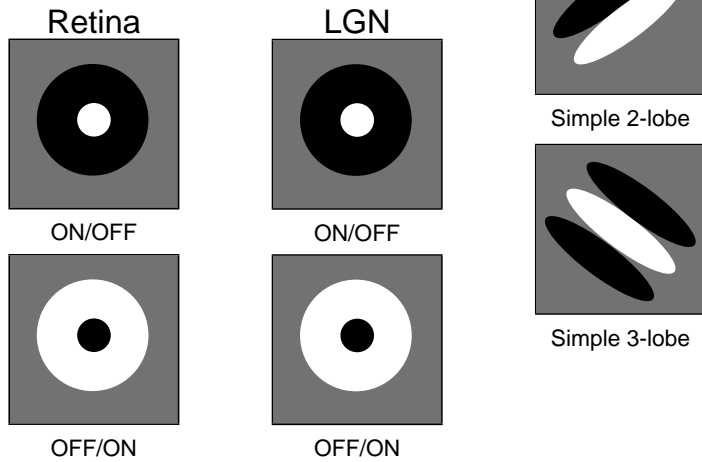


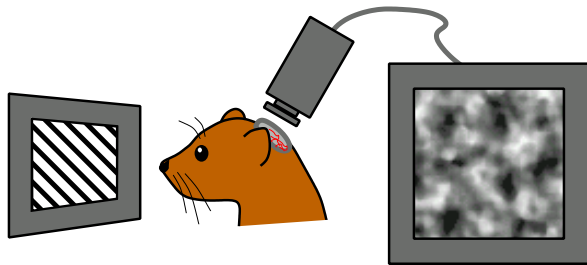
Receptive Fields



Spatiotemporal

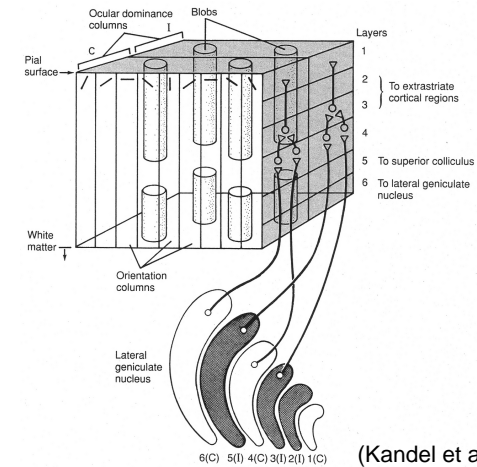
- Center-surround; static and moving lines; combinations

Measuring Cortical Maps



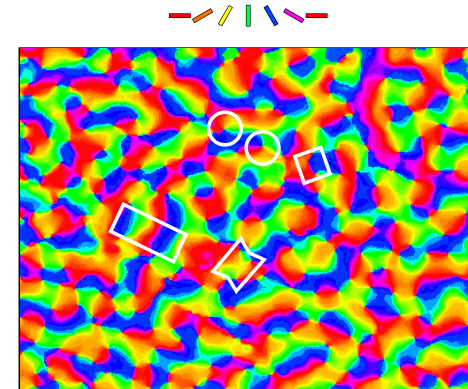
- Surface reflectance changes with activity
- Optical imaging can be used to detect

Columnar Organization of V1



- Roughly hierarchical ordering:
 - Retinotopy, OD, OR, DR
 - Color, spatial frequency, disparity?
- Within column, similar responses: 2D structure

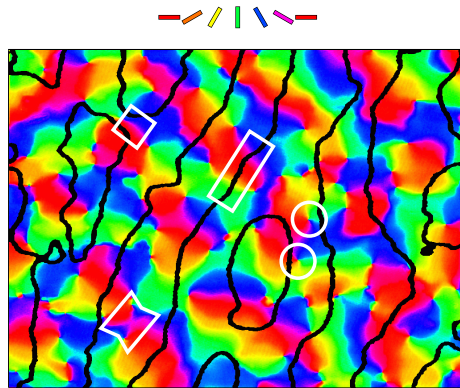
Orientation Map



(7.5 mm × 5.5 mm in macaque V1; Blasdel, 1992)

- Preferences mapped systematically
- Linear zones, pinwheels, saddles, fractures

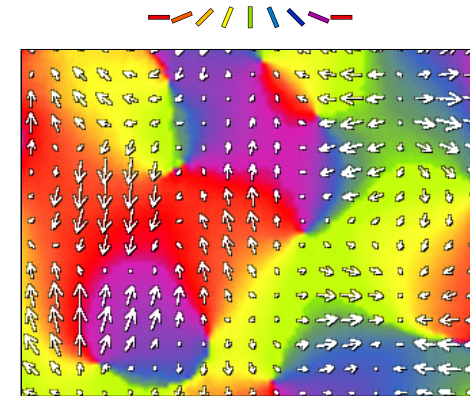
Orientation & Ocular Dominance Map



(4 mm × 3 mm in macaque V1; Blasdel, 1992)

- Systematic interactions
 - OD, OR boundaries at right angles
 - Pinwheels, saddles in the middle

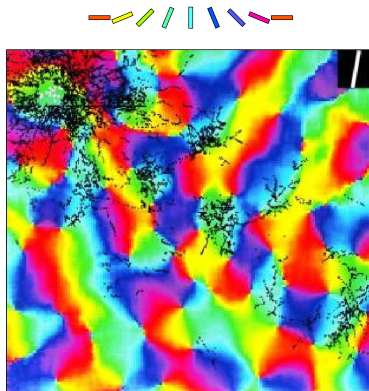
Orientation & Direction Map



(1.4 mm × 1.1 mm in ferret V1; Weliky et al. 1996)

- Systematic interactions
 - OD, OR boundaries at right angles
 - OR patches contain opposite DR

