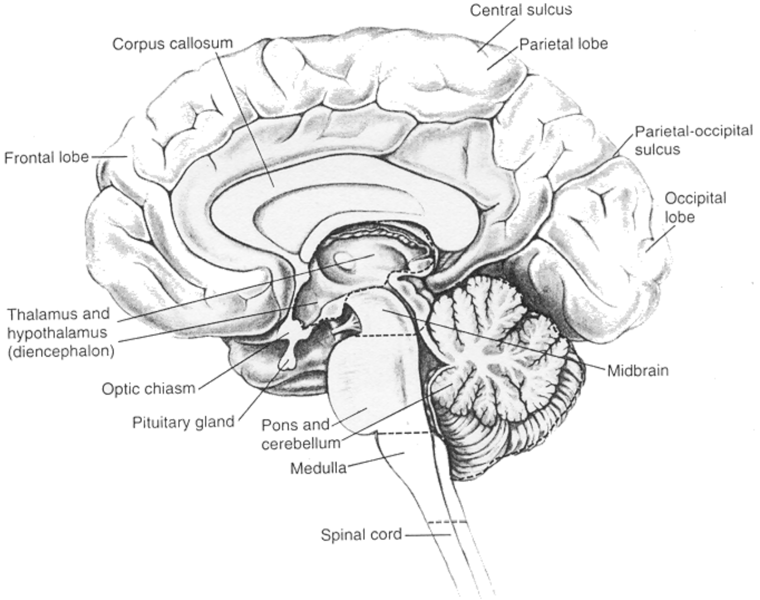
Introduction to Neural Coding

Peter Latham / Maneesh Sahani

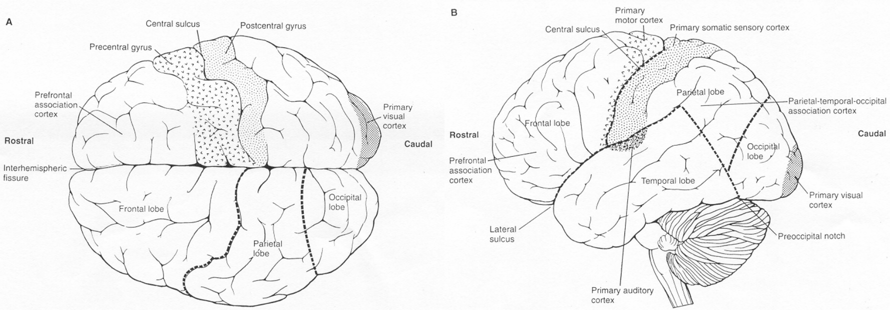
Gatsby Computational Neuroscience Unit
University College London

Term 1, Autumn 2013

The CNS


Central sulcus
Corpus callosum
Parietal lobe
Parietal-occipital sulcus
Frontal lobe
Occipital lobe
Thalamus and hypothalamus (diencephalon)
Midbrain
Optic chiasm
Pituitary gland
Pons and cerebellum
Medulla
Spinal cord

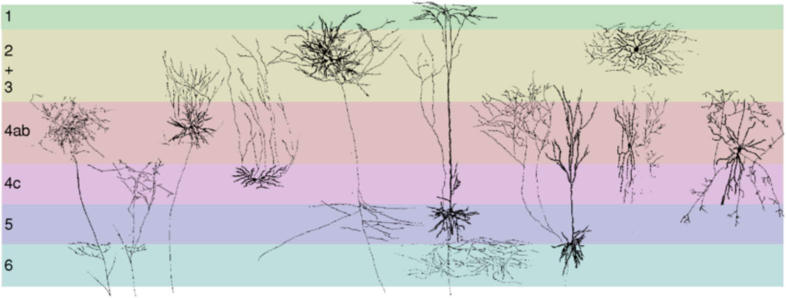
Neocortex



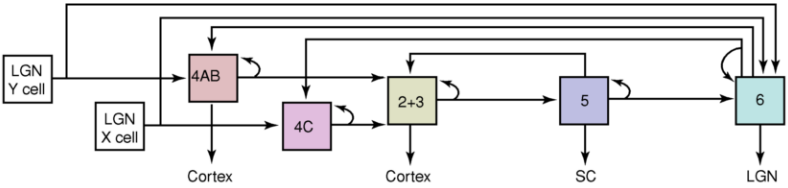
A
Central sulcus
Postcentral gyrus
Precentral gyrus
Prefrontal association cortex
Primary visual cortex
Rostral
Caudal
Interhemispheric fissure
Frontal lobe
Occipital lobe
Parietal lobe
B
Primary motor cortex
Central sulcus
Primary somatic sensory cortex
Parietal lobe
Parietal-temporal-occipital association cortex
Frontal lobe
Rostral
Caudal
Occipital lobe
Prefrontal association cortex
Temporal lobe
Primary visual cortex
Lateral sulcus
Preoccipital notch
Primary auditory cortex

