ICON 2014
Brisbane, Australia

(How the thalamus changes) what the cat’s eye tells the cat’s brain

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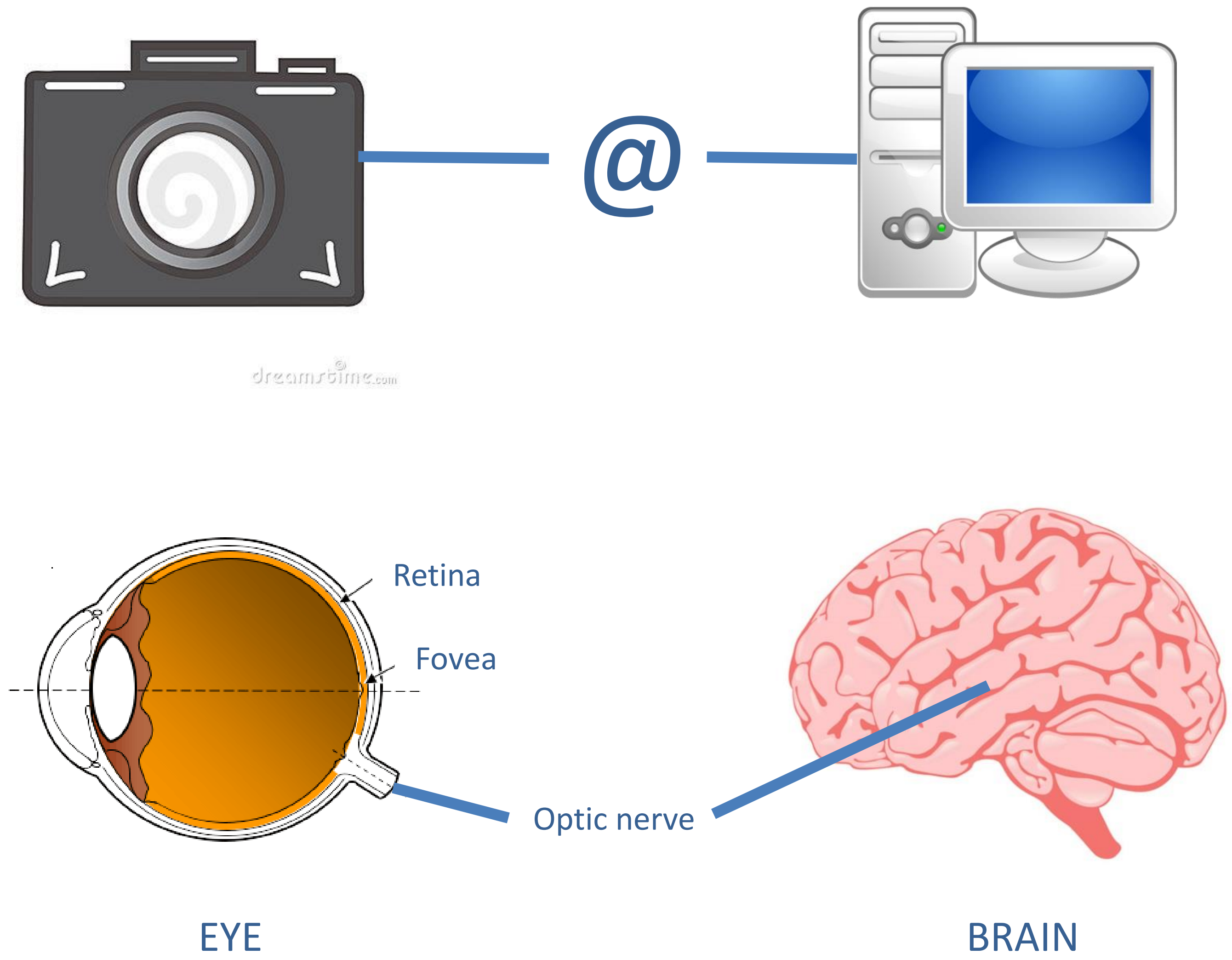
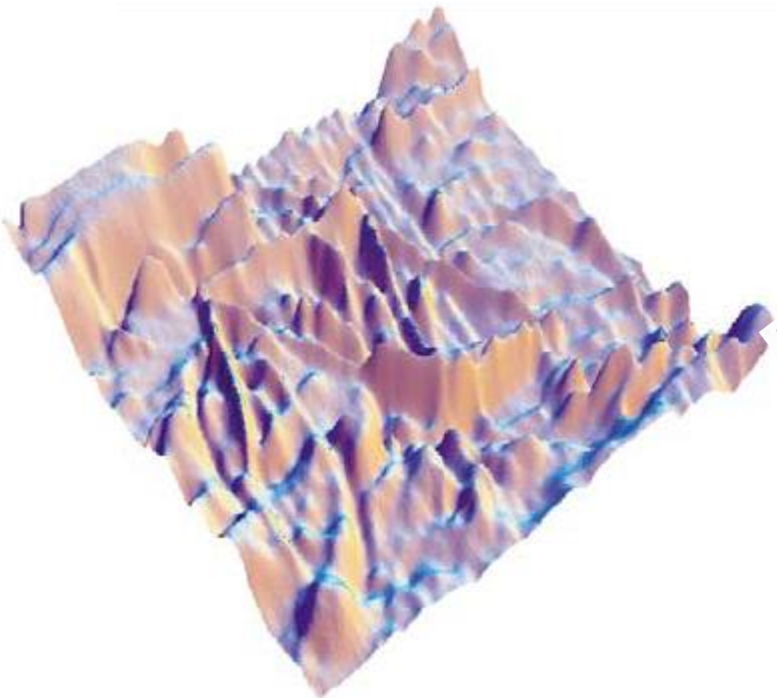
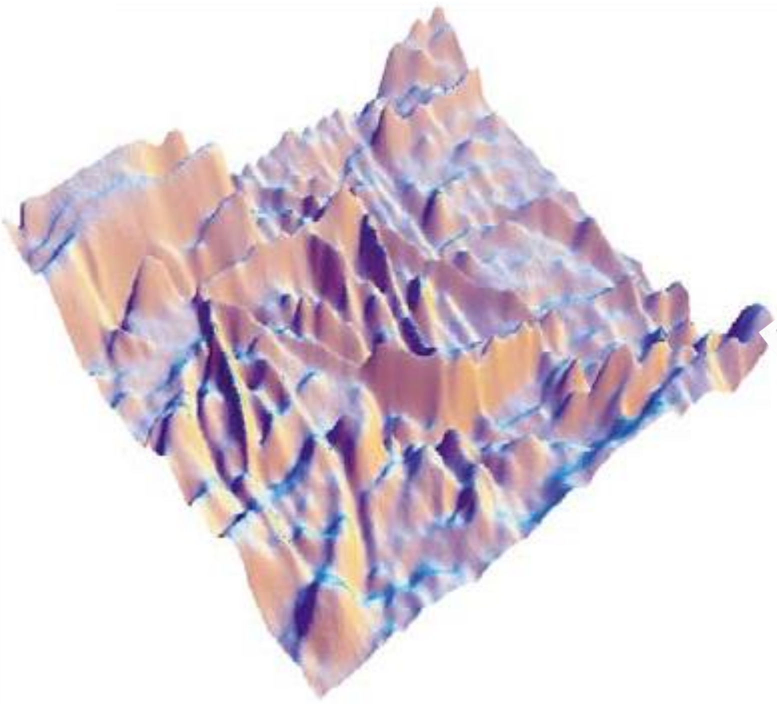
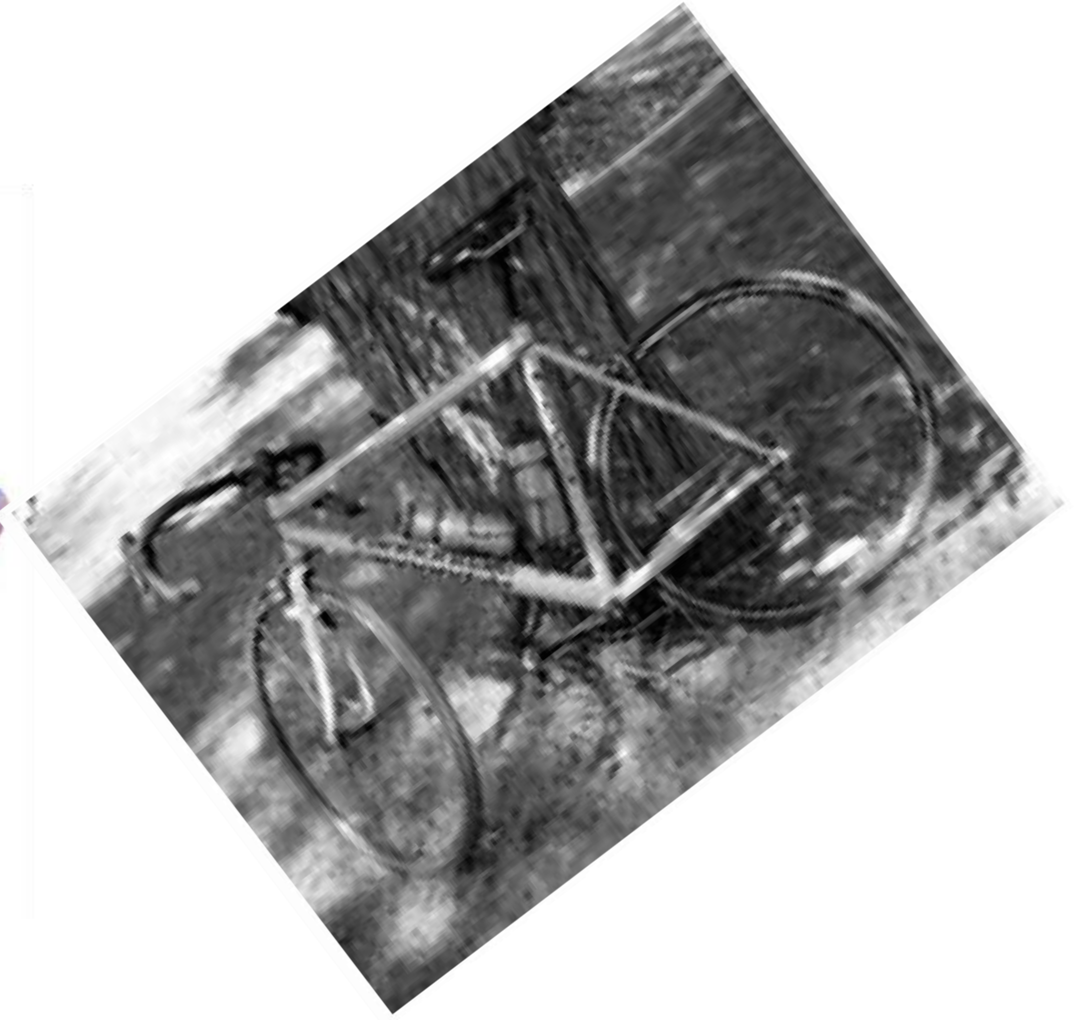

@
dreamstime.com
Retina
Fovea
Optic nerve
EYE
BRAIN



Kersten and Yuille (2003) Current Opinion in Neurobiology, 13:1–9





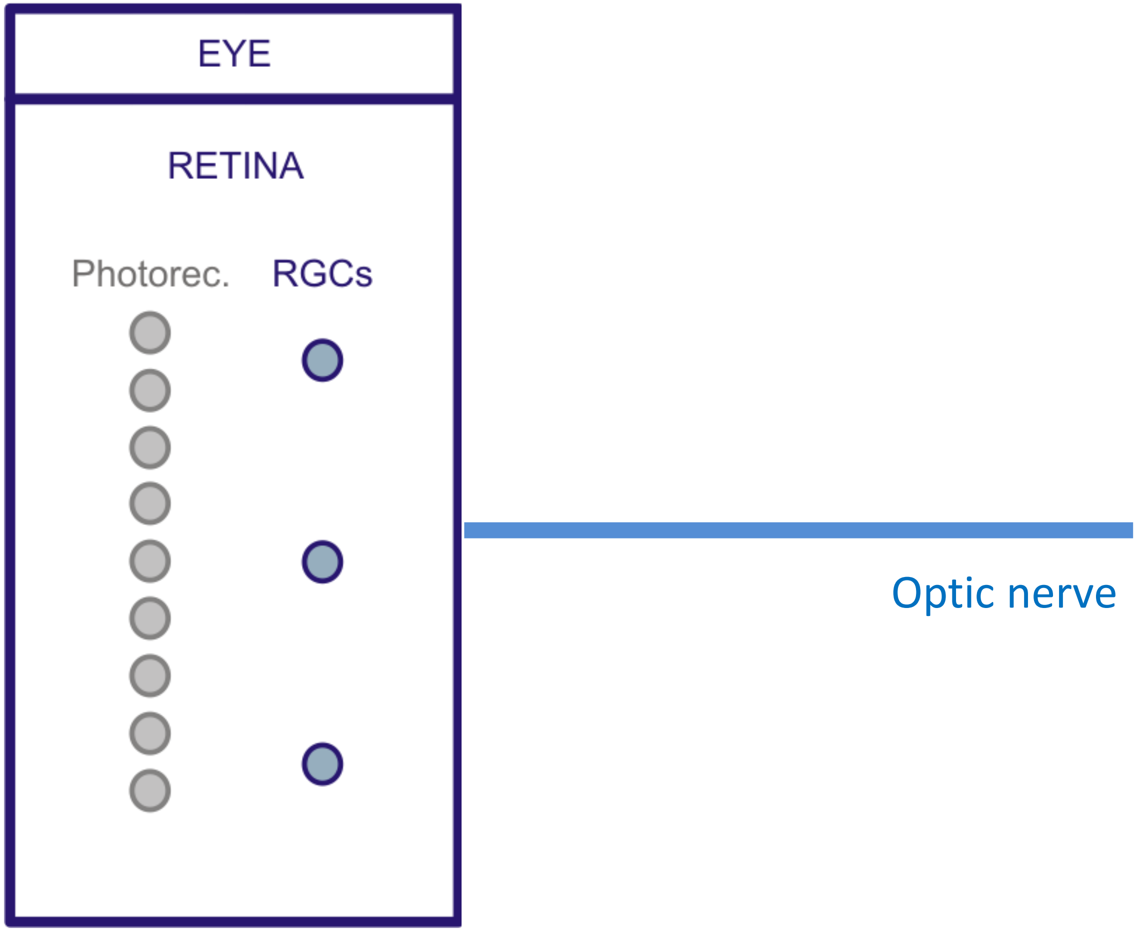
Highly correlated at the local level!

