

# Cortical Coding of Visual Information

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In the last decade the opportunity emerges to exceed the formal framework of ANNs, by referring more decisively to models derived in Neurosciences

### ***Getting physical***

*“Just as in analogue computation, where the physical process is the computation, so in the neocortex the physical structure provides us with constraints that are so conspicuously absent from current ‘computational’ approaches. It is precisely a belief in the indivisibility of structure and function in the neocortex that now drives us back to confront the cortical microcircuits and ask in what sense they can be said to transform their biology into computation.”*

R.J. Douglas and K.A.C. Martin, *Opening the grey box*. TINS (1991)

## **Objective:**

individuation of structural principles underlying visual perception.

- To steer new experimental research
- To foster modeling studies on visual perception and cortical functional architecture
- To conceive innovative hardware and software artificial systems (analog computation, reactive systems)

A case study:

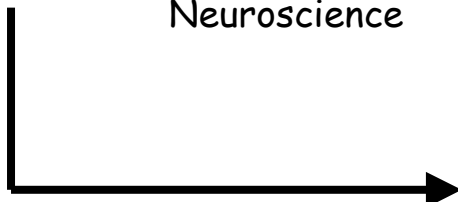
Gabor operators through neurophysiology,  
computational neuroscience, signal processing,  
neuromorphic engineering, computational vision

# Gabor operators



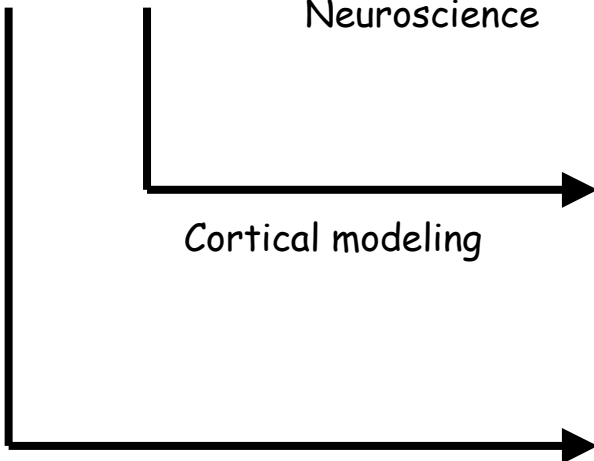
Neuroscience

Neurophysiological evidence of Gabor-like RFs in V1



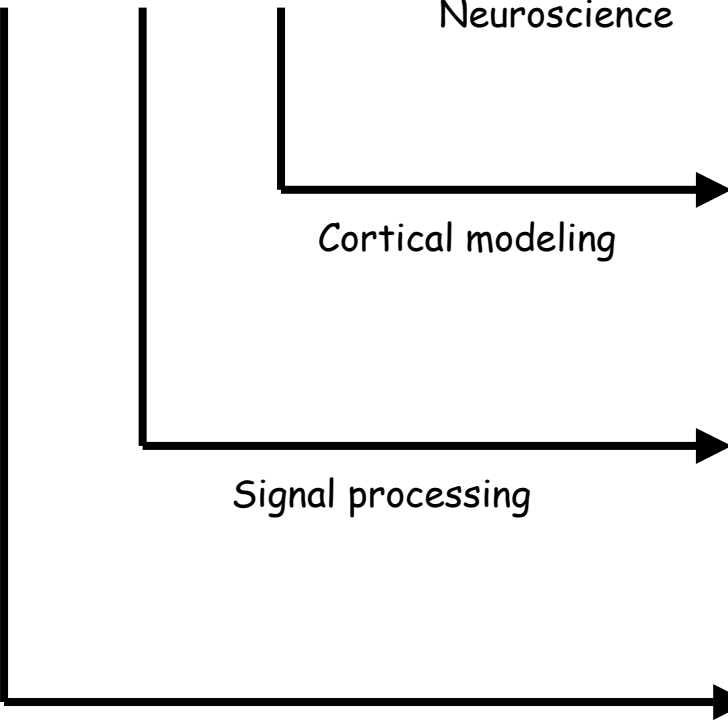
Cortical modeling

Optimal representation properties of Gabor functions



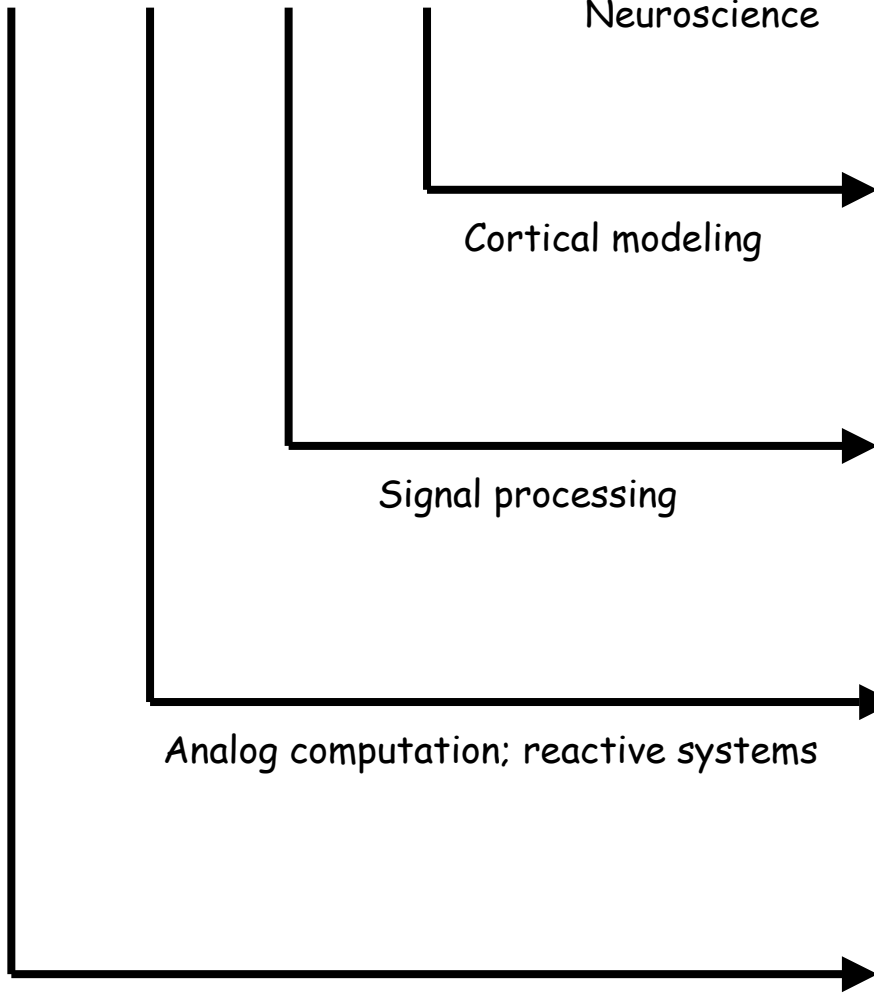
Signal processing

Gabor-like RF formation through a recurrent neural field model



Analog computation; reactive systems

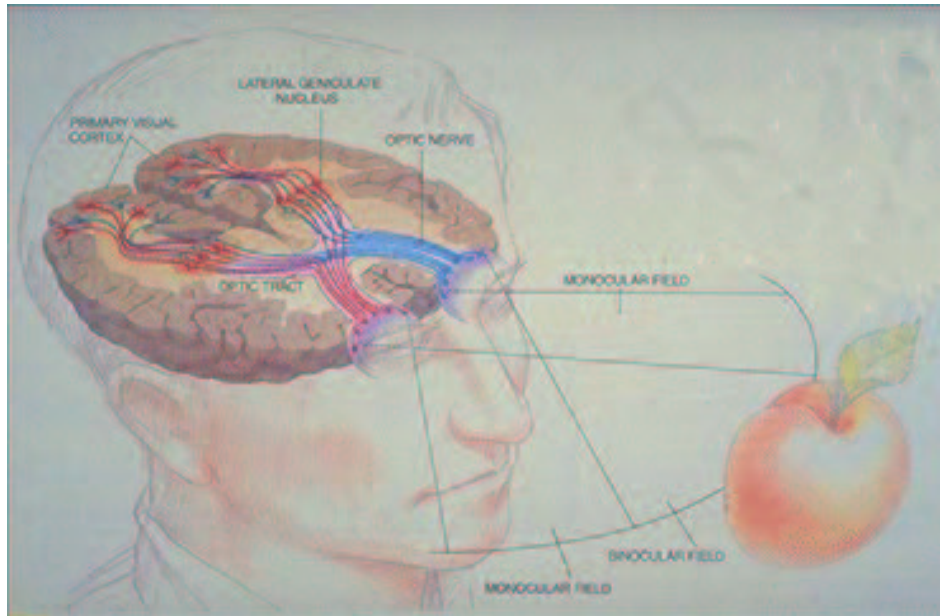
Analog Gabor-like filters on cooperative lattice networks



Applications to perceptual problems

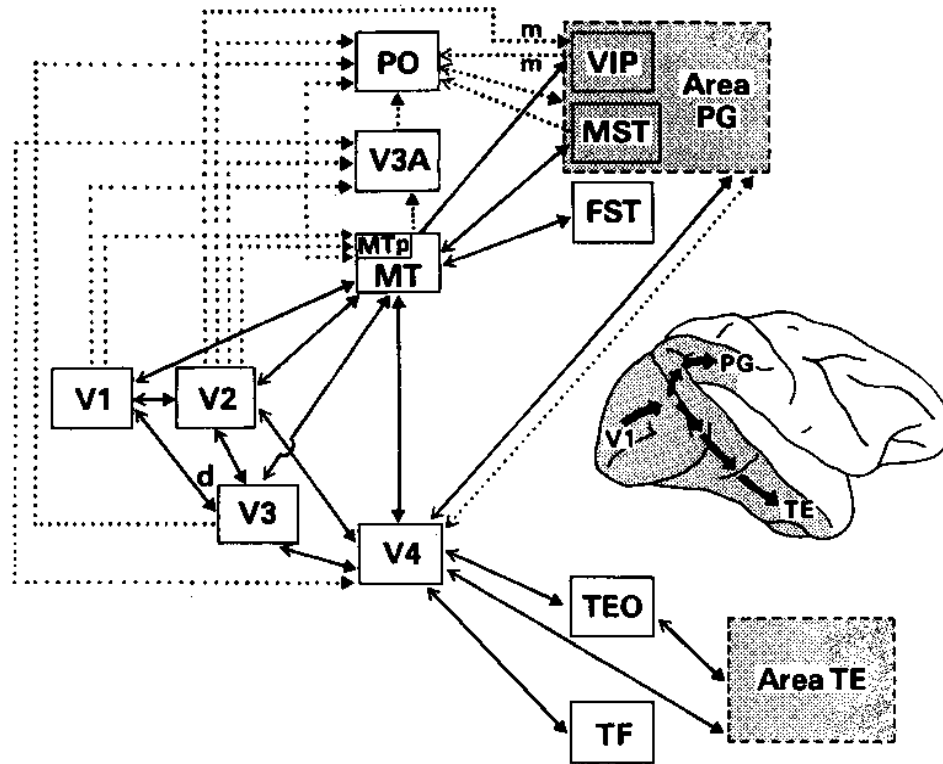
Biologically plausible algorithms for depth estimation based on Gabor filtering of stereo image pairs

# RETINOCORTICAL VISUAL PROCESSING

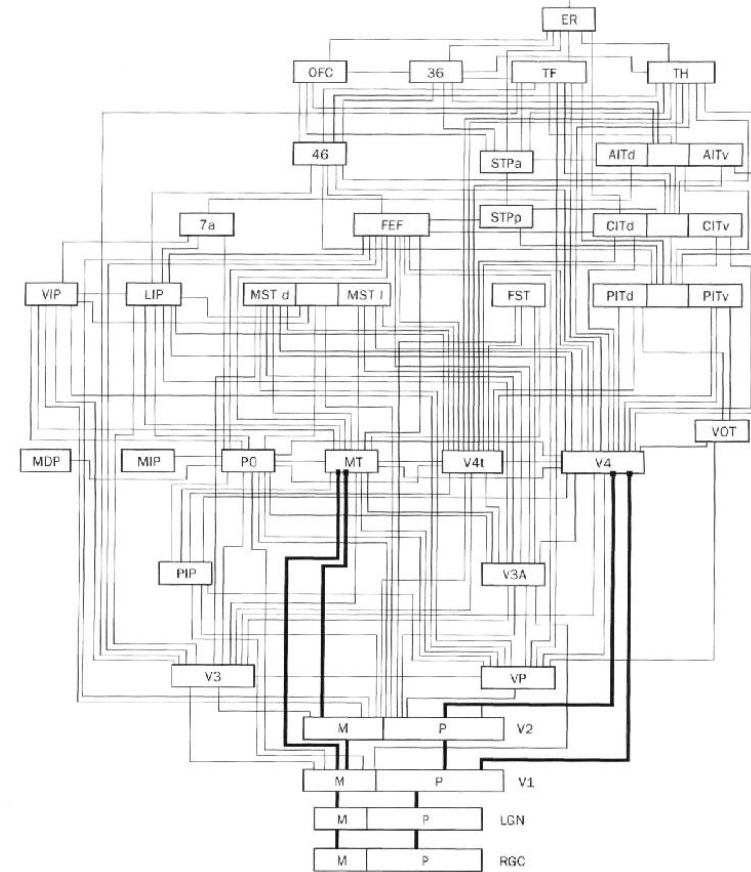


- Different neuronal nuclei (cortical and subcortical)
- More than 20 cortical areas
- $10^3 - 10^5$  neurons/ $mm^3$
- $10^6 - 10^9$  synapses/ $mm^3$

# CORTICAL FLOW CHARTS

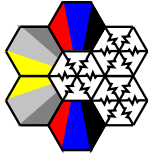


Desimone and Ungerleider, 1989



Van Essen *et al.*, 1991

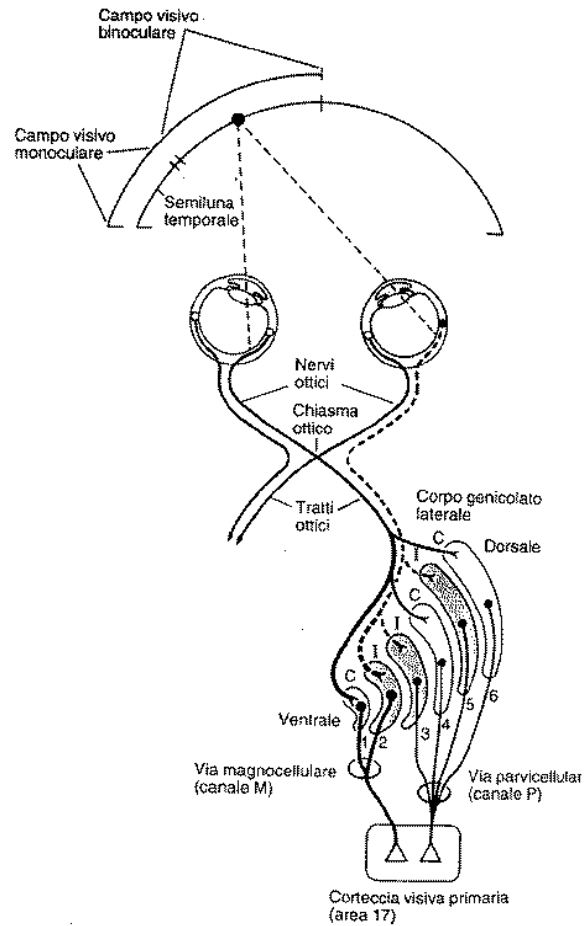
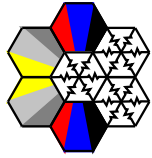
# GLOBAL RETINOTOPY