Cortical layers

A



B



Neural signals (in vivo)

Aggregate

- aggregate fields – EEG, MEG, LFP
- aggregate membrane voltage – dye imaging (voltage/calcium)
- metabolism – fMRI, PET, intrinsic imaging

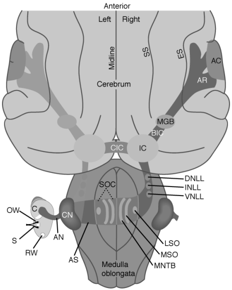
Single neuron

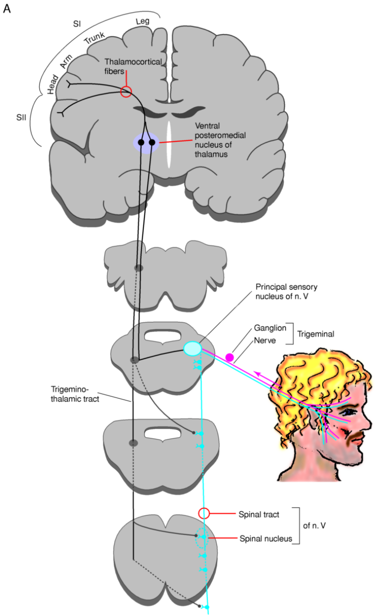
- extracellular – single neuron, spike sorting, cell attach
- intracellular – sharp electrode, whole cell
- imaging – 2-photon calcium (and soon voltage) dyes.

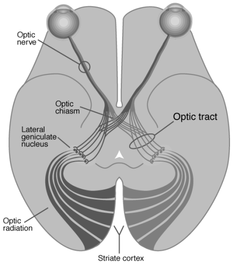
Senses

How many senses do you have?

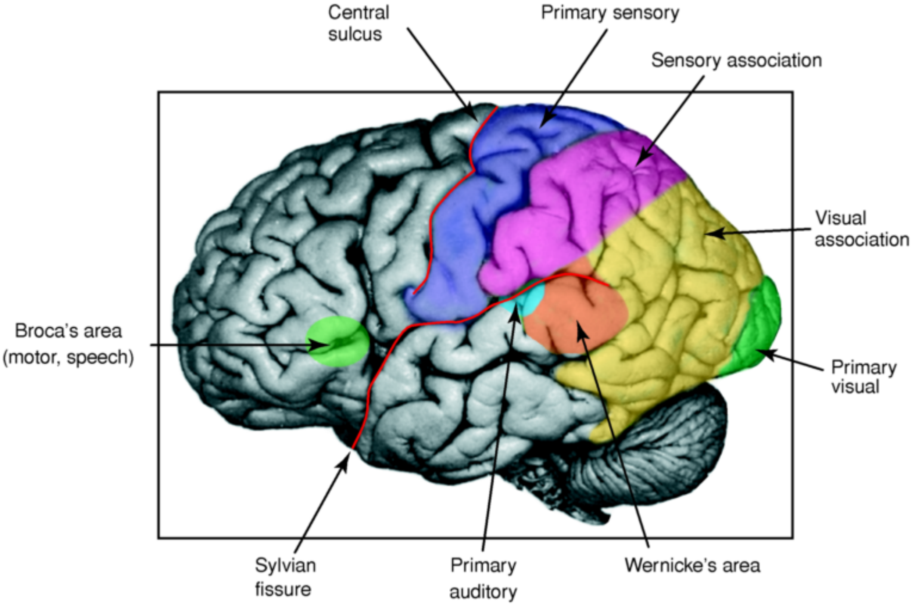
Neocortical senses







Sensory areas



Common features of neocortical senses

- common pathways: receptors – subctx nuclei – thalamus – primary ctx – higher ctx
- thalamic loops between cortical areas
- feedback
- parallel hierarchy
- alternate pathways – tectal, para-lemniscal

Common processing

- receptor discretisation – sampling
- receptive fields
- centre-surround processing
- contrast sensitivity – Weber’s law
- adaptation
    - neural vs. psychological
    - adaptation to higher features
    - mismatch negativity
    - statistical adaptation

