LISSOM Orientation Maps

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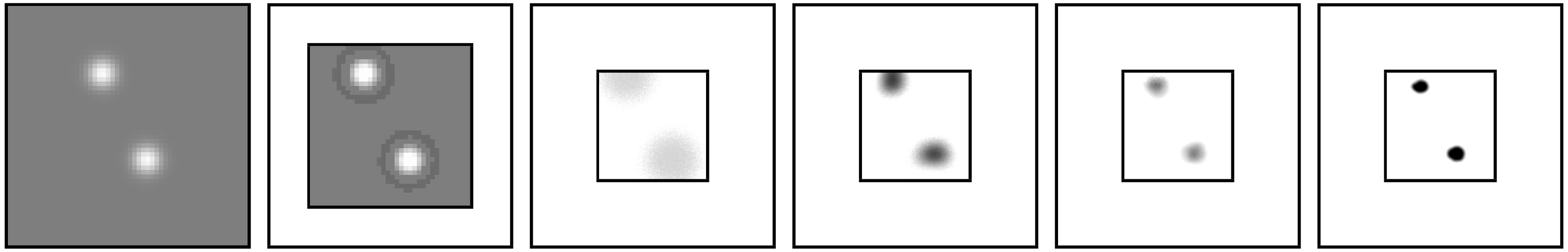
Modeling Orientation

- 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

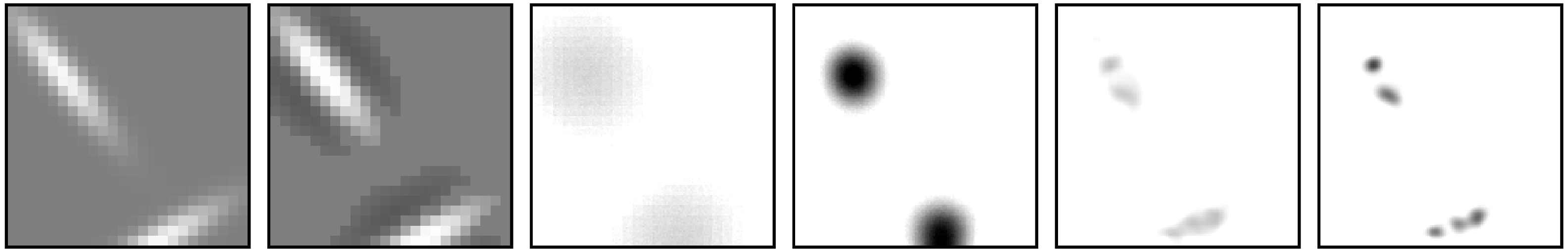


Retinal activation	LGN response	Iteration 0: Initial V1 response	Iteration 0: Settled V1 response	10,000: Initial V1 response	10,000: Settled V1 response

CMVC figure 4.4

(Reminder from previous slides)

Orientation input and response

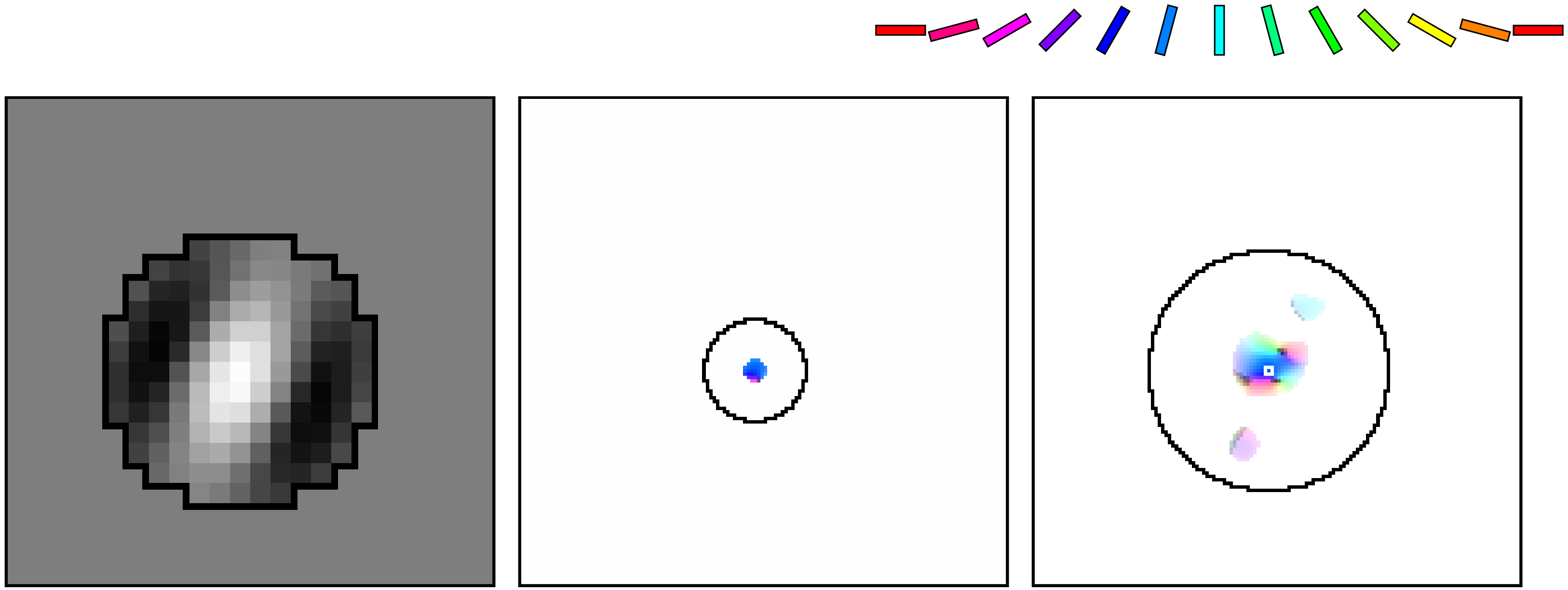


Retinal activation	LGN response	Iteration 0: Initial V1 response	Iteration 0: Settled V1 response	10,000: Initial V1 response	10,000: Settled V1 response

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



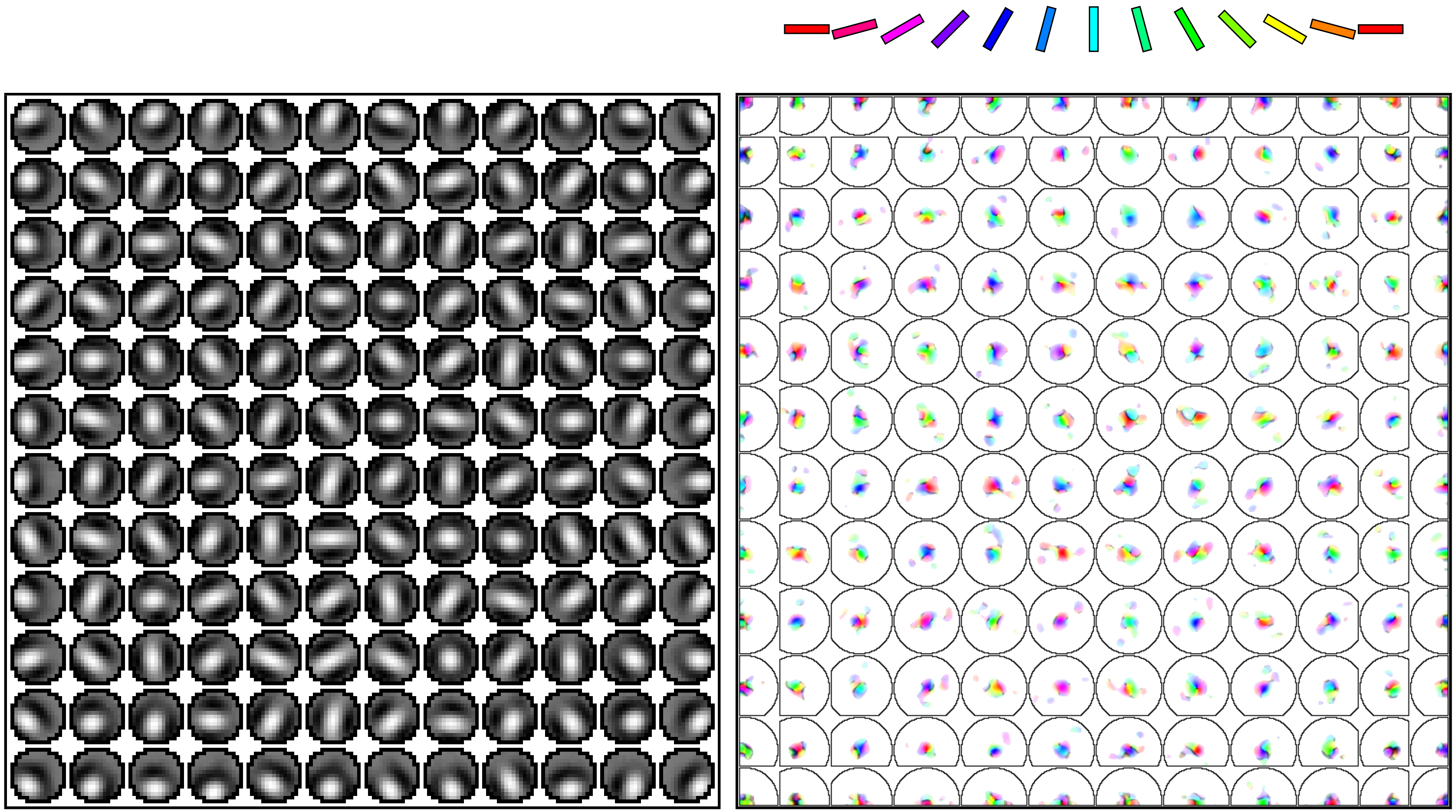
Afferent (ON—OFF) Lateral excitatory Lateral inhibitory

CMVC figure 5.7

Typical:

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

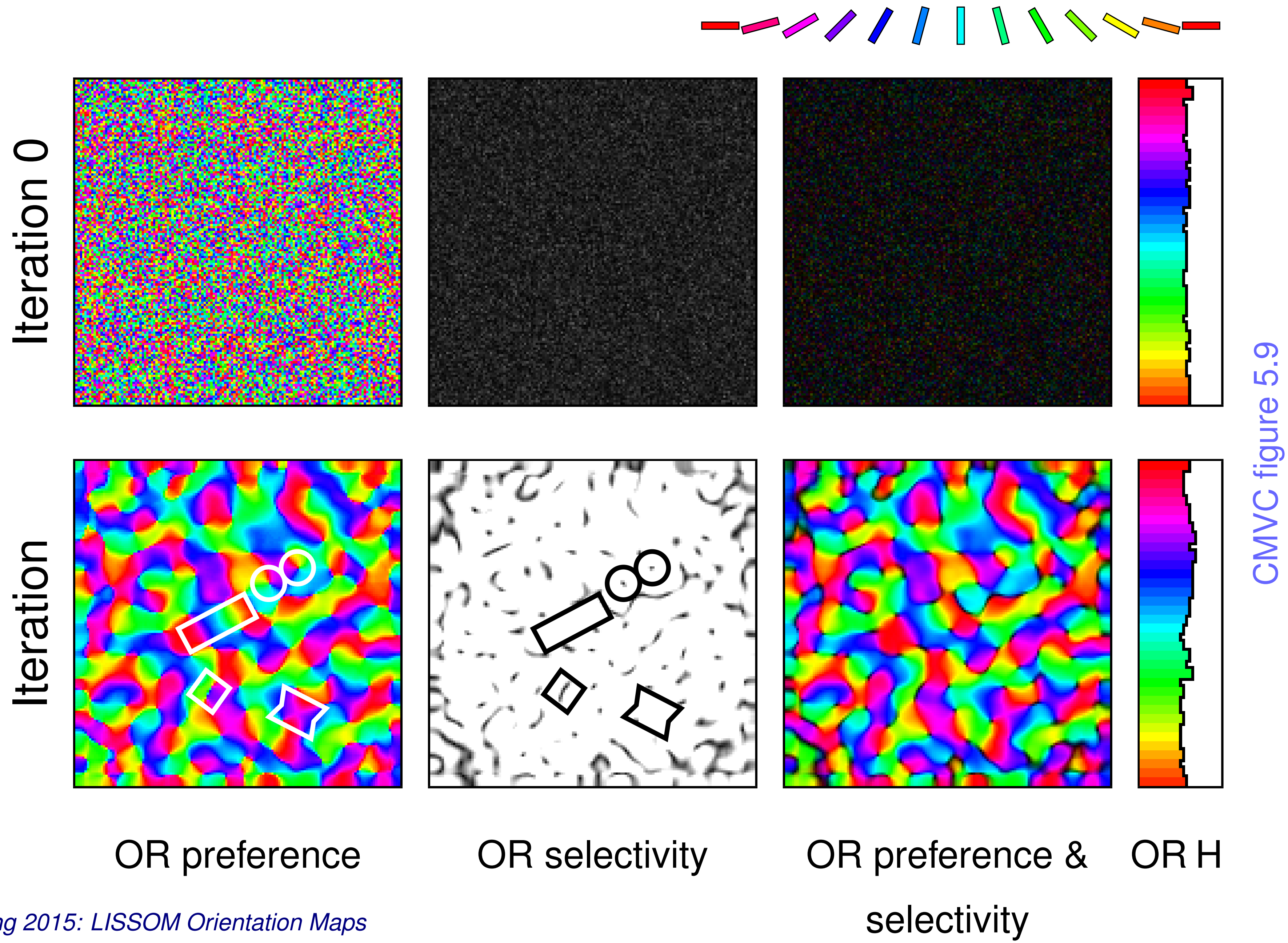
Self-organized weights across V1



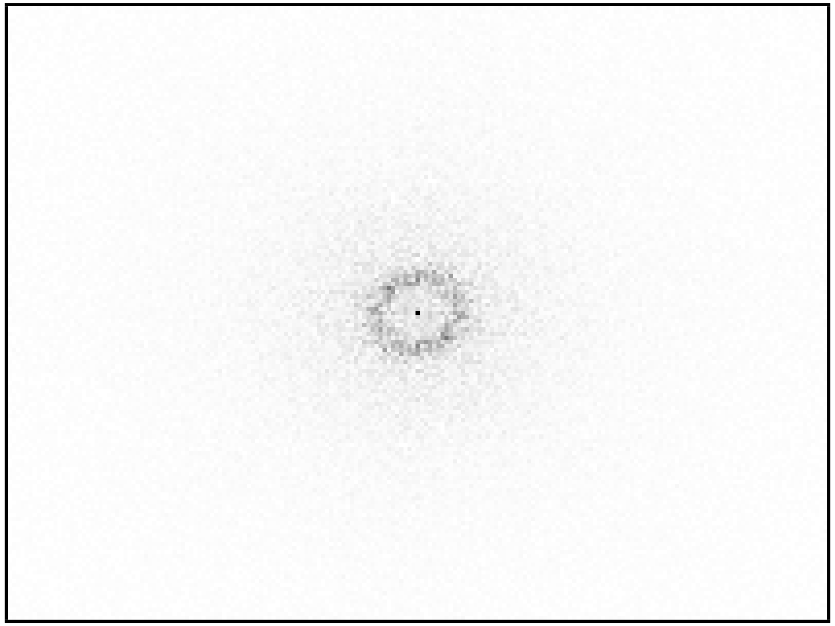
Afferent (ON—OFF) Lateral inhibitory

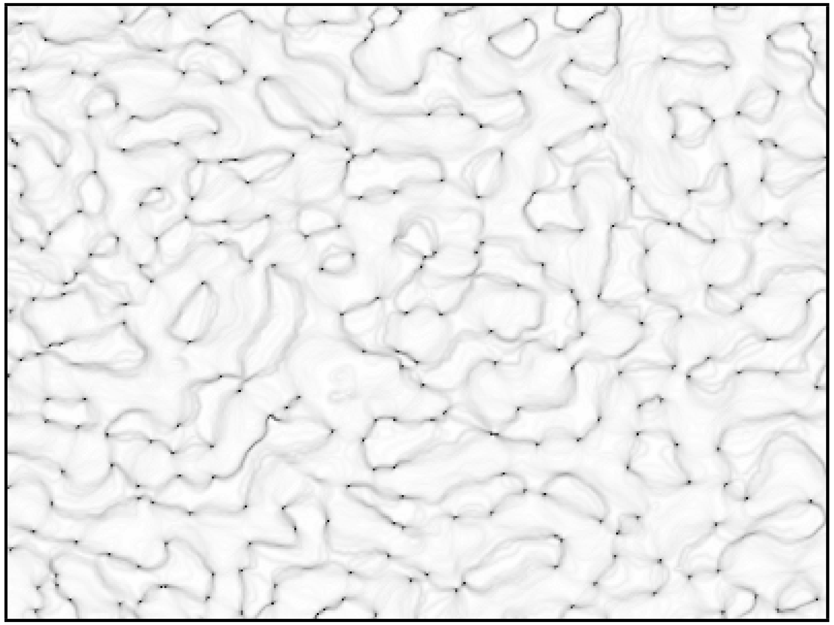
CMVC figure 5.8

OR map self-organization



Macaque ORmap: Fourier,gradient





CMVC figure 5.1

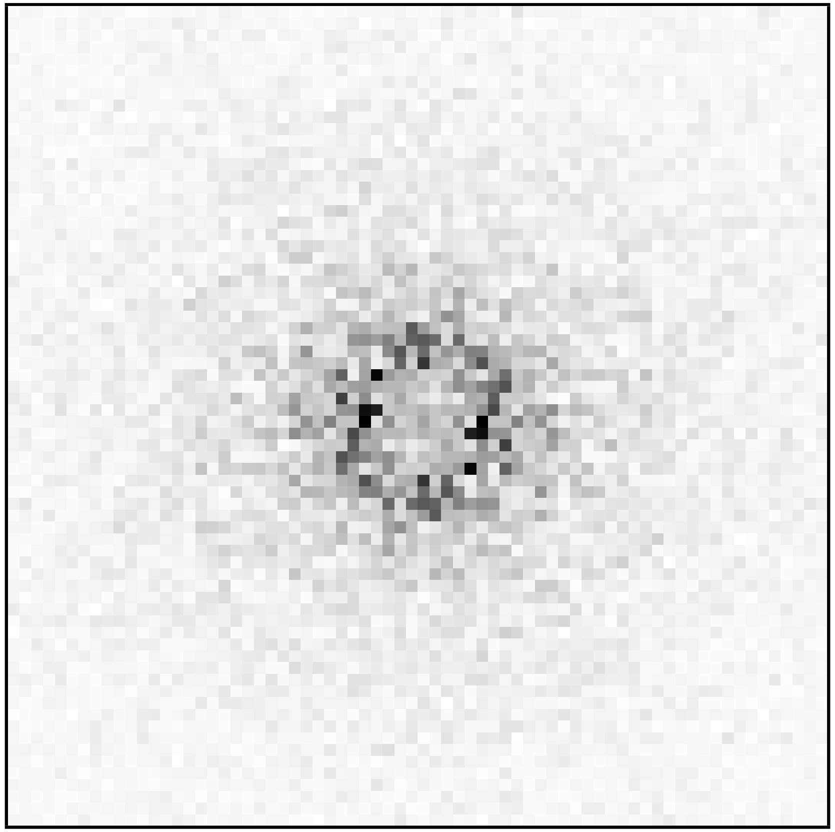
Fourier spectrum

Gradient

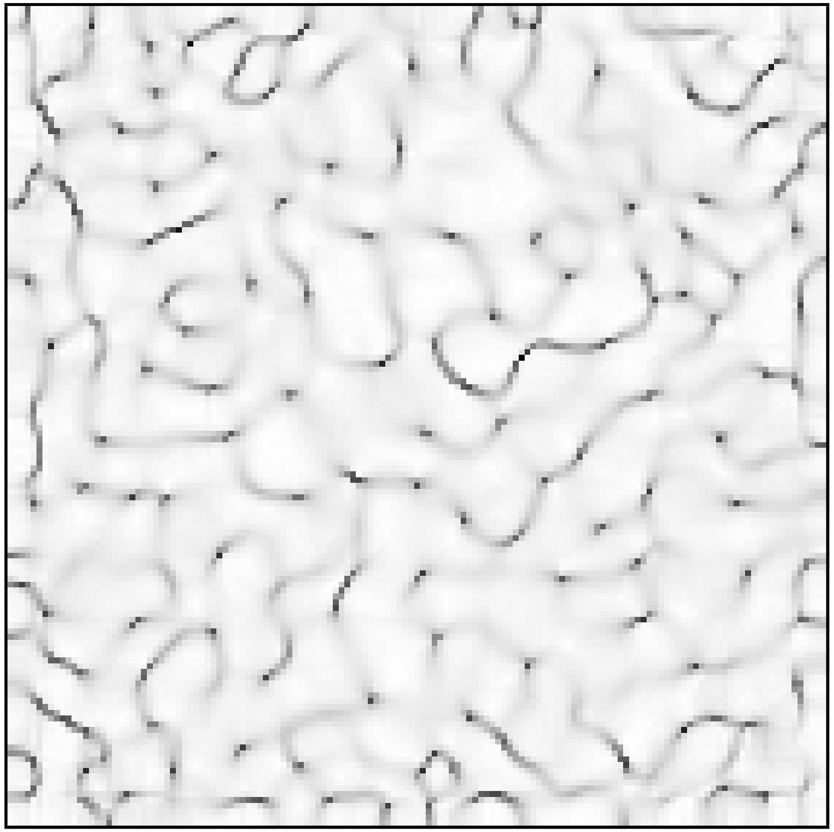
In monkeys:

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

OR Map: Fourier, gradient



Fourier spectrum

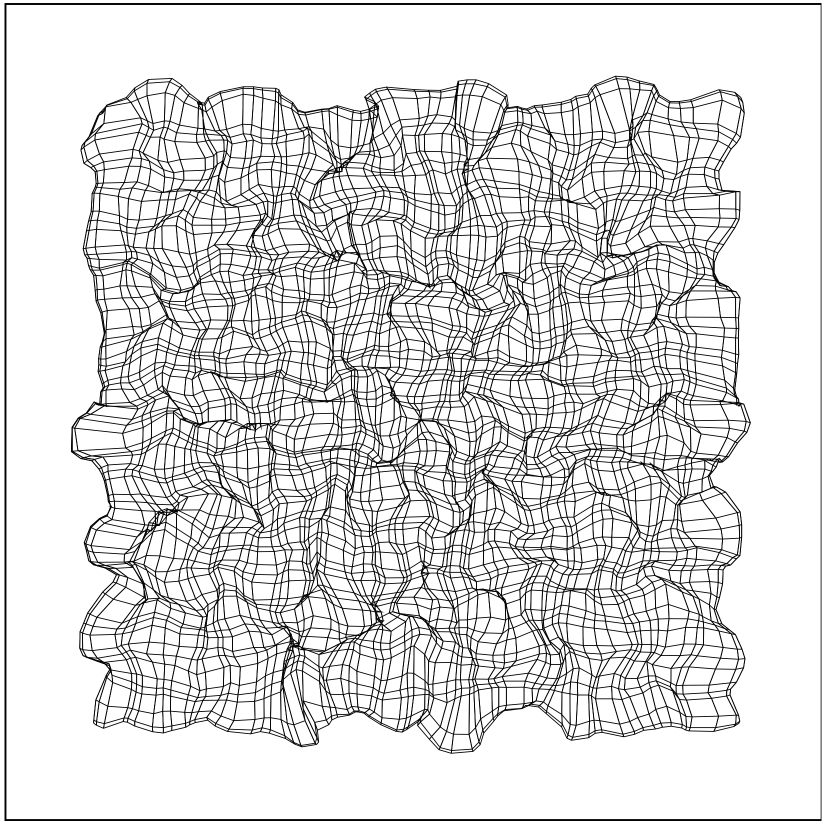


Gradient

CMVC figure 5.10

LISSOM model has similar spectrum, gradient

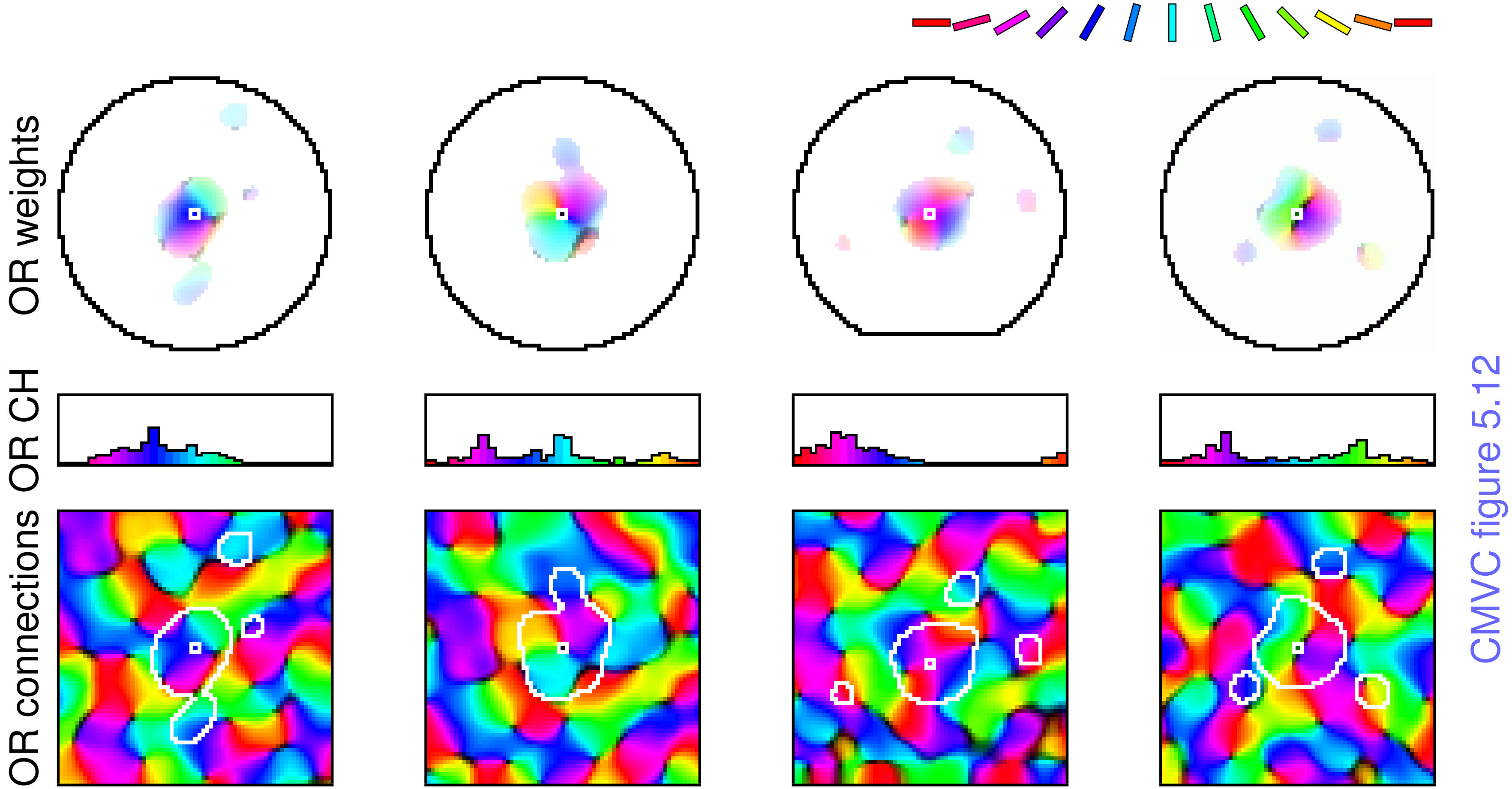
OR Map: Retinotopic organization



CMVC figure 5.11

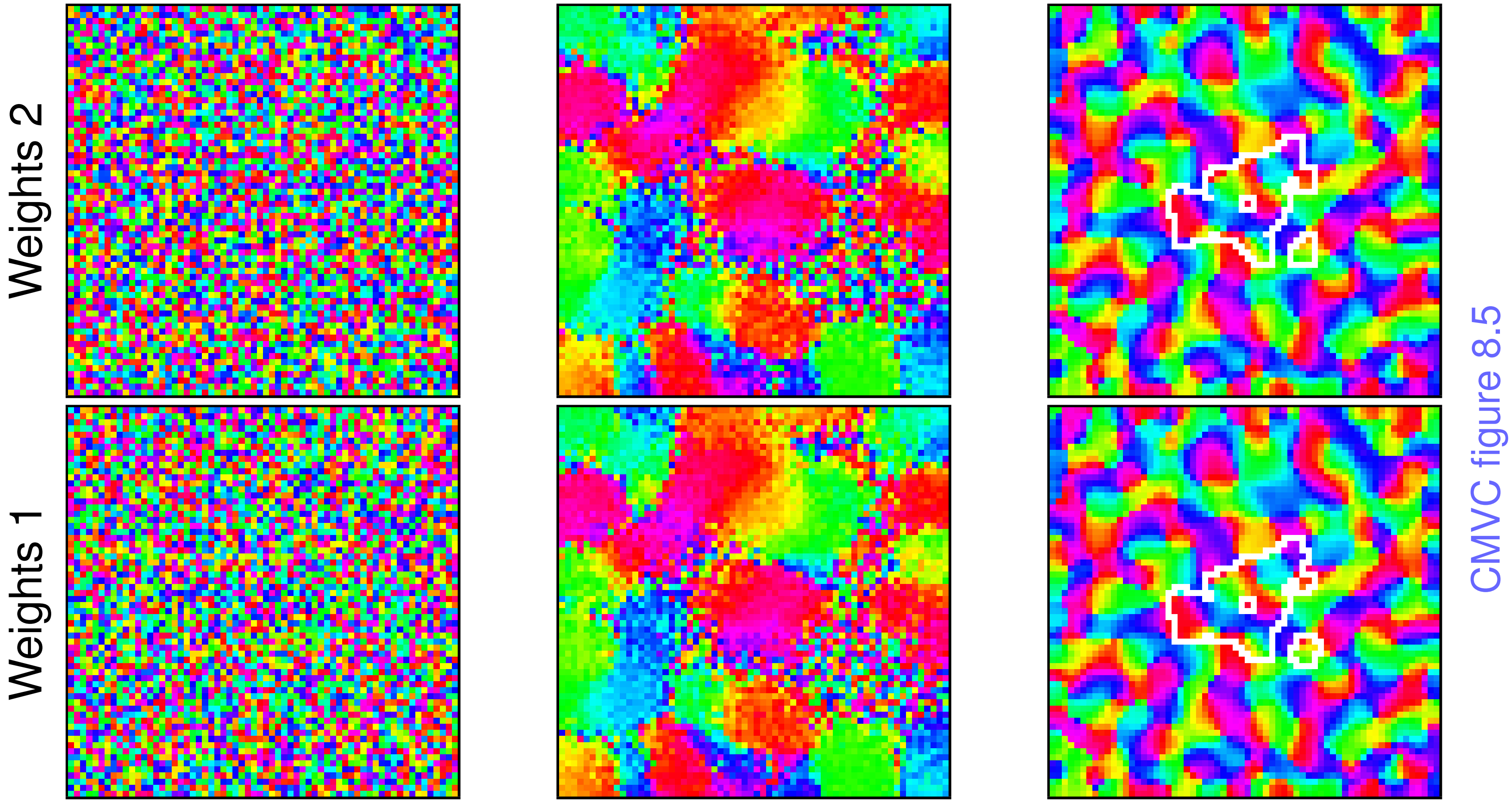
- Retinotopy is distorted locally by orientation prefs
- Matches distortions found in animal maps?

OR Map: Lateral connections



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

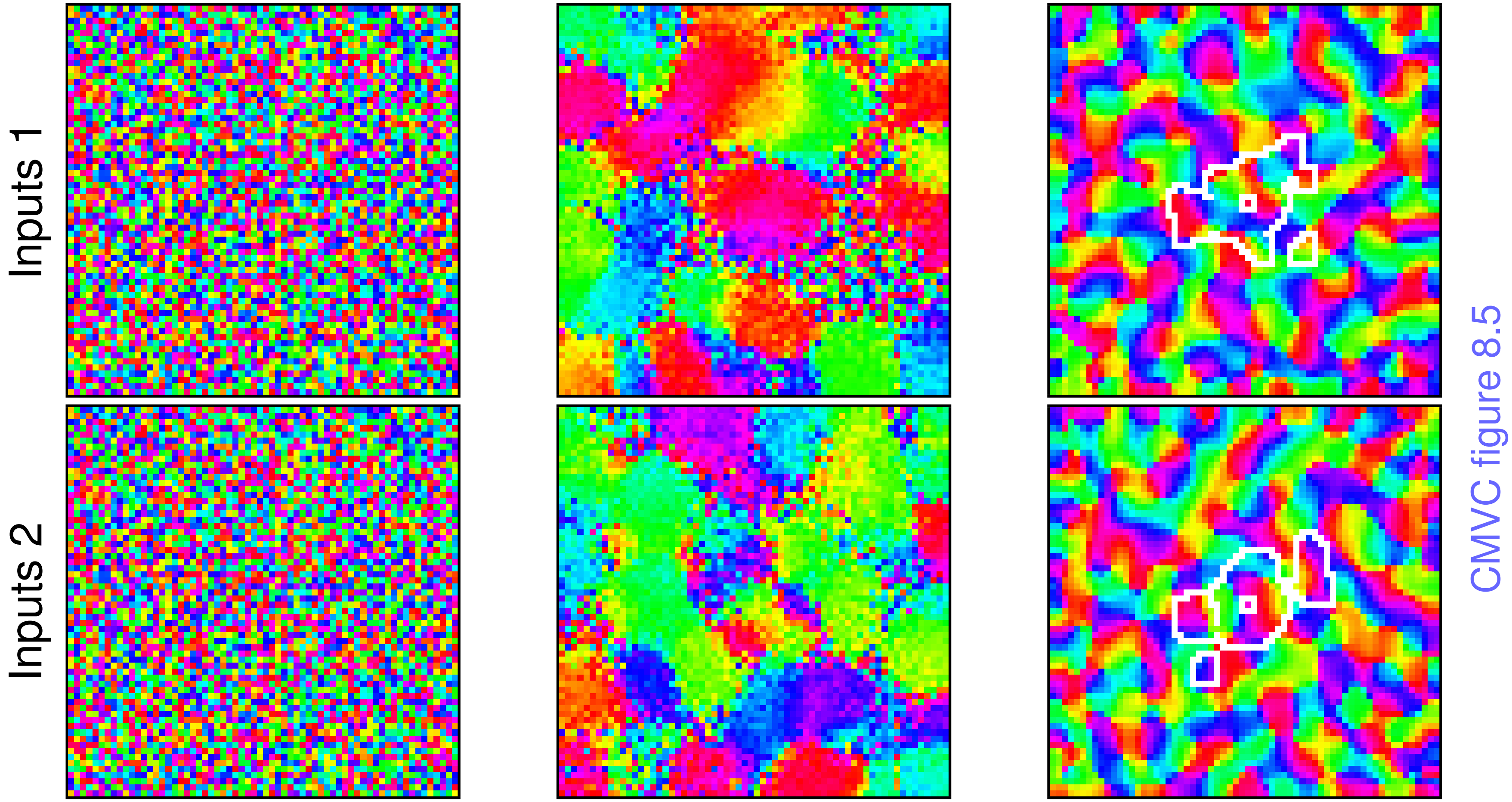
Effect of initial weights



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

Changing weights doesn't change map folding pattern.

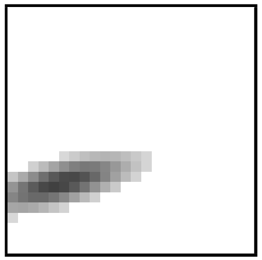
Effect of input streams



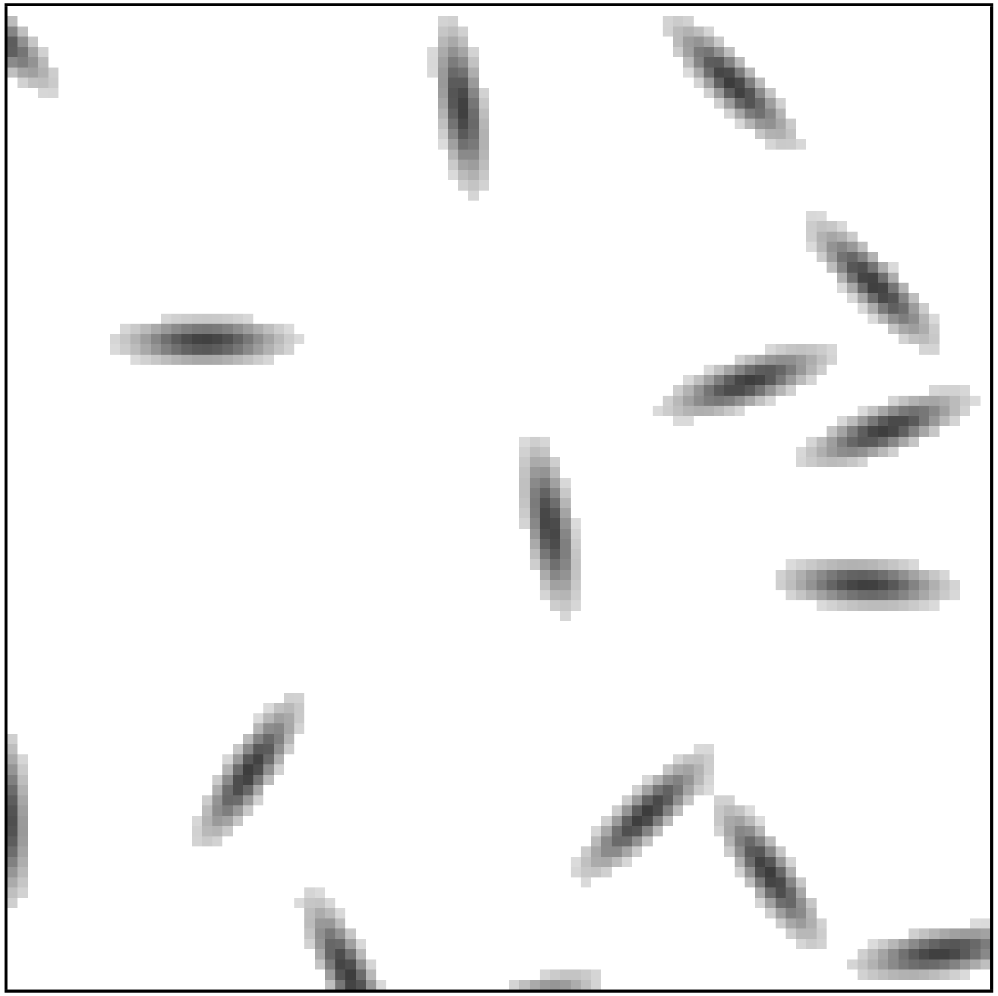
(*a*) Iteration 0 (*b*) Iteration 50 (*c*) Iteration 10,000

Changing inputs changes entire pattern.