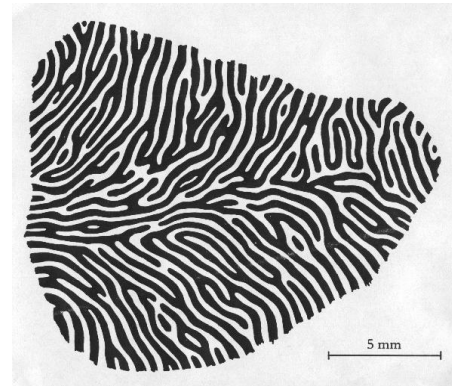
- Cortical mapping of inputs from the left and the right eyes and the ocular dominance columns
- Topographic (retinotopic) mapping



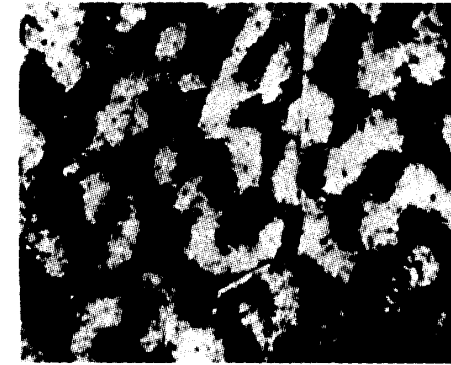
# OCULAR DOMINANCE COLUMNS



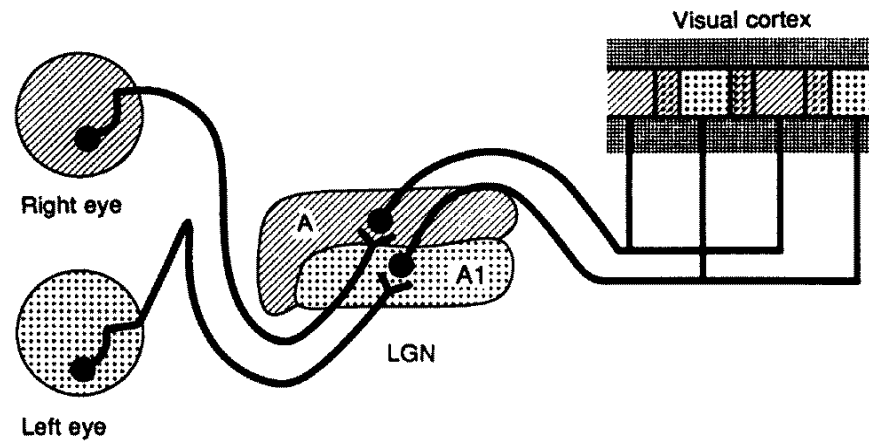
Kandel *et al.*, 1991



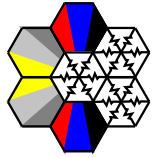
LeVay *et al.*, 1975



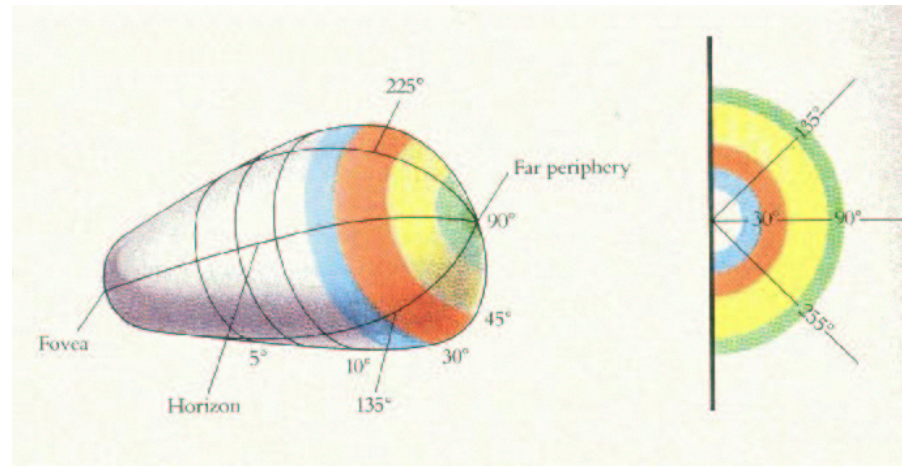
Miller *et al.*, 1989



Miller *et al.*, 1989



# RETINOTOPIC MAPPING

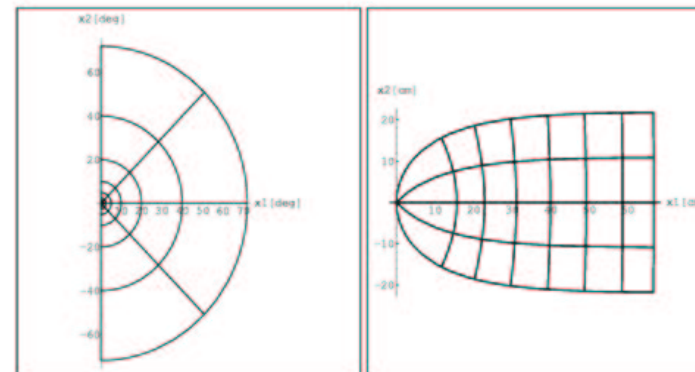


Hubel, 1988

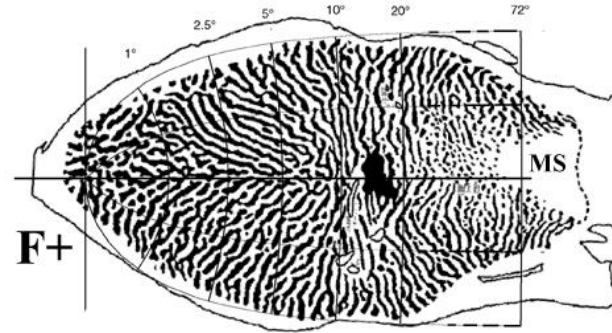
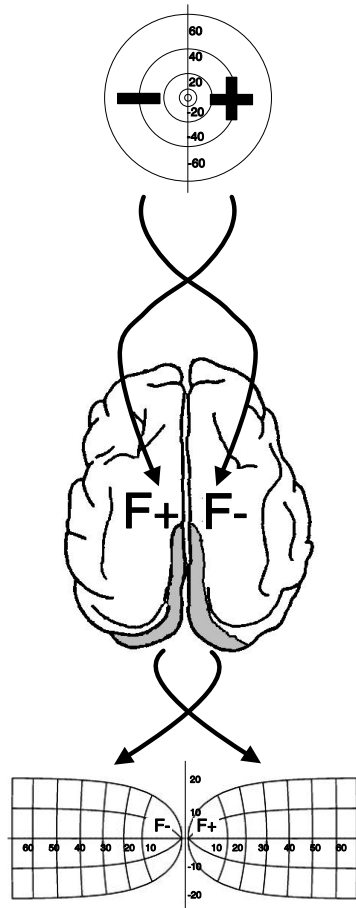
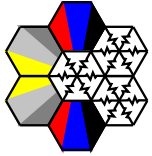
Formally:

$$\mathbf{x} = \log(\mathbf{z} + \alpha)$$

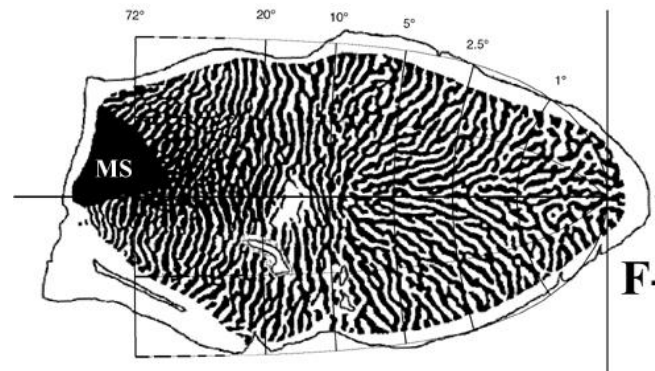
Schwartz, 1977



# RETINOTOPIC MAPPING (cont'd)

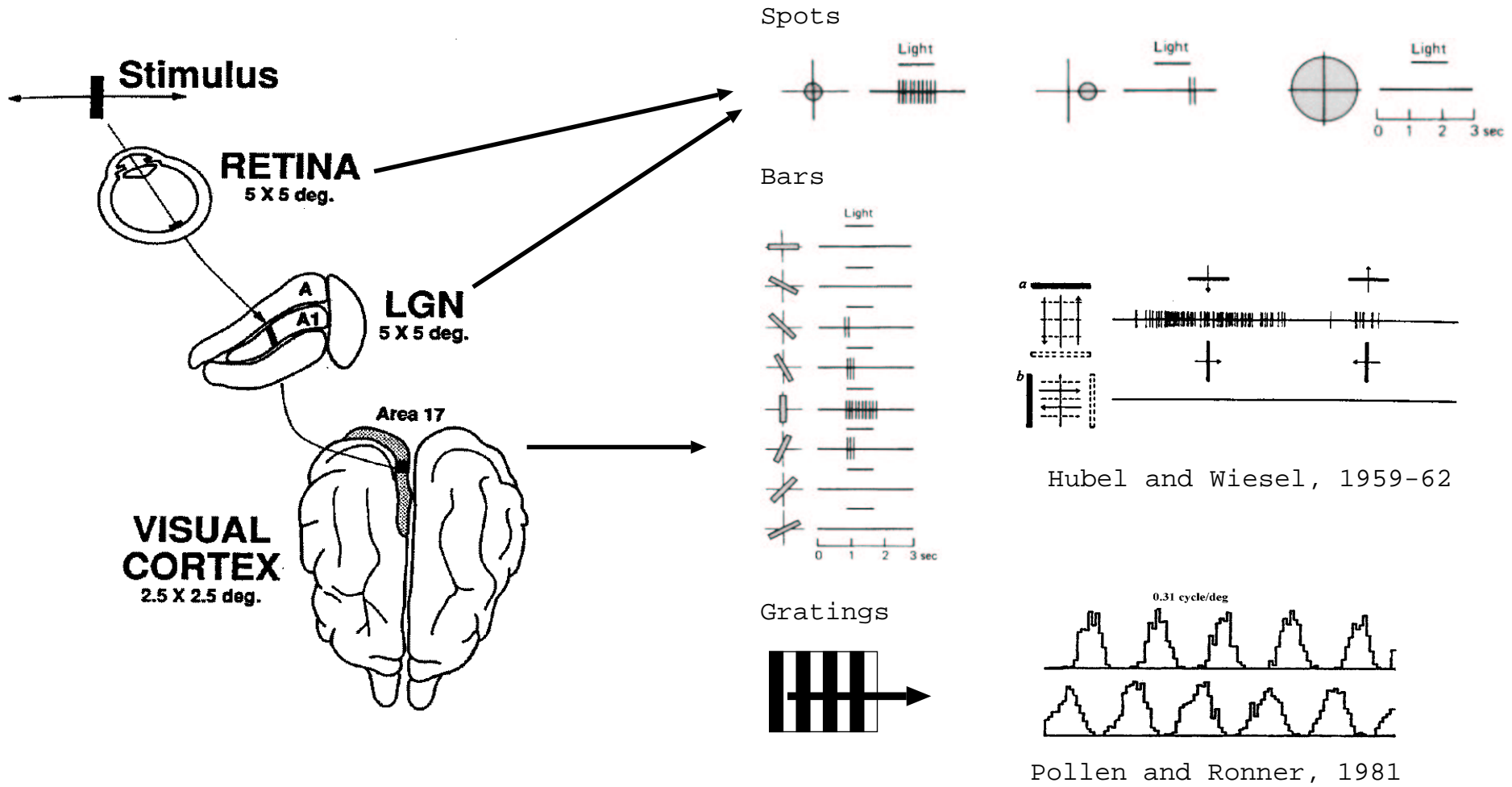


left hemisphere  
right hemifield



right hemisphere  
left hemifield

# THE PRIMARY VISUAL PATHWAY

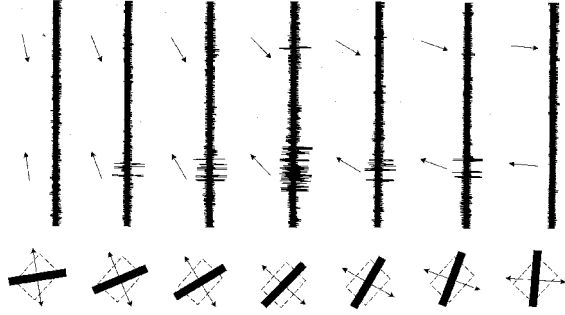


# Responses of neurons in the primary visual cortex (V1)



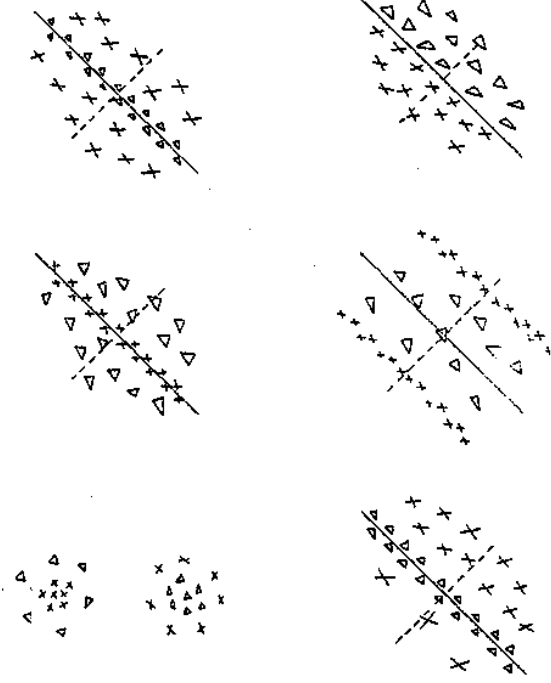
Hubel and Wiesel, circa 1969  
in Nicholls et al. (1992)

### Selectivity for stimulus orientation and direction



Hubel and Wiesel (1968)  
in Wandell (1995)

