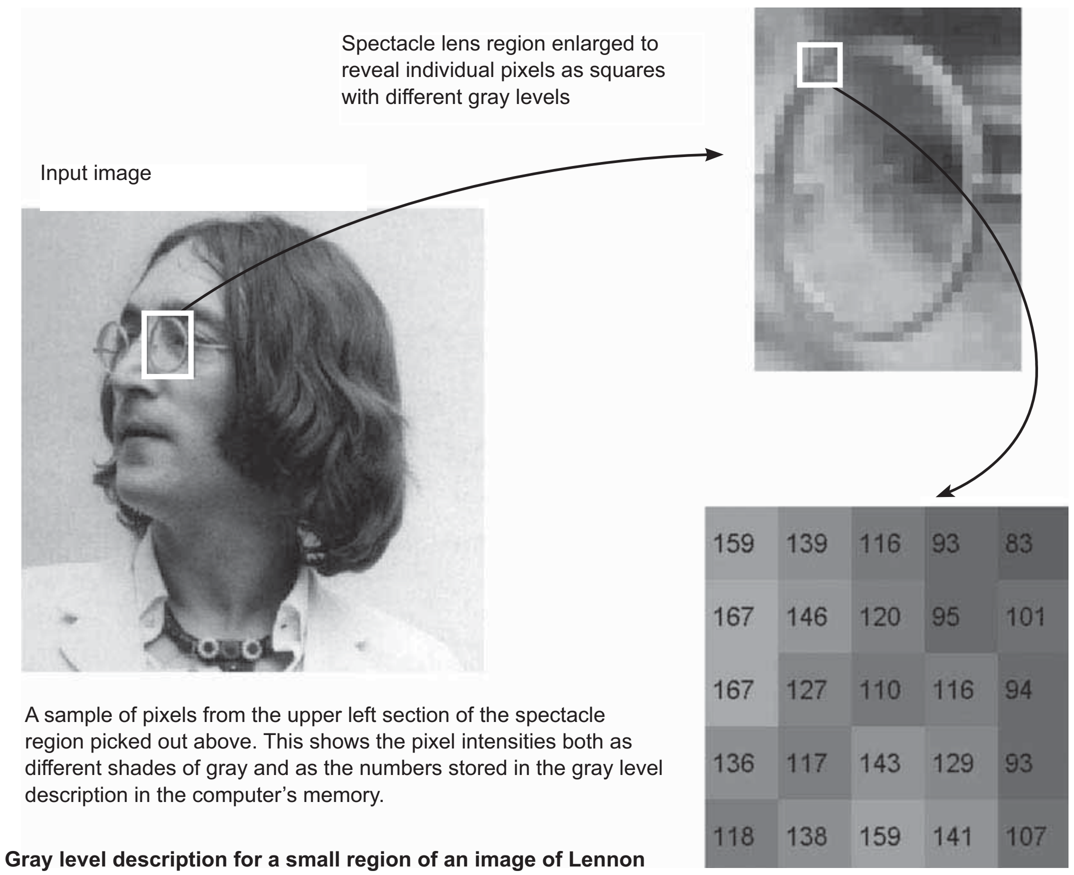
Computational Vision

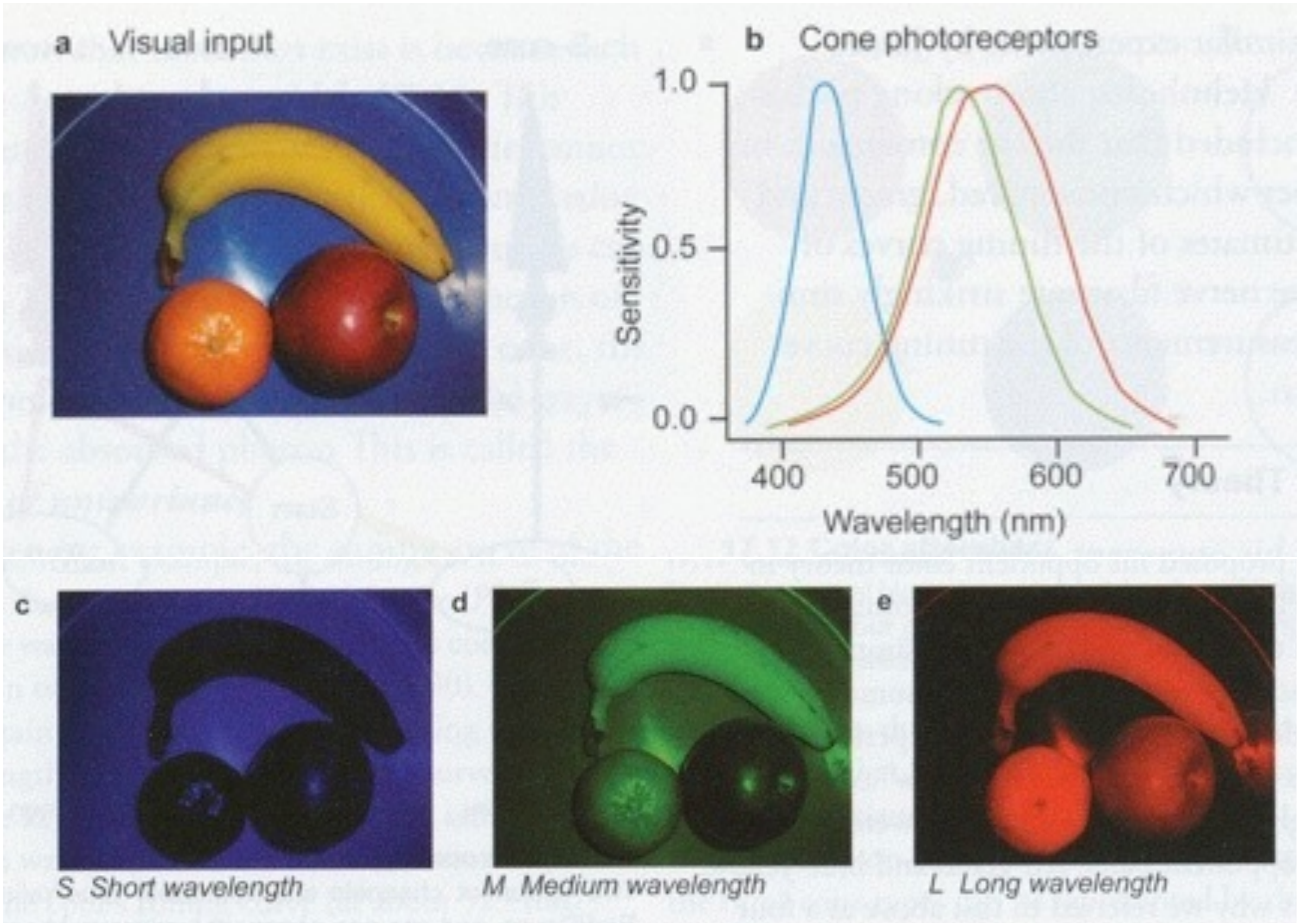
LGN

- Opponent theory
- Feature detection

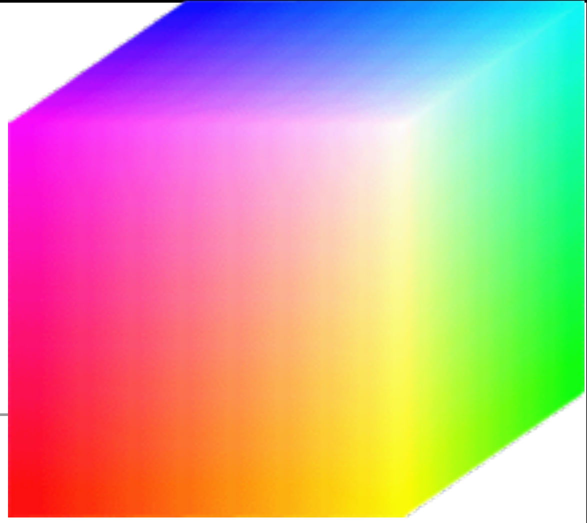
Past lecture

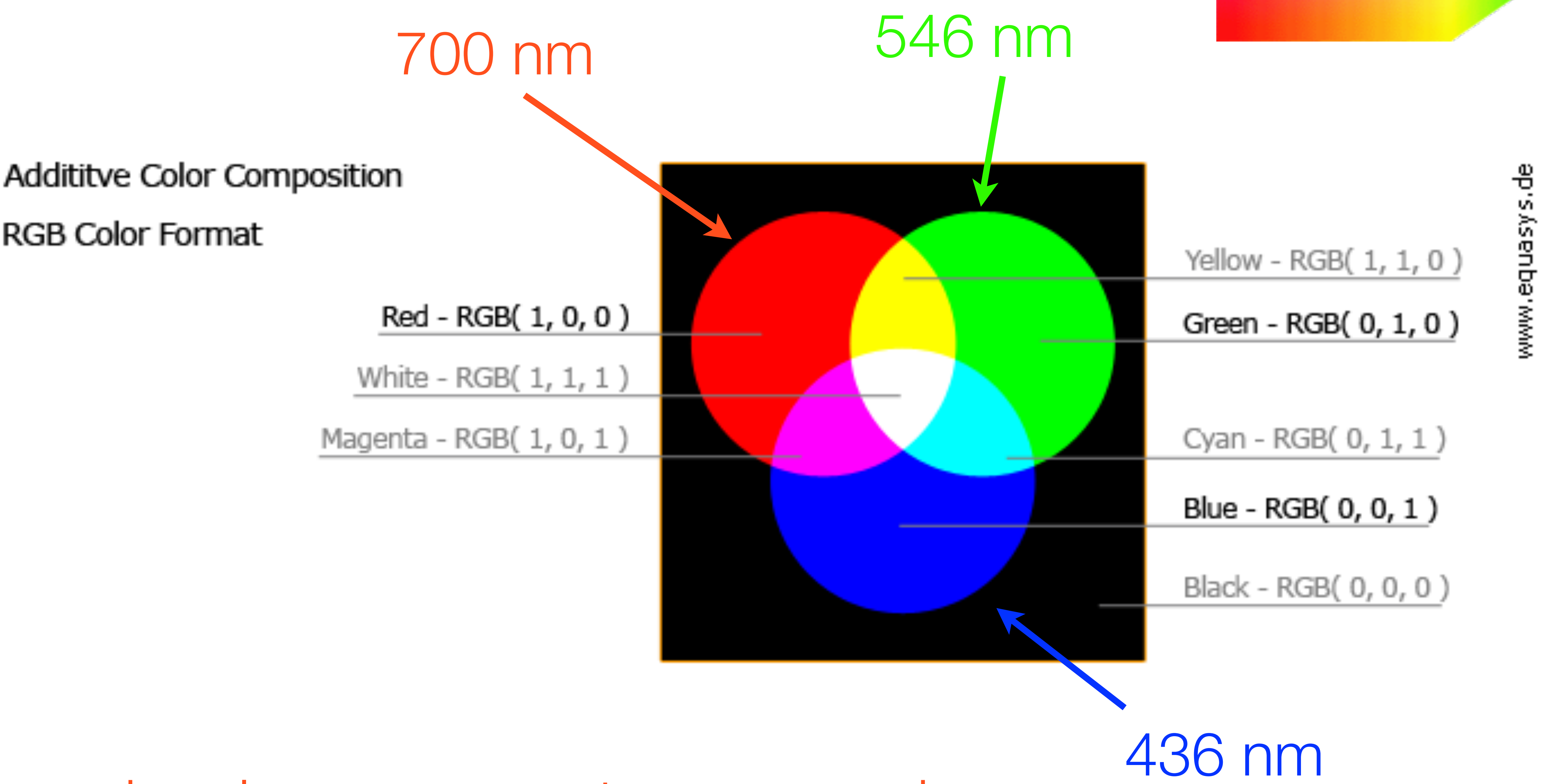


1.8 Gray level description for a small region of an image of Lennon



Representing colors: RGB space

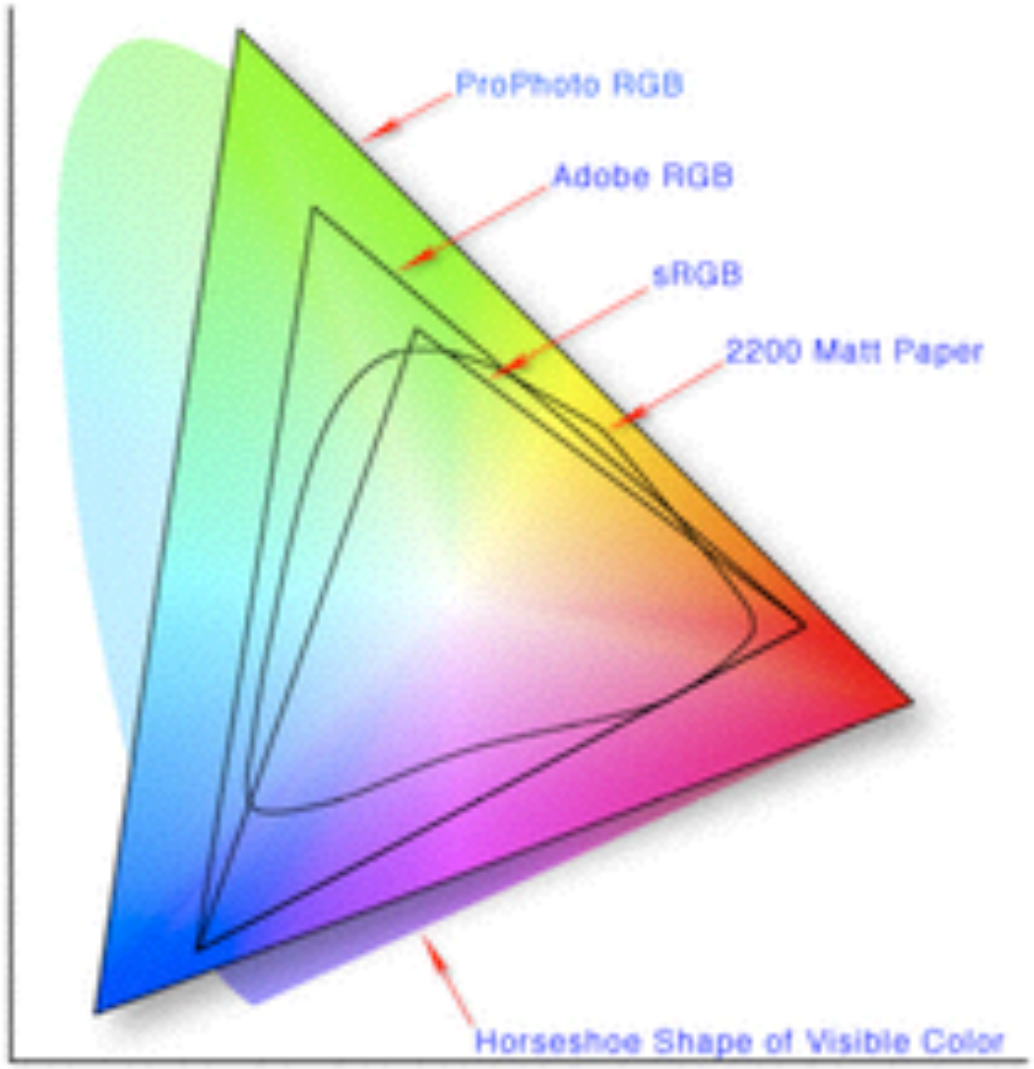




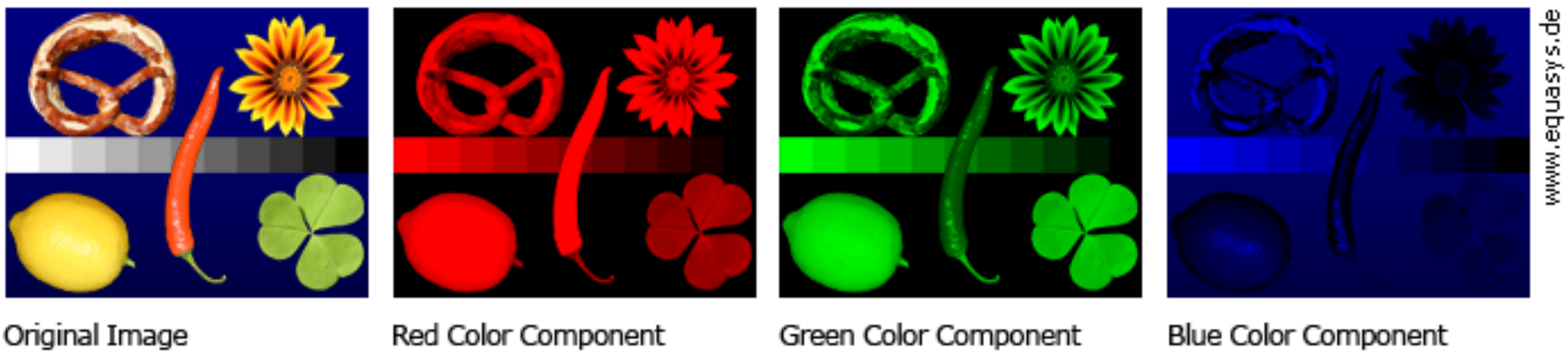
each color component corresponds to a specific wavelength

Representing colors: RGB space

- Ideally each component represented with floating point in the range (0,1)
- In practice: 8 bits per component or 24 bits per color, i.e., 16M possible colors
- For higher accuracy people use 10 bits or even 12 bits



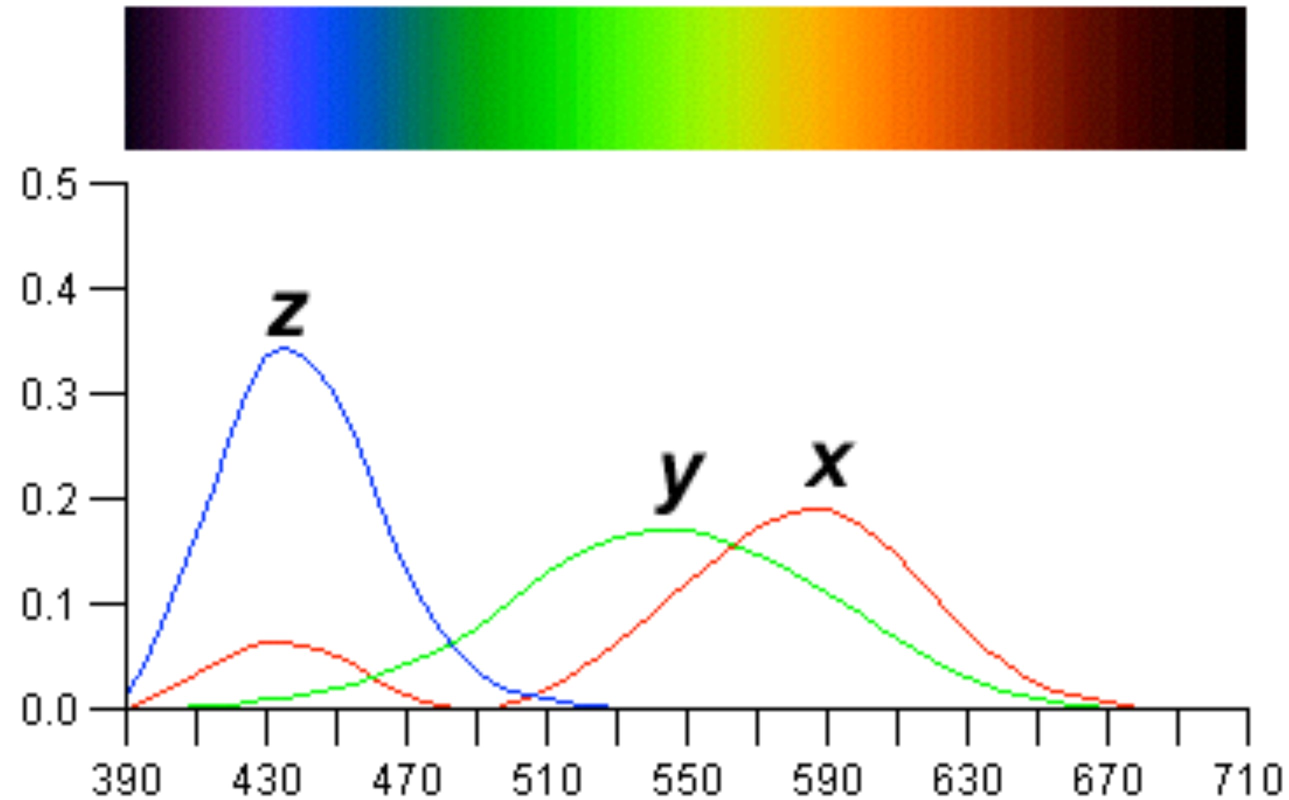
Source: wikipedia



Representing colors

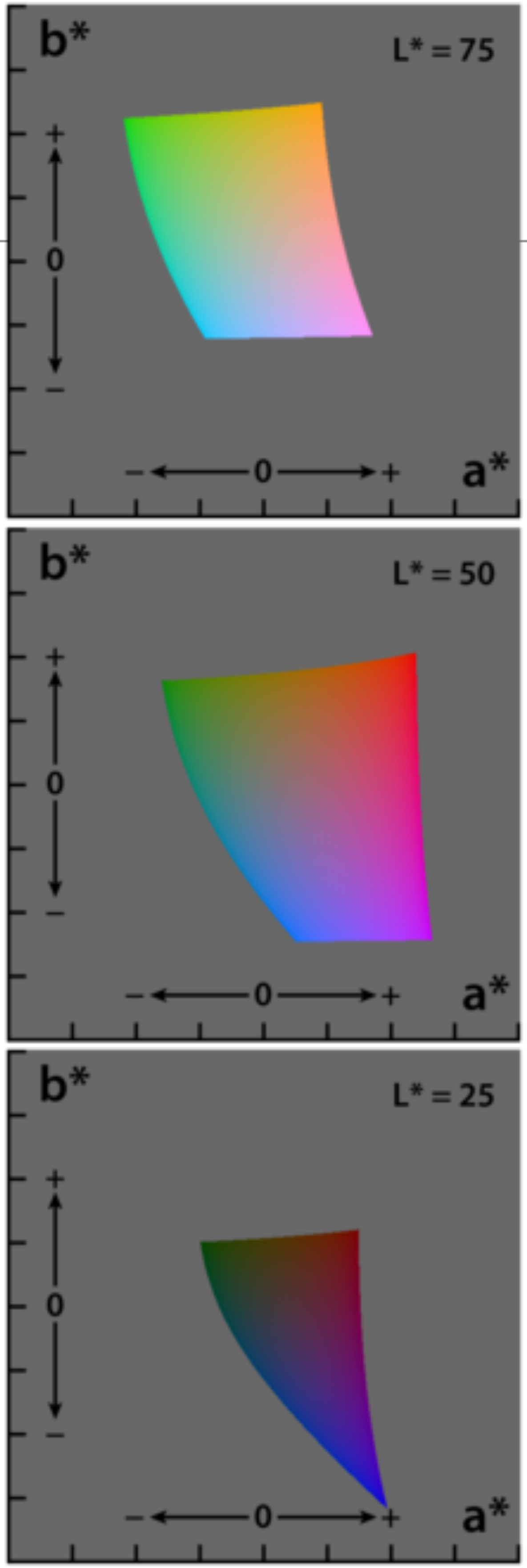
- Color space conversions correspond to matrix multiplications

types used in makecform	Color spaces
'lab2lch', 'lch2lab'	L*a*b* and L*ch
'lab2srgb', 'srgb2lab'	L*a*b* and sRGB
'lab2xyz', 'xyz2lab'	L*a*b* and XYZ
'srgb2xyz', 'xyz2srgb'	sRGB and XYZ
'upvpl2xyz', 'xyz2upvpl'	u′v′L and XYZ
'uvl2xyz', 'xyz2uvl'	uvL and XYZ
'xyl2xyz', 'xyz2xyl'	xyY and XYZ



