Computational Maps in the Visual Cortex

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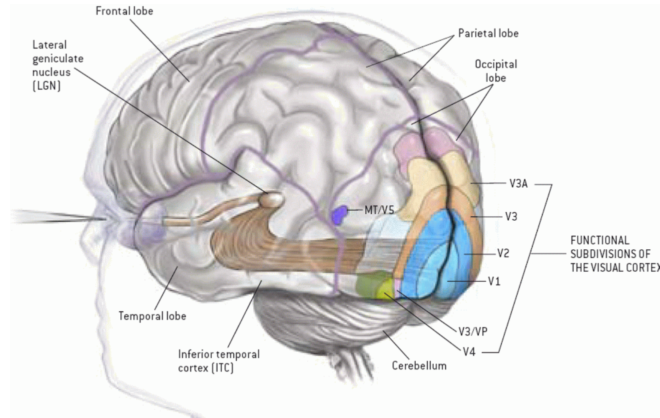
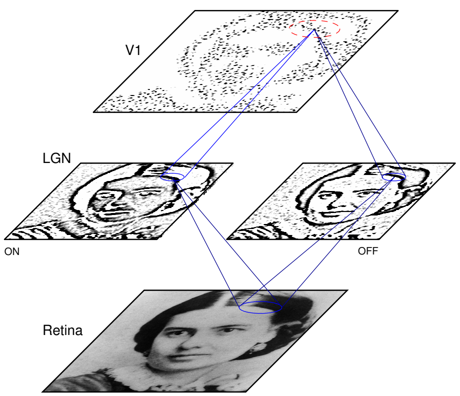
Understanding Vision



(Logothetis 2002)

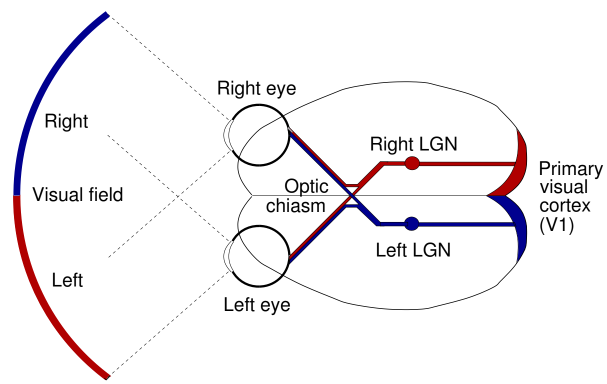
- How is a system as complex as the human visual system constructed?
- How can it be both genetically and environmentally determined?
- How does its structure support functions such as perceptual grouping?

Role of Computational Modeling



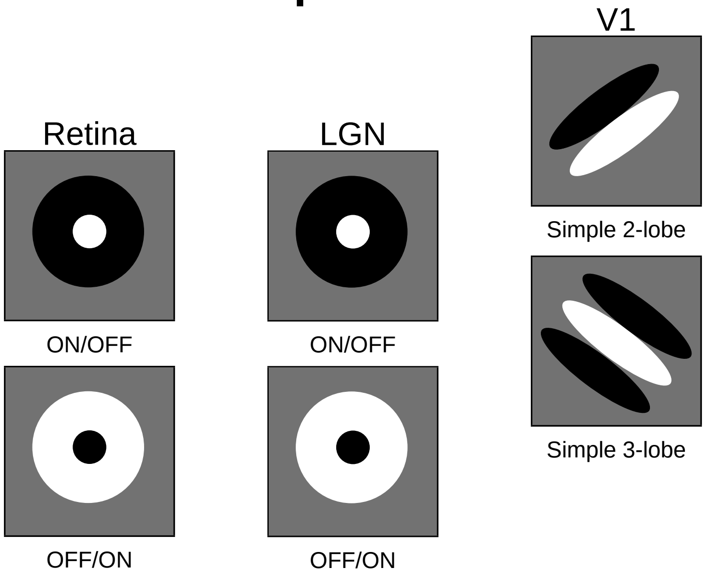
- Computational model is an artificial subject with full access
  - Test hypotheses computationally, make predictions
- Computational theory of the visual cortex
  - Build better artificial systems
  - Improve medical treatment

Human Visual System



- Retina, LGN, V1...etc.
- Structure well known

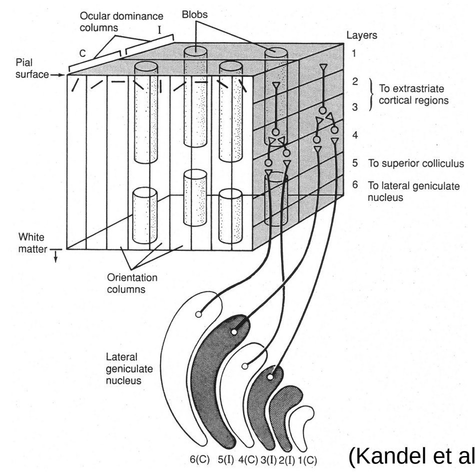
Receptive Fields



Spatiotemporal

- Center-surround; static and moving lines; combinations

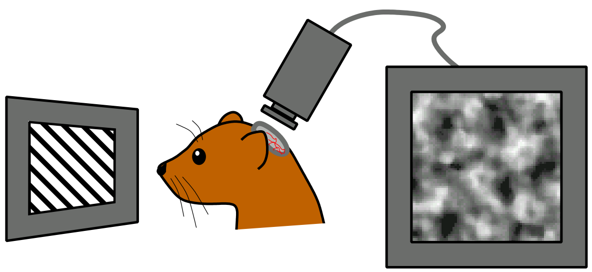
Columnar Organization of V1



(Kandel et al. 1991)

