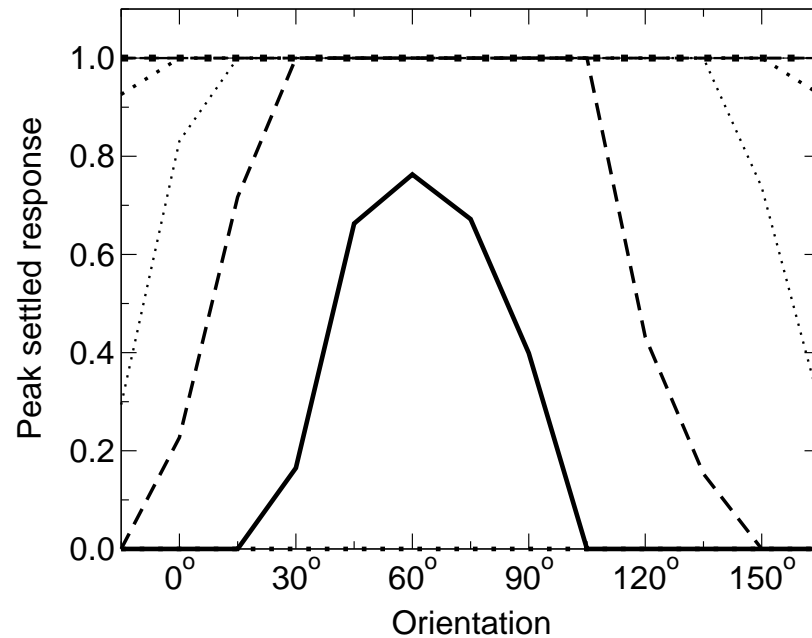
V1 response:

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

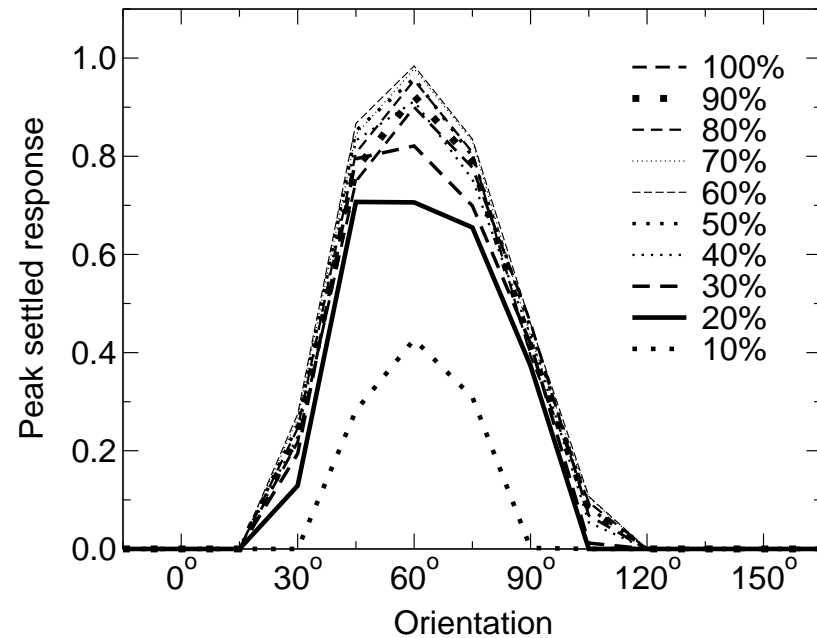
Responds based on contour, not contrast

CMVC figure 8.2c-e

Tuning with afferent normalization



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



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

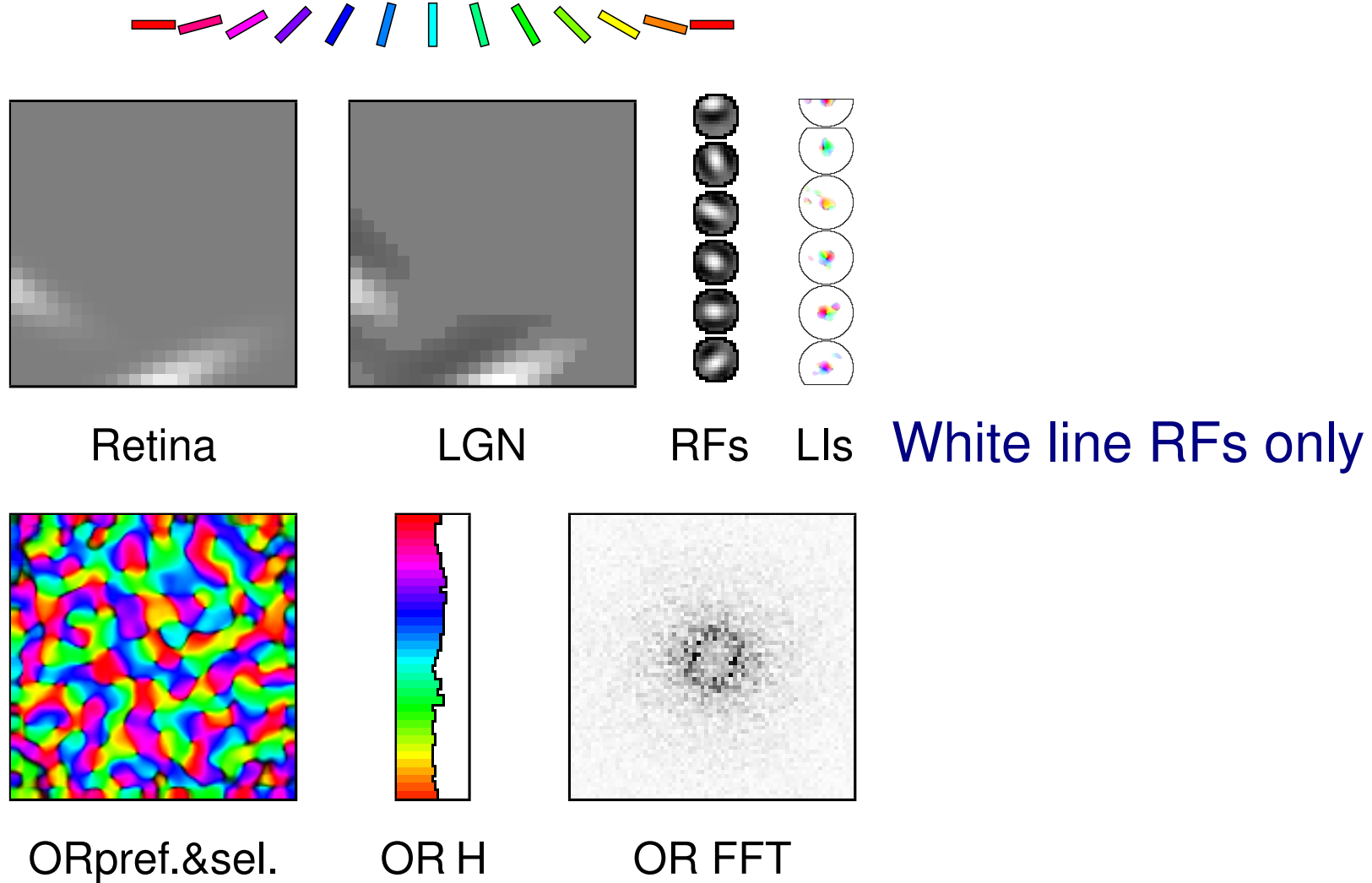
CMVC figure 8.3

Sine grating tuning curve:

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

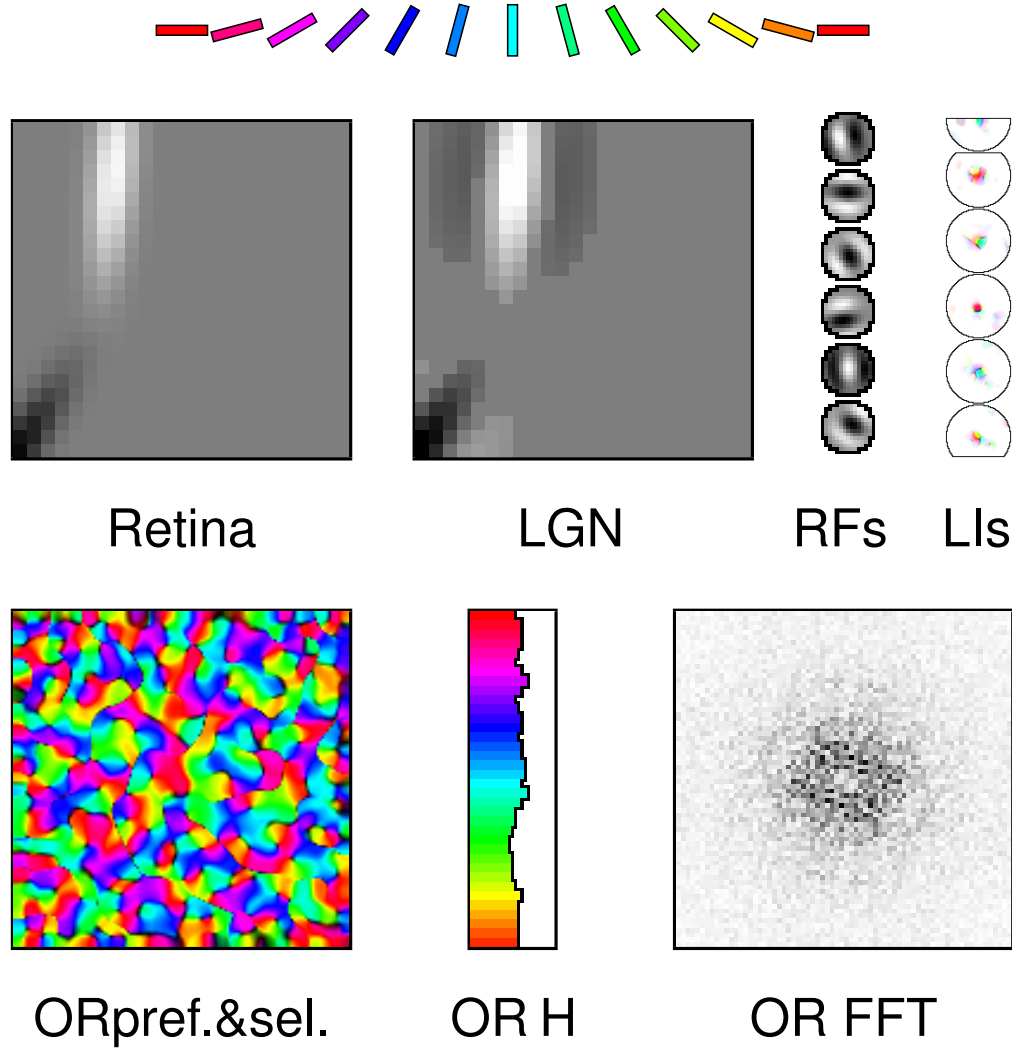
OR Map: Gaussian

CMVC figure 5.13



OR Map: +/- Gaussian

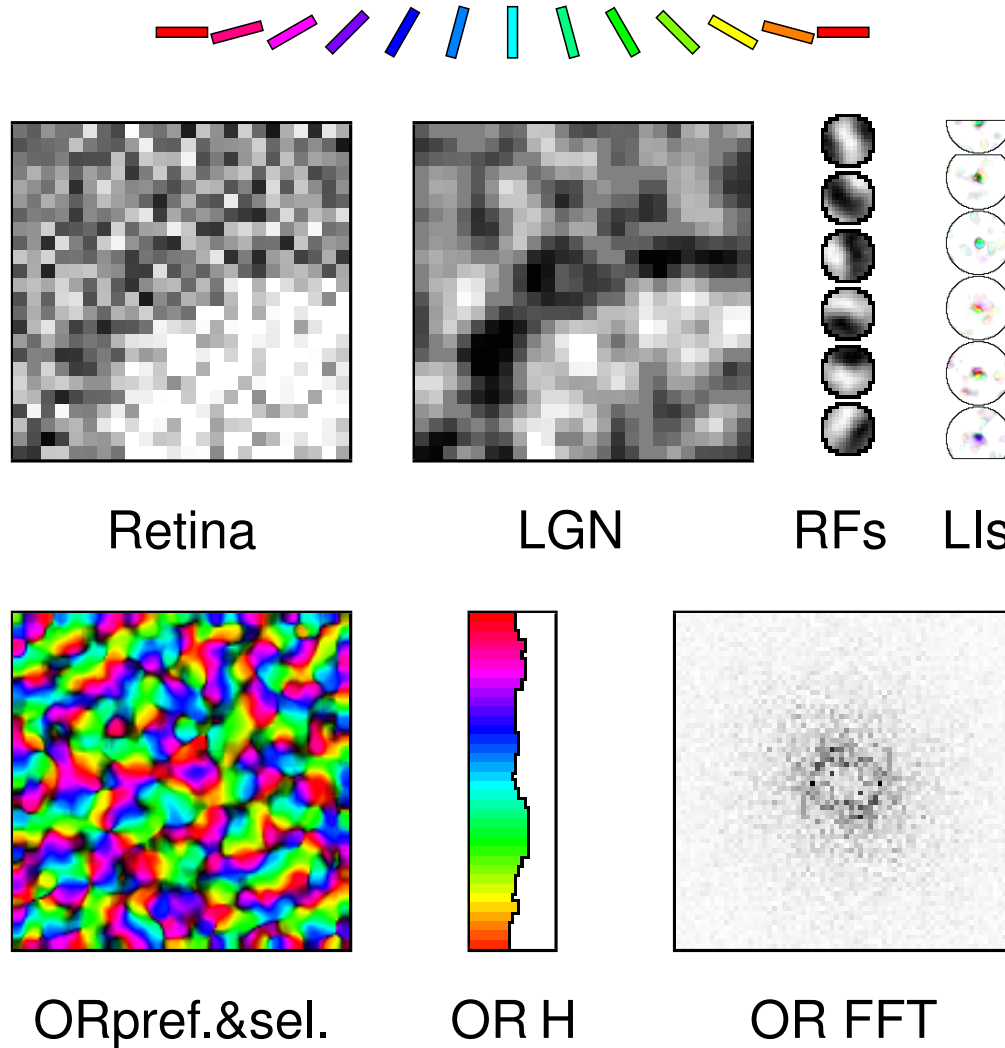
CMVC figure 5.13



White or black line
