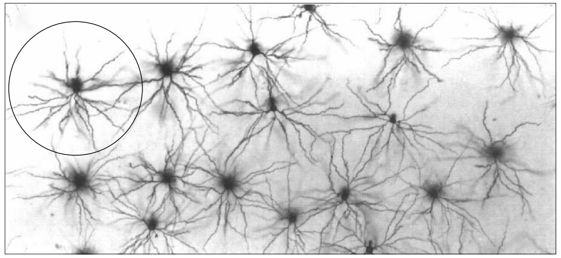
Modeling the Visual System

Dr. James A. Bednar

jbednar@inf.ed.ac.uk

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

Sample network to model

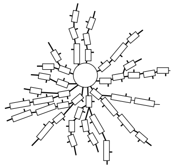


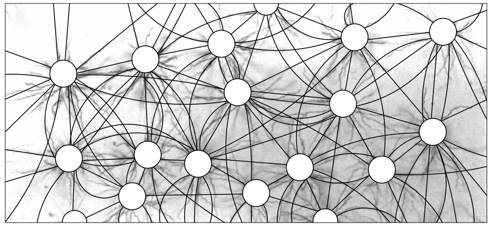
CMVC figure 3.1a

Tangential section with a small subset of neurons labeled

Where do we begin?

Modeling approaches





CMVC figure 3.1b,e

Compartmental neuron model

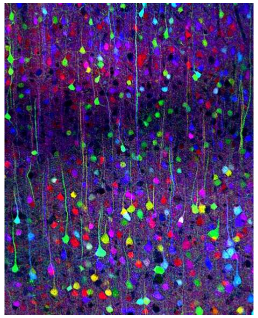
Integrate-and-fire / firing-rate model of the network

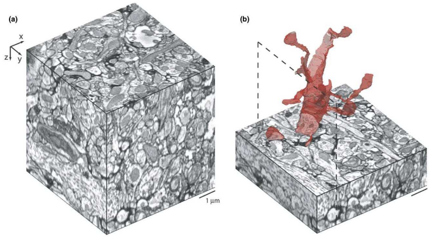
One approach: model single cells extremely well

Our approach: many, many simple single-cell models

Dense connectivity

(Livet et al. 2007)





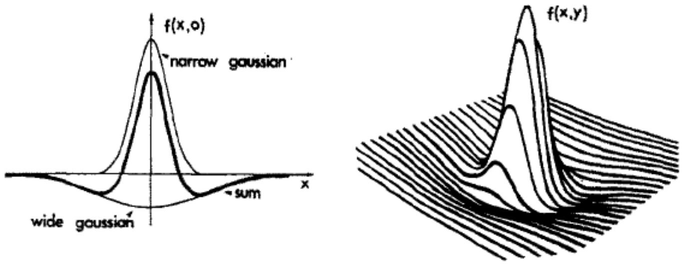
(Briggman & Denk 2006)

Brainbow mouse cortex

Electron microscopy of rat cortex

Remember that the actual network is far denser than in the previous slides, with many opportunities for contact between neurons and neurites.

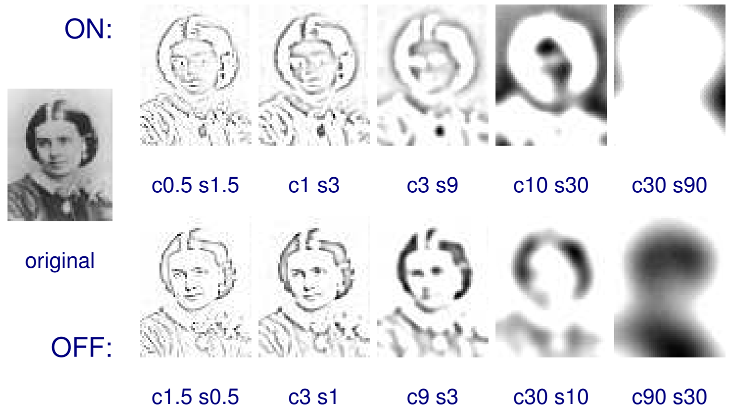
Adult retina and LGN cell models



(Rodieck 1965)

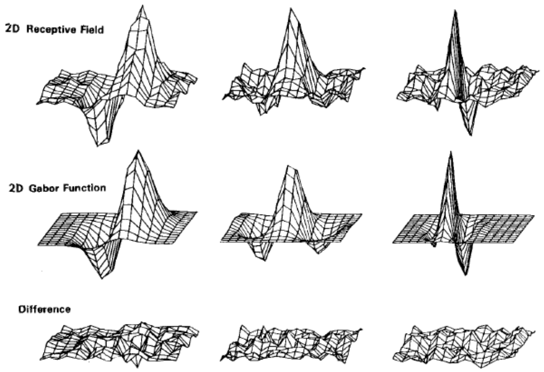
- Standard model of adult RGC or LGN cell activity: Difference of Gaussians weight matrix
- Firing rate: dot product of weight and input matrices
- Can be tuned for quantitative match to firing rate
- Can add temporal component (transient+sustained)