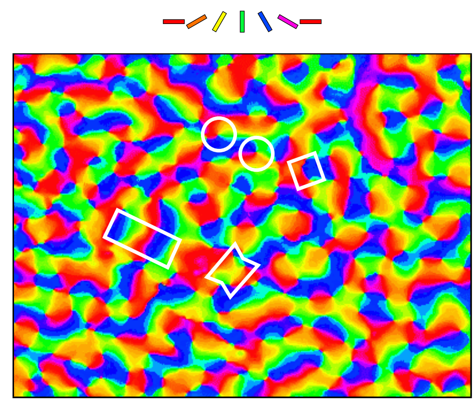
- Roughly hierarchical ordering:
  - Retinotopy, OD, OR, DR
  - Color, spatial frequency, disparity?
- Within column, similar responses: 2D structure

Measuring Cortical Maps



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

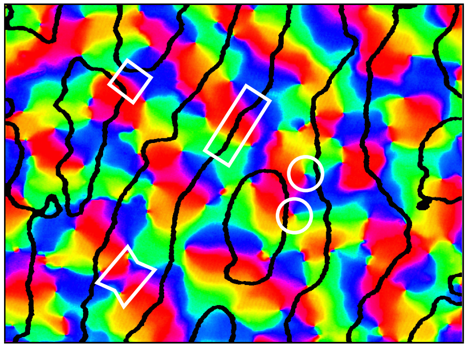
Orientation Map



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

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

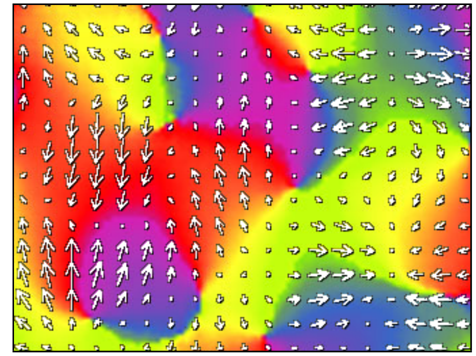
Orientation & Ocular Dominance Map



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

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

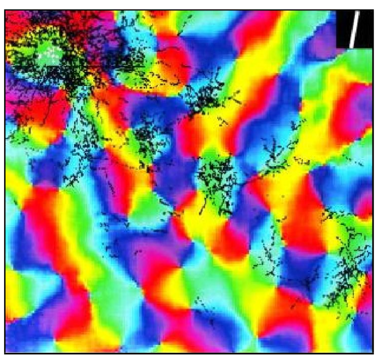
Orientation & Direction Map



(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)

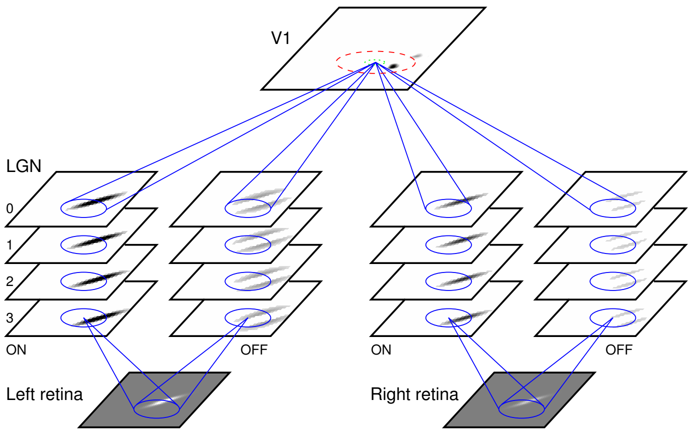
- Link to similar responses
- Patchy structure, extend along OR preference

Development

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

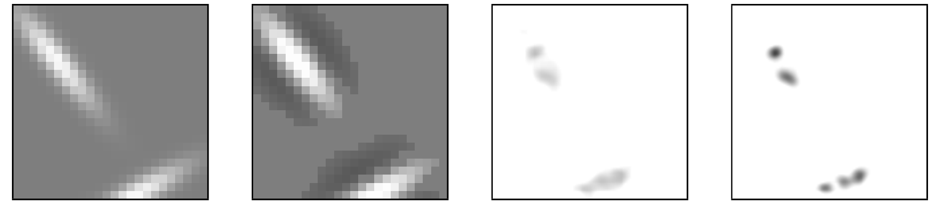
- Structure emerges during development
- Some prenatally, much postnatally
- How and why?

LISSOM Model



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

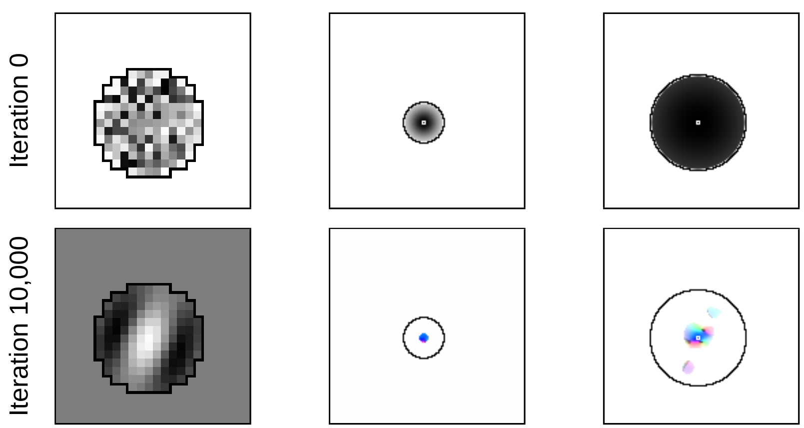
Activation



Retinal activation | LGN response | V1 initial | V1 settled

- Luminance adjustment in retina
- Sharpening in LGN (ON—OFF shown)
- Settling in V1:
  $\eta'_i = \sigma\left(\Sigma_k \chi_k A_{ki} + \Sigma_j \eta_j E_{ji} - \Sigma_j \eta_j I_{ji}\right)$