RFs

OR Map: Retinal wave model

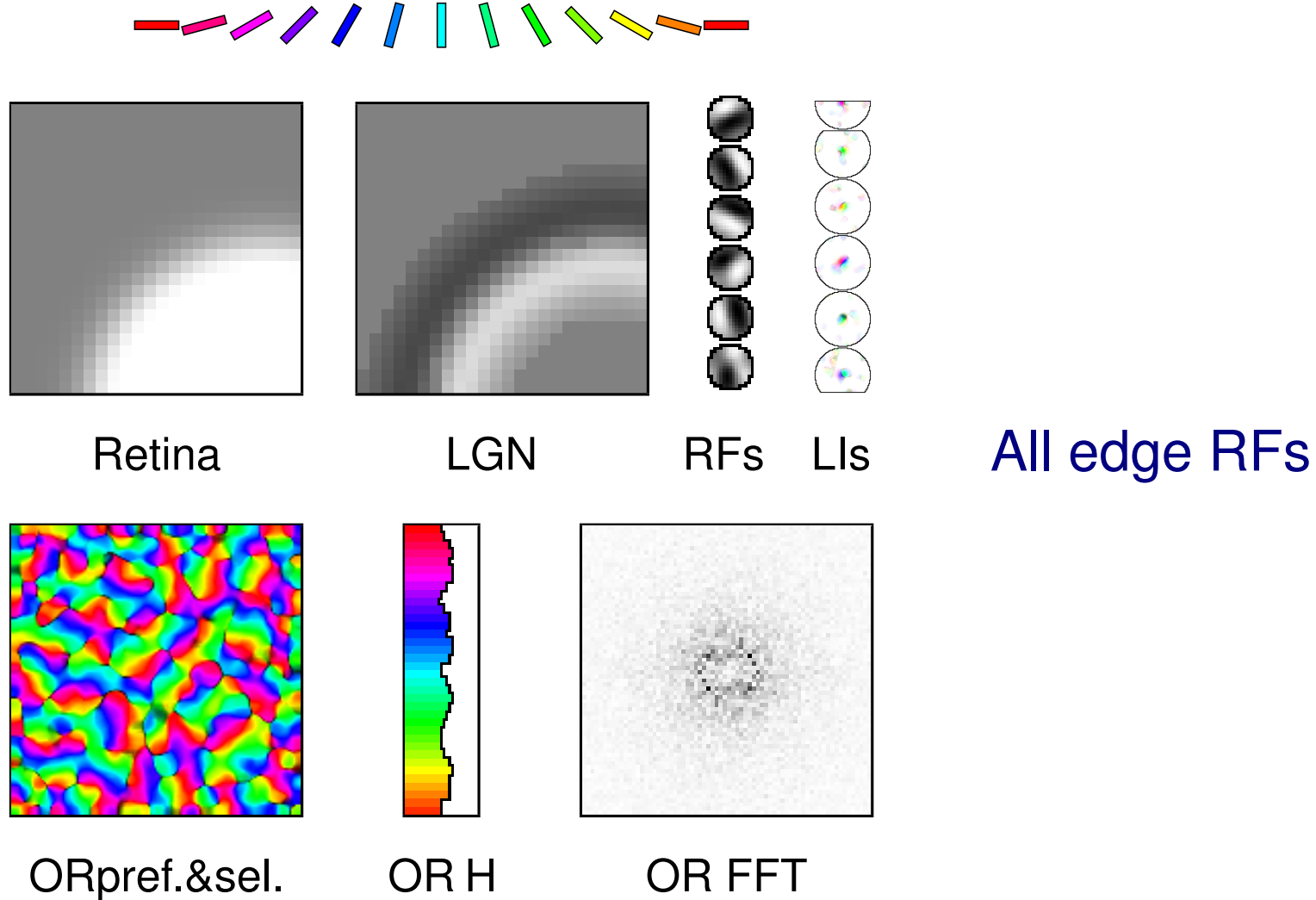
CMVC figure 5.13



Some line, mostly
edge RFs

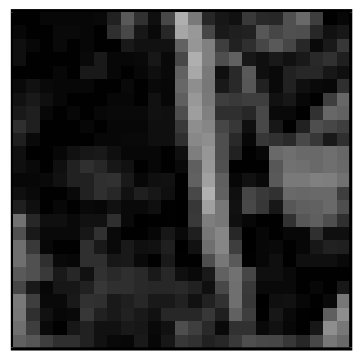
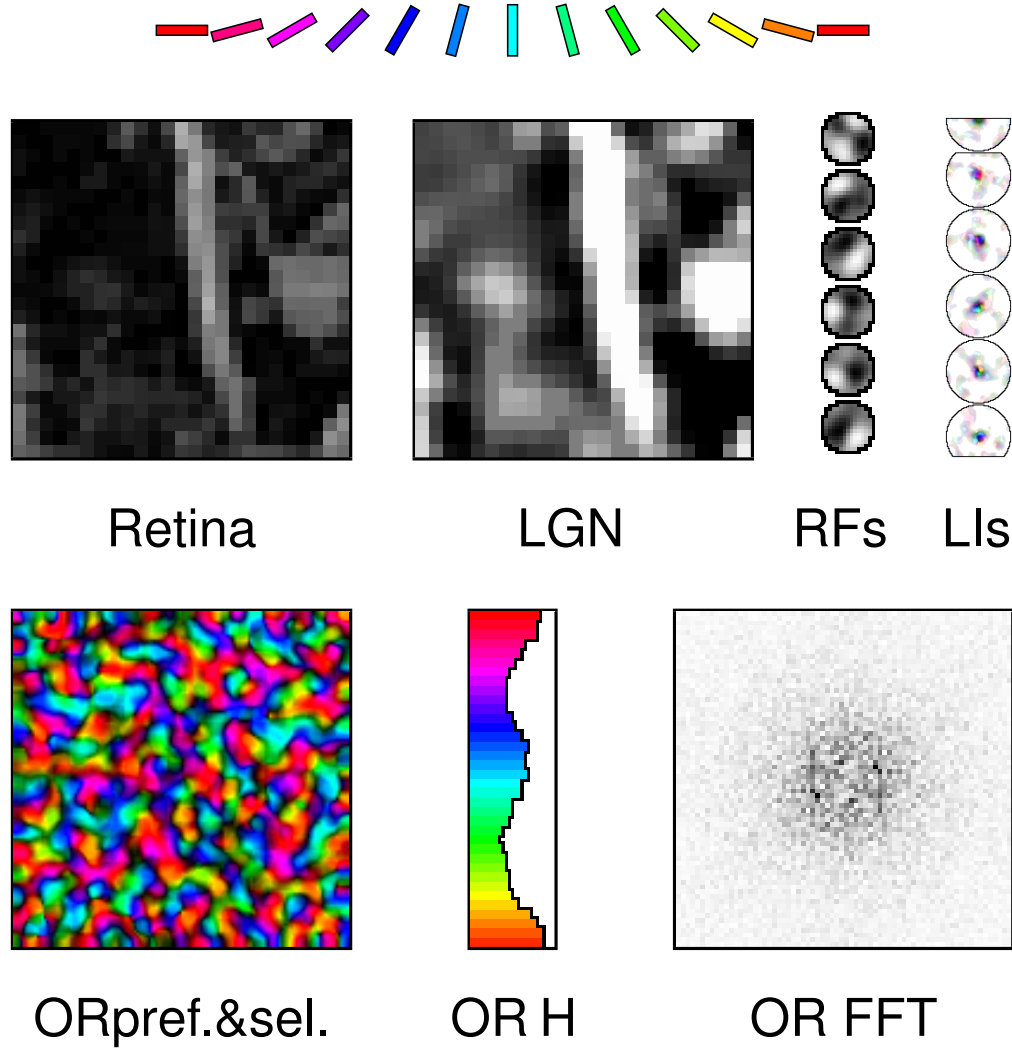
OR Map: Smooth disks