Scaling retinal and cortical area



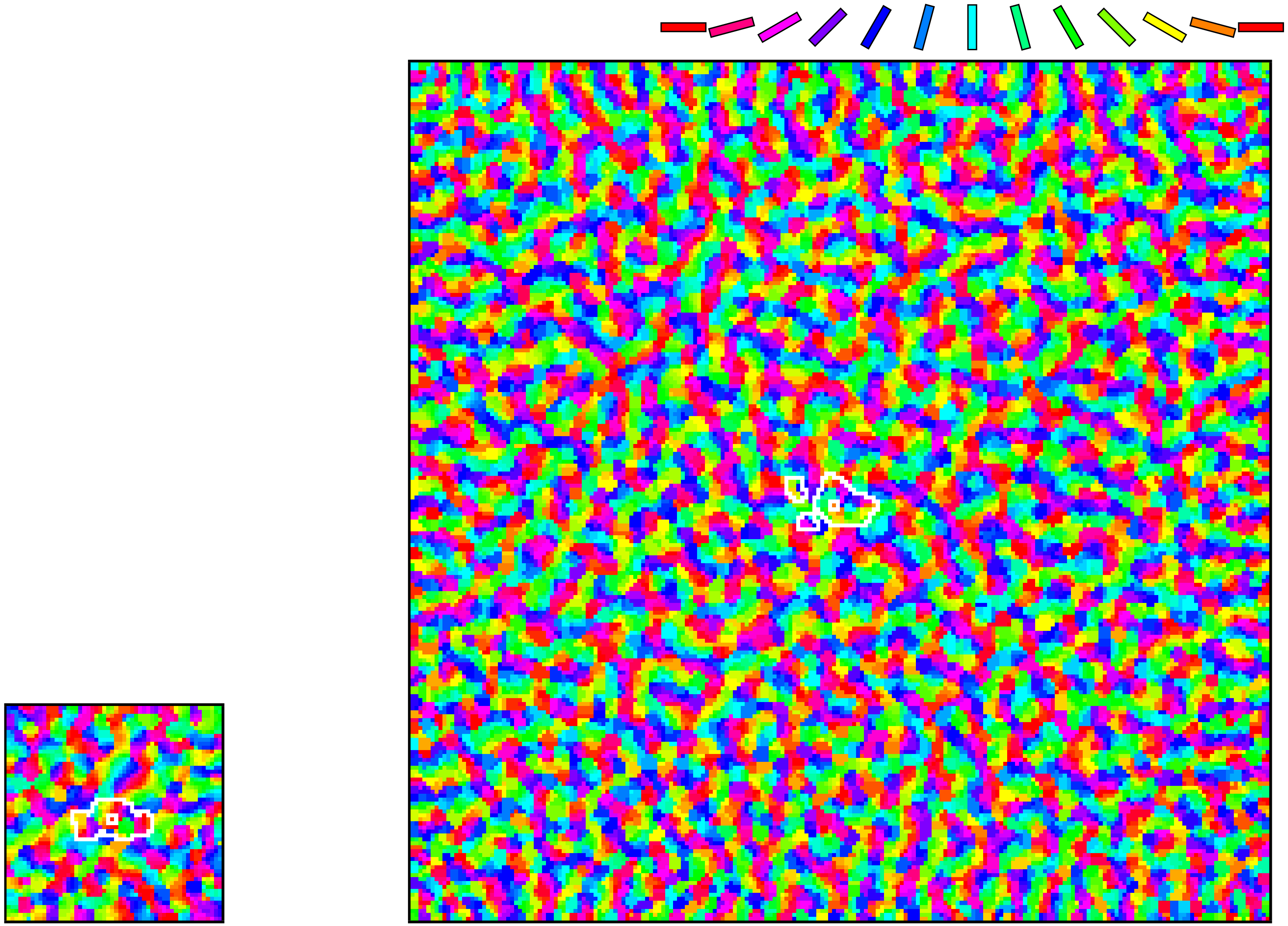
(*a*) Original retina: $R = 24$



(*b*) Retinal area scaled by 4.0: $R = 96$

CMVC figure 15.1a,b

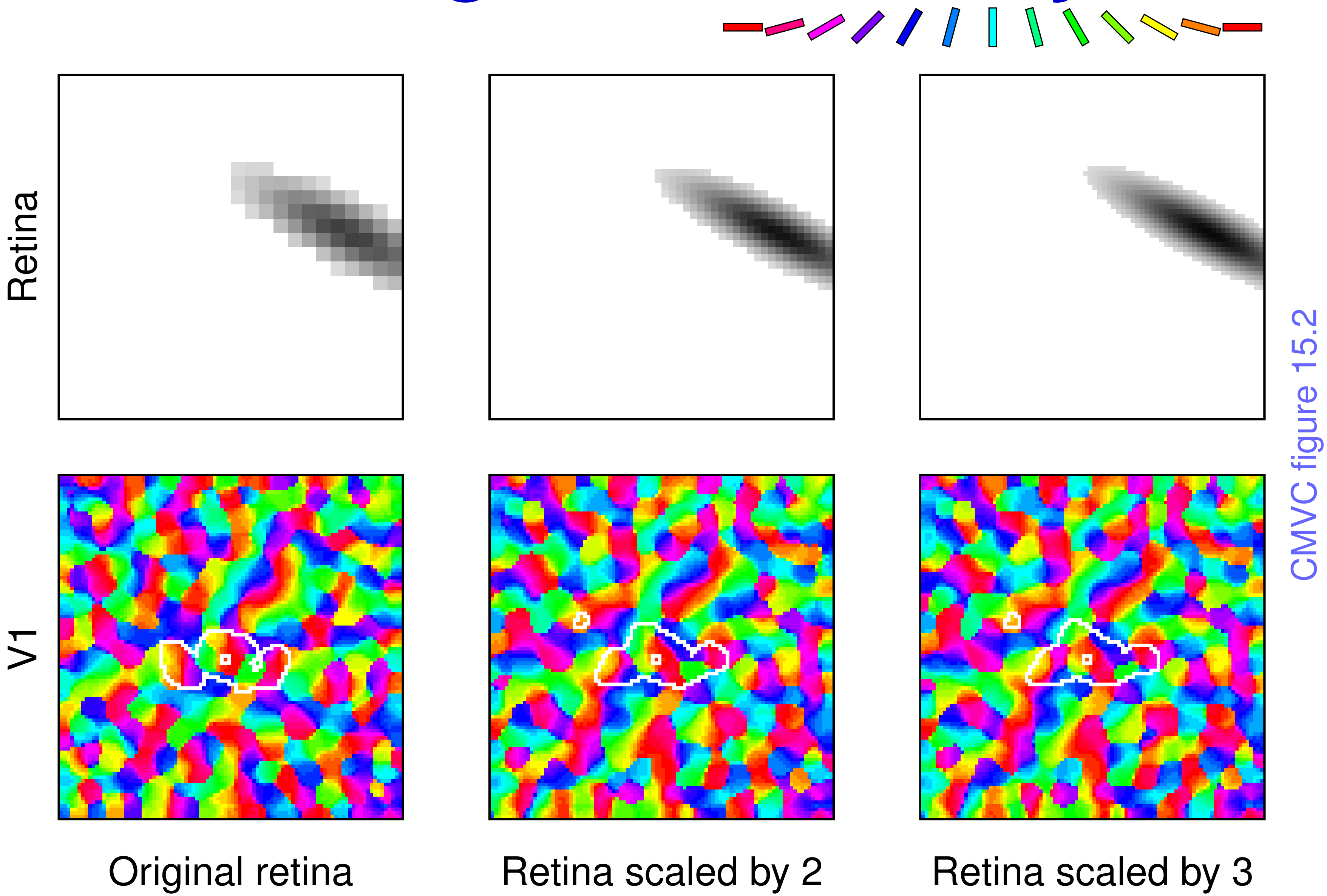
Scaling retinal and cortical area



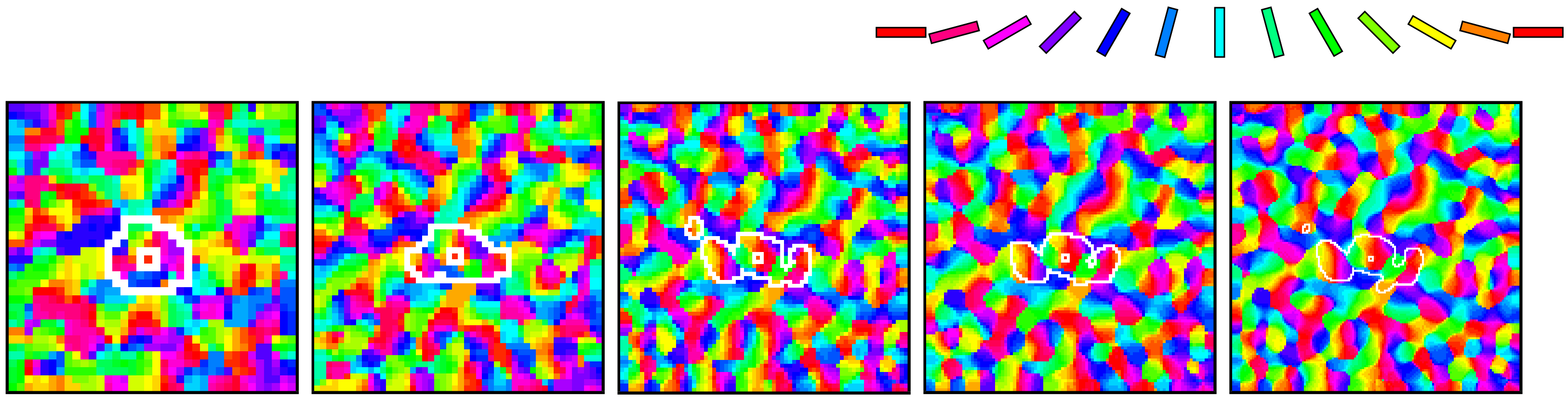
(*c*) Original V1:
$N = 54$, 0.4 hours, 8 MB

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

Scaling retinal density



Scaling cortical density



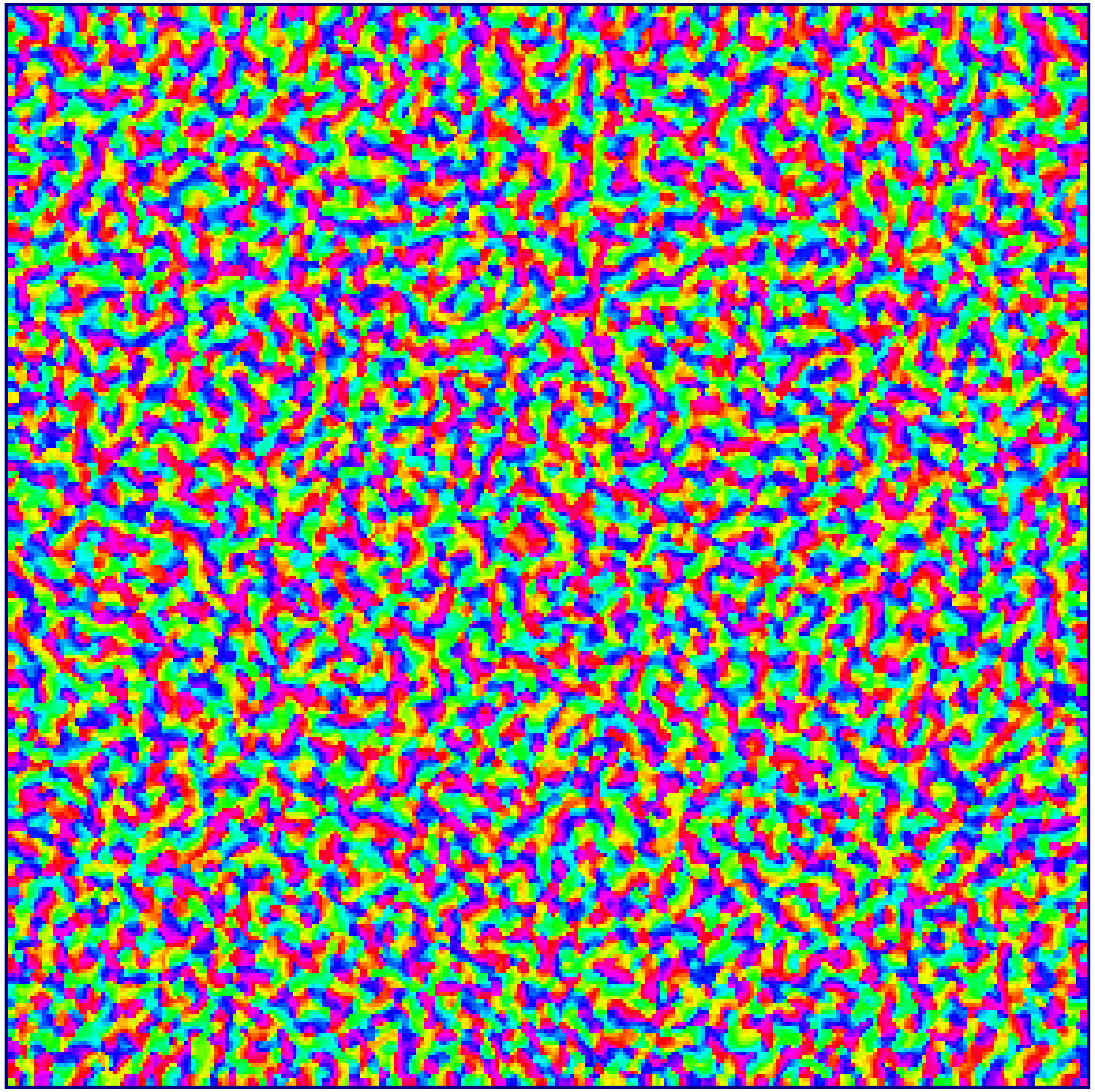
CMVC figure 15.3

(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

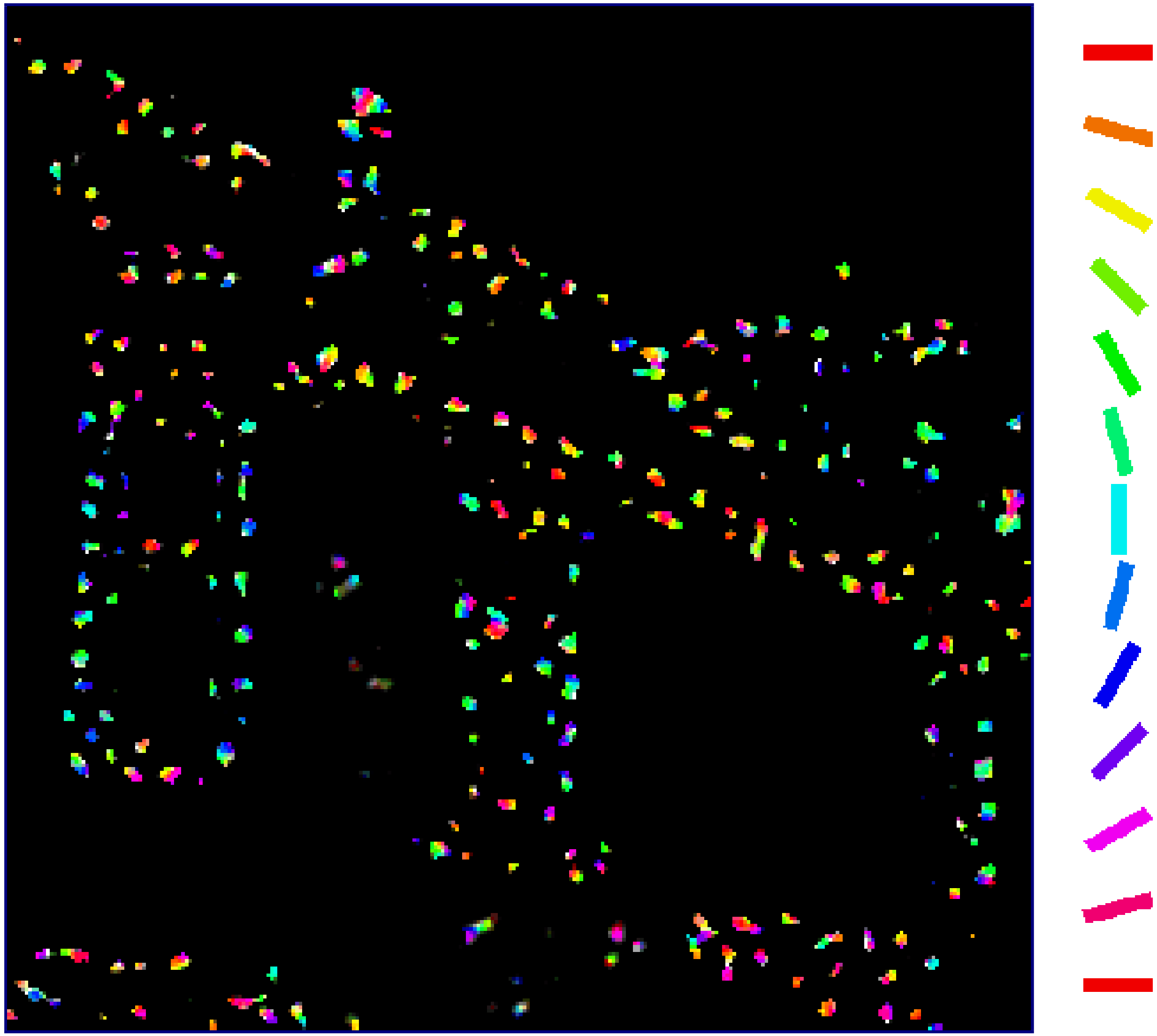


- Map scaled to cover most of visual field
- Allows testing with full-size images
- 30 million connections