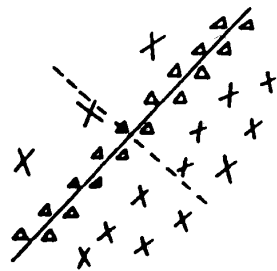
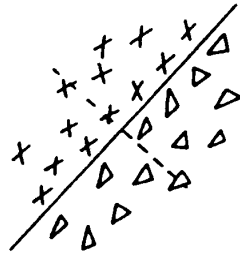
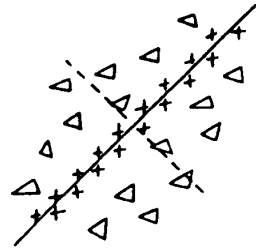
### Receptive fields of LGN and V1 simple cells



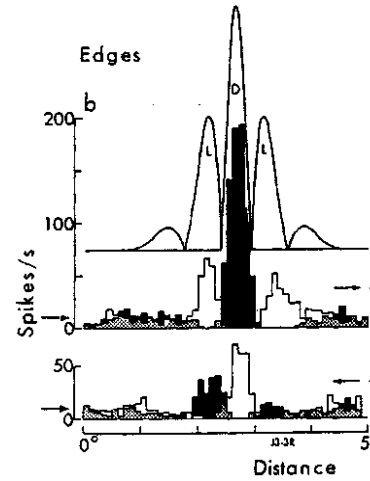
Hubel & Wiesel (1963)



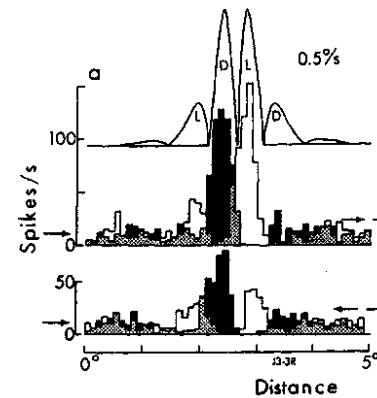
# THE SPATIAL STRUCTURE OF RECEPTIVE FIELDS IN V1



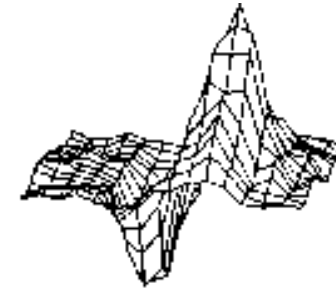
Hubel and Wiesel, 1962



Bars(0.1°) C=0.2

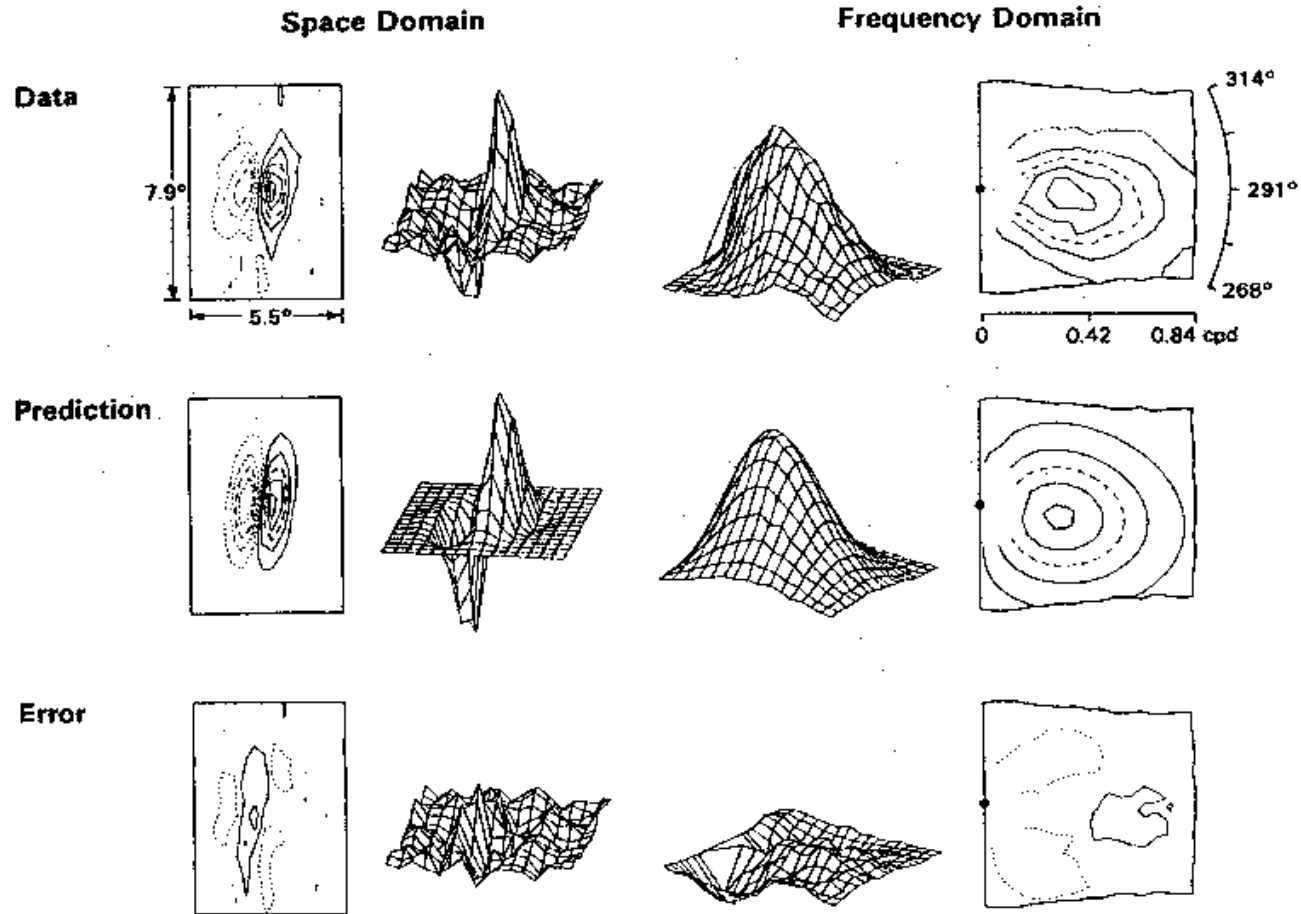


Kulikowski and Bishop, 1981



Jones and Palmer, 1987

# THE LINEARITY ASSUMPTION

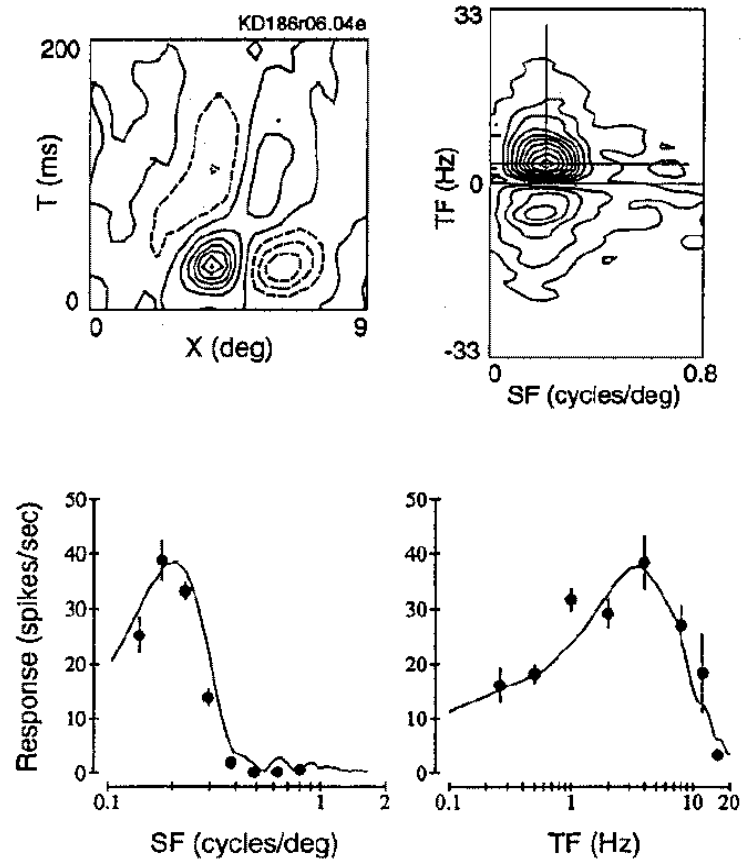


Jones and Palmer, 1987

*PSPC-Group*



# THE LINEARITY ASSUMPTION

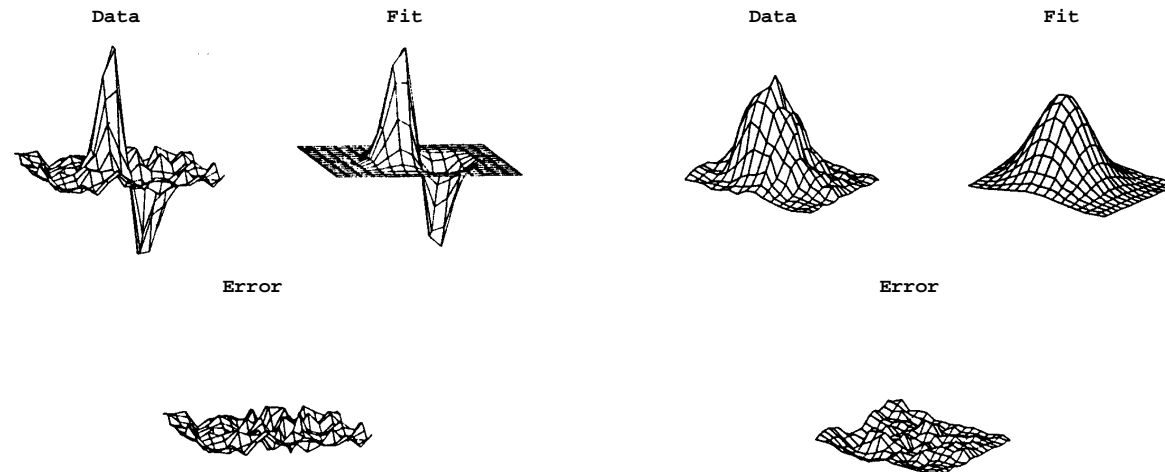


DeAngelis *et al.*, 1993

# GABOR-LIKE RECEPTIVE FIELDS



$$h(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \cos(f_0x + \phi) \quad \bullet \quad H(f_x, f_y) = \frac{1}{2} e^{-2\pi^2\sigma^2(f_x^2+f_y^2)} * [e^{j\phi}\delta(f_x - f_0) + e^{-j\phi}\delta(f_x + f_0)]$$

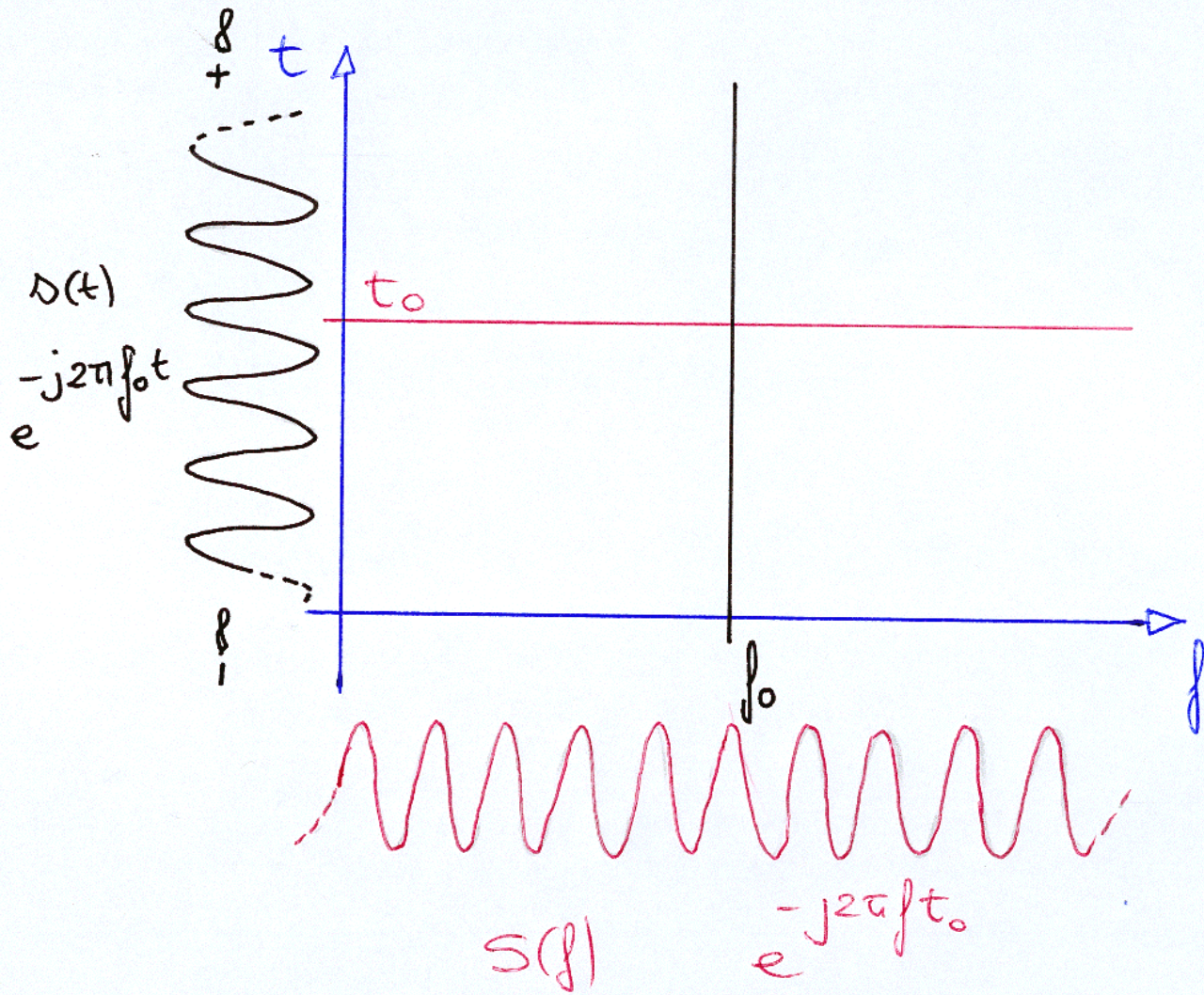


Jones and Palmer, 1987

Gabor functions are characterized by optimal localization properties in both spatial and spatial-frequency domains (Daugman, 1984)