CMVC figure 5.13

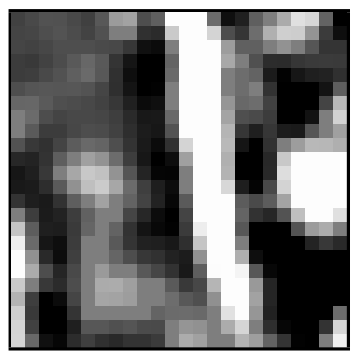


OR Map: Natural images

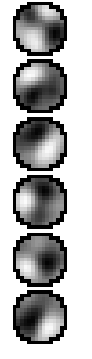
CMVC figure 5.13



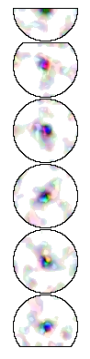
Retina



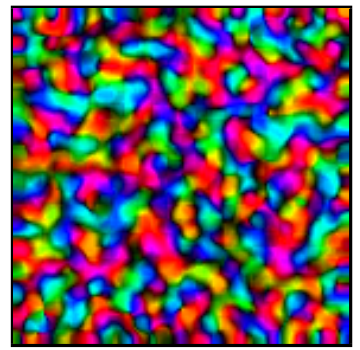
LGN



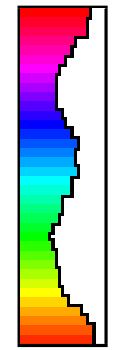
RFs



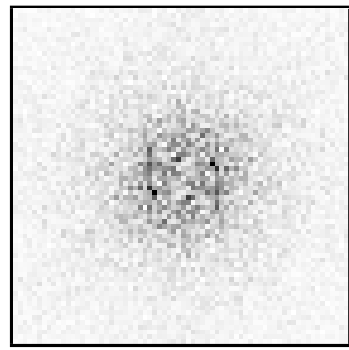
LIs



ORpref.&sel.



