

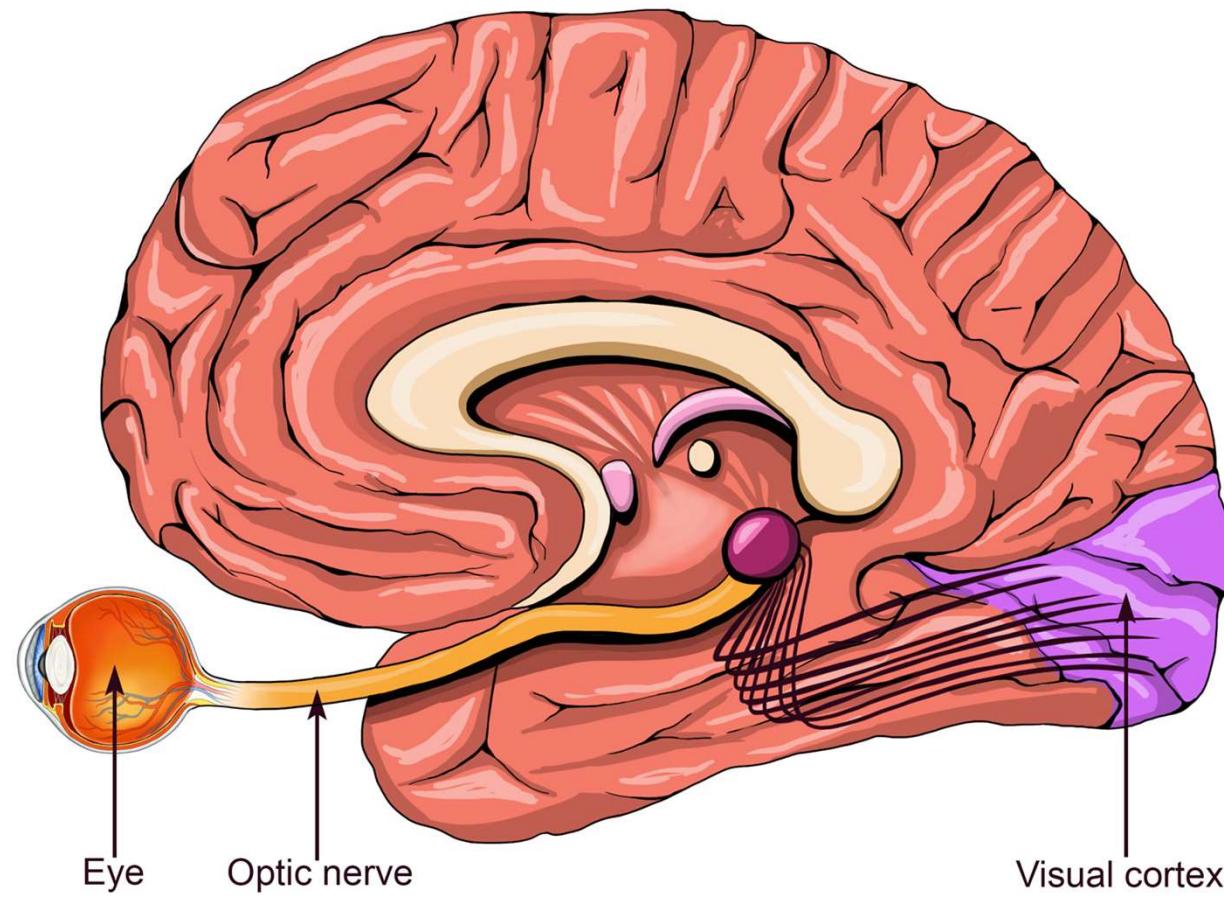
Human visual system and perception

Javier Vazquez-Corral
Universitat Autònoma de Barcelona

javier.vazquez@cvc.uab.cat

Slide credits: Marcelo Bertalmío and David Kane

Biological basis



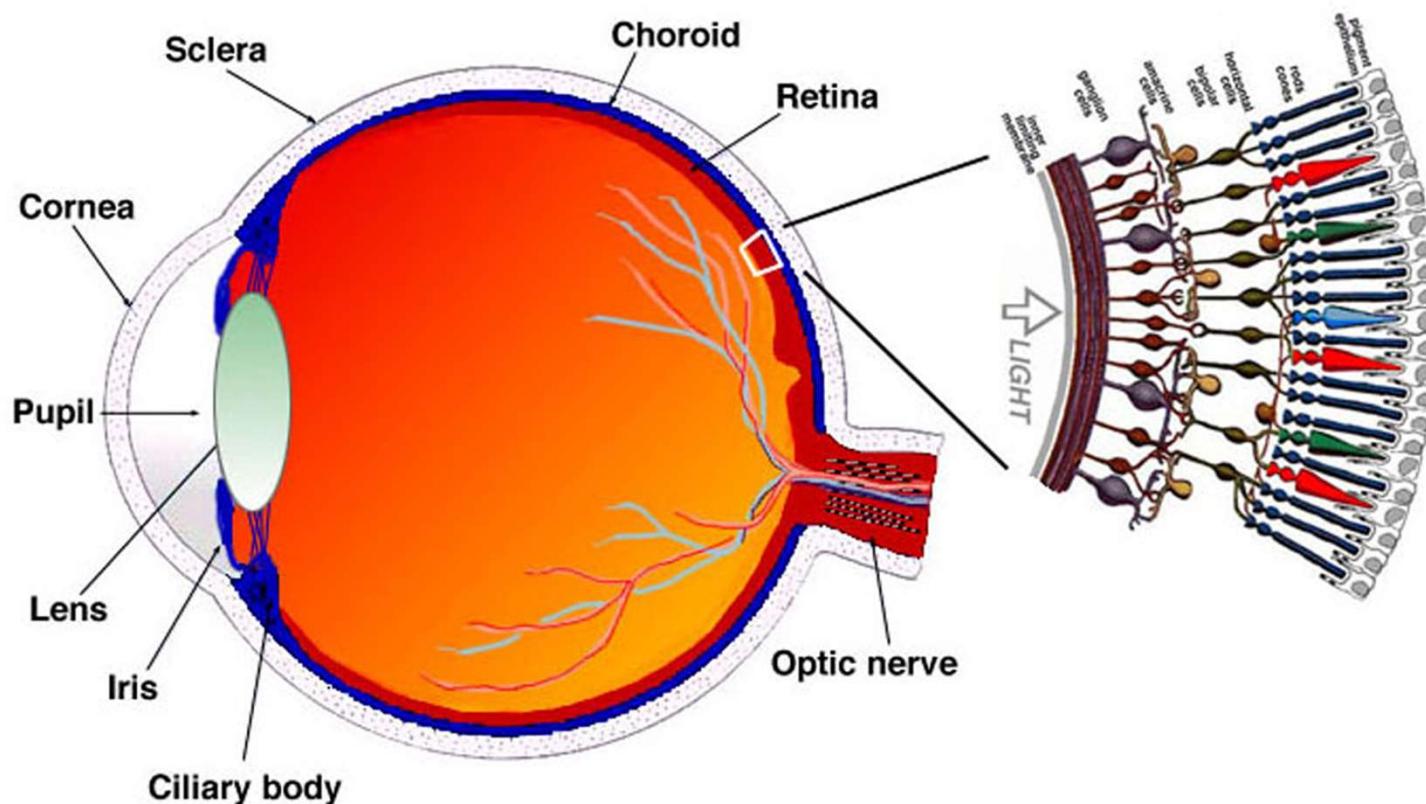
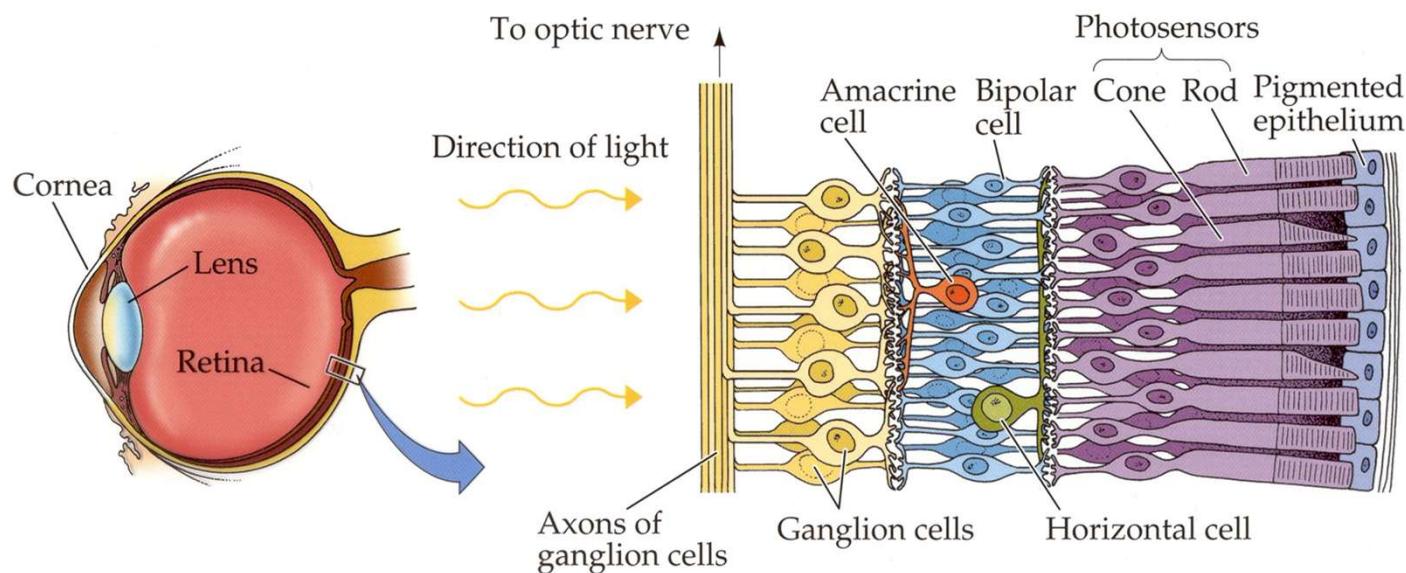
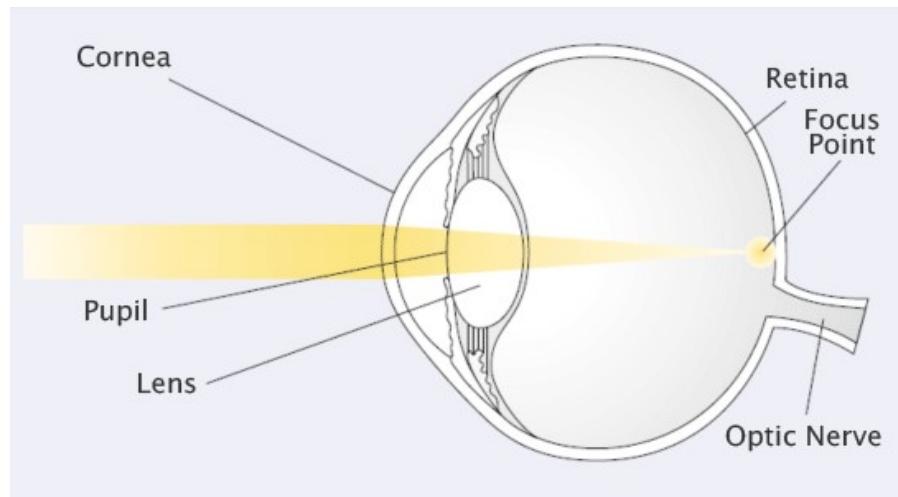


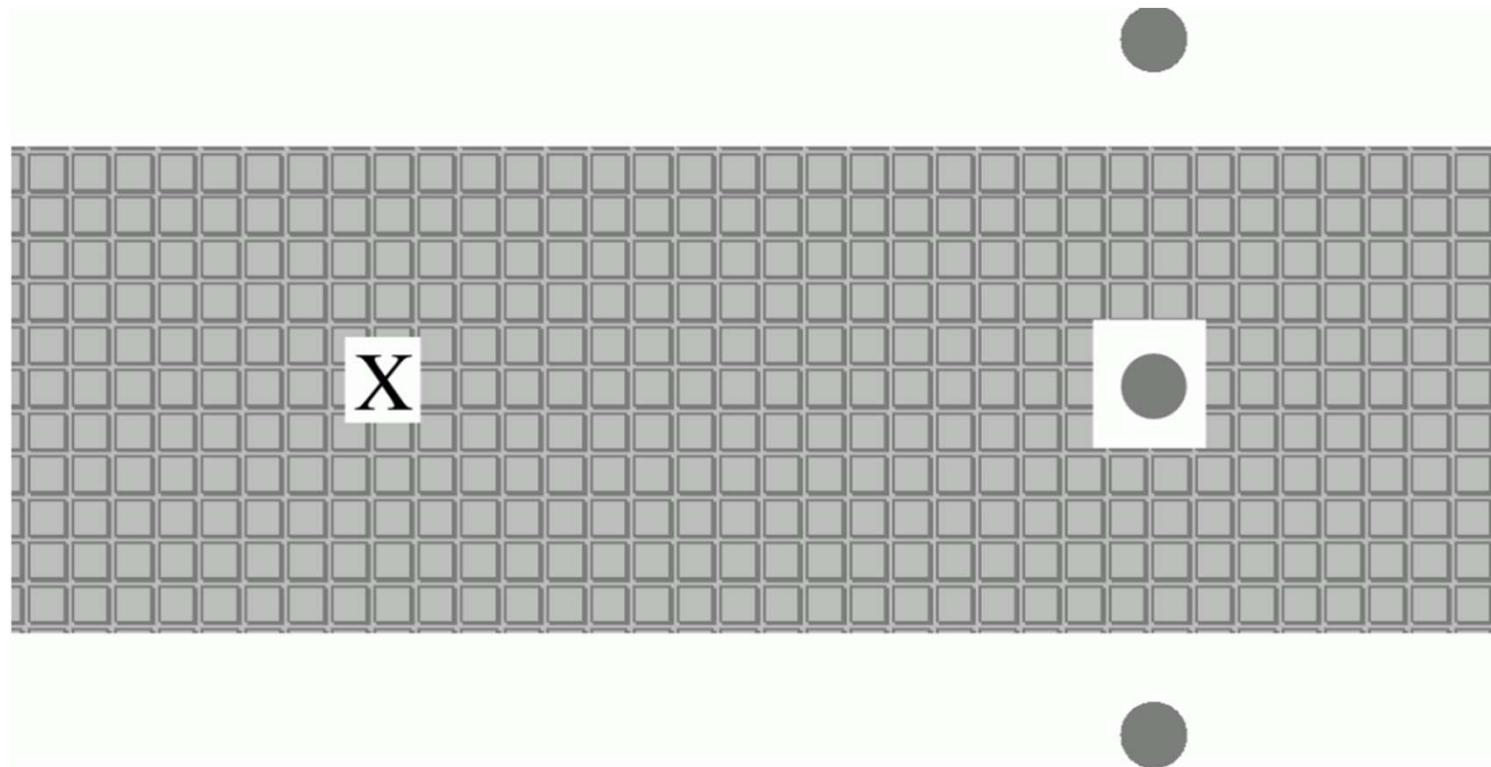
Fig. 1.1. A drawing of a section through the human eye with a schematic enlargement of the retina.



The eye



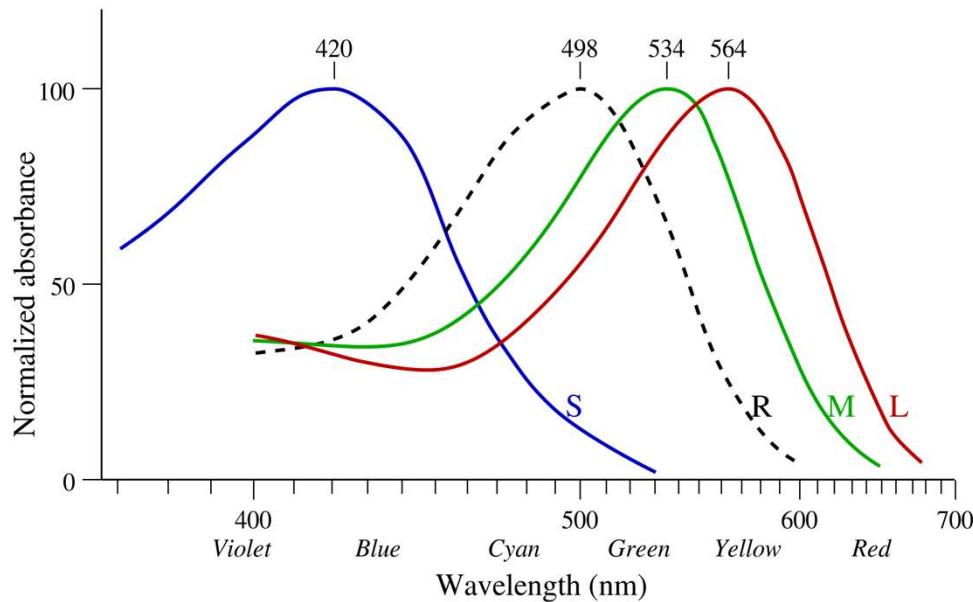
The blindspot



Filling in

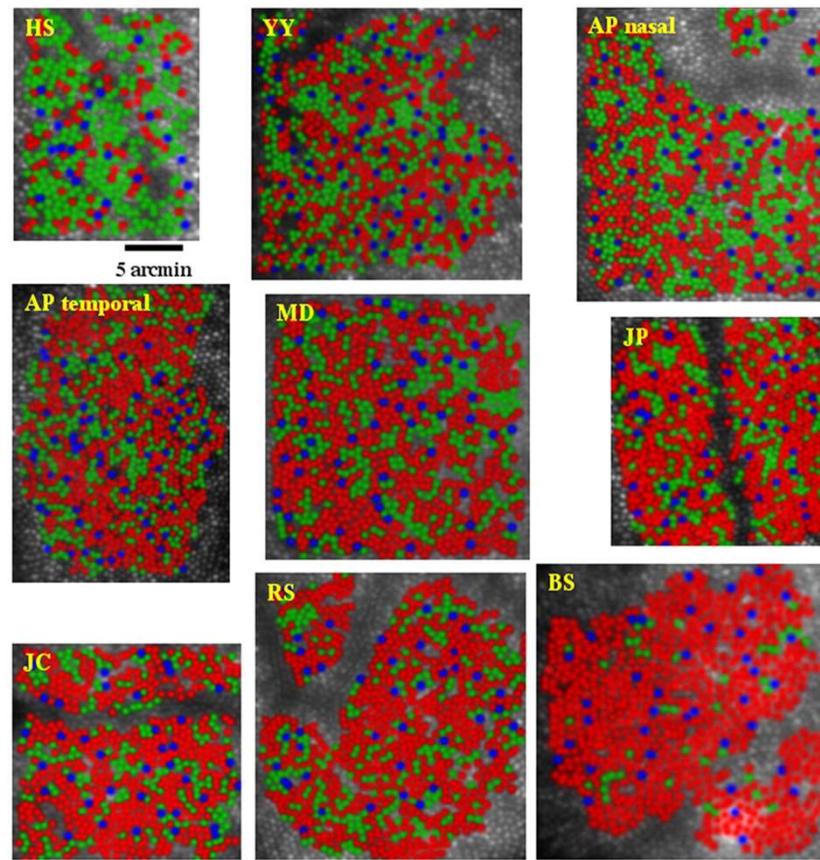


Rod and Cone vision



- Rods are more sensitive to low luminance levels but to only one wavelength
- Cones are sensitive to different wavelength
 - Short, medium and long, roughly corresponding to blue green and red