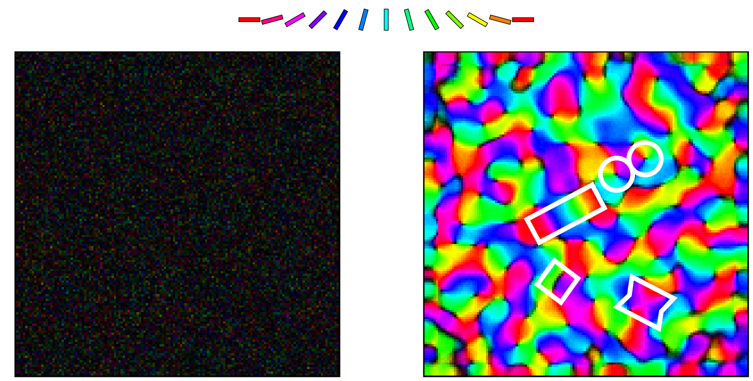
Adaptation



Afferent | Lateral excitatory | Lateral inhibitory

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

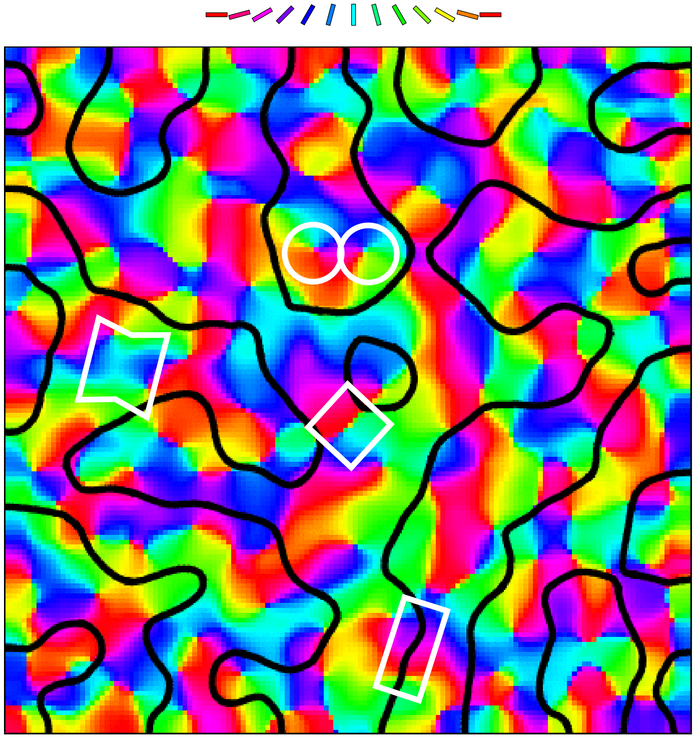
Orientation Map



OR+selectivity, iteration 0 | OR+selectivity, iteration 10,000

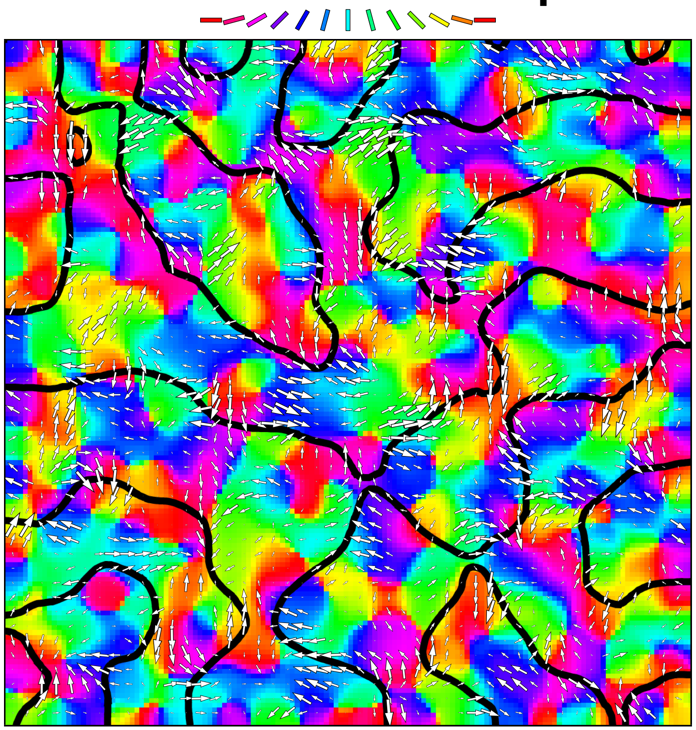
- Systematic preferences emerge
- Similar structures as in biology

