LISSOM Orientation Maps

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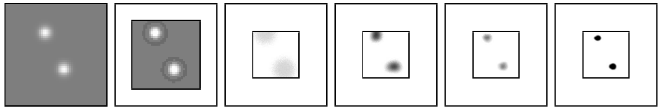
Modeling Orientation

- 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

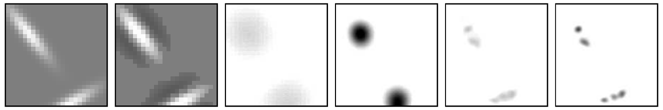


Retinal activation | LGN response | Iteration 0: Initial V1 response | Iteration 0: Settled V1 response | 10,000: Initial V1 response | 10,000: Settled V1 response

CMVC figure 4.4

(Reminder from last time)

Orientation input and response

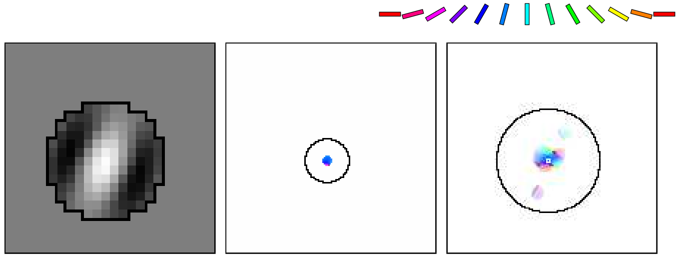


Retinal activation | LGN response | Iteration 0: Initial V1 response | Iteration 0: Settled V1 response | 10,000: Initial V1 response | 10,000: Settled V1 response

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



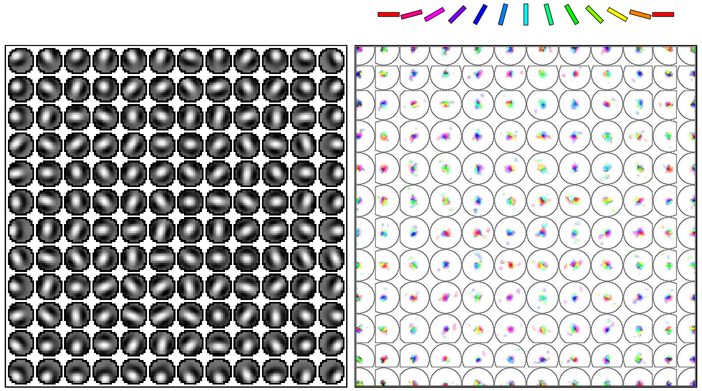
Afferent (ON—OFF) Lateral excitatory Lateral inhibitory

CMVC figure 5.7

Typical:

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

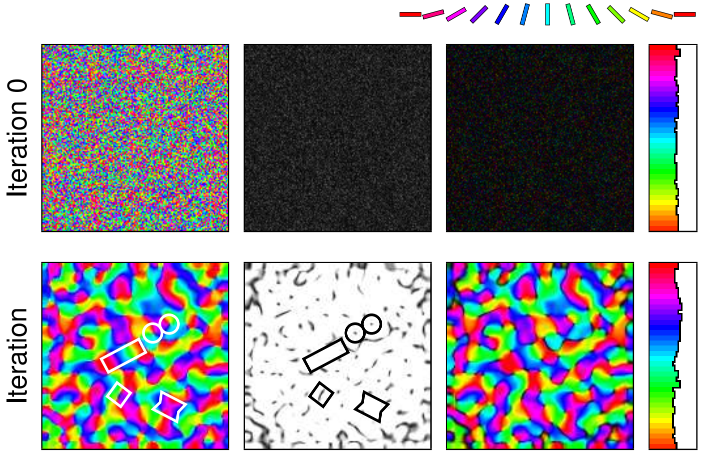
Self-organized weights across V1



Afferent (ON—OFF) Lateral inhibitory

CMVC figure 5.8

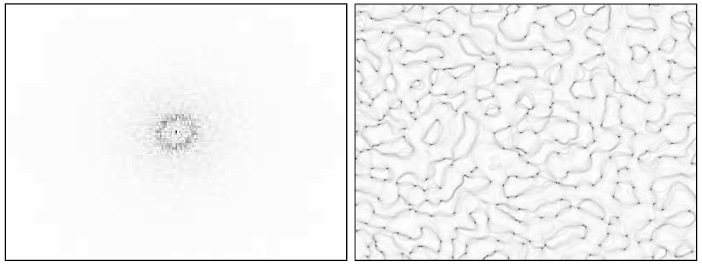
OR map self-organization



OR preference OR selectivity OR preference & selectivity OR H

CMVC figure 5.9

Macaque ORmap: Fourier,gradient



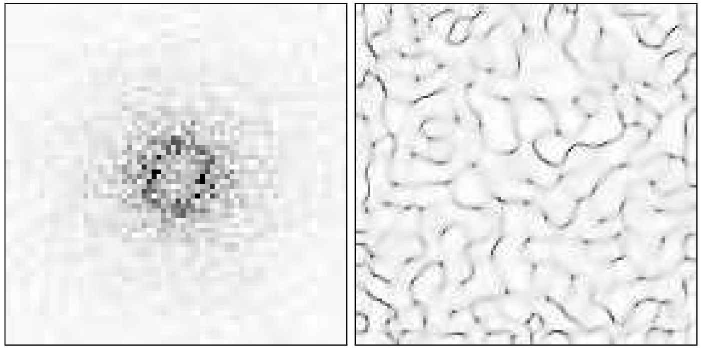
Fourier spectrum Gradient

CMVC figure 5.1

In monkeys:

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

OR Map: Fourier, gradient

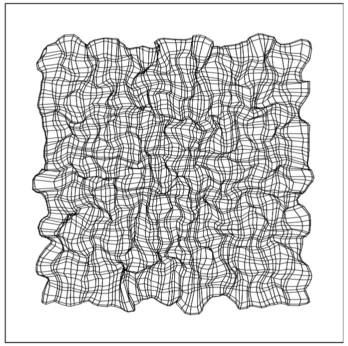

CMVC figure 5.10

Fourier spectrum

Gradient

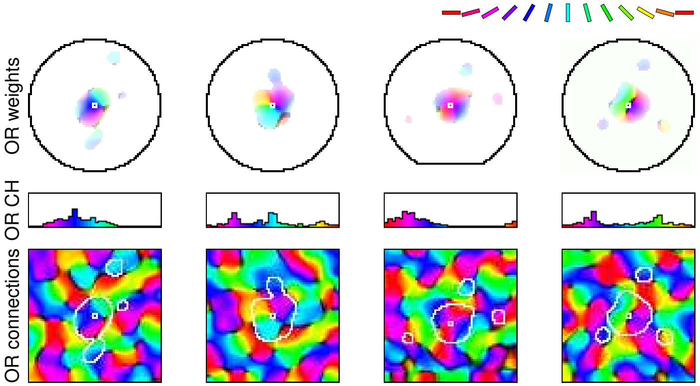
LISSOM model has similar spectrum, gradient

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

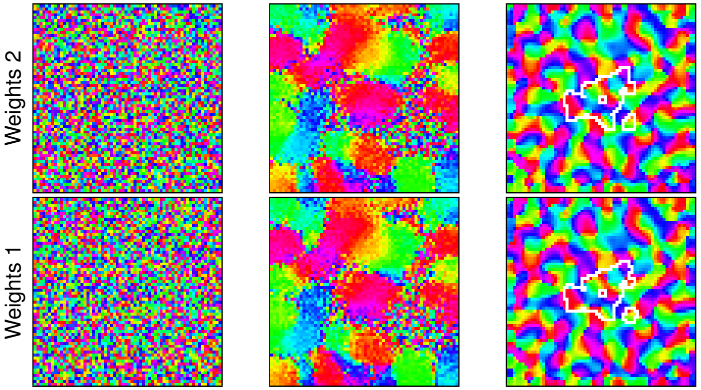
Connections in iso-OR patches

Connections in OR pinwheels

Connections in OR saddles

Connections in OR fractures

Effect of initial weights

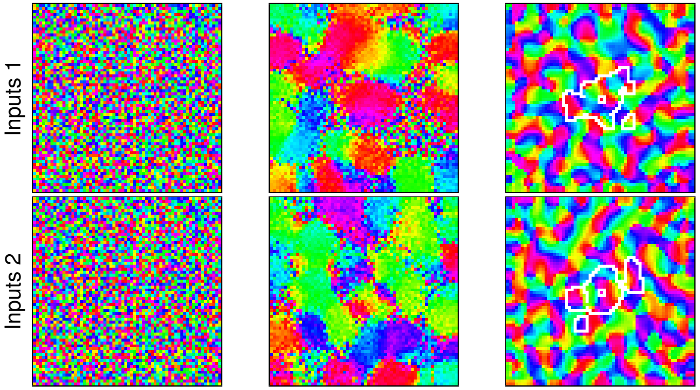


CMVC figure 8.5

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

Changing weights doesn't change map folding pattern.