Effect of DoG



Each DoG, if convolved with the image, performs edge detection at a certain size scale (spatial frequency band)

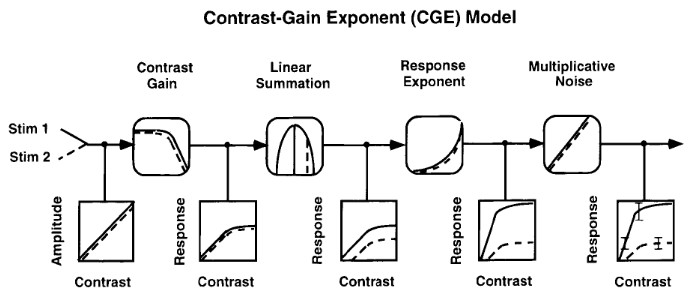
Adult V1 cell model: Gabor



(Adult cat; Daugman 1988)

Standard model of adult V1 simple cell spatial preferences: Gabor (Gaussian times sine grating) (Daugman 1980)

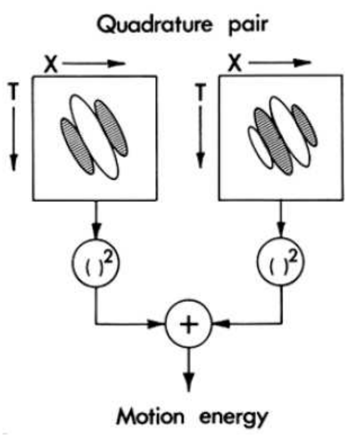
Adult V1 cell model: CGE



(Geisler & Albrecht 1997)

- Gabor model fits spatial preferences
- Simple response function: dot product
- To match observations: need to add numerous nonlinearities
- Example: CGE model (Geisler & Albrecht 1997)

Adult V1 cell model: Energy



- Spatiotemporal energy: Standard model of complex direction cell (Adelson & Bergen 1985)
- Combines inputs from a quadrature pair (two simple cell motion models out of phase)
- Achieves phase invariance, direction selectivity

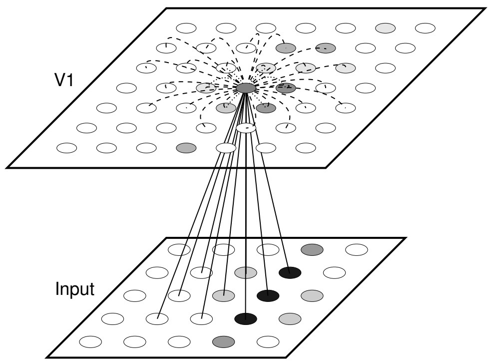
Retina/LGN development models

Relatively rare, but more in recent years:

- Retinal wave generation (e.g. Feller et al. 1997; Godfrey & Swindale 2007; Hennig et al. 2009)
- RGC development based on retinal waves (e.g. Eglen & Willshaw 2002)
- Retinogeniculate pathway based on retinal waves (e.g. Eglen 1999; Haith 1998)

Because of the wealth of data from the retina, such models can now become quite detailed.

Our focus: Cortical map models



CMVC figure 3.3

Basic architecture: input surface mapped to cortical surface + some form of lateral interaction

Kohonen SOM: Feedforward

Popular computationally tractable map model (Kohonen 1982)

Feedforward activity of unit (i, j):

$$\eta_{ij} = \|\vec{V} - \vec{W}_{ij}\| \tag{1}$$

(distance between input vector $\vec{V}$ and weight vector $\vec{W}$)

Not particularly biologically plausible, but easy to compute, widely implemented, and has some nice properties.

Note: Activation function is not typically a dot product; the CMVC book is confusing about that.

Kohonen SOM: Lateral

Abstract model of lateral interactions:

- Pick winner (r, s)
- Assign it activity $\eta_{\max}$
- Assume that activity of unit (i, j) can be described by a neighborhood function, such as a Gaussian:

$$h_{rs,ij} = \eta_{\max} \exp\left(-\frac{(r-i)^2 + (s-j)^2}{\sigma_{\mathrm{h}}^2}\right), \tag{2}$$

Models lateral interactions that depend only on distance from winning unit.