OR H



OR FFT

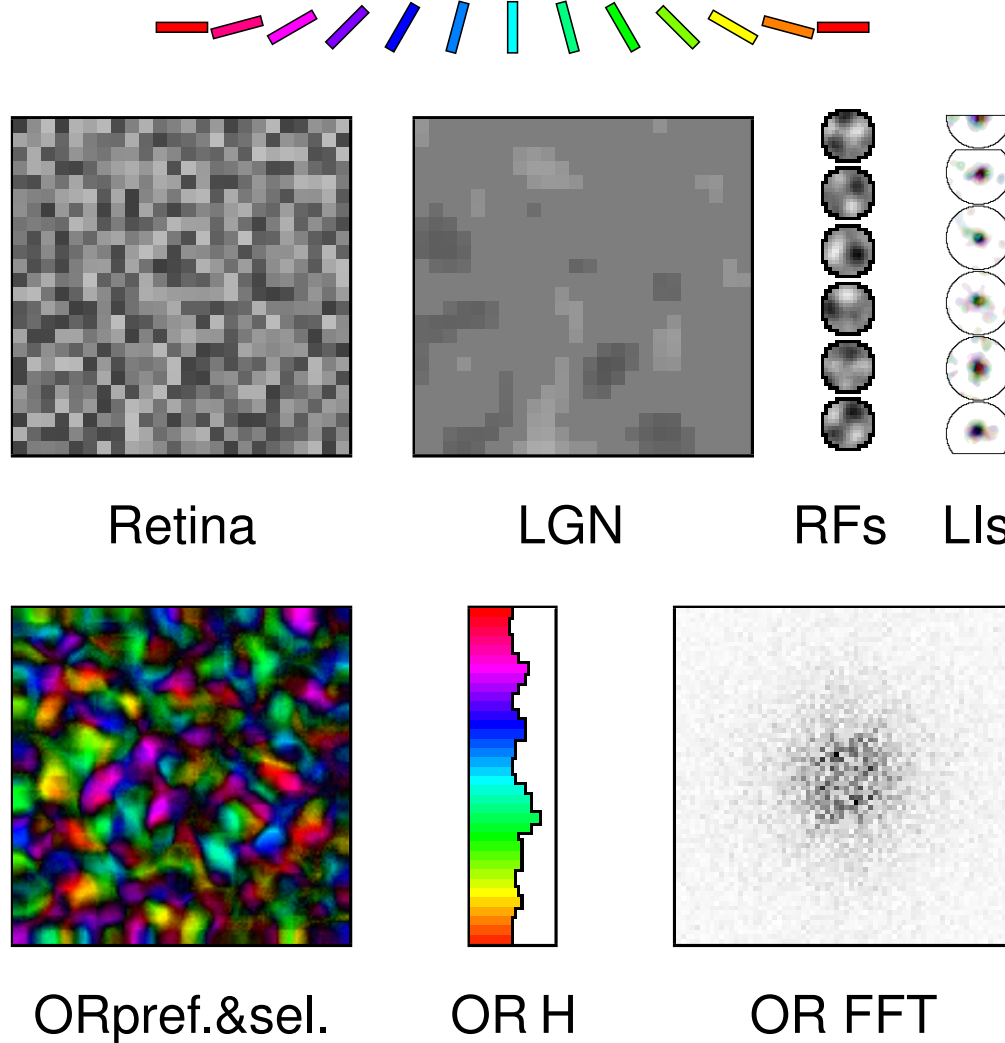
All types of RFs

Longer range lateral weights

Histogram:
horizontal, vertical bias

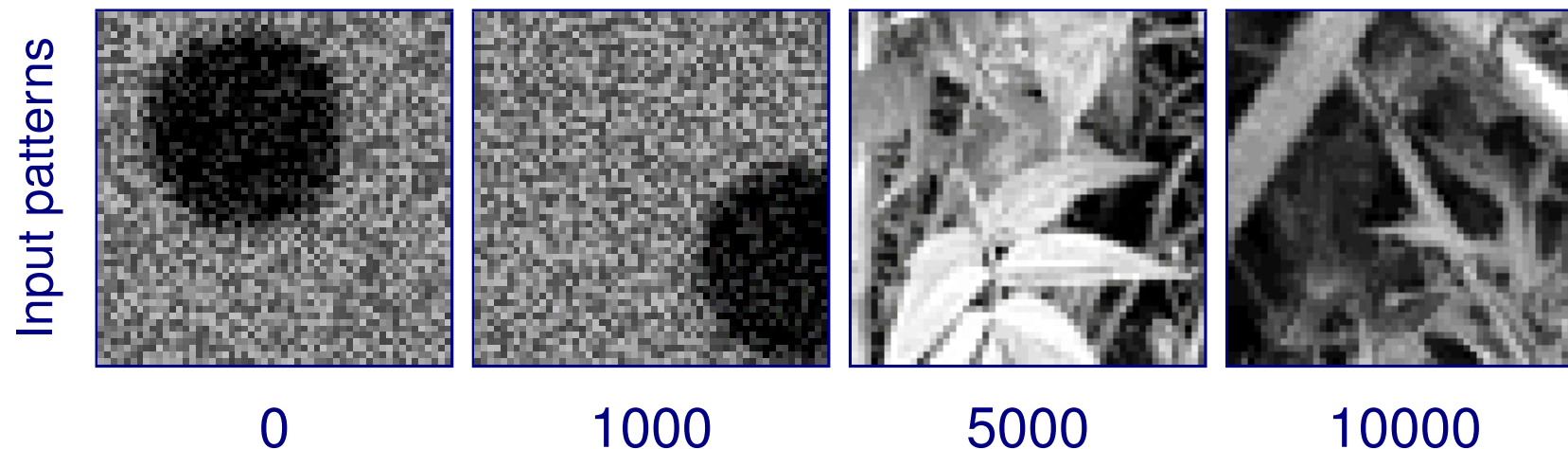
OR Map: Uniform noise