$$\Delta x \Delta y \Delta f_x \Delta f_y \longrightarrow 1/16\pi^2$$

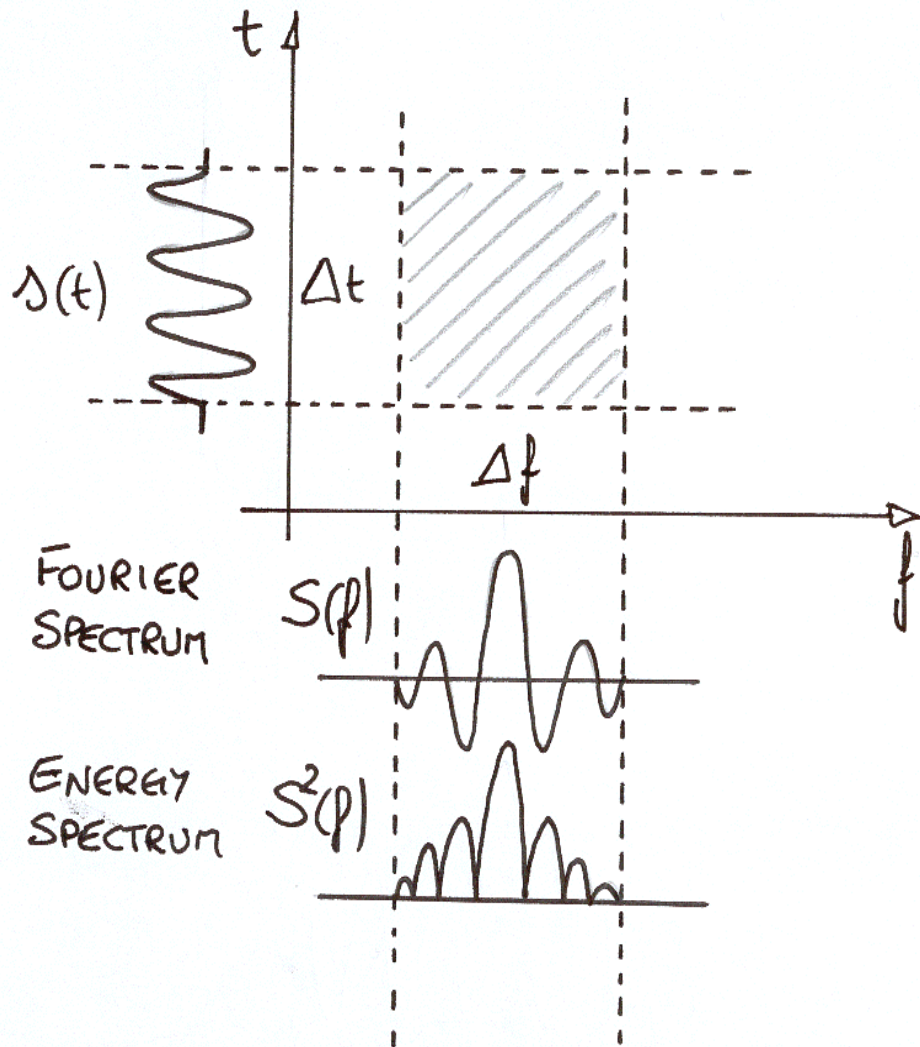
# JOINT LOCALIZATION IN TIME (SPACE) AND FREQUENCY



INFORMATION  
DIAGRAMS



# JOINT LOCALIZATION IN TIME (SPACE) AND FREQUENCY (CONT'D)



INFORMATION  $\propto \Delta t \Delta f$

HEISENBERG PRINCIPLE

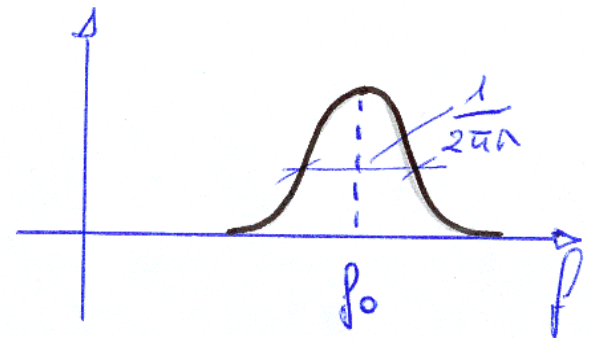
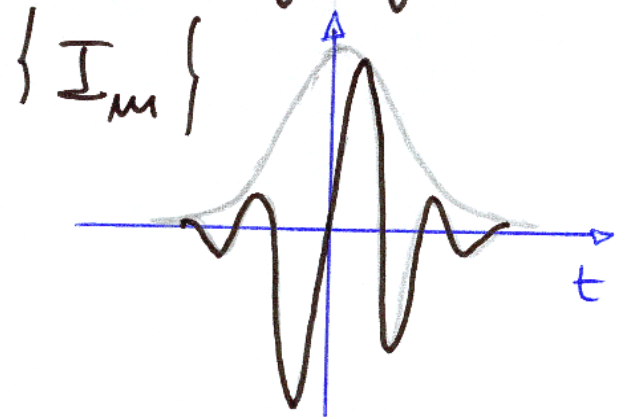
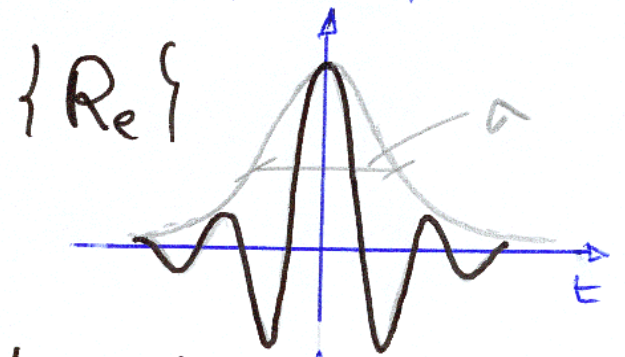
$$\Delta t \Delta f \geq \frac{1}{4\pi}$$

# THE 1-D GABOR LOGON (GABOR, 1946)

$$h(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t-t_0)^2}{2\sigma^2}} \cdot e^{2\pi j f_0 t}$$

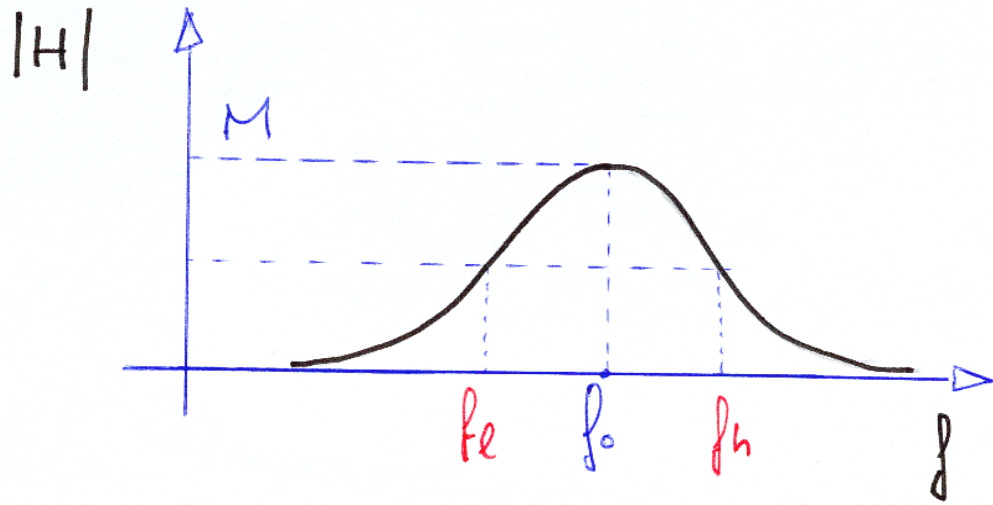
$$\Delta t \Delta f = \frac{1}{4\pi}$$

$$H(f) = e^{-2(f-f_0)^2 \pi^2 \sigma^2} \cdot e^{-2\pi j f t_0}$$



BAND-PASS FILTER

# FREQUENCY CHARACTERIZATION



$$|H(f)| = \frac{1}{2} |H(f)|_{\text{MAX}} = \frac{M}{2}$$

$$f = f_e \cdot f_h$$

$$f_0 = \text{PEAK FREQUENCY}$$

ABSOLUTE BANDWIDTH :

$$\Delta f = f_h - f_e$$

RELATIVE BANDWIDTH :

$$B_{df} = \frac{\Delta f}{f_0} = \frac{f_h}{f_0} - \frac{f_e}{f_0}$$

OCTAVE RELATIVE  
BANDWIDTH :

$$B_{\text{oct}} = \log_2 \frac{f_h}{f_e}$$

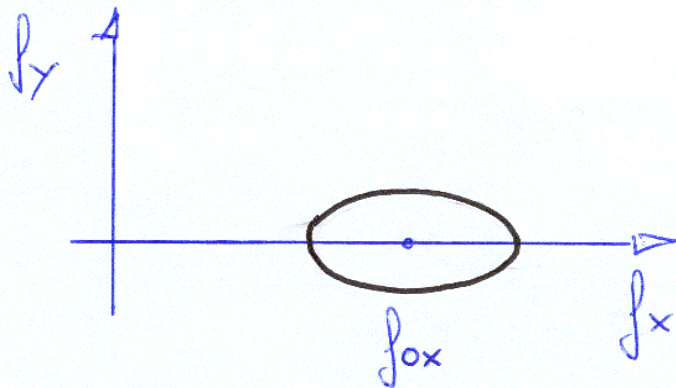
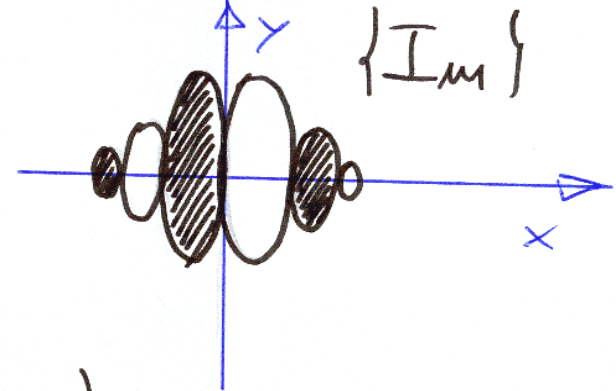
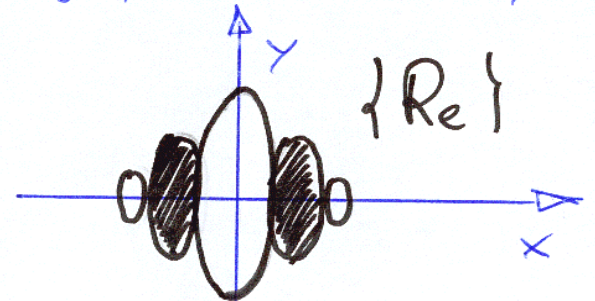


# THE 2-D GABOR LOGION (MARČELJA, 1980; DAUGHTAN, 1985)

$$h(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{(x-x_0)^2}{2\sigma_x^2} - \frac{(y-y_0)^2}{2\sigma_y^2}} \cdot e^{2\pi j f_{0x} x}$$

$$\Delta x \Delta y \Delta f_x \Delta f_y = \frac{1}{16\pi^2}$$

$$H(f_x, f_y) = e^{-2(f_x - f_{0x})^2 \sigma_x^2 \pi^2 - 2f_y^2 \sigma_y^2 \pi^2} \cdot e^{-2\pi j (f_x x_0 + f_y y_0)}$$



in general ....

# THE 2-D GABOR LOGION

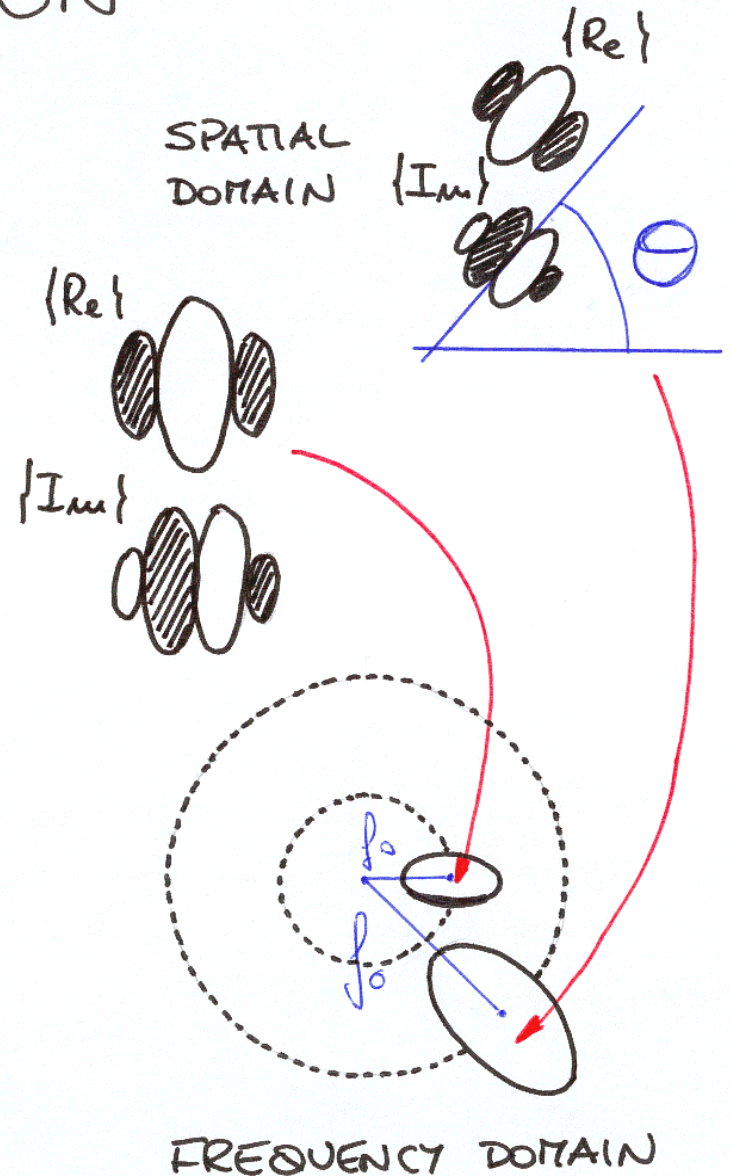
$$h(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{(x')^2}{2\sigma_x^2} - \frac{(y')^2}{2\sigma_y^2}} e^{2\pi j f_0 x'}$$

WITH

$$\begin{cases} x' = (x-x_0)\cos\theta + (y-y_0)\sin\theta \\ y' = -(x-x_0)\sin\theta + (y-y_0)\cos\theta \end{cases}$$