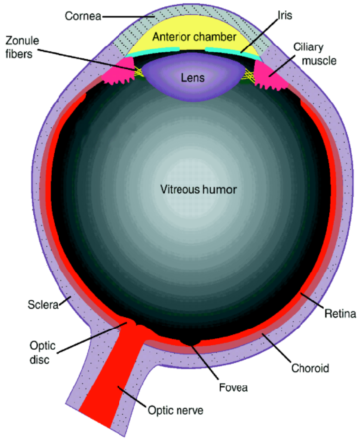
Quantifying responses

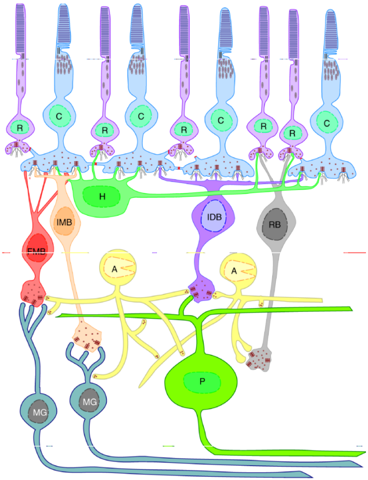
- receptive fields
- motor fields
- stimulus-response functions
- sensory computation and encoded variables
- tuning curves

Optimality of coding

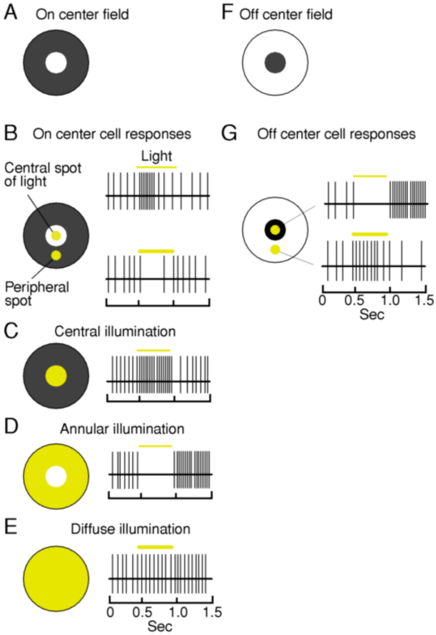
- “impedence” matching between different components
- matching to natural statistics
- matching to behaviourally relevant features
- redundancy reduction