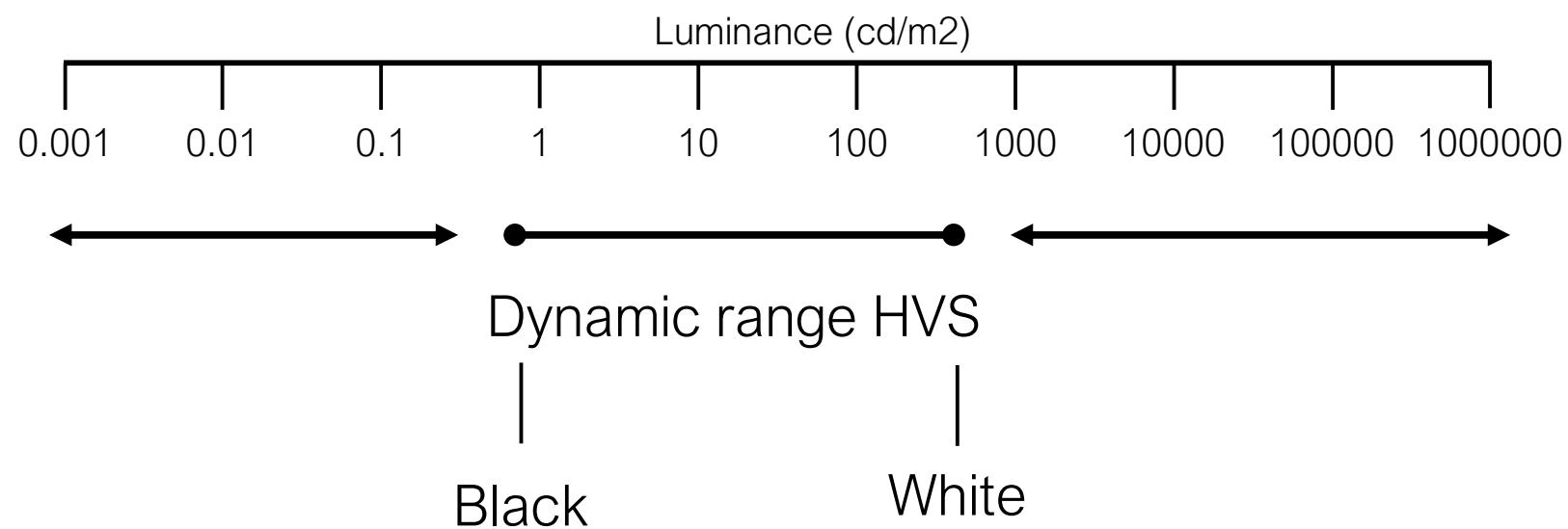
Rod and Cone vision



Scotopic, mesozoic & photopic vision

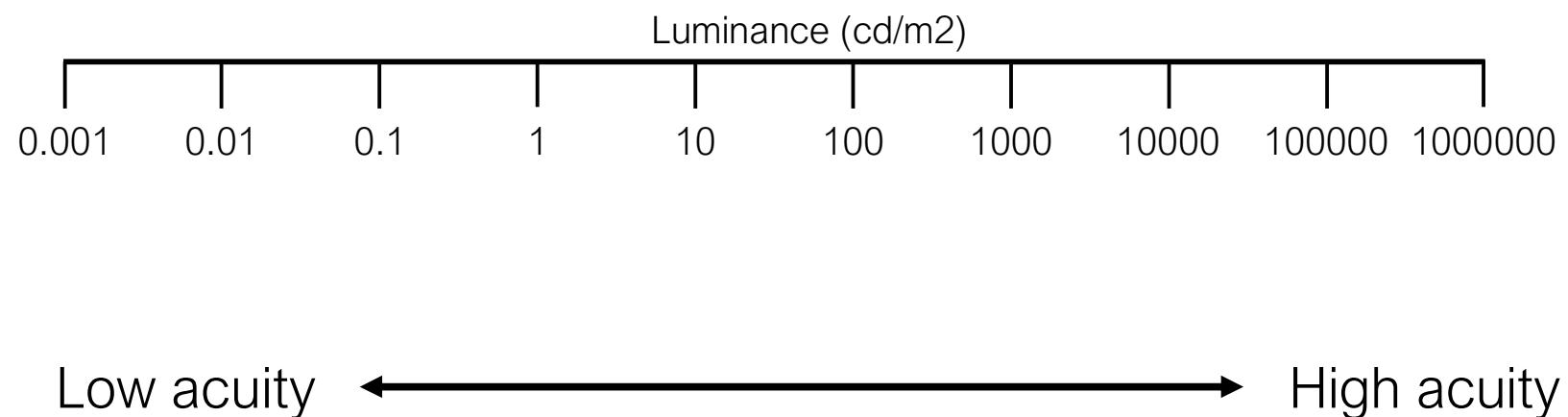
Condition	cd/m ²		Cells
Clear night sky	0.001	Scotopic	Rods
Quarter moon	0.01	Scotopic	Rods
Full moon	0.1	Mesozoic	Rods & Cones
Late twilight	1	Mesozoic	Rods & Cones
Twilight	10	Photopic	Cones
Heavy overcast	100	Photopic	Cones
Overcast sky	1000	Photopic	Cones
Full daylight	10000	Photopic	Cones
Direct sunlight	100000	Photopic	Cones

Dynamic range/luminance adaption

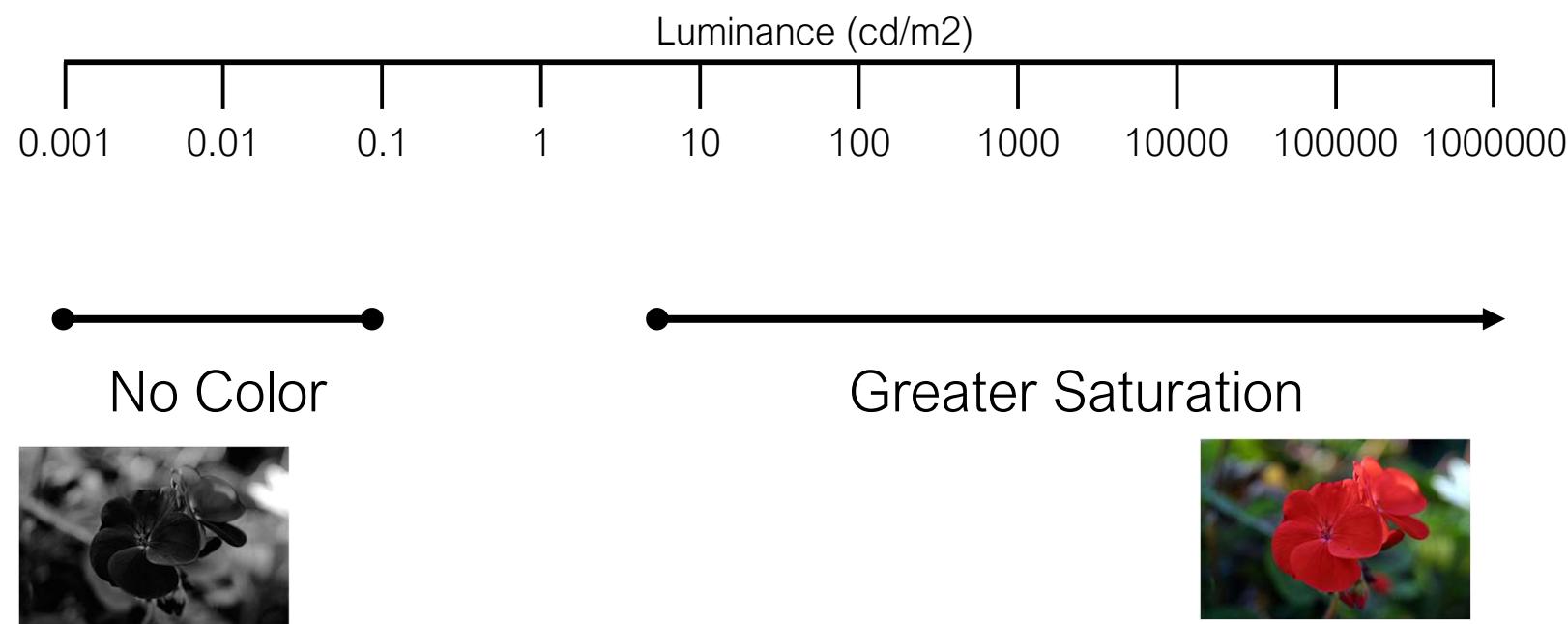


- Insensitive to absolute luminance

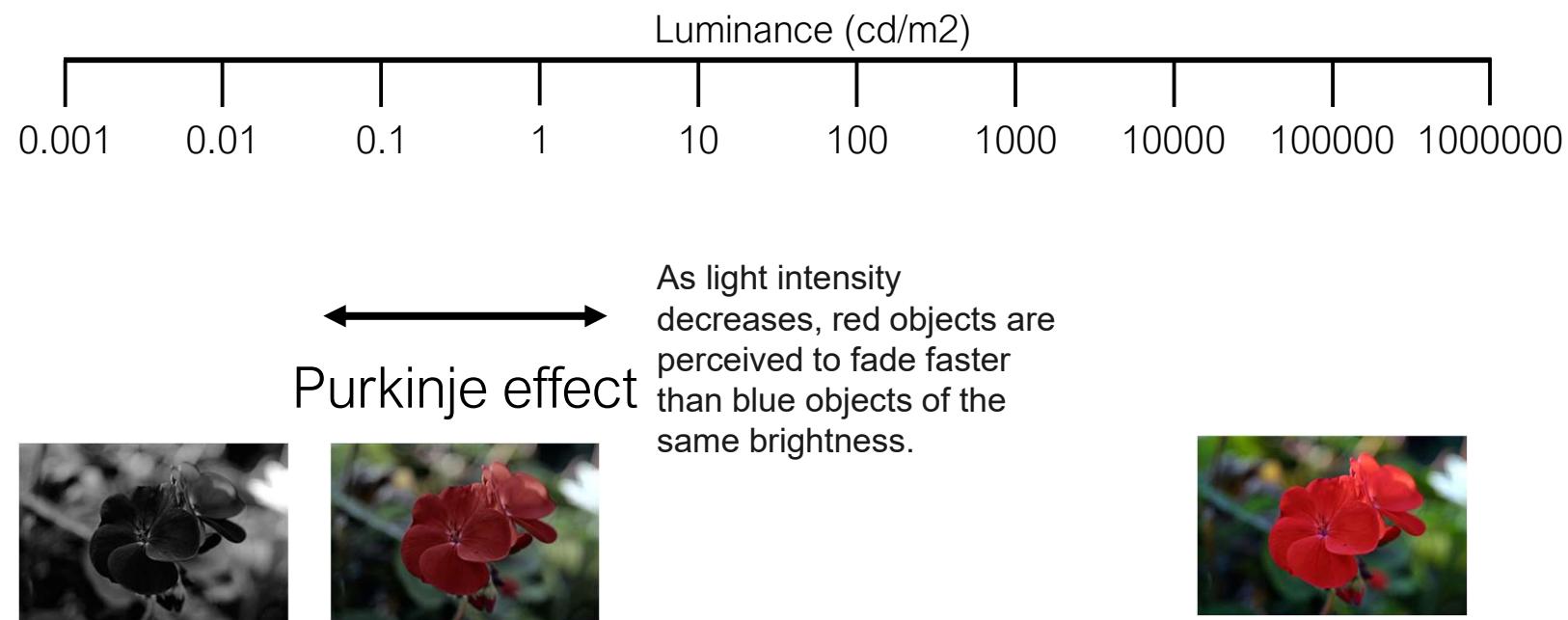
Dynamic range/luminance adaption



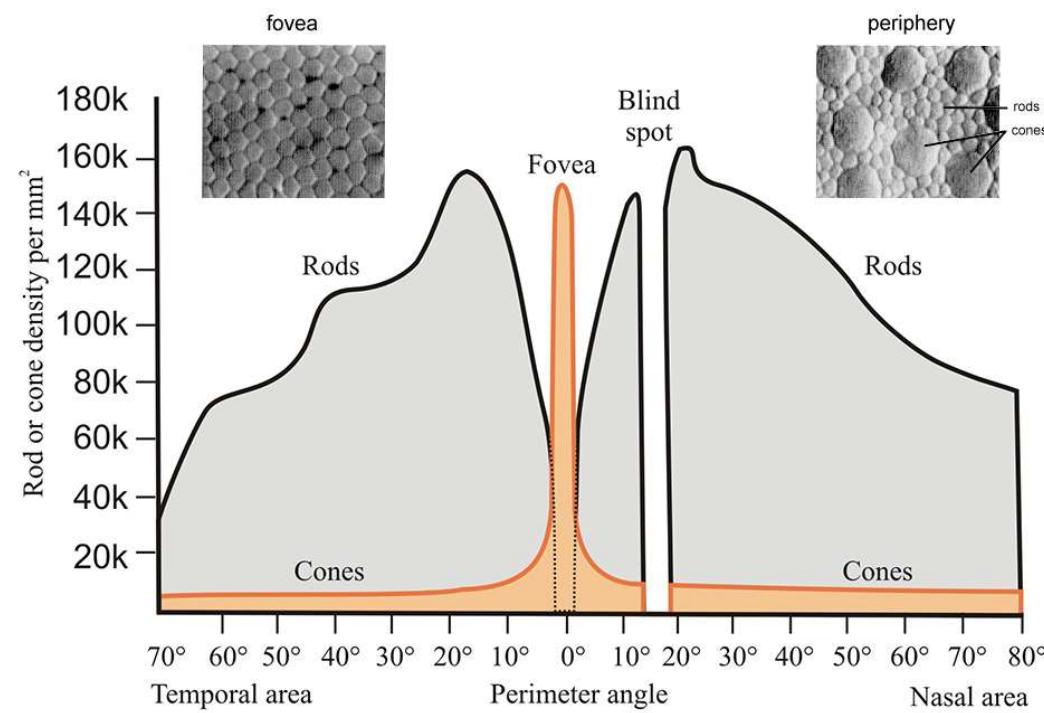
Dynamic range/luminance adaption



Dynamic range/luminance adaption



Rod and Cone Vision



Opponent Colors

Trichromatic

Long (ρ)

Med. (γ)

Short (β)

Opponent channels

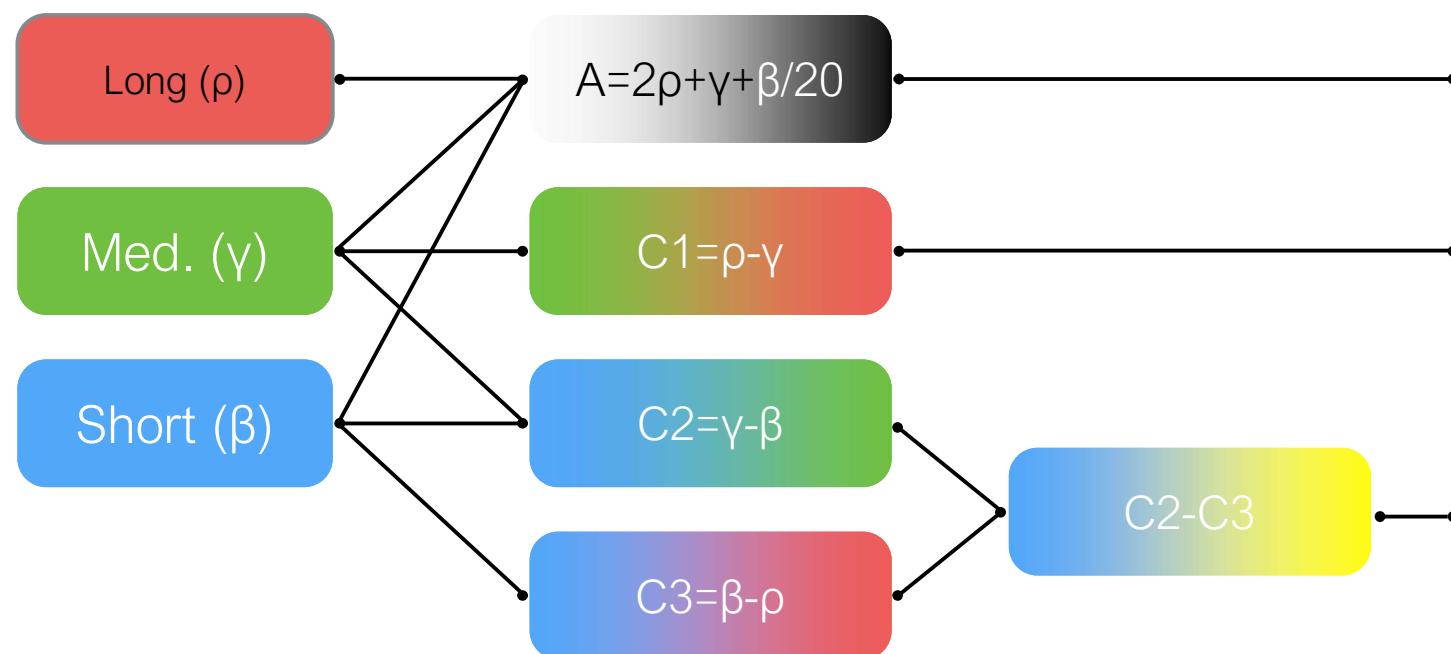
$$A=2\rho+\gamma+\beta/20$$

$$C1=\rho-\gamma$$

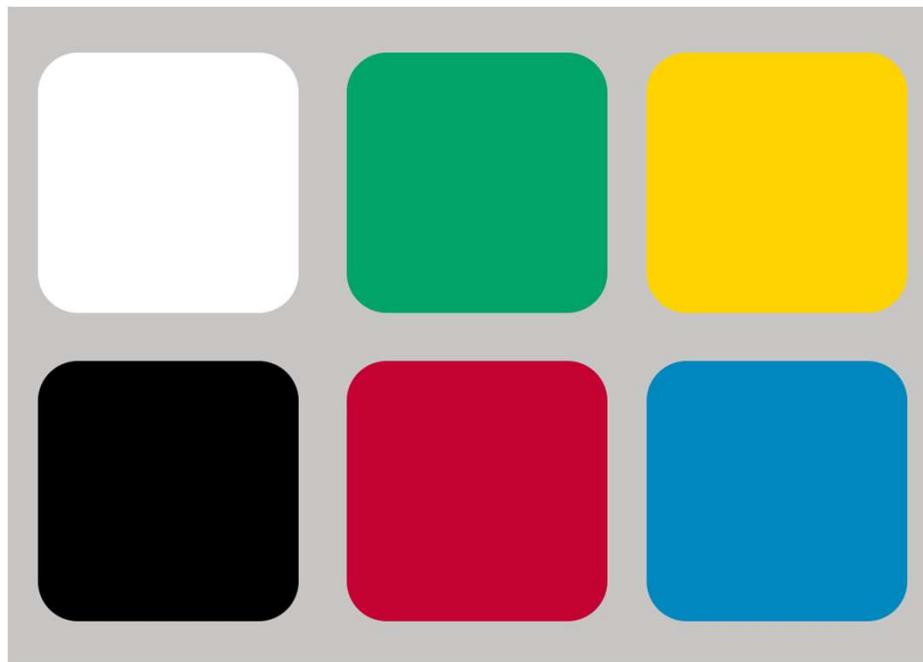
$$C2=\gamma-\beta$$

$$C3=\beta-\rho$$

$$C2-C3$$

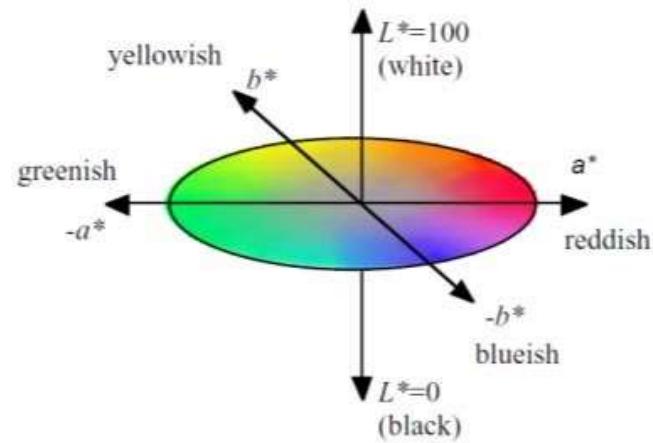


Opponent Colors



Opponent Colors

- People don't perceive
 - Reddish-greens
 - Blueish-yellows
- CIE-LAB color space