Kohonen SOM: Learning

Inspired by basic Hebbian rule (Hebb 1949):

$$w' = w + \alpha\eta\chi \tag{3}$$

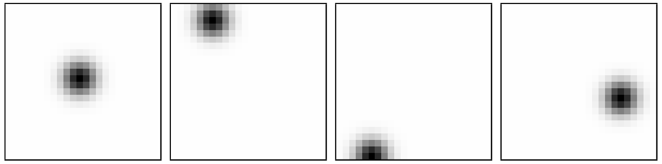
where the weight increases in proportion to the product of the input and output activities.

In SOM, the weight vector is shifted toward the input vector based on the Euclidean difference:

$$w'_{k,ij} = w_{k,ij} + \alpha(\chi_k - w_{k,ij})h_{rs,ij}. \tag{4}$$

Hebb-like, but depending on distance from winning unit

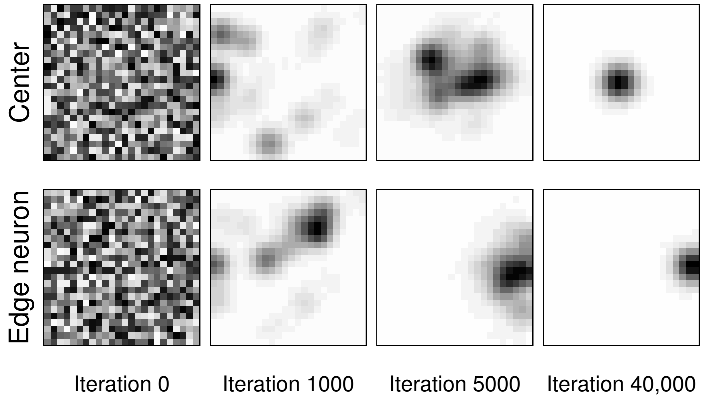
SOM example: Input



CMVC figure 3.4

- SOM will be trained with unoriented Gaussian activity patterns
- Random (x, y) positions anywhere on retina
- 576-dimensional input, but the x and y locations are the only source of variance

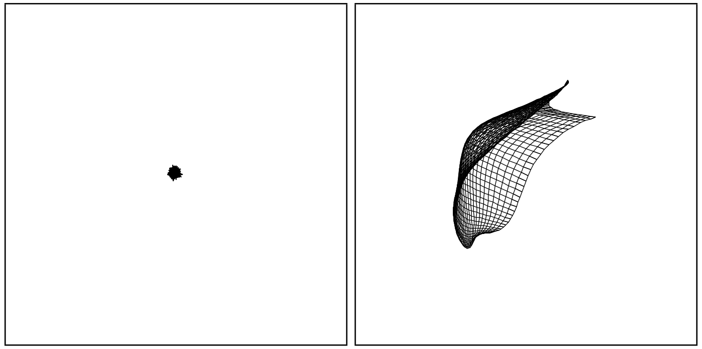
SOM: Weight vector self-org



CMVC figure 3.5

Combination of input patterns; eventually settles to an exemplar

SOM: Retinotopy self-org



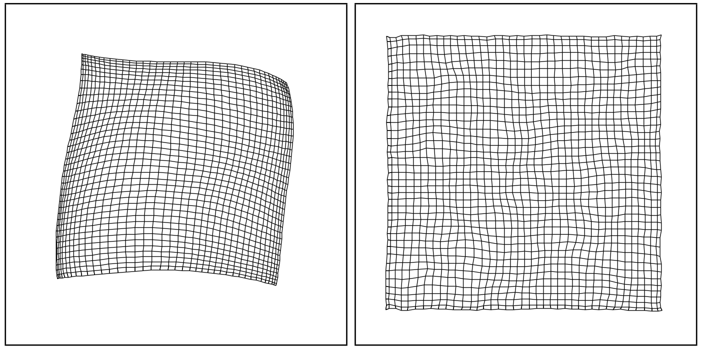
Iteration 0: Initial Iteration 1000: Unfolding

CMVC figure 3.6a-b

Initially bunched (all average to zero)

Unfolds as neurons differentiate

SOM: Retinotopy self-org

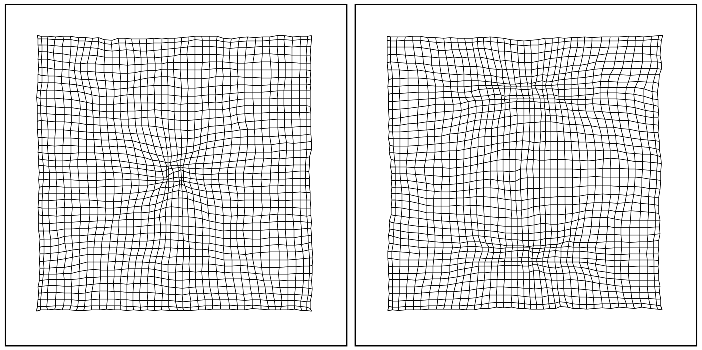


Iteration 5000: Expanding Iteration 40,000: Final

CMVC figure 3.6c-d

Expands to cover usable portion of input space.