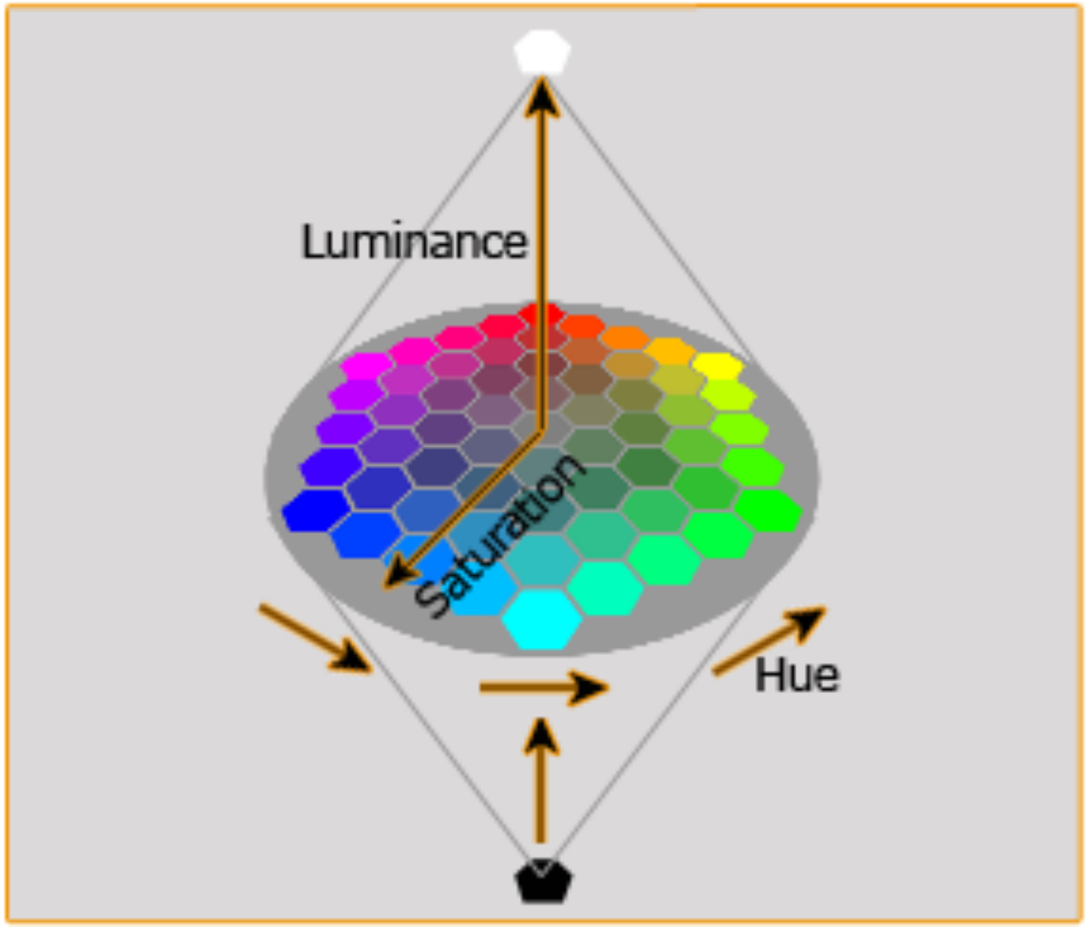
Representing colors cont'd

- LAB space
  - L: lightness (matched to human lightness sensitivity)
  - A & B correspond to opponent channels (more next)
- LMS space:
  - Long, Medium and Short wavelength based on primate cone sensitivity
- HSV space:
  - Hue, Saturation and Value
- etc etc



Psychological description of color

- Subjective experience of color has a very different structure from that of the physical light
- Only 3 variables needed to describe the perception of color!
  - hue (dimension we associate with 'color')
  - saturation (also called chroma | color purity)
  - lightness (also called luminance or value)

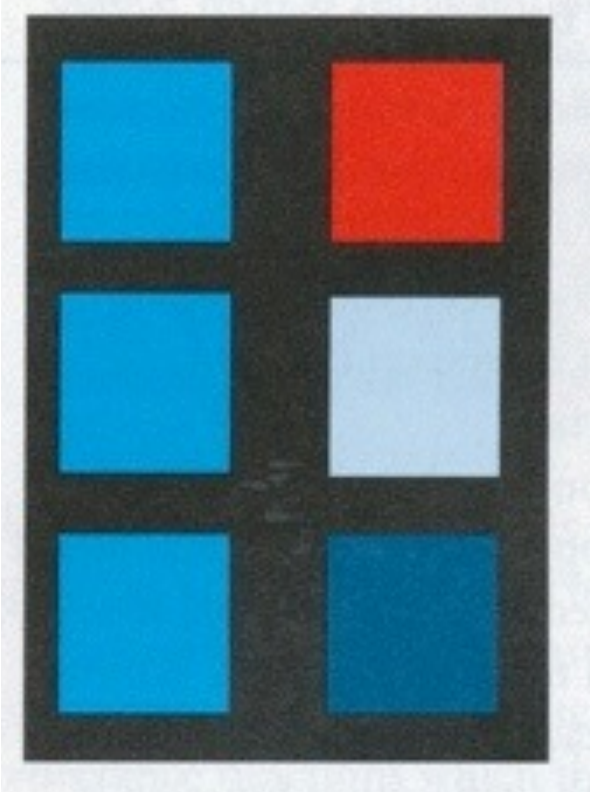


Source: unknown

change in hue

change in saturation

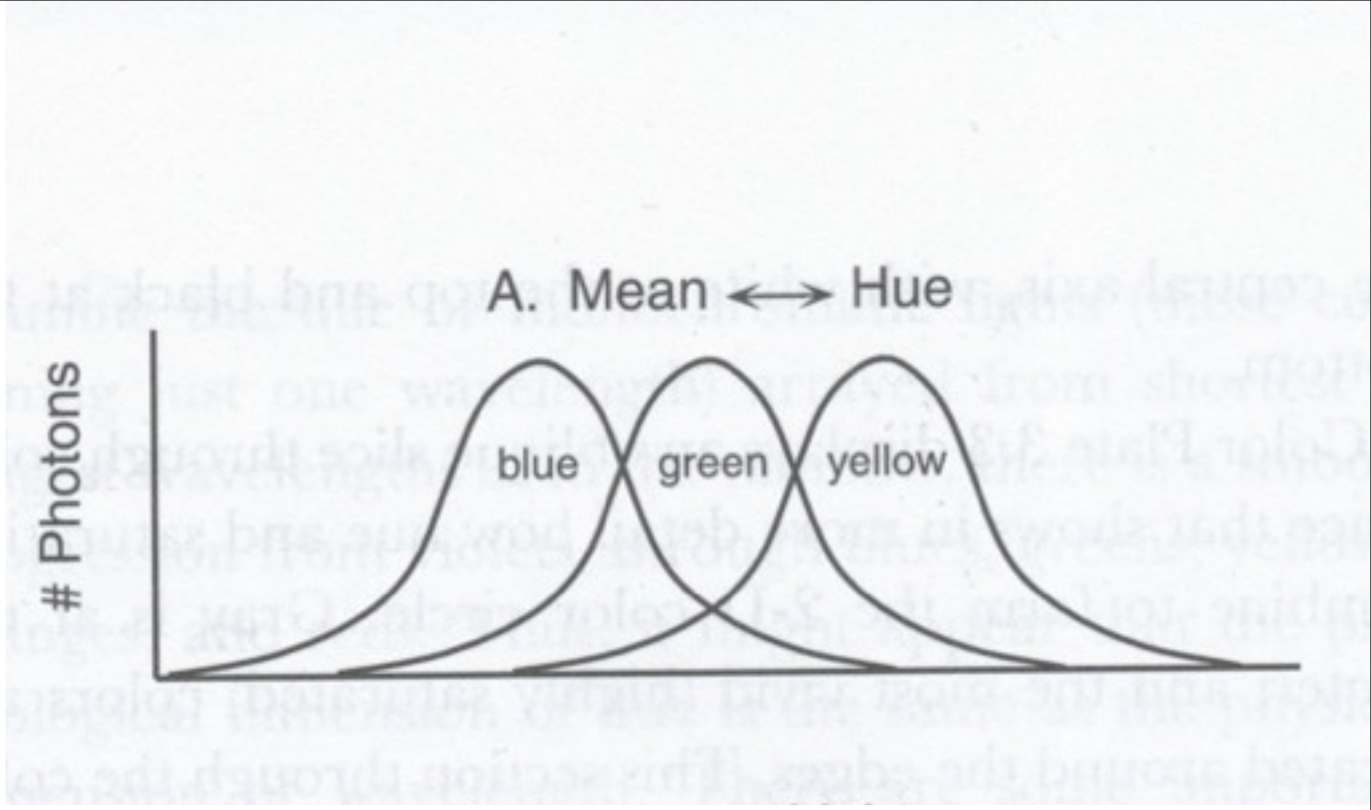
change in lightness



Source: http://equasys.de/colorformat.html

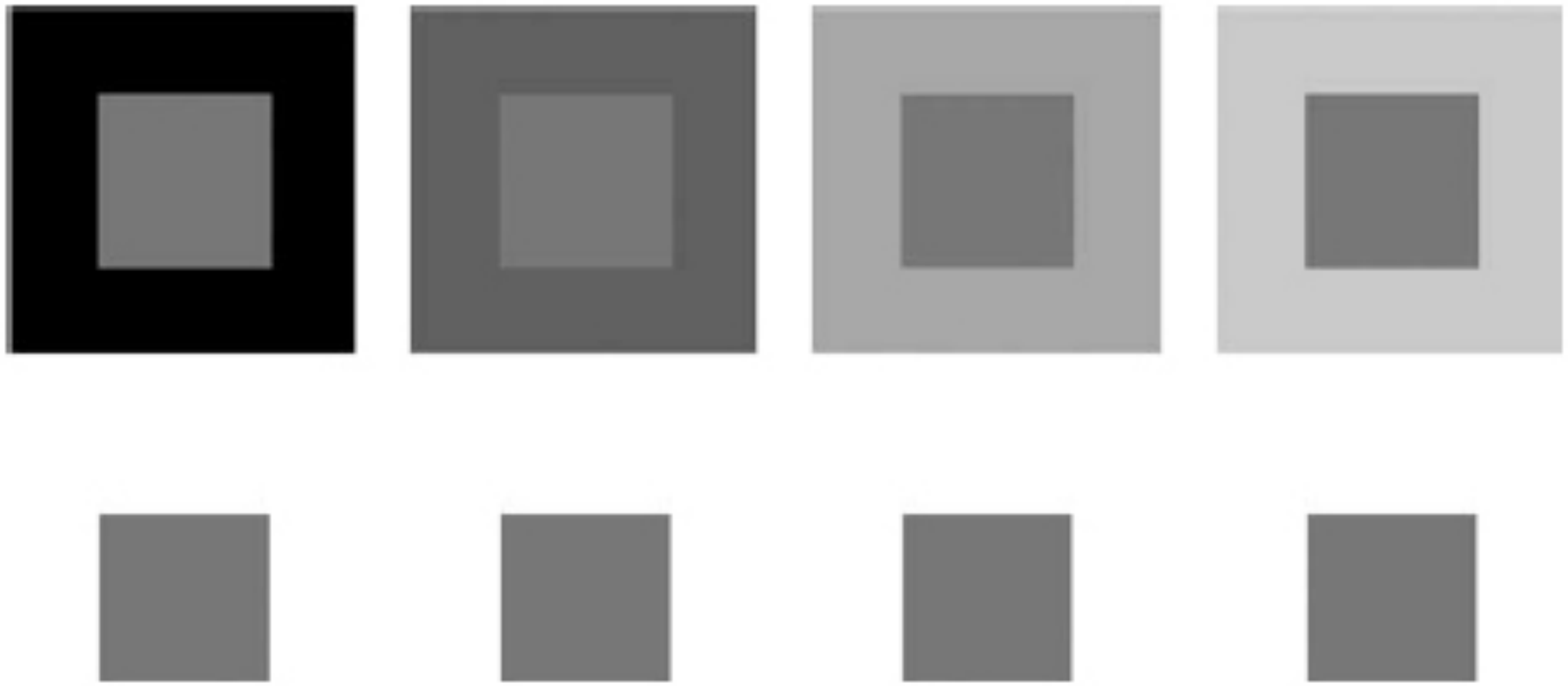
Psychophysical correspondences

- Spectra with approx. normal distributions (~monochromatic lights)



Source: Frisby & Stone

Color and brightness perception depends on context!



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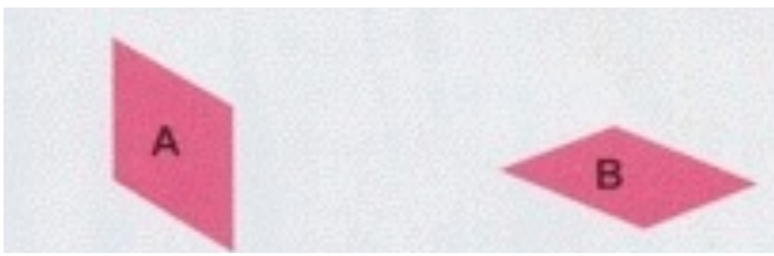
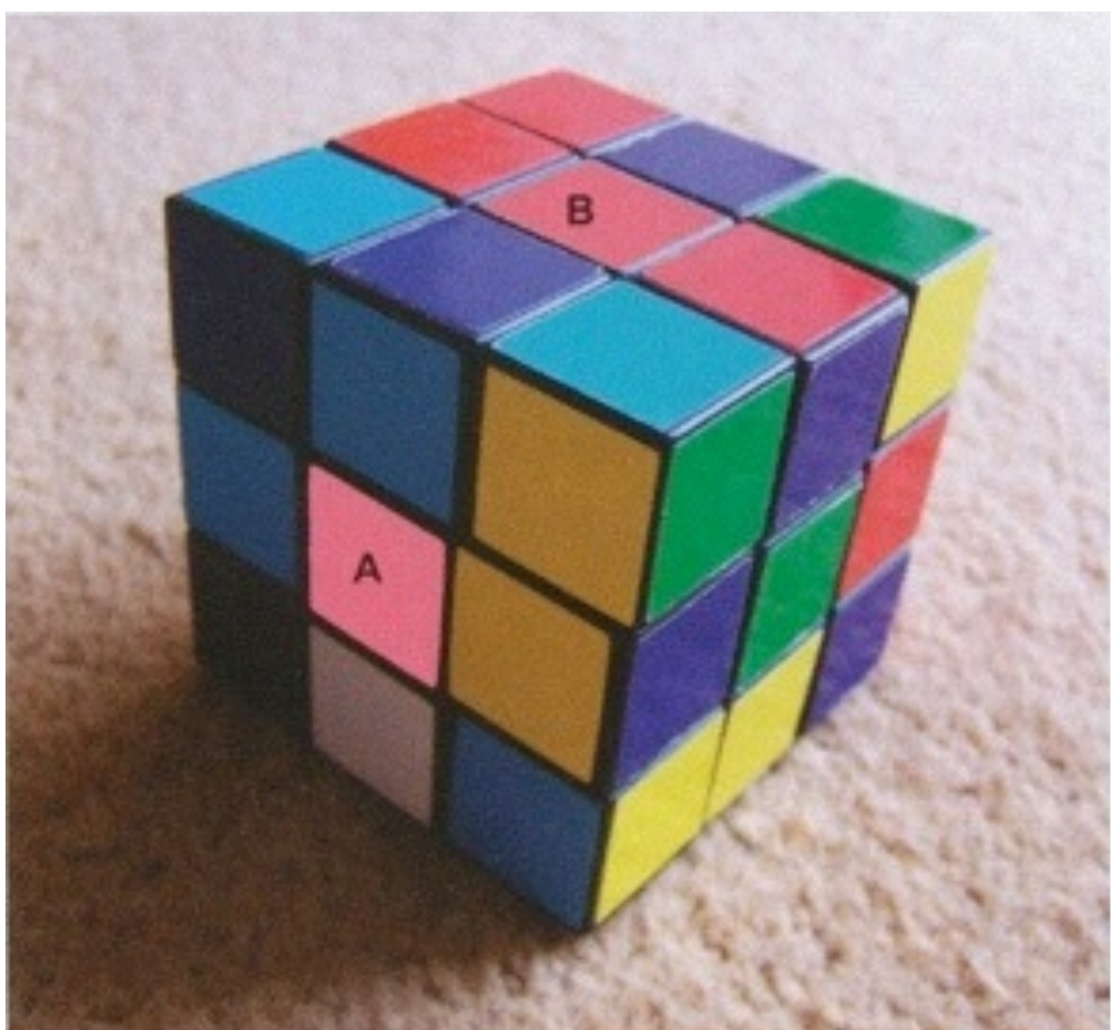
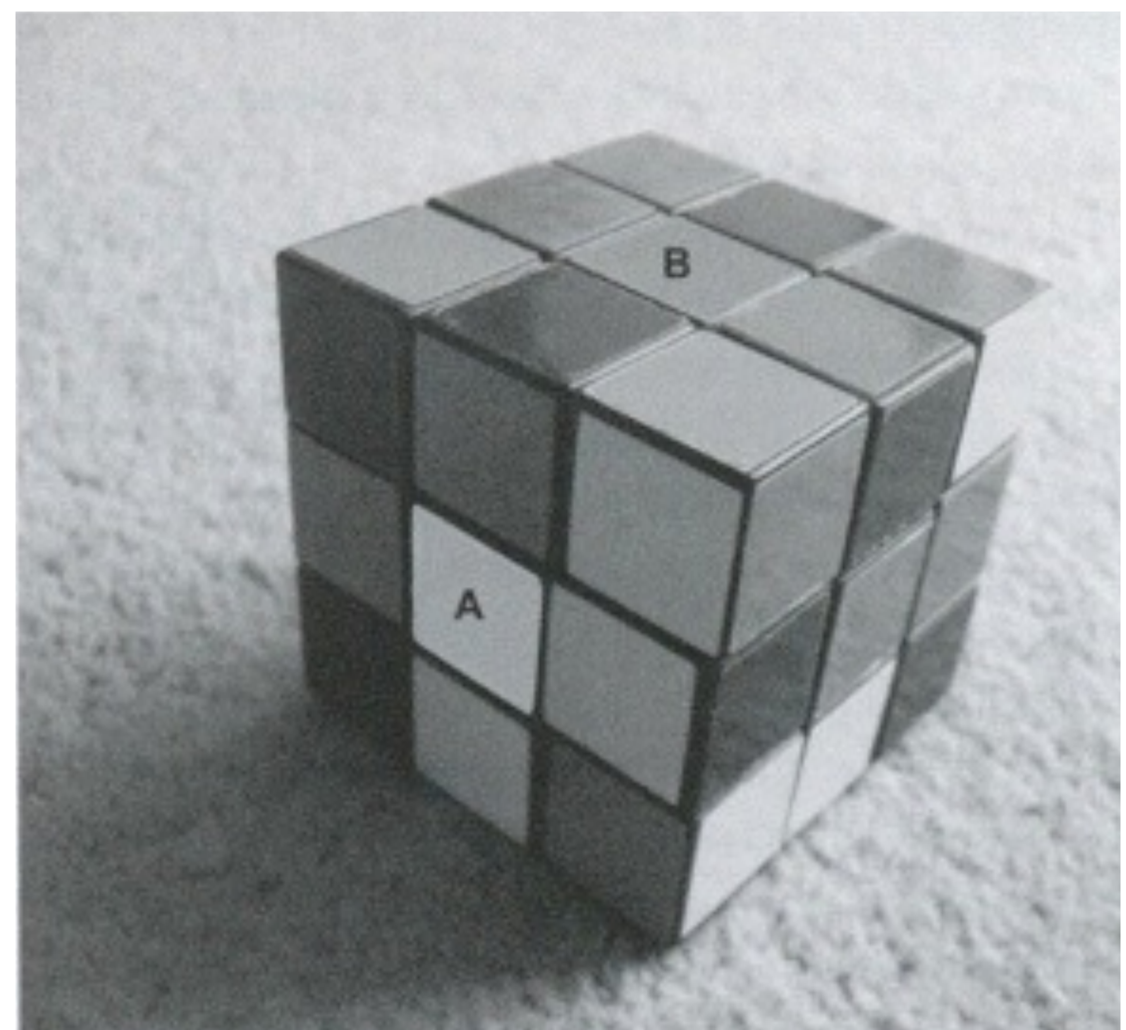
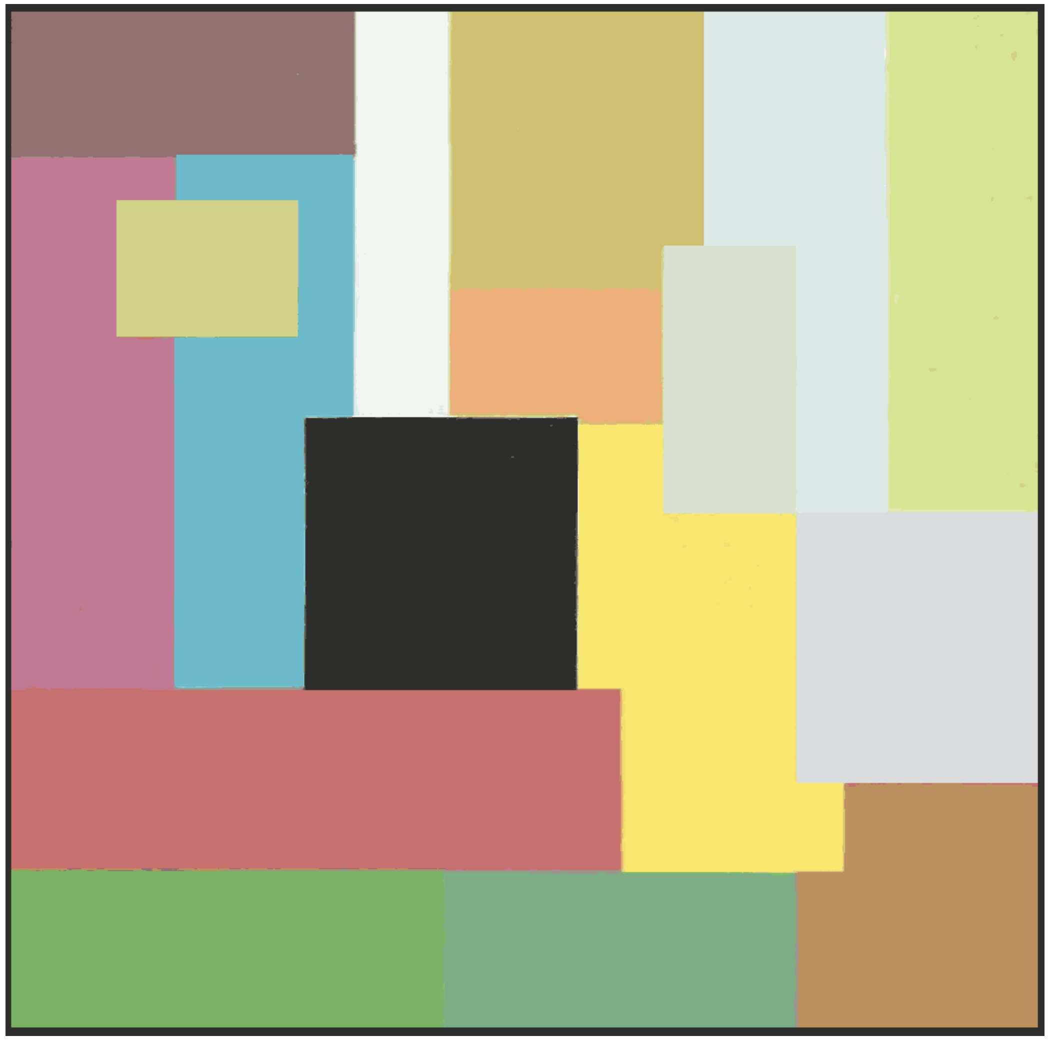






The Land-Mondrian experiments (1964)



Beyond trichromaticity theory

- Until mid 20th century trichromaticity theory widely accepted
- Color opponency proposed by Hering in the 19th century based on perception of pure colors
- Four color primaries arranged in pairs:
  - red/green
  - blue/yellow

Afterimages:

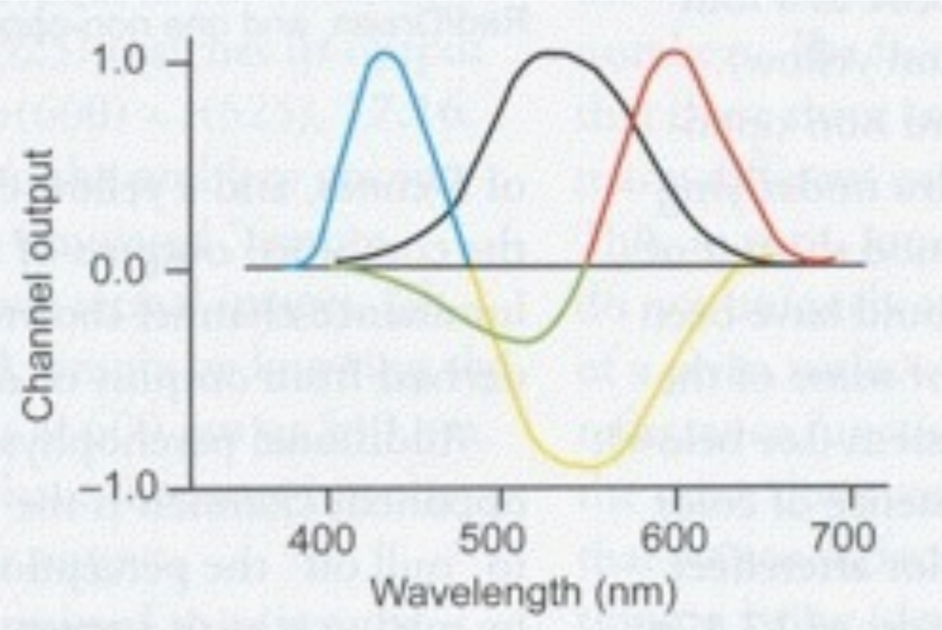
- red spot -> green afterimage
- blue dot -> yellow afterimage

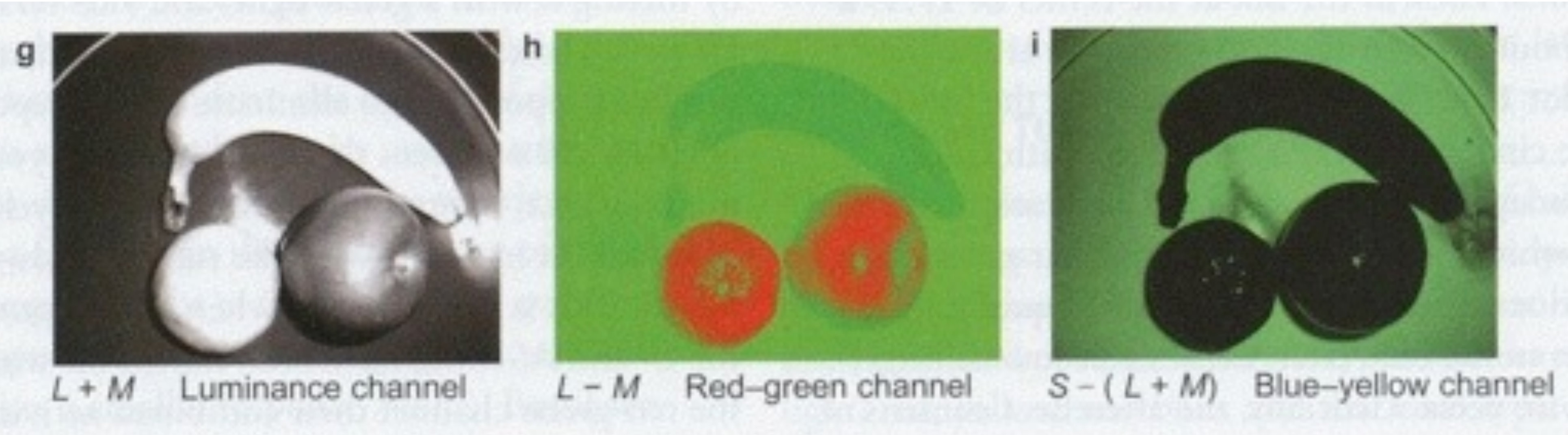
Opponent color theory

- Color opponency proposed by Hering in the 19th century based on perception of pure colors
  - colors never lost singly as predicted by trichromatic theory but in specific pairs
  - no bluish yellow or reddish green
- Clearly something is going on outside the retina...