Effect of input streams

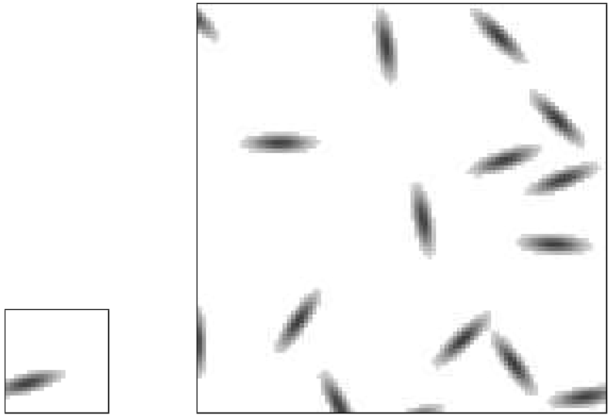


(*a*) Iteration 0 (*b*) Iteration 50 (*c*) Iteration 10,000

CMVC figure 8.5

Changing inputs changes entire pattern.

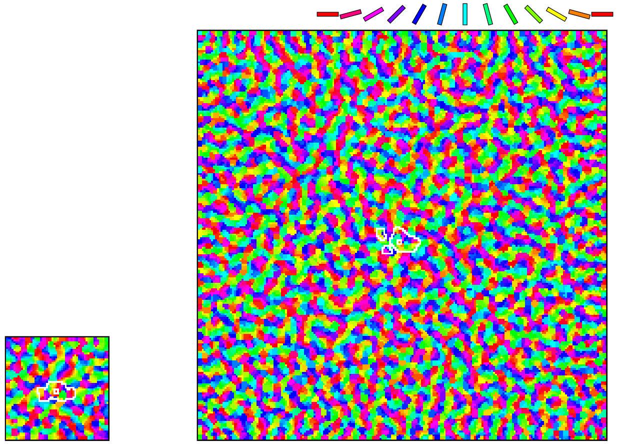
Scaling retinal and cortical area



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

CMVC figure 15.1a,b

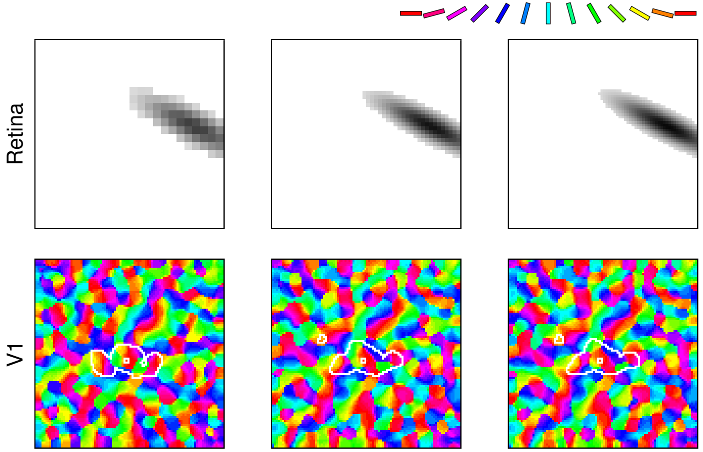
Scaling retinal and cortical area



(*c*) Original V1: $N = 54$, 0.4 hours, 8 MB (*d*) V1 area scaled by 4.0: $N = 216$, 9 hours, 148 MB

CMVC figure 15.1c,d

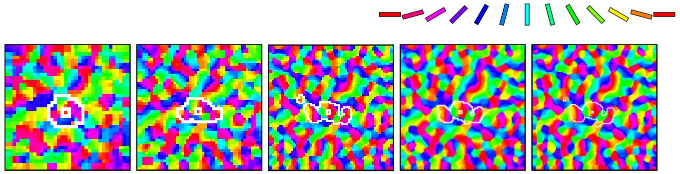
Scaling retinal density



Original retina Retina scaled by 2 Retina scaled by 3

CMVC figure 15.2

Scaling cortical density



(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

CMVC figure 15.3

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

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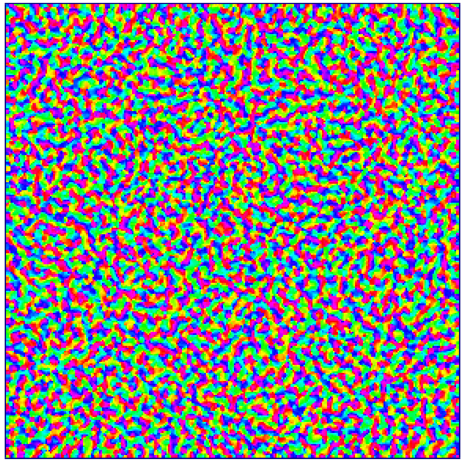
Full-size V1 Map