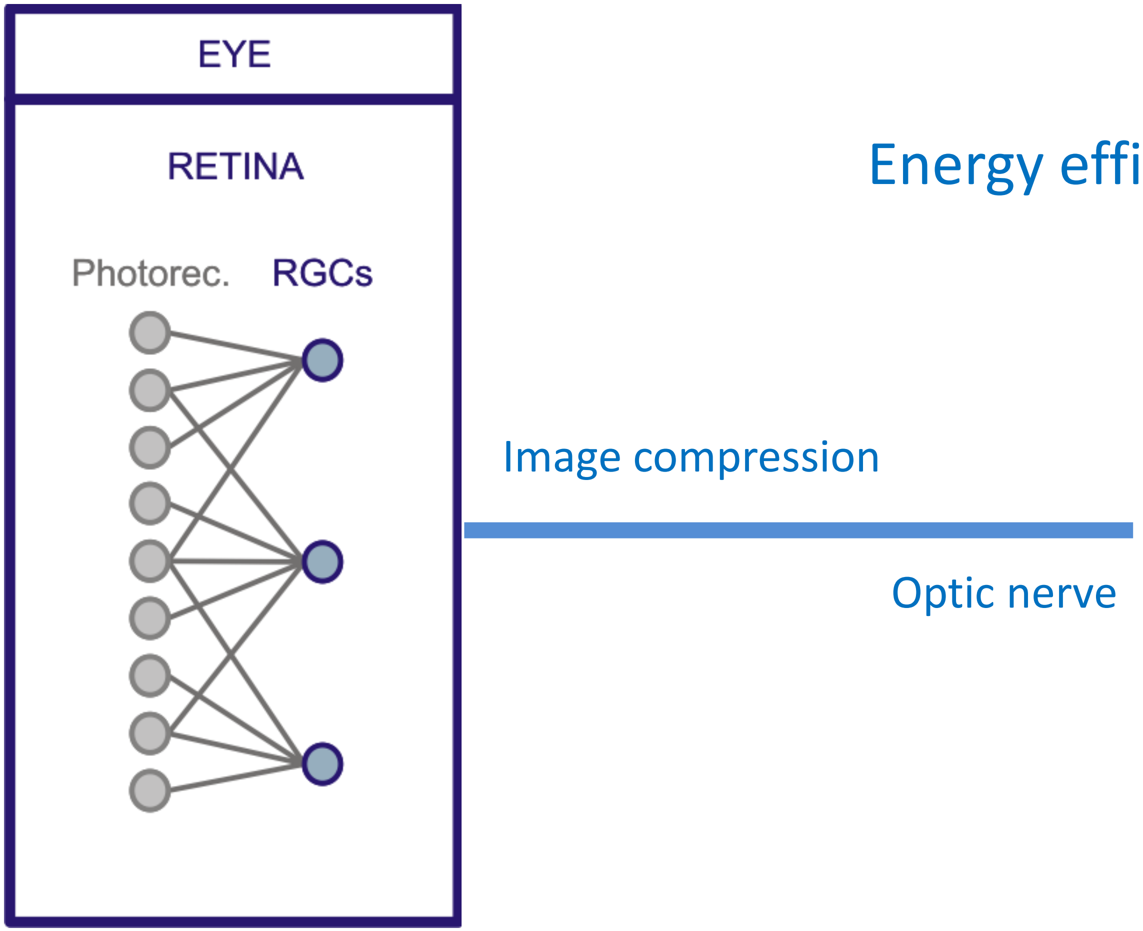
Kersten and Yuille (2003) Current Opinion in Neurobiology, 13:1–9

How does the visual system deal with these problems?

Large amount of information (and related energy cost)

Efficient coding (redundancy in natural images, finite capacity)


EYE
RETINA
Photorec.
RGCs
Optic nerve



Energy efficient

Biological efficiency

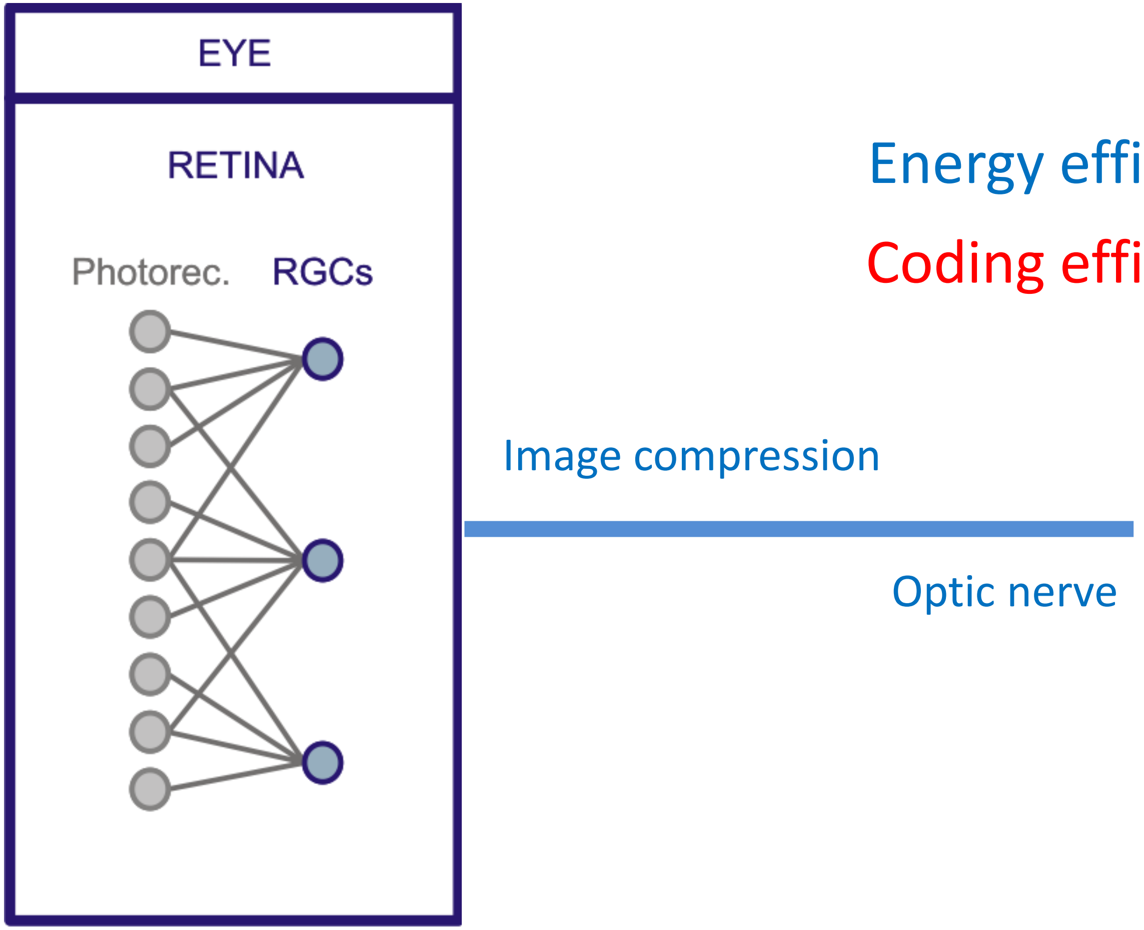
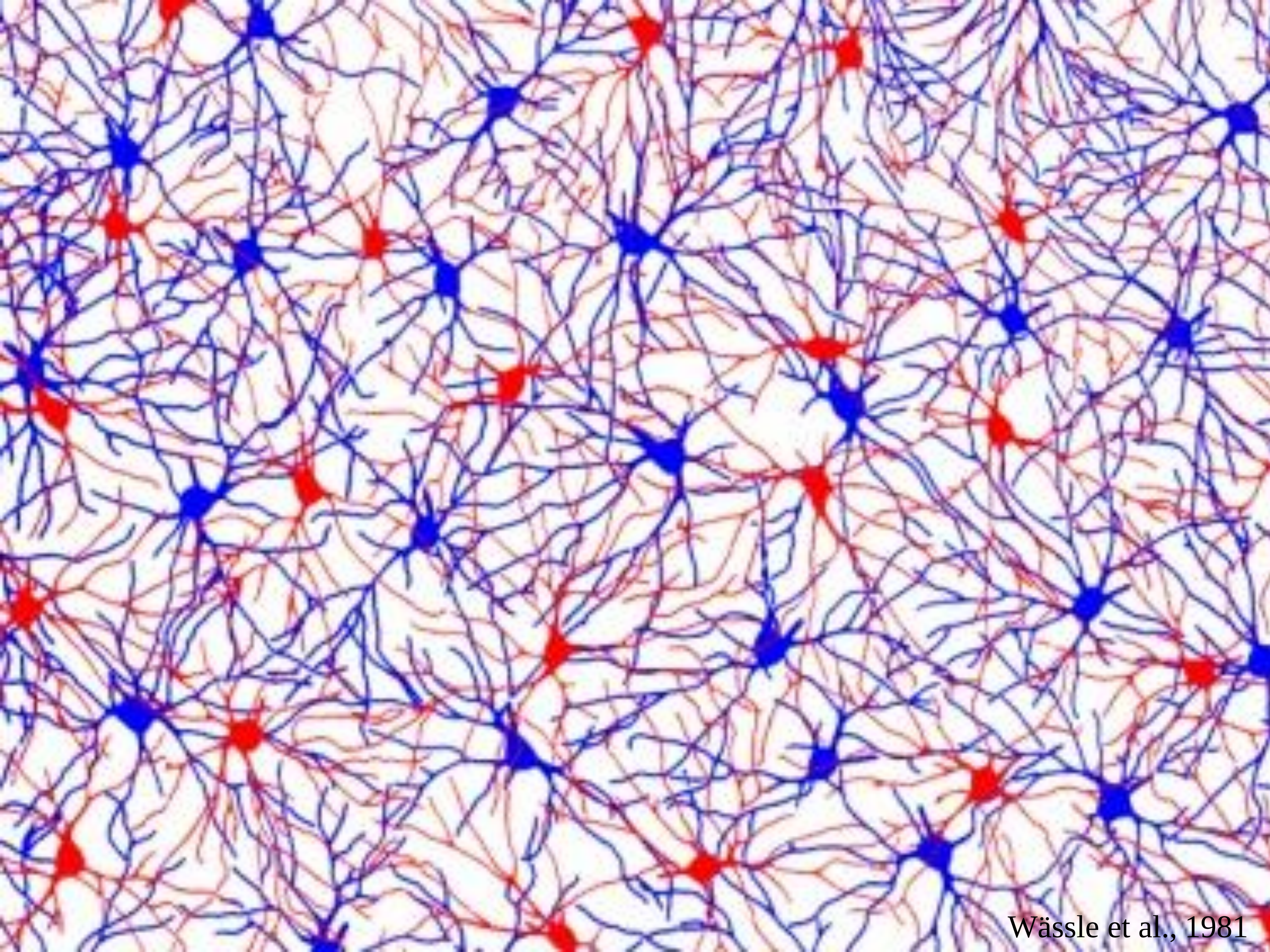


Image compression

Optic nerve

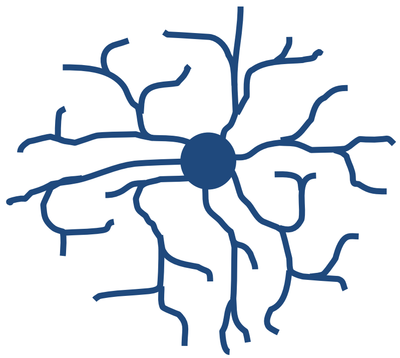
Energy efficient

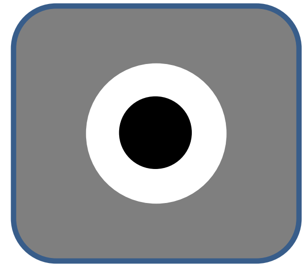
Coding efficiency?