Ewald Hering
(1878 – 1964)

Opponent color theory





Hierarchical organization in the retina and beyond

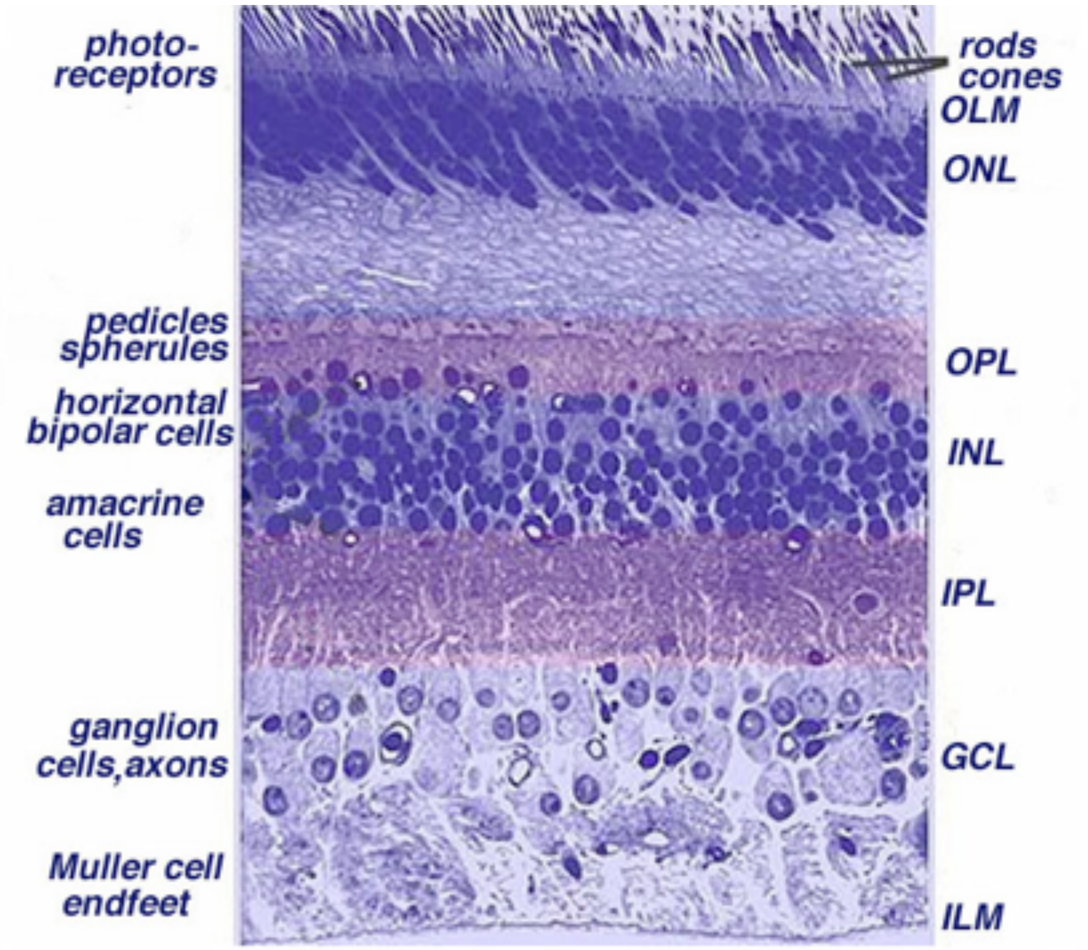
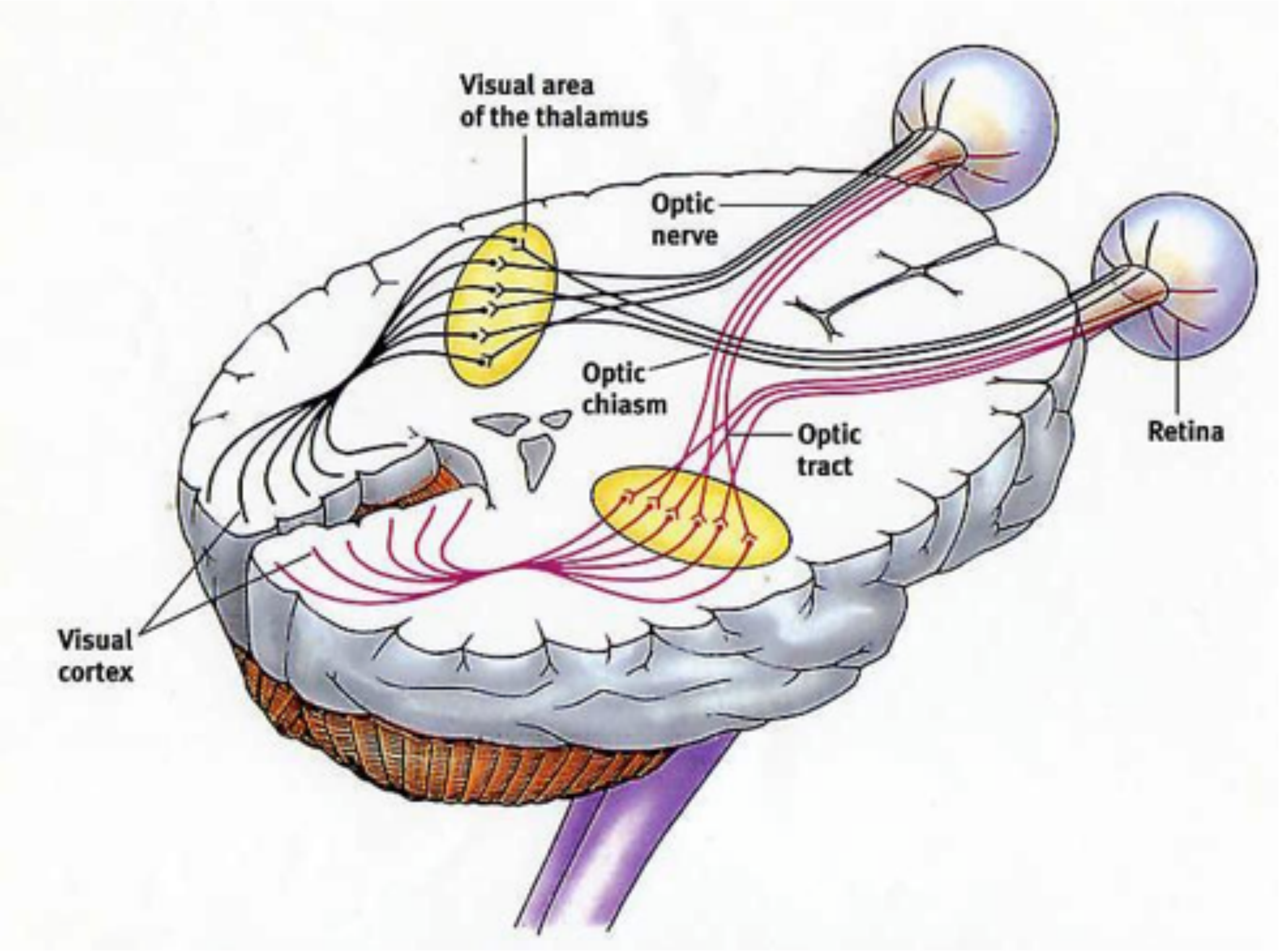


Fig. 3. Light micrograph of a vertical section through central human retina.



source: webvision

source: http://camelot.mssm.edu/~ygyu/research.html

Computing neurons

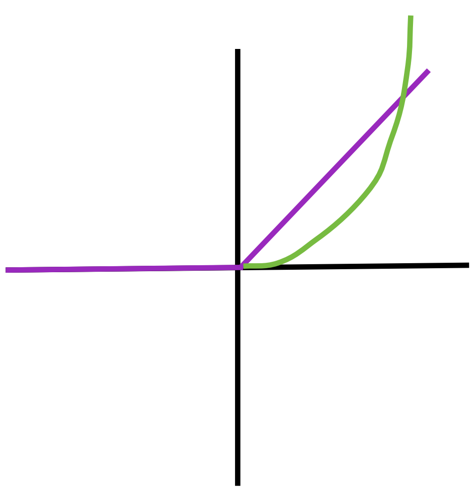
$$y(x) = \mathbf{w}^T \mathbf{x}$$

Synaptic efficacies

$$y(x) = \sum w_i x_i$$

Summation at the soma

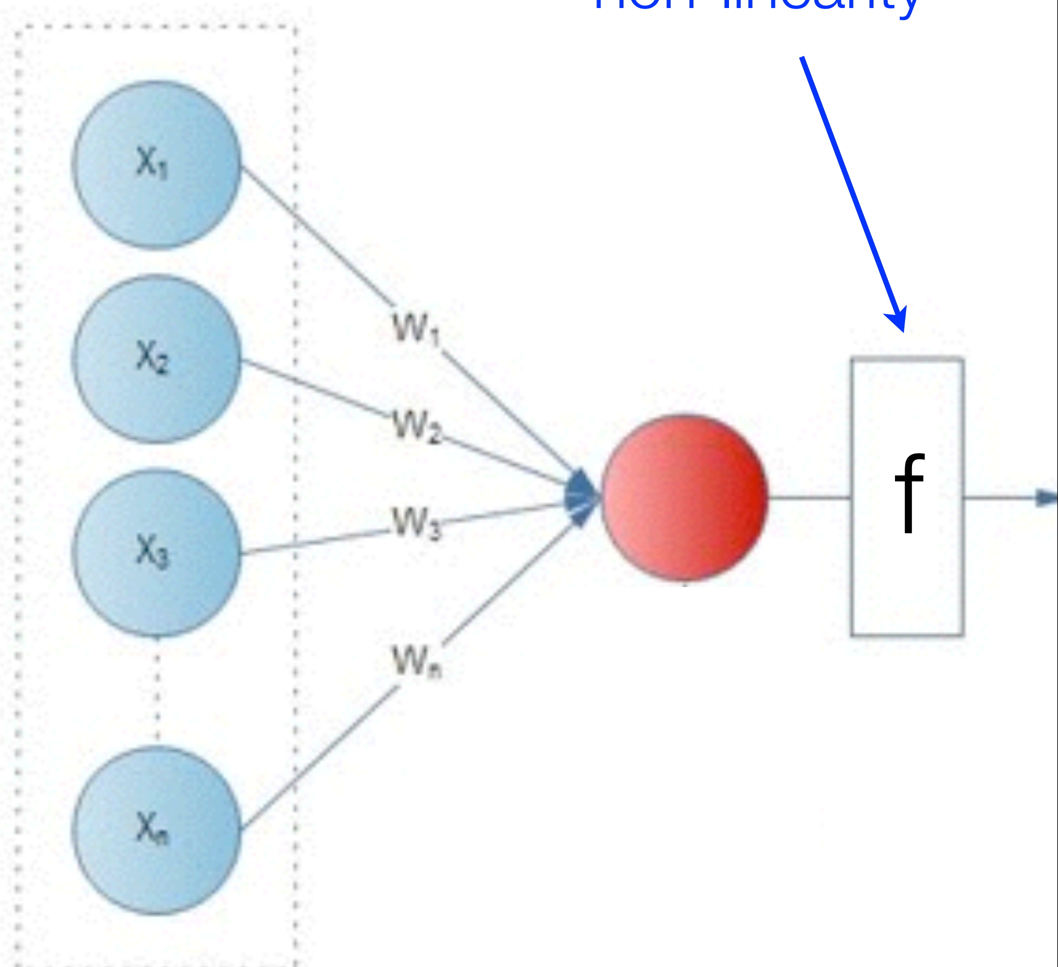
Spike trains / firing rates coming from each afferent neuron



f(u) = u if u>0 and 0 otherwise

f(u) = u^2 if u>0 and 0 otherwise

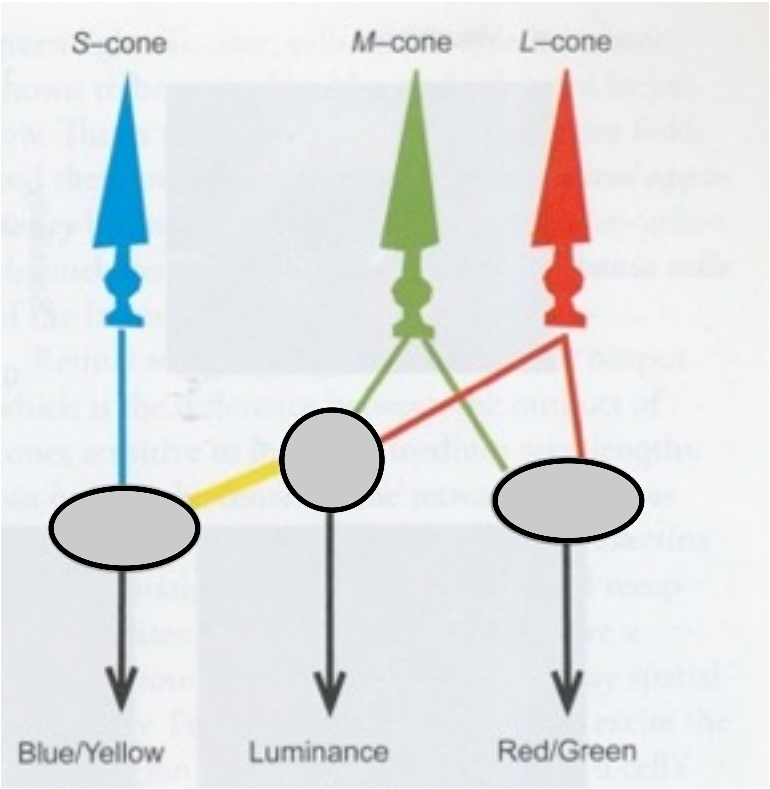
Spike generation process introduces non-linearity

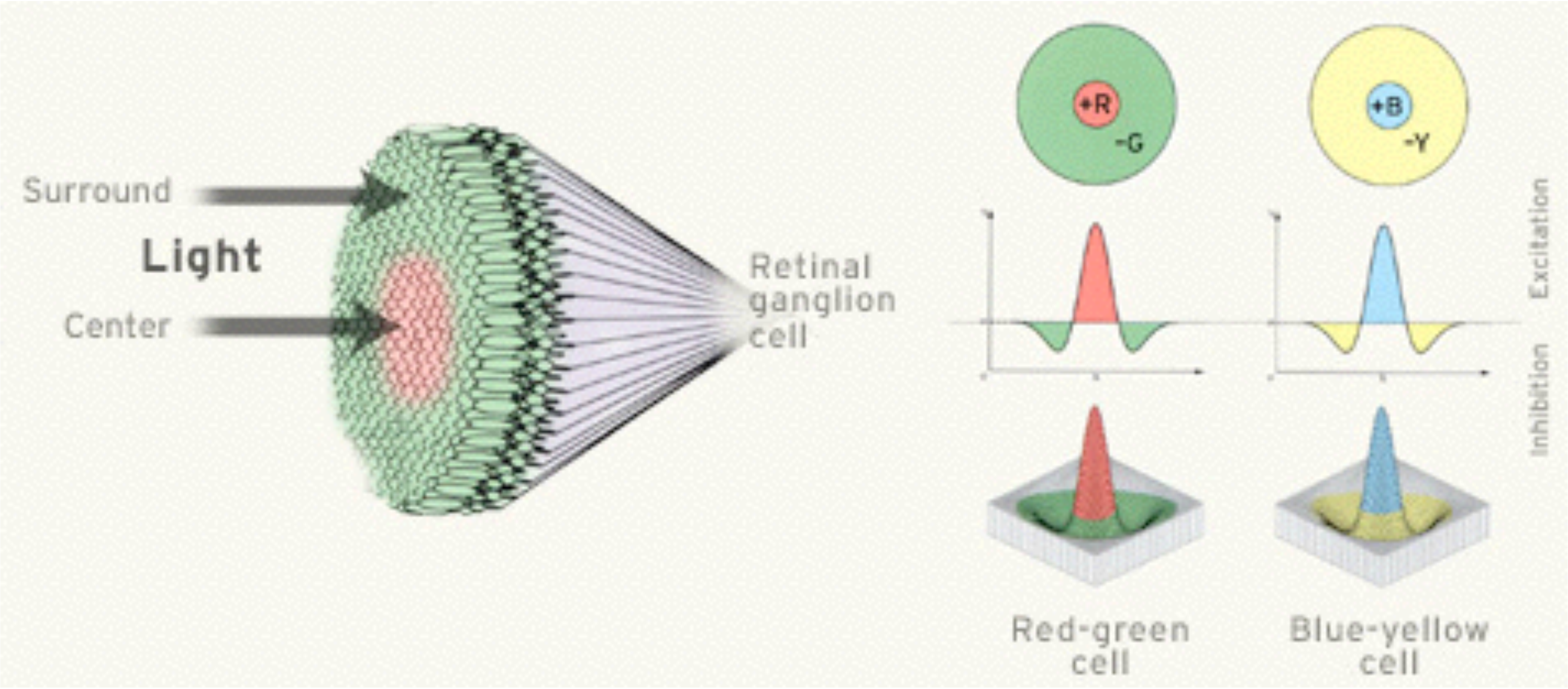


several layers of processing in the retina

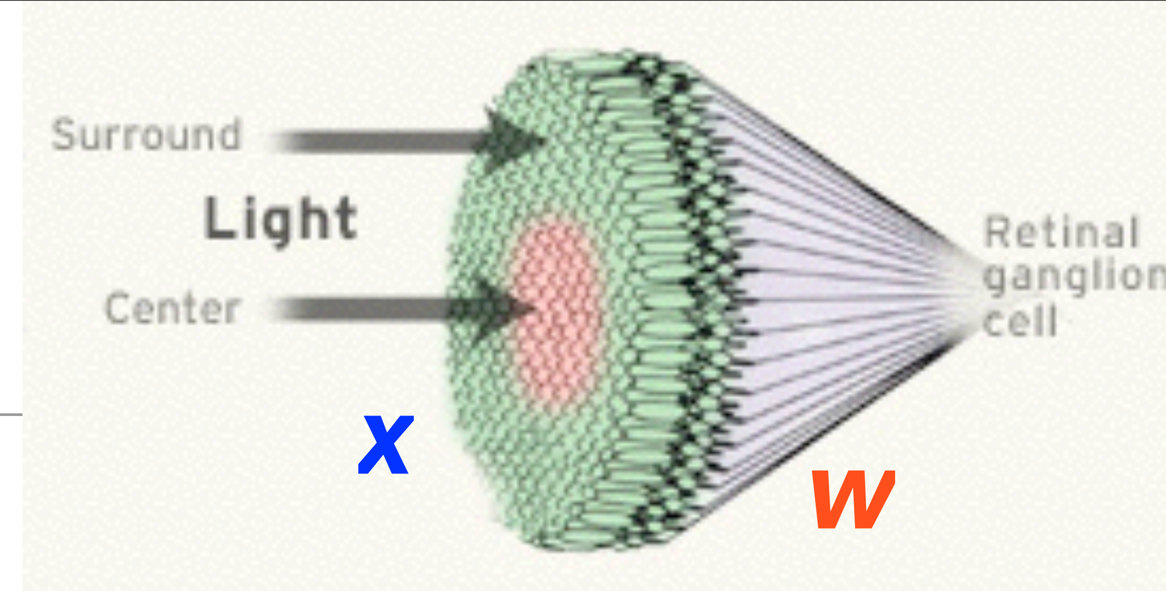
ganglion cells = retinal output / LGN

Center surround organization





What do neurons compute?