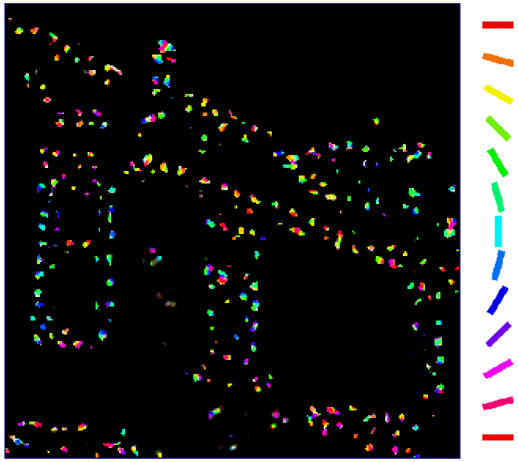


- Map scaled to cover most of visual field
- Allows testing with full-size images
- 30 million connections

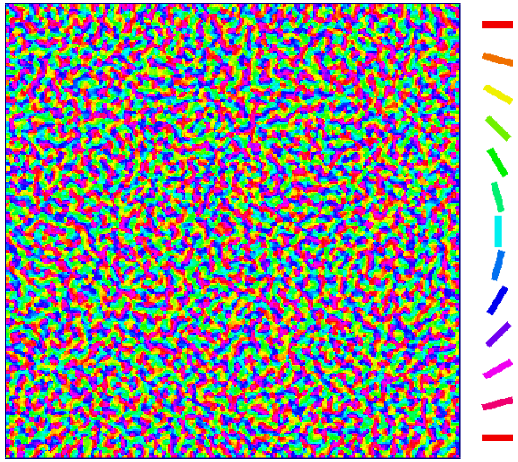
Sample Image

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

LGN response to large image

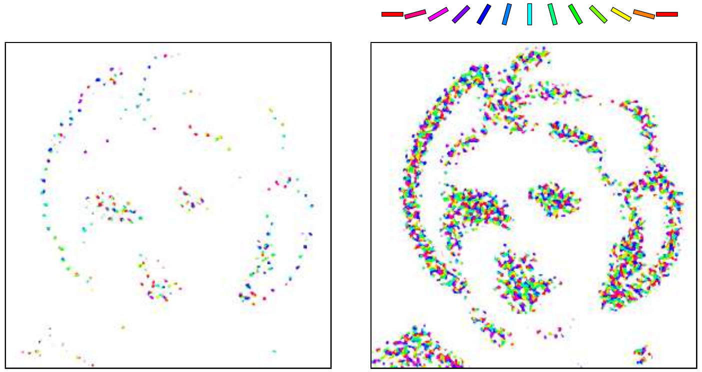
Retinal activation

LGN response

CMVC figure 8.2a,b

LGN responds to most of the visible contours

V1 without afferent normalization



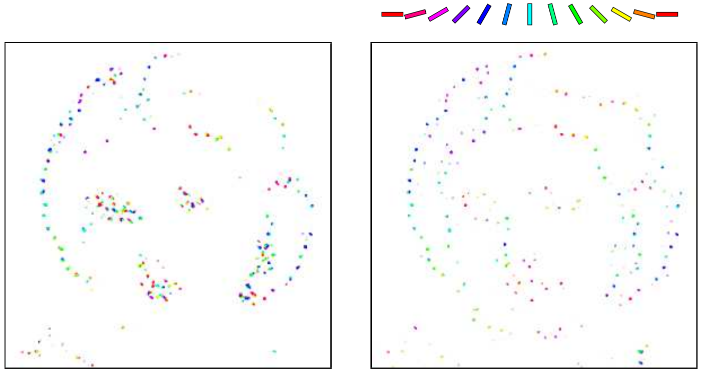
CMVC figure 8.2c-e

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

V1 response:
$\gamma_{\rm n} = 0, \gamma_{\rm A} = 7.5$

Cannot get selective response to all contours

V1 with afferent normalization



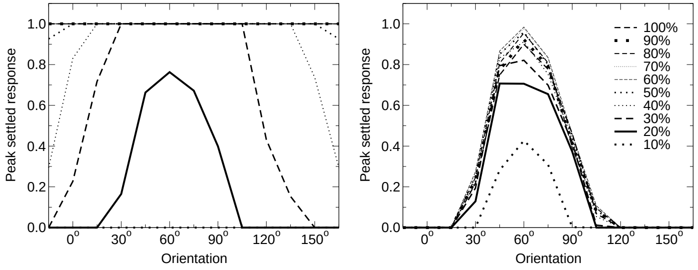
CMVC figure 8.2c-e

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

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

Responds based on contour, not contrast

Tuning with afferent normalization



CMVC figure 8.3

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

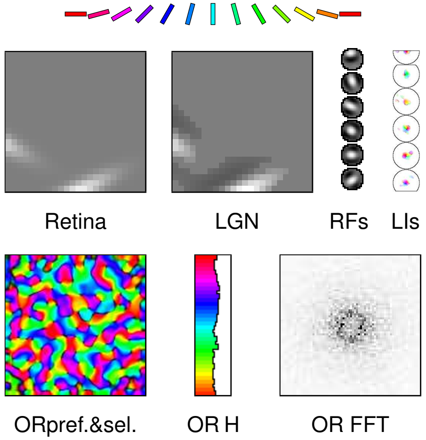
$\gamma_{\rm n} = 80, \gamma_{\rm A} = 30$

Sine grating tuning curve:

- Without $\gamma_{\rm n}$: selectivity lost as contrast increases
- With $\gamma_{\rm n}$: always orientation-specific