Wässle et al., 1981

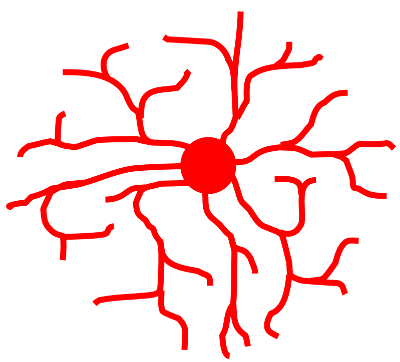
Off Center cells

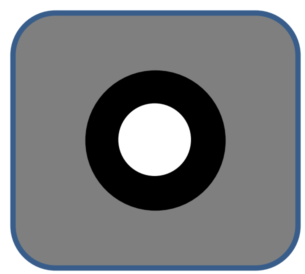




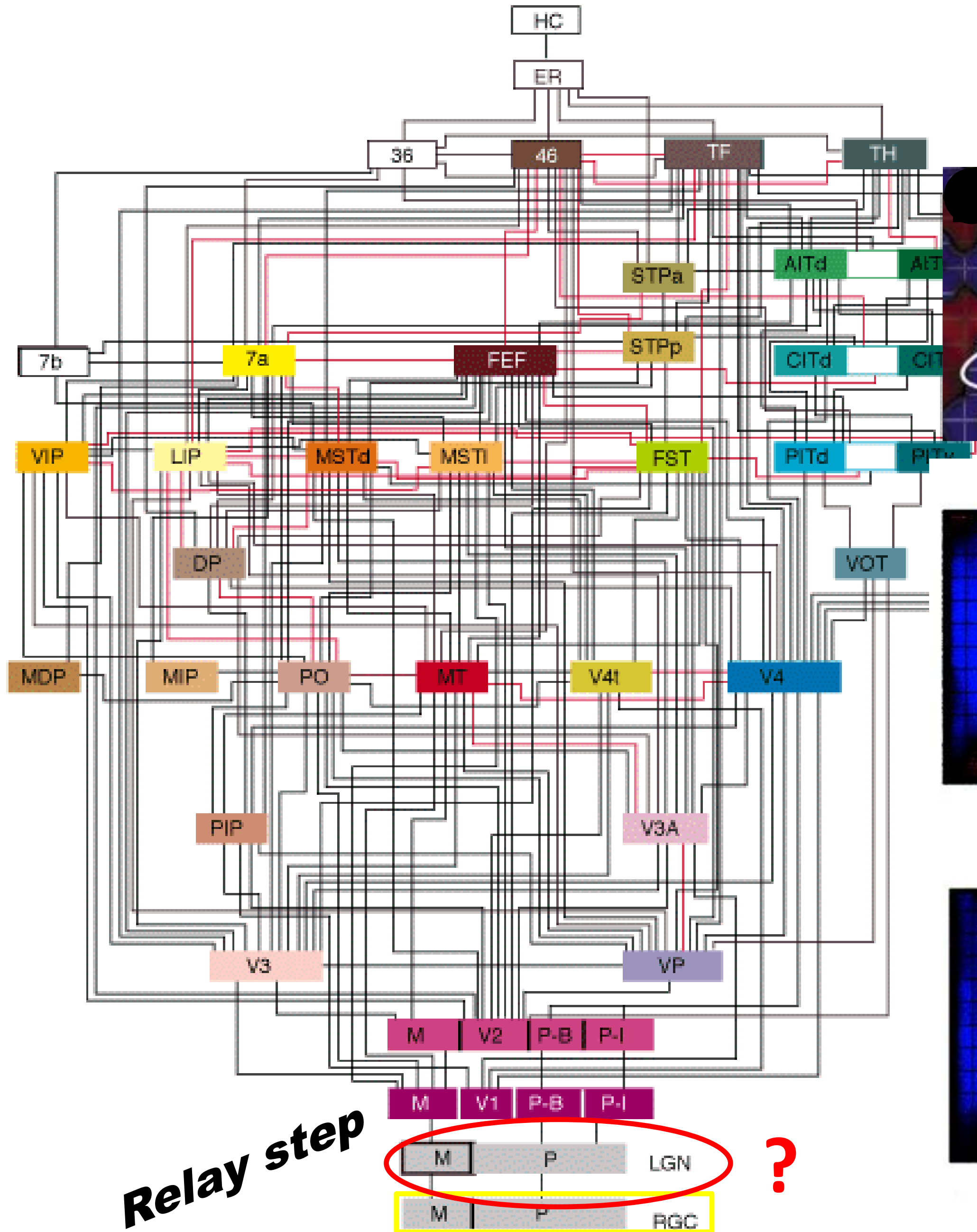
Light decrements

On Center cells

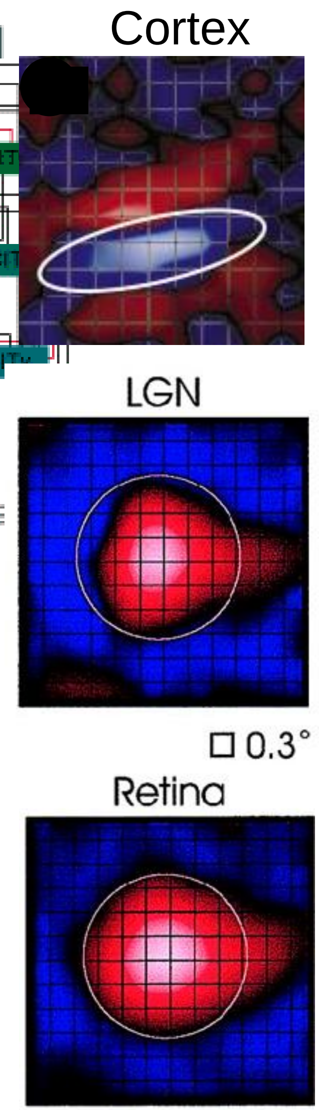




Light increments

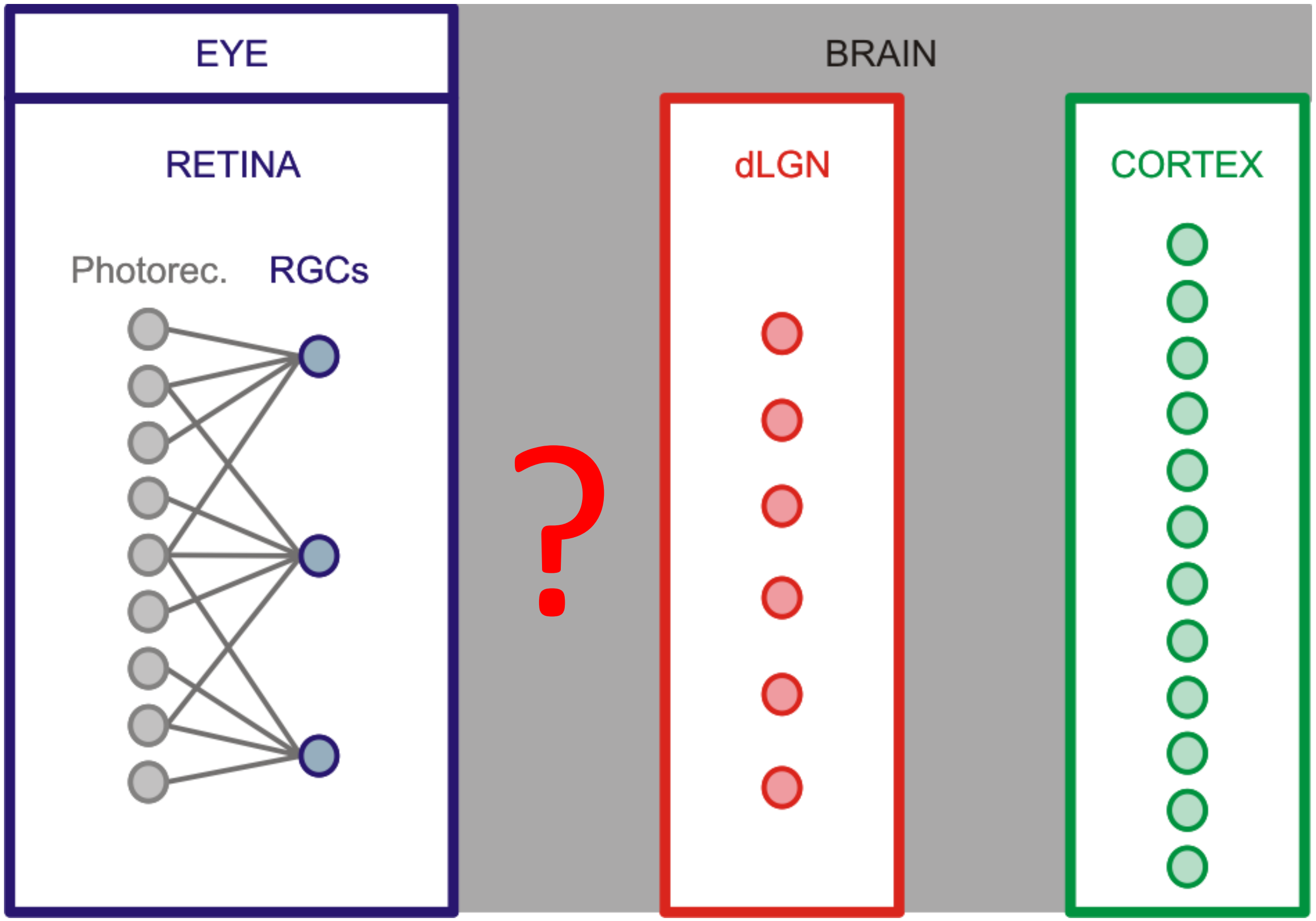


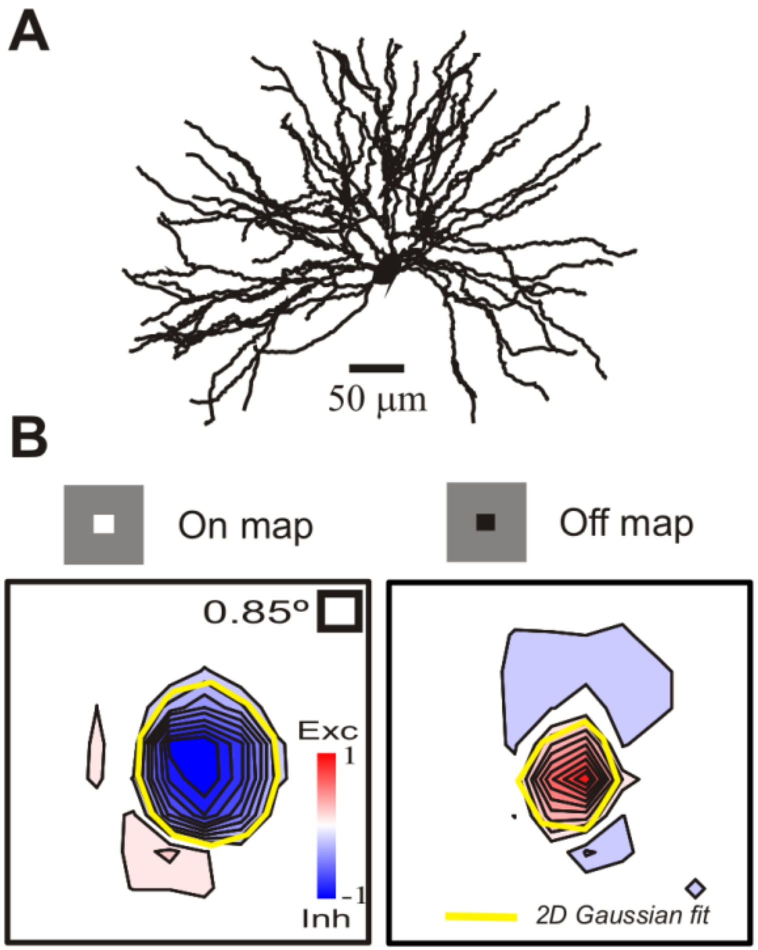
Adapted from Felleman & Van Essen, 1991

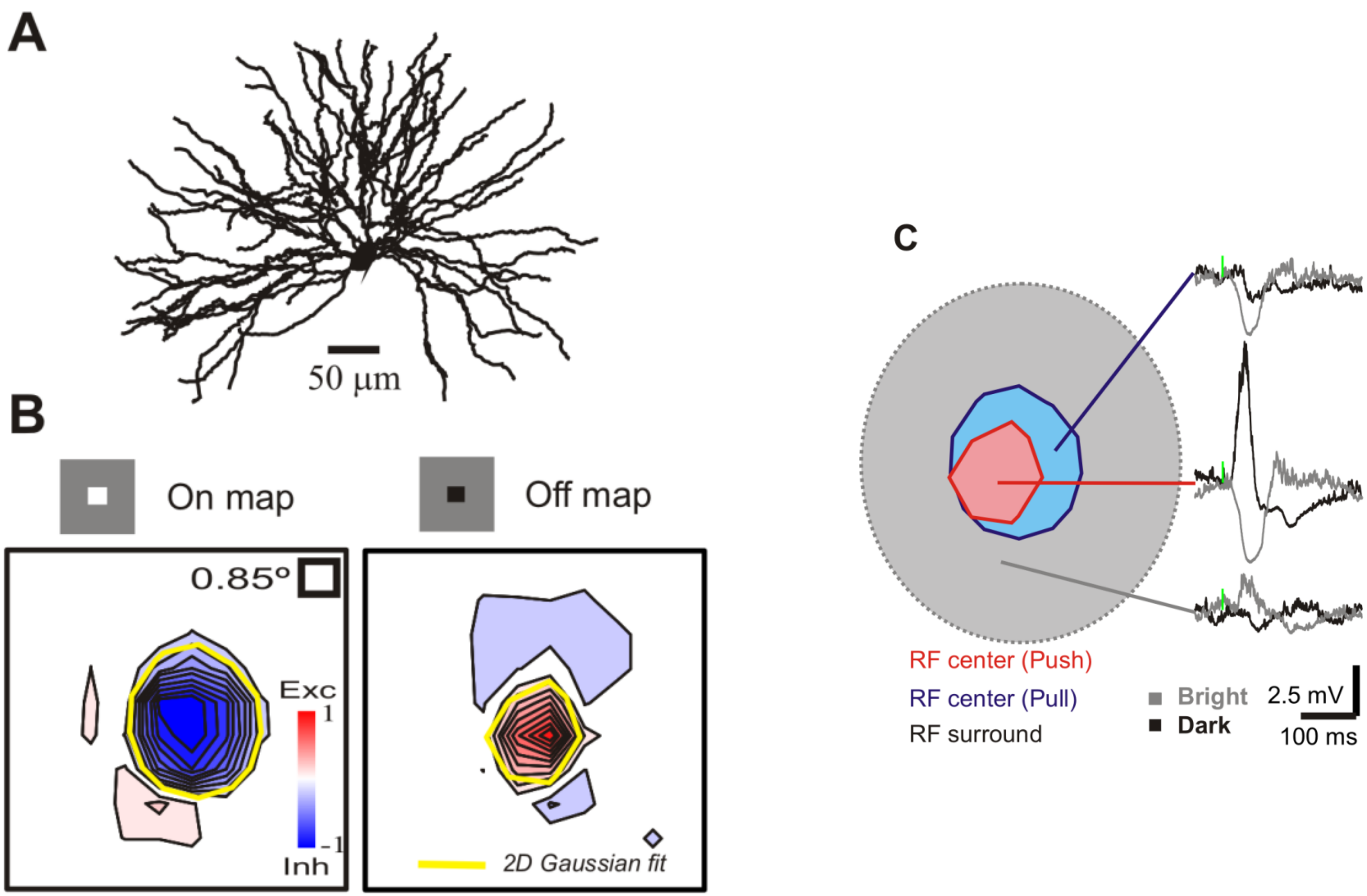


Usrey et al., 1999.