Lateral Connections



(2.5 mm × 2 mm in tree shrew V1; Bosking et al. 1997)

- Link to similar responses
- Patchy structure, extend along OR preference

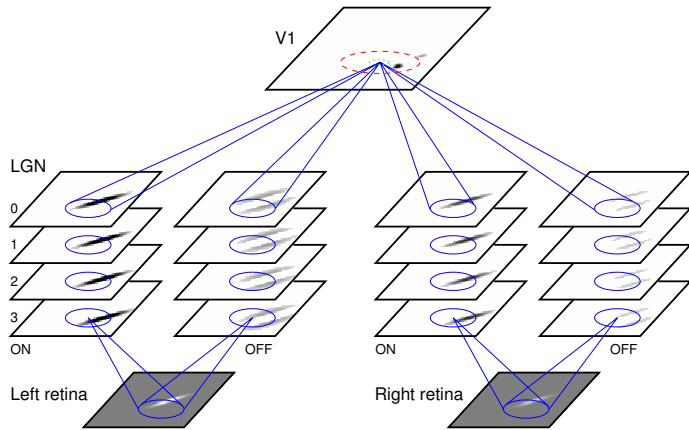
Development



(4 mm × 3 mm OR+select in ferret V1; Chapman et al. 1996)

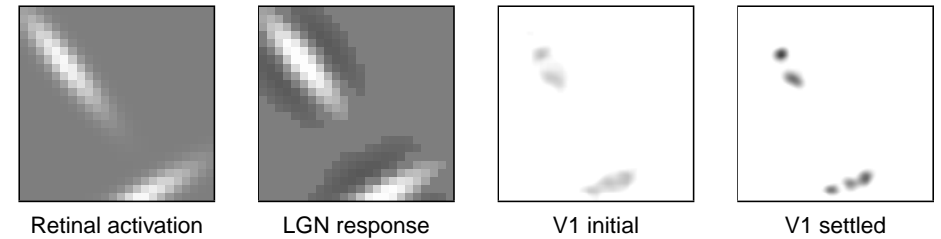
- Structure emerges during development
- Some prenatally, much postnatally
- How and why?

LISSOM Model



- Combined OR, OD, DR
- Retina, LGN, V1 (+ other areas)
- 2D sheets, afferent and lateral connections
- Hebbian learning in V1

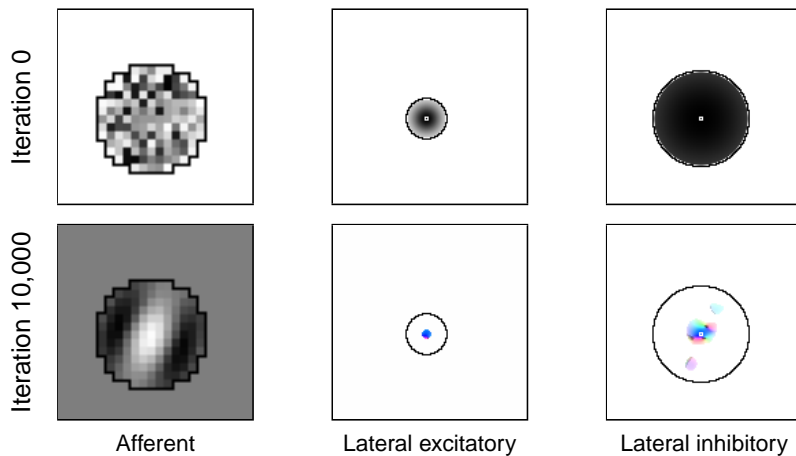
Activation



- Luminance adjustment in retina
- Sharpening in LGN (ON—OFF shown)
- Settling in V1:

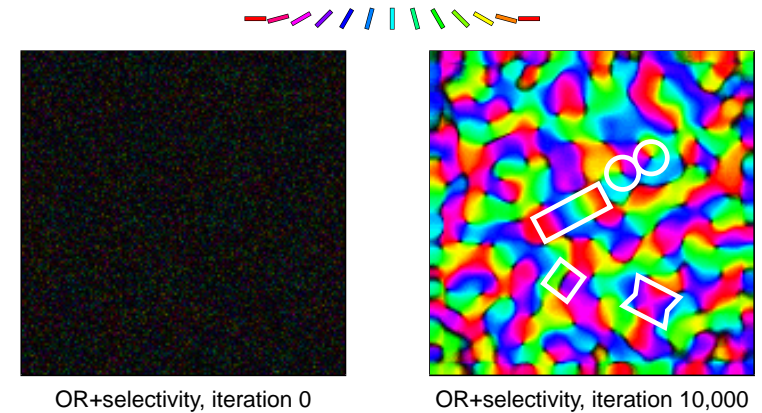
$$\eta'_i = \sigma(\sum_k \chi_k A_{ki} + \sum_j \eta_j E_{ji} - \sum_j \eta_j I_{ji})$$