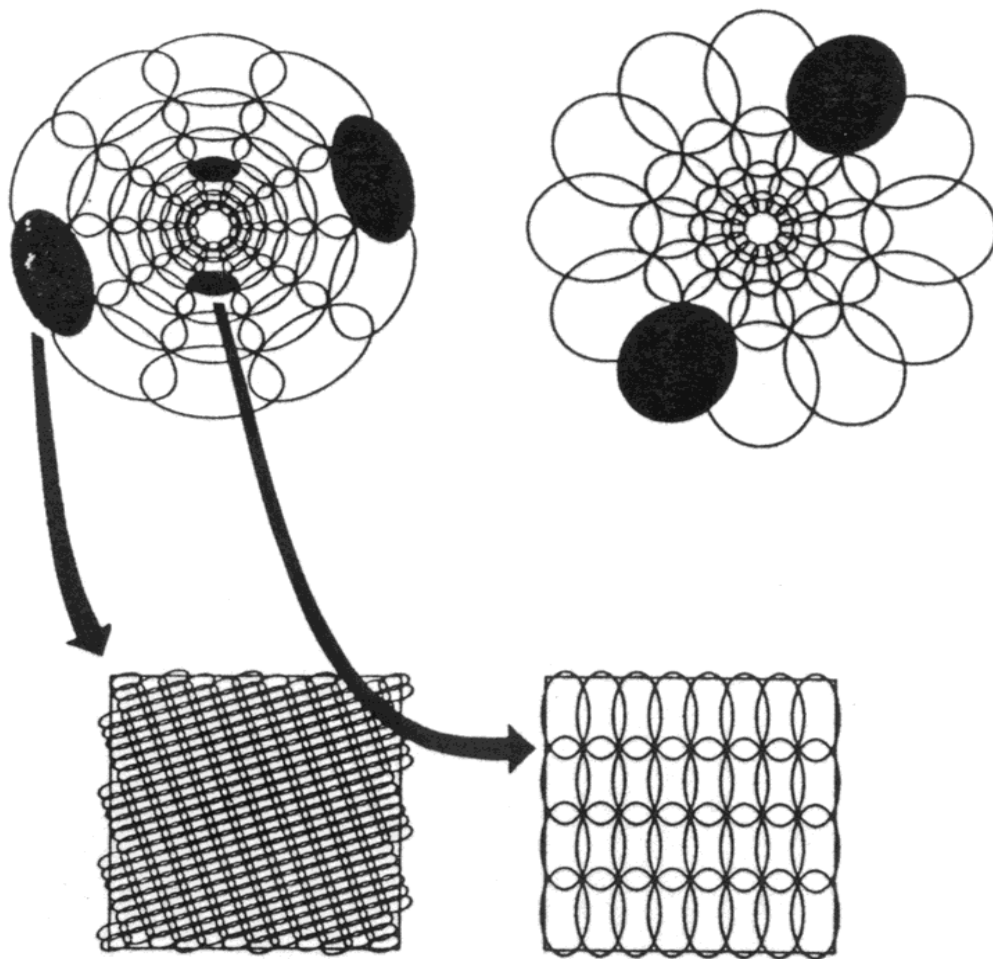
$$\theta = \arctan \frac{f_{0y}}{f_{0x}}$$

$$f_0 = \sqrt{f_{0x}^2 + f_{0y}^2} = \text{RADIAL PEAK FREQUENCY}$$





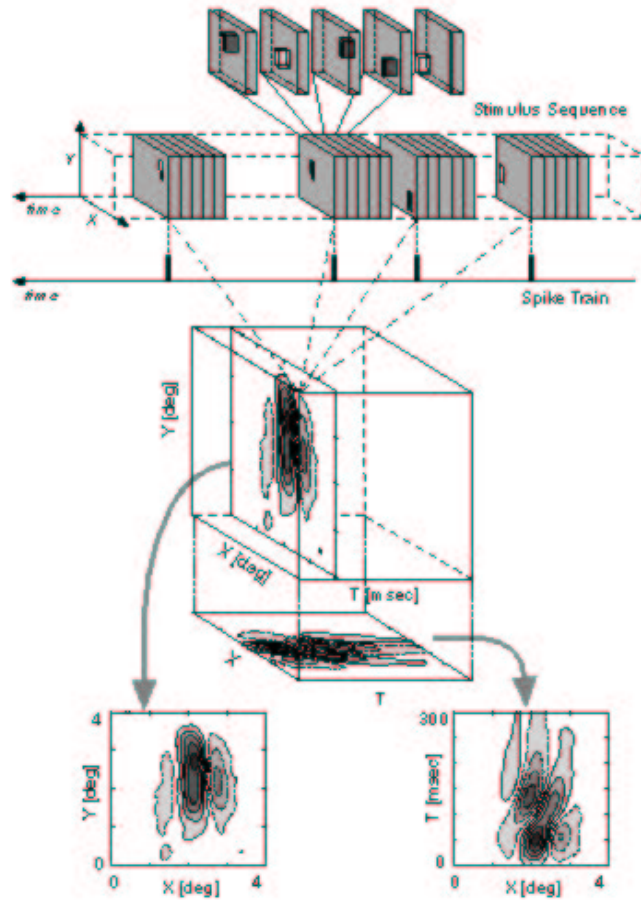
# DAISY DIAGRAMS



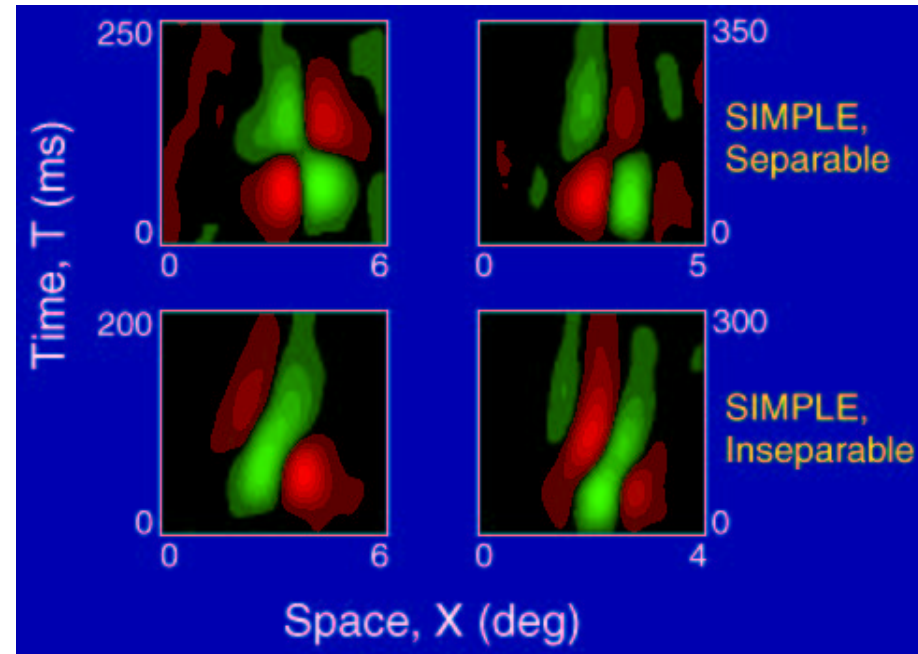
Frequency domain

Spatial domain

# SPATIO-TEMPORAL RFs IN V1



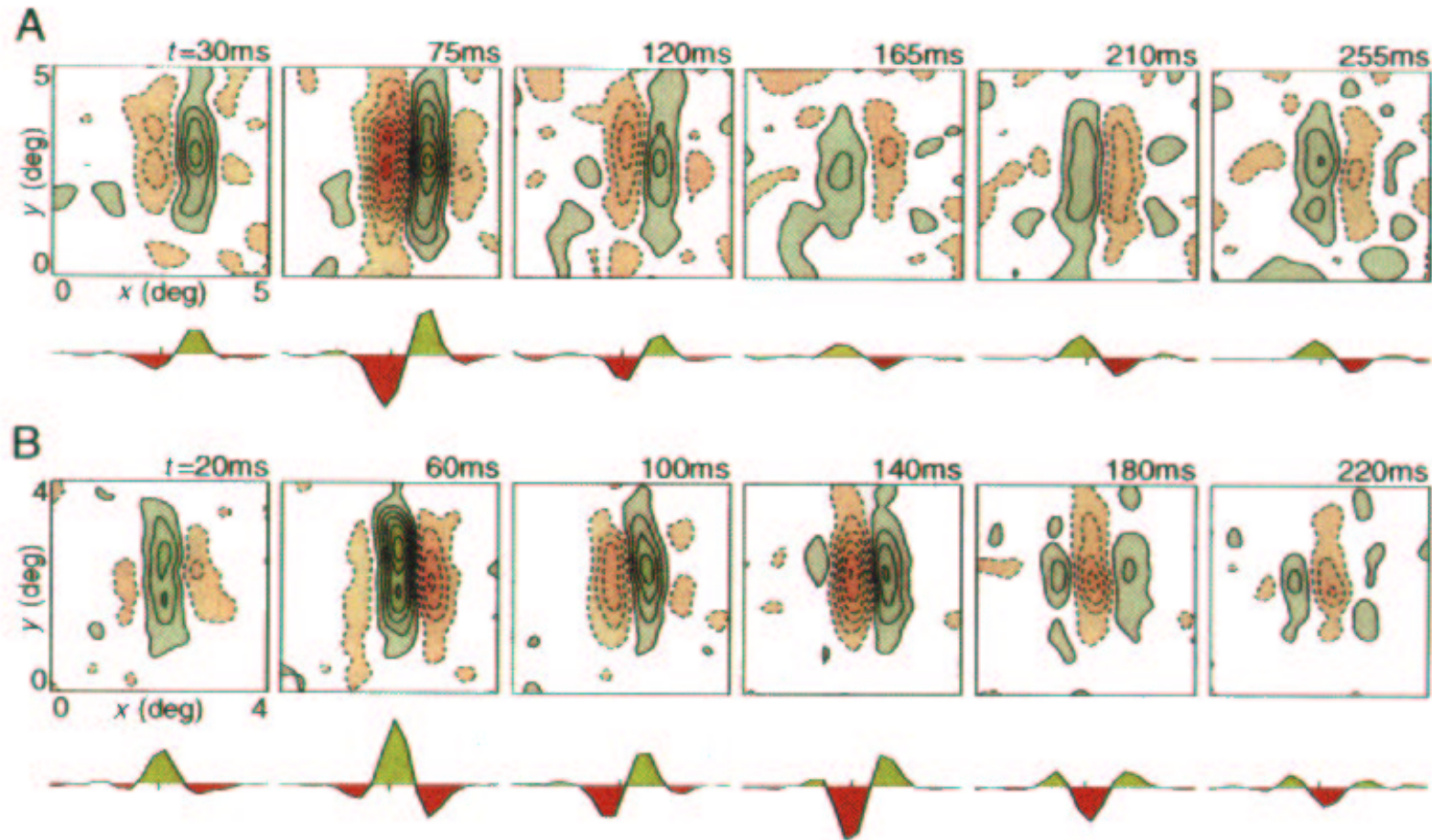
Ohzawa *et al.*, 1996



DeAngelis *et al.*, 1995



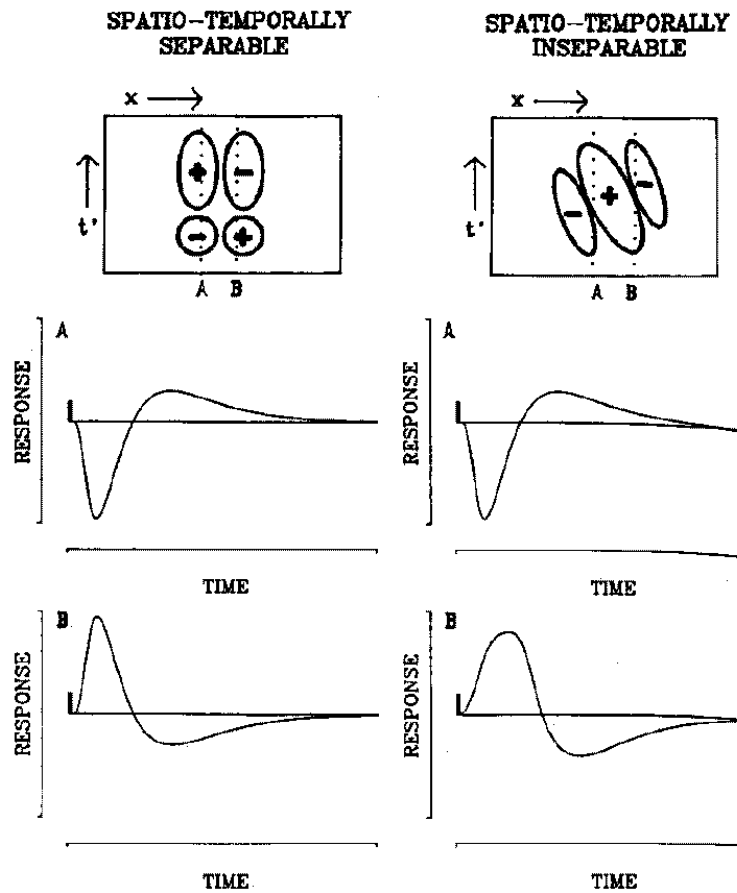
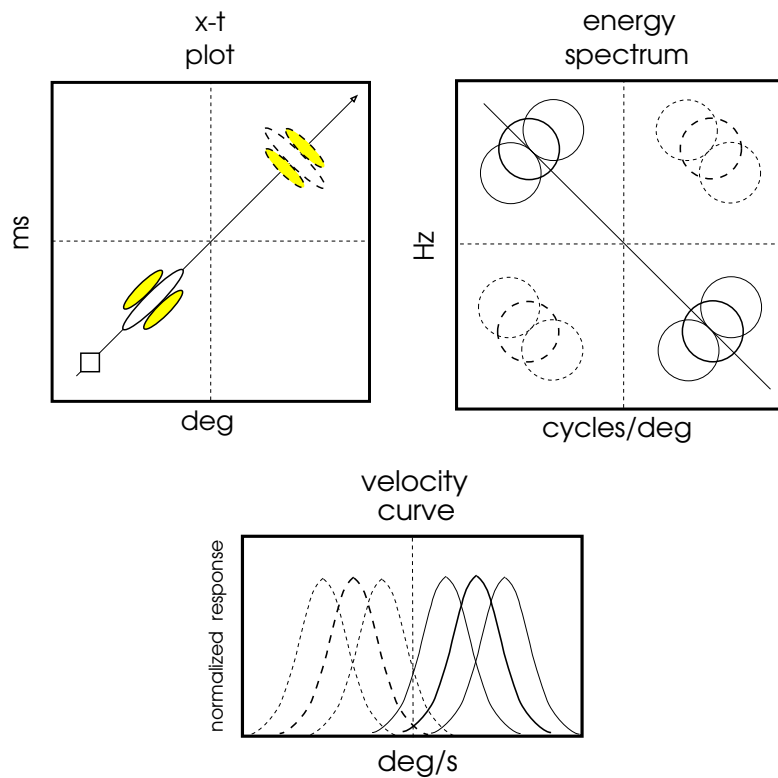
# DYNAMICS OF THE RF STRUCTURE OF SIMPLE CELLS



DeAngelis *et al.*, 1995

*PSPC-Group*

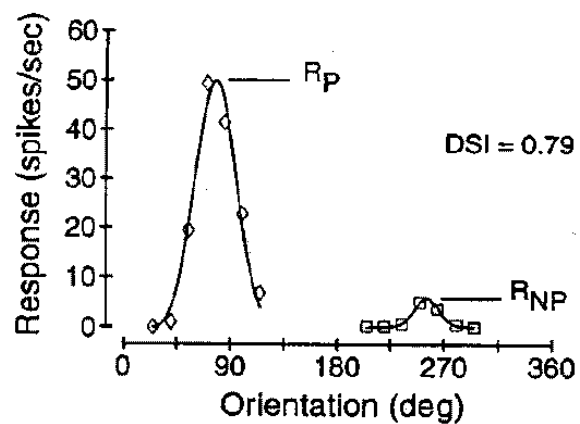
# SPATIO-TEMPORAL FUNCTIONALITY



Reid *et al.*, 1991

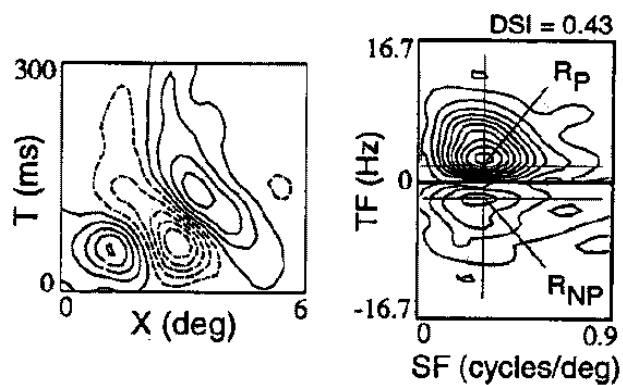


# DIRECTION SELECTIVITY



Direction Selectivity Index

$$DSI = \frac{R_P - R_{NP}}{R_P}$$



DeAngelis *et al.*, 1993



## Structural

- Presence of a surprising regularity
  - Subregions wax and wane smoothly in every direction
  - Spatial phase is continuously variable (not just odd and even symmetry)
- Highly specific joint space-time behaviour

## Functional

- Frequency selectivity
- Direction selectivity
- ...
- Orientation tuning
- End-stopping

but how do they acquire their properties?