Orientation & Ocular Dominance

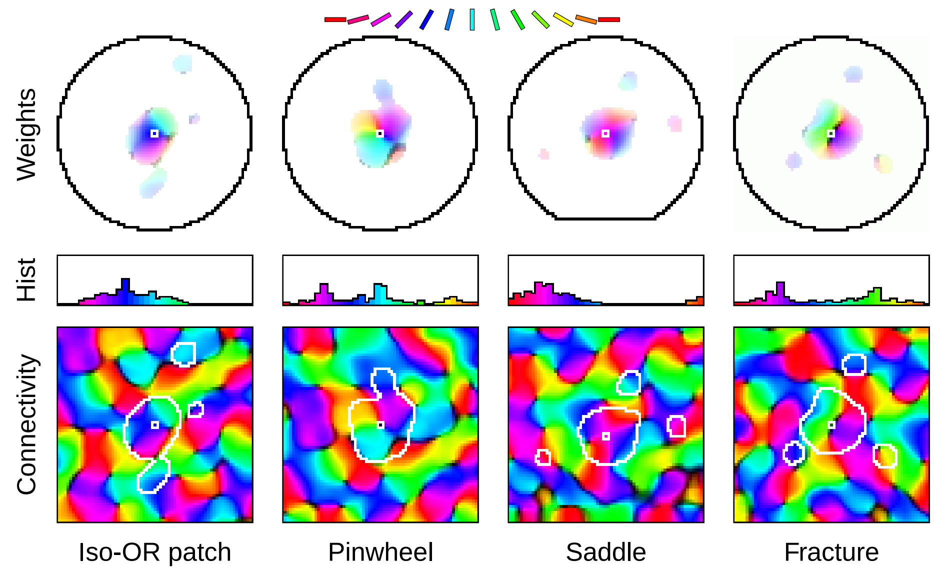


Orientation & Direction

OR & OD & DR Map



Lateral Connections

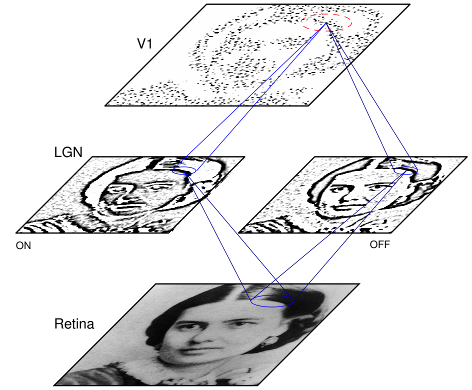


- Link similar responses
- OR primary factor
- Matches biology; detailed predictions

Self-Organization Conclusions

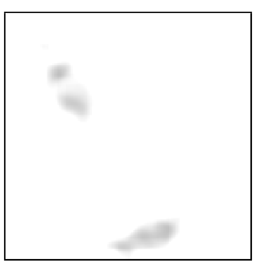
- How is V1 constructed?
  - Input-driven self-organization
- Predictions:
  - Input deprivation (e.g. strabismus)
  - Connection patterns
  - Plasticity
  - Illusions and aftereffects
  - Visual coding

What Is the Goal of Visual Coding?

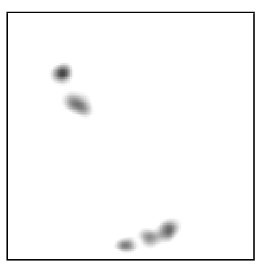


- Representing the important features of the input
- Efficient use of resources:
  Can represent more information within a limited system

How is Such a Coding Constructed?



Initial response

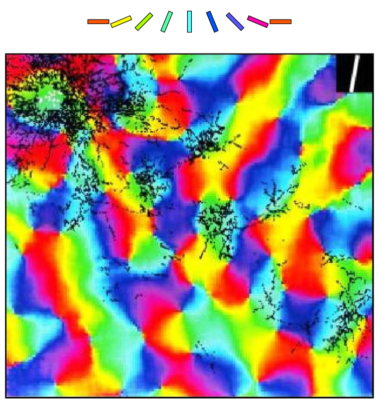


Redundancy-reduced
sparse response

- 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)

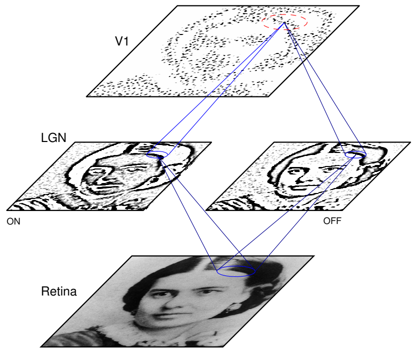
Lateral Connection Hypothesis



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

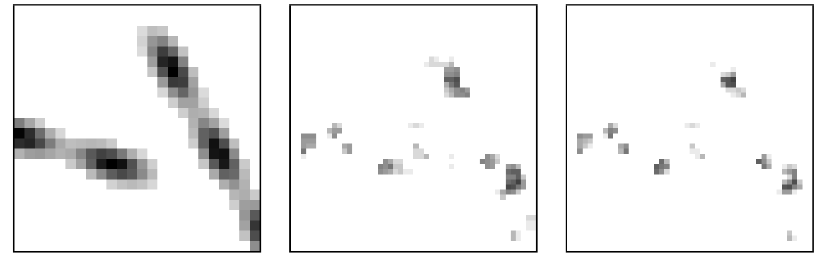
- Afferent connections respond to input features
- Inhibitory lateral connections *decorrelate* the response
  - Connect neurons that respond to similar inputs
  - Response of one neuron can be predicted from the other
  - Can be suppressed without losing information

Testing the Hypothesis



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

Does LISSOM Form a Sparse Code?



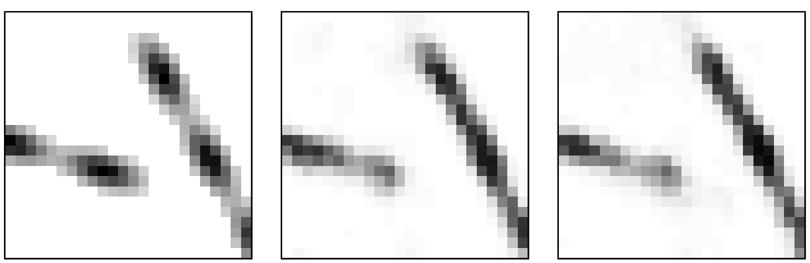
Retinal activation

Initial V1: Kurtosis 37.9

Settled V1: Kurtosis 63.0

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

Does LISSOM Reduce Redundancy?