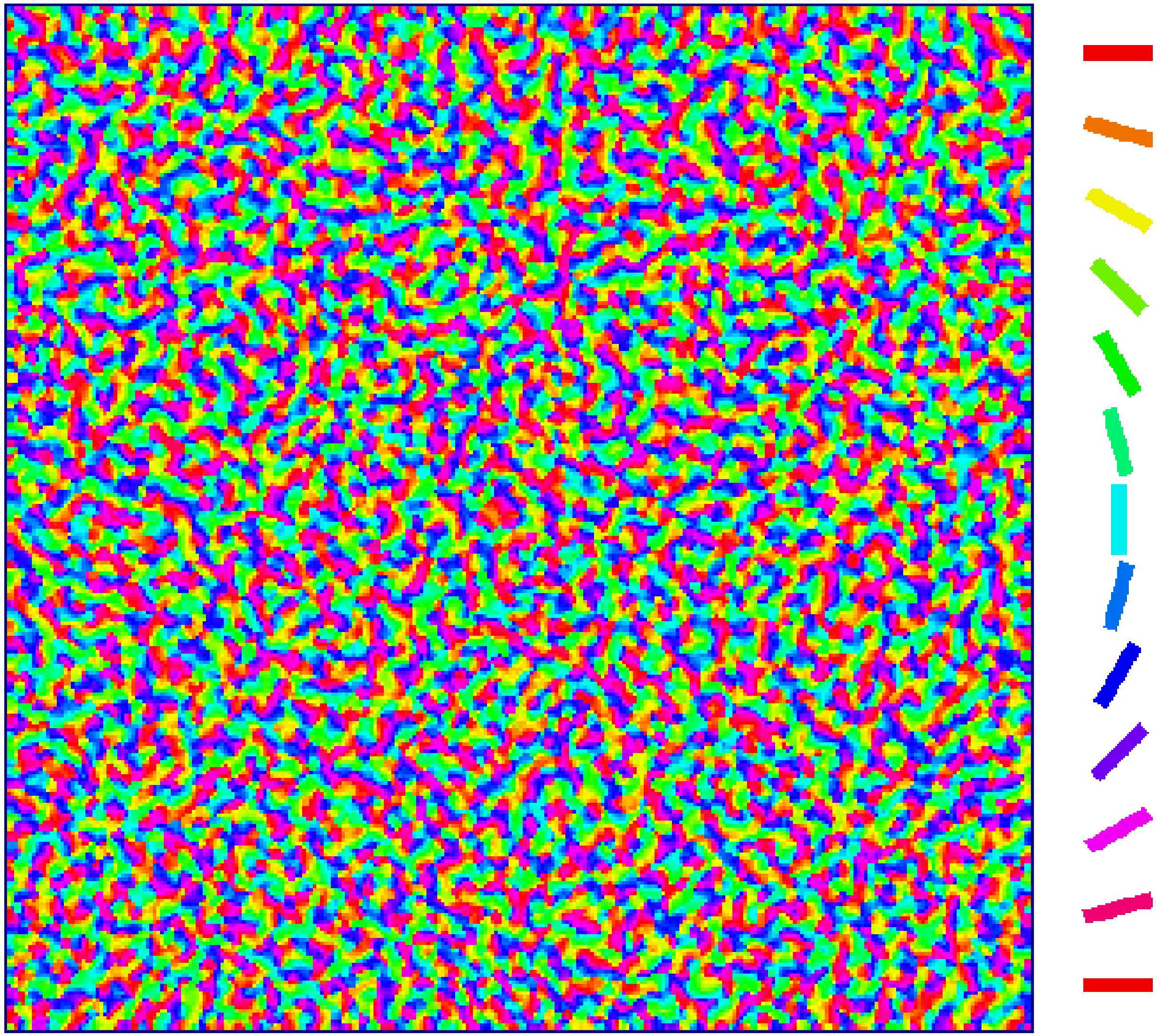
Sample Image

RGC/LGN Response

V1 Response with γ_n



V1 Orientation Map



Afferent normalization

LISSOM mechanism for contrast invariant tuning:

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

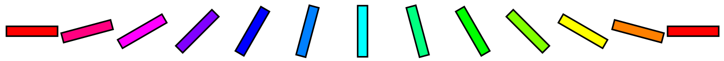
$\xi_{\rho ab}$: activation of unit (a, b) in afferent CF ρ of neuron (i, j)

$A_{ab,ij}$ 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



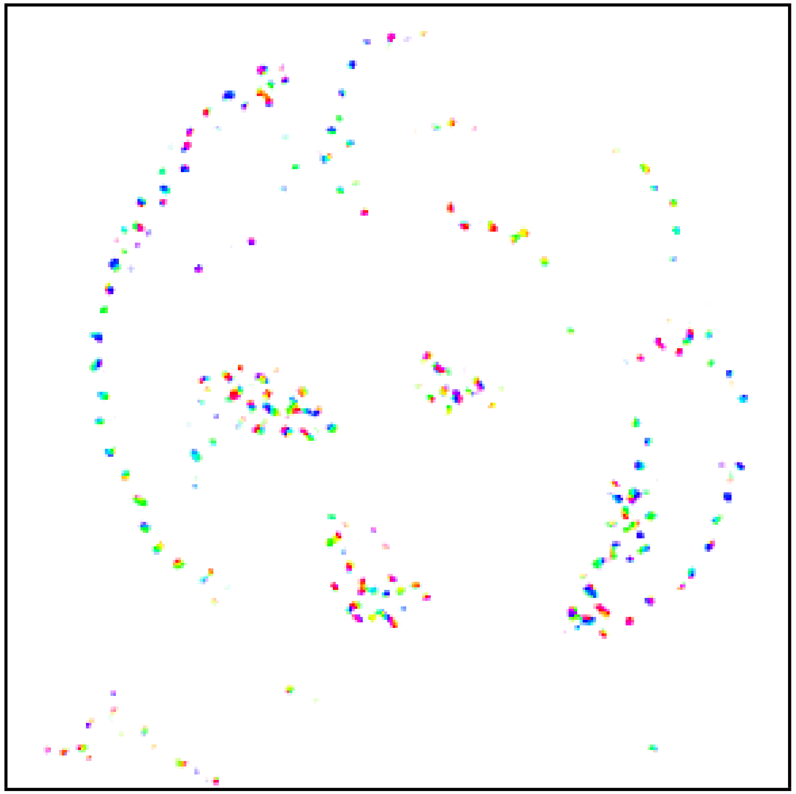
Retinal activation

LGN response

CMVC figure 8.2a,b

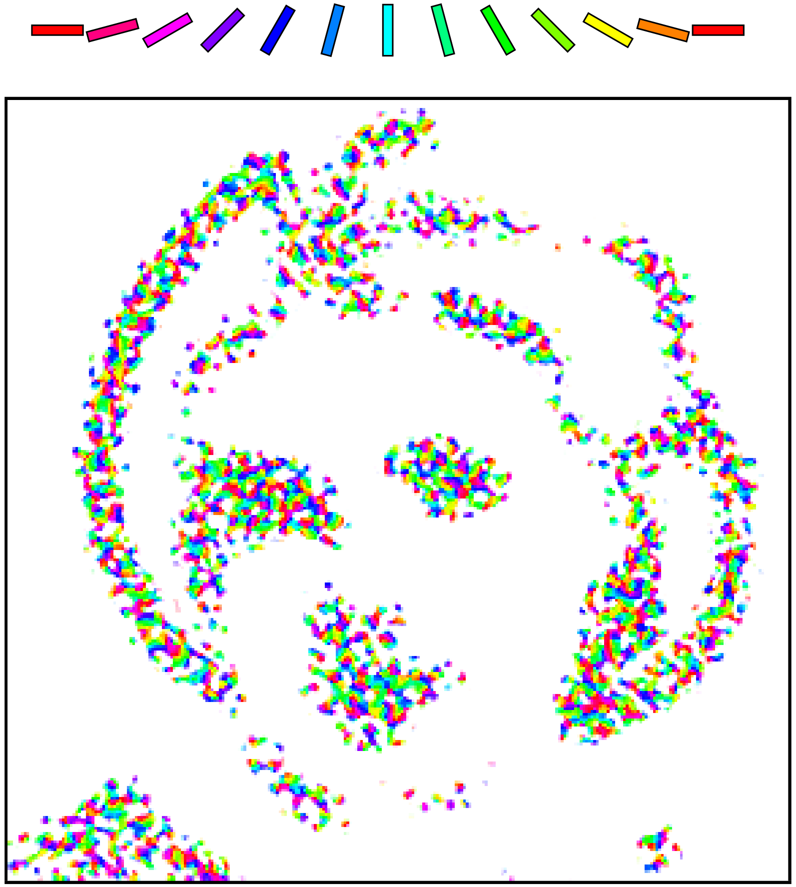
RGC/LGN responds to most of the visible contours

V1 without afferent normalization



V1 response:

$$\gamma_{\rm n} = 0, \gamma_{\rm A} = 3.25$$



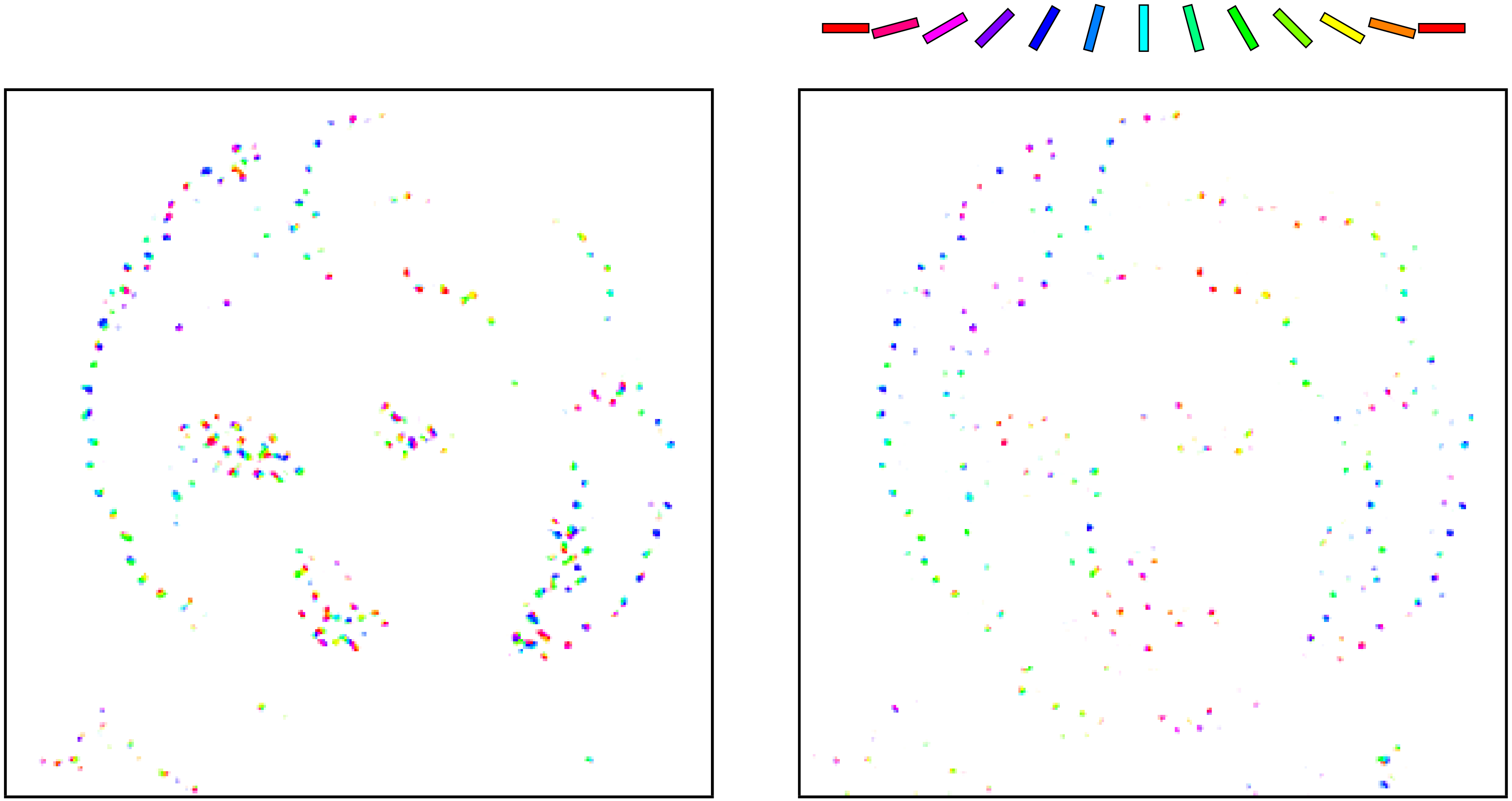
V1 response:

$$\gamma_{\rm n} = 0, \gamma_{\rm A} = 7.5$$

CMVC figure 8.2c-e

Cannot get selective response to all contours

V1 with afferent normalization



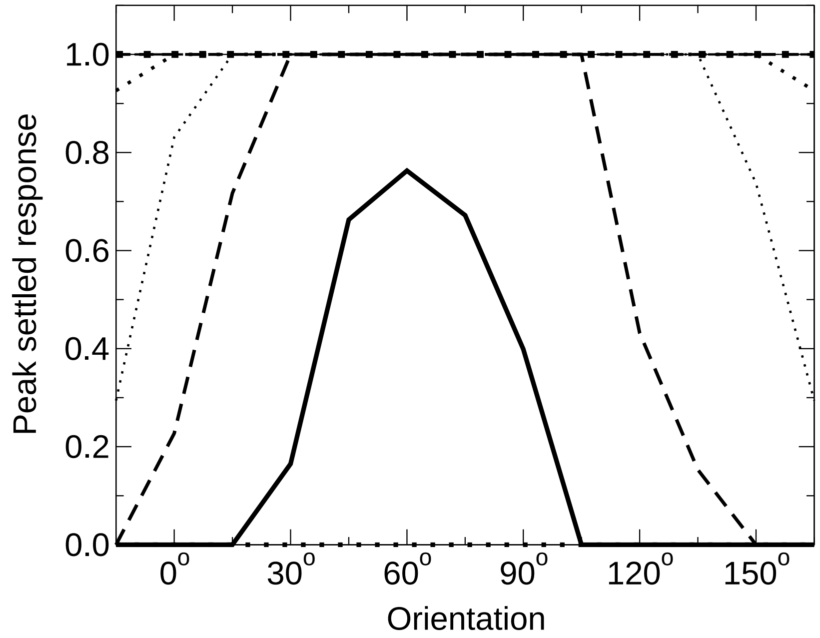
CMVC figure 8.2c-e

V1 response: $\gamma_{\mathrm{n}} = 0, \gamma_{\mathrm{A}} = 3.25$

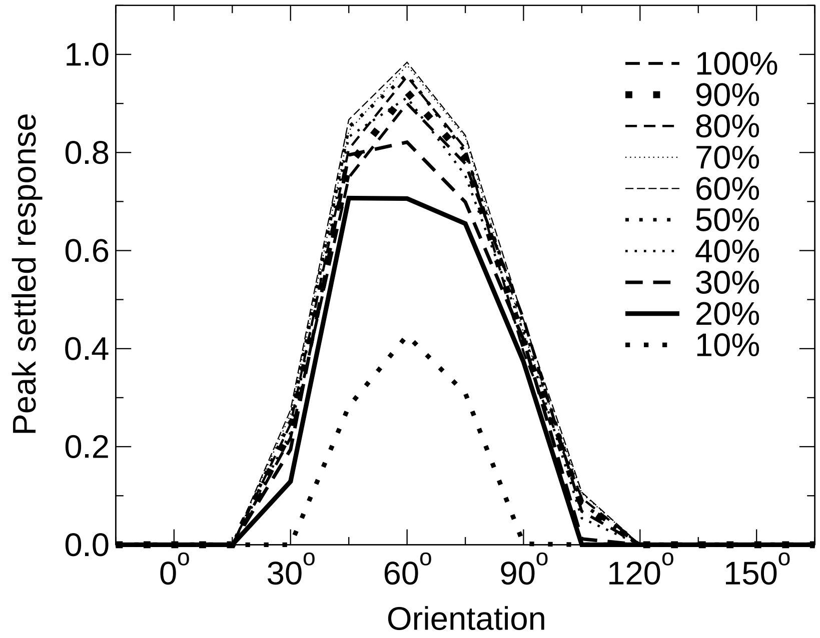
V1 response: $\gamma_{\mathrm{n}} = 80, \gamma_{\mathrm{A}} = 30$