Adaptation



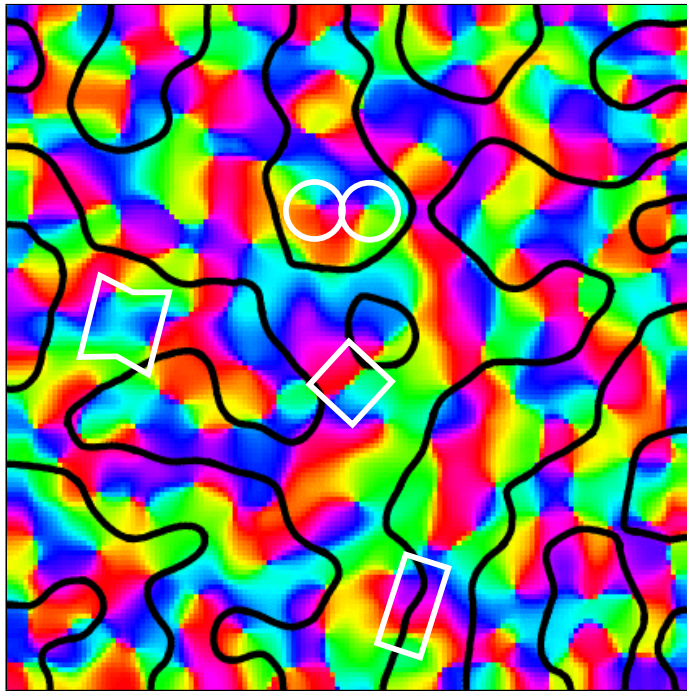
- Normalized Hebbian learning: $A'_{ki} = \frac{A_{ki} + \alpha \chi_k \eta_i}{\sum_{mn} (A_{kn} + \alpha \chi_k \eta_n)}$
→ Input-driven self-organization
- Pruning unused connections
- Results in realistic receptive fields, patchy lateral connections

Orientation Map

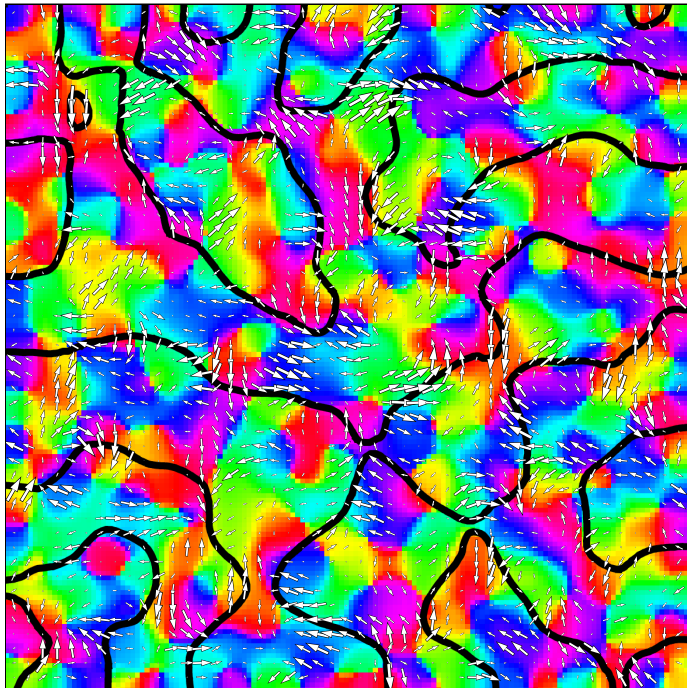


- Systematic preferences emerge
- Similar structures as in biology

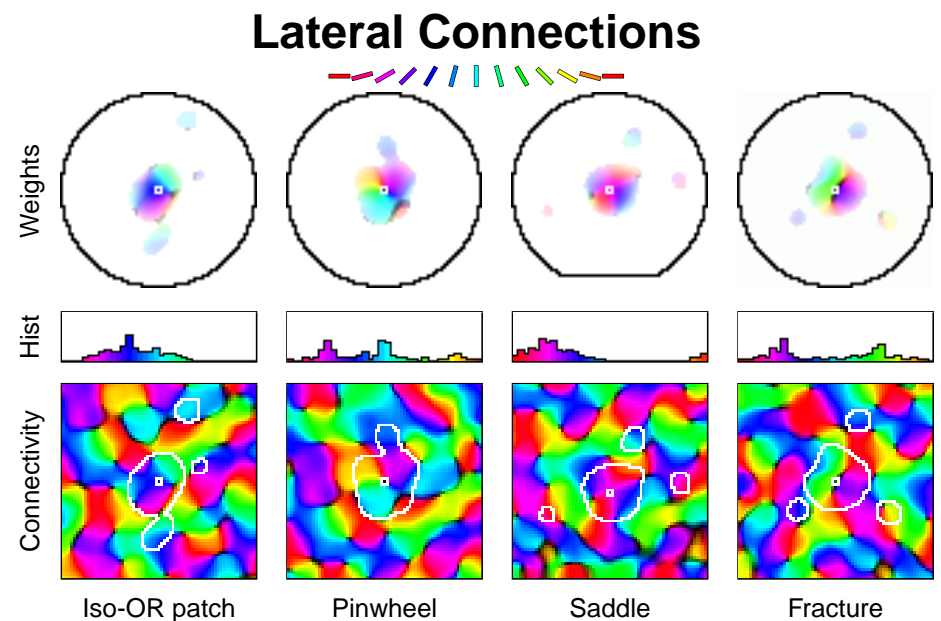
Orientation & Ocular Dominance



OR & OD & DR Map



Orientation & Direction

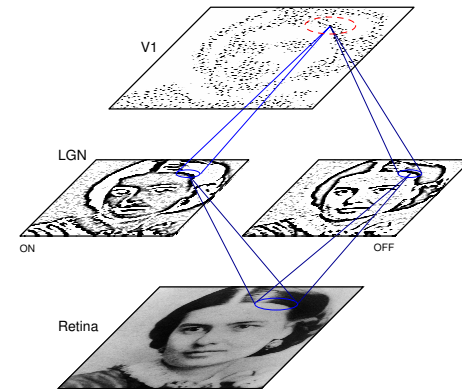


- Link similar responses
- OR primary factor
- Matches biology; detailed predictions

Self-Organization Conclusions

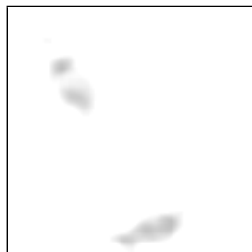
- How is V1 constructed?
 - Input-driven self-organization
- Predictions:
 - Input deprivation (e.g. strabismus)
 - Connection patterns
 - Plasticity
 - Illusions and aftereffects
 - Visual coding

What Is the Goal of Visual Coding?