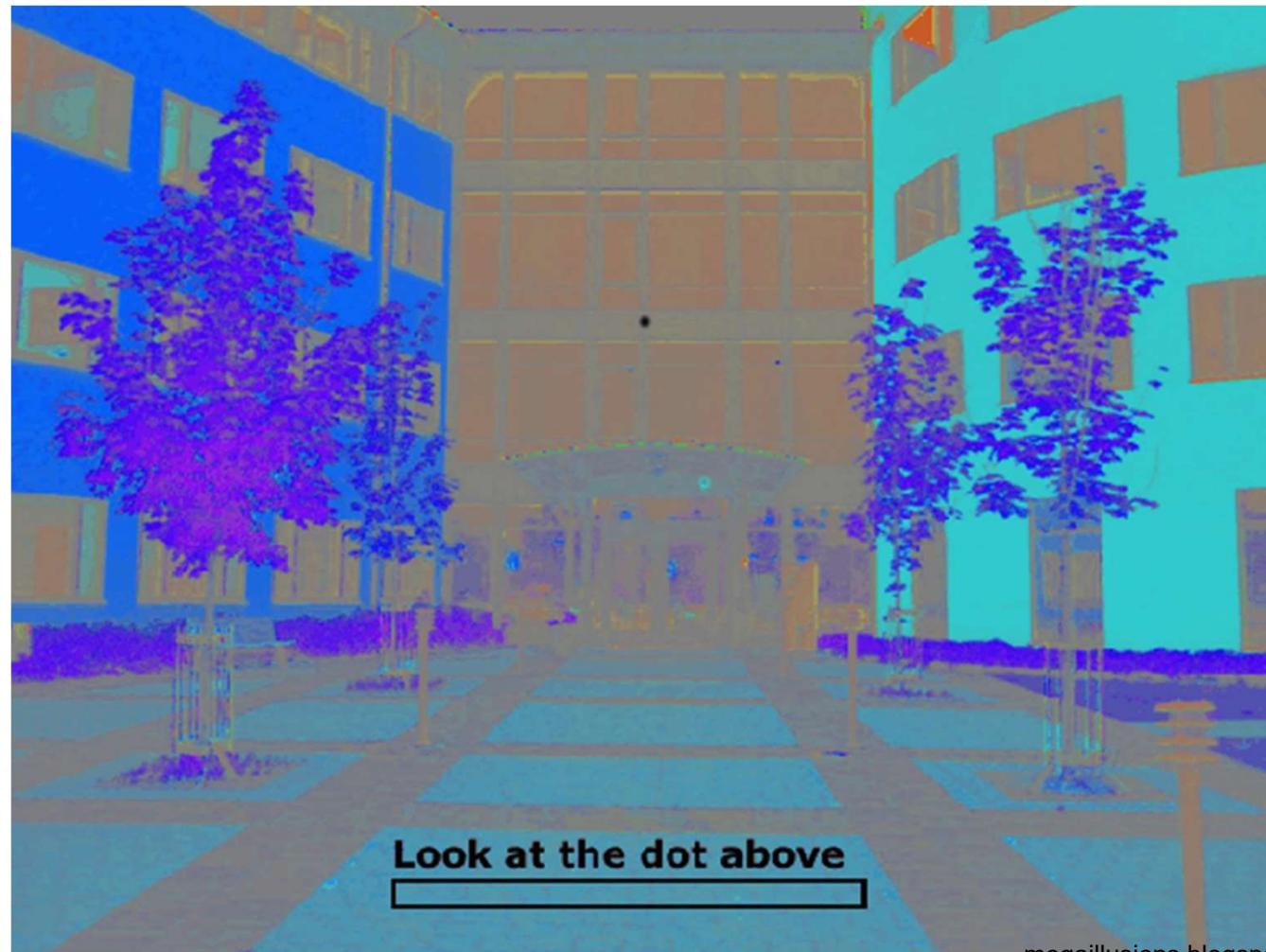
Rod and Cone Vision



Rod and Cone Vision



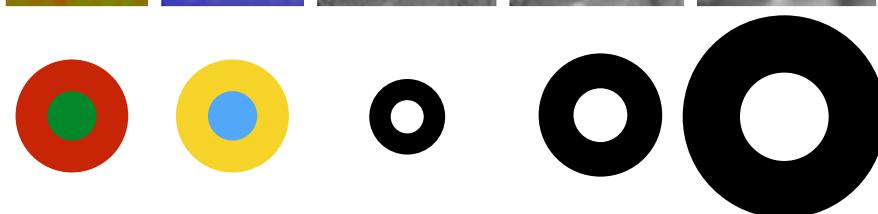
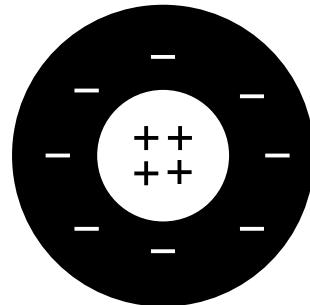
Rod and Cone Vision



Basic Transformations

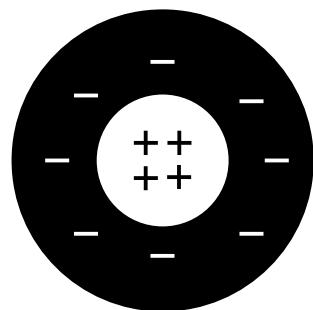
The retina

- Cones: Red/Green/Blue
- Rods: Grayscale
- Ganglion Cells: Centre-Surround



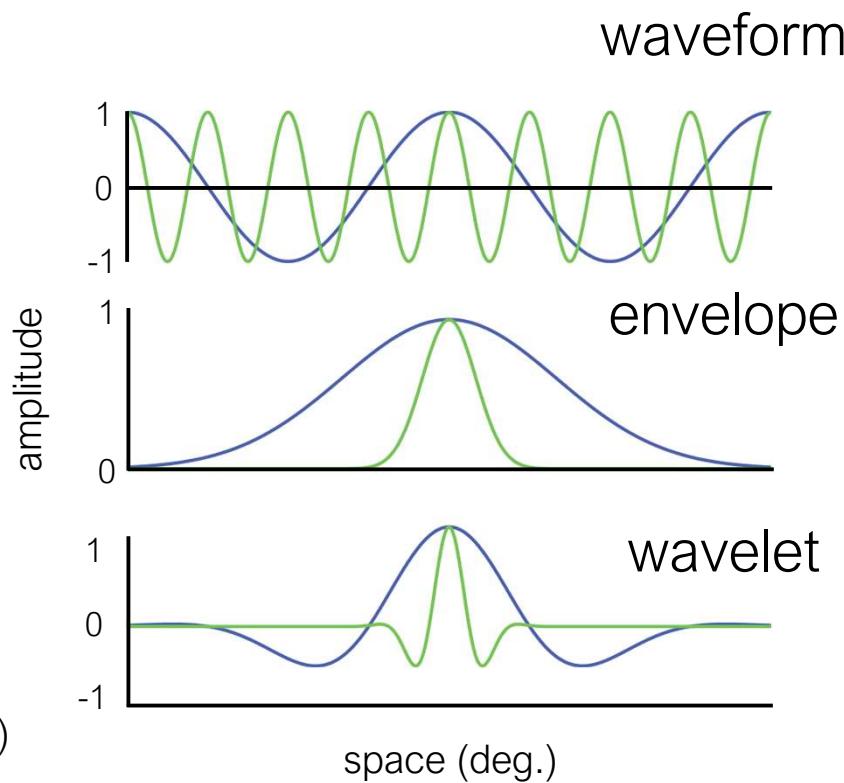
Basic Transformations

The centre surround

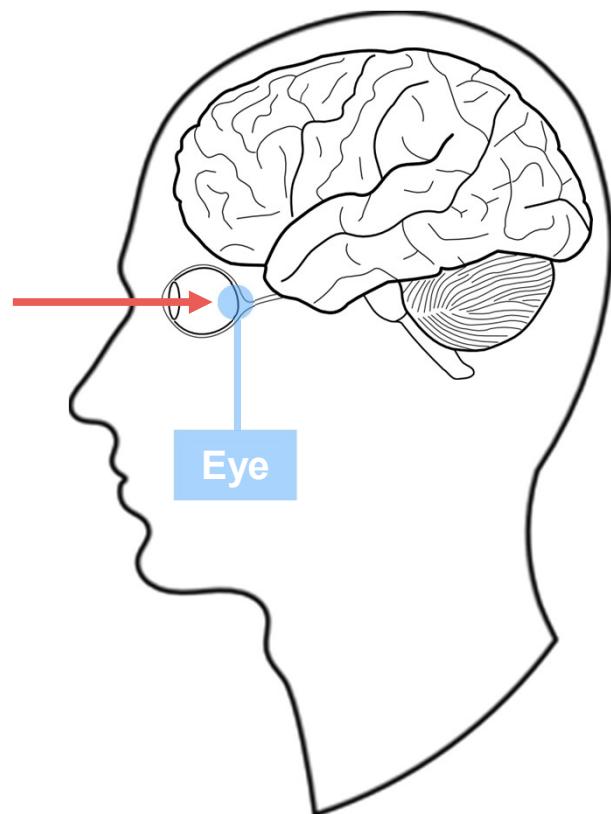


Low spatial frequency (coarse detail)

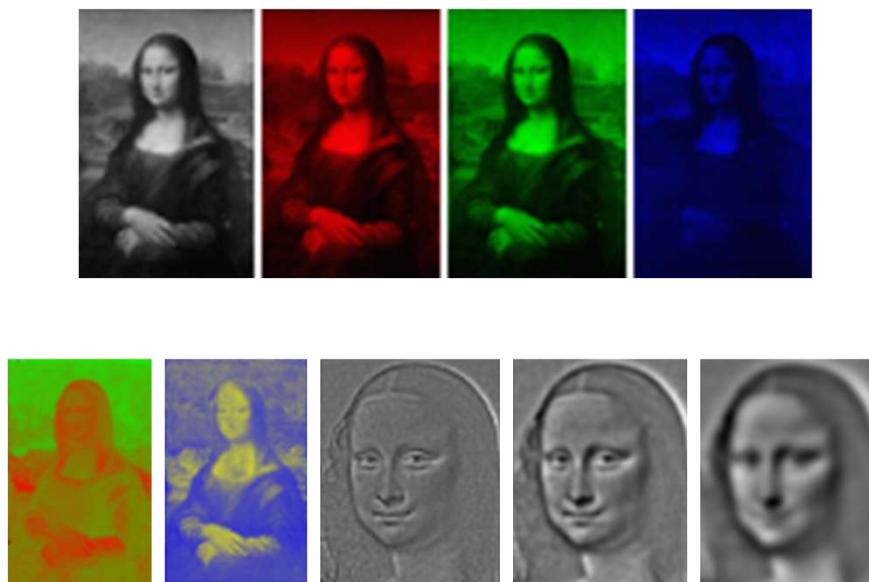
High spatial frequency (fine detail)



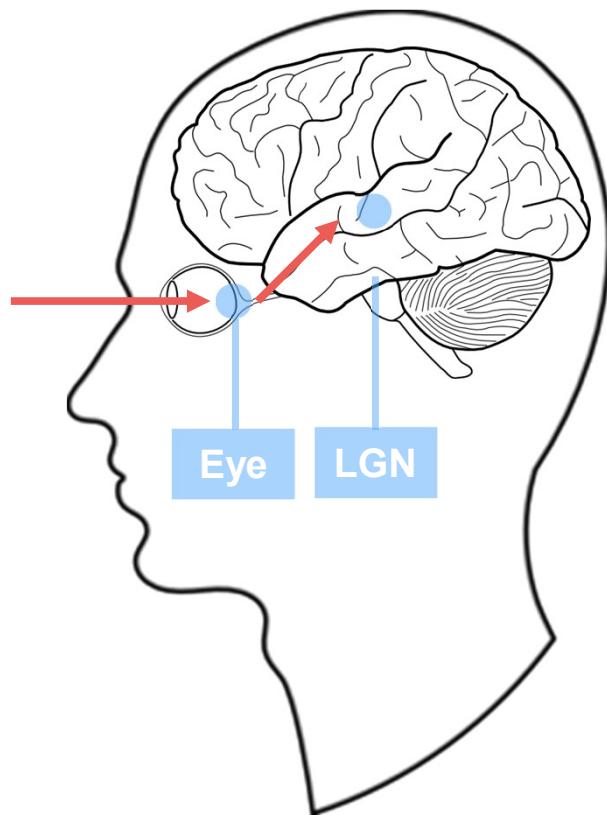
(very) Basic Overview



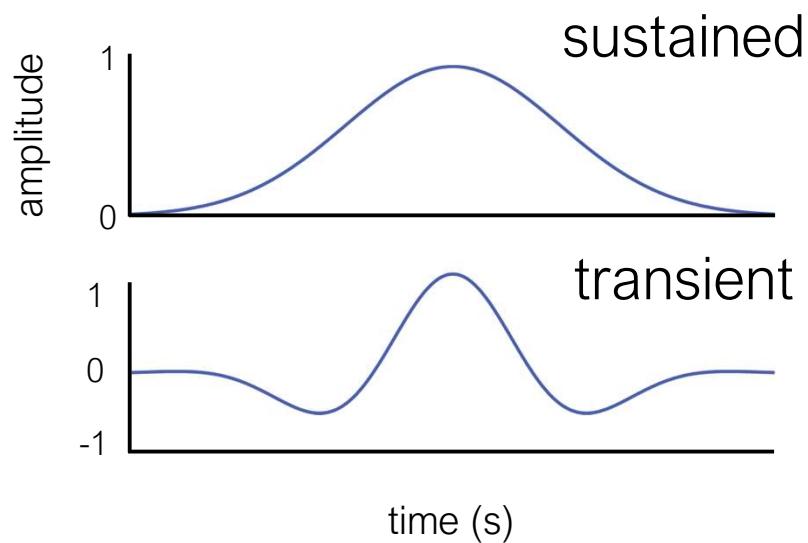
Retina



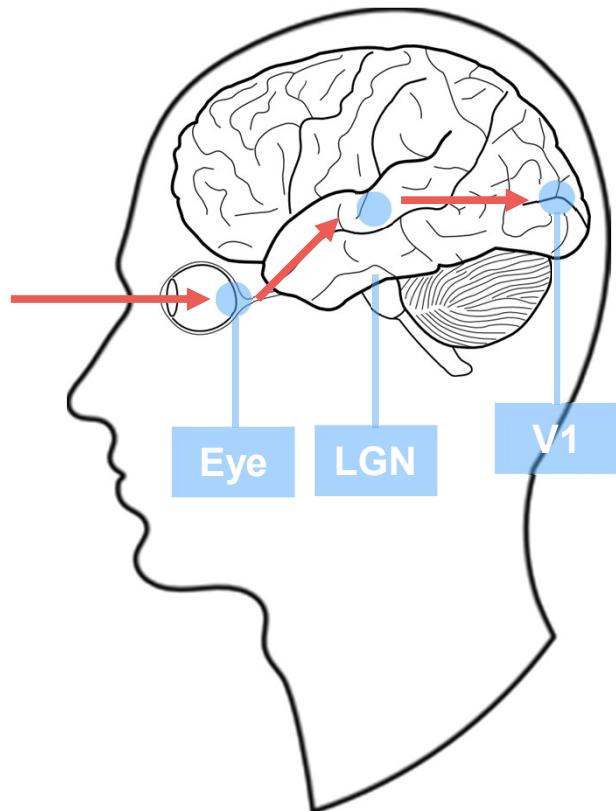
(very) Basic Overview



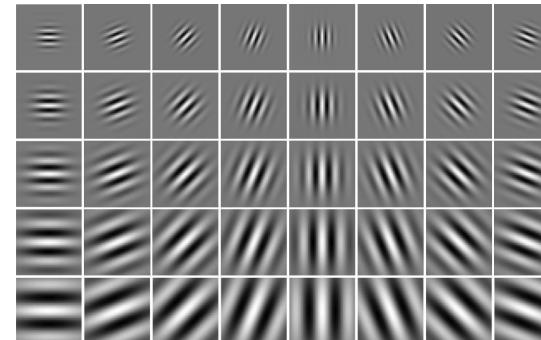
Lateral Geniculate Nucleus



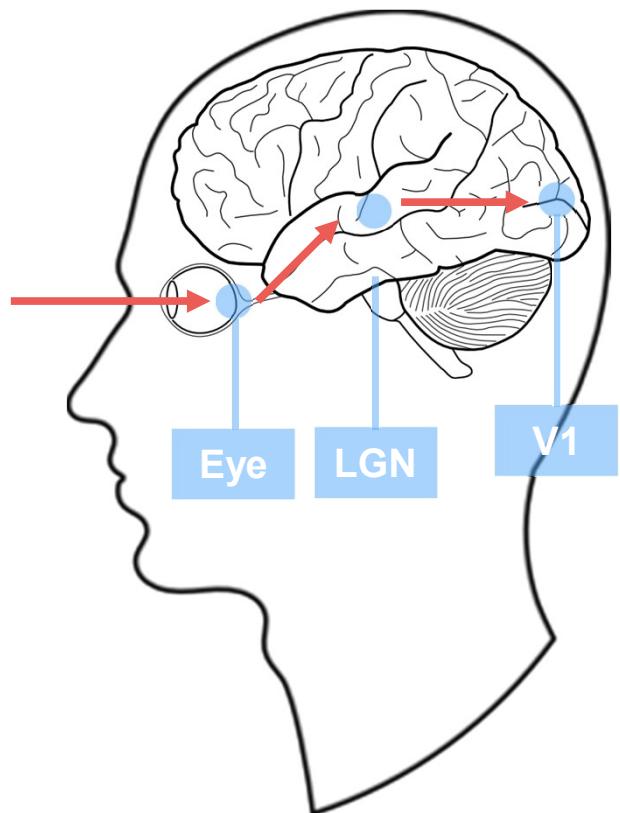
(very) Basic Overview



Visual Cortex: Area V1



(very) Basic Overview

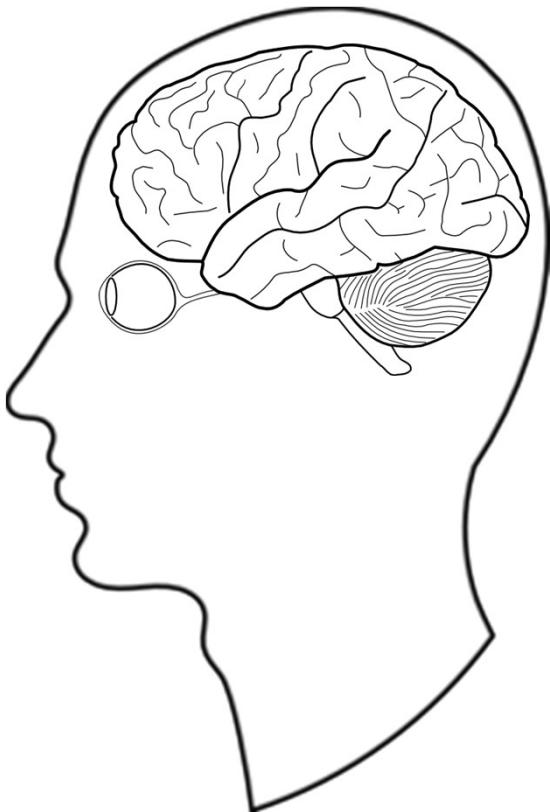


Visual Cortex: Area V1



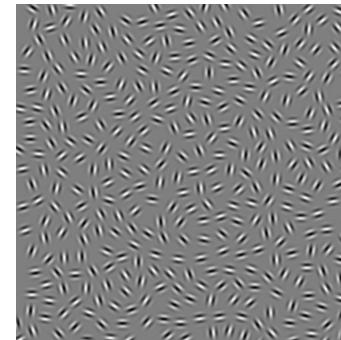
Motion is detected not by tracking objects, but through spatio-temporal energy.