The eye and retina

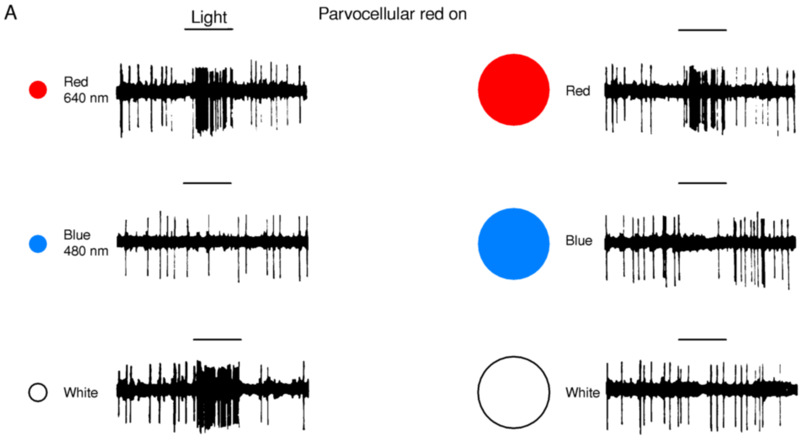




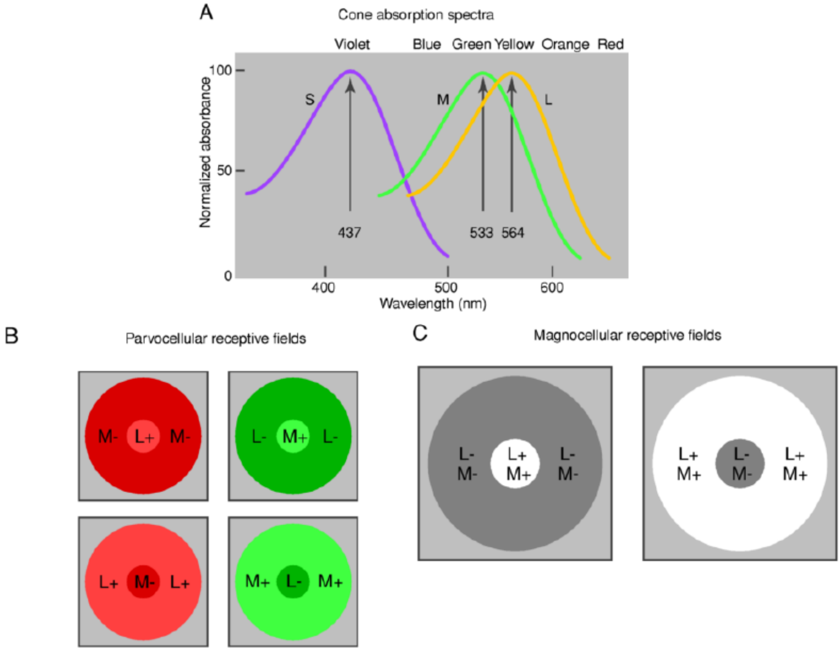
Centre-surround receptive fields



Colour at the retina



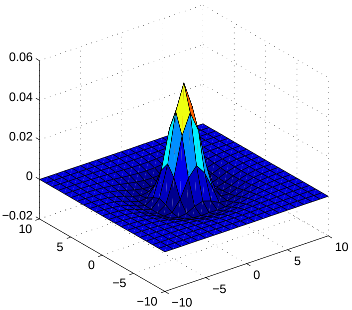
Colour at the retina

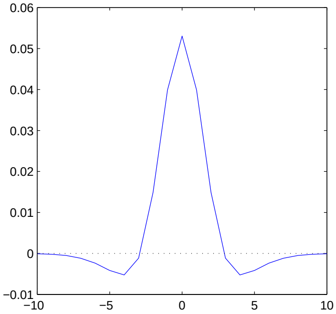


Centre-surround models

Centre-surround receptive fields are commonly described by one of two equations, giving the scaled response to a point of light shone at the retinal location (x, y).
A difference-of-Gaussians (DoG) model:

$$D_{\text{DoG}}(x, y) = \frac{1}{2\pi\sigma_c^2} \exp\left(-\frac{(x-c_x)^2 + (y-c_y)^2}{2\sigma_c^2}\right) - \frac{1}{2\pi\sigma_s^2} \exp\left(-\frac{(x-c_x)^2 + (y-c_y)^2}{2\sigma_s^2}\right)$$

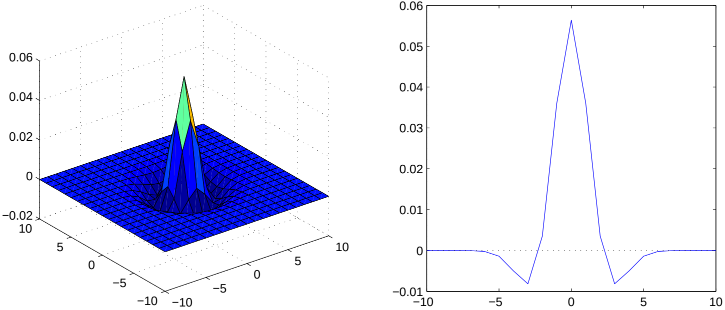




Centre-surround models

. . . or a Laplacian-of-Gaussian (LoG) model:

$$D_{\mathrm{LoG}}(x, y) = -\nabla^2 \left[\frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x - c_x)^2 + (y - c_y)^2}{2\sigma^2} \right) \right]$$



Linear receptive fields

The linear-like response apparent in the prototypical experiments can be generalised to give a predicted firing rate in response to an arbitrary stimulus $s(x, y)$:

$$r(c_x, c_y; s(x, y)) = \int dx\, dy\, D_{c_x, c_y}(x, y) s(x, y)$$

The receptive field centres (c_x, c_y) are distributed over visual space.

If we let $D()$ represent the RF function centred at 0, instead of at (c_x, c_y), we can write:

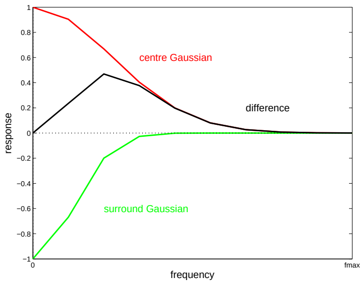
$$r(c_x, c_y; s(x, y)) = \int dx\, dy\, D(c_x - x, c_y - y) s(x, y)$$

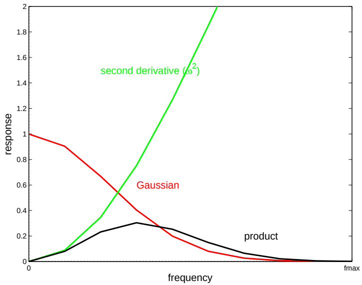
which looks like a convolution.

Transfer functions

Thus a repeated linear receptive field acts like a spatial filter, and can be characterised by its frequency-domain transfer function. (Indeed, much early visual processing is studied in terms of linear systems theory.)