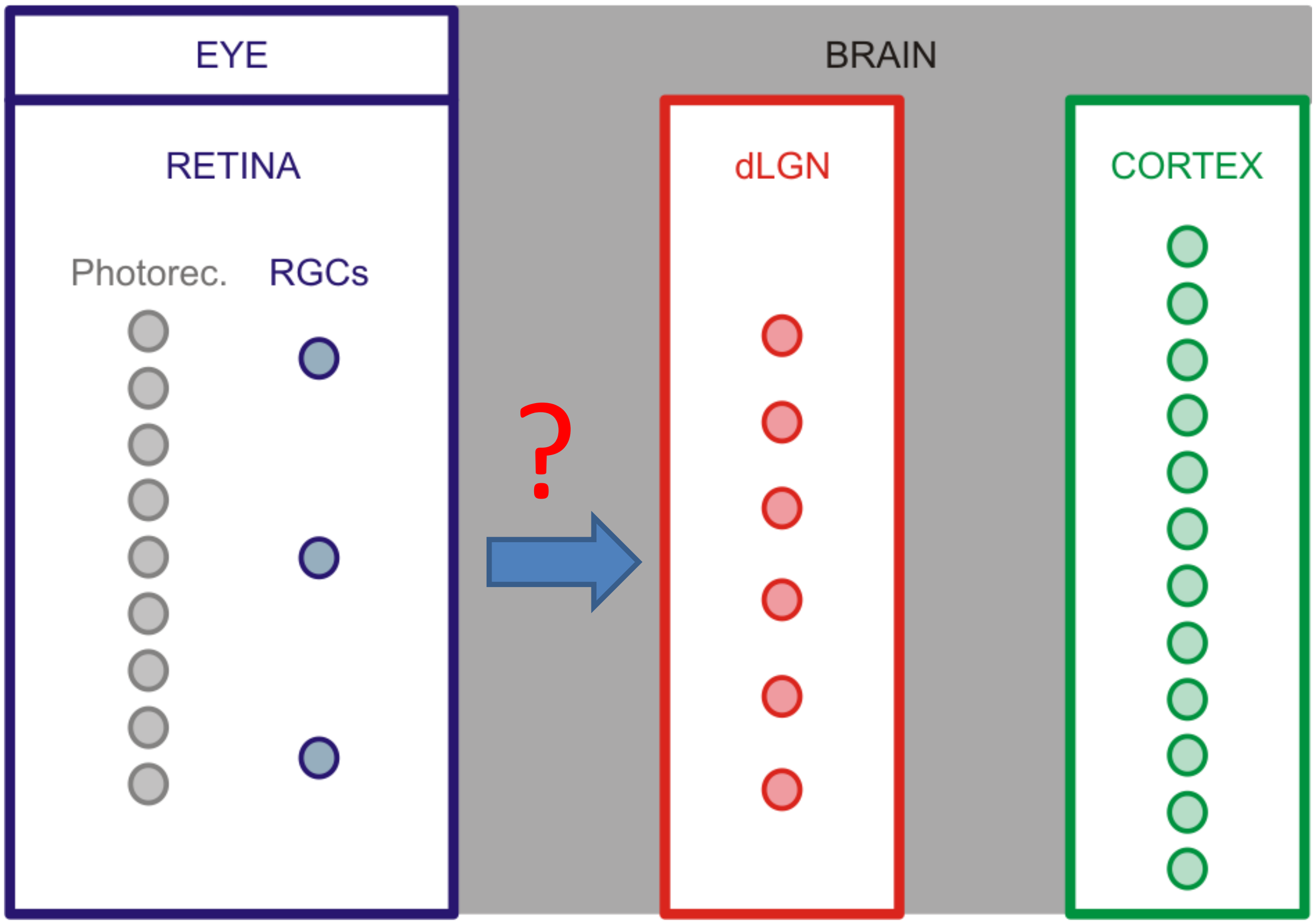
How the thalamus changes the retinal output



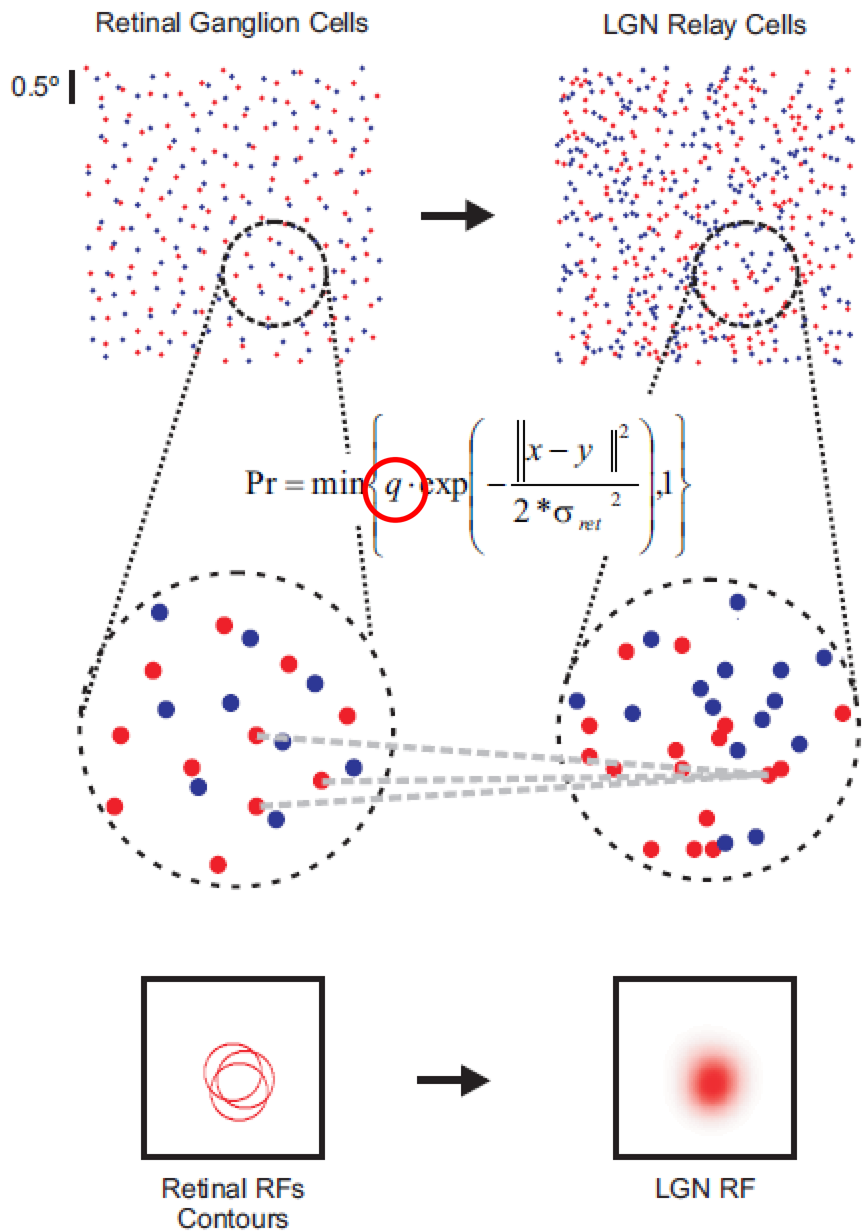

A
50 µm
B
On map
Off map
0.85°
Exc
1
-1
Inh
2D Gaussian fit


A
50 µm
B
On map
Off map
0.85°
Exc
1
-1
Inh
2D Gaussian fit
C
RF center (Push)
RF center (Pull)
RF surround
Bright
Dark
2.5 mV
100 ms

Retinothalamic model

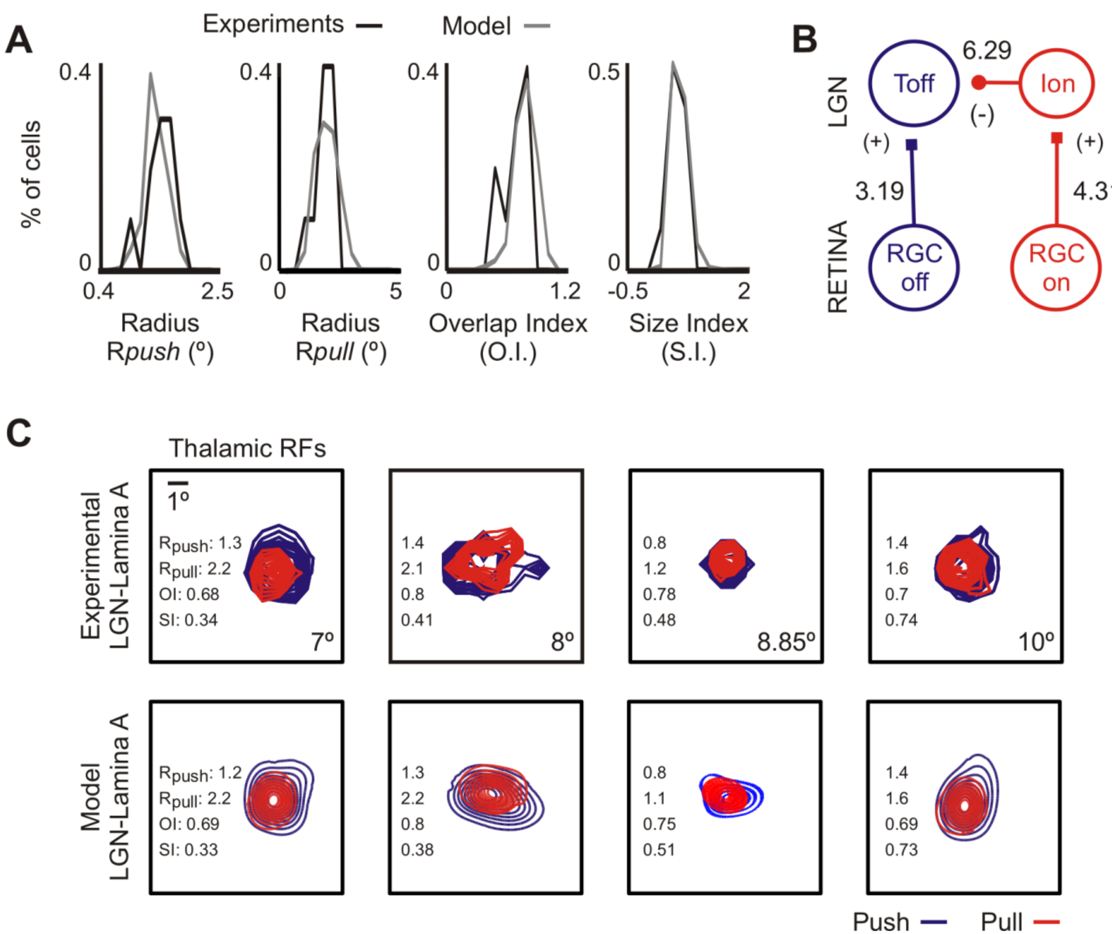


Retinothalamic model

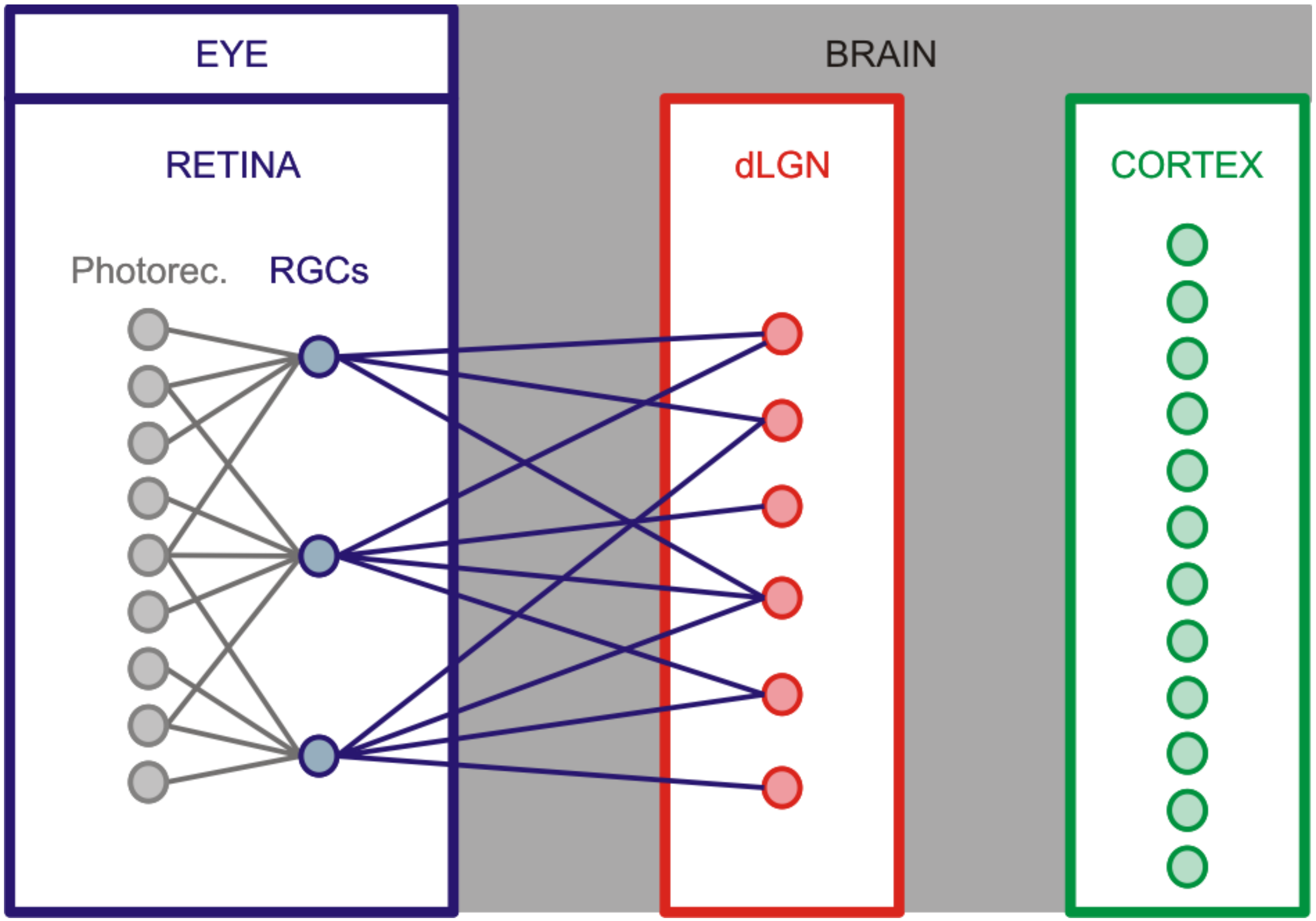


$$\Pr = \min\left\{ q \cdot \exp\left(- \frac{\left\| x - y \right\|^2}{2 * \sigma_{ret}^{\;2}} \right), 1 \right\}$$

Martinez et al 2014. Neuron 81:943-956.