- Neurons detect features (=patterns or templates) that are stored in their synaptic weights

			1	1	1	1	1			
			1	1	1	1	1			
			1	1	1	1	1			
			1	1	1	1	1			
			1	1	1	1	1			

-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
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-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
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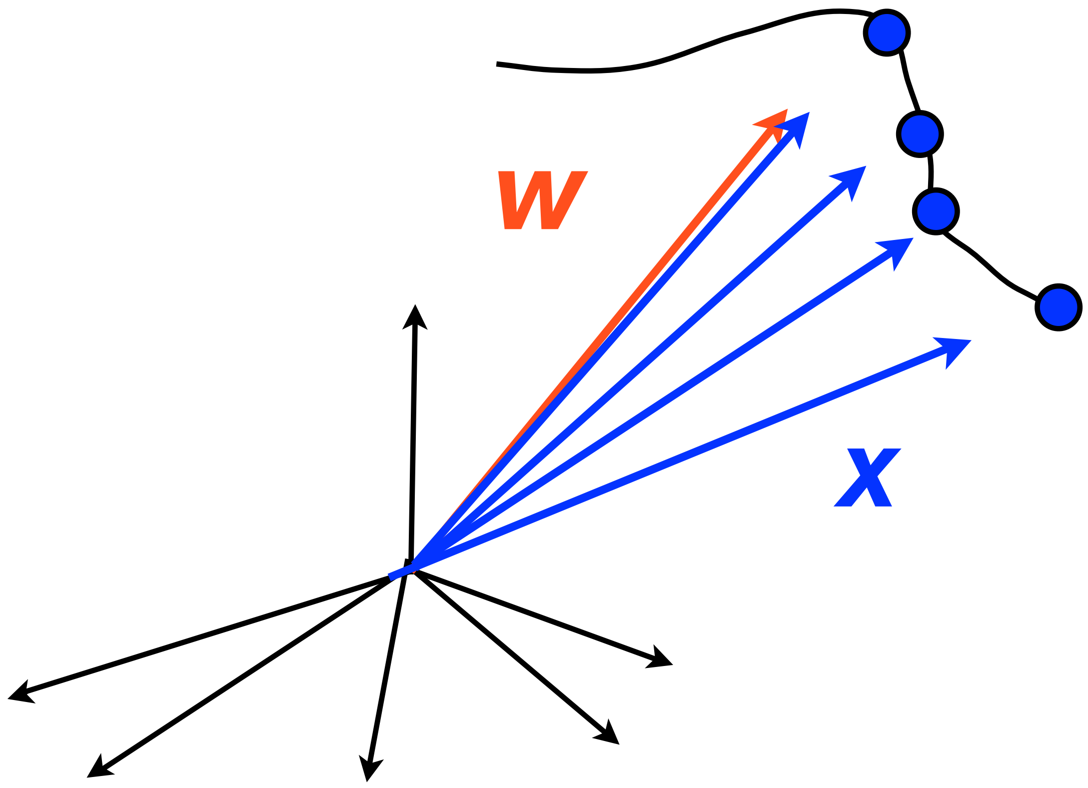
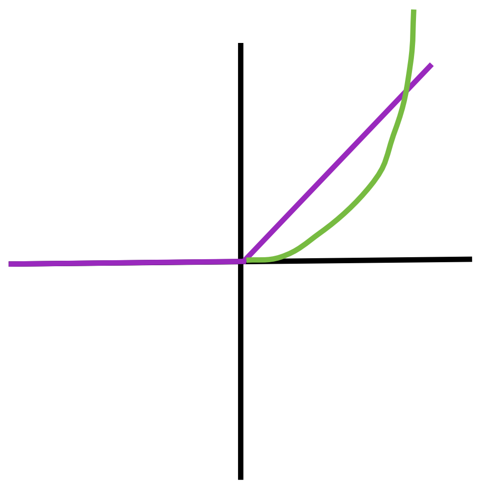
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Receptive fields (RFs)

$$
\begin{aligned}
y(x) &= \sum w_i x_i \\
&= \mathbf{w} \cdot \mathbf{x} \\
&= ||\mathbf{w}|| \, ||\mathbf{x}|| \cos(\theta)
\end{aligned}
$$





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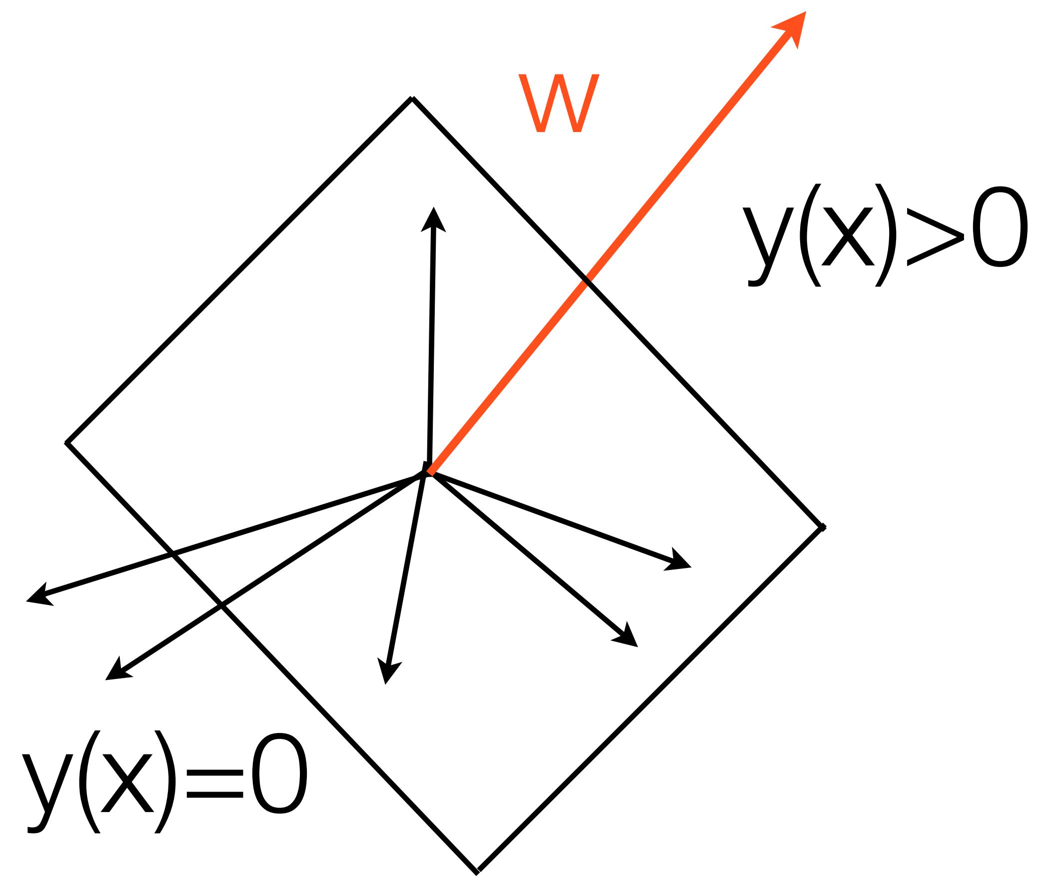
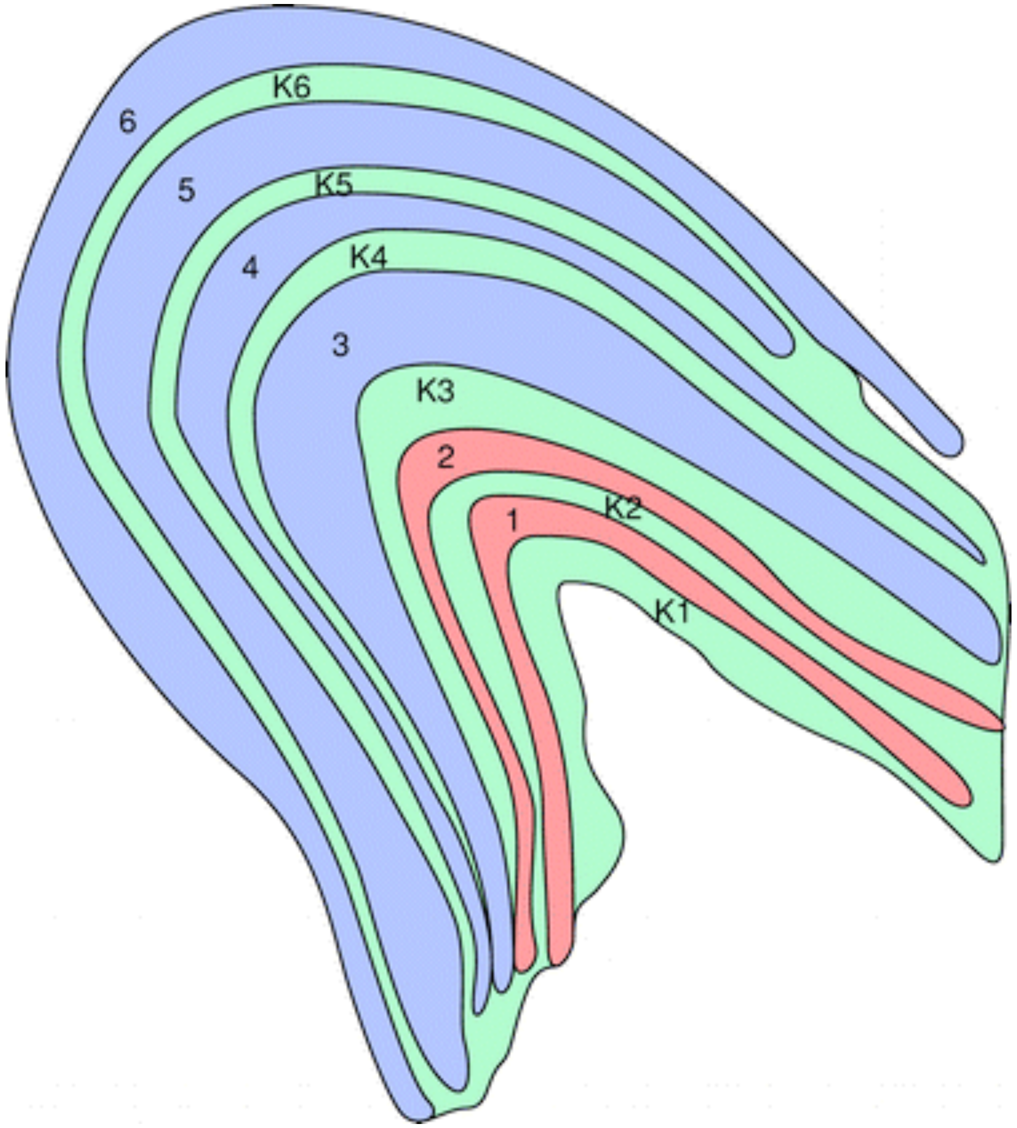


LGN

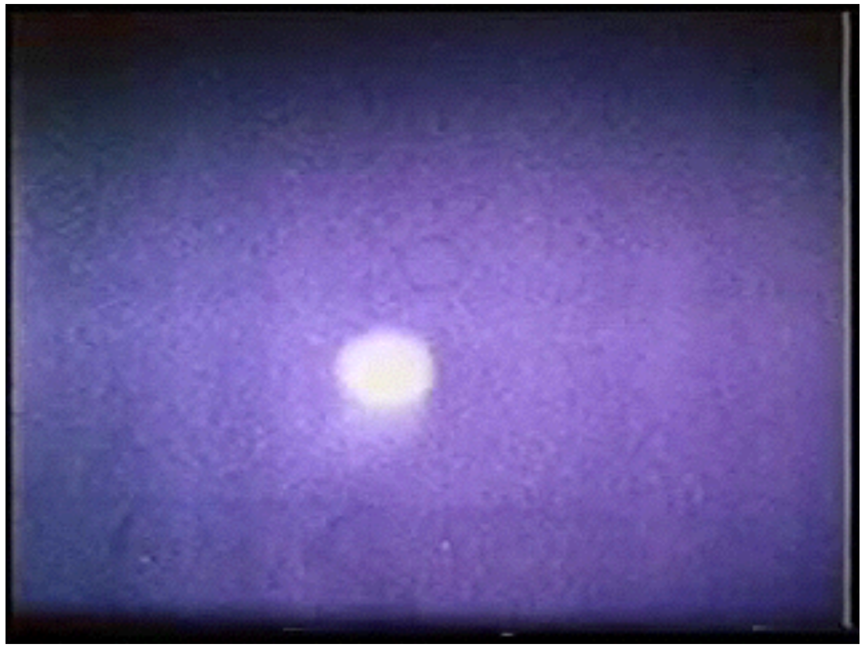
- Magno vs. parvo (more when we talk about spatial frequencies)



source: http://www.els.net/WileyCDA/ElsArticle/refId-a0000230.html

Center surround organization

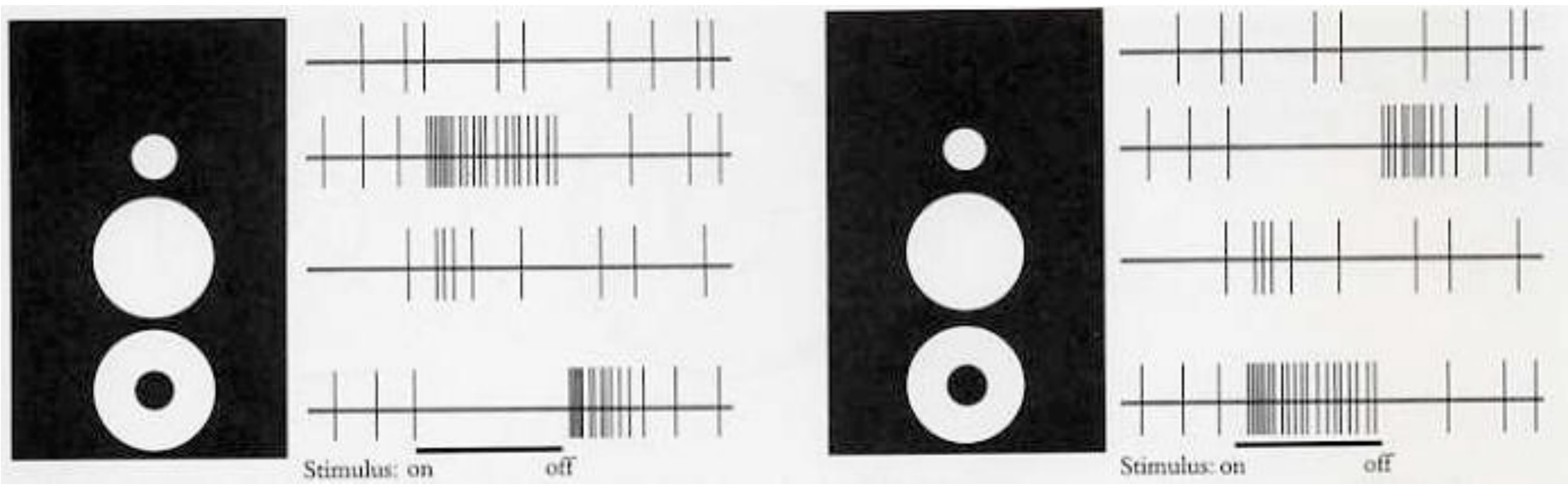
on center - off surround



off center - on surround

Center surround organization

on center - off surround **off center - on surround**



Source: Hubel

Linear system theory

- A linear system is one in which the input-output behavior may be described in terms of a linear function:
  - e.g., $y = a*x + b$
- What is a linear function?
  - obeys the rules of superposition and scaling
- Linear algebra provides a powerful tool for the analysis of complex, multivariate systems
- Although most systems in nature are non-linear, our understanding of them can still be aided by the intuitions and insights gained from linear systems analysis

Reverse correlation

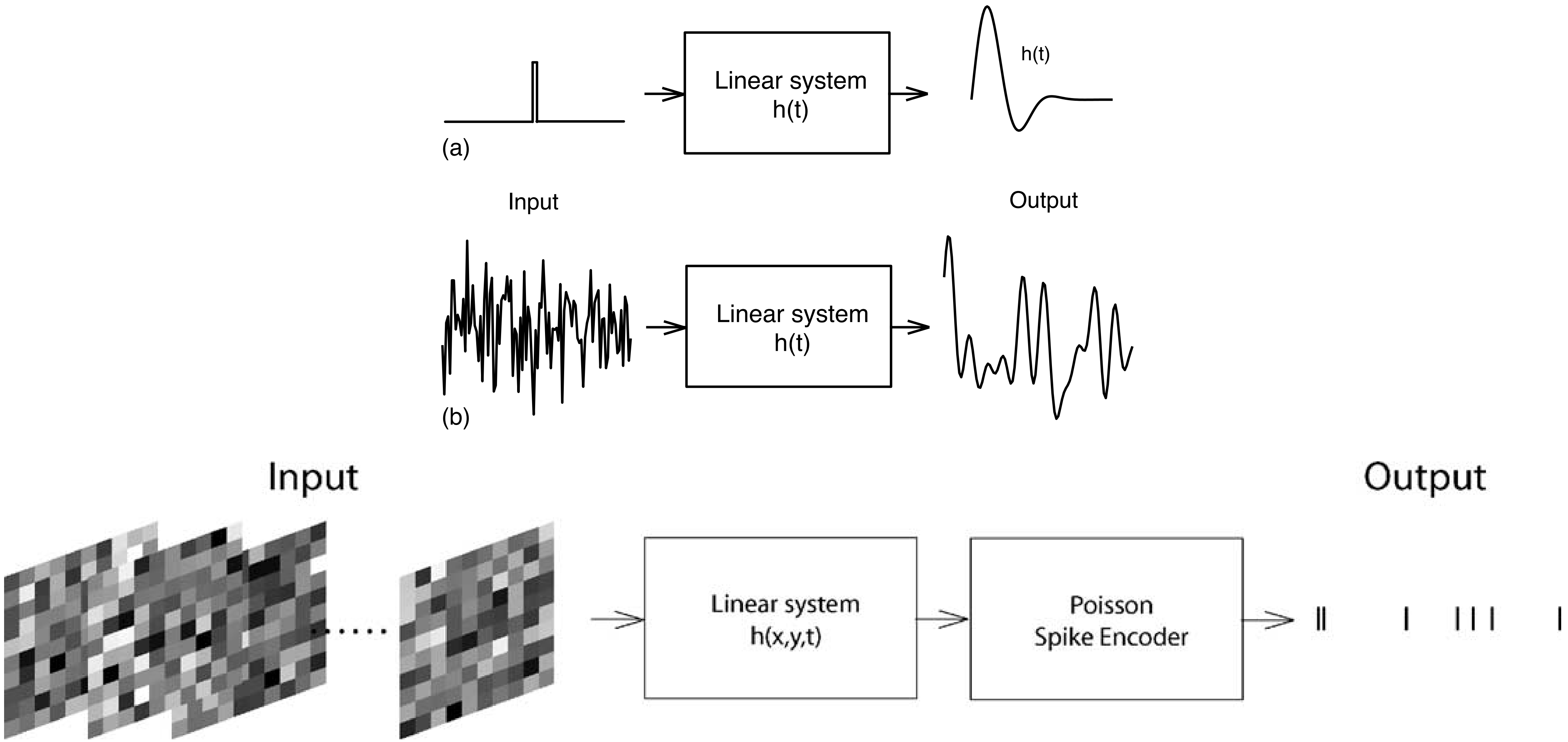
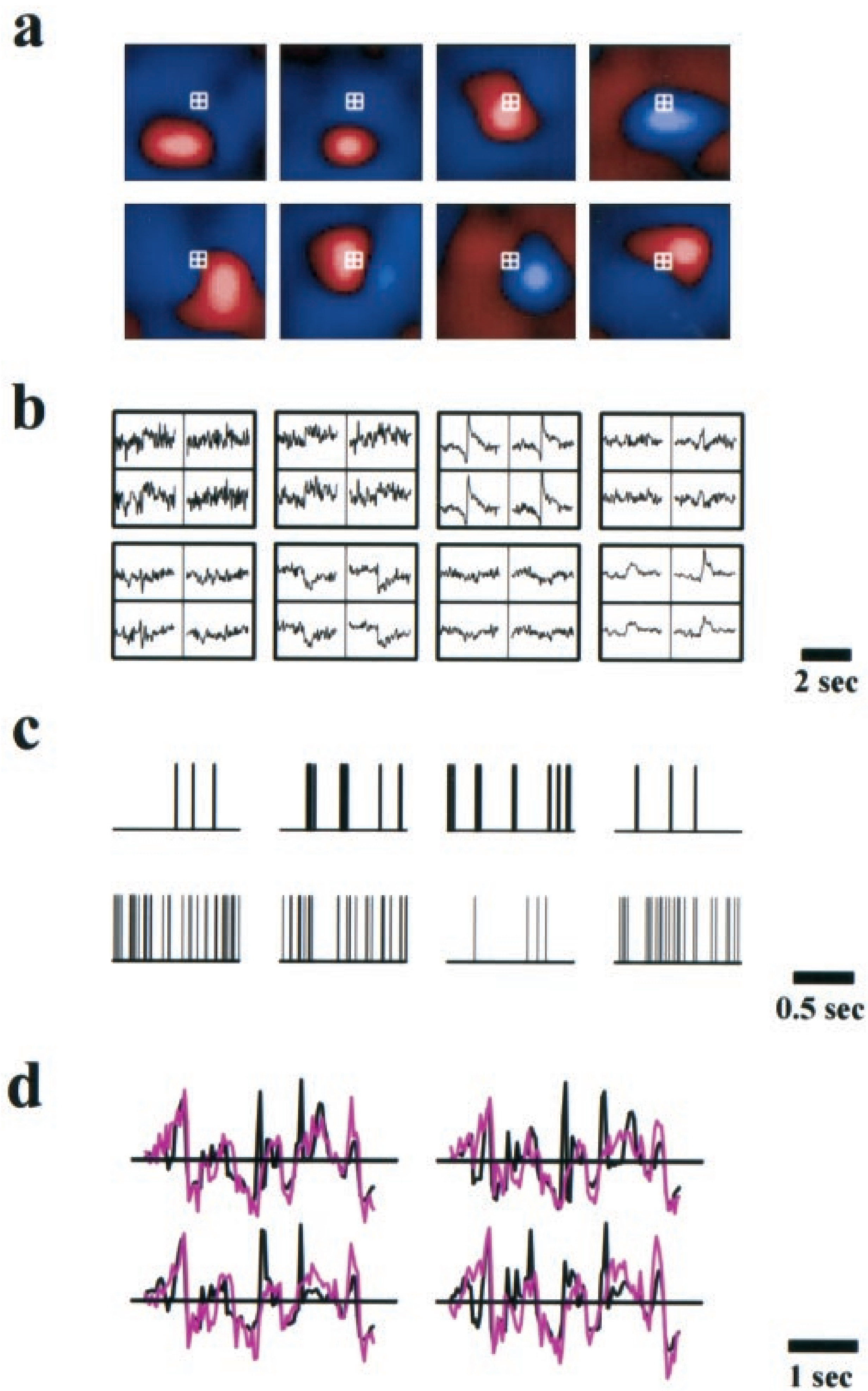


Fig. 3. Simple cortical cells can be modeled as a linear system acting on a spatio-temporal volume followed by a spike encoder. The impulse response of the linear system, $h(x, y, t)$, can be measured via reverse correlation when the system is stimulated with spatio-temporal white noise.

D. Ringach, R. Shapley / Cognitive Science 28 (2004) 147–166

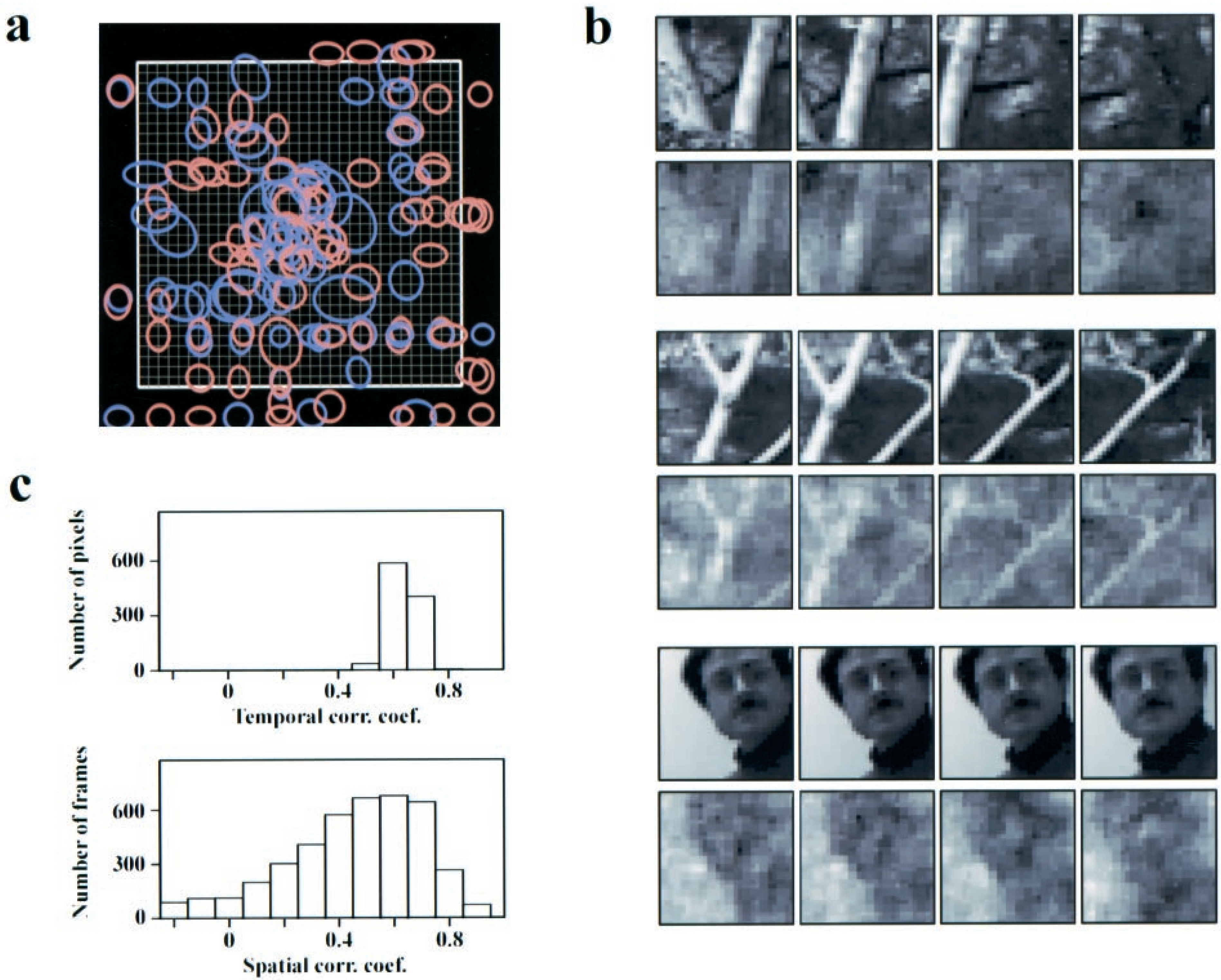
Reconstruction of natural scenes from ensemble responses in the LGN

Figure 1. The procedure for reconstructing visual stimuli from the responses of multiple neurons. *a*, Receptive fields of eight neurons recorded simultaneously with multielectrodes. These receptive fields were mapped with white-noise stimuli and the reverse correlation method (Sutter, 1987; Reid et al., 1997). *Red,* On responses. *Blue,* Off responses. The brightest colors correspond to the strongest responses. The area shown is 3.6 × 3.6°. The responses of these cells were used to reconstruct visual inputs at the four pixels (0.2°/pixel) outlined with the *white squares*. *b*, Linear filters for input reconstruction. The eight blocks correspond to the eight cells shown in *a*. Shown in each block are the four filters from that cell to the four pixels outlined in *a*. They represent the linear estimates of the input signals at these pixels immediately preceding and following a spike of that cell. Each filter is 3.1-sec-long, with 1.55 sec before and 1.55 sec after the spike. *c,* Spike trains of the eight neurons in response to movie stimuli. *d*, The actual (*black*) and the reconstructed (*magenta*) movie signals at the four pixels outlined in *a*. Unlike white noise, natural visual signals exhibit more low-frequency, slow variations than high-frequency, fast variations. Such temporal features are well captured by the reconstruction.