Responds based on contour, not contrast

Tuning with afferent normalization



$\gamma_n = 0, \gamma_A = 3.25$



$\gamma_n = 80, \gamma_A = 30$

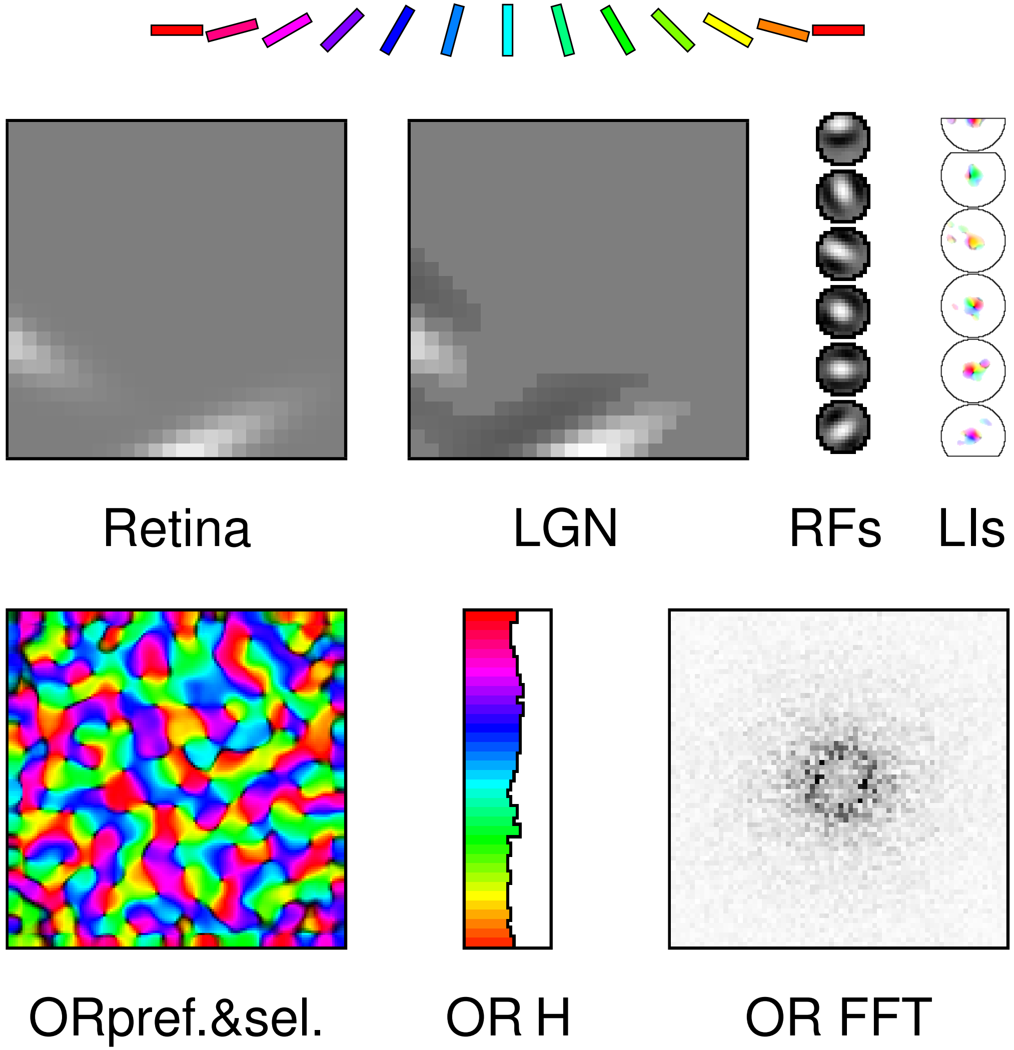
CMVC figure 8.3

Sine grating tuning curve:

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

OR Map: Gaussian

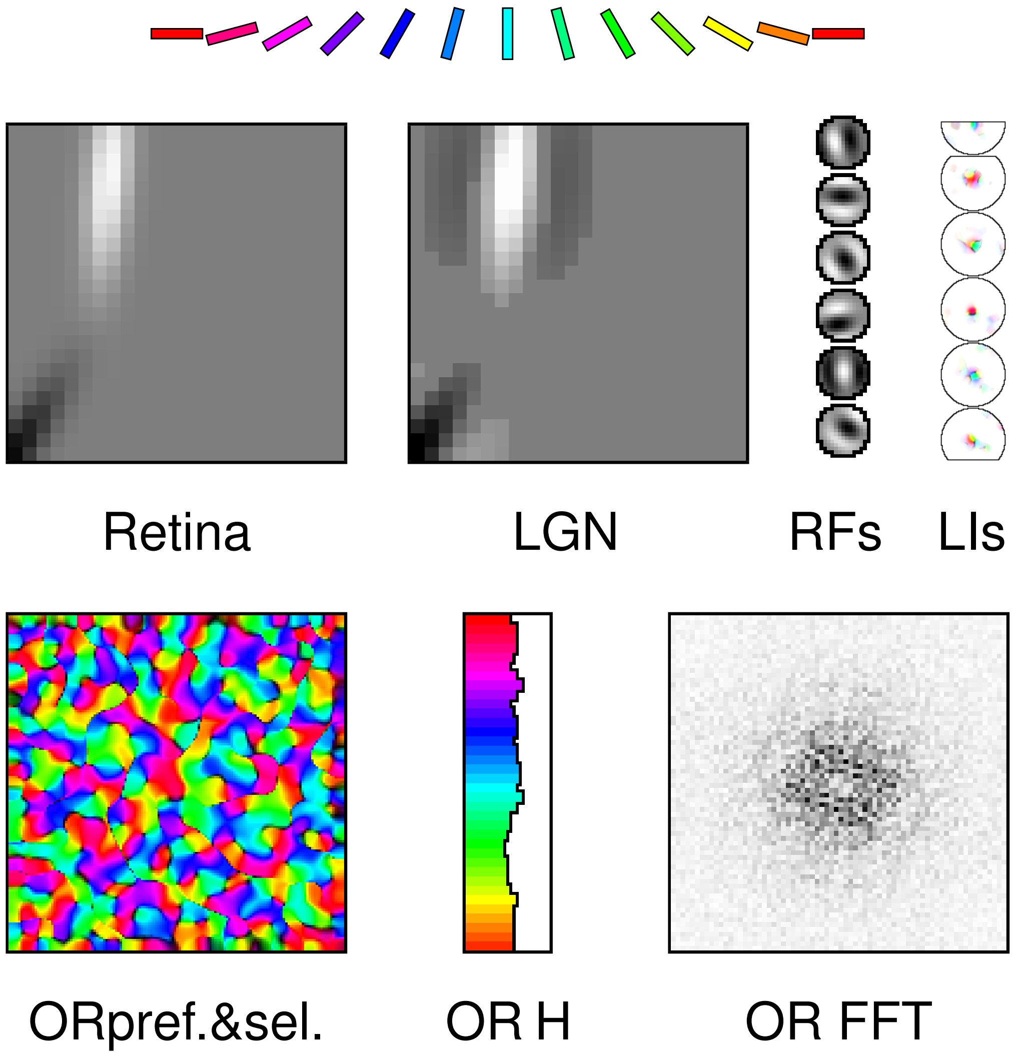
CMVC figure 5.13



White line CFs only

OR Map: +/- Gaussian

CMVC figure 5.13



White or black

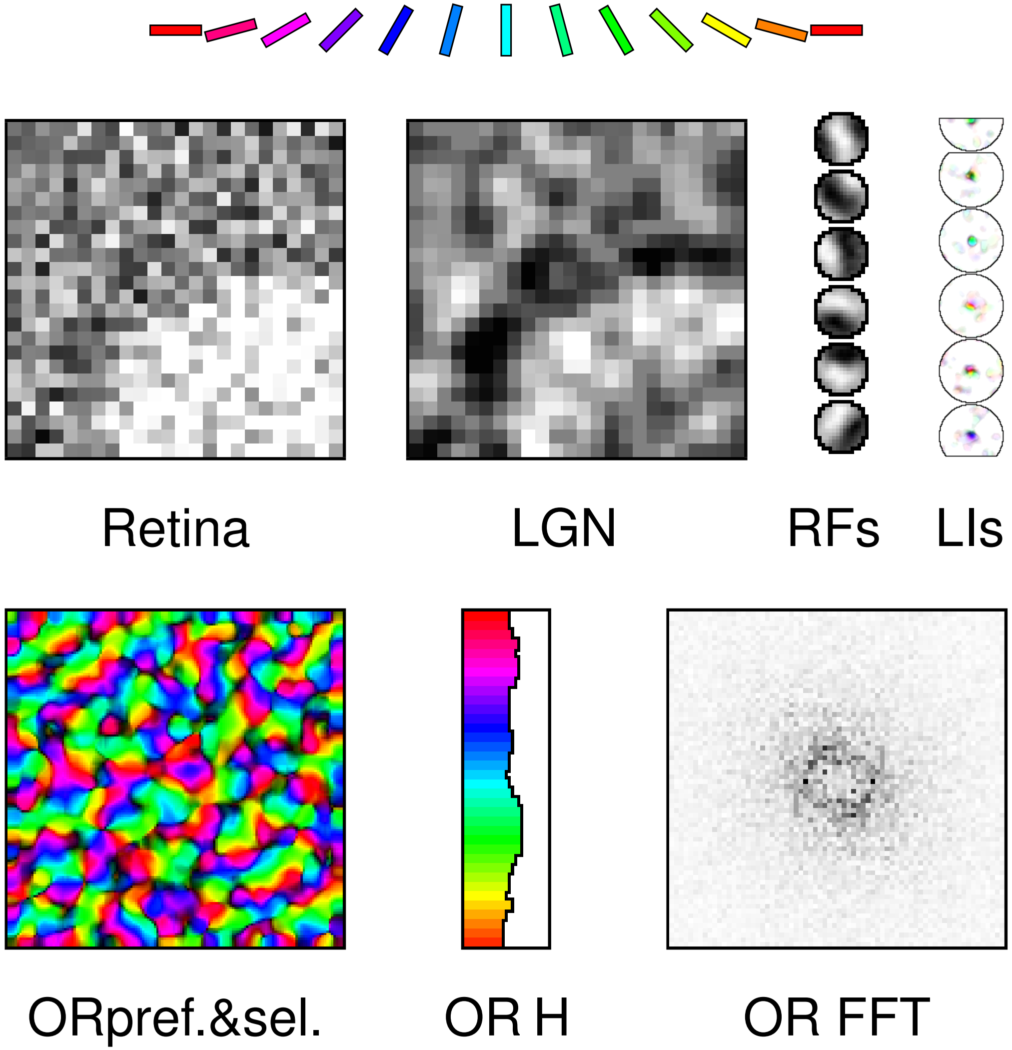
line CFs

OR map disrupted

due to phase

columns

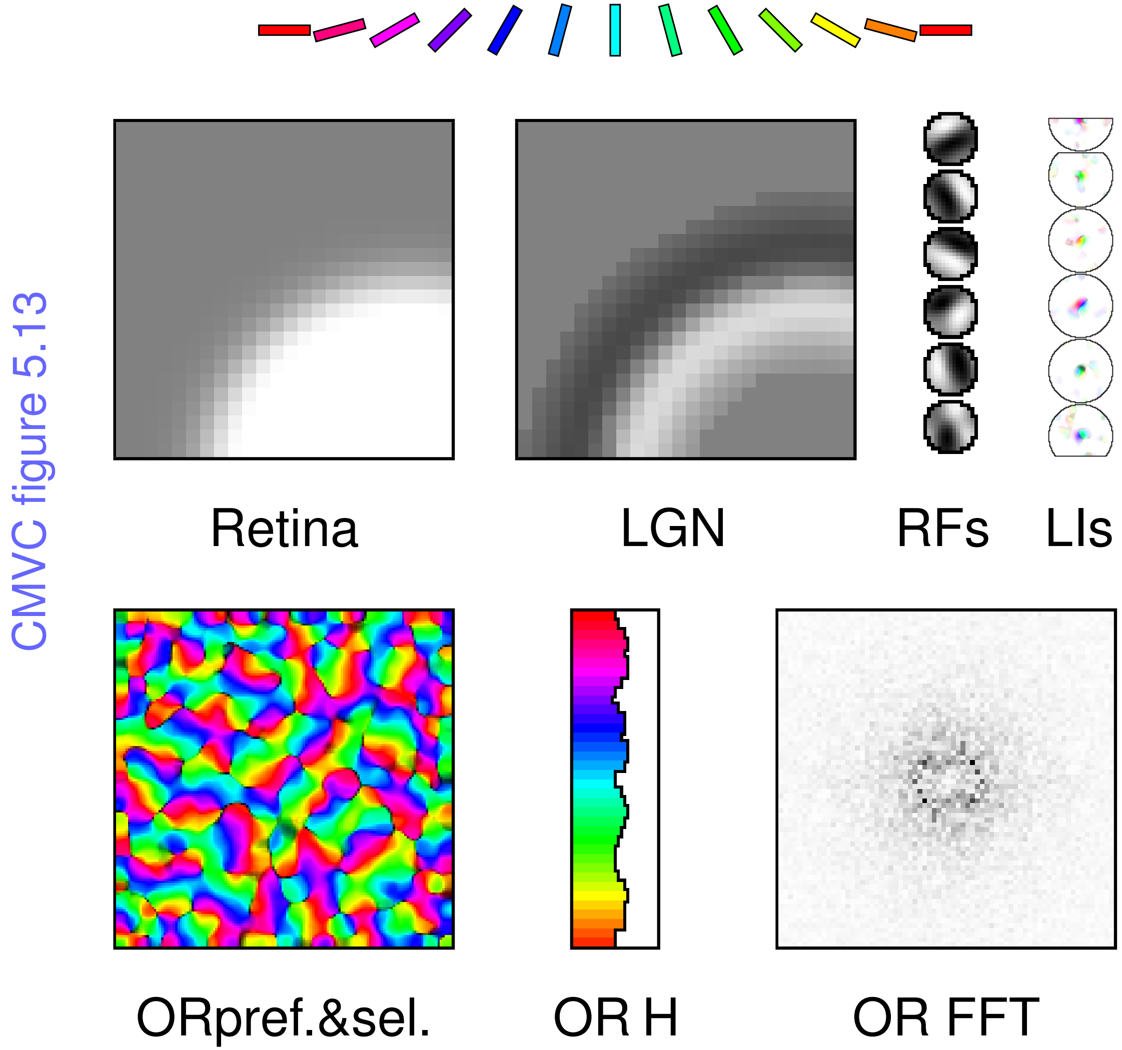
OR Map: Retinal wave model



CMVC figure 5.13

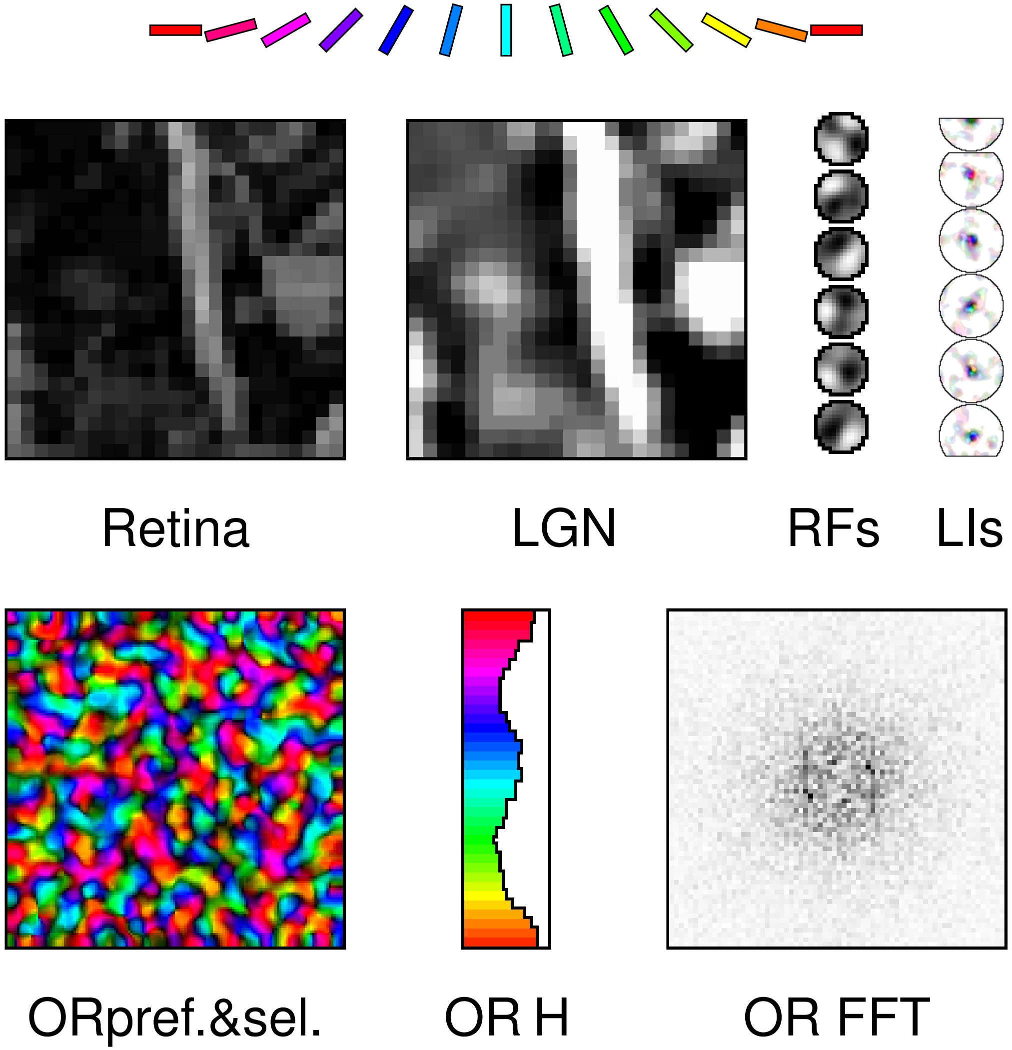
Some line, mostly
edge CFs

OR Map: Smooth disks



All edge CFs

OR Map: Natural images



CMVC figure 5.13

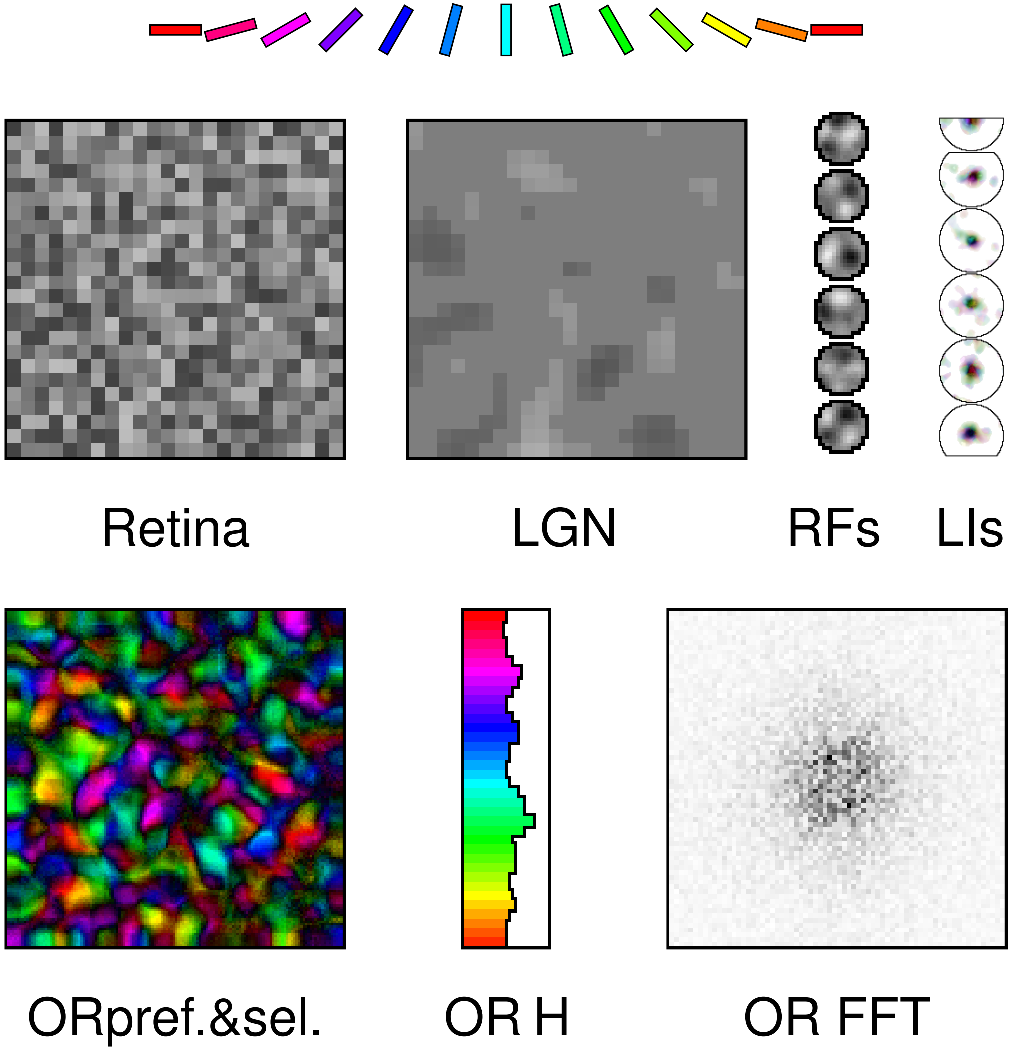
All types of CFs

Longer range lateral weights

Histogram: horizontal, vertical bias

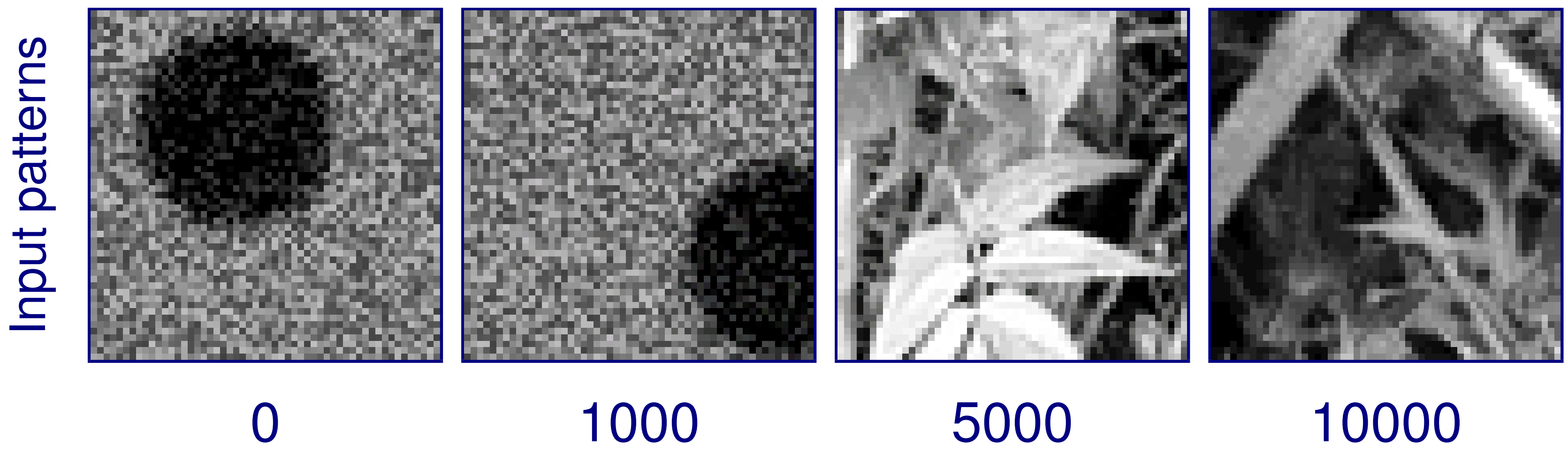
OR Map: Uniform noise

CMVC figure 5.13



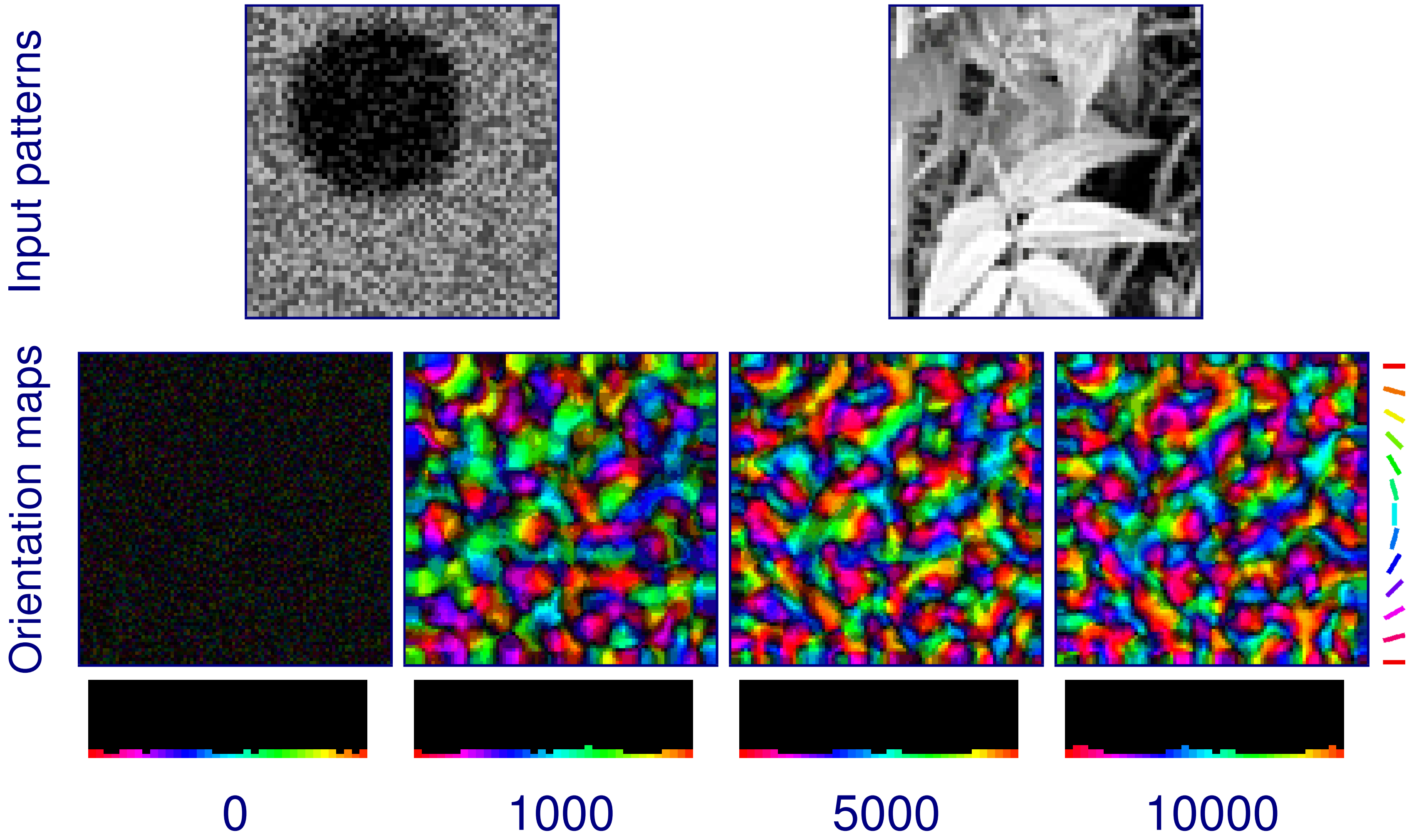
Relatively unselective CFs