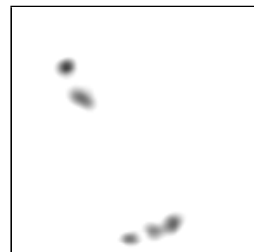


- Representing the important features of the input
- Efficient use of resources:
 - Can represent more information within a limited system

How is Such a Coding Constructed?



Initial response

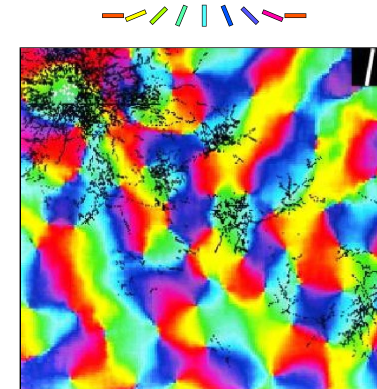


Redundancy-reduced
sparse response

- Not by reducing units: V1 is much larger than the retina
- Could be a sparse code with few active units
- Need to make sparse by reducing redundancy

(Barlow 1972; Atick 1992; Field 1994; Simoncelli & Olshausen 2001)

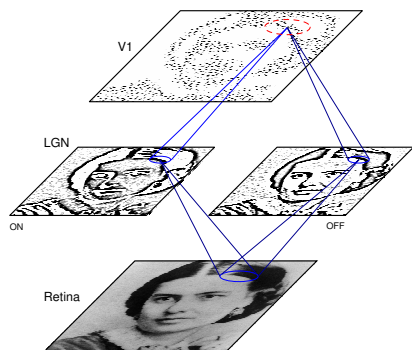
Lateral Connection Hypothesis



(2.5 mm × 2 mm in tree shrew V1; Bosking et al. 1997)

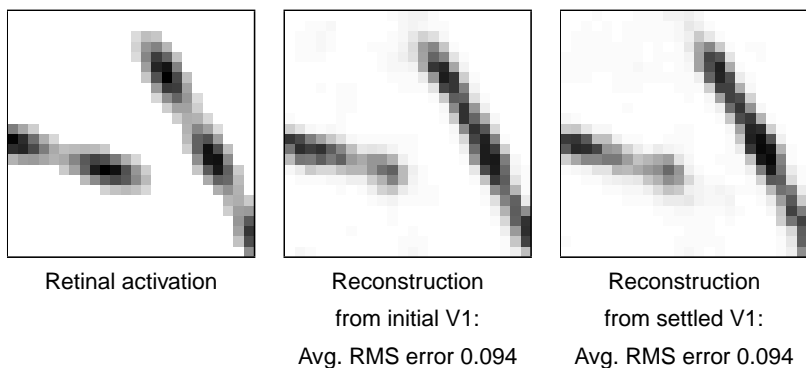
- Afferent connections respond to input features
- Inhibitory lateral connections *decorrelate* the response
 - Connect neurons that respond to similar inputs
 - Response of one neuron can be predicted from the other
 - Can be suppressed without losing information

Testing the Hypothesis



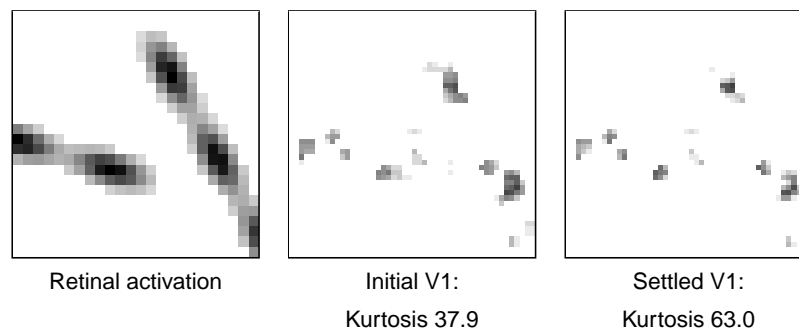
- Difficult to test experimentally
 - Requires many neurons, short time scales
- Can be tested in computational models

Does LISSOM Reduce Redundancy?



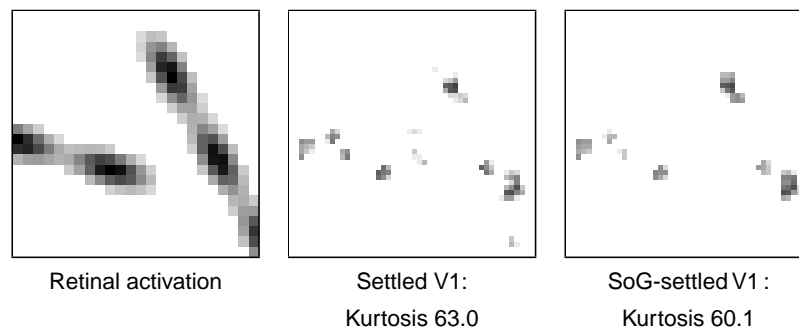
- Reconstruct the input from V1 activity
- Nonlinear: train a backprop net to map back
- → No information lost

Does LISSOM Form a Sparse Code?