# MODELS OF SIMPLE CELL *RF* SPECIFICITY

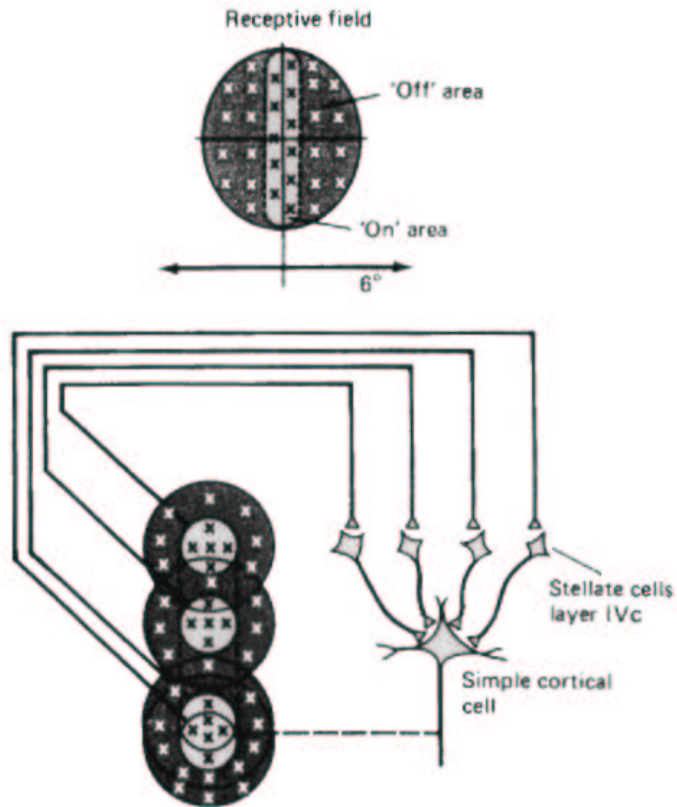


- Filter Models (Marcelja, 1980; Daugman, 1984; Adelson and Bergen, 1985)
- Developmental Models (von der Malsburg, 1973; Linsker, 1986; Miller, 1994; Wimbauer *et al.*, 1997)
- Architectural Models
  - Biophysically Realistic Models (Wörgötter and Koch, 1991; Somers, 1997; Suarez *et al.*, 1995)
  - Functional/Structural Models (Mitchison, 1985; Matsubara *et al.*, 1985)
  - Neural Field Models (Krone *et al.*, 1986; Mallot, 1996; Amari, 1977)

# FEED-FORWARD vs FEED-BACK MODELS

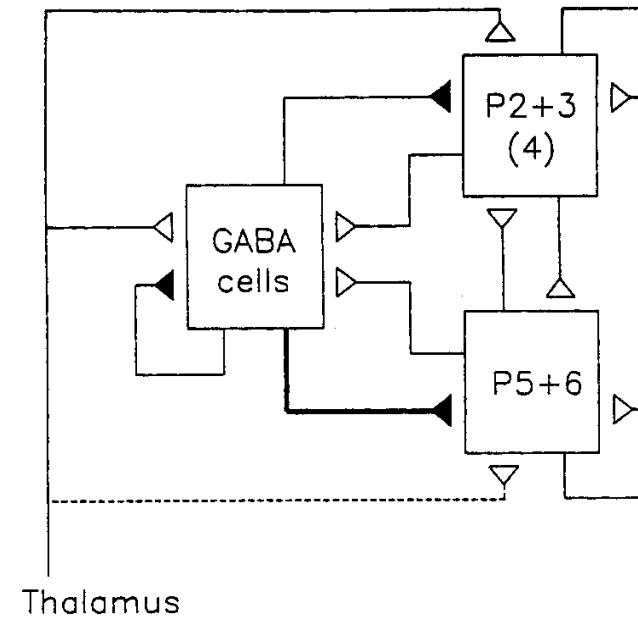


Geniculo-cortical convergence



Hubel and Wiesel, 1962

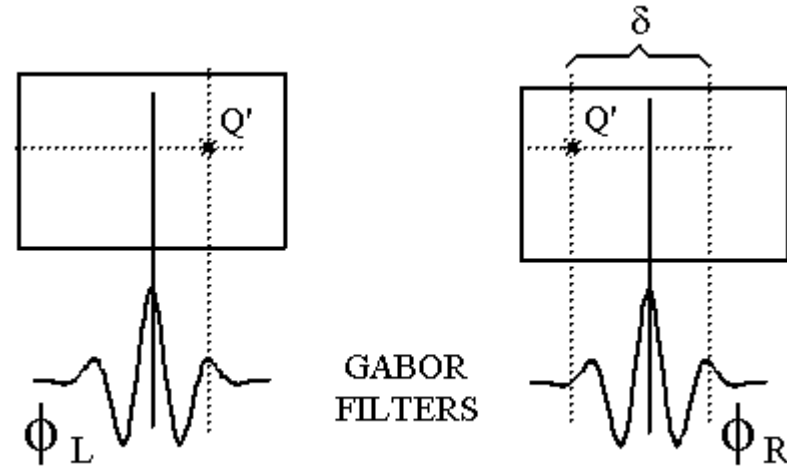
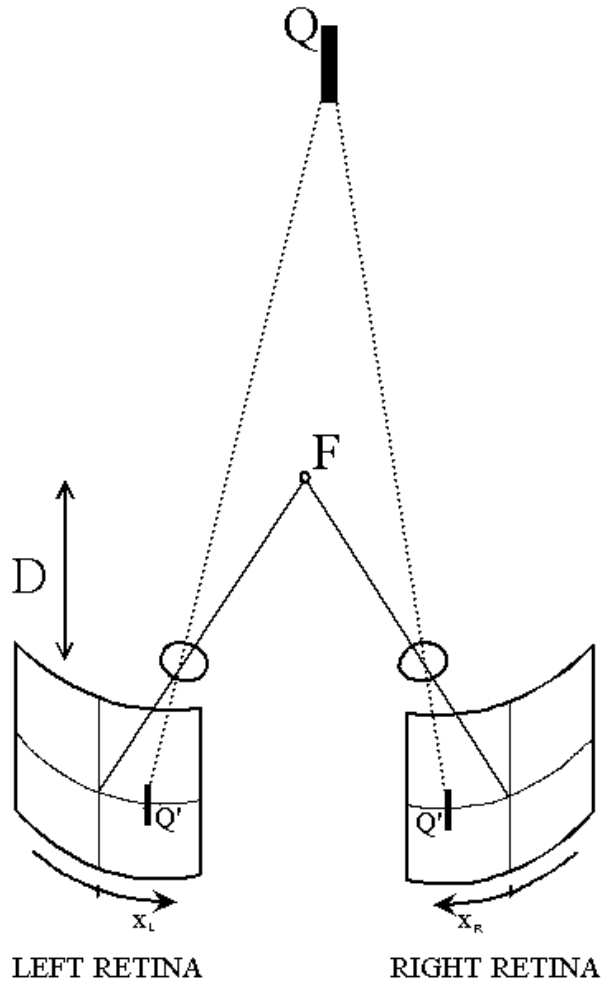
Canonical cortical microcircuit



Douglas *et al.*, 1989



# THE STEREO PROBLEM



$$\delta \propto \Delta\phi = \phi_R - \phi_L$$

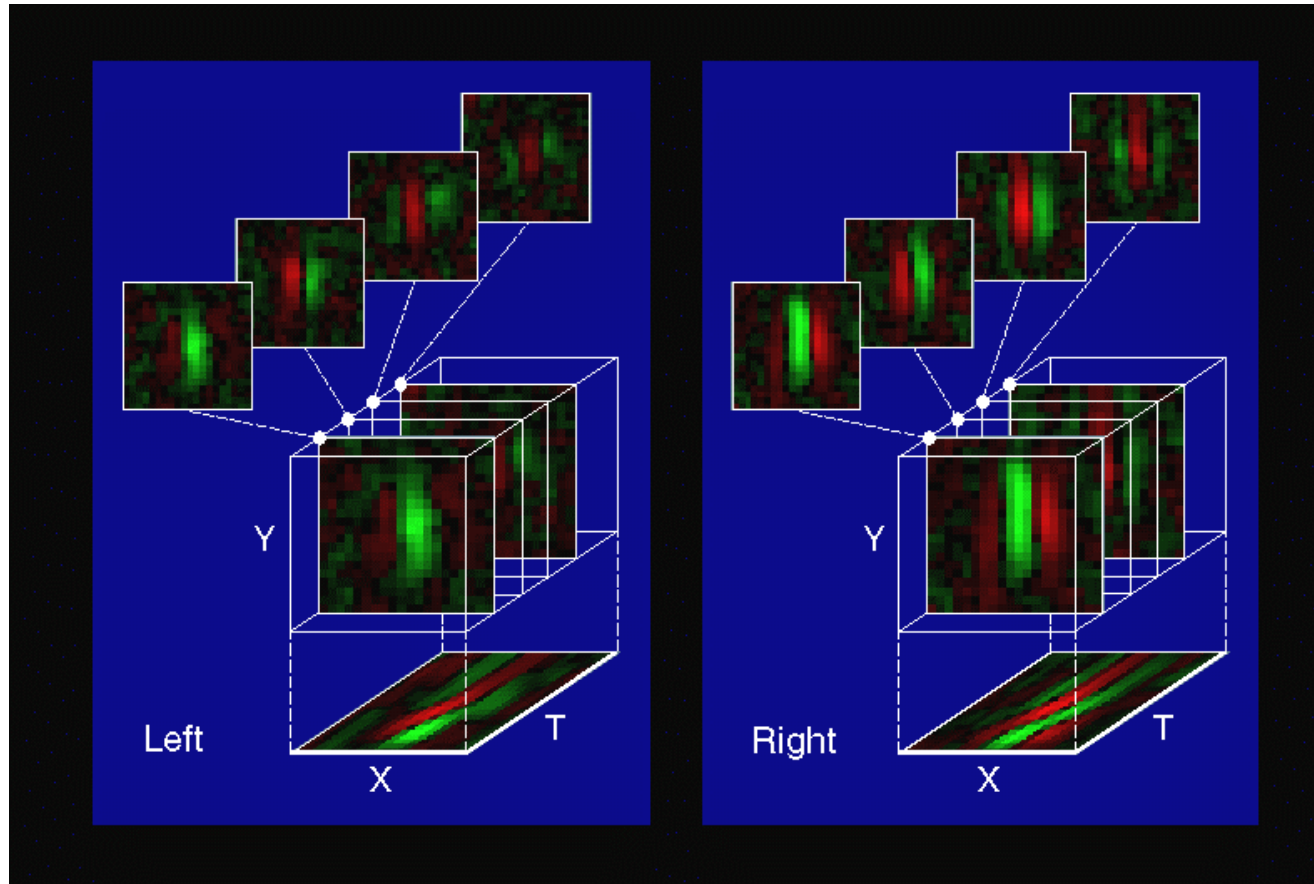
Fourier shift theorem

$$I^L(n) = I^R(n + \delta(n))$$

# THE STEREO PROBLEM



## The natural solution



Ohzawa I. et al., The Neural Coding of Stereoscopic Depth. *NeuroReport*, 8 (no. 3): 3-12, 1997

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# BINOCULAR PERCEPTION OF MID