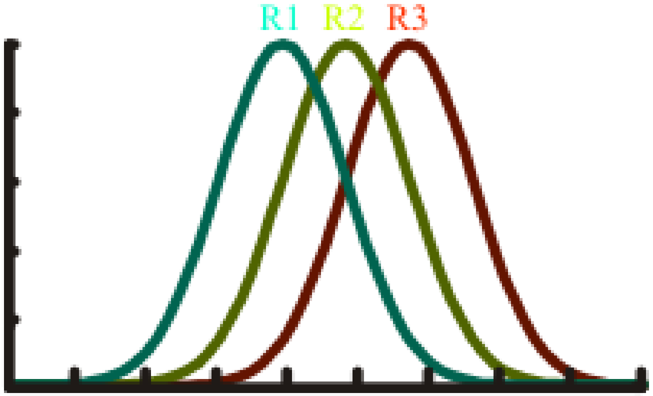

A
Experiments
Model
0.4
0
0.4
2.5
% of cells
Radius
Rpush (º)
0.4
0
0
5
Radius
Rpull (º)
0.4
0
0
1.2
Overlap Index
(O.I.)
0.5
0
-0.5
2
Size Index
(S.I.)
B
LGN
RETINA
Toff
Ion
6.29
(-)
(+)
(+)
3.19
4.31
RGC
off
RGC
on
C
Thalamic RFs
Experimental
LGN-Lamina A
1º
Rpush: 1.3
Rpull: 2.2
OI: 0.68
SI: 0.34
7º
1.4
2.1
0.8
0.41
8º
0.8
1.2
0.78
0.48
8.85º
1.4
1.6
0.7
0.74
10º
Model
LGN-Lamina A
Rpush: 1.2
Rpull: 2.2
OI: 0.69
SI: 0.33
1.3
2.2
0.8
0.38
0.8
1.1
0.75
0.51
1.4
1.6
0.69
0.73
Push
Pull

Statistical wiring of thalamic receptive fields

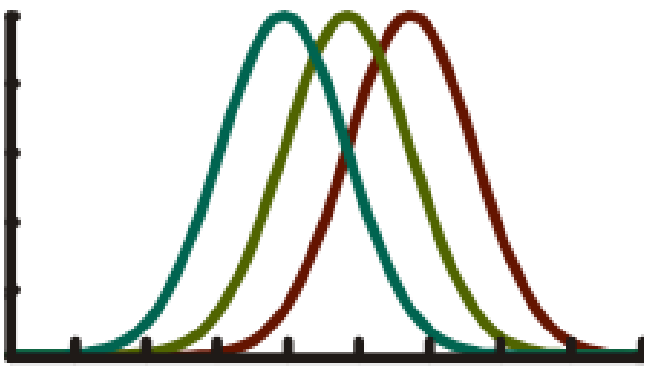


Functional consequences of the thalamic relay

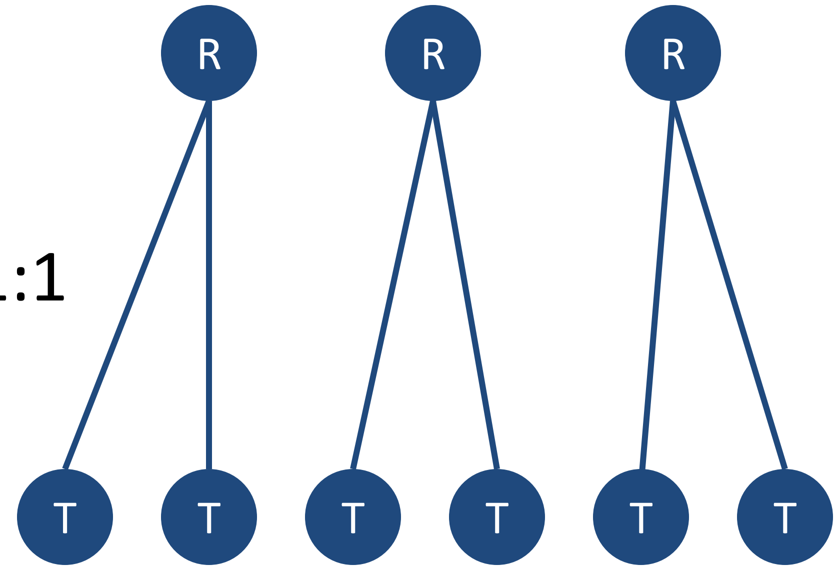
Retina



LGN

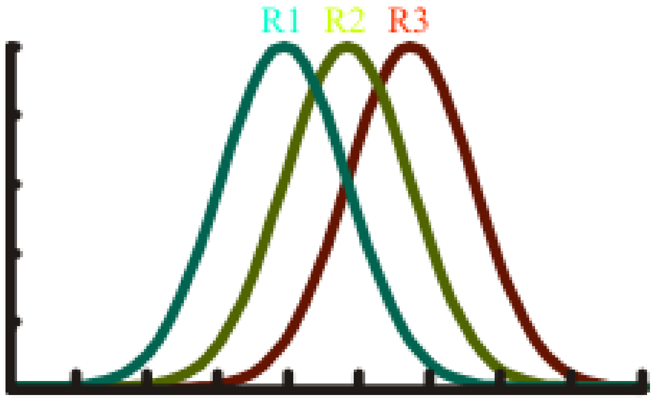


1:1

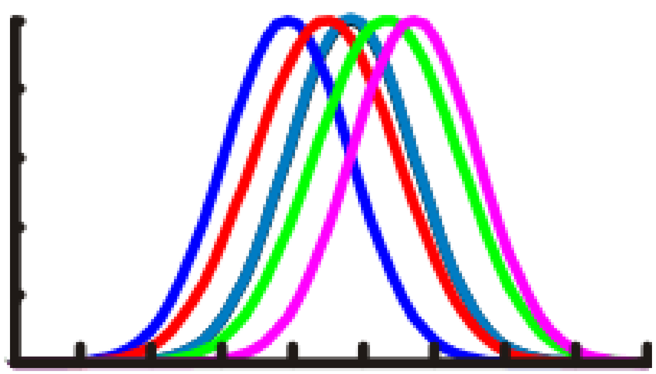


Functional consequences of the thalamic relay

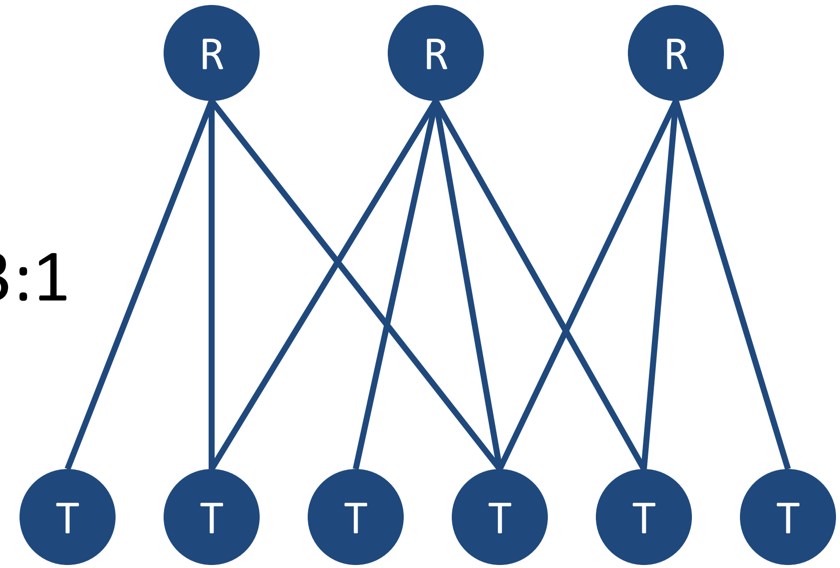
Retina



LGN



3:1



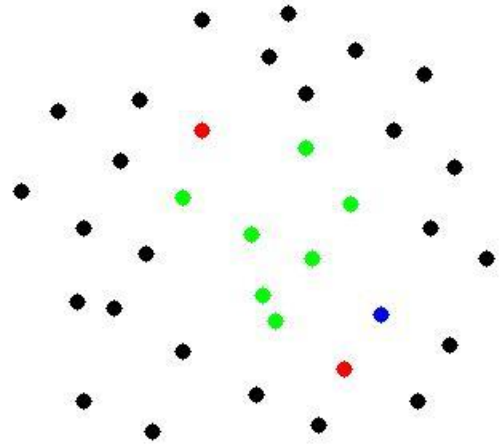
Diversity index

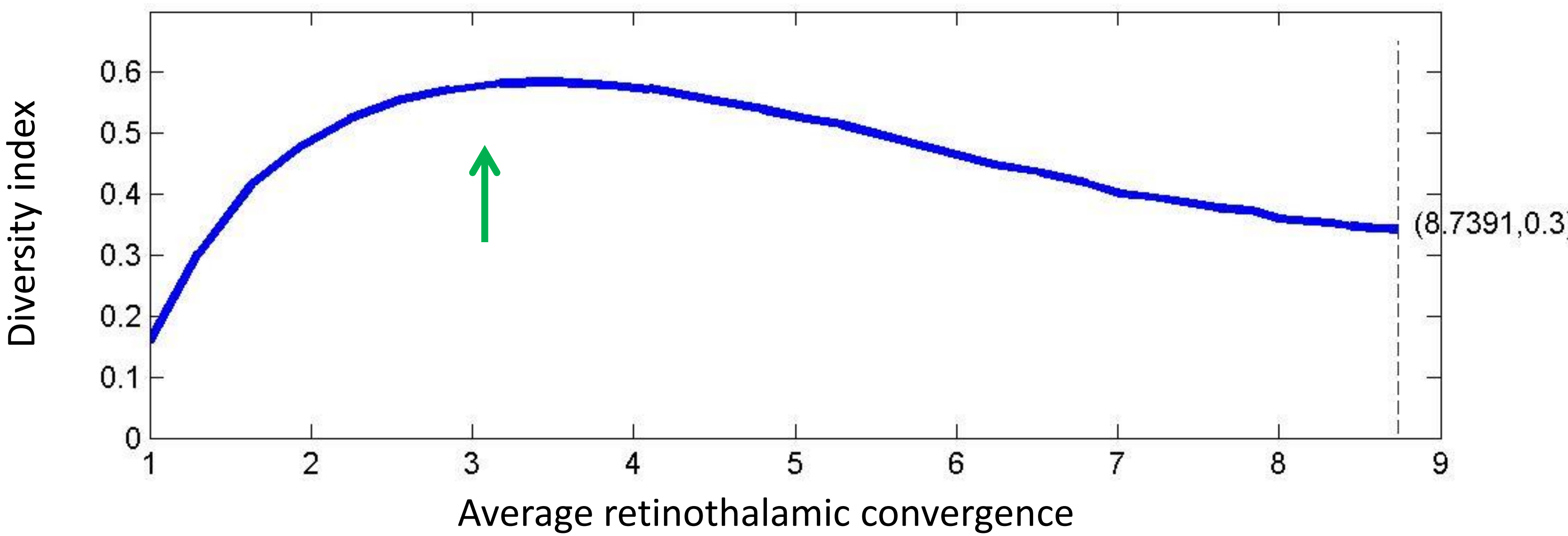
How different are the receptive fields of neighboring LGN relay cells?

$$D.I. = 1 - \left(\frac{2 \bullet NEI}{NI\_C1 + NI\_C2}\right)$$

Functional consequences of the thalamic relay

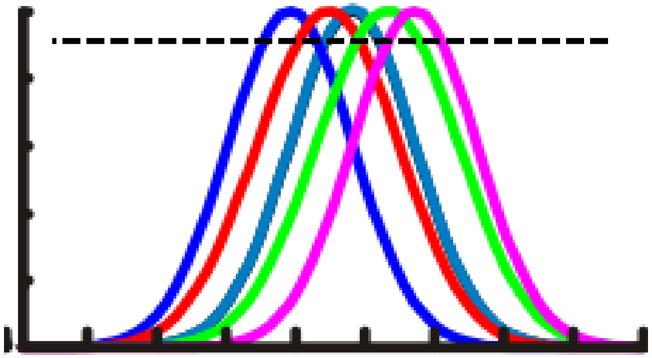
# inputs neuron 1	8
# inputs neuron 2	9
# common inputs	7
Diversity index	0.2