(very) Basic Overview



Examples

- Contours

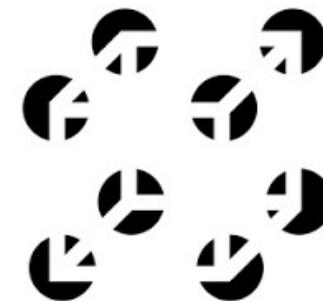


(very) Basic Overview



Examples

- Illusory contours



(very) Basic Overview



Examples

- Spatial invariance

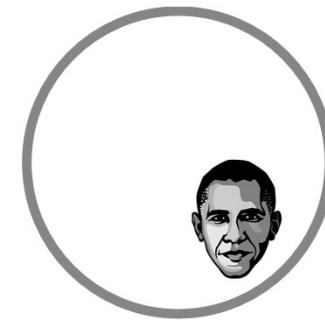


(very) Basic Overview

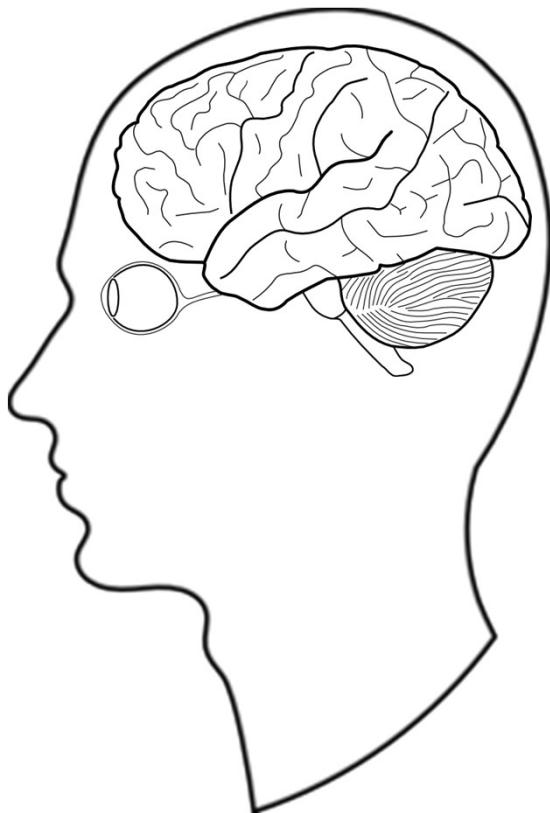


Examples

- Spatial invariance



(very) Basic Overview

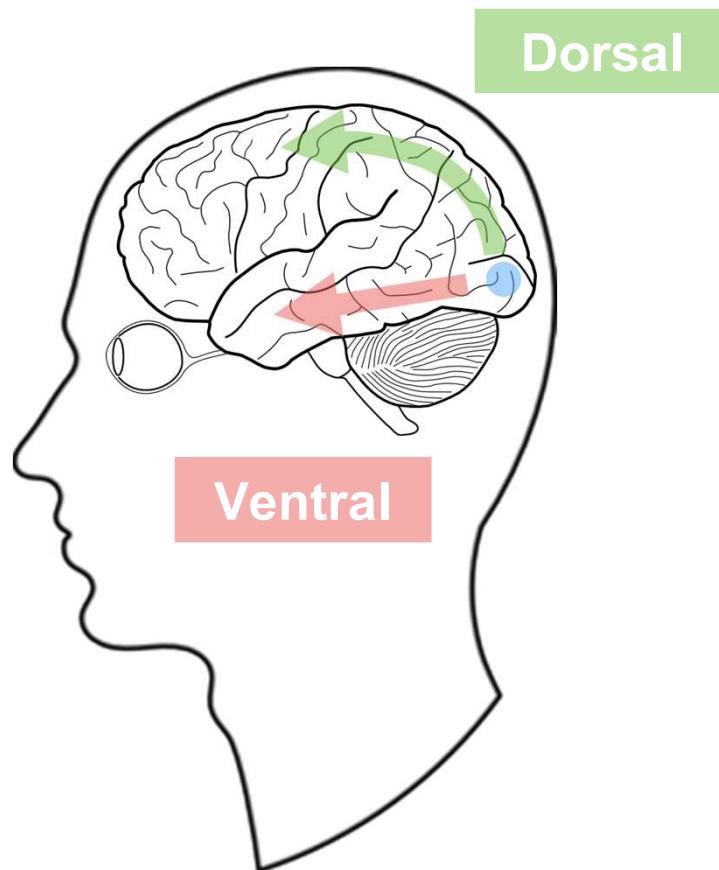


Examples

- Viewpoint invariance



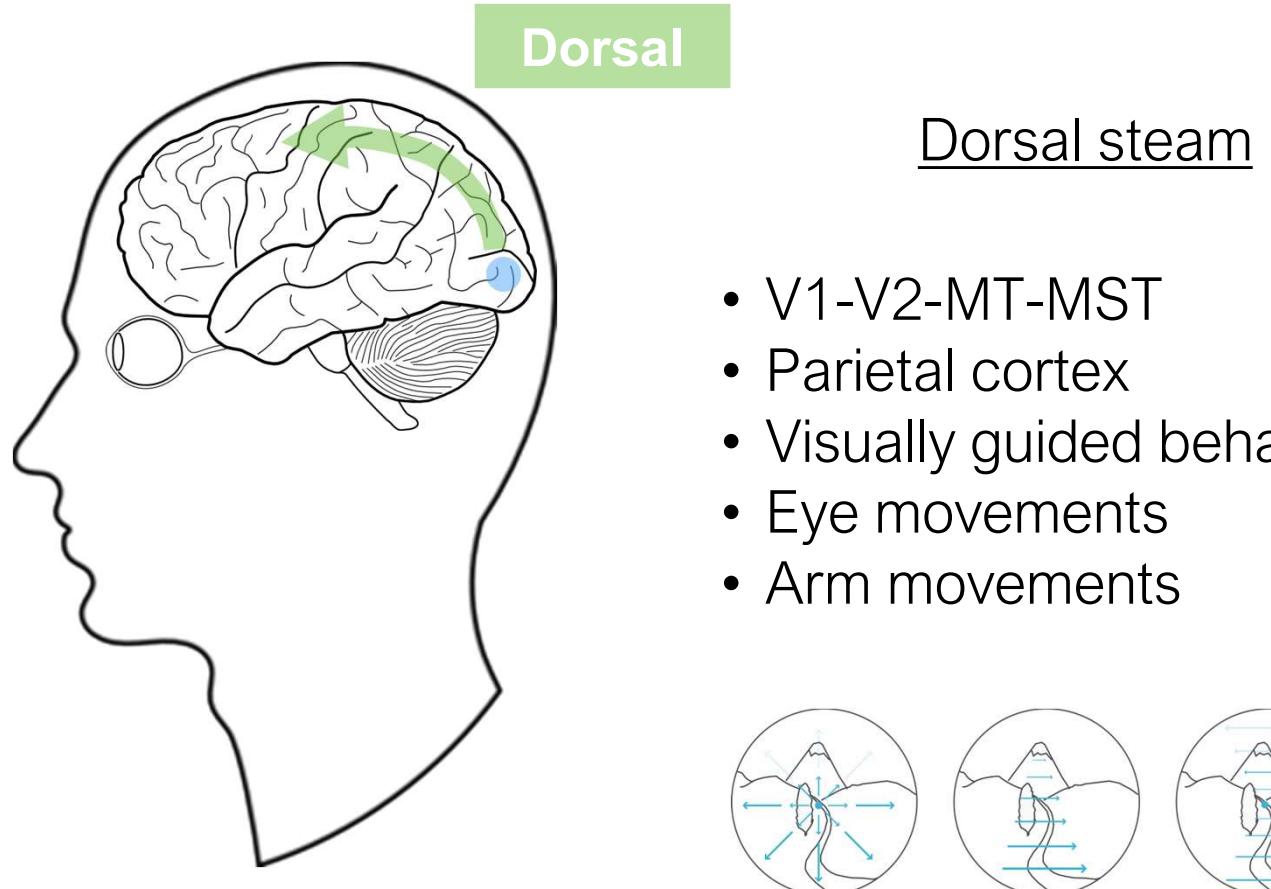
(very) Basic Overview



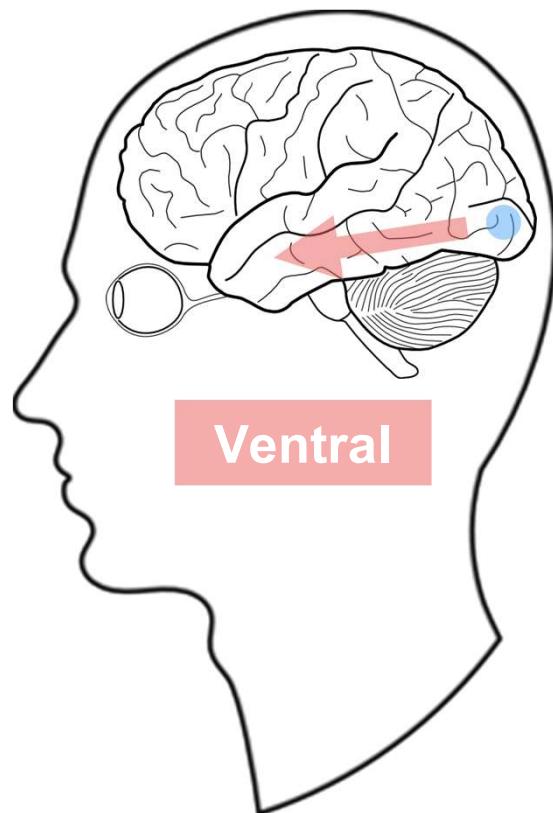
Feed Forward

- Dorsal stream
 - Identification
 - What?
- Ventral stream
 - Localisation
 - Where?

(very) Basic Overview

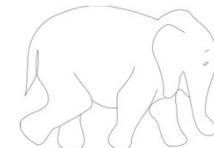


(very) Basic Overview



Ventral Stream

- V1-V2-V4-
- Inferior temporal cortex (IP)
- Form processing
- Object recognition
- Long term memory



(very) Basic Overview



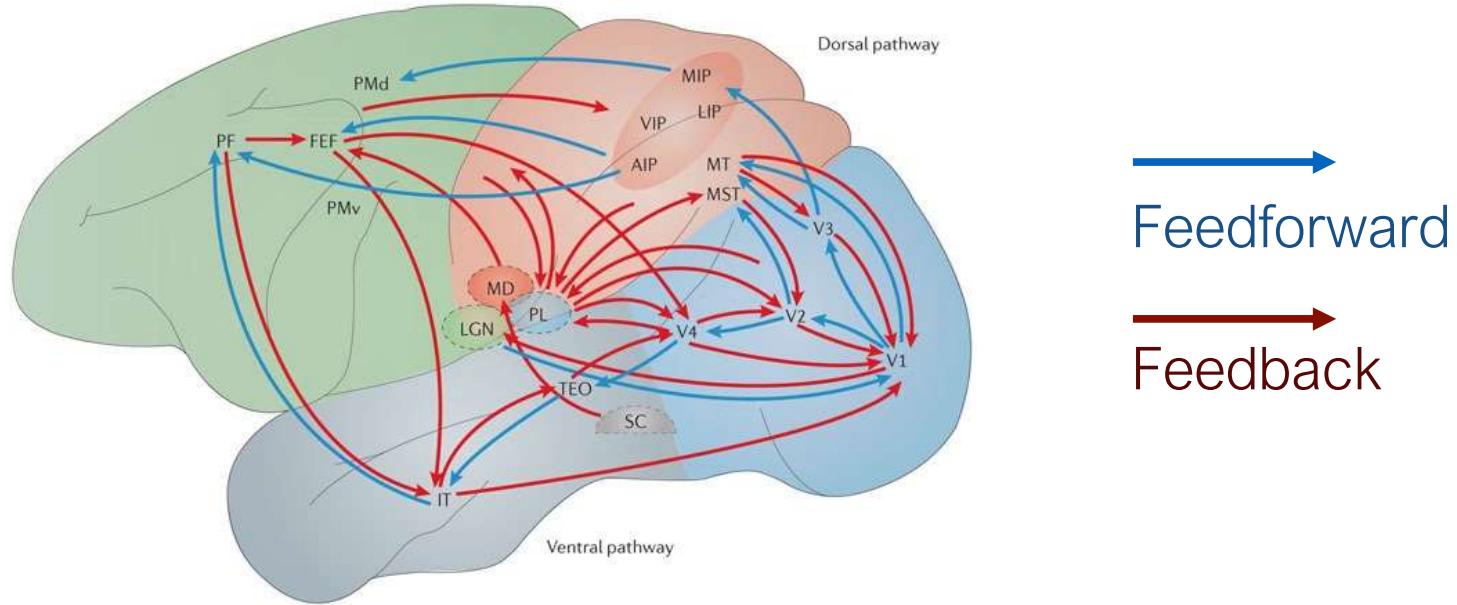
Downstream

- Retinatopic
- Simple features

- Increasing complexity
- Spatial invariance
- More abstract qualities

Upstream

(very) Basic Overview

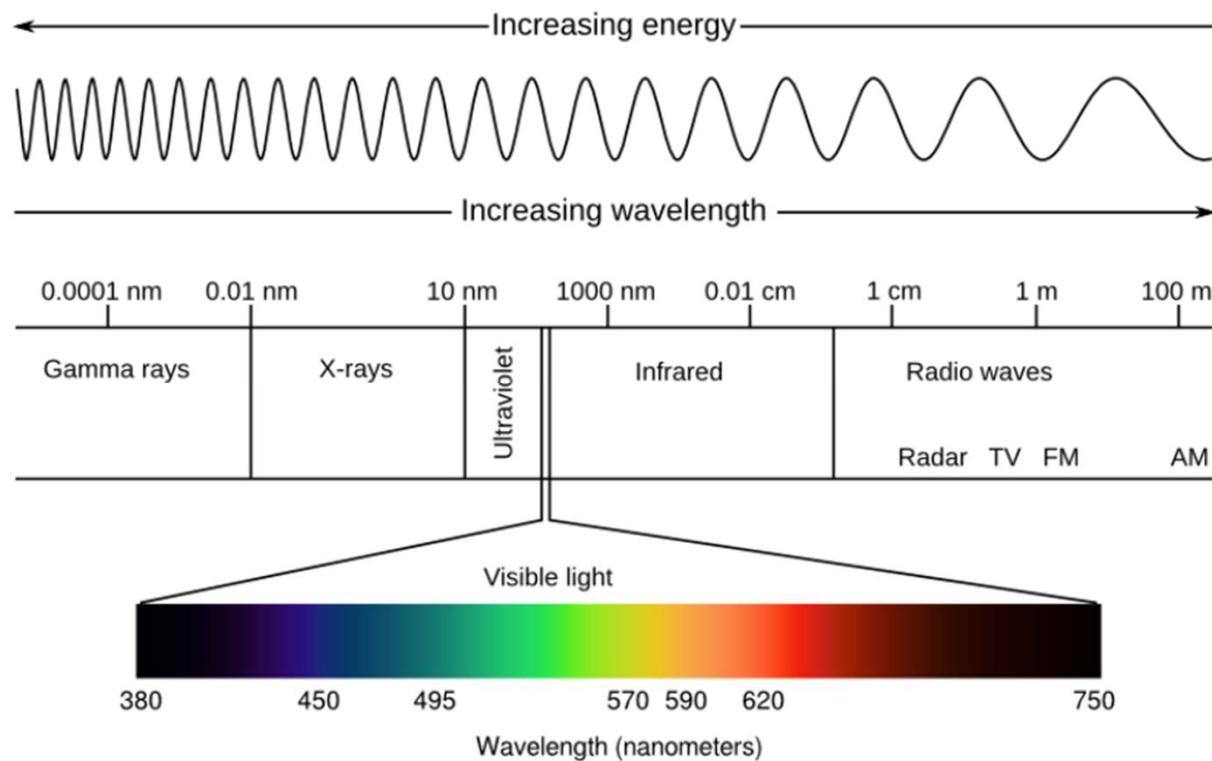


Gilbert & Wu Li (2013). Top-down influences on visual processing. Nature Reviews Neuroscience.



Light and color

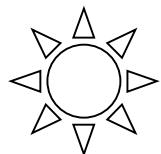
Electromagnetic spectrum



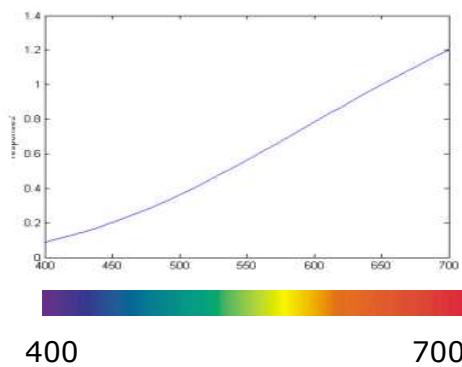
How is colour formed?