CMVC figure 5.13



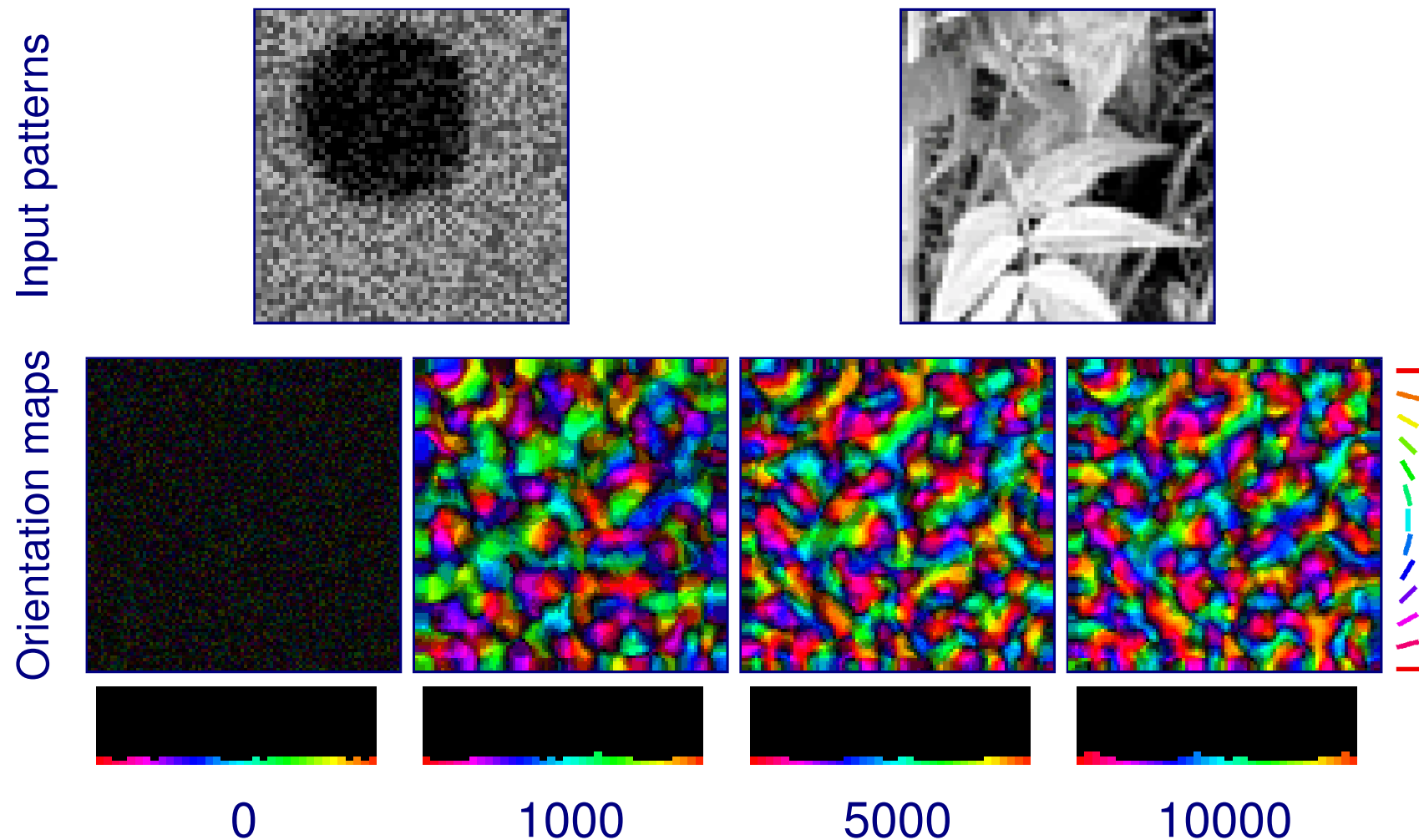
Relatively
unselective RFs

Modeling pre/post-natal phases



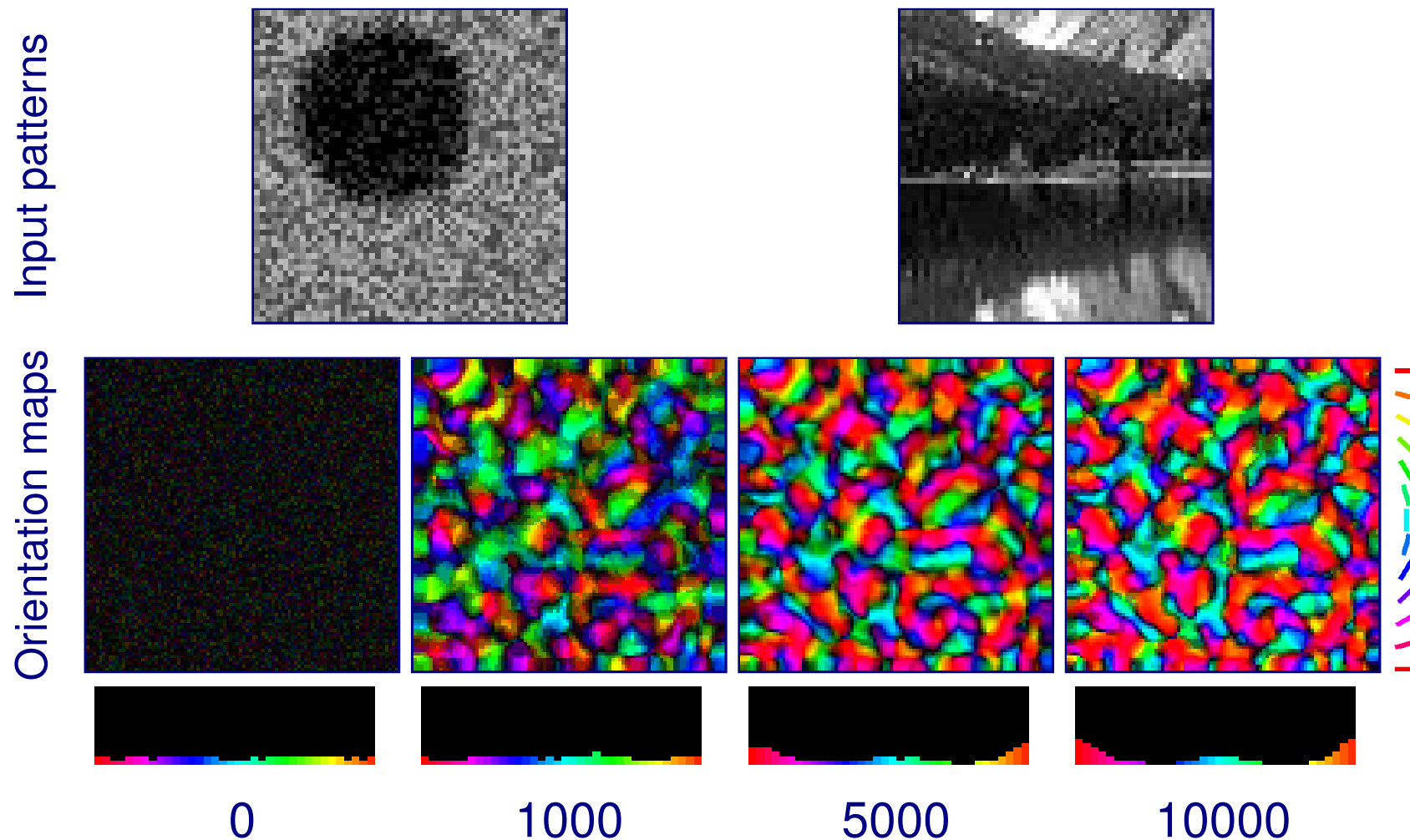
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