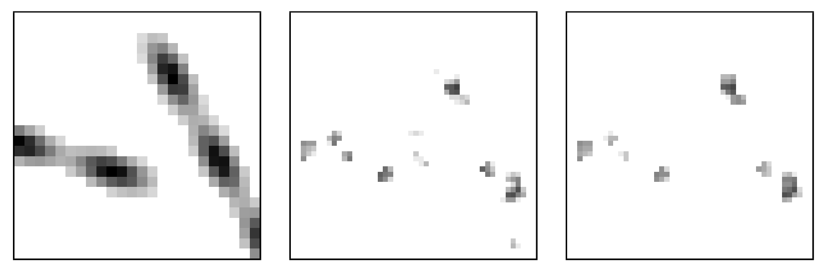
Retinal activation

Reconstruction from initial V1: Avg. RMS error 0.094

Reconstruction from settled V1: Avg. RMS error 0.094

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

Is Self-Organization Necessary?



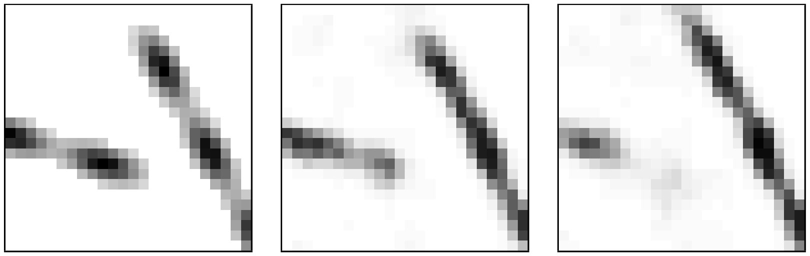
Retinal activation

Settled V1: Kurtosis 63.0

SoG-settled V1 : Kurtosis 60.1

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

Is Self-Organization Necessary?



Retinal activation | Reconstruction from LISSOM V1: Avg. RMS error 0.094 | Reconstruction from SoG V1: Avg. RMS error 0.137

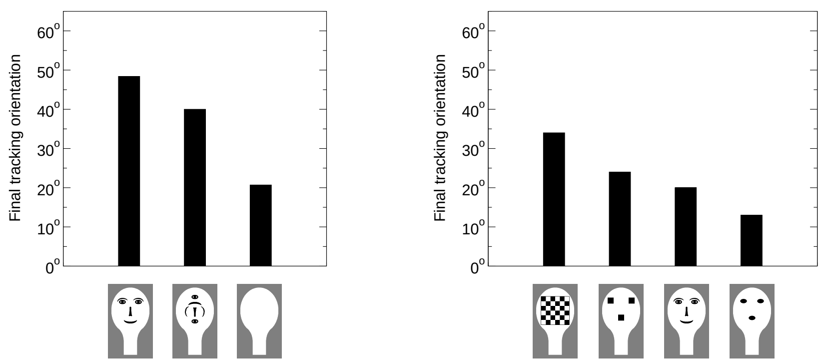
- Reconstruction no longer works!
- Information reduced, not just redundancy
- $\longrightarrow$ Self-organization is necessary
- $\longrightarrow$ Forms a sparse, redundancy-reduced code

Nature vs. Nurture

(Johnson and Morton 1991)

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

Newborn Face Preferences



Within 1 hour — 21 hours

(Johnson et al. 1991)

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

Retinal Waves

(1 mm $\times$ 1 mm in ferret retina; Feller et al. 1996)

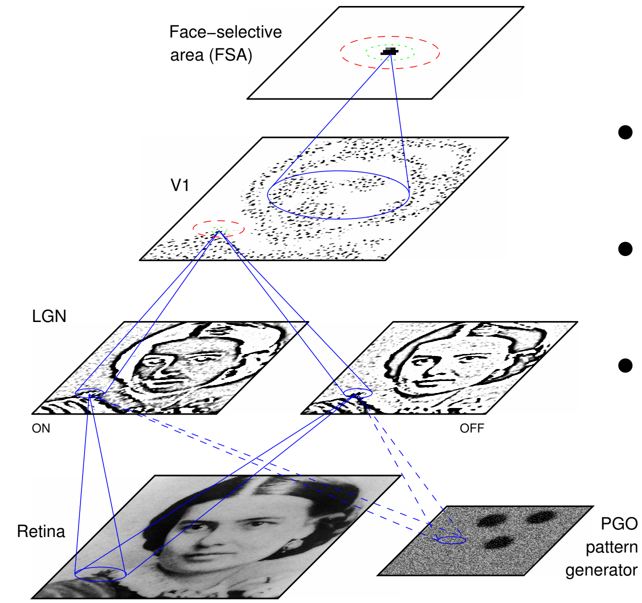
- Traveling waves in the retina before birth
- Could serve as input for self-organization

PGO Waves

(Marks et al. 1995)