Colour is based on 3 properties

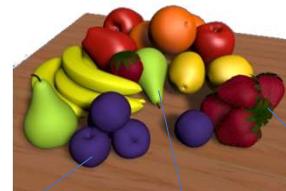
The incoming light



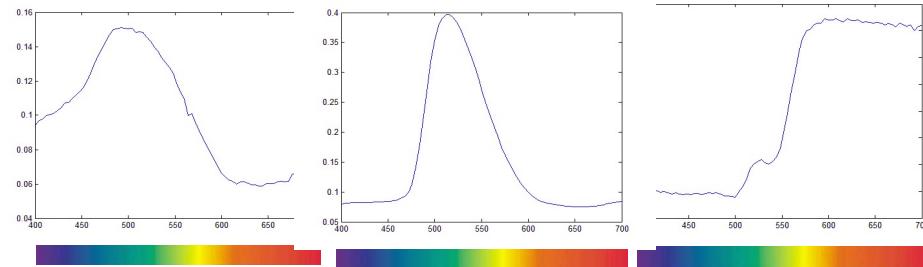
$$I(\lambda)$$



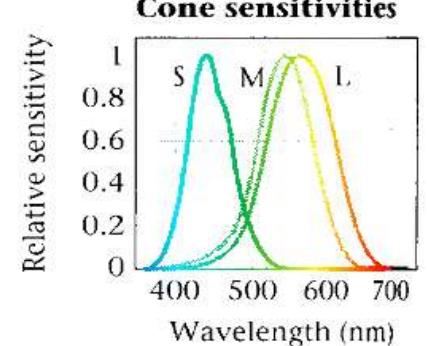
The reflectance of the object



$$R(\lambda)$$



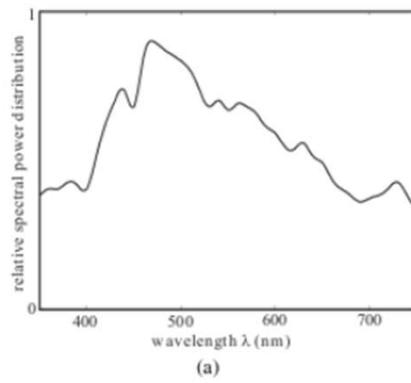
The cons in the retina



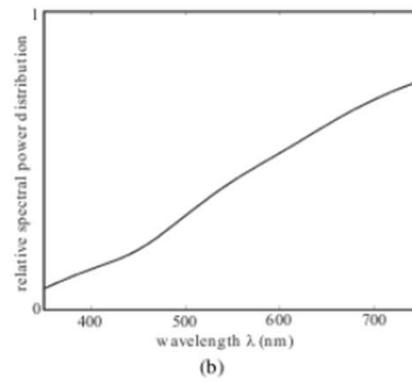
$$L(\lambda), M(\lambda), S(\lambda)$$

Some illuminants

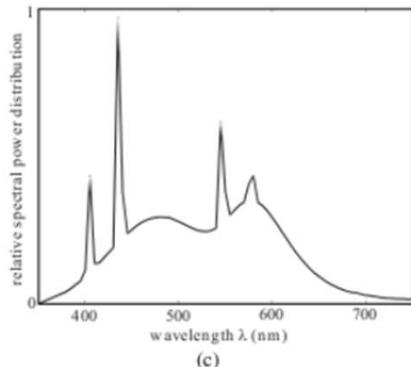
Daylight



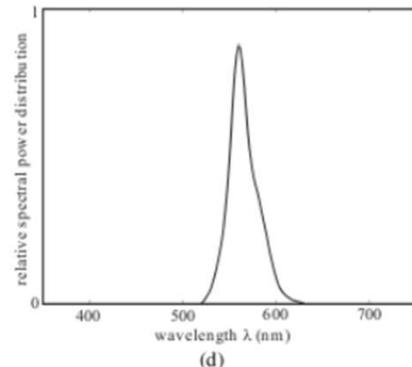
Tungsten



Fluorescent

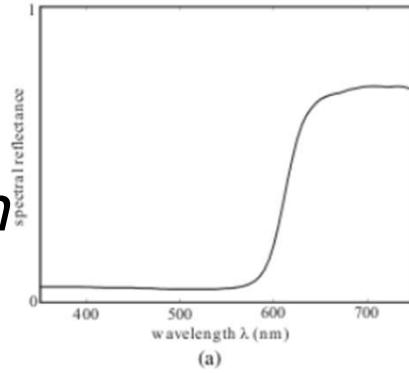


LED



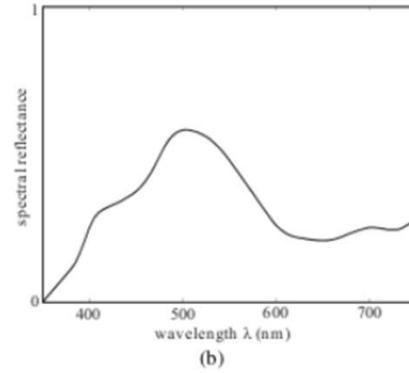
Some reflectances

Red patch



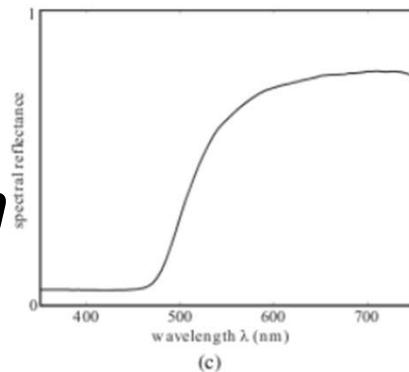
(a)

Blue patch



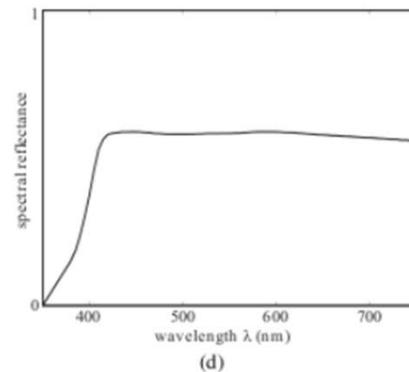
(b)

Yellow patch



(c)

Gray patch



(d)

How the color is formed?

The colour signal (i.e. the light reaching at our eye) is the point-wise multiplication of illuminant and reflectance

$$E(\lambda) = I(\lambda) \times R(\lambda)$$

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$$E(\lambda) = I(\lambda) \times R(\lambda)$$

This value is point-wise multiplied by the cones, and integrated over the visual spectra

$$\begin{aligned} L &= \int_{380}^{740} l(\lambda) E(\lambda) d\lambda \\ M &= \int_{380}^{740} m(\lambda) E(\lambda) d\lambda \\ S &= \int_{380}^{740} s(\lambda) E(\lambda) d\lambda. \end{aligned}$$

Tristimulus
values

How the color is formed?

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Practically, this integration is done by sampling over the different wavelengths

$$L = \sum_{i=380}^{740} l(\lambda_i) E(\lambda_i)$$

$$M = \sum_{i=380}^{740} m(\lambda_i) E(\lambda_i)$$

$$S = \sum_{i=380}^{740} s(\lambda_i) E(\lambda_i),$$

Corollaries from the colour formation equation

- 1) Two different reflectances under two different illuminants can have exactly the same tristimulus values:

This is called the metamerism problem. It is supposed to occur around a 3% in natural images.

Corollaries from the colour formation equation

1) Two different reflectances under a particular illuminant can have exactly the same tristimulus values:

This is called the metamerism problem. It is supposed to occur around a 3% in natural images.

2) From the colour formation equation it can be proved (see notes) that we can generate any color by mixing three given colors –called primaries-, just by adjusting the amount of each one:

This is called the trichromacy property. It is a fundamental property of human color vision.

The first color spaces

Deriving the CIE R,G,B colour space

Guild and Wright in two independent studies.

Very few observers (10 and 7). All male. All Brits. Is it really then a good standard?

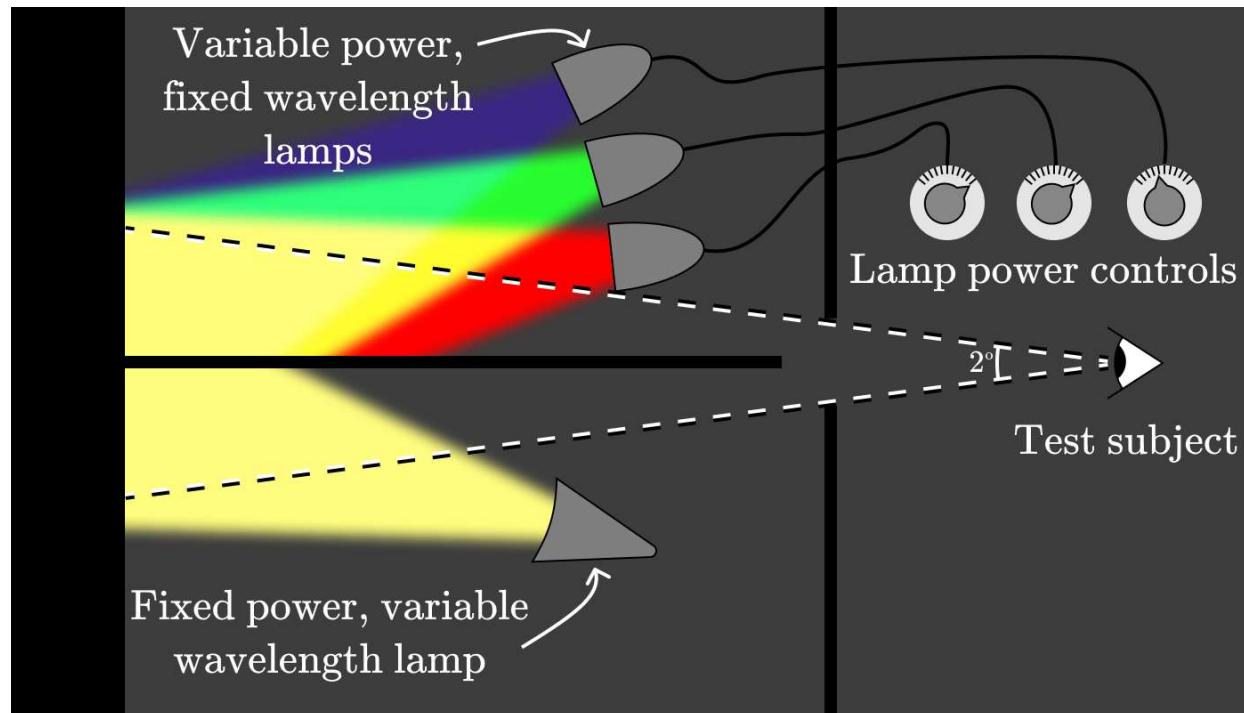


Image from: <http://jamie-wong.com/post/color/>

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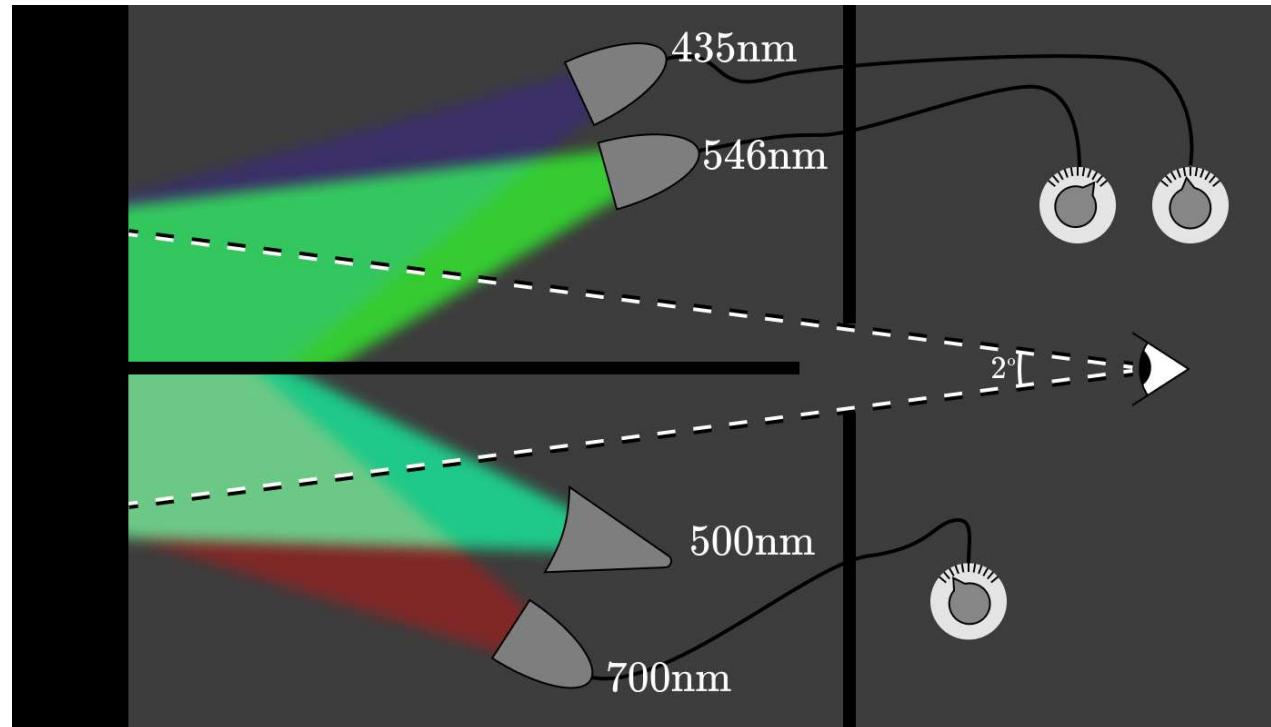


Image from: <http://jamie-wong.com/post/color/>

Deriving the CIE R,G,B colour space

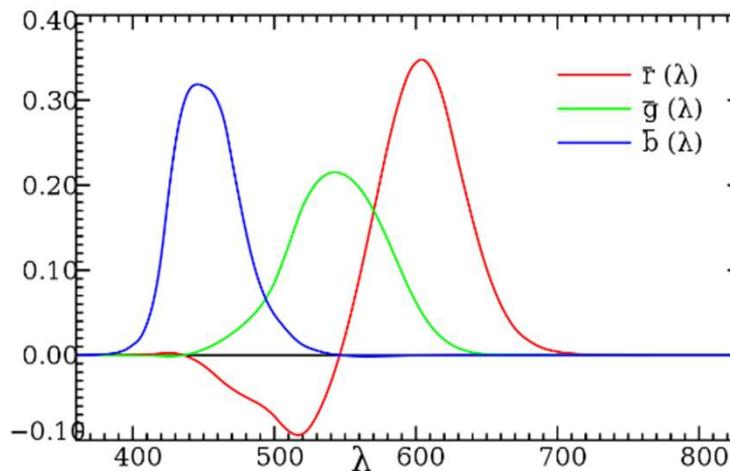


FIGURE 1.5: Color matching functions. Figure from [13].

It can be seen that the CIE R,G,B color marching functions and the L,M,S cone functions are just a linear correction apart (see notes).

Deriving the CIE R,G,B colour space

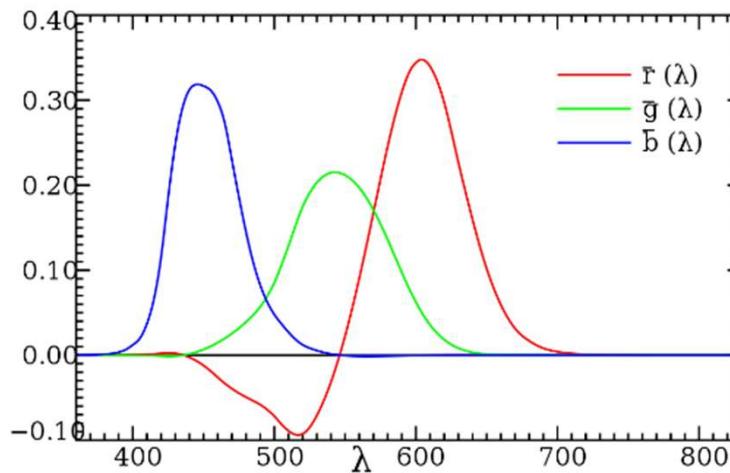


FIGURE 1.5: Color matching functions. Figure from [13].

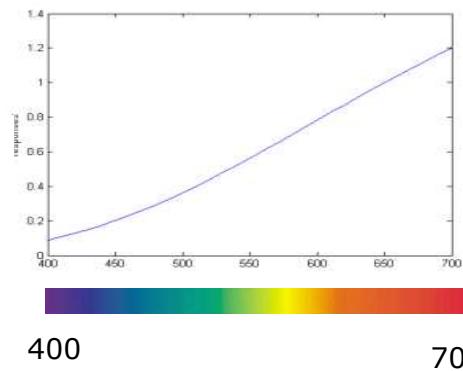
It can be seen that the CIE R,G,B color matching functions and the L,M,S cone functions are just a linear correction apart (see notes).

In other words, they generate the same 3-dimensional space, the space of the colours we are able to see.

Deriving the CIE R,G,B colour space

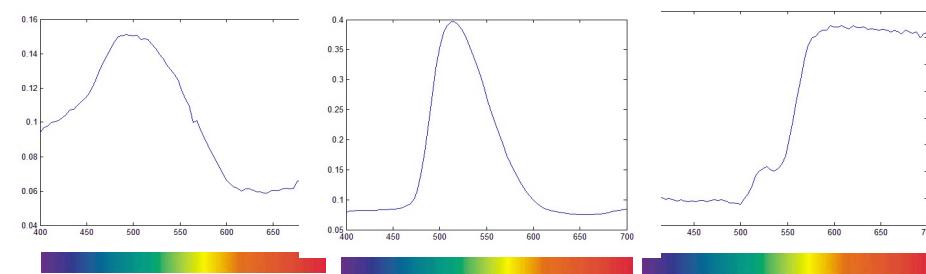
The incoming light

$$I(\lambda)$$



The reflectance of the object

$$R(\lambda)$$



The CIE RGB

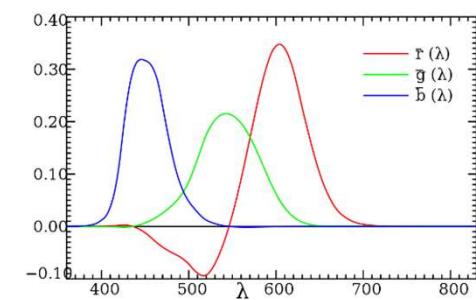
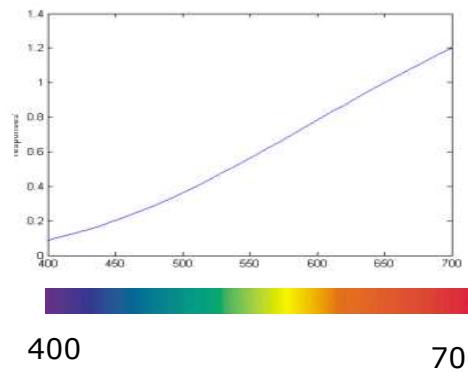


FIGURE 1.5: Color matching functions. Figure from [13].