Source: Stanley et al 99

Reconstruction of natural scenes from ensemble responses in the LGN



Source: Stanley et al 99

Reverse correlation: Color opponent neurons in the LGN

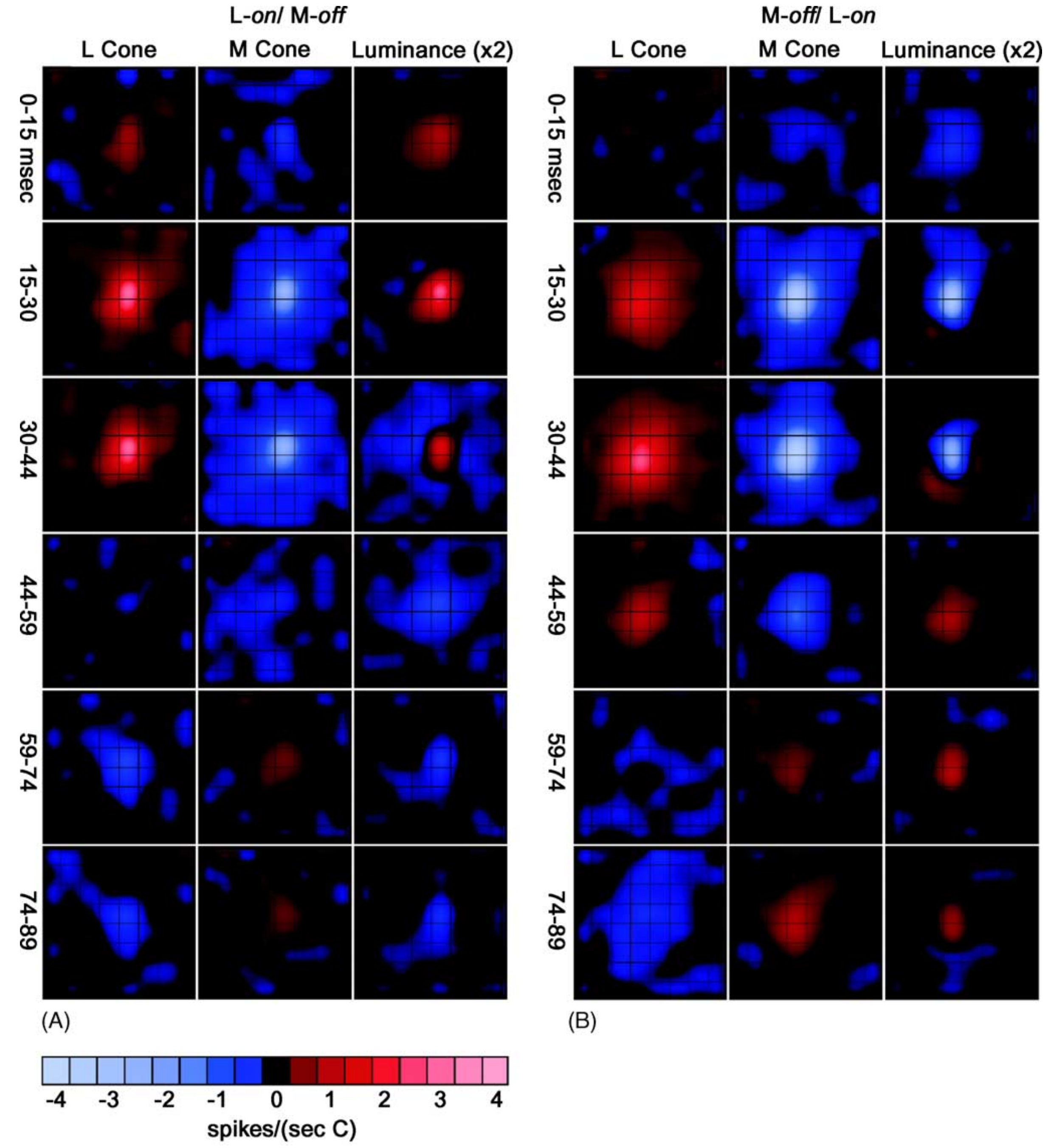
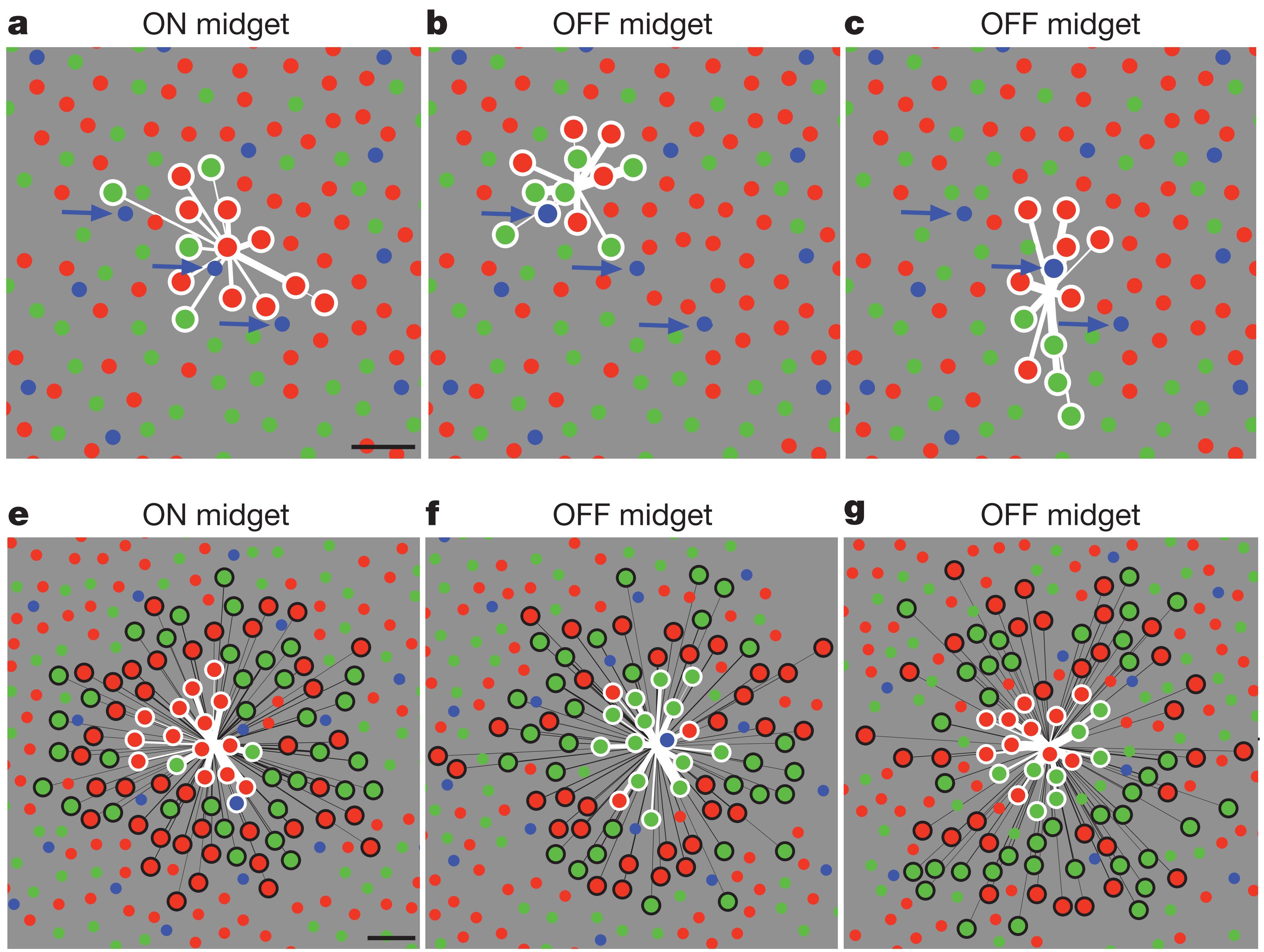


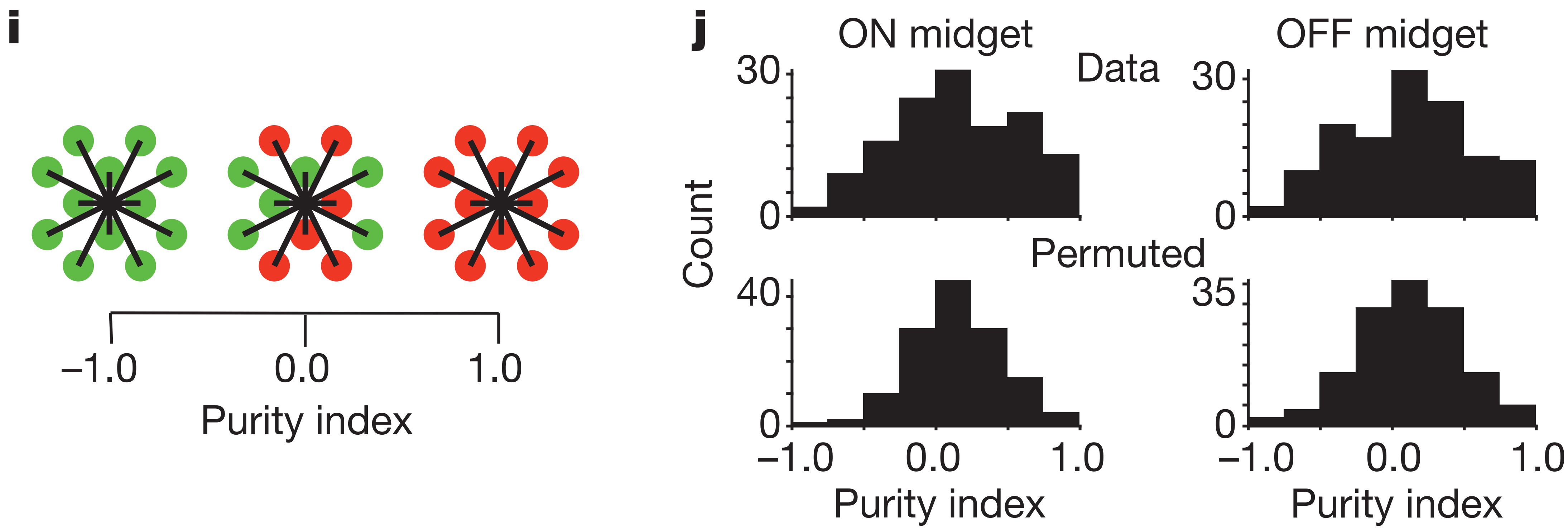
Fig. 5. (A and B) Spatial kernels for parvocellular LGN cells obtained by performing reverse correlation in cone-isolating directions (Reid & Shapley, 2002).

Functional connectivity in the retina



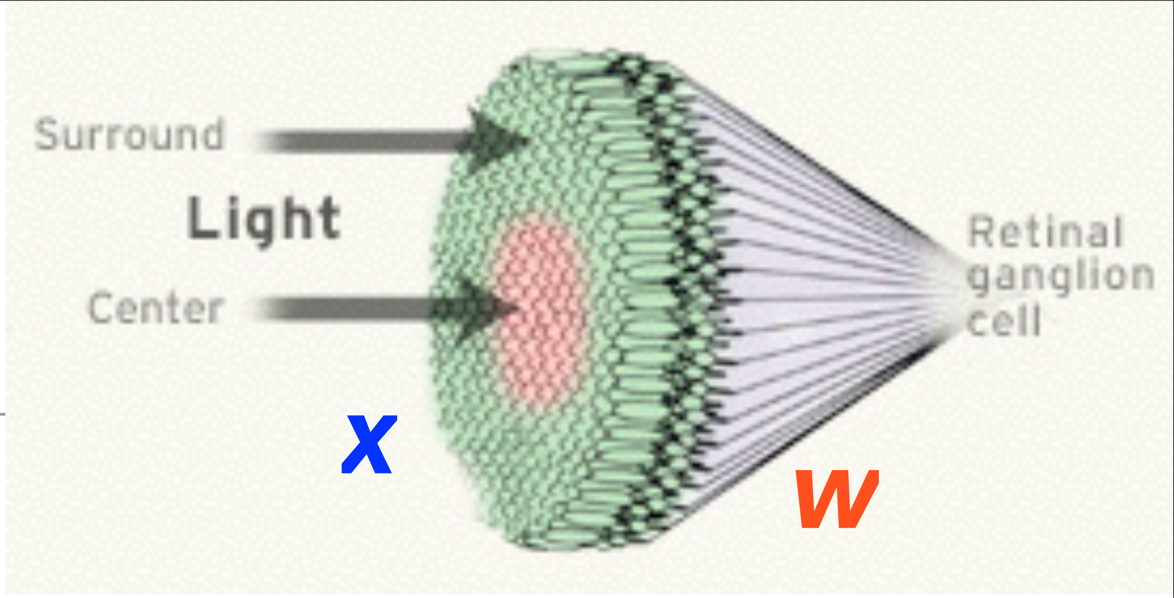
Field et al ’10

Functional connectivity in the retina



Field et al ’10

What do neurons compute?



- Neurons detect features (=patterns or templates) that are stored in their synaptic weights

$$
\begin{aligned}
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&= ||\mathbf{w}||||\mathbf{x}|| \cos(\theta)
\end{aligned}
$$

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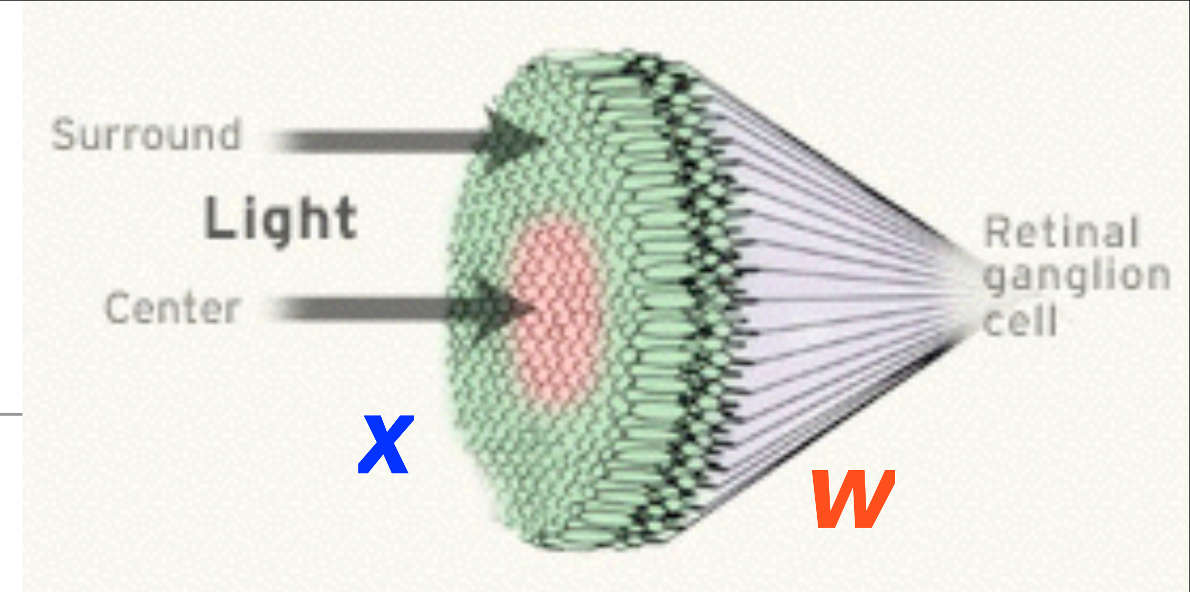


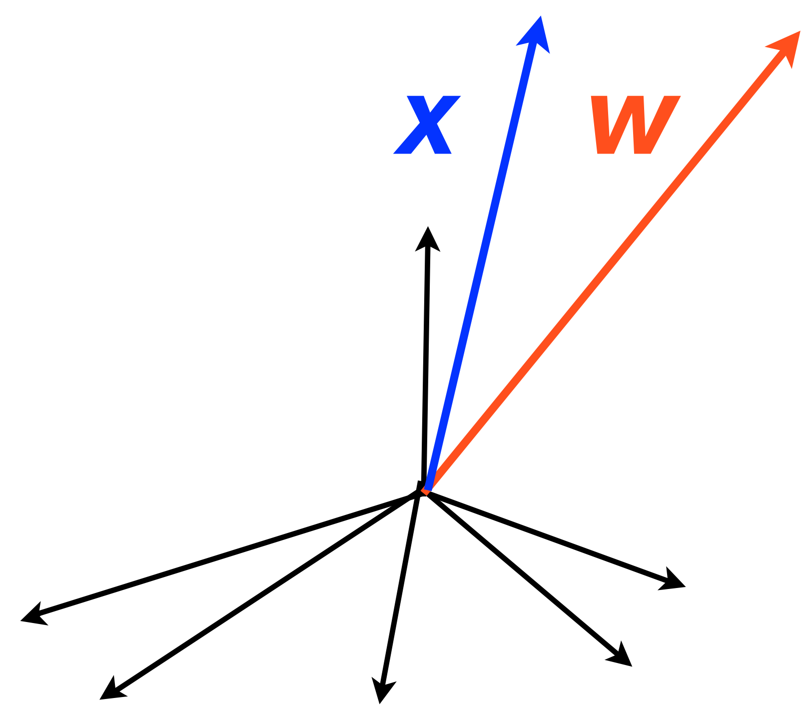
- Neurons detect features (=patterns or templates) that are stored in their synaptic weights

w *x*

dot( , )

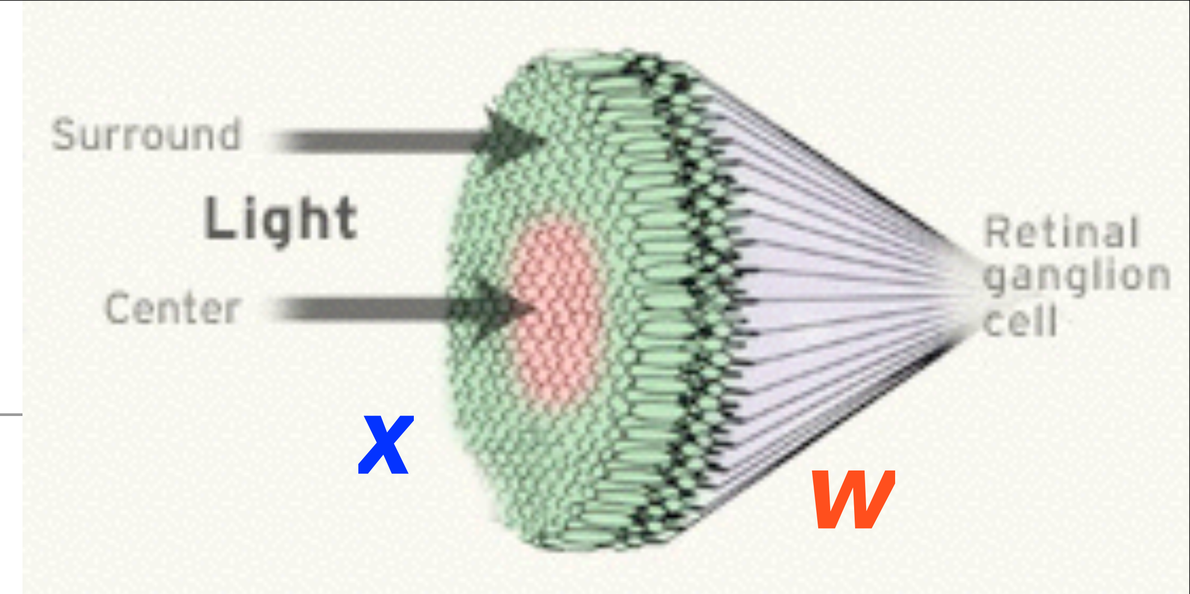
preferred stimulus

input pattern



What stimulus should I present to elicit the max response from the model unit?

What do neurons compute?