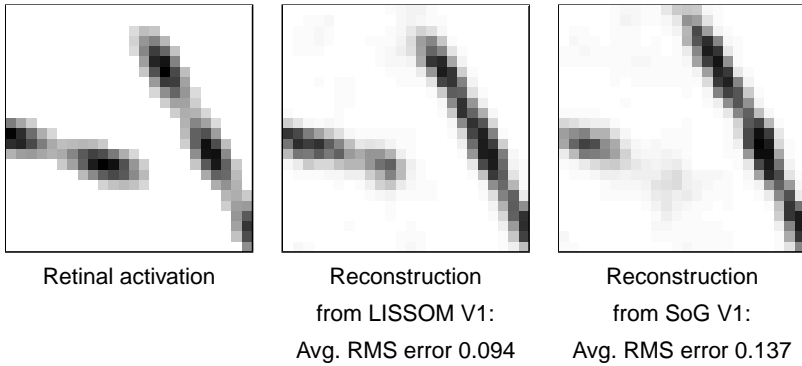
- Self-organize a LISSOM map
- Measure kurtosis of the response
- → The settled response is sparser

Is Self-Organization Necessary?



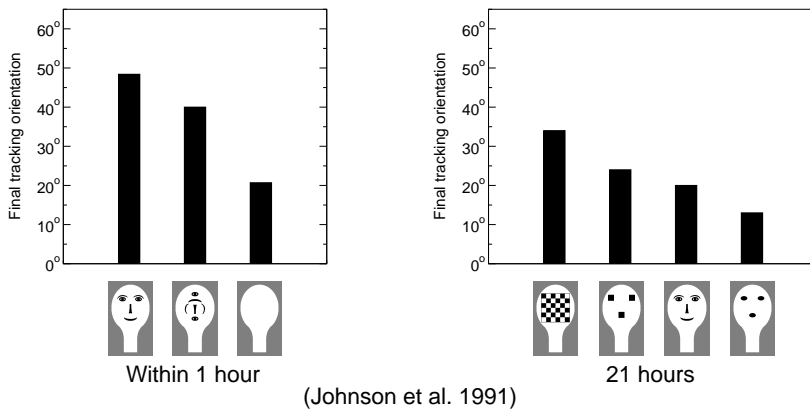
- Isotropic (Sum-of-Gaussians; SoG) lateral connections instead
- Can be adjusted to match kurtosis
- → Sparse code can be formed

Is Self-Organization Necessary?



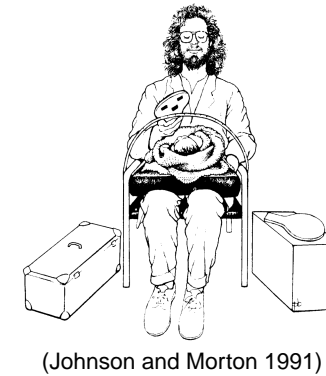
- Reconstruction no longer works!
- Information reduced, not just redundancy
- → Self-organization is necessary
- → Forms a sparse, redundancy-reduced code

Newborn Face Preferences



- Significant preference for face-like schematics
- Genome too small to specify connectivity, behavior
- Three-dot patterns strongest; why?

Nature vs. Nurture



- Development through input-driven self-organization
- But some order appears innate
 - E.g. orientation maps
 - E.g. newborn face preferences

Retinal Waves

(1 mm × 1 mm in ferret retina; Feller et al. 1996)

- Traveling waves in the retina before birth
- Could serve as input for self-organization

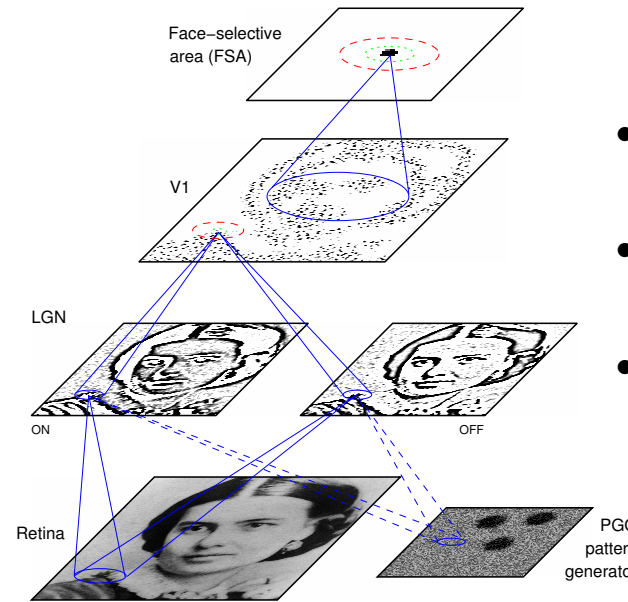
PGO Waves



(Marks et al. 1995)

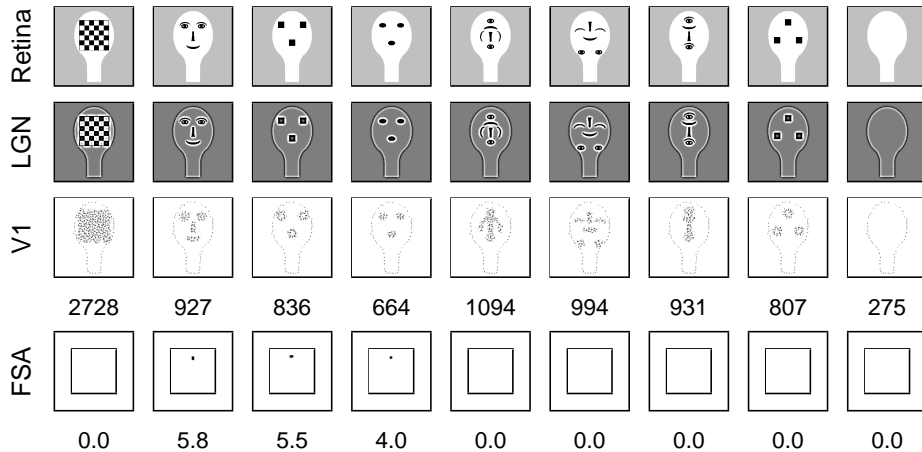
- Ponto-geniculo-occipital waves
- Shape unknown, but activates V1
- Could introduce the three-dot bias