Deriving the CIE R,G,B colour space

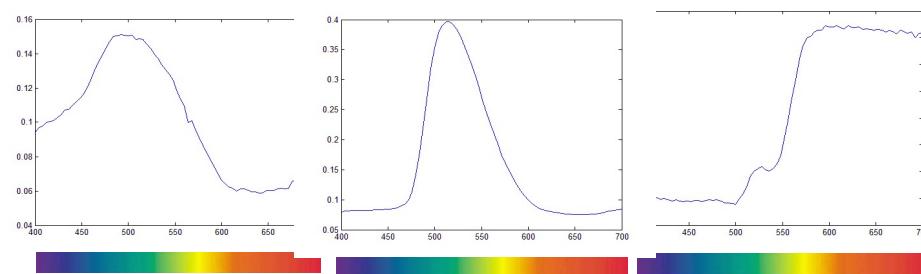
The incoming light

$$I(\lambda)$$



The reflectance of the object

$$R(\lambda)$$



The CIE RGB

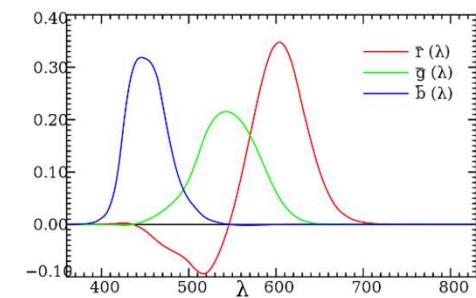


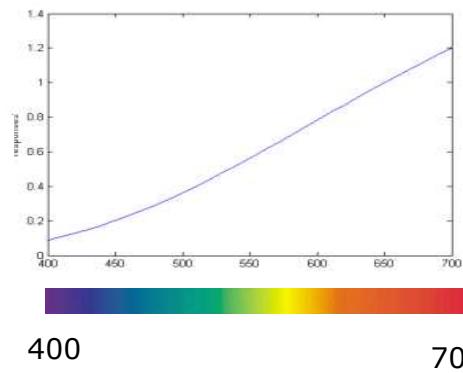
FIGURE 1.5: Color matching functions. Figure from [13].

$$E(\lambda) = I(\lambda) \times R(\lambda)$$

Deriving the CIE R,G,B colour space

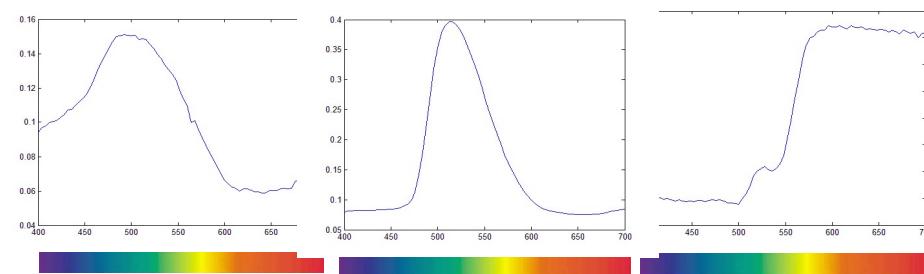
The incoming light

$$I(\lambda)$$



The reflectance of the object

$$R(\lambda)$$



The CIE RGB

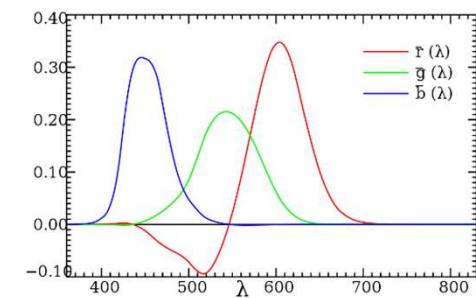


FIGURE 1.5: Color matching functions. Figure from [13].

$$E(\lambda) = I(\lambda) \times R(\lambda)$$

$$R = \int_{380}^{740} \bar{r}(\lambda) E(\lambda) d\lambda$$

$$G = \int_{380}^{740} \bar{g}(\lambda) E(\lambda) d\lambda$$

$$B = \int_{380}^{740} \bar{b}(\lambda) E(\lambda) d\lambda,$$

$$R = \sum_{i=380}^{740} \bar{r}(\lambda_i) E(\lambda_i)$$

$$G = \sum_{i=380}^{740} \bar{g}(\lambda_i) E(\lambda_i)$$

$$B = \sum_{i=380}^{740} \bar{b}(\lambda_i) E(\lambda_i).$$

From CIE R,G,B colour space to CIE XYX colour space

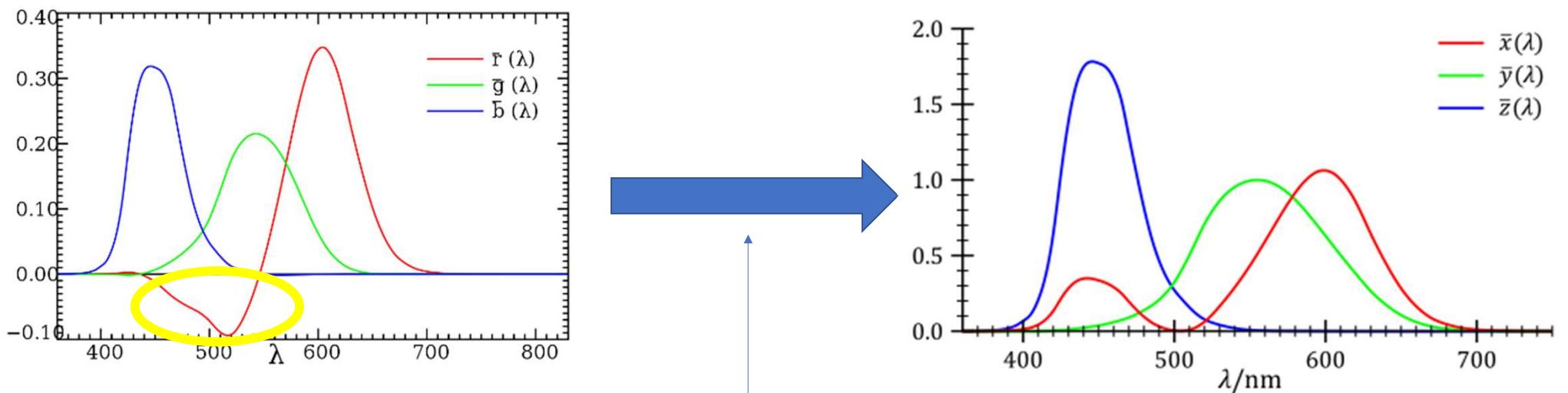


FIGURE 1.5: Color matching functions. Figure from [13].

Also just a linear correction apart (and forcing Y to be the luminosity function).

From CIE X,Y,Z to xyY

Color has two main parts: chromaticity (2-dimensional), and intensity (Black-White axis).

How can we create a color space that represent this?

xyY color space

x, y chromatic
coordinates

Y intensity

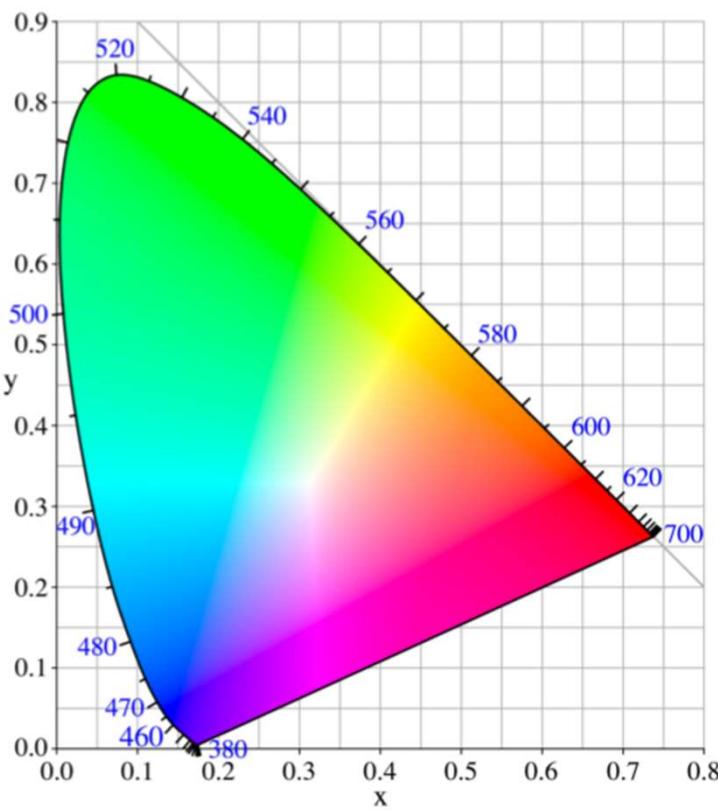
$$x = \frac{X}{X + Y + Z}$$

$$y = \frac{Y}{X + Y + Z}$$

The x,y chromaticity diagram

Represents all the colors humans are able to see.

Pure colors are in the Edge of the horseshoe shape

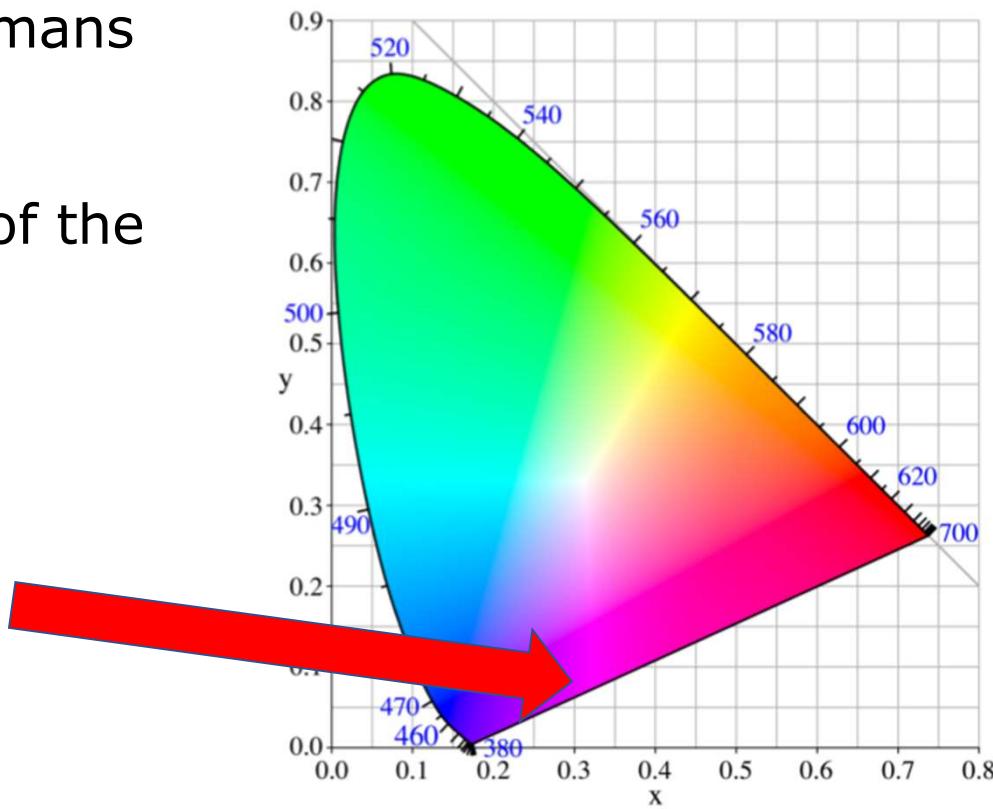


The x,y chromaticity diagram

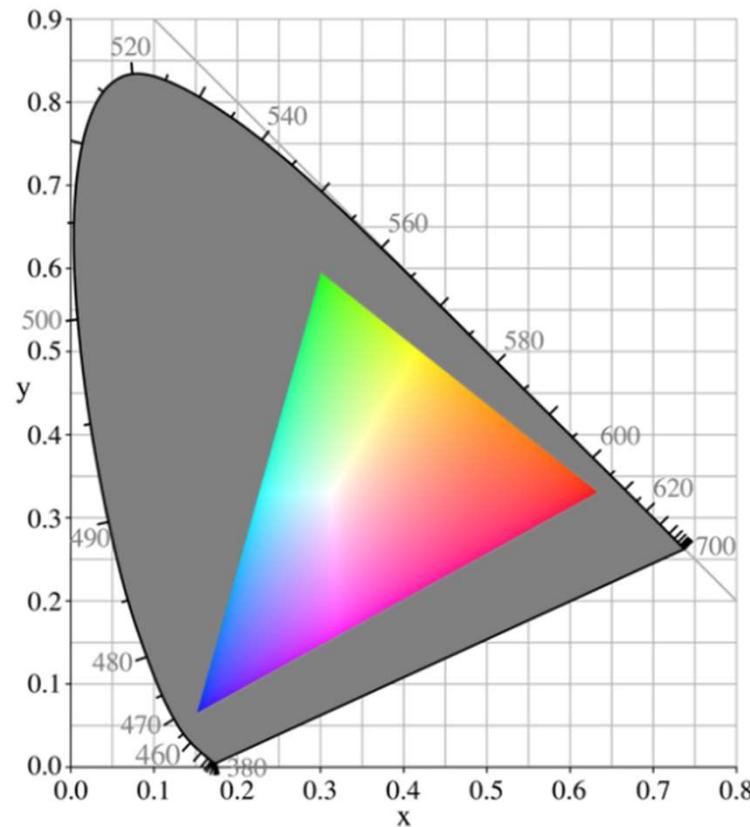
Represents all the colors humans are able to see.

Pure colors are in the Edge of the horseshoe shape

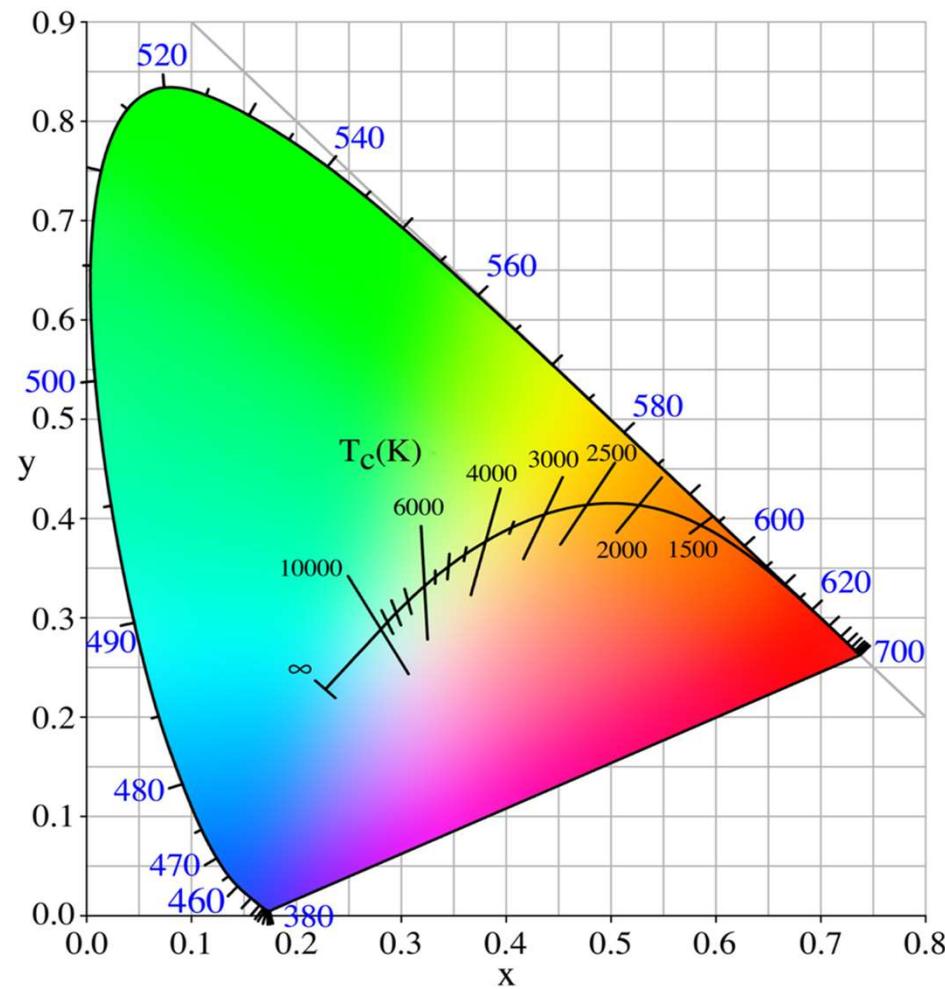
Line of purples



A standard gamut display in the x,y diagram

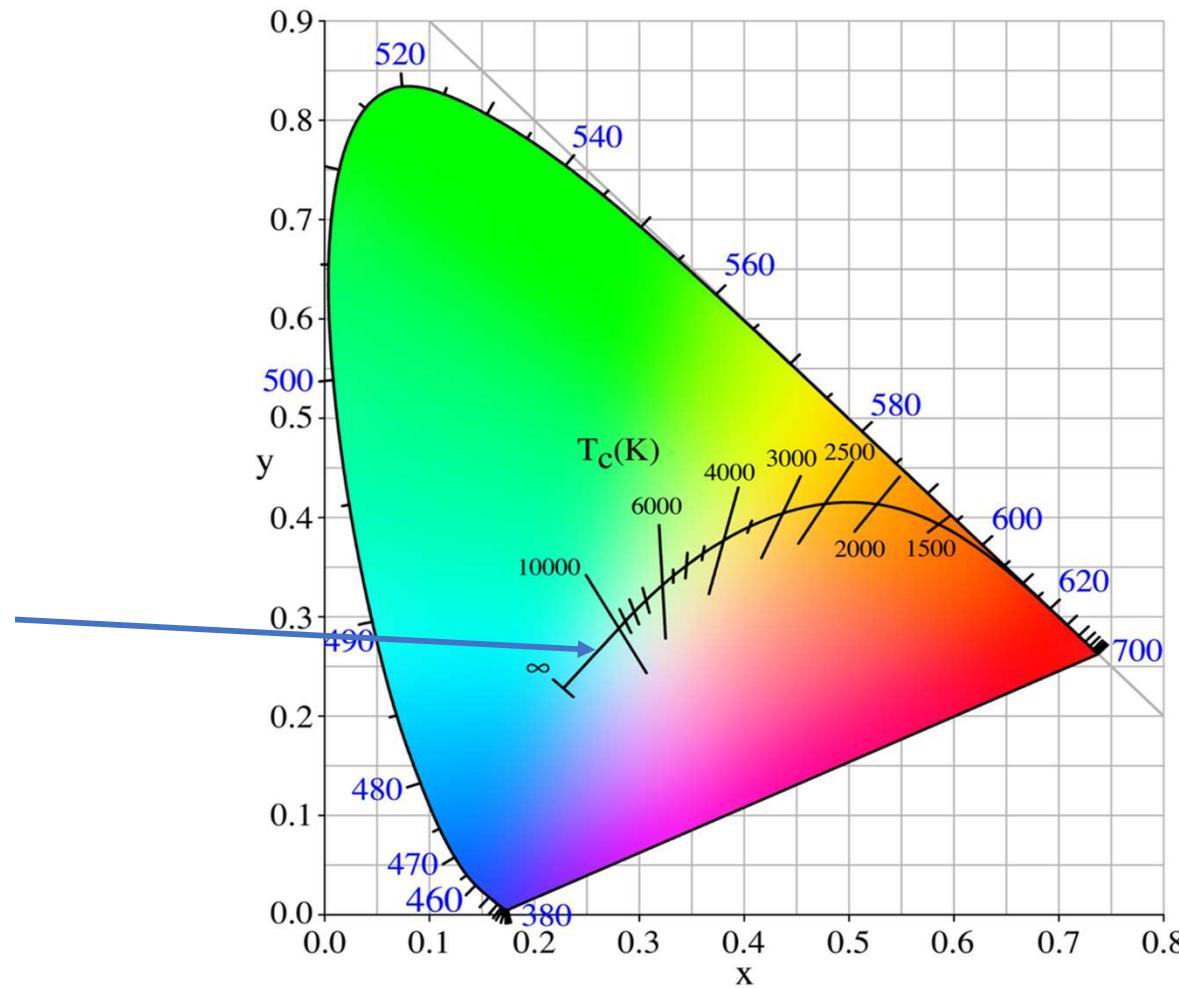


Daylight illuminants in the x,y diagram



Daylight illuminants in the x,y diagram

Planckian
locus

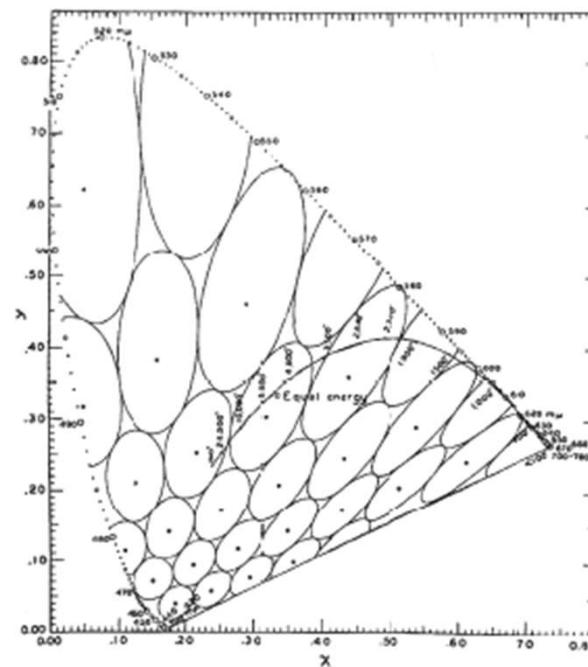


A problem with CIE XYZ

CIE XYZ is not a perceptual color space, in the sense that distances in this space does not correspond to perceptual distances.