Motion-in-depth

$d/dt$

Disparity

Left  
eye

Right  
eye

Disparity rate  
of change

Motion-in-depth

Velocity differences

$d/dt$

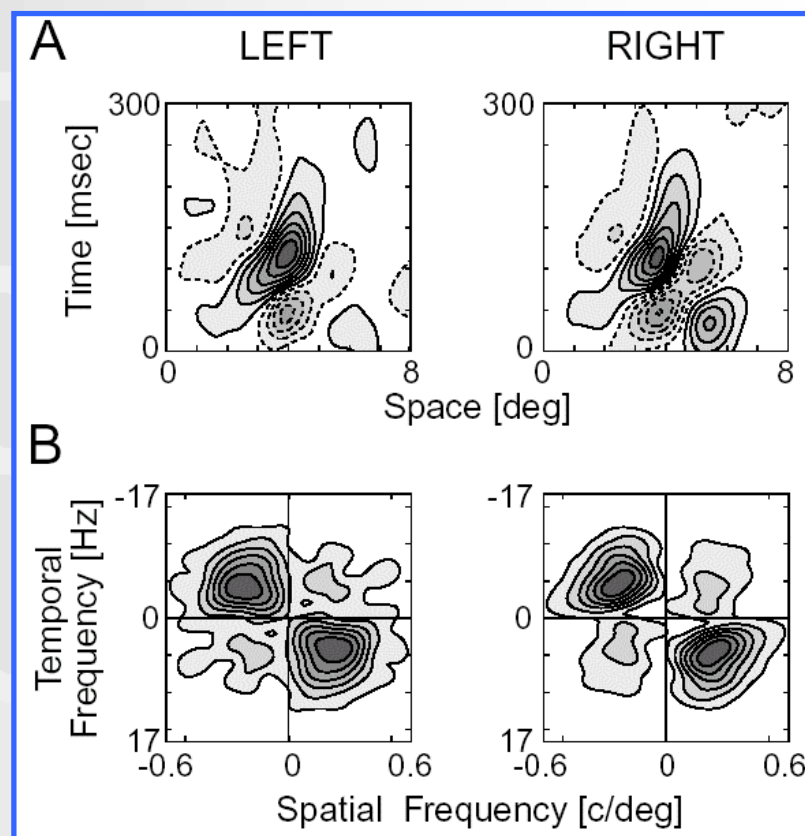
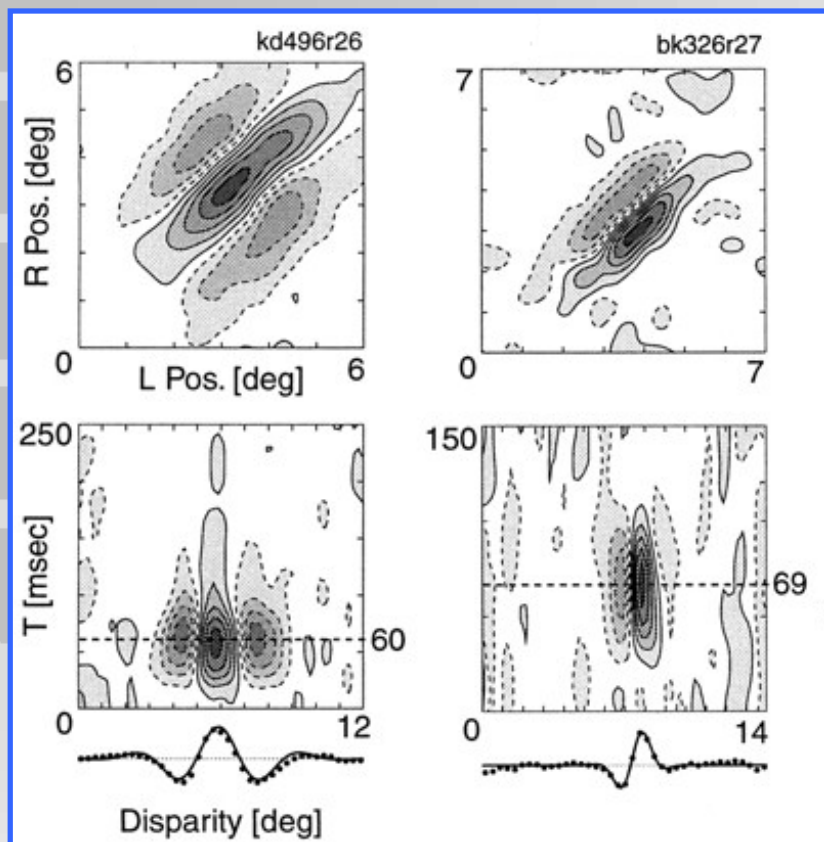
$d/dt$

Left  
eye

Right  
eye

Interocular velocity  
difference

# ENCODING OF DYNAMIC 3-D VISUAL INFORMATION IN THE VISUAL CORTEX

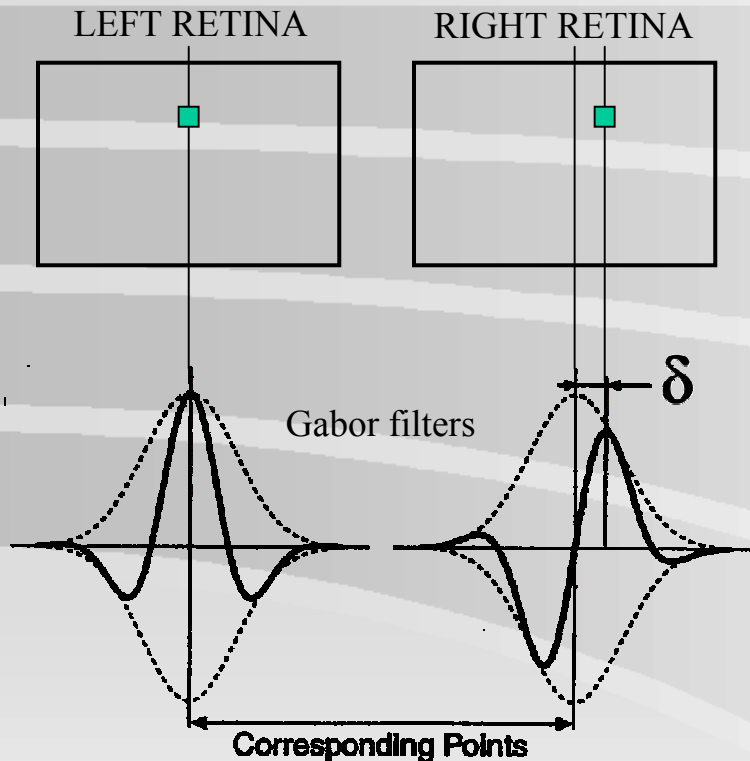


[Ohzawa *et al.* 1997]

[Ohzawa *et al.* 1996]

# PHASE-BASED DYNAMIC STEREOPSIS

## Disparity as phase difference



$$I^R(x) = I^L[x + \delta(x)]$$

$$I^L[x + \delta(x)] \xleftrightarrow{\mathcal{F}} \tilde{I}(k)e^{jk\delta}$$

$$\delta(x) = \frac{|\Delta\phi(x)|_{2\pi}}{k_0} = \frac{\arg[Q^L] - \arg[Q^R]}{k_0}$$

where

$$\begin{aligned} Q(x) &= \int I(\xi)h(x - \xi; k_0)d\xi = \\ &= C(x) + jS(x) \end{aligned}$$

with  $h(x; k_0) = e^{-x^2 / \sigma^2} e^{jk_0x}$

# PHASE-BASED DYNAMIC STEREOPSIS

## Motion-in-depth

The total rate of variation of disparity can be written as

$$\frac{d\delta}{dt} = \frac{\partial\delta}{\partial t} + \frac{v^L}{k_0} (\phi_x^L - \phi_x^R)$$

Considering the conservation properties of local phase

$$\phi_x^L = -\frac{\phi_t^L}{v^L} \quad \text{and} \quad \phi_x^R = -\frac{\phi_t^R}{v^R}$$

# PHASE-BASED DYNAMIC STEREOPSIS

## Motion-in-depth

The total rate of variation of disparity can be written as

$$\frac{d\delta}{dt} = \frac{\partial\delta}{\partial t} + \frac{v^L}{k_0} (\phi_x^L - \phi_x^R)$$

Considering the conservation properties of local phase

$$\phi_x^L = -\frac{\phi_t^L}{v^L} \quad \text{and} \quad \phi_x^R = -\frac{\phi_t^R}{v^R}$$

Thus

$$\frac{d\delta}{dt} = \frac{\phi_x^R}{k_0} (v^R - v^L) \simeq \frac{\partial\delta}{\partial t} = \frac{\phi_t^L - \phi_t^R}{k_0} \simeq v^R - v^L$$

# PHASE-BASED DYNAMIC STEREOPSIS

## Motion-in-depth

The total rate of variation of disparity can be written as

$$\frac{d\delta}{dt} = \frac{\partial\delta}{\partial t} + \frac{v^L}{k_0} (\phi_x^L - \phi_x^R)$$

Considering the conservation properties of local phase

$$\phi_x^L = -\frac{\phi_t^L}{v^L} \quad \text{and} \quad \phi_x^R = -\frac{\phi_t^R}{v^R}$$

*Information hold in the interocular velocity difference is the same of that derived from the derivative of binocular disparity, if a phase-based disparity encoding scheme is assumed*



# PHASE-BASED DYNAMIC STEREOPSIS

## Spatio-temporal operators

Partial derivative of disparity can be directly computed by convolutions  $(S, C)$  of stereo image pairs and by their temporal derivatives  $(S_t, C_t)$

$$\frac{\partial \delta}{\partial t} = \left[ \frac{S_t^L C^L - S^L C_t^L}{(S^L)^2 + (C^L)^2} - \frac{S_t^R C^R - S^R C_t^R}{(S^R)^2 + (C^R)^2} \right] \frac{1}{k_0}$$

where

$$4SC_t = (S + C_t)^2 - (C_t - S)^2, \quad 4S_tC = (S_t + C)^2 - (S_t - C)^2$$

# PHASE-BASED DYNAMIC STEREOPSIS

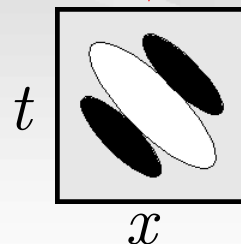
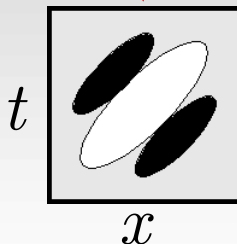
## Spatio-temporal operators

Partial derivative of disparity can be directly computed by convolutions ( $S, C$ ) of stereo image pairs and by their temporal derivatives ( $S_t, C_t$ )

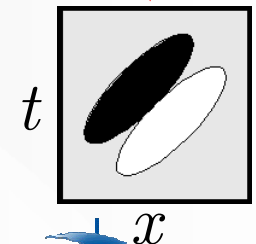
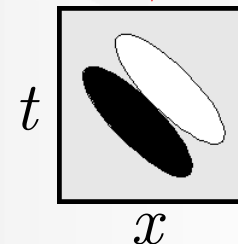
$$\frac{\partial \delta}{\partial t} = \left[ \frac{S_t^L C^L - S^L C_t^L}{(S^L)^2 + (C^L)^2} - \frac{S_t^R C^R - S^R C_t^R}{(S^R)^2 + (C^R)^2} \right] \frac{1}{k_0}$$

where

$$4SC_t = \underbrace{(S + C_t)^2}_{\downarrow} - \underbrace{(C_t - S)^2}_{\downarrow},$$



$$4S_t C = \underbrace{(S_t + C)^2}_{\downarrow} - \underbrace{(S_t - C)^2}_{\downarrow}$$



# PHASE-BASED DYNAMIC STEREOPSIS

## Spatio-temporal operators

Partial derivative of disparity can be directly computed by convolutions ( $S, C$ ) of stereo image pairs and by their temporal derivatives ( $S_t, C_t$ )

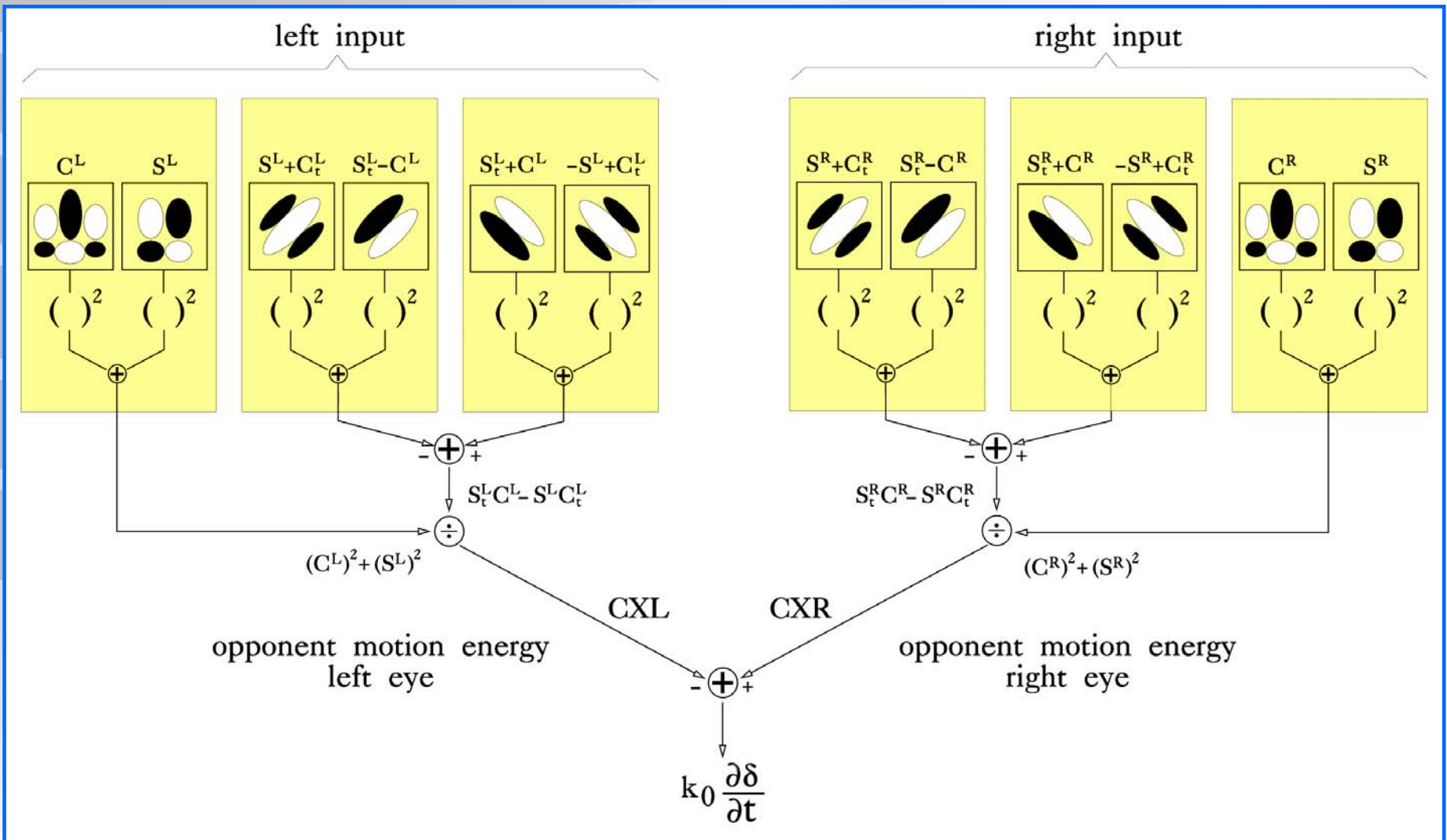
$$\frac{\partial \delta}{\partial t} = \left[ \frac{S_t^L C^L - S^L C_t^L}{(S^L)^2 + (C^L)^2} - \frac{S_t^R C^R - S^R C_t^R}{(S^R)^2 + (C^R)^2} \right] \frac{1}{k_0}$$

where

$$4SC_t = (S + C_t)^2 - (C_t - S)^2, \quad 4S_tC = (S_t + C)^2 - (S_t - C)^2$$

*$\partial \delta / \partial t$  is expressed through convolutions with a set of spatio-temporal filters whose shapes resemble simple cell RFs*