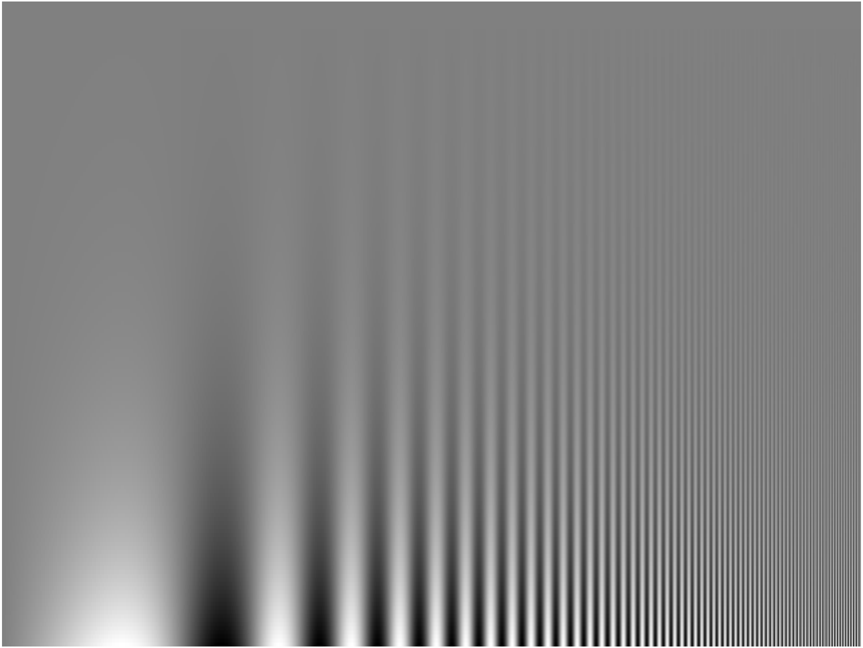
Transfer functions for both DoG and LoG centre-surround models are **bandpass**. Taking 1D versions:





This accentuates mid-range **spatial** frequencies.

Transfer functions



Edge detection

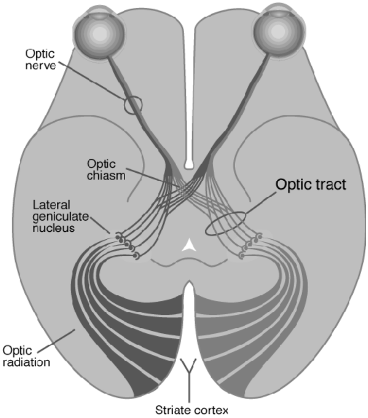
Bandpass filters emphasise edges:

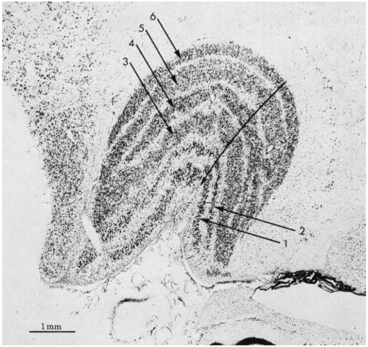
orginal image

DoG responses

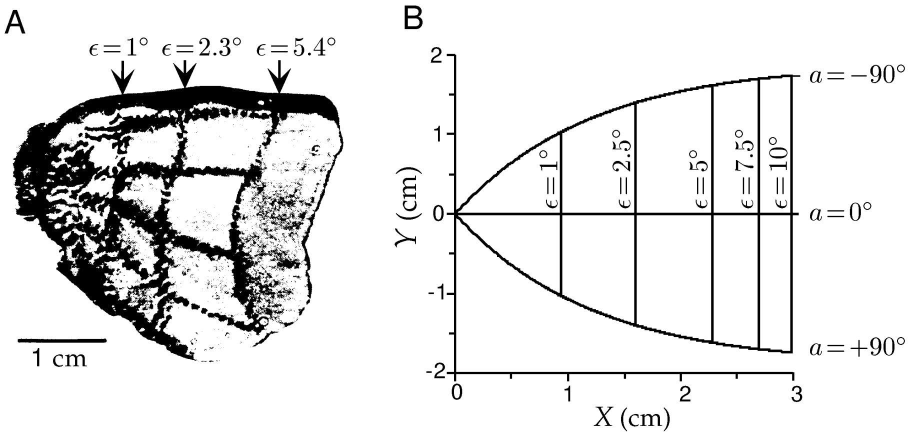
thresholded

Thalamic relay

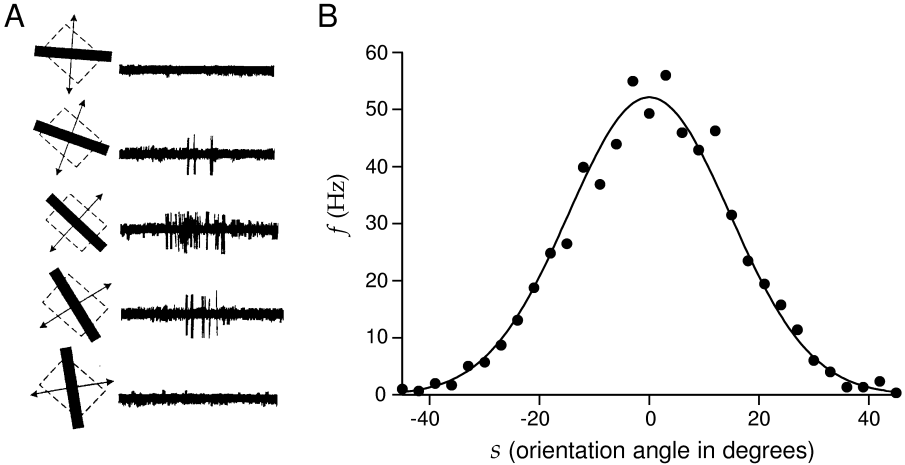




Visual cortex



Orientation selectivity



Linear receptive fields – simple cells

Linear response encoding:

$$r(t_0, s(x, y, t)) = \int_0^{\infty} d\tau \int dx\, dy\, s(x, y, t_0 - \tau) D(x, y, \tau)$$

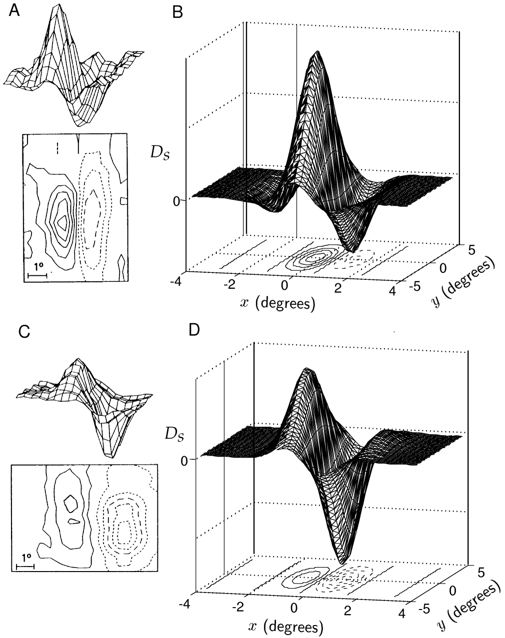
For separable receptive fields:

$$D(x, y, \tau) = D_s(x, y) D_t(\tau)$$

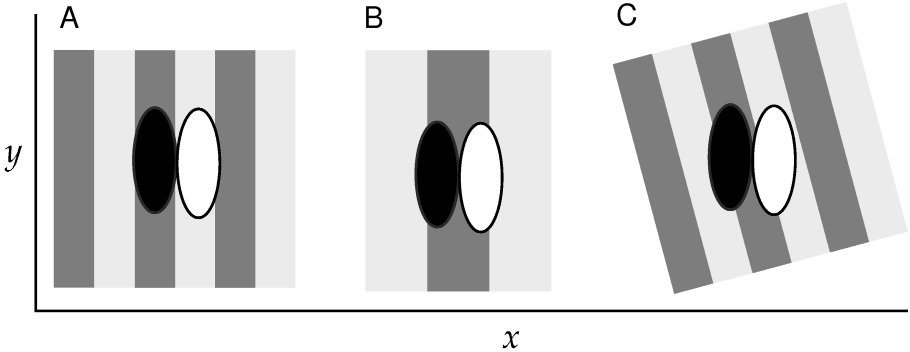
For simple cells:

$$D_s = \exp\left(-\frac{(x - c_x)^2}{2\sigma_x^2} - \frac{(y - c_y)^2}{2\sigma_y^2}\right) \cos(kx - \phi)$$

Linear response functions – simple cells



Simple cell orientation selectivity



2D Fourier Transforms

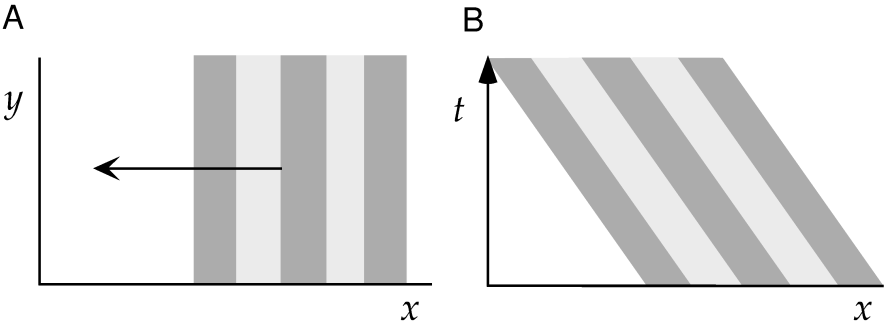
Again, the best way to look at a filter is in the frequency domain, but now we need a 2D transform.