Pre/post-natal V1 development



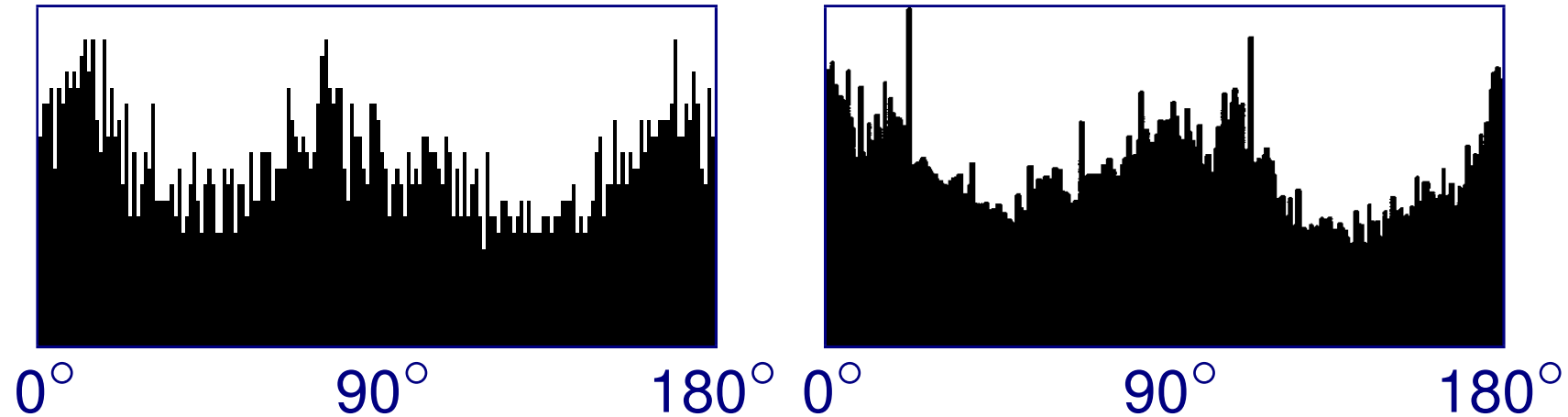
- Neonatal map smoothly becomes more selective

Statistics drive development



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

OR Histograms



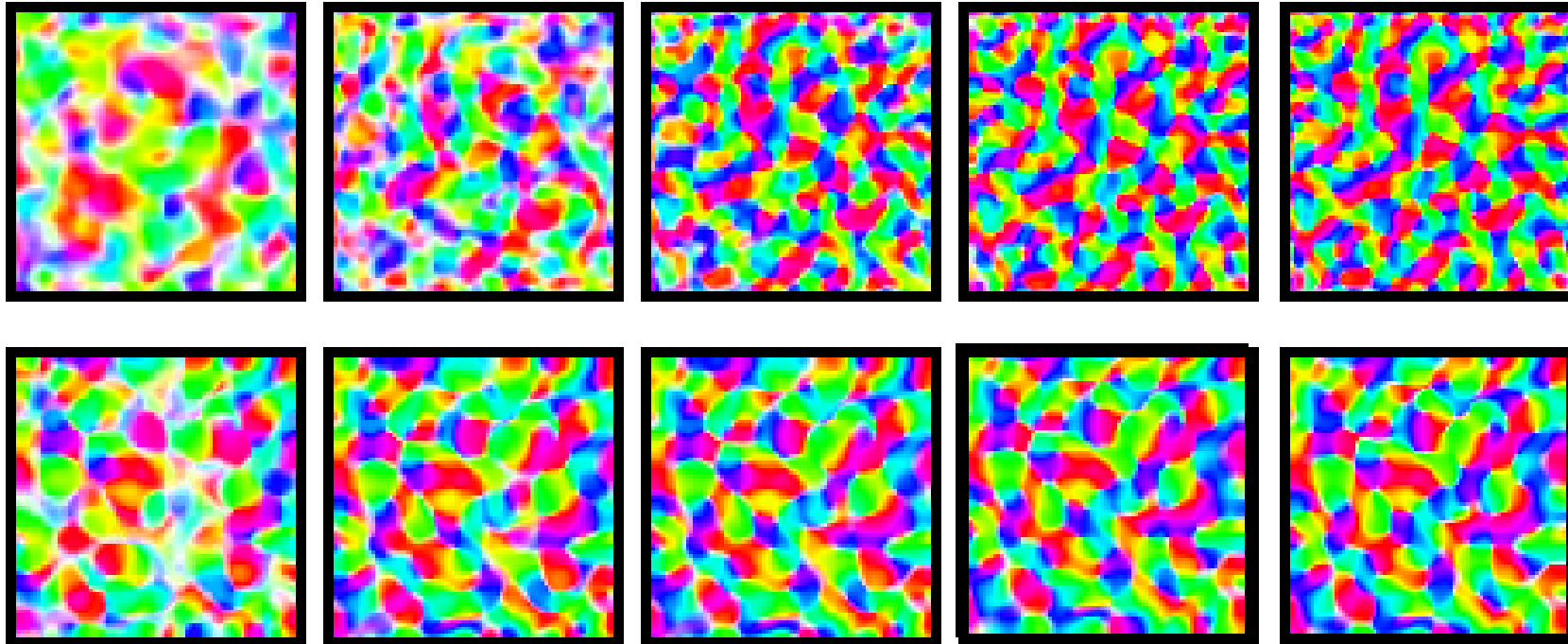
HLISSOM model

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



(Law 2009)

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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development of orientation maps and receptive fields. Tech. rep., School of Informatics, The University of Edinburgh. EDI-INF-RR-1404.

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.