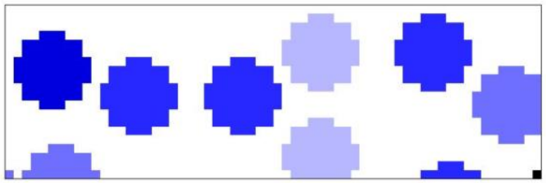


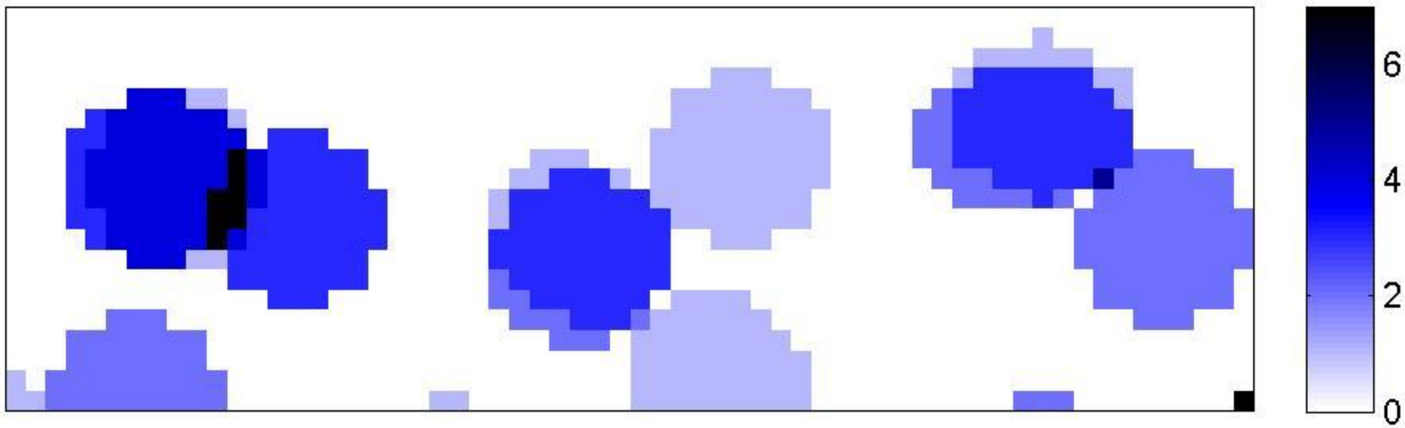


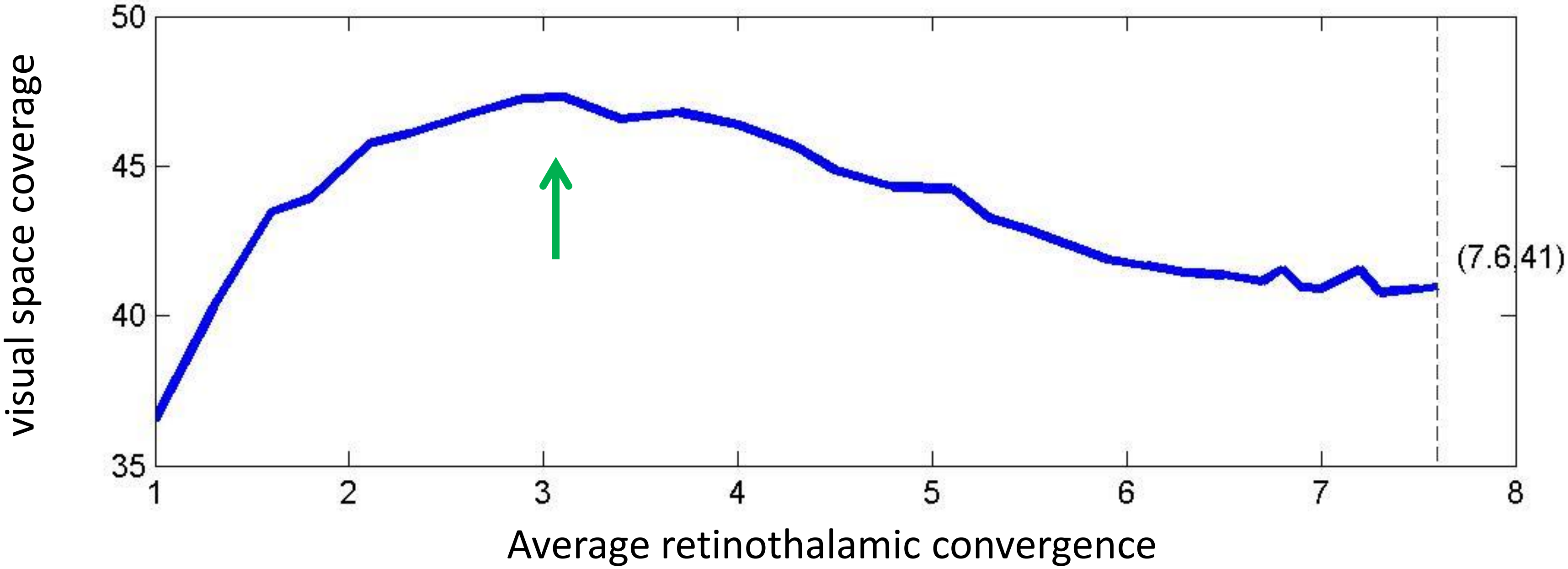
Coverage index

How homogeneously do LGN relay cells cover visual space?






6
4
2
0


50
45
40
35
1
2
3
4
5
6
7
8
(7.6,41)
visual space coverage
Average retinothalamic convergence

BAYESIAN DECODER

In short, we assume the response of each neuron follows a Gaussian distribution centered on a point of the space:

$$y_i = f_i(x) + \eta$$

where x is small localized point stimulus, with $\eta \in N(0,\sigma)$ being some sensor noise and $f_i(x) = \max \cdot e^{\frac{-(x-x_i)^2}{2 \cdot \chi^2}}$ the ideal response of the i-th neuron. We also assume that the sensor noise is additive and independent in each channel. Given a response pattern y, the decoder determines the stimulus x which maximizes the posterior distribution:

$$\hat{x} = \max_x \{\log(p(x/y)\}$$

With Gaussian sensor noise, the conditional probability of a neural response is:

$$p\ (y_i / x) \approx e^{\frac{-(y_i - f_i(x))^2}{2 \cdot \sigma^2}}$$

Since the responses of individual neurons are conditionally independent we have:

$$p(y/x) = \prod p(y_i / x)$$

By virtue of Bayes theorem, we can now write the maximization of the posterior probability as:

$$\max_x \{\log(p(y/x) \cdot p(x) / p(y)\}$$

Note, p(y) acts only as a normalization constant as it is independent on the stimulus. Thus, the previous equation simplifies to:

$$\max_x \{\log(p(y/x) \cdot p(x)\}$$

which is equal to:

$$\max_x \{-\frac{1}{2 \cdot \sigma^2} \sum_i (y_i - f_i(x))^2 + \log(p(x))\}$$

If we finally assume a uniform or flat prior distribution (i.e., make no prior assumptions about the location of the stimulus), we have to solve the following maximization problem:

$$\max_x \{-\sum_i (y_i - f_i(x))^2\}$$

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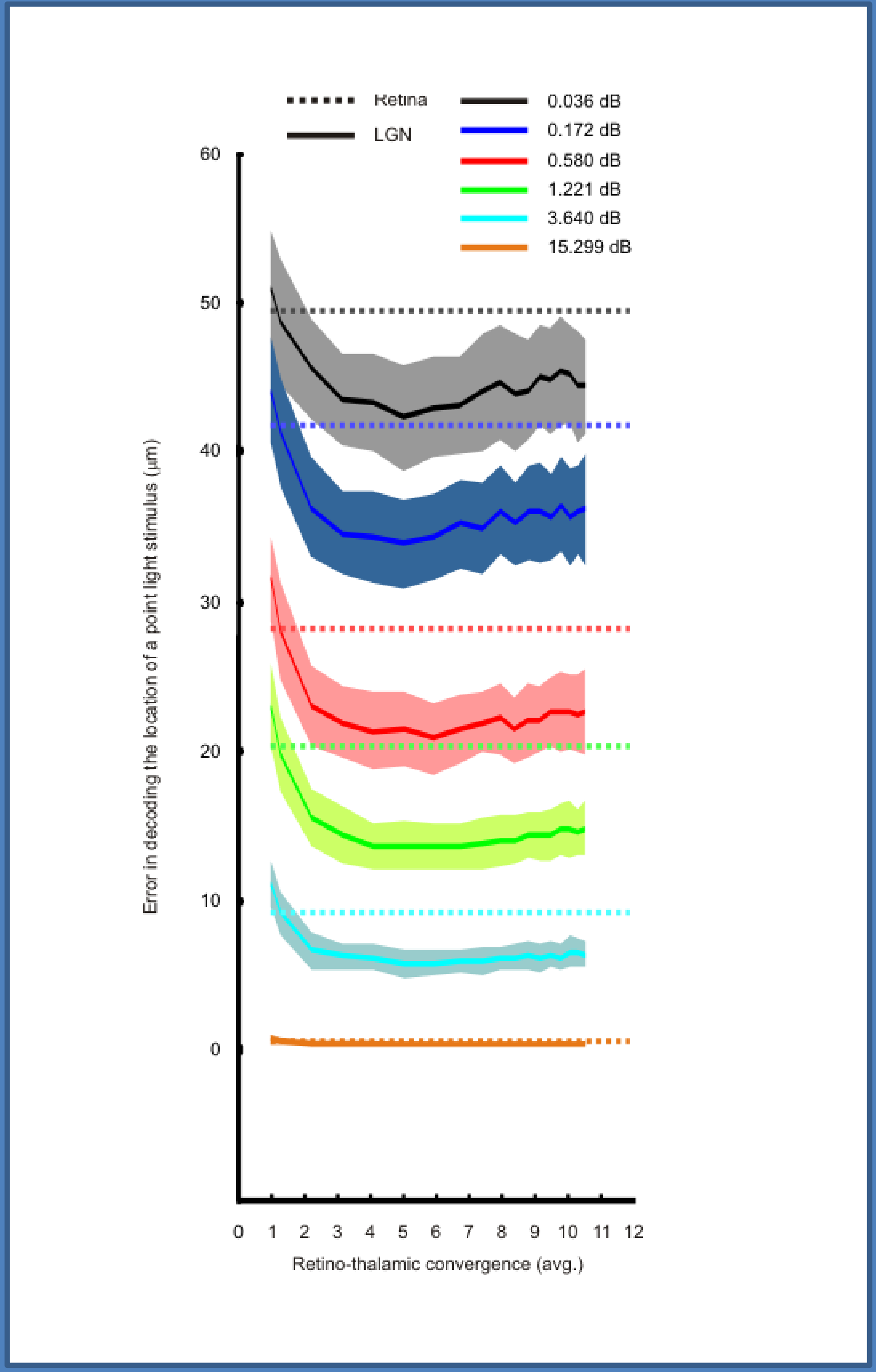
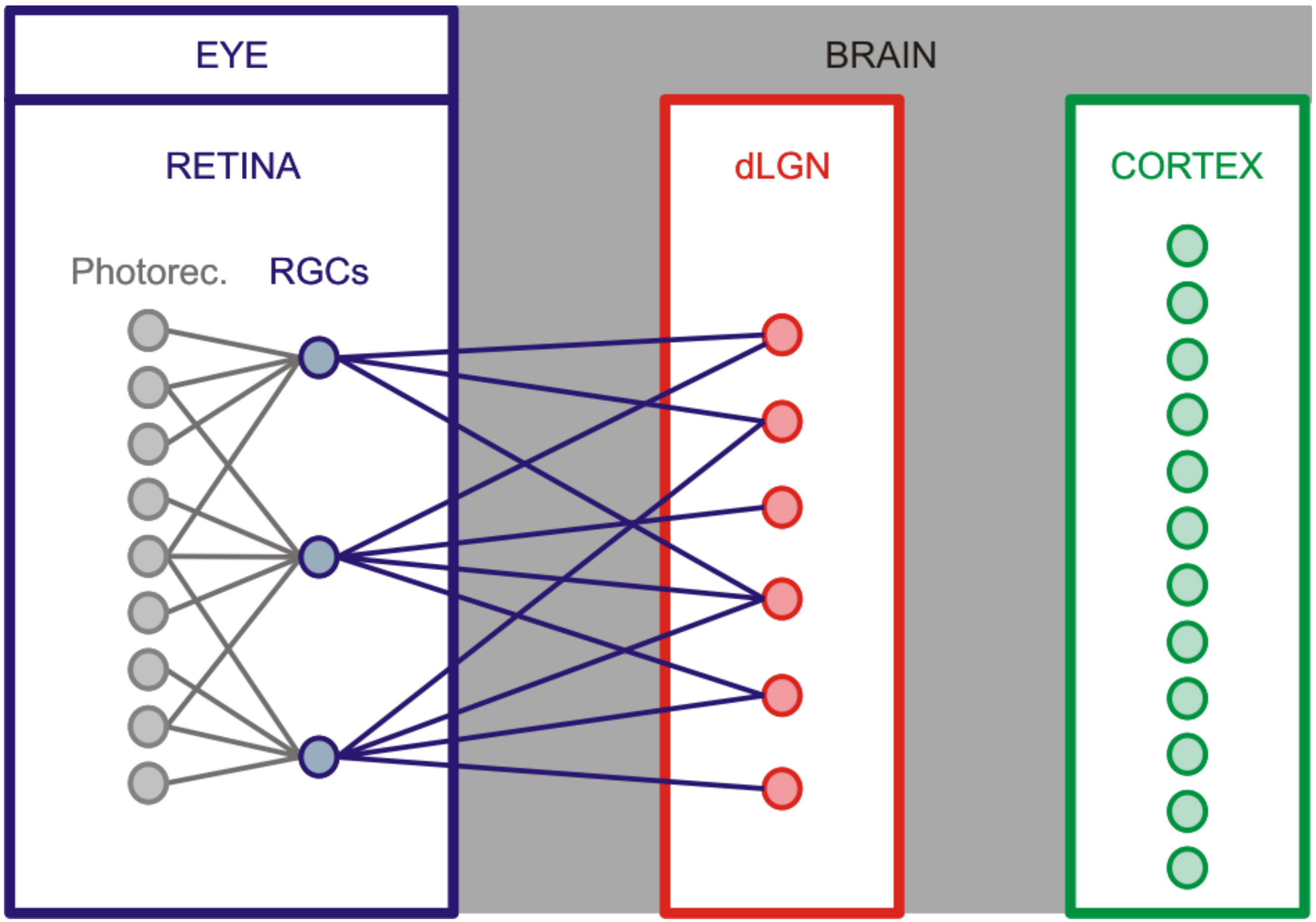


Statistical wiring of thalamic RFs increases visual (interpolated) resolution

Bayesian decoder

Martinez et al 2014. Neuron 81:943-956.