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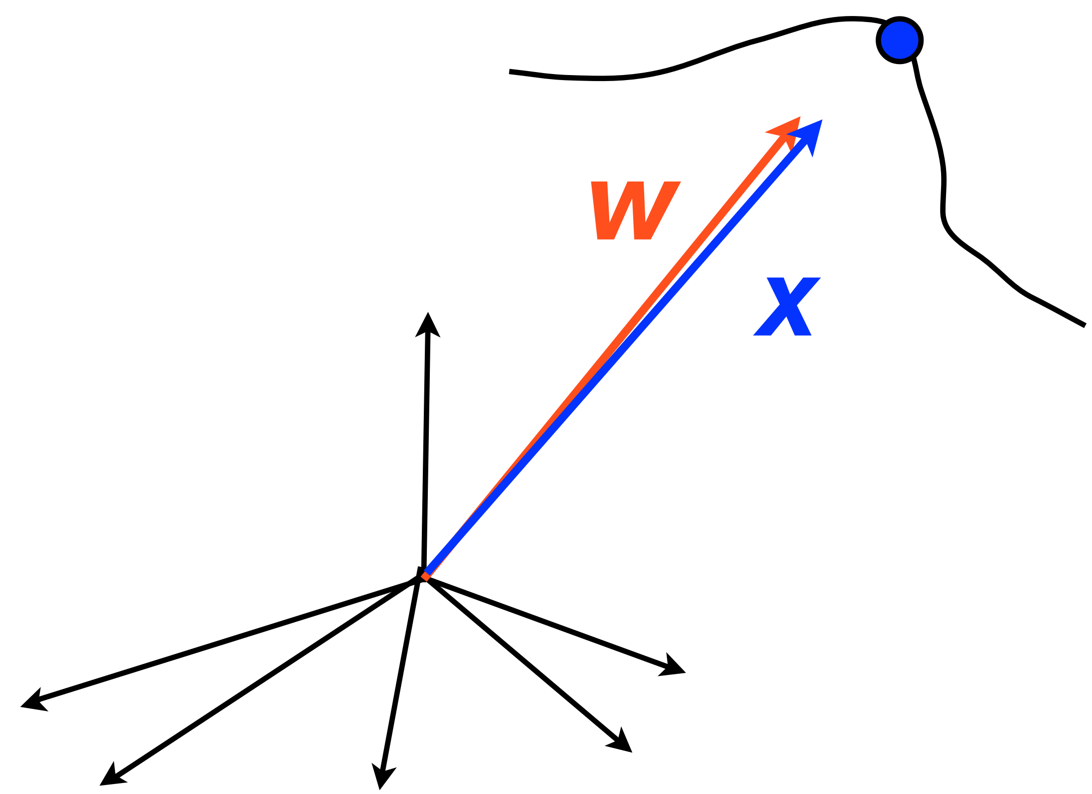
w **x**

dot( , )

input pattern

preferred stimulus



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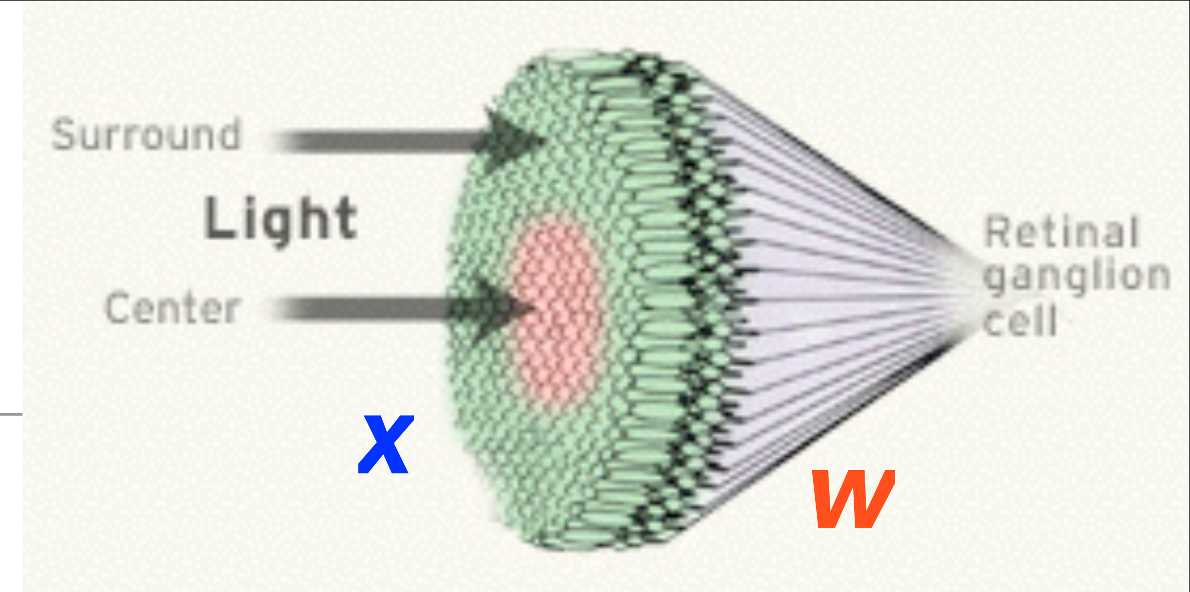
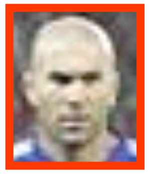


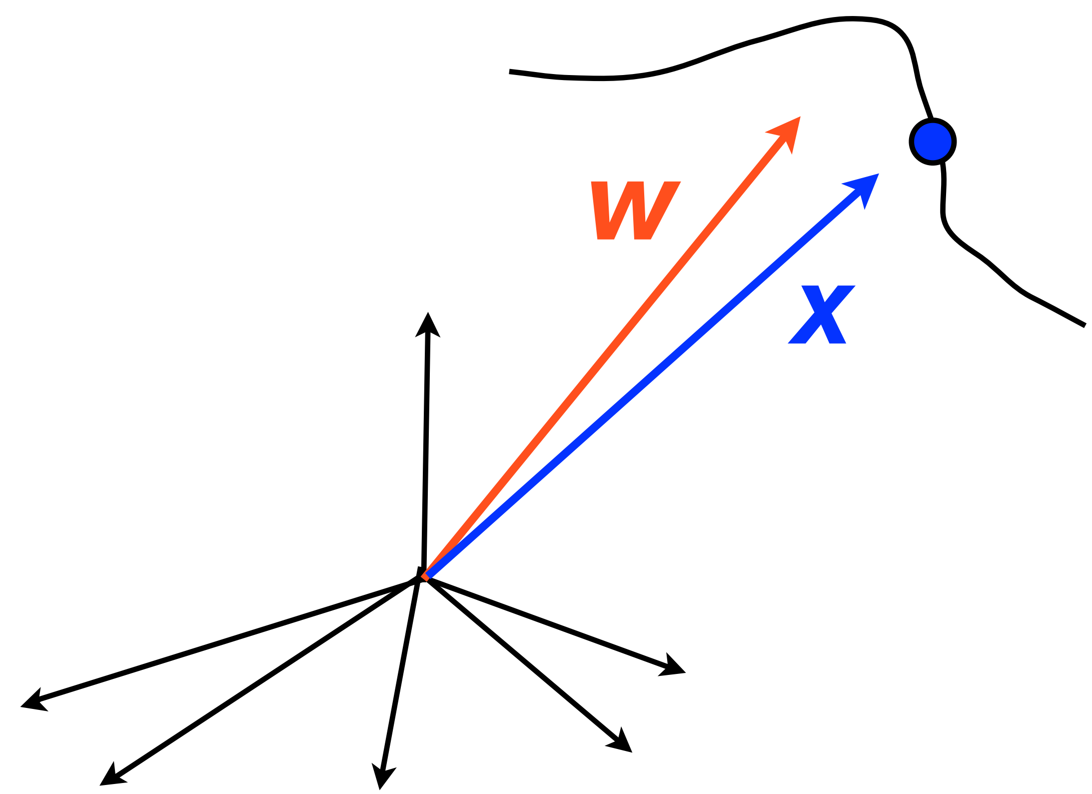
- Neurons detect features (=patterns or templates) that are stored in their synaptic weights

w x

dot( , )

input pattern

preferred stimulus



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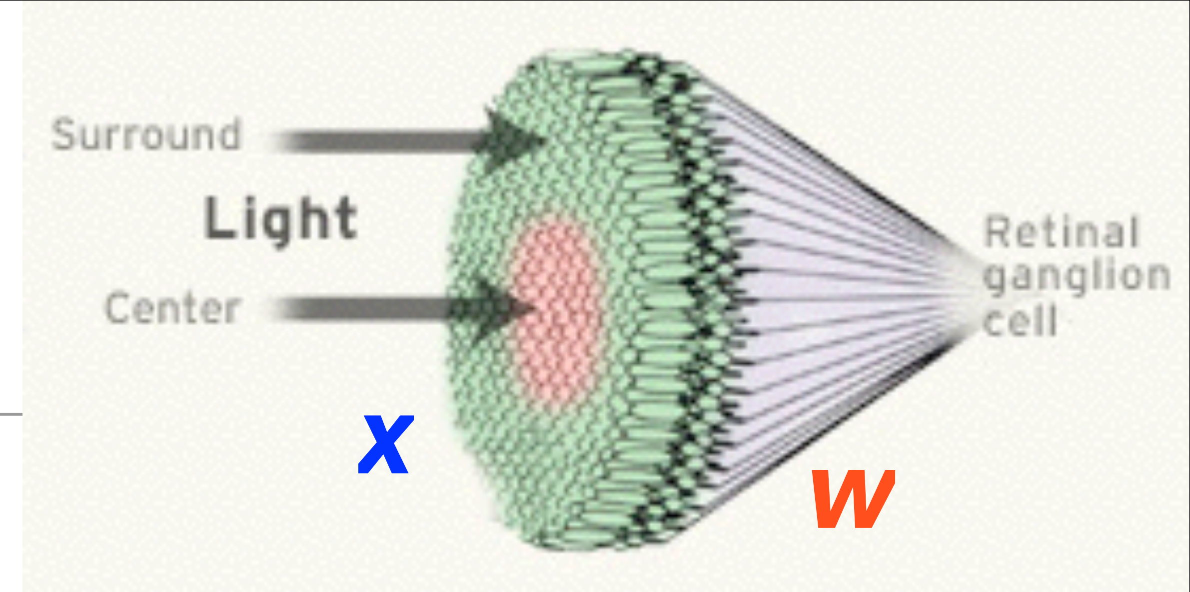

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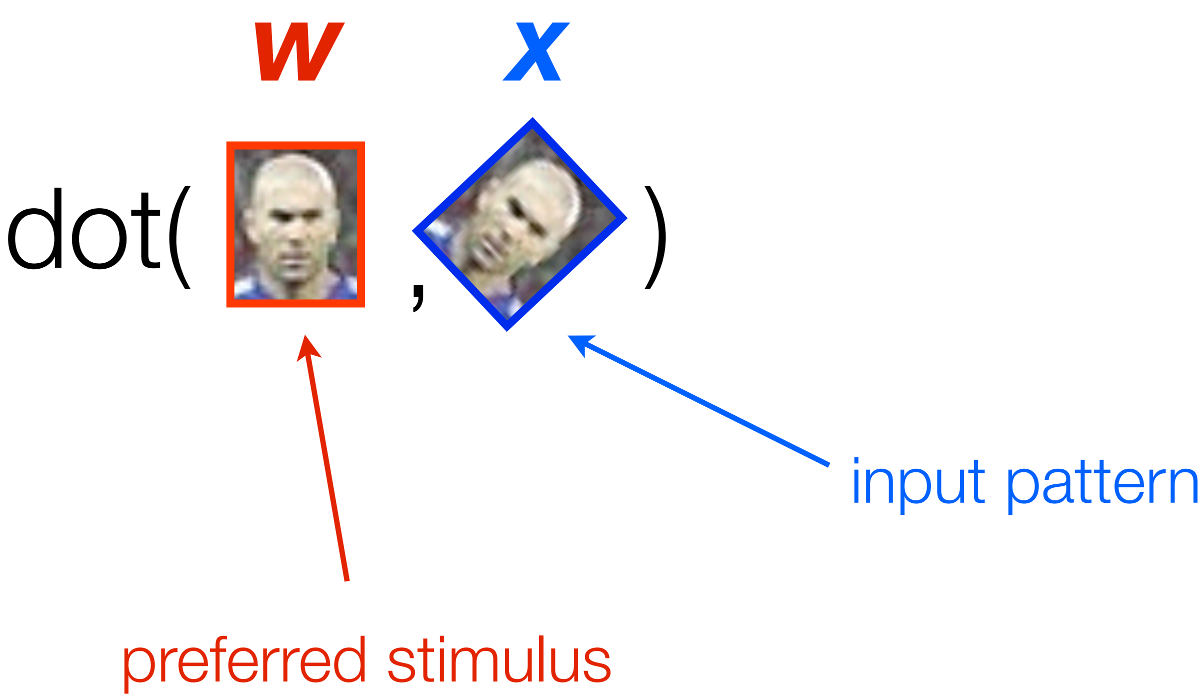

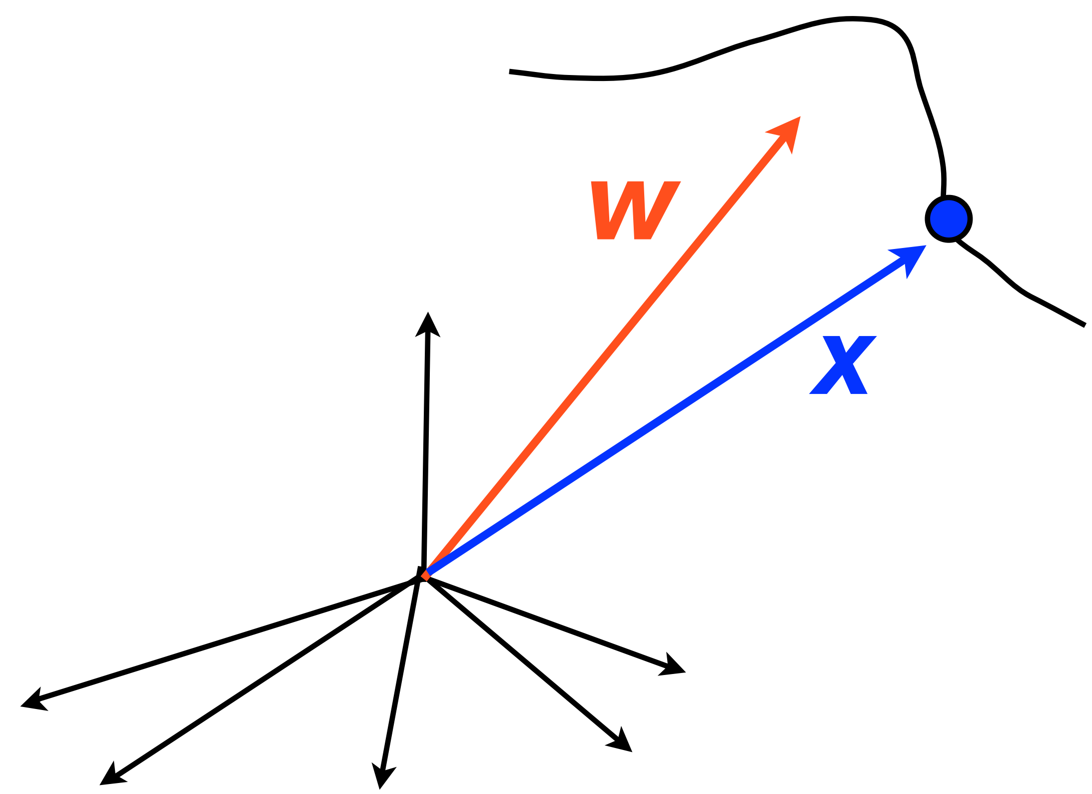

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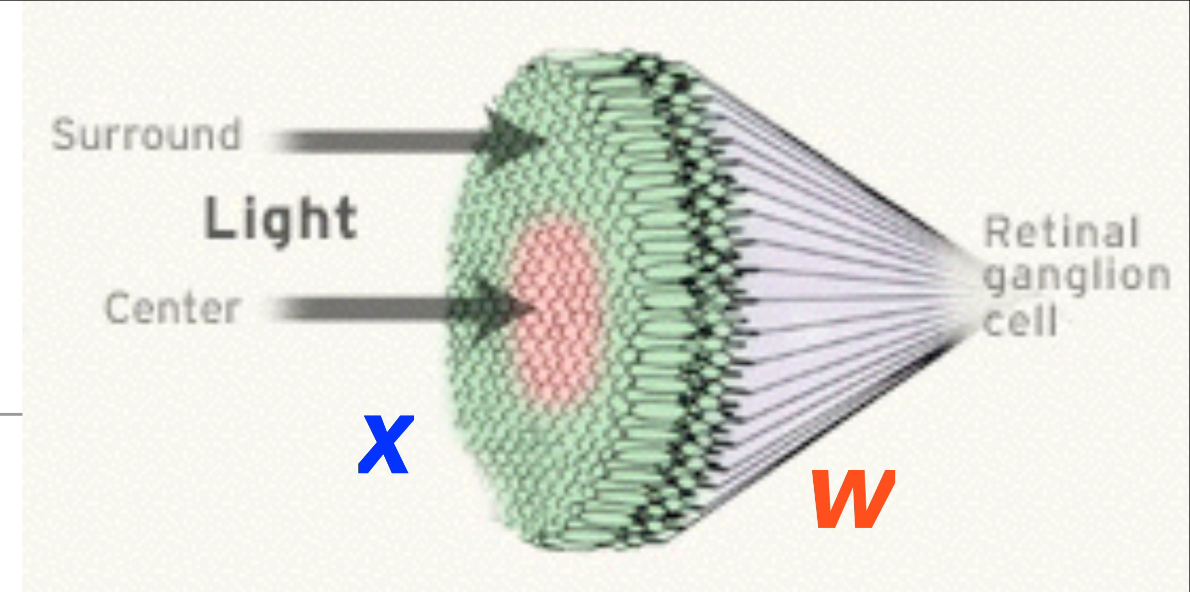

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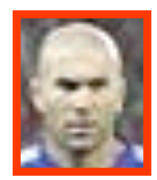
w x w x

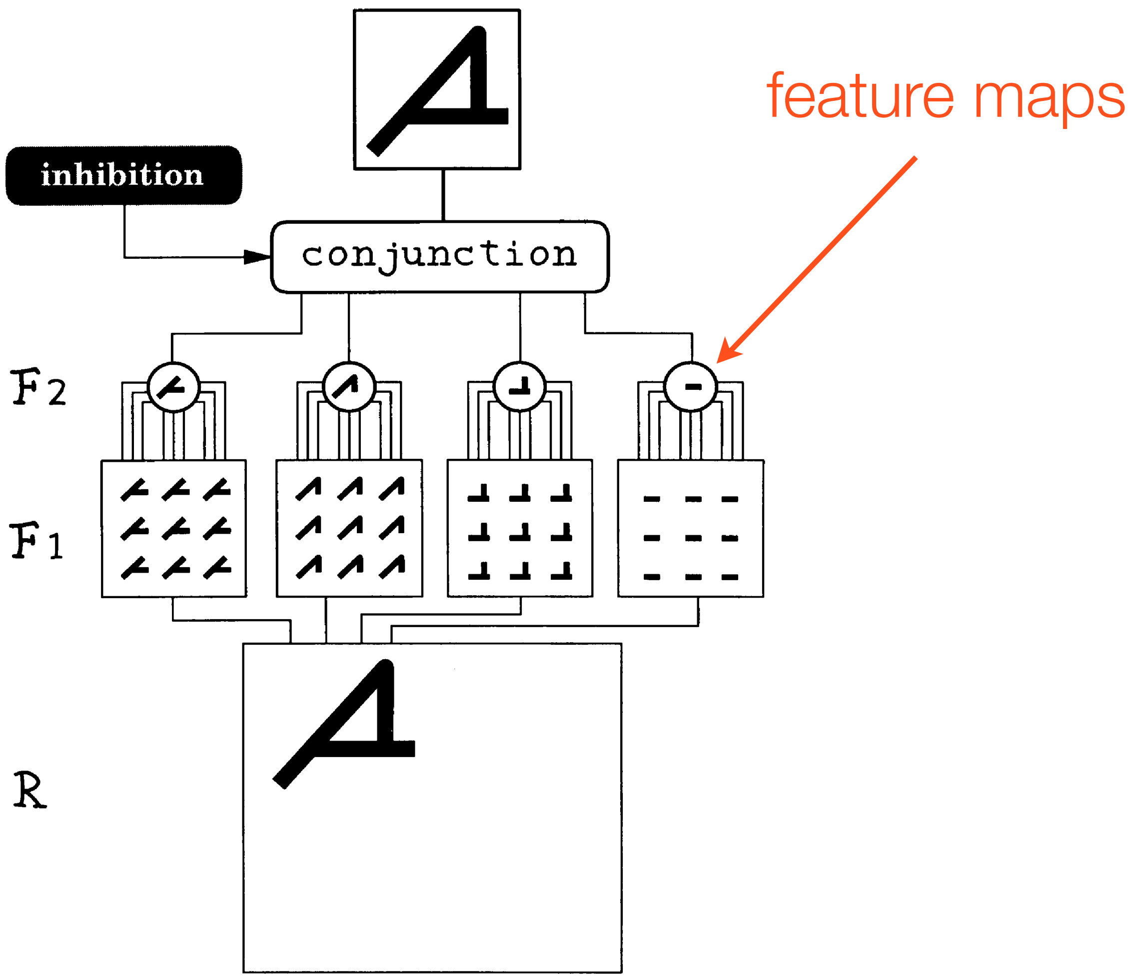
dot( , ) dot( , ) ...

Filtering in image processing

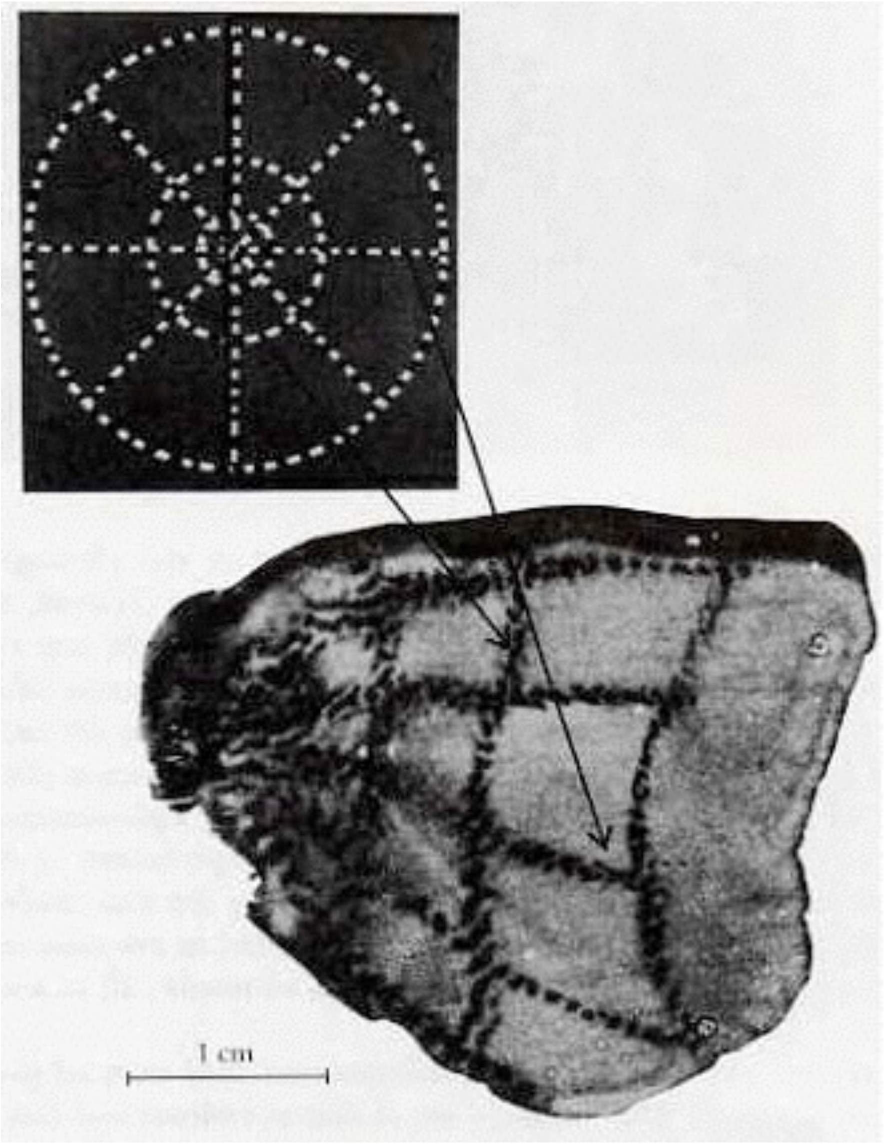
- Filtering the image is a set of dot-products
- **Insight:** Filters look like the effects they are intended to find