HLISSOM Model



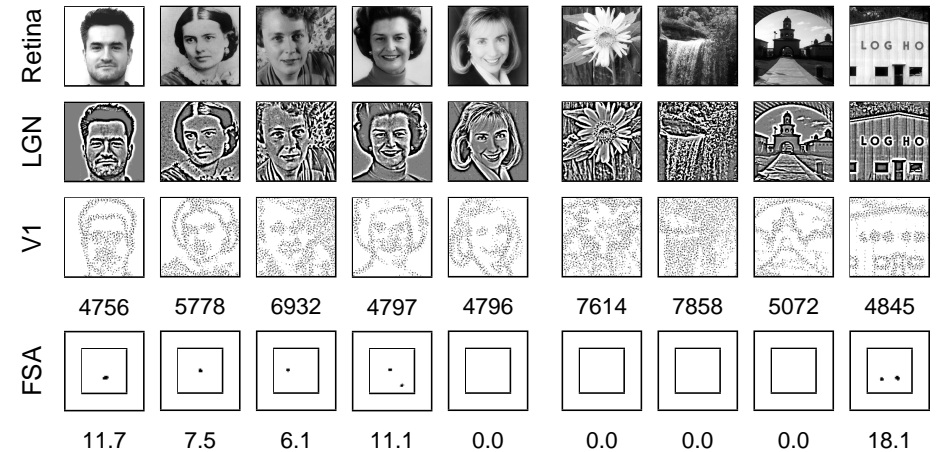
- Include PGO & FSA sheets
- Three-dot input patterns in PGO
- Study prenatal and postnatal self-organization

Newborn LISSOM Face Preferences



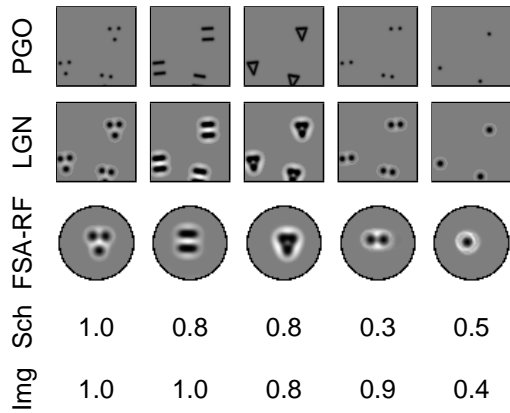
- Matches newborn preferences in every known case

Newborn LISSOM Face Preferences (2)



- Prefers top-lit faces; not objects
- Images not tested on infants

Effect of Pattern Types

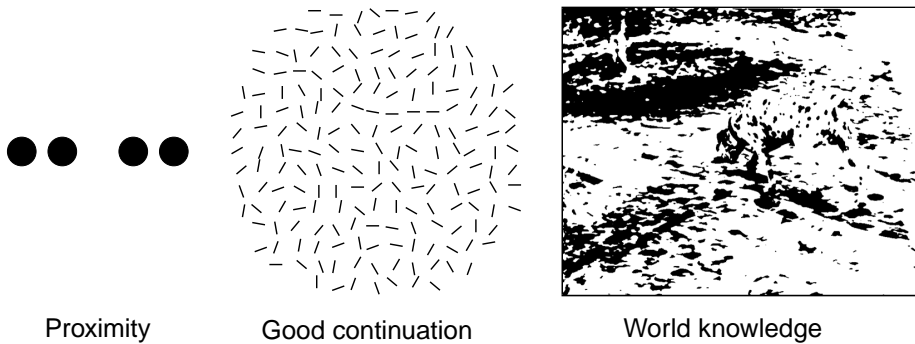


- Three dots not the only possible pattern
- Not all patterns work

Pattern Generation Conclusions

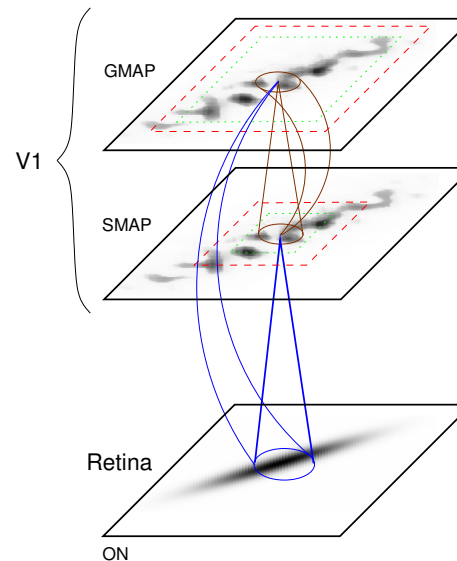
- How are nature and nurture combined?
 - Through internal pattern generation
- Predictions
 - Types of internal patterns
 - Postnatal decline of preferences
 - Holistic perception of the face develops
 - Mother preferences develop

Perceptual Grouping



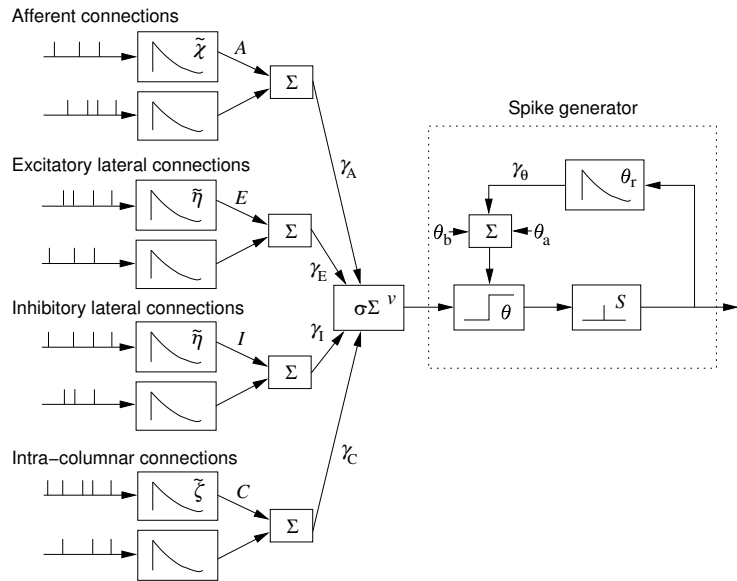
- Perceiving whole objects
- Low-level based on “Gestalt” principles
- Mediated by lateral connections in V1?