Statistical wiring of thalamic RFs increases visual (interpolated) resolution



Energy and coding efficient

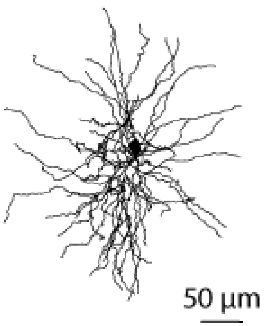
Increasing visual acuity through RF interpolation

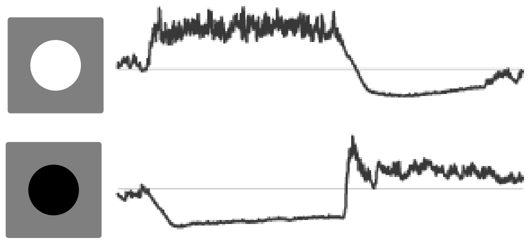
Increasing visual acuity through RF interpolation

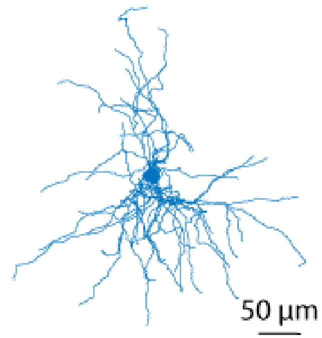
LGN Receptive Fields. Push-pull inhibition

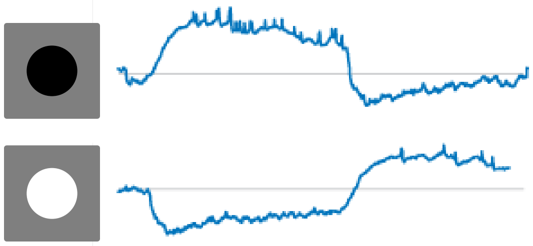
ON-center relay cell

OFF-center interneuron



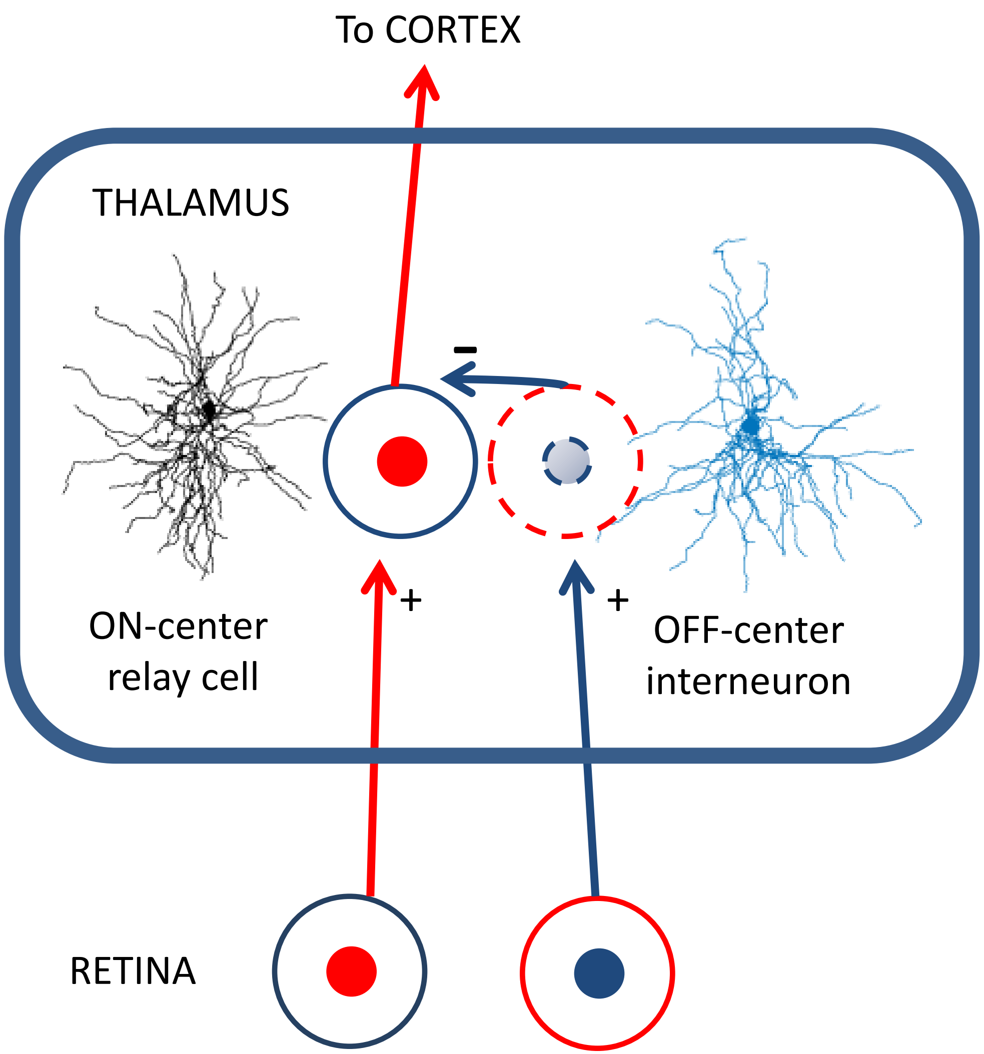




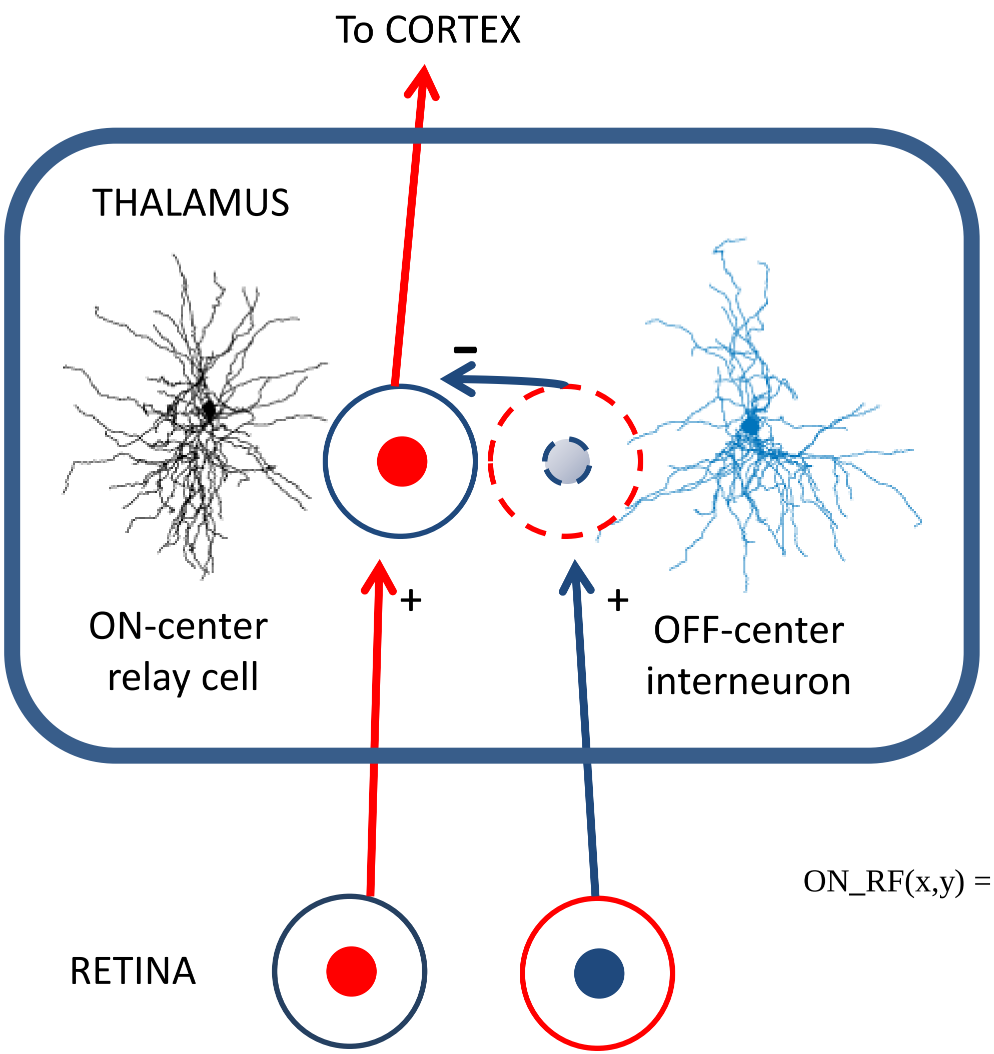


ON_RF(x,y) = $ON_{center}(x,y) - Off_{pull}(x,y) = k_c e^{-\left(\frac{x^2+y^2}{2\sigma_c^2}\right)} - k_p e^{-\left(\frac{x^2+y^2}{2\sigma_p^2}\right)}$

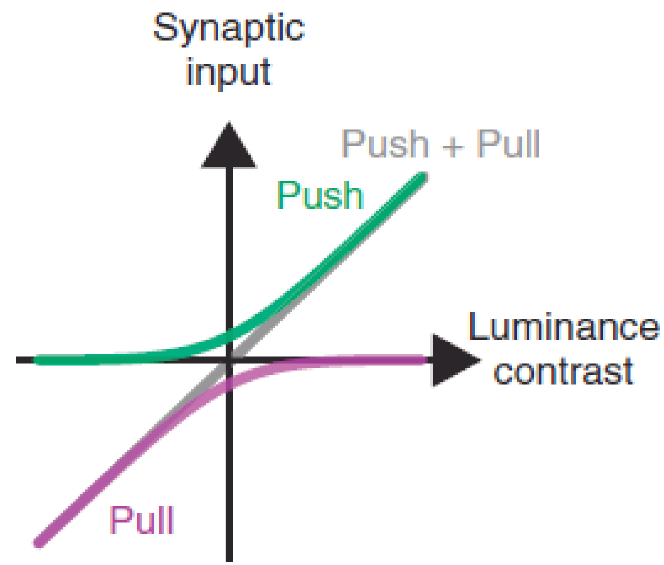
LGN relay cells and interneurons form functional PUSH-PULL “pairs”



LGN relay cells and interneurons form functional PUSH-PULL "pairs"

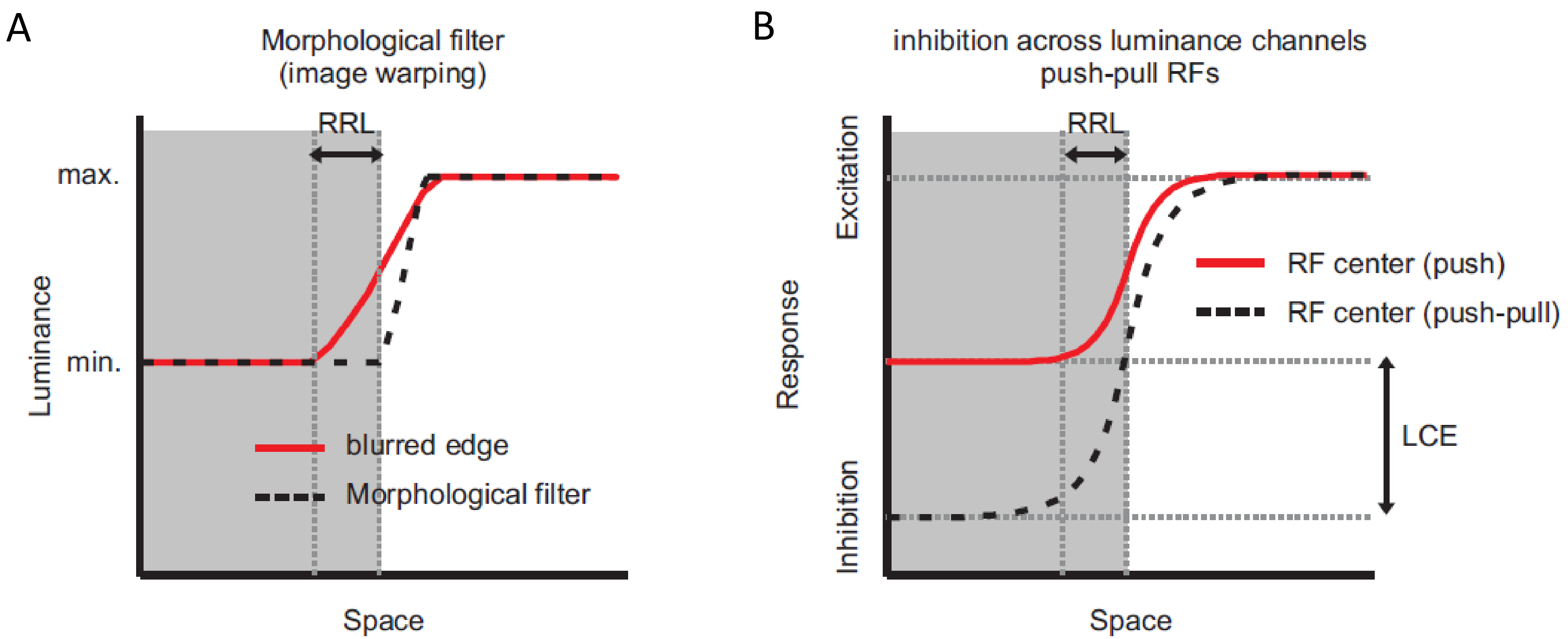


Increase in dynamic range
of visual responses



ON_RF(x,y) = $ON_{center}(x,y) - Off_{pull}(x,y) = k_c e^{-\left(\frac{x^2+y^2}{2\sigma_c^2}\right)} - k_p e^{-\left(\frac{x^2+y^2}{2\sigma_p^2}\right)}$

Functional consequences of Push-Pull in the LGN



RRL: Reduction in ramp length

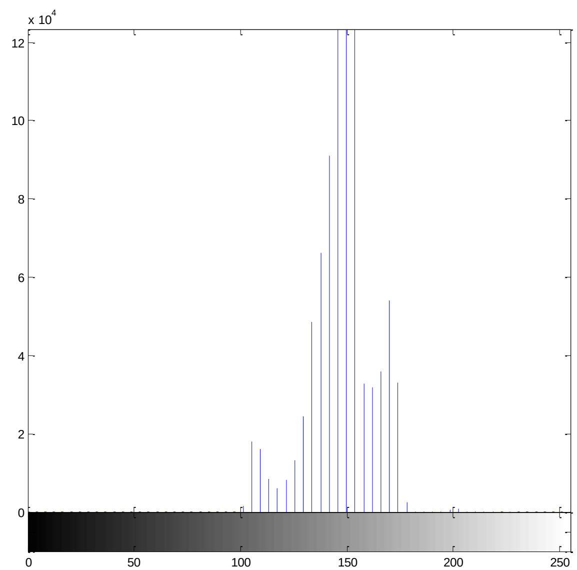
LCE: Local contrast enhancement

ON_RF(x,y) = $ON_{center}(x,y) - Off_{pull}(x,y) = k_c e^{-\left(\frac{x^2+y^2}{2\sigma_c^2}\right)} - k_p e^{-\left(\frac{x^2+y^2}{2\sigma_p^2}\right)}$