Cortex vs. computers

Brains: Full-replication scheme



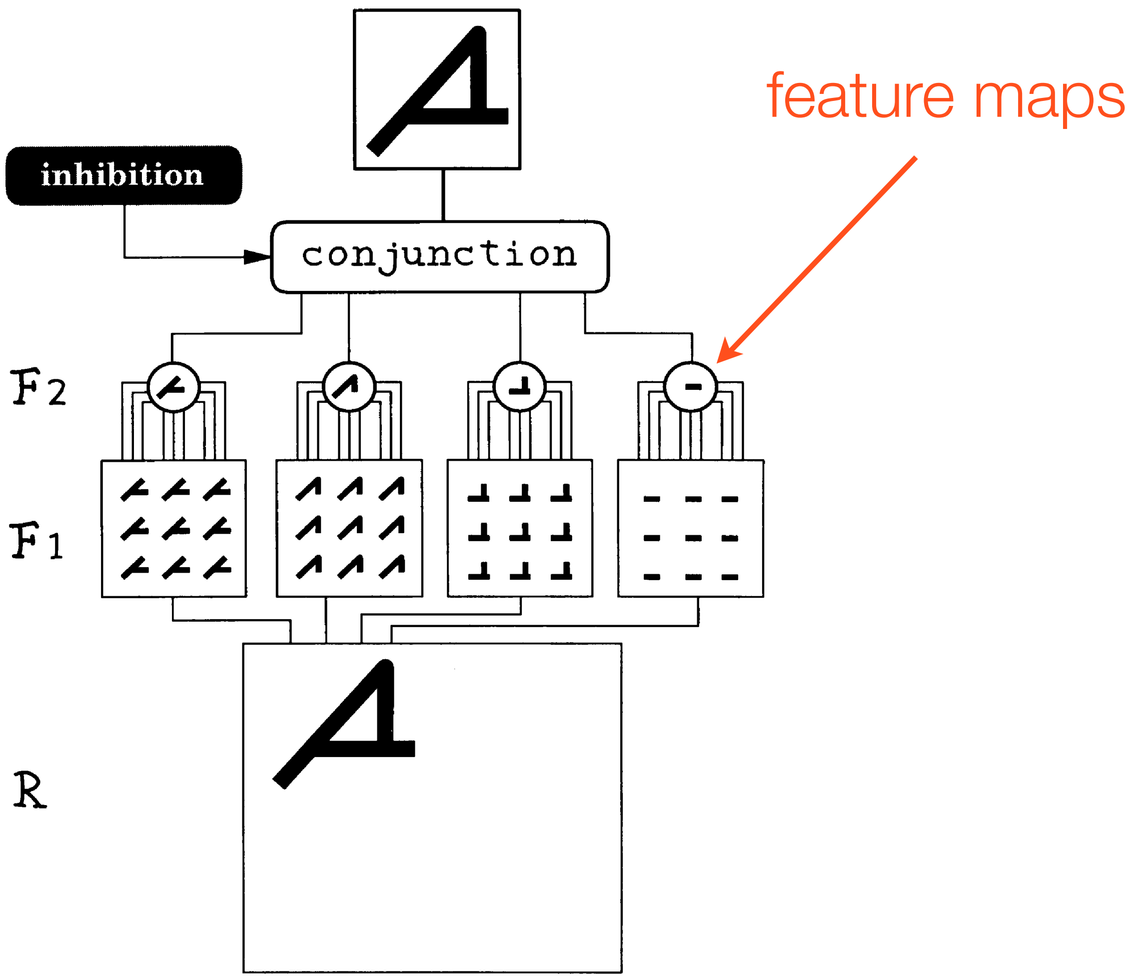
Retinotopy in early visual areas



source: Hubel

Cortex vs. computers

Brains: Full-replication scheme



Computers: Convolution

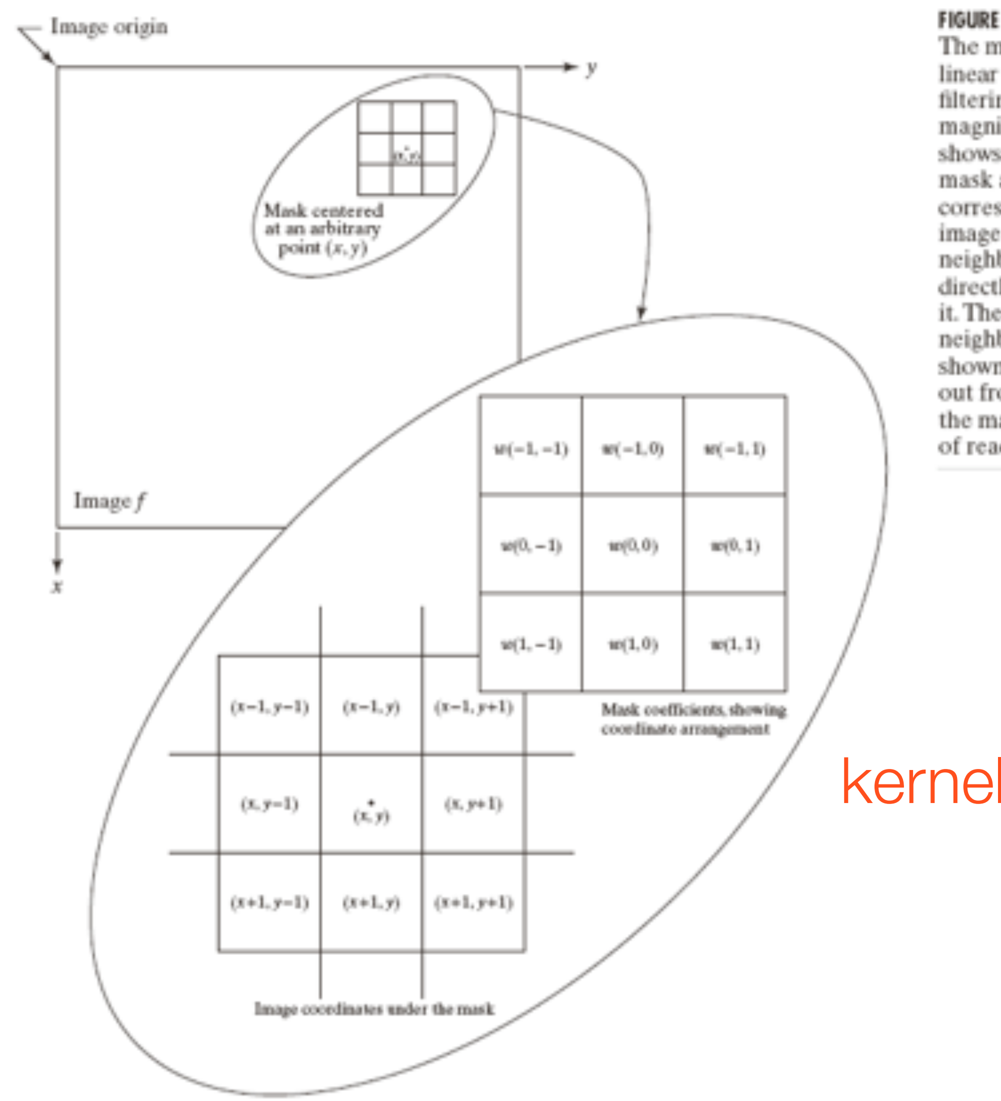


FIGURE 3.13 The mechanics of linear spatial filtering. The magnified drawing shows a 3 × 3 filter mask and the corresponding image neighborhood directly under it. The image neighborhood is shown displaced out from under the mask for ease of readability.

Neurons as feature detectors

- ~1M receptors
- 2.5-3.5M connecting neurons
- 0.5 M ganglion cells
- Each ganglion cell receives many inputs from the receptors
- Each receptor projects to many ganglion cells

Neurons as feature detectors

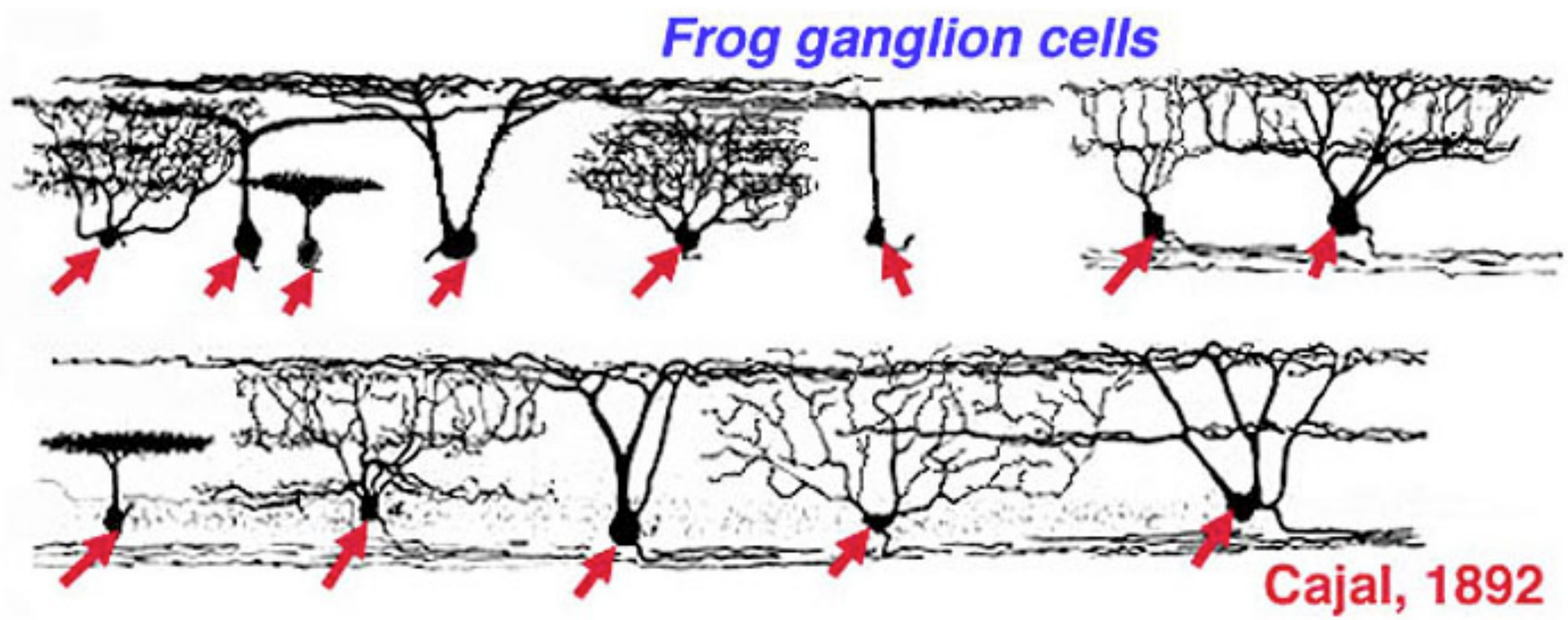
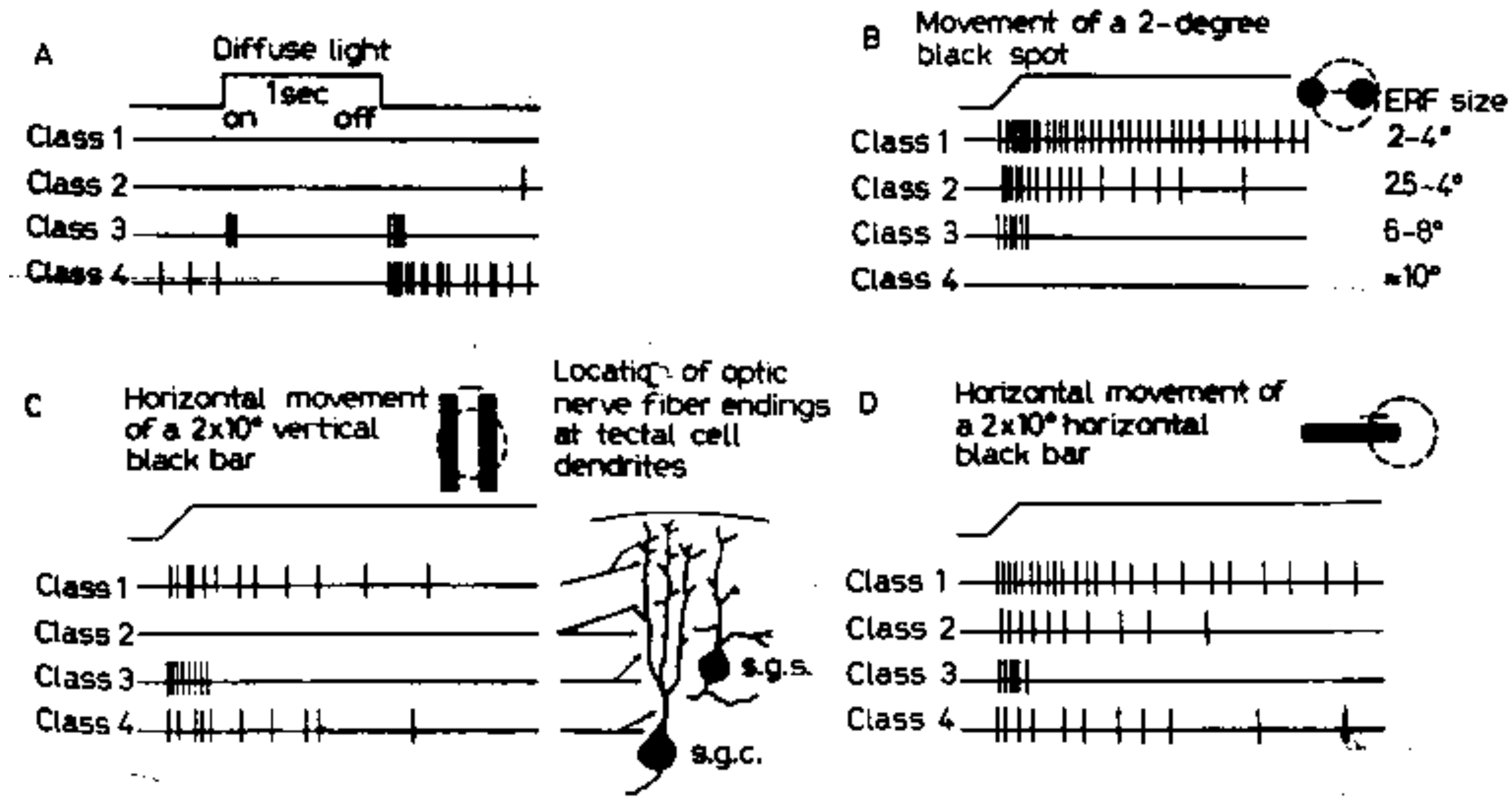


Fig. 1.Cajals drawing of ganglion cells of the frogs retina.

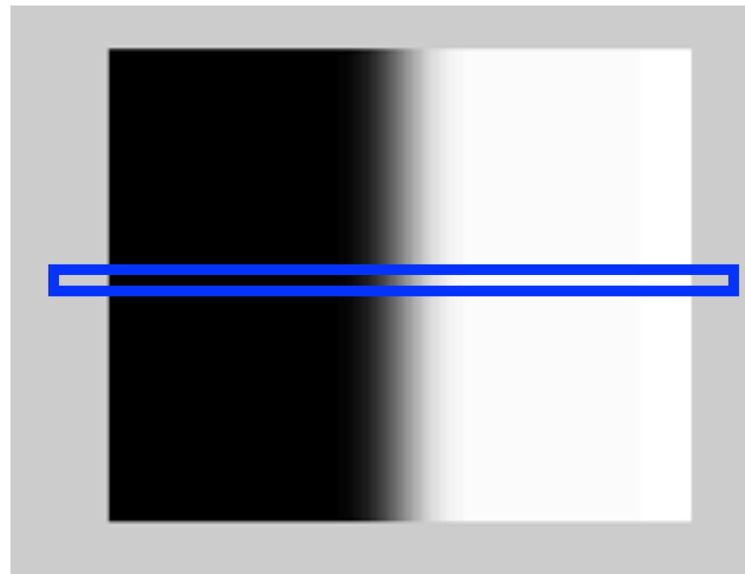
source: webvision

Neurons as feature detectors



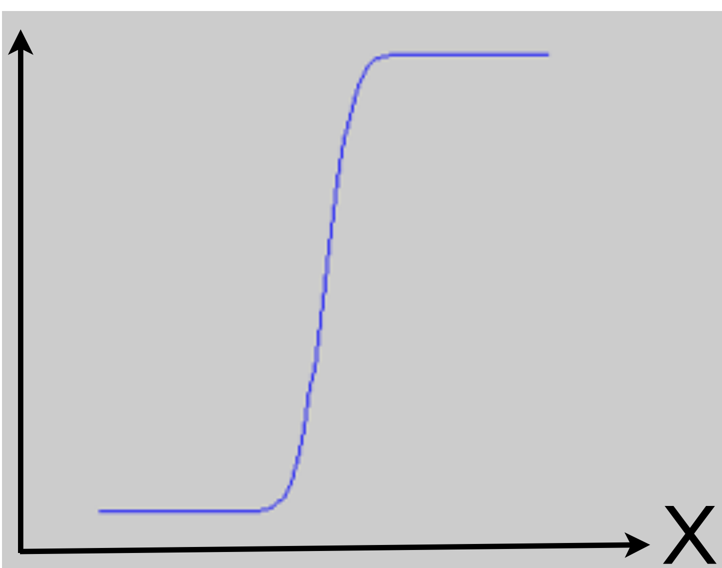
We have been tempted for example, to call the convexity detectors [class 2] “bug perceivers”. Such a fiber responds best when a dark object, smaller than a receptive field, enters that field, stops, and moves about intermittently thereafter. The response is not affected if the lighting changes or if the background (say a picture of grass and flowers) is moving, and is not there if only the background, moving or still, is in the field. Could one better describe a system for detecting an accessible bug? [Lettvin et al 1959]

Neurons as edge detectors

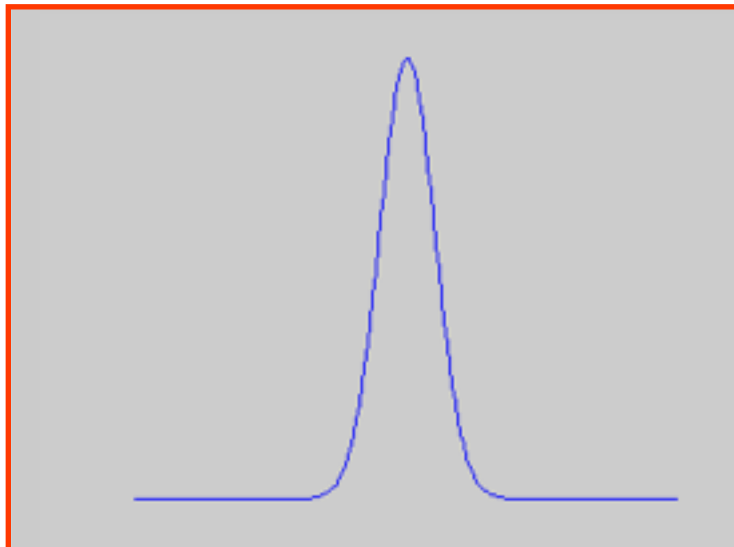


edge

I(x)