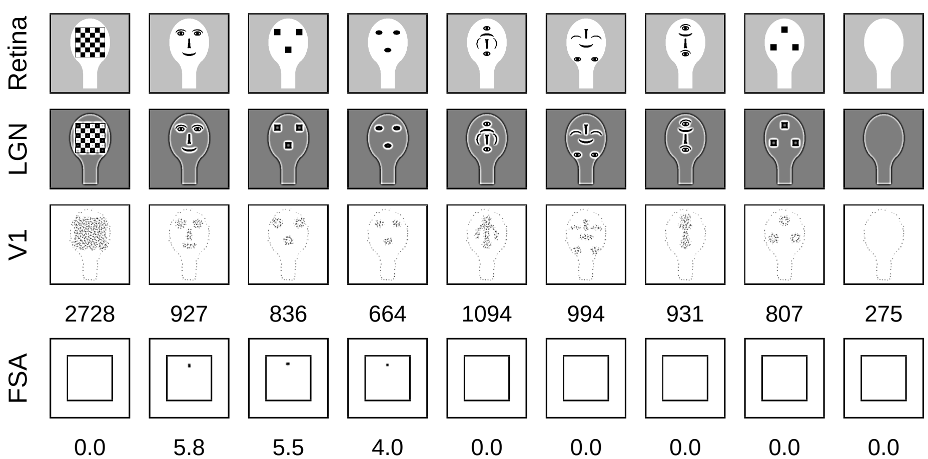
- Ponto-geniculo-occipital waves
- Shape unknown, but activates V1
- Could introduce the three-dot bias

HLISSOM Model



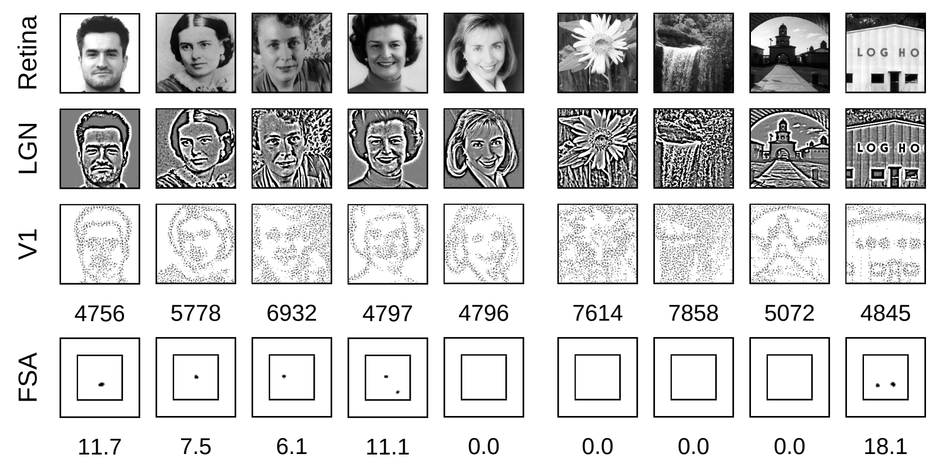
- Include PGO & FSA sheets
- Three-dot input patterns in PGO
- Study prenatal and postnatal self-organization

Newborn LISSOM Face Preferences



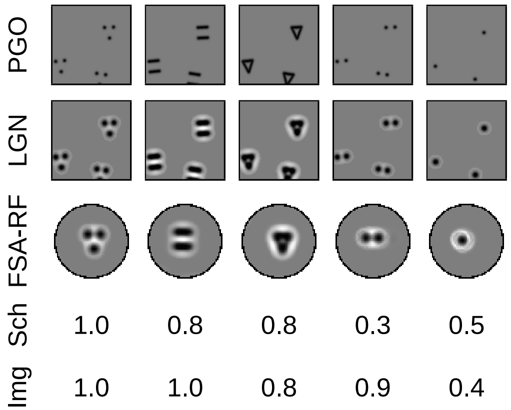
- Matches newborn preferences in every known case

Newborn LISSOM Face Preferences (2)