The same XYZ distance will be perceptually small in the green region, but perceptually large in the blue region

MacAdam ellipses

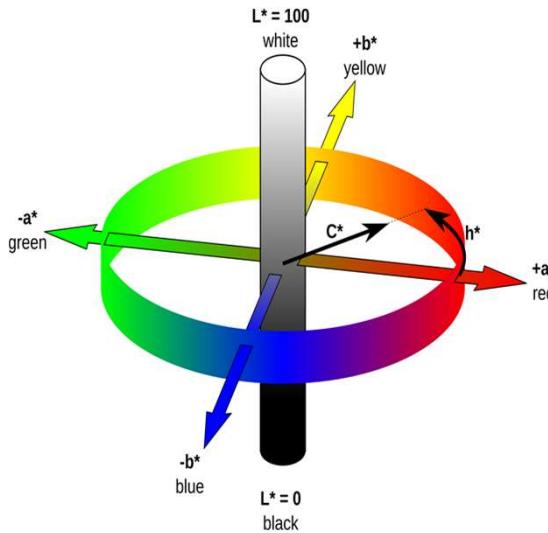


Solution: The CIE Lab colour space

CIE Lab was defined with the goal of being perceptually uniform.

It is based in the idea of opponency:

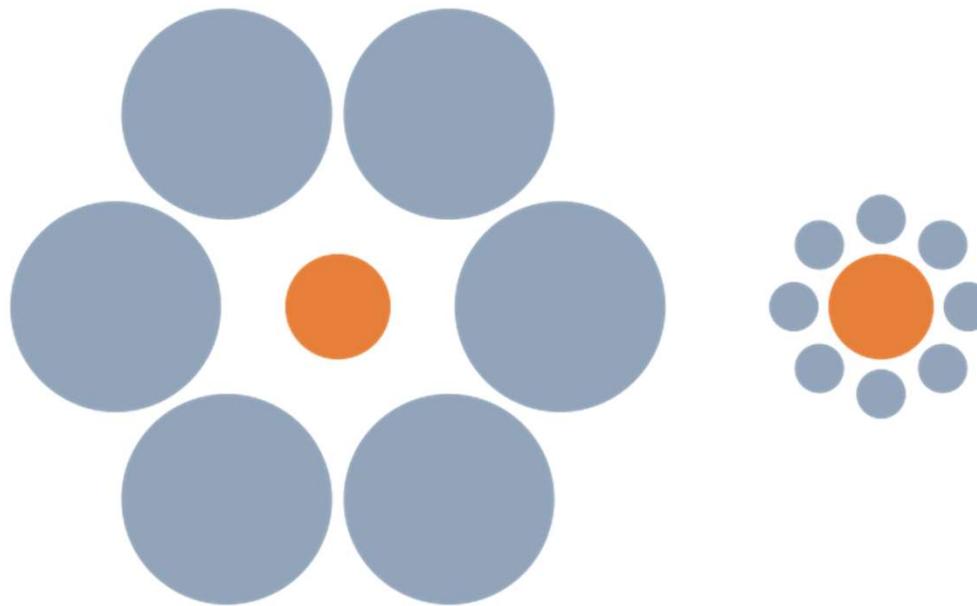
- 1 channel is based on the Y channel of CIE XYZ.
- The other two channels are subtractions between the XYZ channels.



Contextual Effects

(Human vision is not just a point-wise thing)

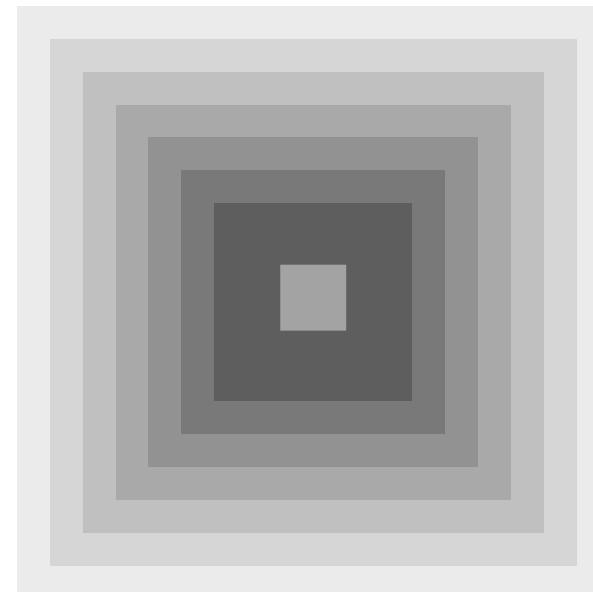
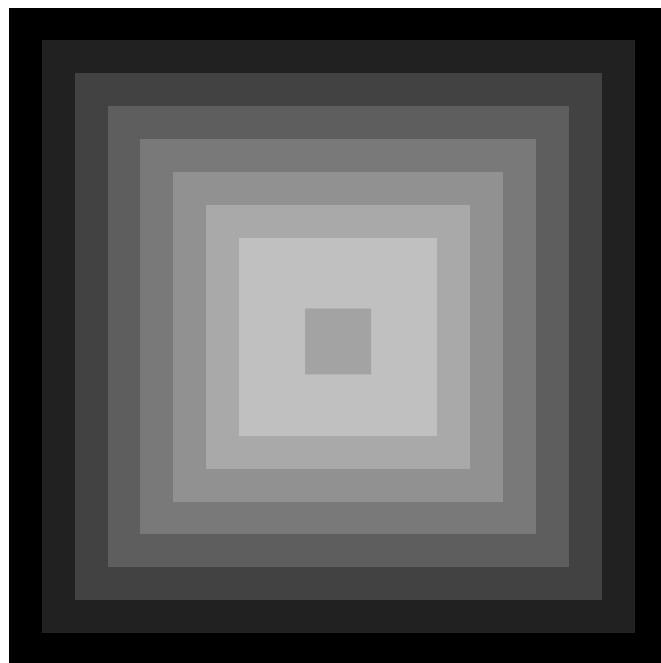
Ebbinghaus illusion or Titchener circles