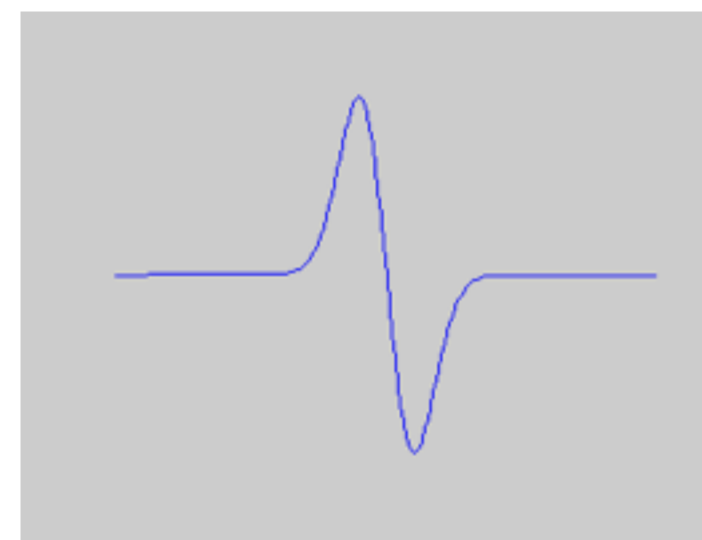


I



First derivative of I

$$\frac{\delta I}{\delta x}$$



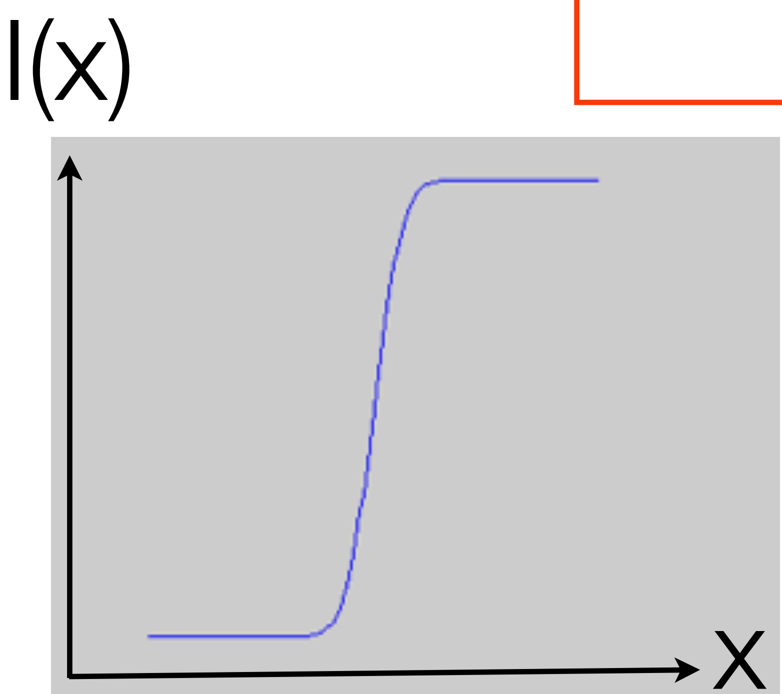
Second derivative of I

$$\frac{\delta^2 I}{\delta x^2}$$

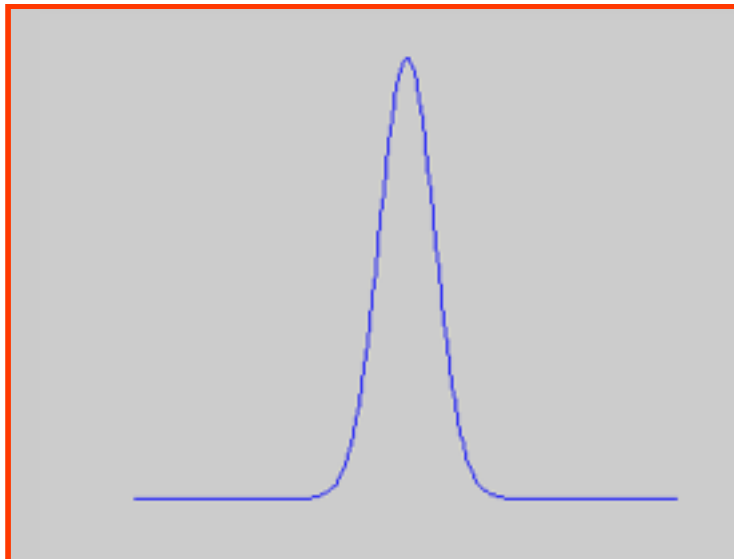
Neurons as edge detectors

$$\frac{\Delta I(x,y)}{\Delta x} \approx \frac{I(x+\Delta x) - I(x)}{\Delta x}$$

$$\approx I(x+1) - I(x)$$

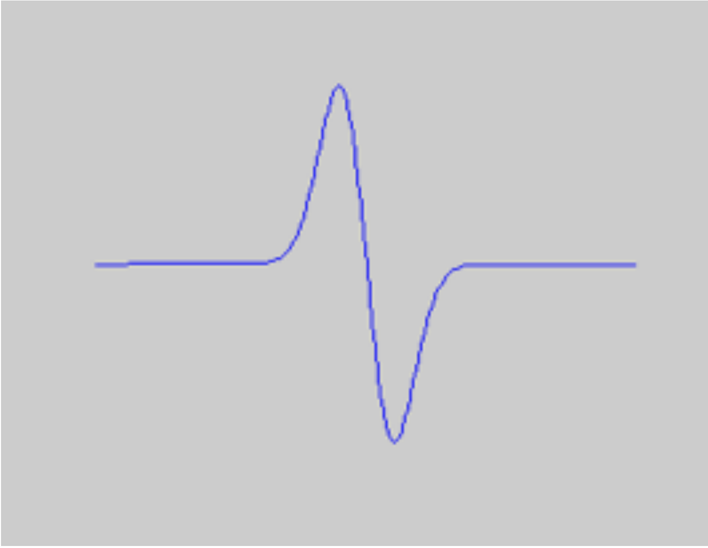


I



First derivative of I

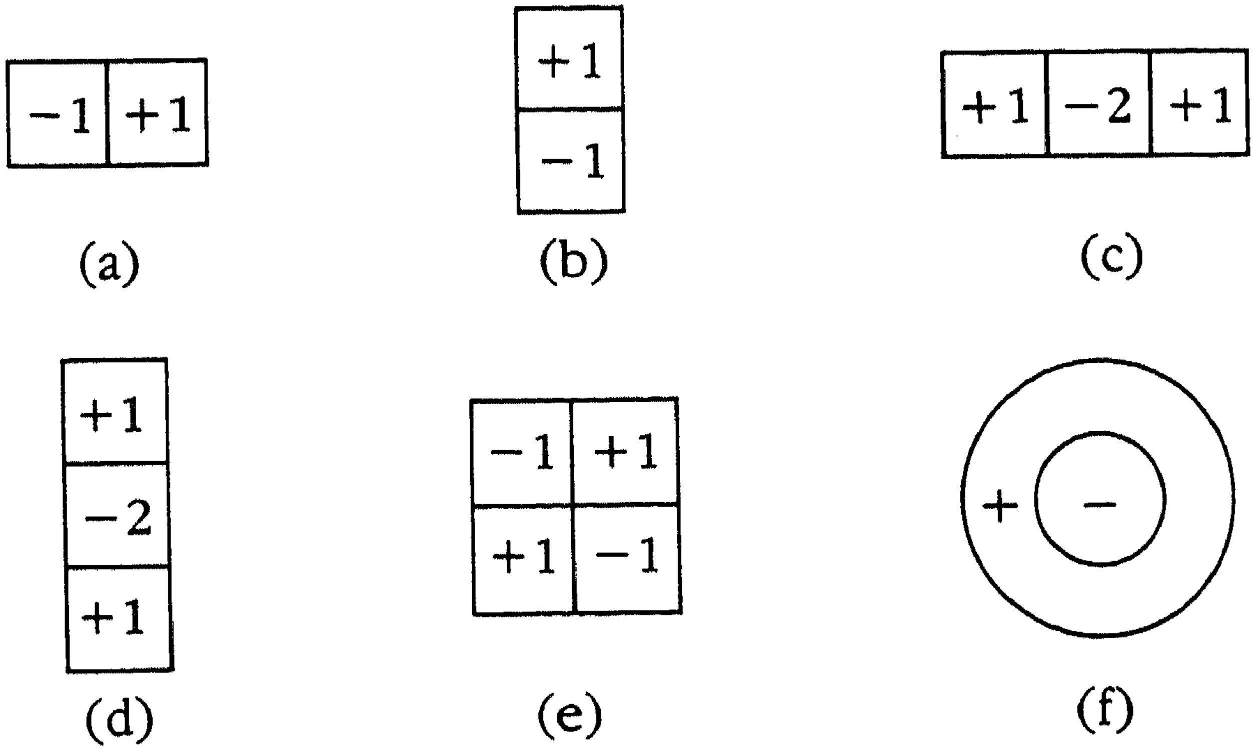
$$\frac{\delta \; I}{\delta \; x}$$

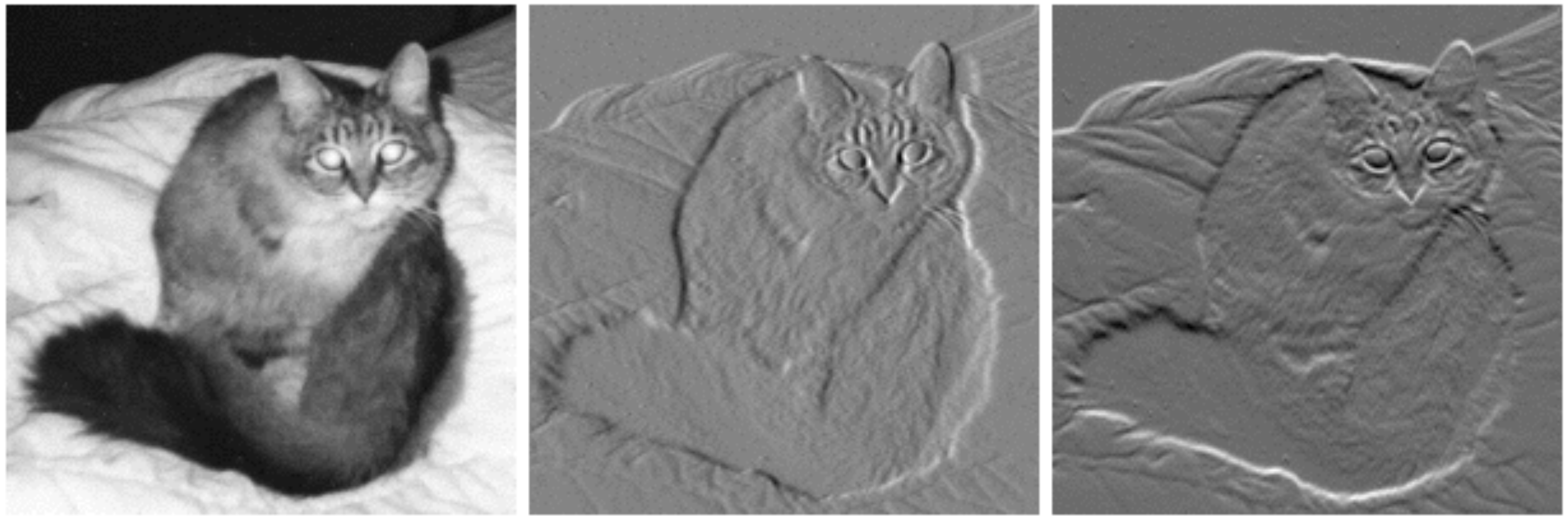


Second derivative of I

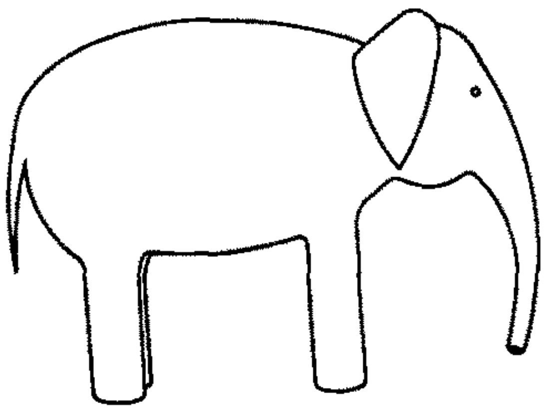
$$\frac{\delta^2 I}{\delta \; x^2}$$

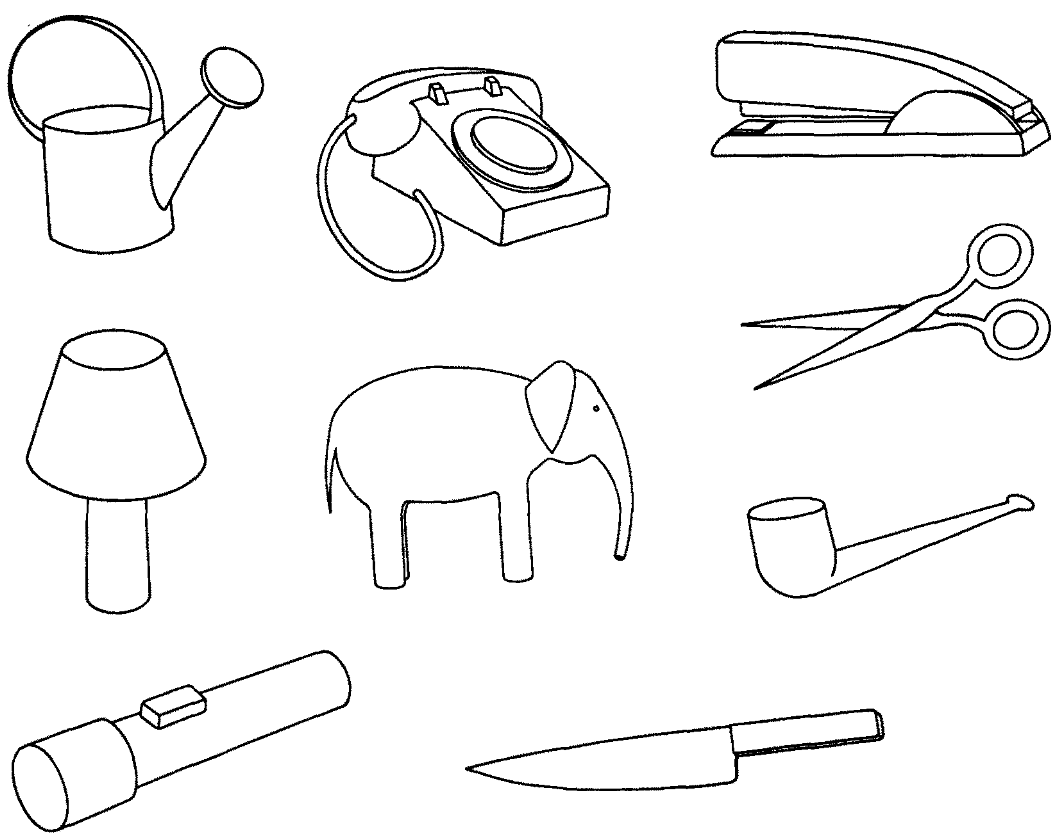
Differential operators





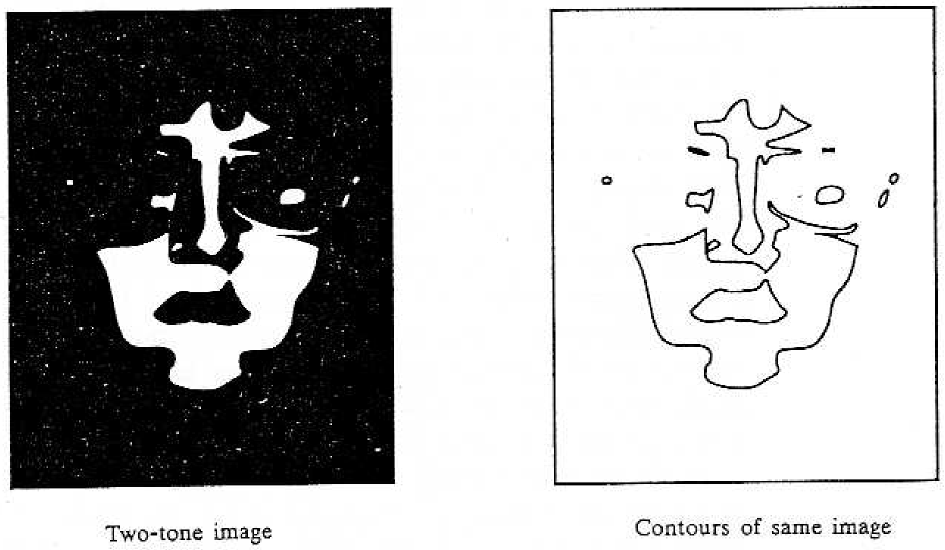
Edges and contours play a special role in vision





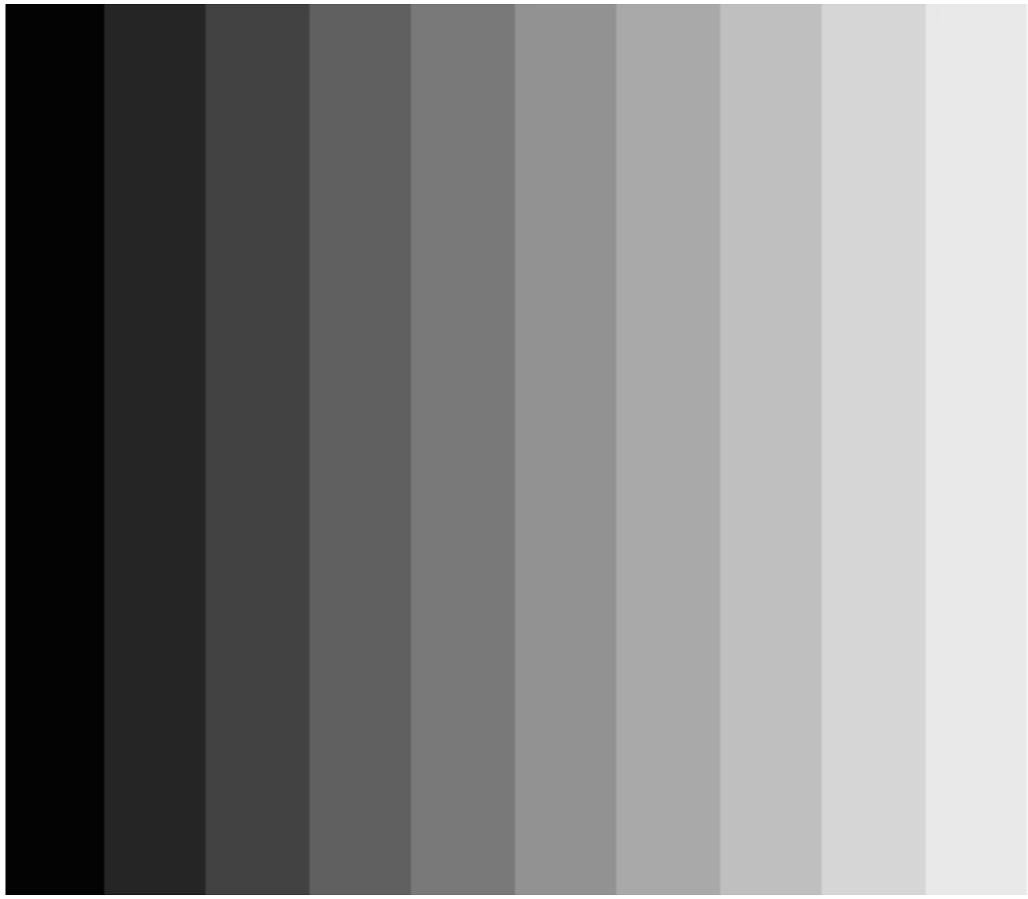
Source: Biederman

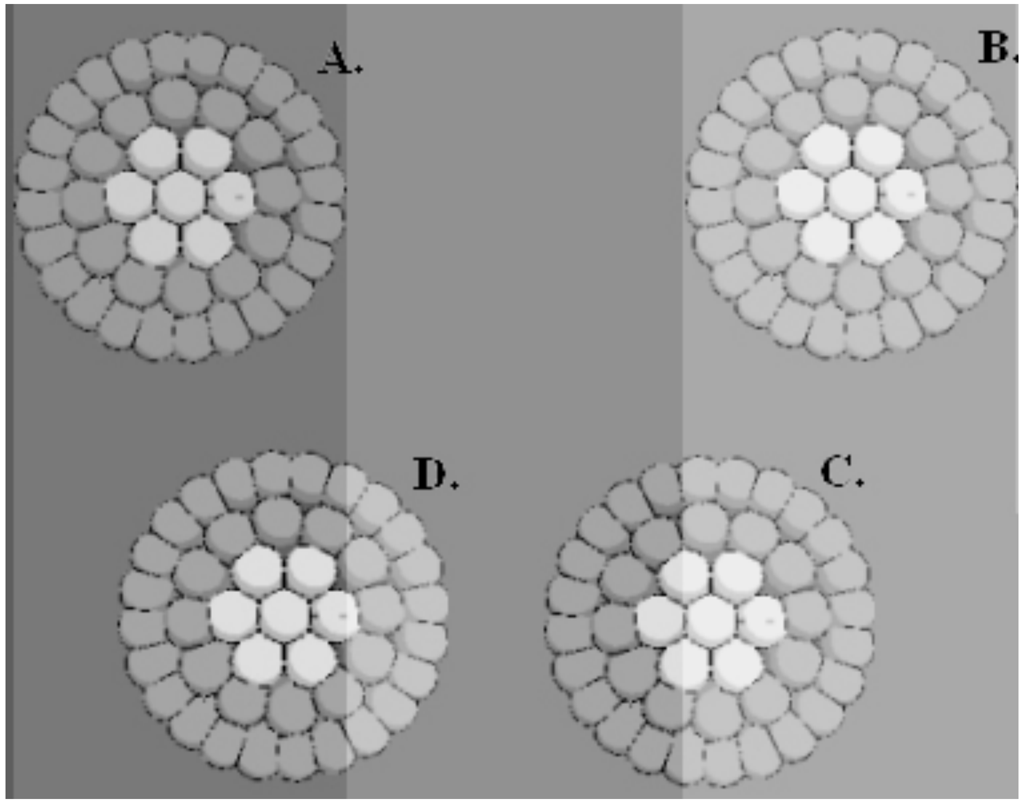
Figure 11. Nine of the experimental objects.



Source: Cavanagh '95

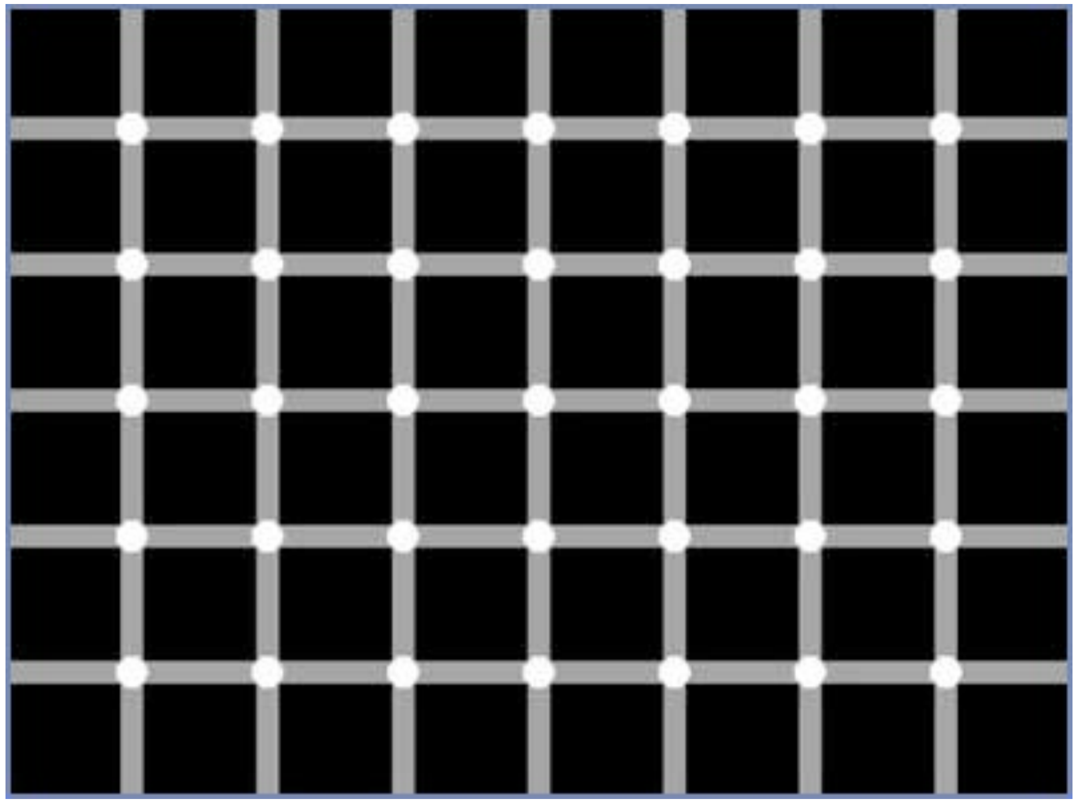
Illusions and center-surround processing

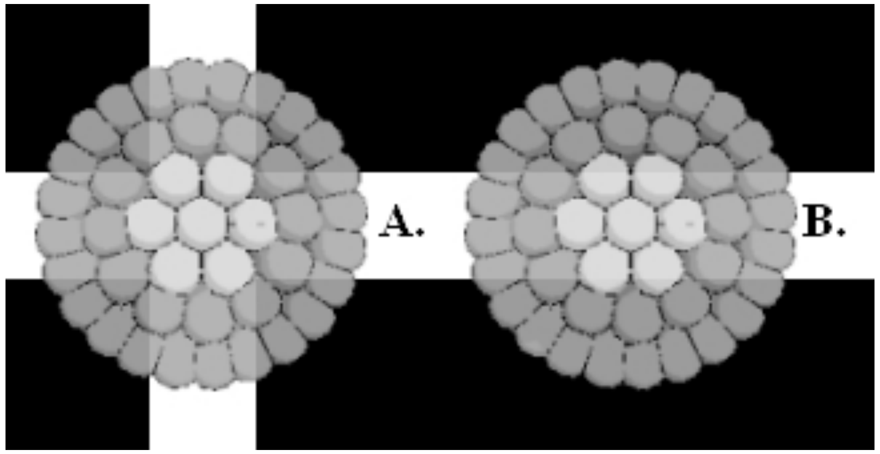




Source: http://www.nku.edu/~issues/illusions

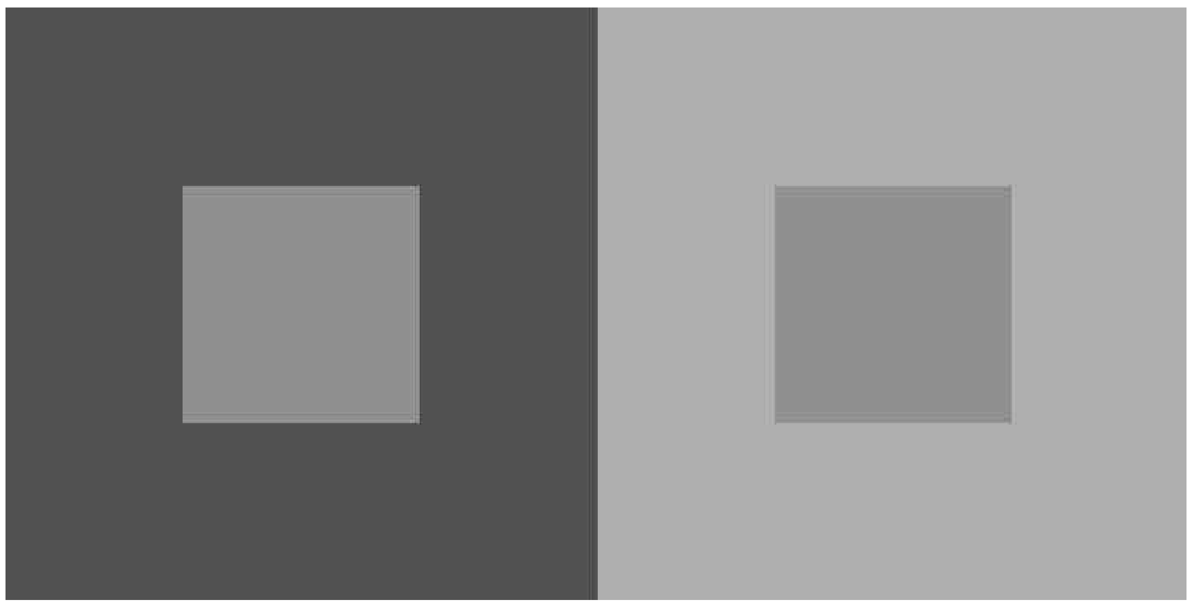
Illusions and center-surround processing

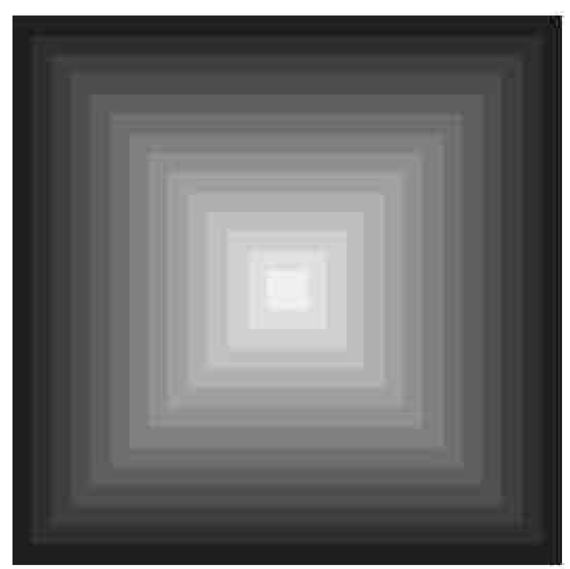




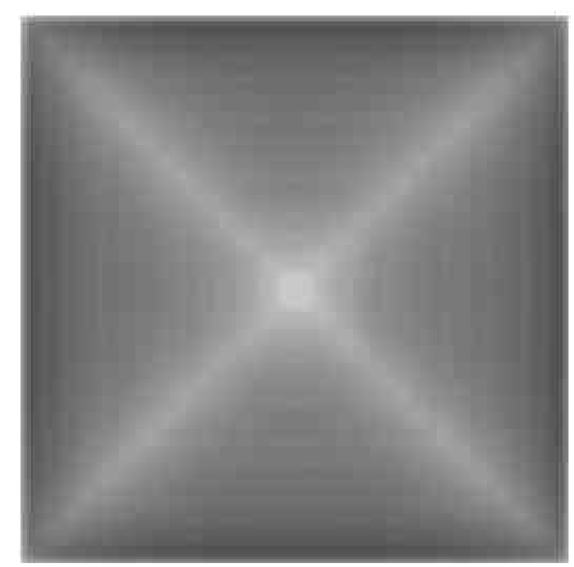
Source: http://www.nku.edu/~issues/illusions

Illusions and center-surround processing





a



b

Source: Adelson (2000)

Computing with RFs: Summary

- Basic model of neural processing
- Reverse engineering computations by trying to interpret synaptic weights
- Filtering, convolution, preferred stimulus, template matching