# CORTICAL MODEL (I)



# CORTICAL MODEL (II)

$$S_1 = (1 - \alpha)(C_t^L + S^L) - \alpha(C^R - S_t^R)$$

$$S_2 = (1 - \alpha)(C^L + S_t^L) + \alpha(C_t^R + S^R)$$

$$S_3 = (1 - \alpha)(C_t^L - S^L) - \alpha(C^R + S_t^R)$$

$$S_4 = (1 - \alpha)(C^L + S_t^L) + \alpha(C_t^R - S^R)$$

$$S_5 = \alpha(C_t^L + S^L) - (1 - \alpha)(C^R - S_t^R)$$

$$S_6 = \alpha(C^L - S_t^L) + (1 - \alpha)(C_t^R + S^R)$$

$$S_7 = \alpha(C_t^L - S^L) - (1 - \alpha)(C^R + S_t^R)$$

$$S_8 = \alpha(C^L + S_t^L) + (1 - \alpha)(C_t^R - S^R)$$

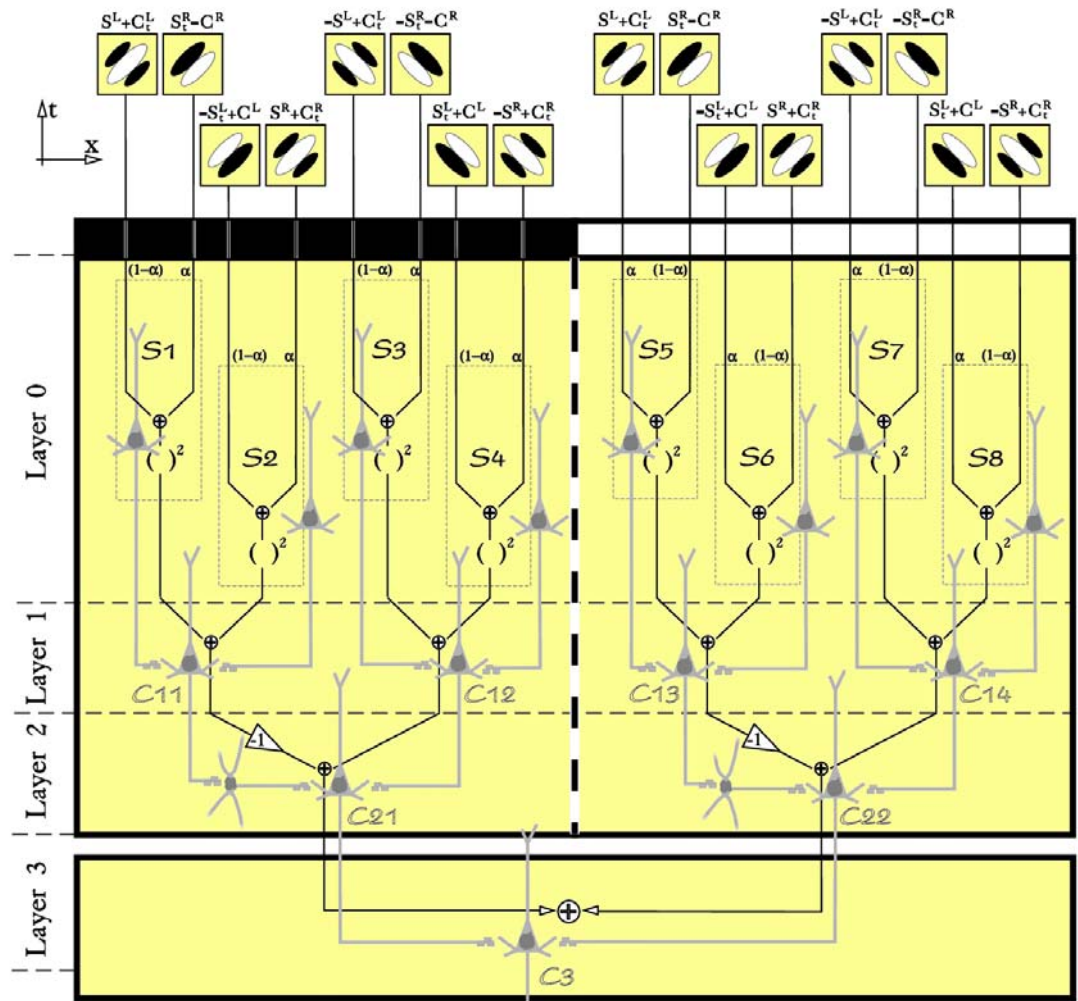
$$C_{11} = S_1^2 + S_2^2 \quad C_{12} = S_3^2 + S_4^2$$

$$C_{13} = S_5^2 + S_6^2 \quad C_{14} = S_7^2 + S_8^2$$

$$C_{21} = C_{12} - C_{11}$$

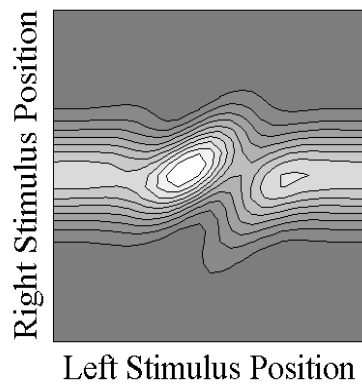
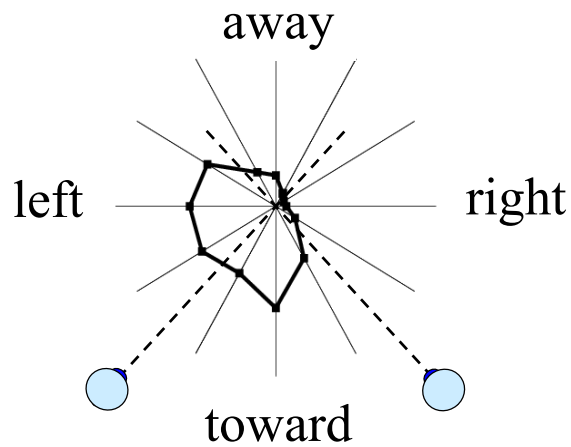
$$C_{22} = C_{13} - C_{14}$$

$$C_3 = C_{12} + C_{22}$$

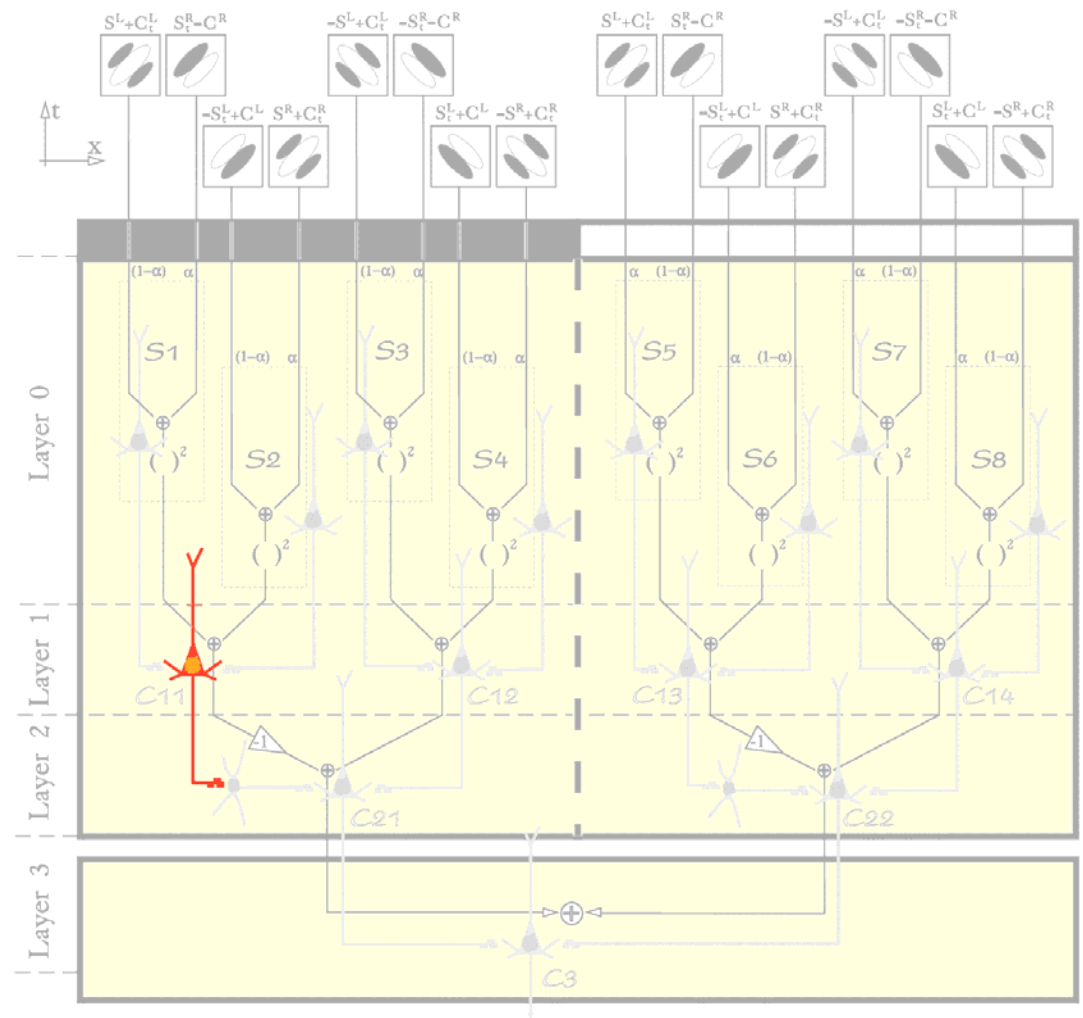


$$(1 - 2\alpha)(S_t^L C^L - S^L C_t^L - S_t^R C^R + S^R C_t^R)$$

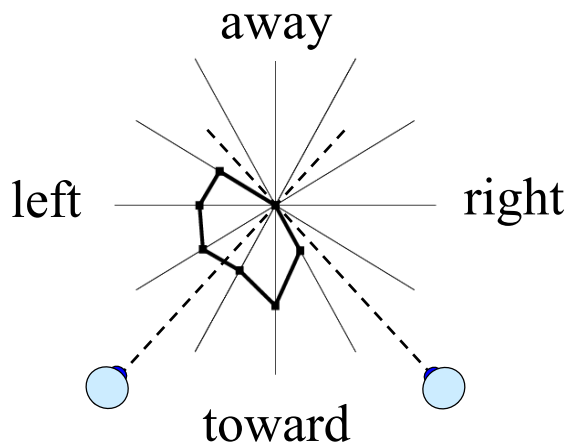
# CORTICAL MODEL (II) – cont'd



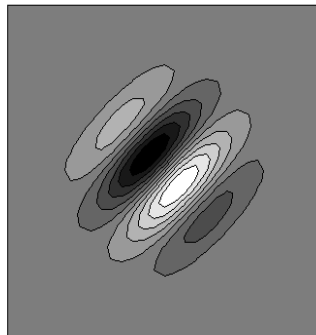
Disparity



# CORTICAL MODEL (II) – cont'd



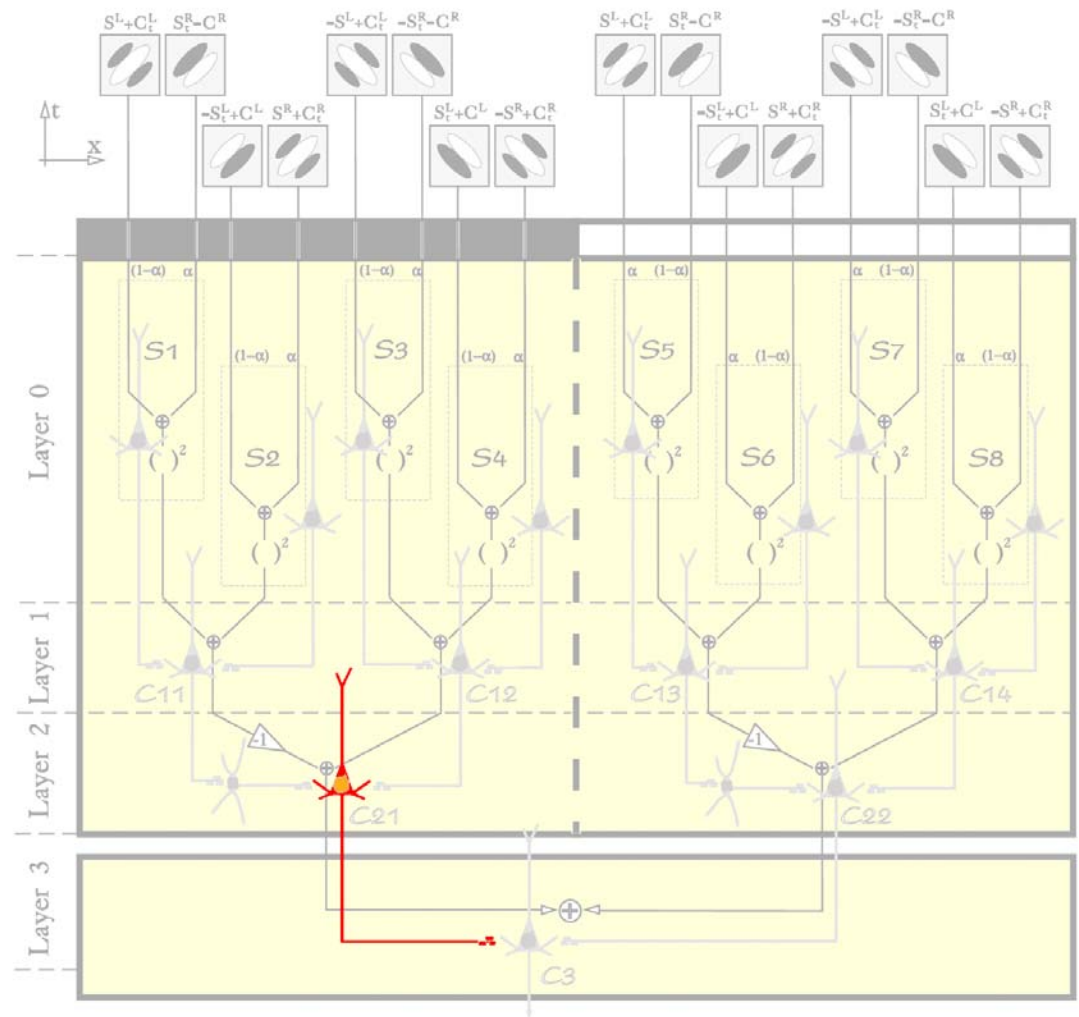
Right Stimulus Position



Left Stimulus Position

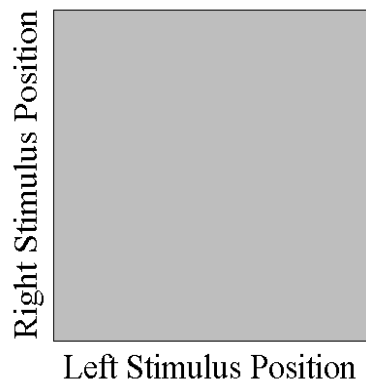
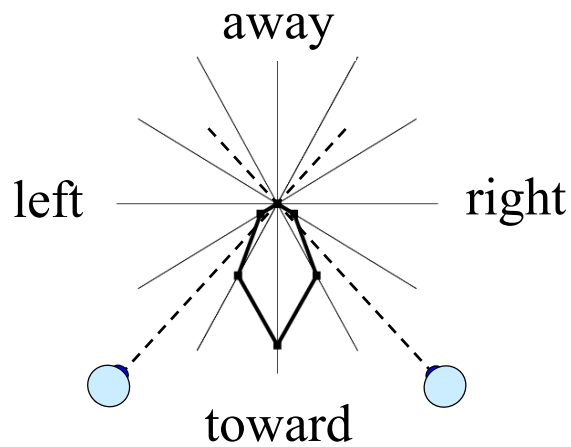


Disparity





# CORTICAL MODEL (II) – cont'd



Disparity