PGLISSOM Model



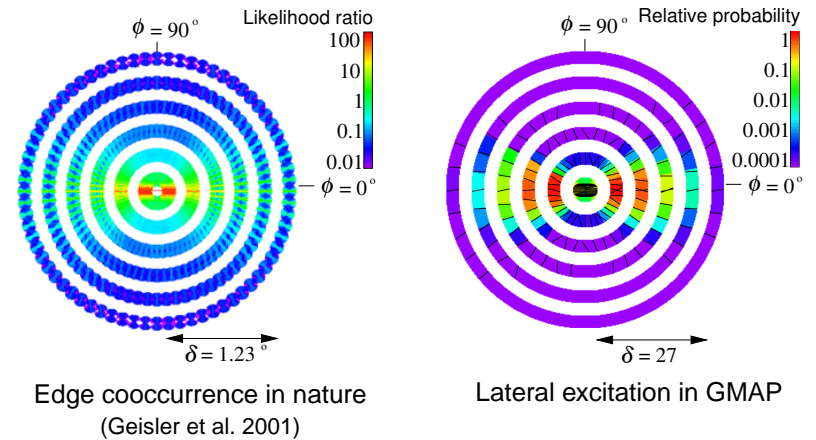
- Self-organization needs long-range inhibition
- Grouping needs long-range excitation
- → 2-layer model of the column

Leaky Integrator Neuron



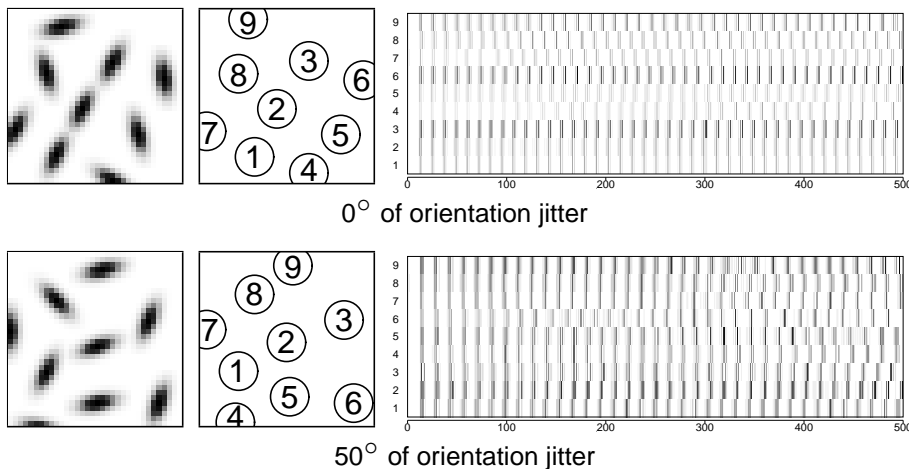
- Binding and segmentation by synchronization
- Need spiking neurons

Self-Organized Lateral Connections



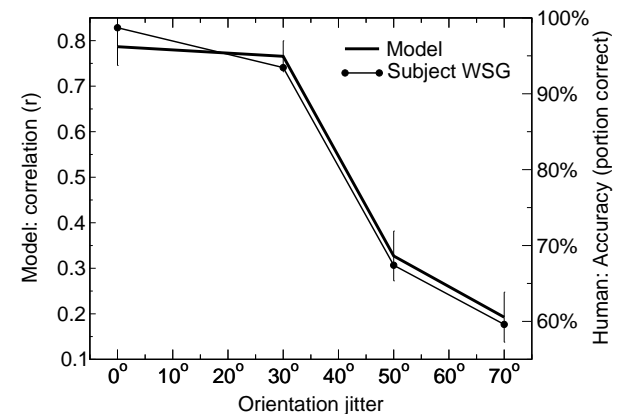
- PGLISSOM self-organizes like LISSOM
- Lateral connections match visual environment

Contour Integration Process



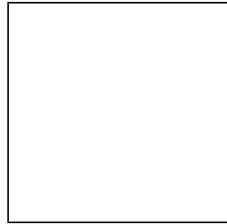
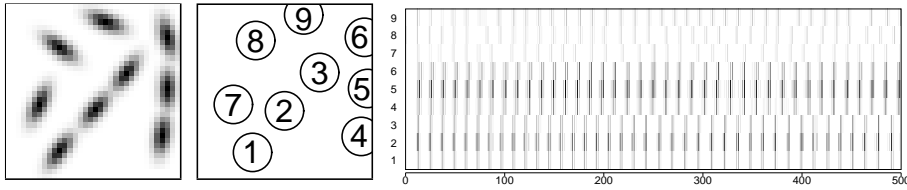
- Synchronizes continuous contours
- Depends on how “good” the contour is