Modeling pre/post-natal phases



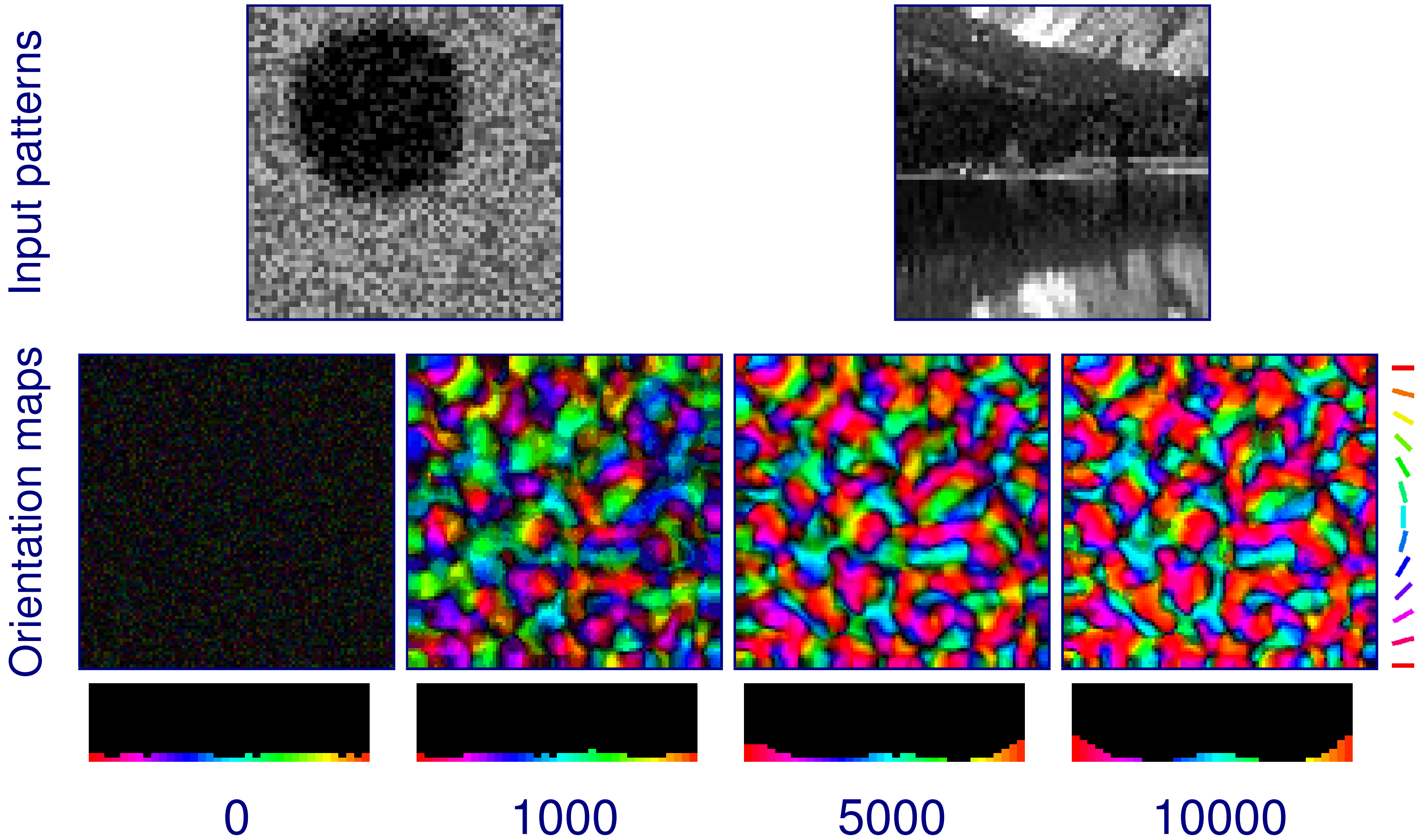
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

Pre/post-natal V1 development



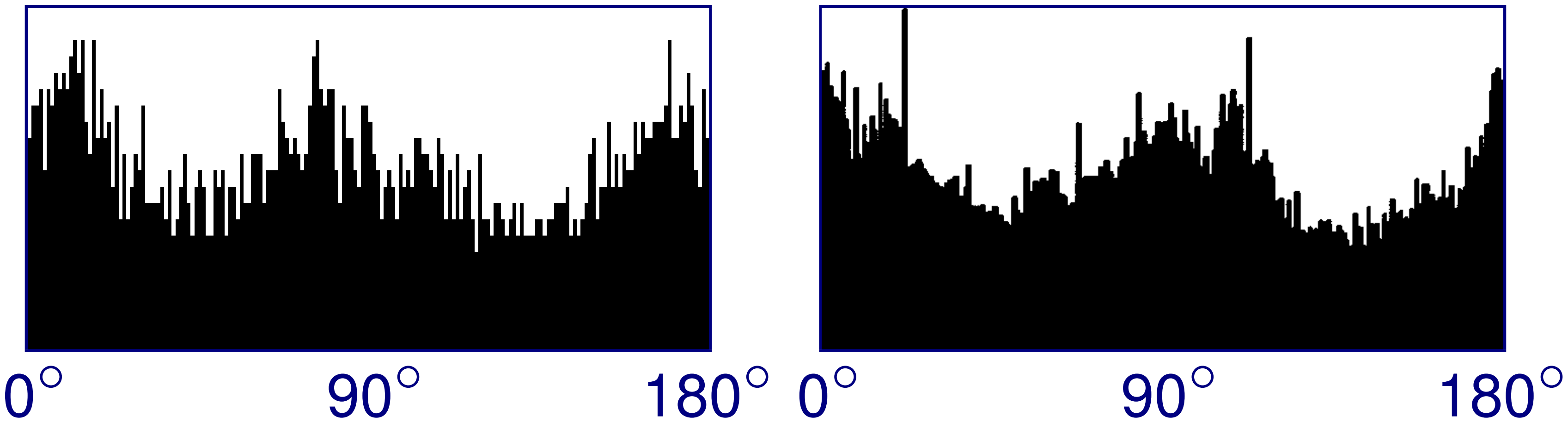
- Neonatal map smoothly becomes more selective

Statistics drive development



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

OR Histograms

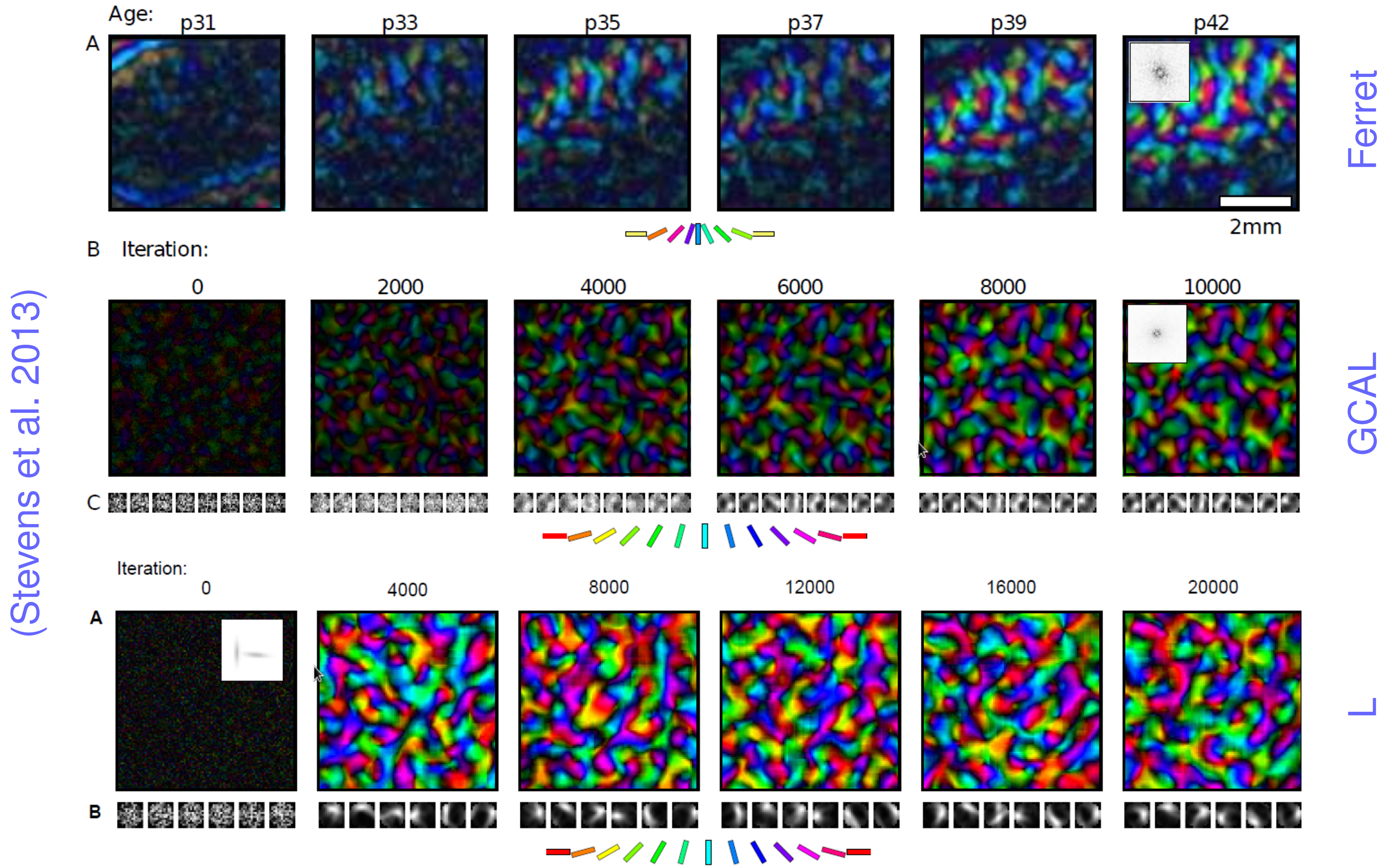


HLISSOM model

Adult ferret V1
(Coppola et al. 1998)

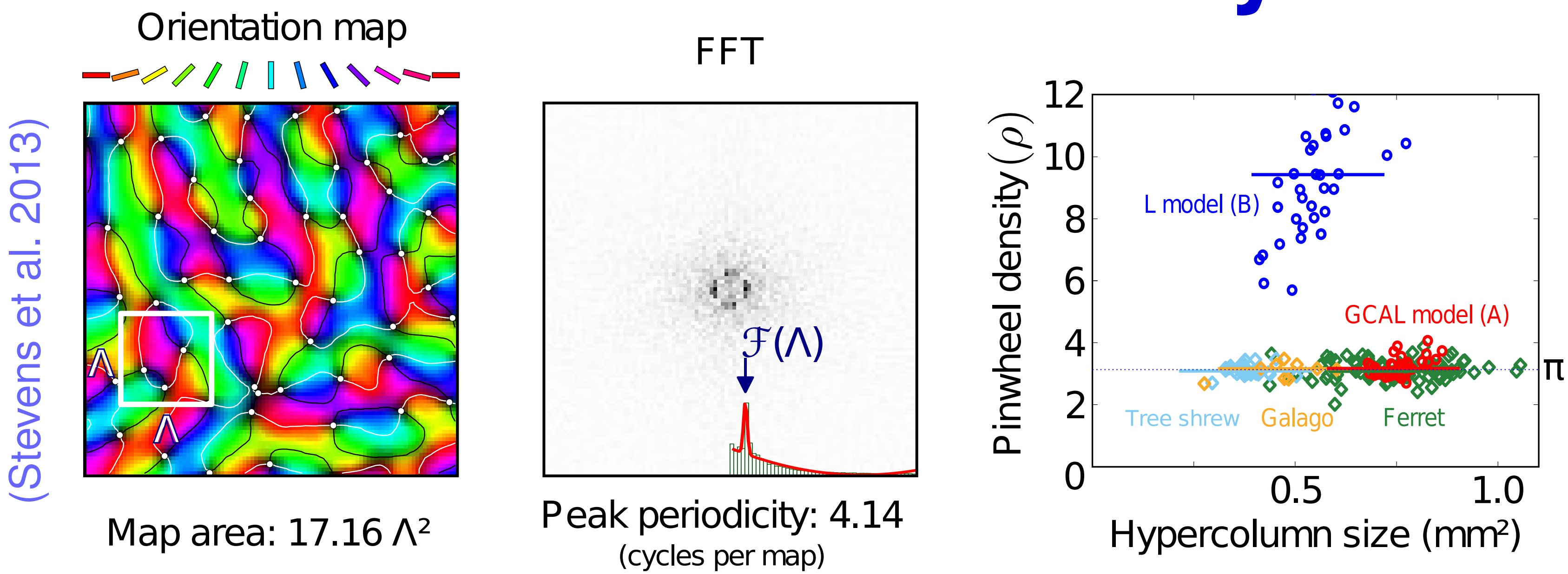
- After postnatal training on Shouval natural images, orientation histogram matches results from ferrets
- Model adapts to statistical structure of images

Stable development



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

Pinwheel density



- 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.