$$D(x,y) = \exp\left(-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}\right)\cos(kx)$$

$$\begin{aligned}
\widetilde{D}(\omega_x,\omega_y) &= \int dx\ dy\ e^{-i\omega_x x} e^{-i\omega_y y} \exp\left(-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}\right)\cos(kx-\phi) \\
&= \int dx\ e^{-i\omega_x x} e^{-x^2/2\sigma_x^2}\cos(kx-\phi) \cdot \int dy\ e^{-i\omega_y y} e^{-y^2/2\sigma_y^2} \\
&= \sqrt{2\pi}\sigma_x \left[e^{-\sigma_x^2\omega_x^2/2} \circ \pi[\delta(\omega_x-k)+\delta(\omega_x+k)]\right] \sqrt{2\pi}\sigma_y e^{-\sigma_y^2\omega_y^2/2} \\
&= 2\pi^2\sigma_x\sigma_y \left[e^{-\frac{1}{2}[(\omega_x-k)^2\sigma_x^2+\omega_y^2\sigma_y^2]} + e^{-\frac{1}{2}[(\omega_x+k)^2\sigma_x^2+\omega_y^2\sigma_y^2]}\right]
\end{aligned}$$

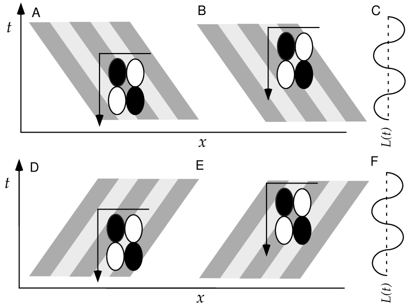
Easy to read spatial frequency tuning, bandwidth; orientation tuning and (for homework) bandwidth.

Drifting gratings

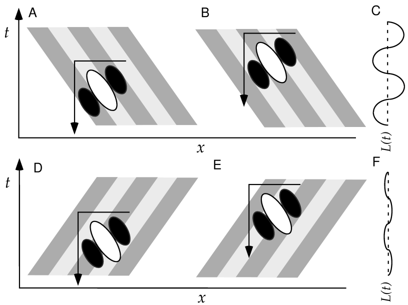


$$s(x, y, t) = G + A\cos(kx - \phi)\cos(\omega t)$$

Separable and inseparable response functions



Separable: motion sensitive;
not direction sensitive



Inseparable: motion sensitive;
and direction sensitive

Complex cells

Complex cells are sensitive to orientation, but, supposedly, not phase.

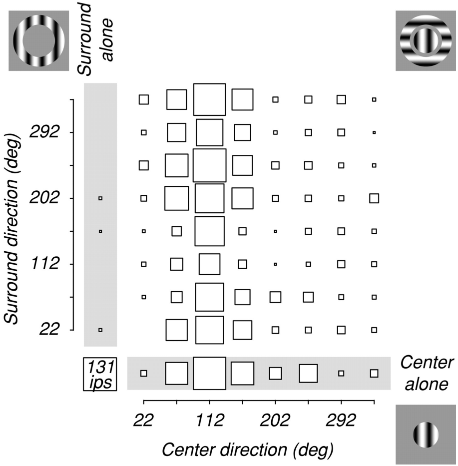
One model might be (neglecting time)

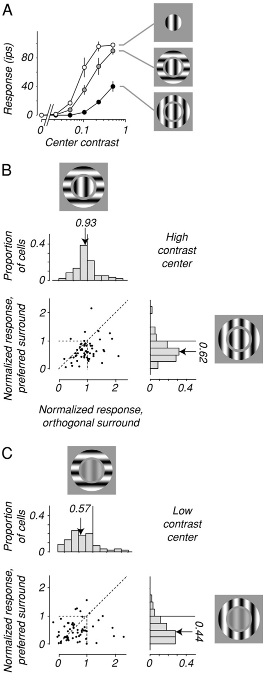
$$r(s(x,y)) = \left[\int dx\ dy\ s(x,y)\exp\left(-\frac{(x-c_x)^2}{2\sigma_x^2}-\frac{(y-c_y)^2}{2\sigma_y^2}\right)\cos(kx)\right]^2 + \left[\int dx\ dy\ s(x,y)\exp\left(-\frac{(x-c_x)^2}{2\sigma_x^2}-\frac{(y-c_y)^2}{2\sigma_y^2}\right)\cos(kx-\pi/2)\right]^2$$

But many cells do have some residual phase sensitivity. Quantified by (f_1/f_0 ratio).

Stimulus-response functions (and constructive models) for complex cells are still a matter of debate.