PGLISSOM vs. Human Performance



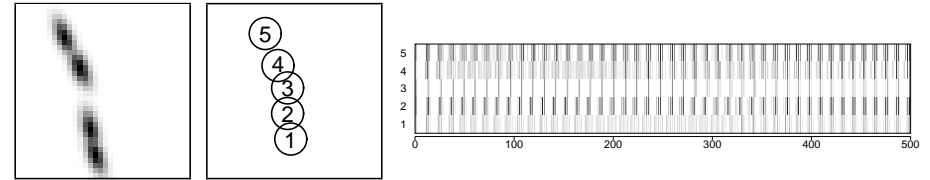
- Depends on jitter like human performance

Contour Segmentation



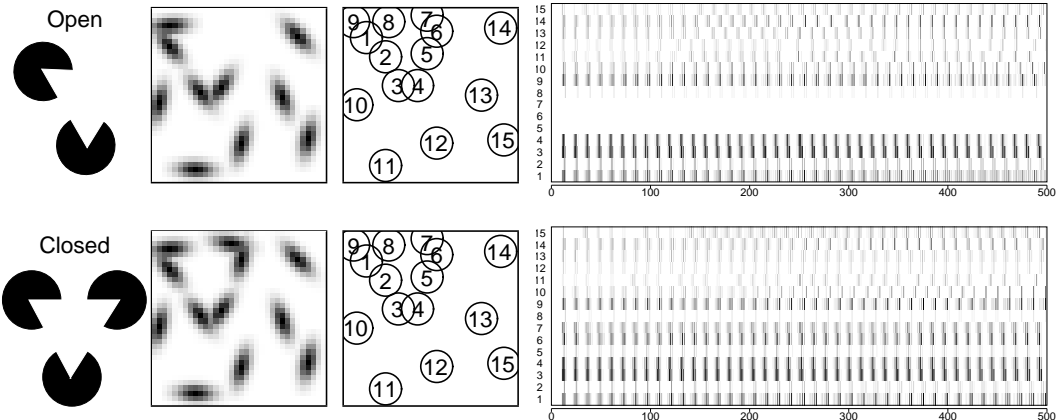
- Multiple contours by alternating
- Upto 5-9 contours

Contour Completion



- Filling in gaps
- Basis for edge-induced illusory contours?

Illusory Contours



- Kanizsa: proximity & continuation
- Closed contours easier
- Matches human performance

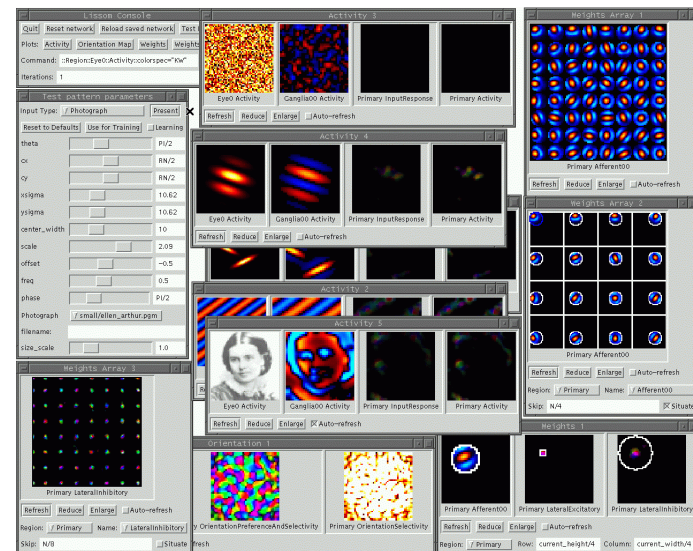
Perceptual Grouping Conclusions

- How does the structure support functions like grouping?
 - Synchronization mediated by self-organized lateral connections
- Predictions:
 - Effect of activation decay, noise, refractory period on synchronization
 - Image statistics → lateral connectivity → performance
 - Frequency, curvature, etc. differ across visual fields
 - Performance differs in fovea vs. periphery, upper vs. lower hemifield

Future Work

- Self-organization
 - Color, frequency, disparity
 - Hierarchy, feedback, multimodal integration
- Development
 - Characterizing internal patterns
 - Constructing complex systems
- Grouping
 - Verify synchronization hypothesis with TMS
 - Line-end-induced illusions in V2?

Topographica

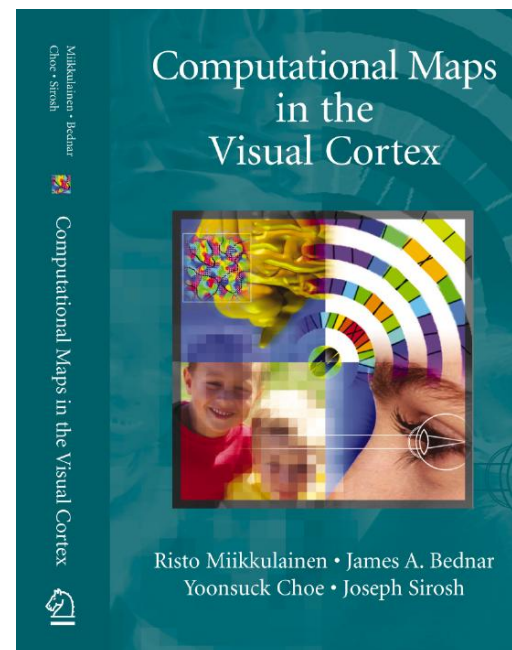


- General simulator for cortical maps (v0.8.2 Feb 2006)

Conclusion

- Wealth of data + powerful computing available
- Neuroscience research in vitro, in vivo, *in silico*
- Computational theory of the visual cortex
 - Continuously adapting self-organizing system
 - Shaped by internal and external input
 - Lateral connections play a major role
- Exciting possibilities for future work

Further Details



(Springer, 2005)

Demos, software, etc.:
www.computationalmaps.org