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

Effect of Pattern Types

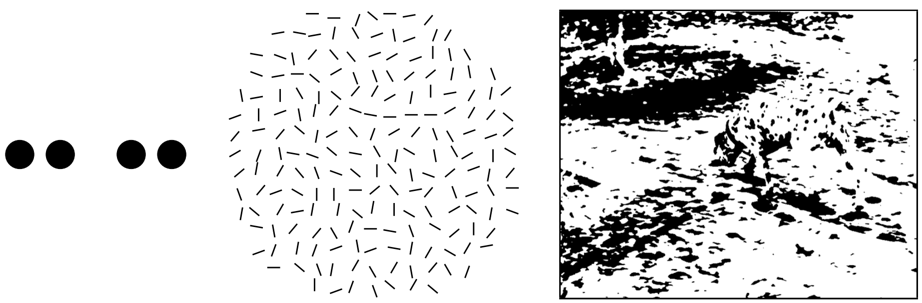


- Three dots not the only possible pattern
- Not all patterns work

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

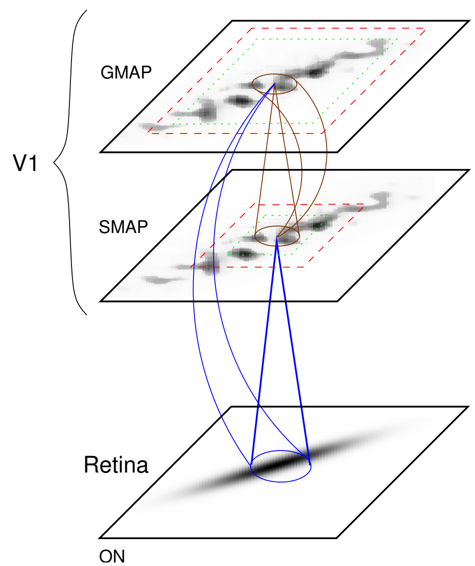
Perceptual Grouping



Proximity   Good continuation   World knowledge

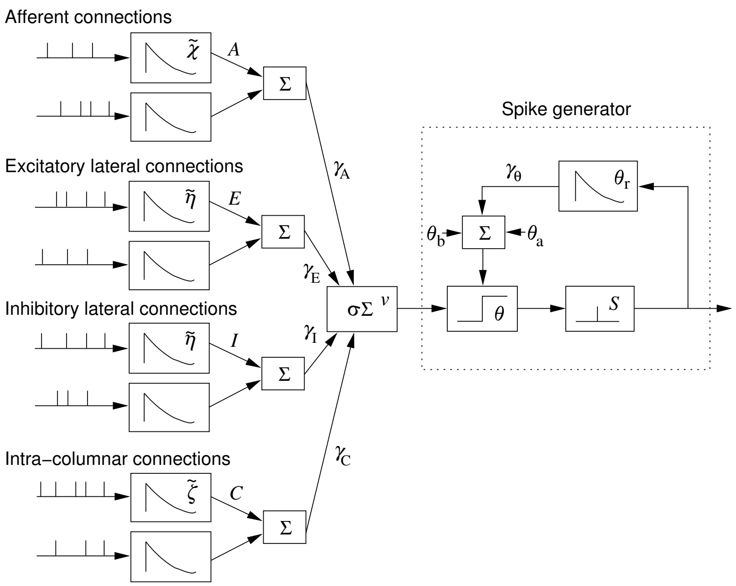
- Perceiving whole objects
- Low-level based on “Gestalt” principles
- Mediated by lateral connections in V1?

PGLISSOM Model



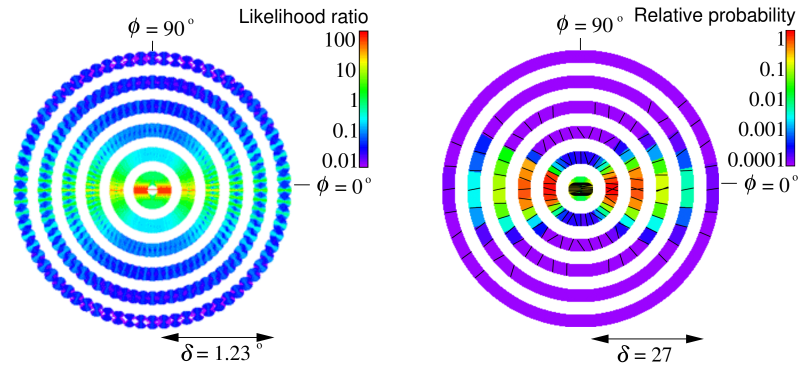
- Self-organization needs long-range inhibition
- Grouping needs long-range excitation
- $\longrightarrow$ 2-layer model of the column

Leaky Integrator Neuron



- Binding and segmentation by synchronization
- Need spiking neurons

Self-Organized Lateral Connections

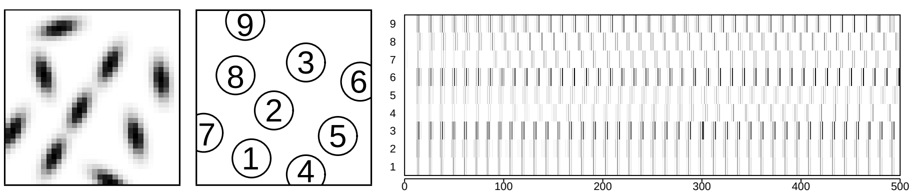


Edge cooccurrence in nature
(Geisler et al. 2001)