Magnification of dense input areas



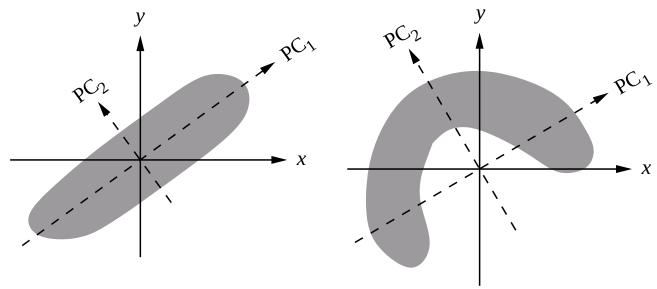
Gaussian distribution Two long Gaussians

CMVC figure 3.7

Density of units receiving input from a particular region

depends on input pattern statistics

Principal components of data distributions

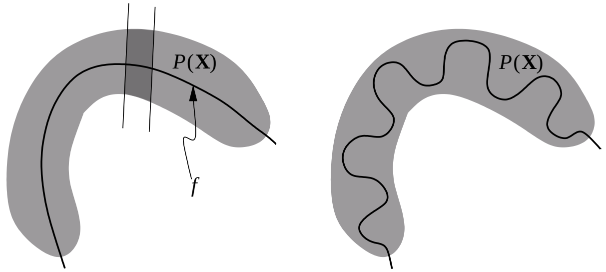


(*a*) Linear distribution (*b*) Nonlinear distribution

CMVC figure 3.8

PCA: linear approximation, good for linear data

Nonlinear distributions: principal curves, folding



CMVC figure 3.9

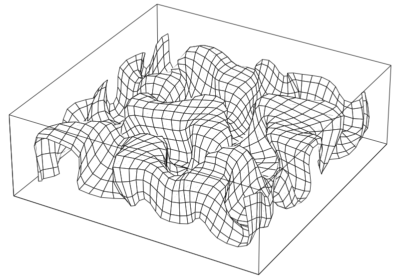
Principal curve

Folded curve

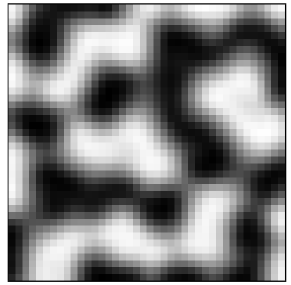
Generalization of idea of PCA to pick best-fit curve(s)

Multiple possible curves

Three-dimensional model of ocular dominance



Representing the third dimension by folding

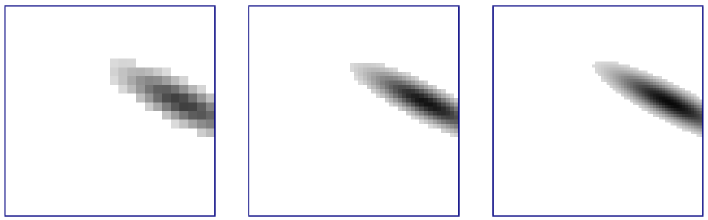


Visualization of ocular dominance

CMVC figure 3.10

Feature maps: Discrete approximations to principal surfaces?

Role of density of input sheet



- Gaussian inputs are nearly band-limited (since Fourier transform is also Gaussian)
- Density of input sampling unimportant, if it's greater than 2X highest frequency in input (Nyquist theorem)

Role of density of SOM sheet

SOM sheet acts as a discrete approximation to a two-dimensional surface.

How many units are needed for the SOM depends on how nonlinear the input distribution is — a smoothly varying input distribution requires fewer units to represent the shape.

Only loosely related to the input density – input density limits how quickly the input varies across space, but only for wideband stimuli.

Other relevant models

ICA Independent Component Analysis yields realistic RFs (Olshausen & Field 1996); also can be applied to maps (Hyvärinen & Hoyer 2001).

InfoMax Information maximization can lead to RFs (Linsker 1986b,c) and basic maps (Kozloski et al. 2007; Linsker 1986a)

Elastic net Achieving good coverage and continuity leads to realistic feature maps (Carreira-Perpiñán et al. 2005; Goodhill & Cimponeriu 2000)

This course focuses on a mechanistic circuit models, not normative models (ICA, Infomax, PCA, principal surfaces) or feature space models (elastic net), both of which are hard to relate directly to the underlying biological systems.

Summary

- Basic intro to visual modeling
- Adult models are well established, but vision-specific
- SOM: maps multiple dimensions down to two
- Feature maps: Principal surfaces?

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