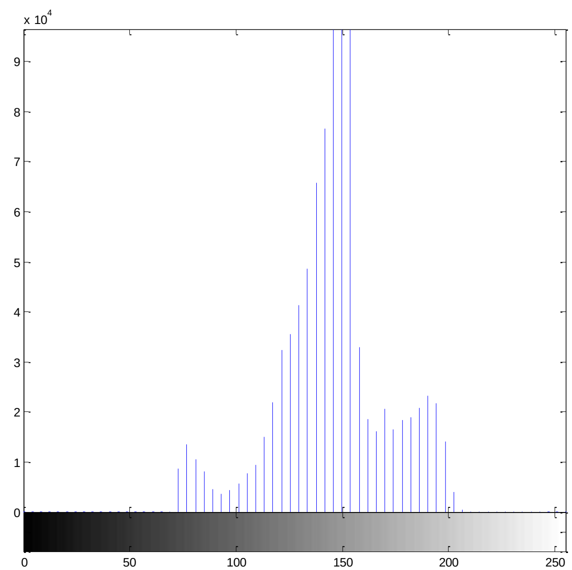
Histogram equalization by retinothalamic circuits

Original image

LCE through thalamic RFs



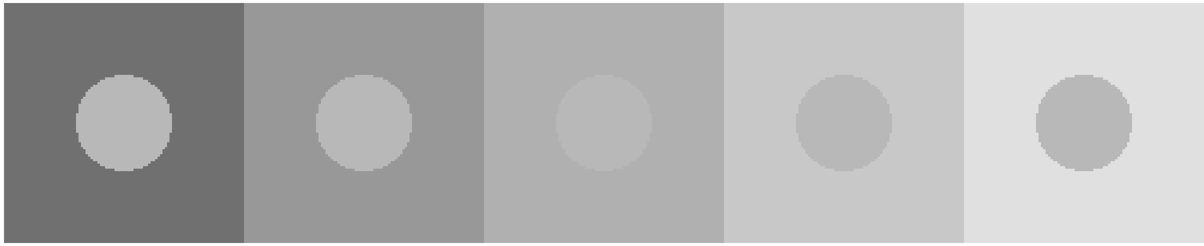
Corresponding histogram



Corresponding histogram

Statistical wiring of thalamic receptive fields

1. Increases visual resolution through interpolation.
2. Decreases local redundancy in the image.
3. Increases the dynamic range of the image (i.e. “flatens” its histogram)
4. Produces a very good local contrast enhancement performance (without halos or visual artifacts)
5. Explains other visual perception phenomena



simultaneous contrast

ICON 2014
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(How the thalamus changes) what the cat's eye tells the cat's brain

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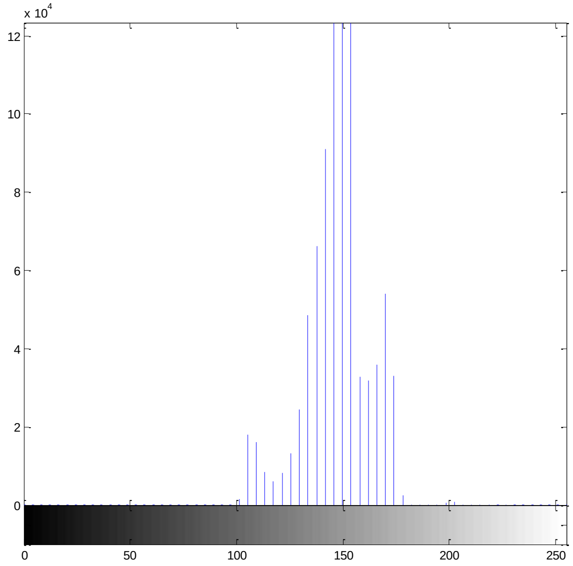
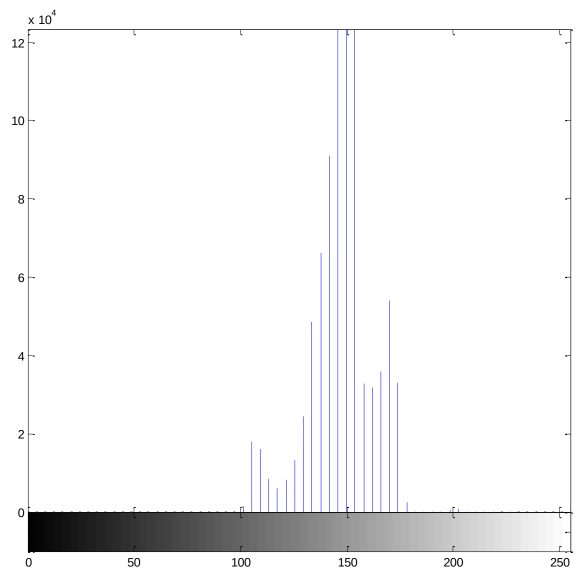
Original image



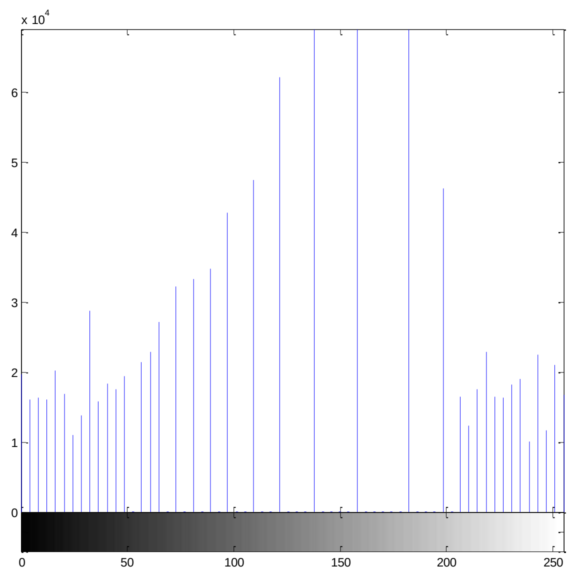
Corresponding histogram

Original image

Histogram equalization



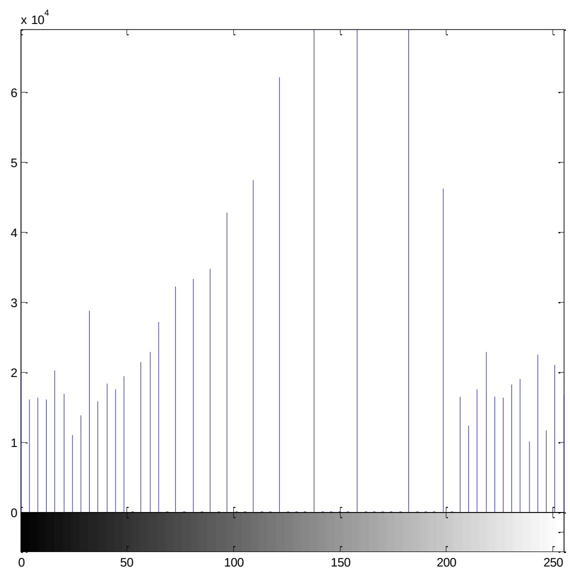
Corresponding histogram



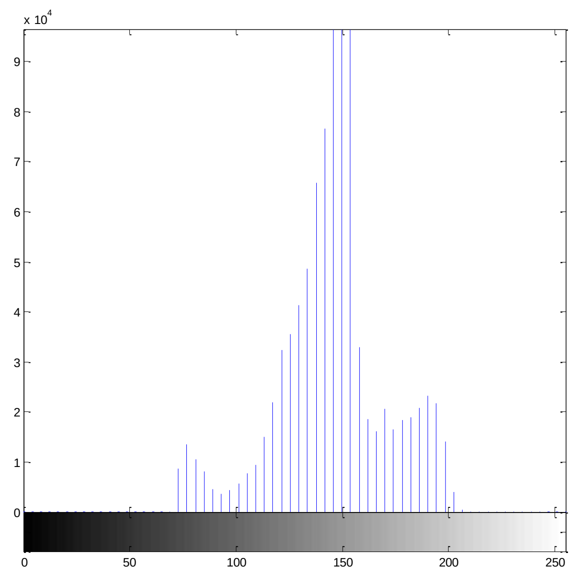
Corresponding histogram

Histogram equalization

LCE through thalamic RFs



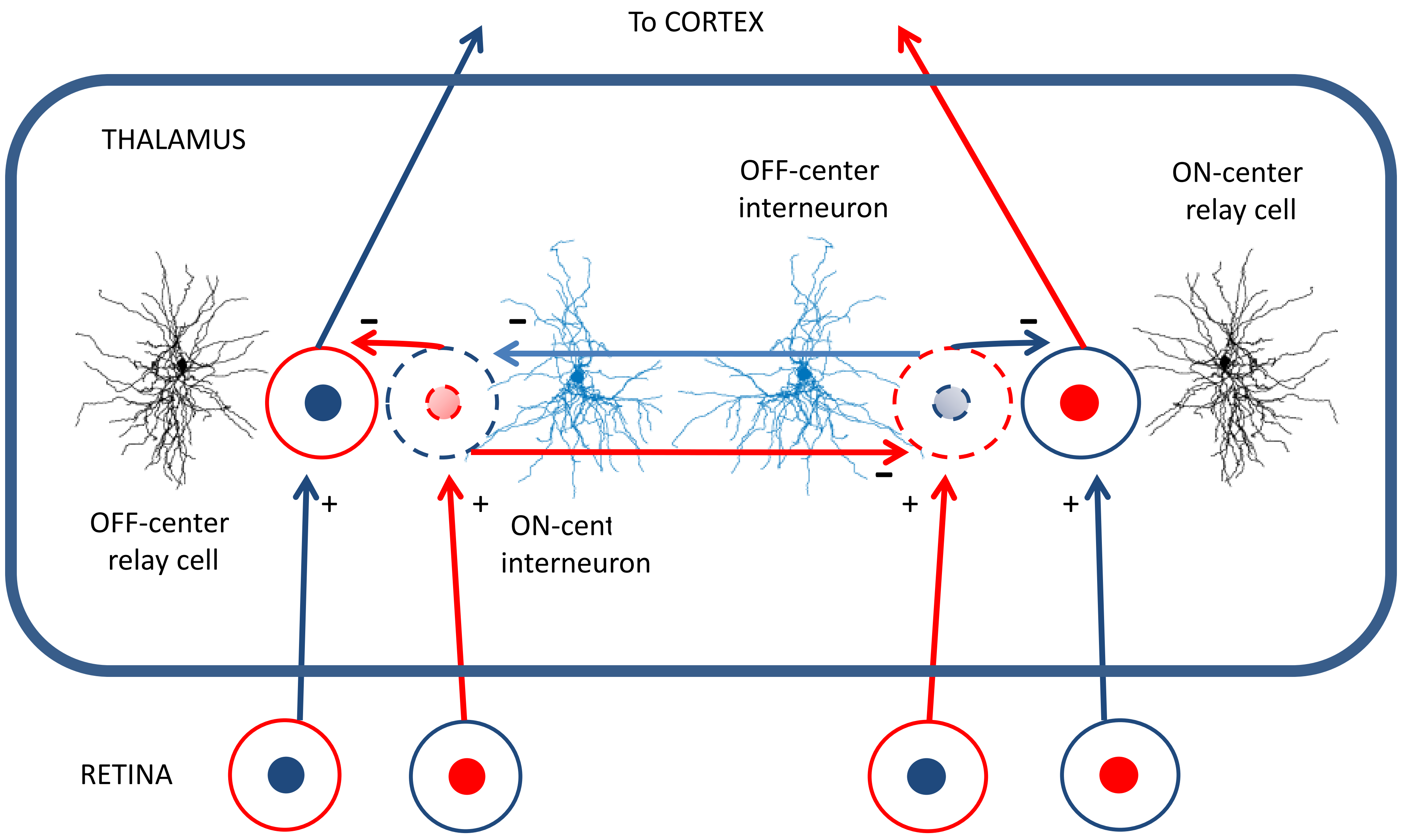
Corresponding histogram



Corresponding histogram

Ferreiroa et al 2014. In preparation

PUSH-PULL “functional units”



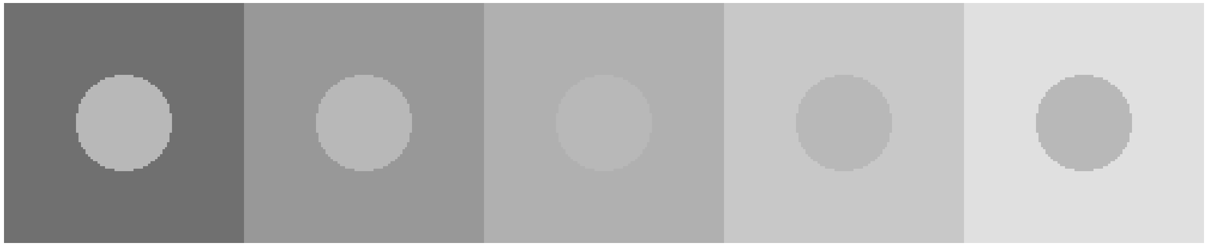
Molano-Mazón, Alonso-Pablos et al 2014. Submitted

PUSH-PULL “functional units”

1. Increase the dynamic range of the image (i.e. “flatens” its histogram)

2. Have a very good local contrast enhancement performance
(without halos or visual artifacts)

3. Explain visual perception phenomena



simultaneous contrast

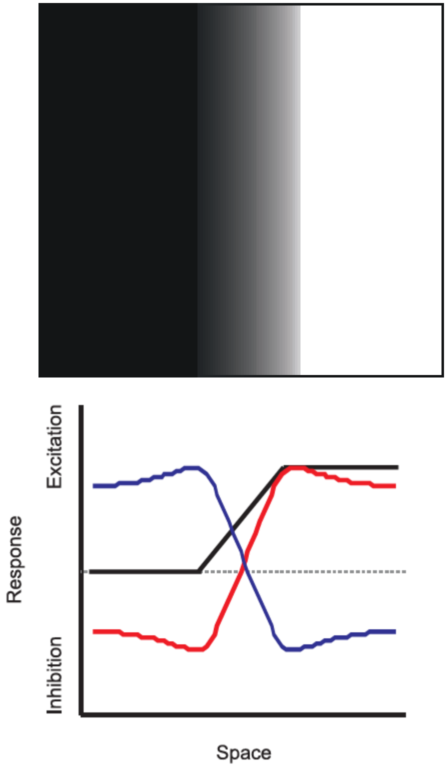
PUSH-PULL “functional units”

1. Increase the dynamic range of the image (i.e. “flatens” its histogram)

2. Have a very good local contrast enhancement performance (without halos or visual artifacts)

3. Explain visual perception phenomena

Mach Bands



PUSH-PULL "functional units"

1. Increase the dynamic range of the image (i.e. "flatens" its histogram)

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Mach Bands

El Greco. Christ carrying the cross

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