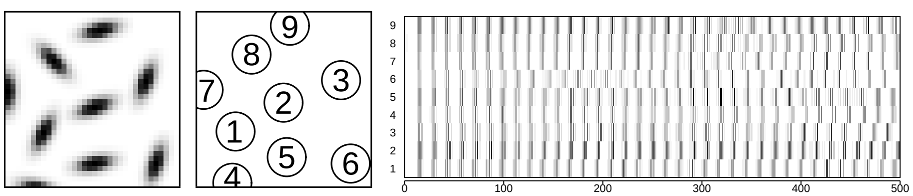
Lateral excitation in GMAP

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

Contour Integration Process



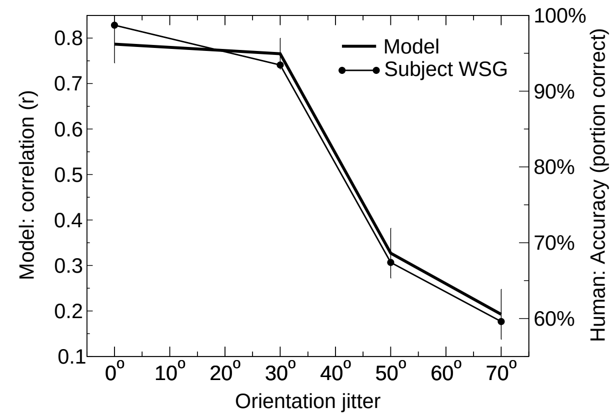
0° of orientation jitter



50° of orientation jitter

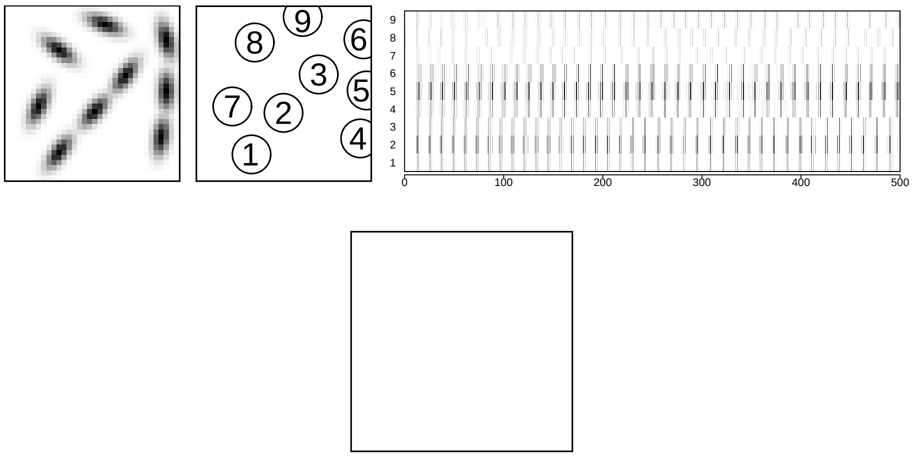
- Synchronizes continuous contours
- Depends on how “good” the contour is

PGLISSOM vs. Human Performance



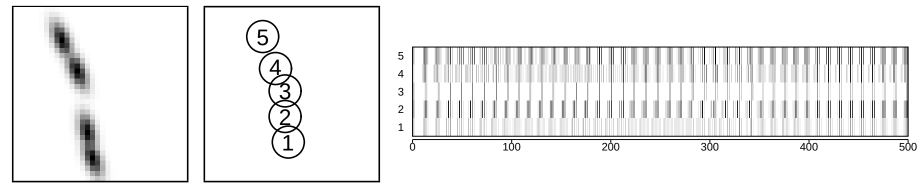
- Depends on jitter like human performance

Contour Segmentation



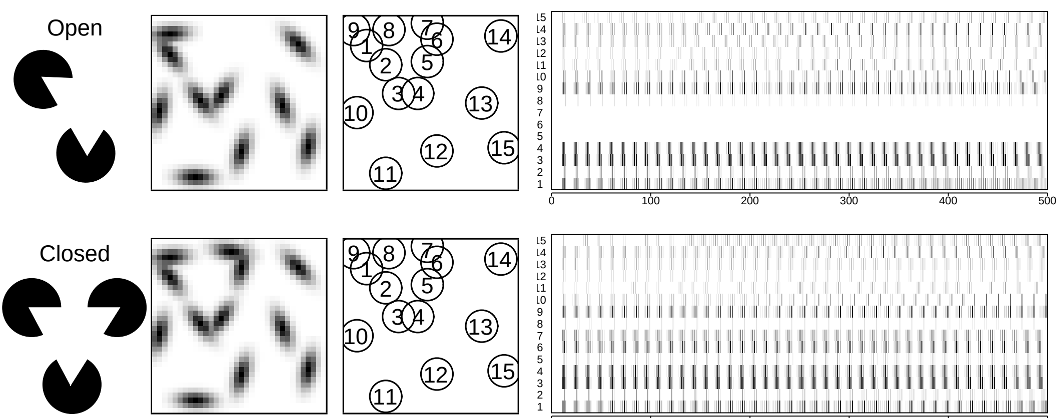
- Multiple contours by alternating
- Upto 5-9 contours

Contour Completion



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

Illusory Contours



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

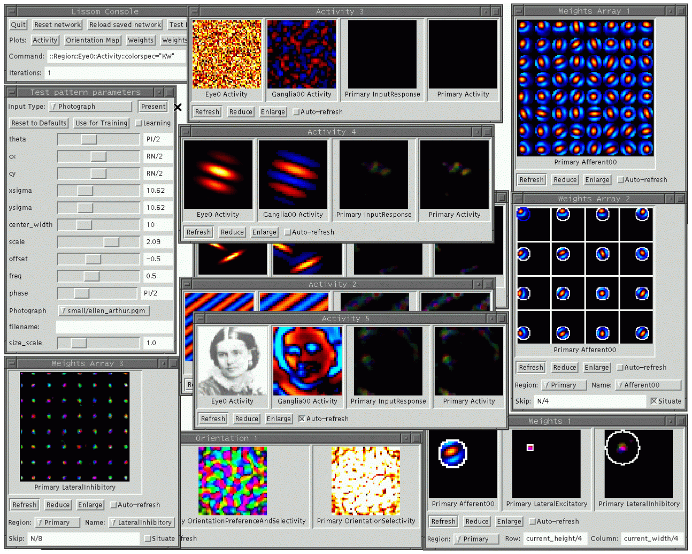
Perceptual Grouping Conclusions

- 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

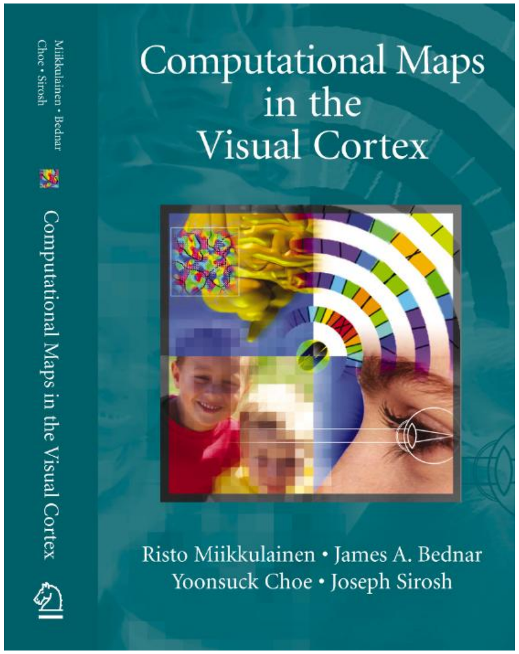


- General simulator for cortical maps (v0.8.2 Feb 2006)

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*