Other V1 responses: surround effects

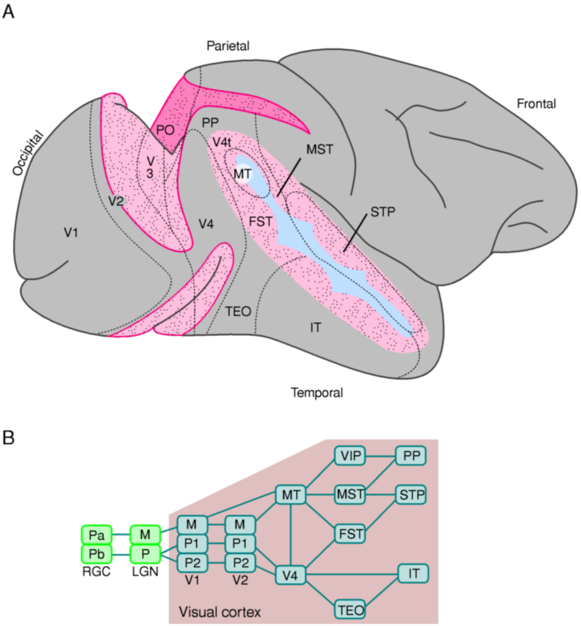




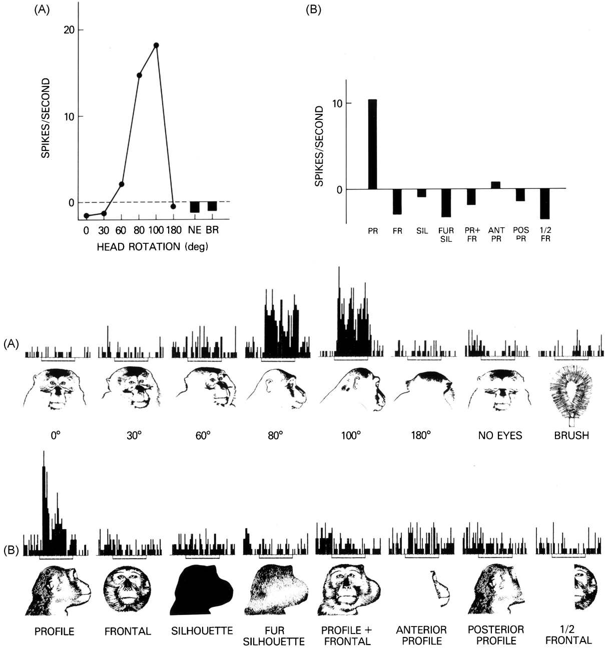
Other V1 responses

- end-stopping
- blobs and colour
- . . .

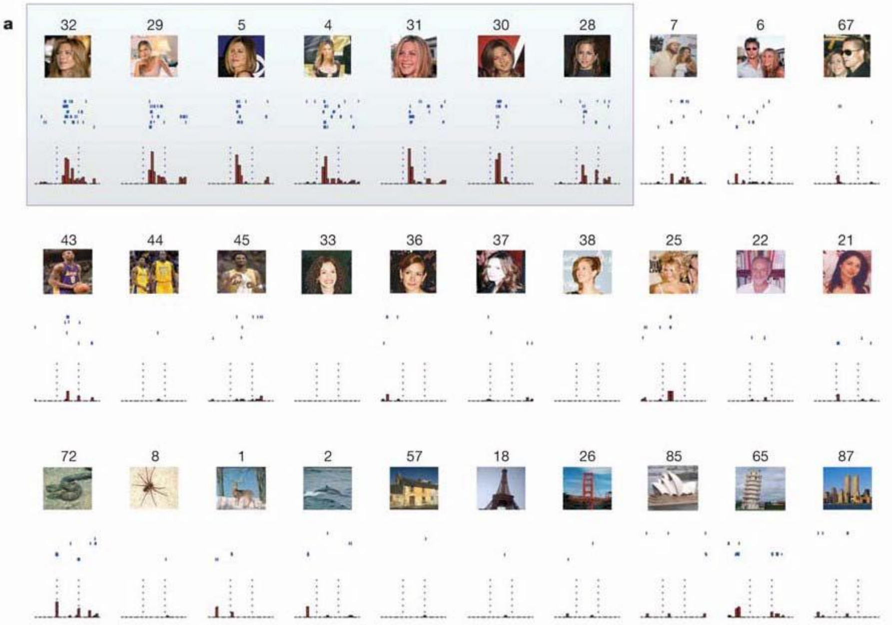
Higher Visual Areas



Object recognition



Grandmother cells (for certain definitions of grandmother)



Grandmother cells (for certain definitions of grandmother)