OR Map: Gaussian

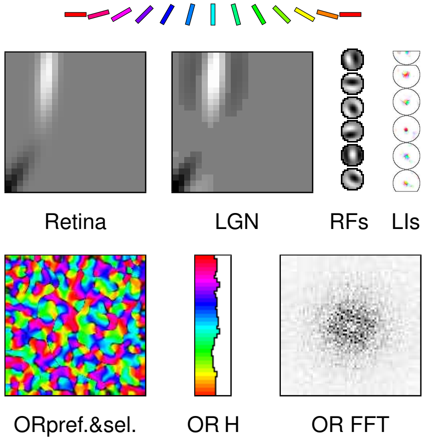
CMVC figure 5.13



White line RFs only

OR Map: +/- Gaussian

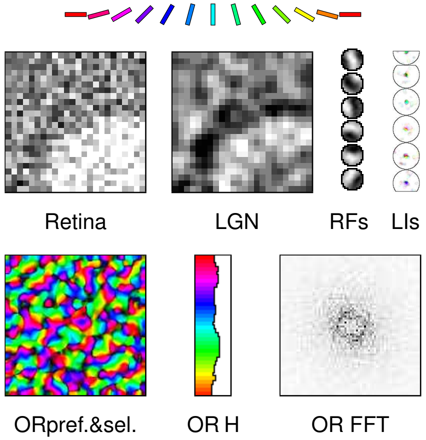
CMVC figure 5.13



White or black line RFs

OR Map: Retinal wave model

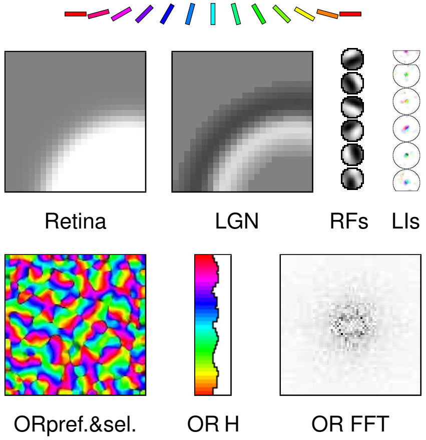
CMVC figure 5.13



Some line, mostly edge RFs

OR Map: Smooth disks

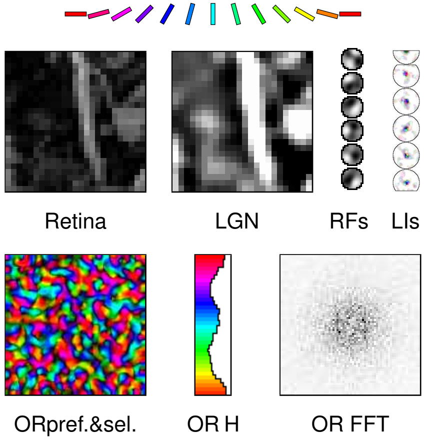
CMVC figure 5.13



All edge RFs

OR Map: Natural images

CMVC figure 5.13



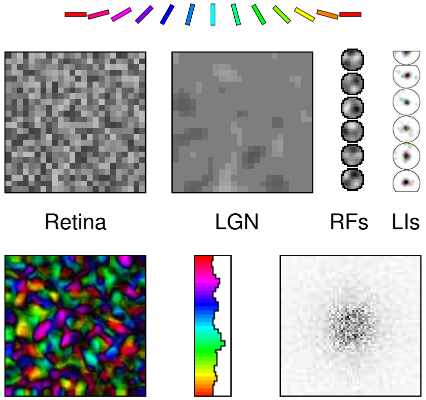
All types of RFs

Longer range lateral weights

Histogram: horizontal, vertical bias

OR Map: Uniform noise

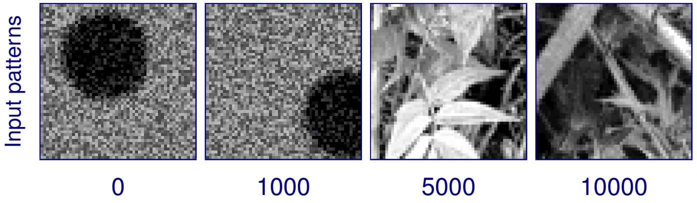
CMVC figure 5.13



ORpref.&sel.   OR H   OR FFT

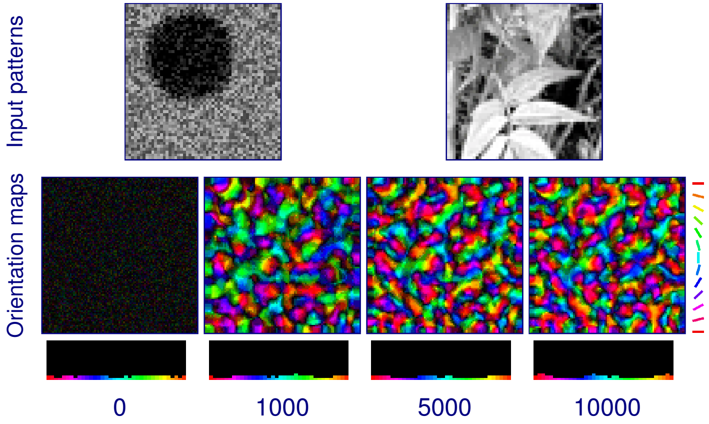
Relatively unselective RFs

Modeling pre/post-natal phases



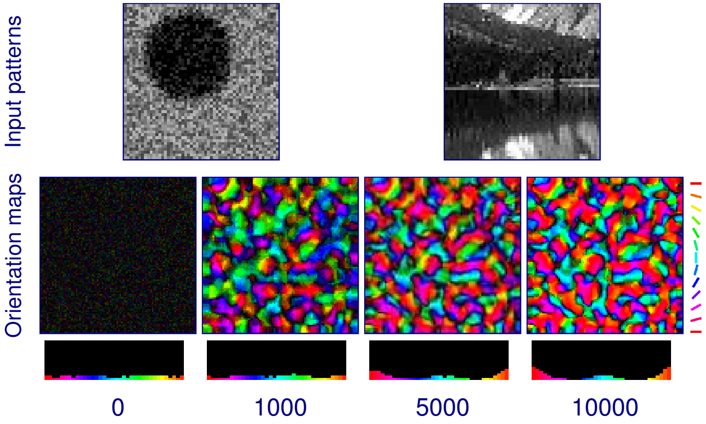
- **Prenatal:** internal activity
- **Postnatal:** natural images (Shouval et al. 1996)

Pre/post-natal V1 development



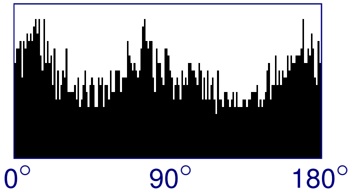
- Neonatal map smoothly becomes more selective

Statistics drive development

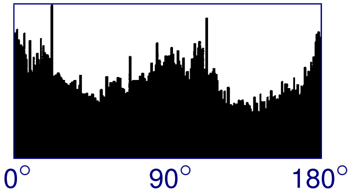


- Biased image dataset: mostly landscapes
- Smoothly changes into horizontal-dominated map

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

Summary

- Development depends on the features of the input pattern
- Orientation maps develop with many different input patterns
- Develops Gabor-type RFs with most inputs
- Breaks up image into oriented patches
- Response must be scaled by local contrast to work well for large images
- Matching biology requires prenatal, postnatal phases

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.

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.