Ebbinghaus illusion or Titchener circles

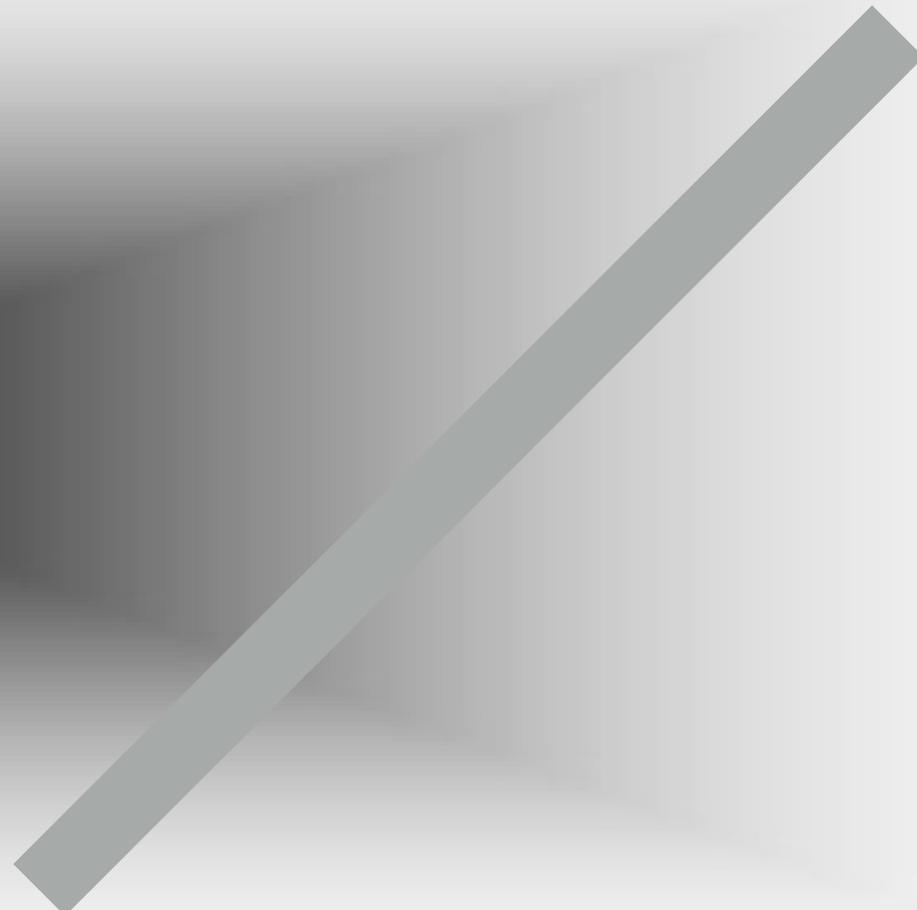


Surround

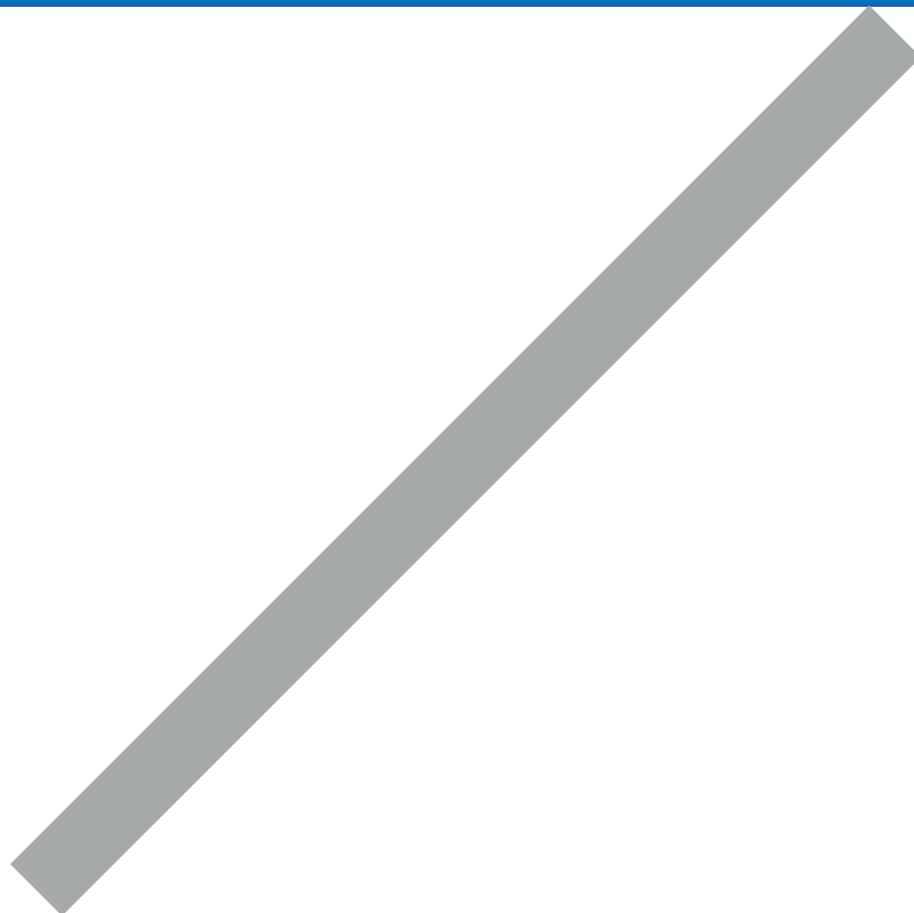


Surround

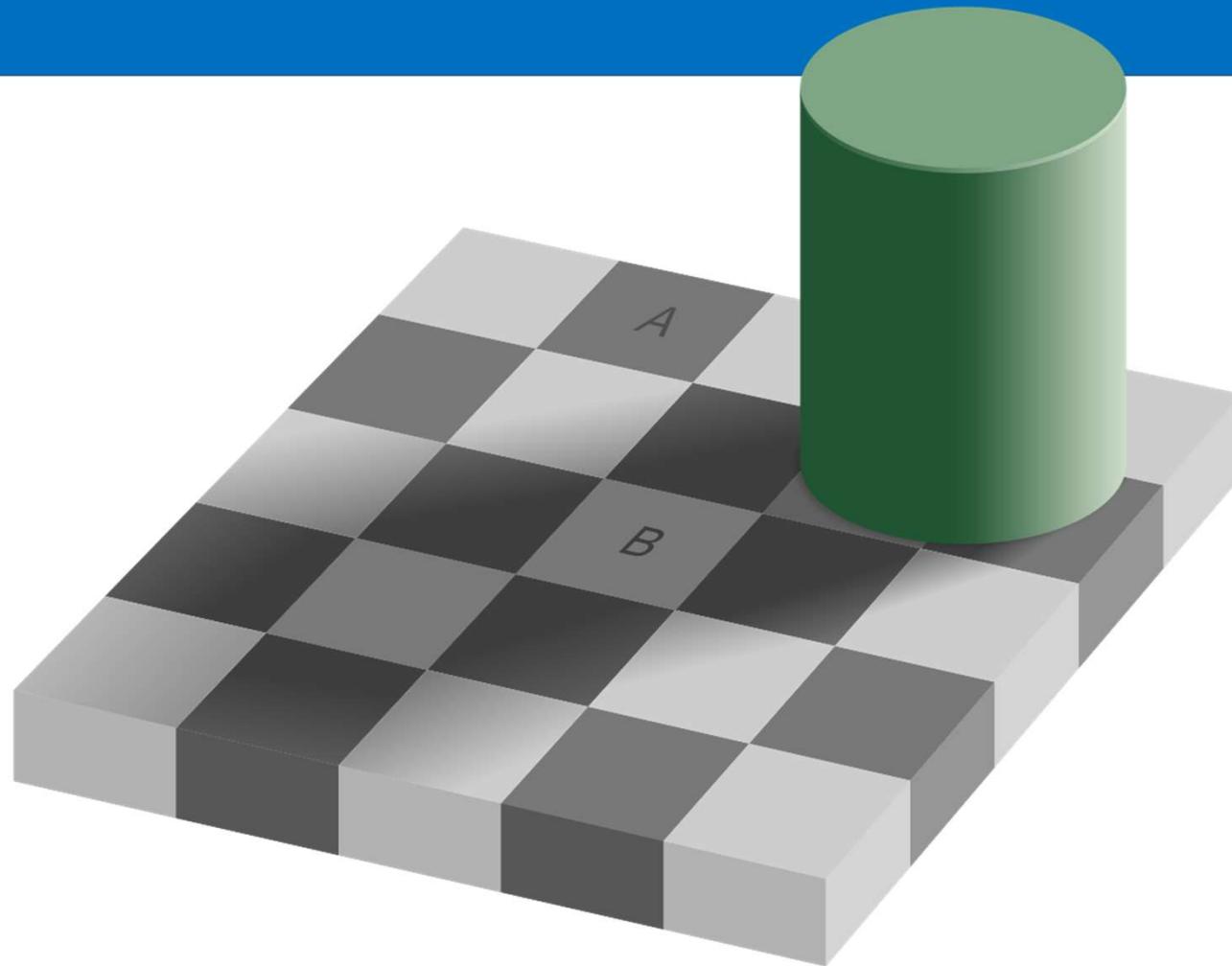




Surround

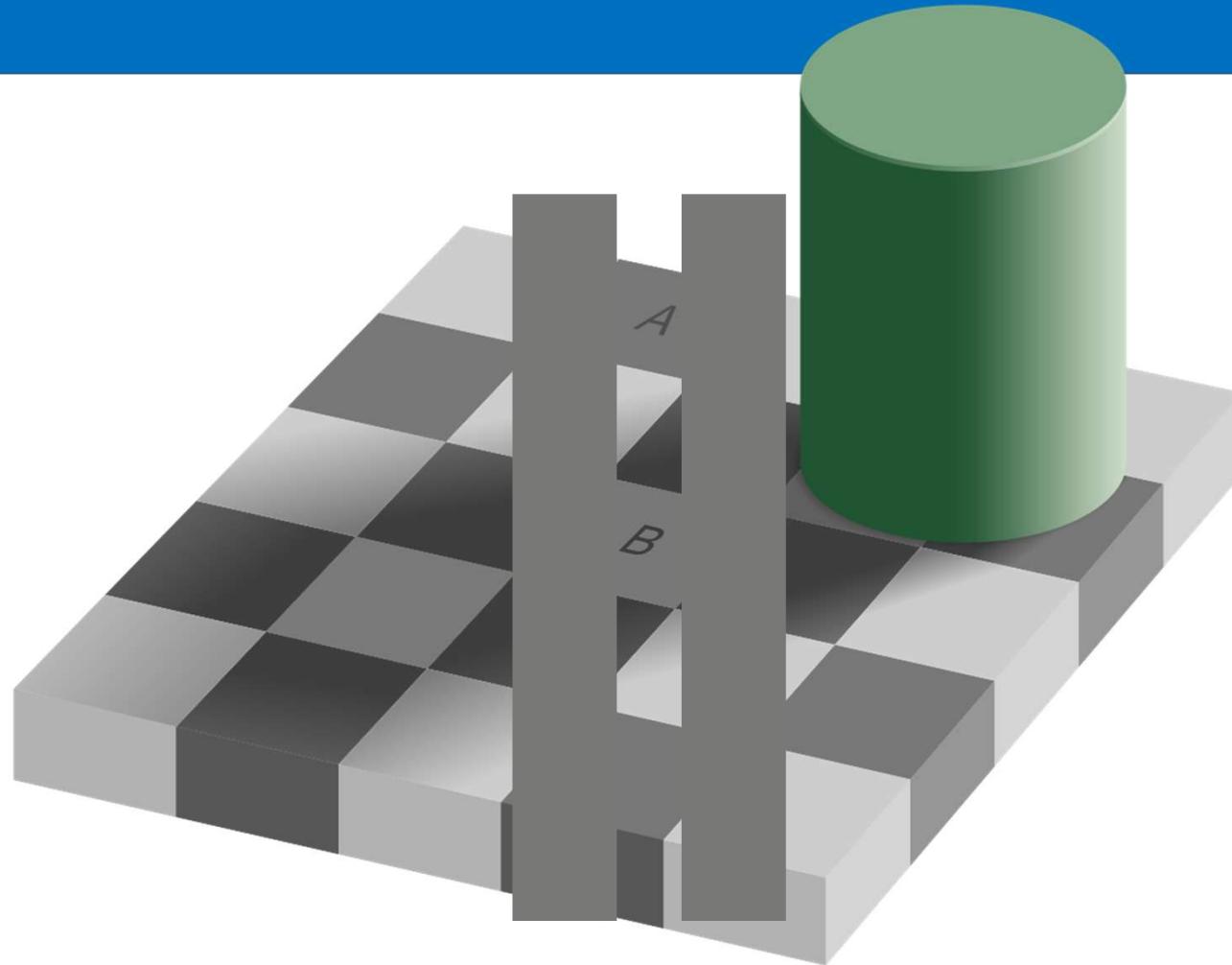


Surround



Adelson illusion

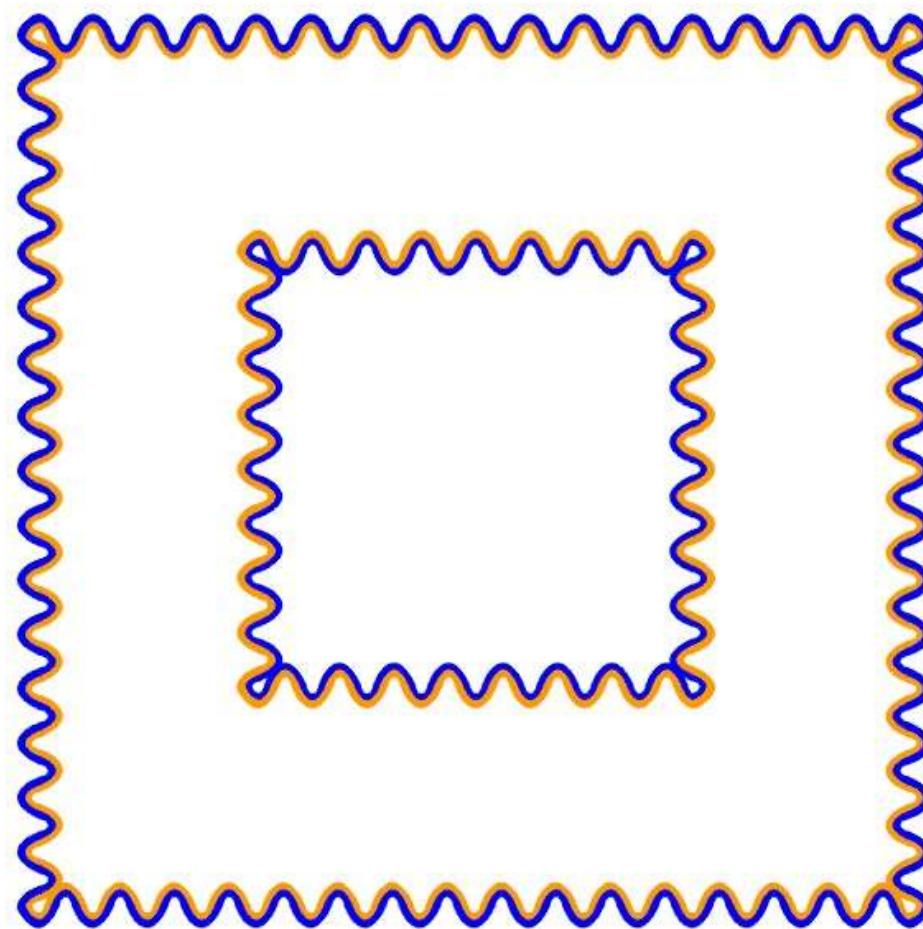
Surround

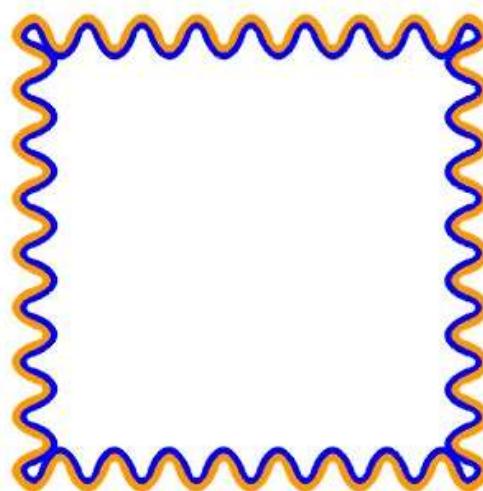


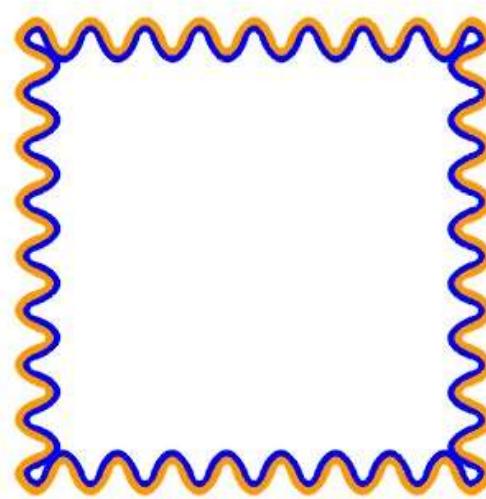
Adelson illusion

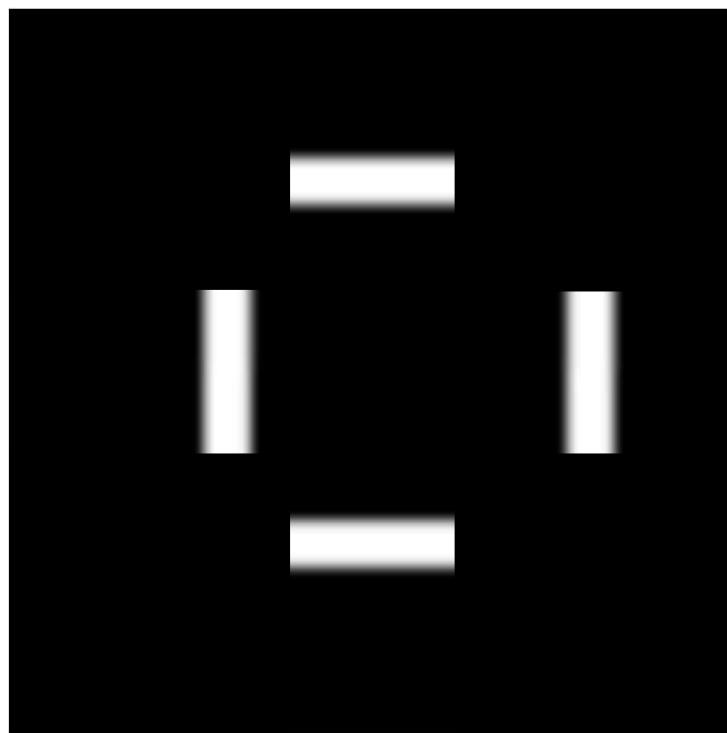
Color Context

SECTOR

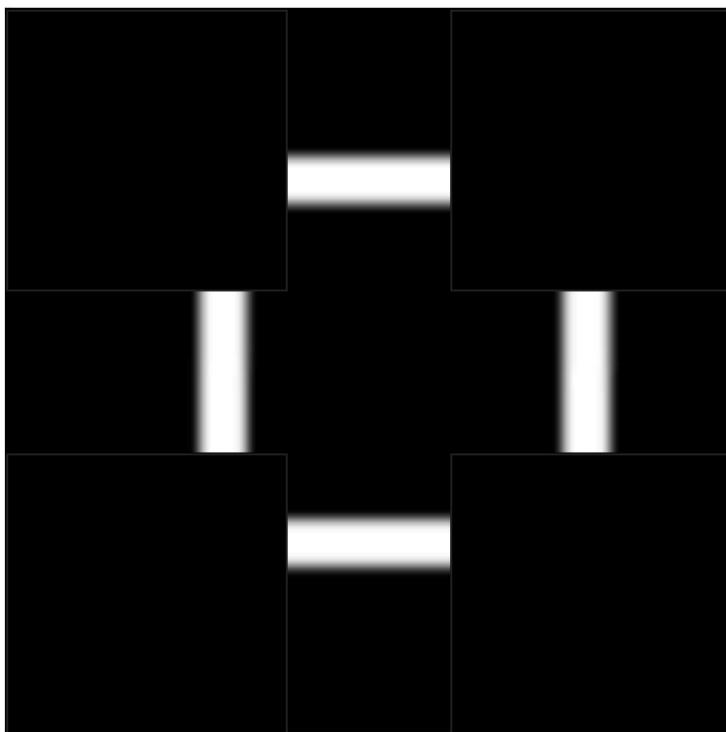








Lorenceau & Alais (2001). Form constraints in motion binding. *Nature Neuroscience*



Lorenceau & Alais (2001). Form constraints in motion binding. *Nature Neuroscience*

Contextual effects

The perception of a point in space is altered by the surround.

Using simplified stimuli we can begin to understand these contextual effects.

There are multiple levels of explanation for such effects.

Adaptation Effects

Adaptation effects

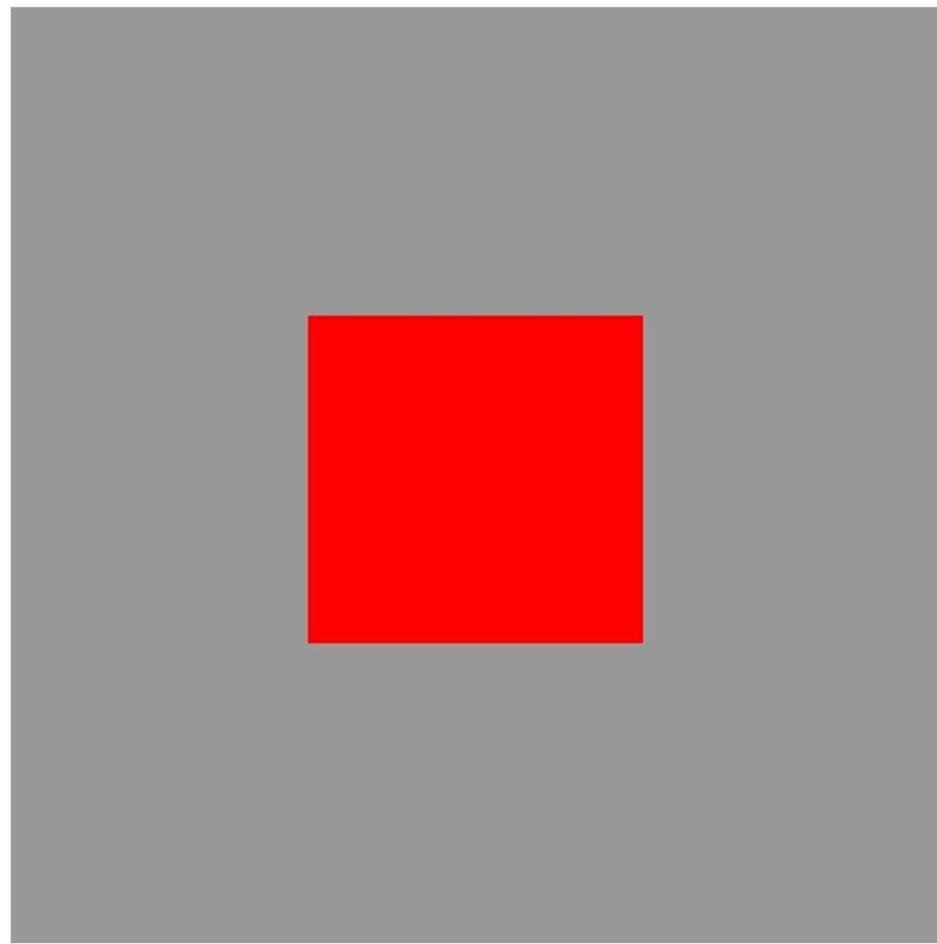
The perception at any point in time is affected by previous stimulation.

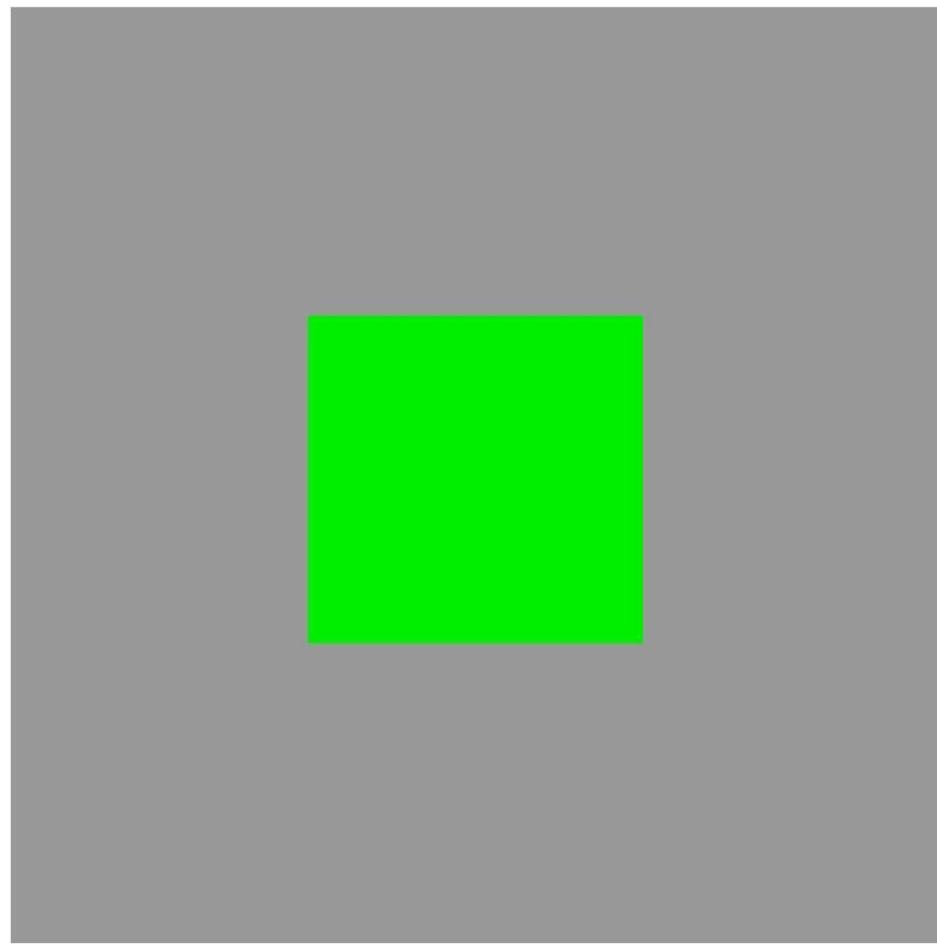
Again, using simplified stimuli we can begin to understand these adaptation effects.

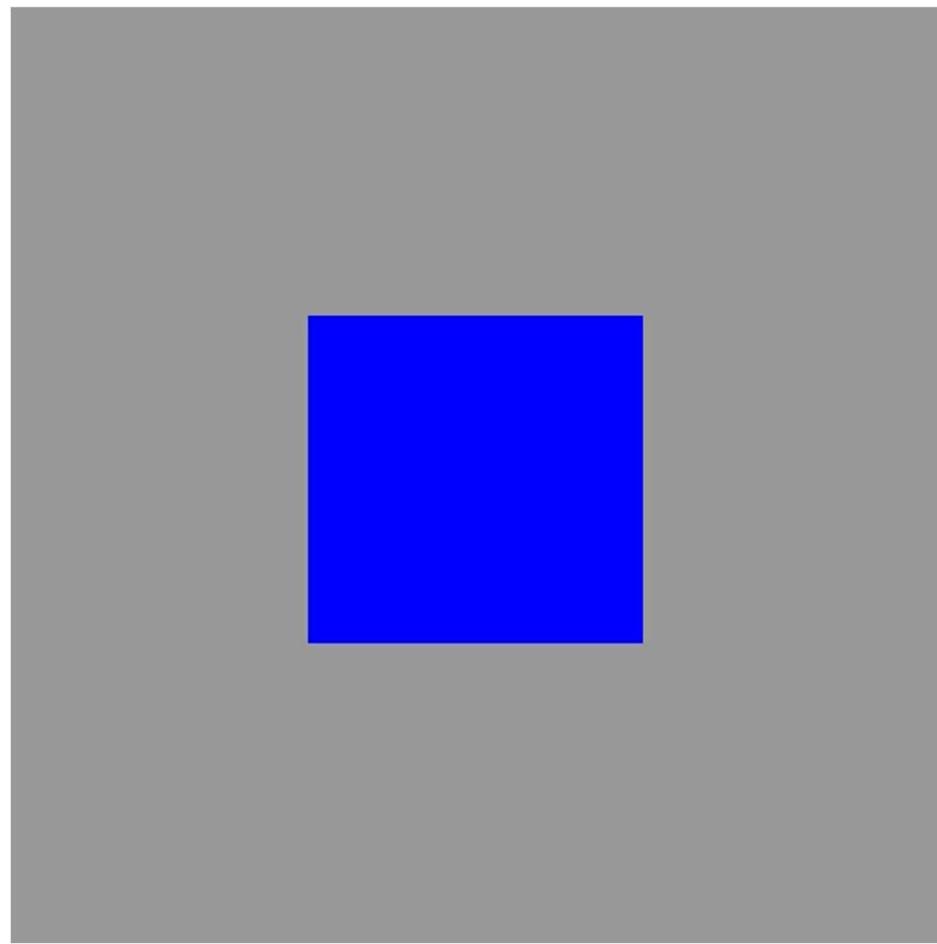
Most adaptation phenomena are explained by a gain mechanism which reduces the response of sensors tuned to the adapting stimulus.

Human color constancy

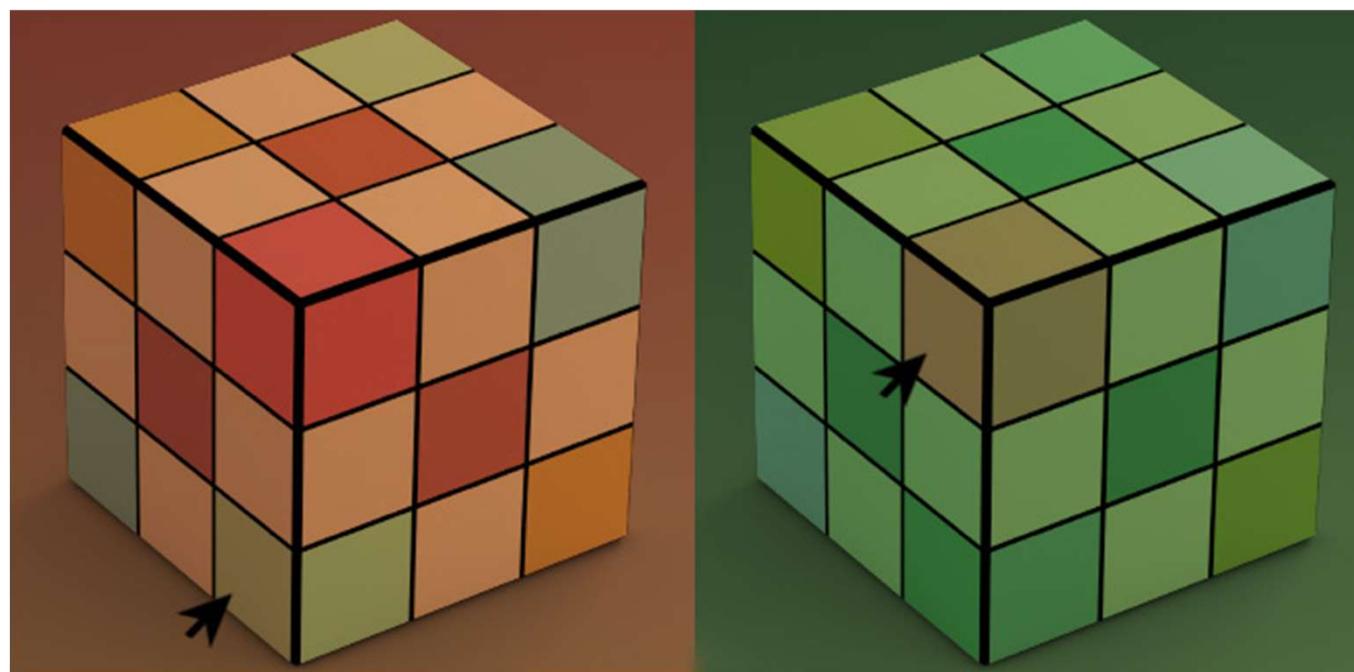
(a case of adaptation)

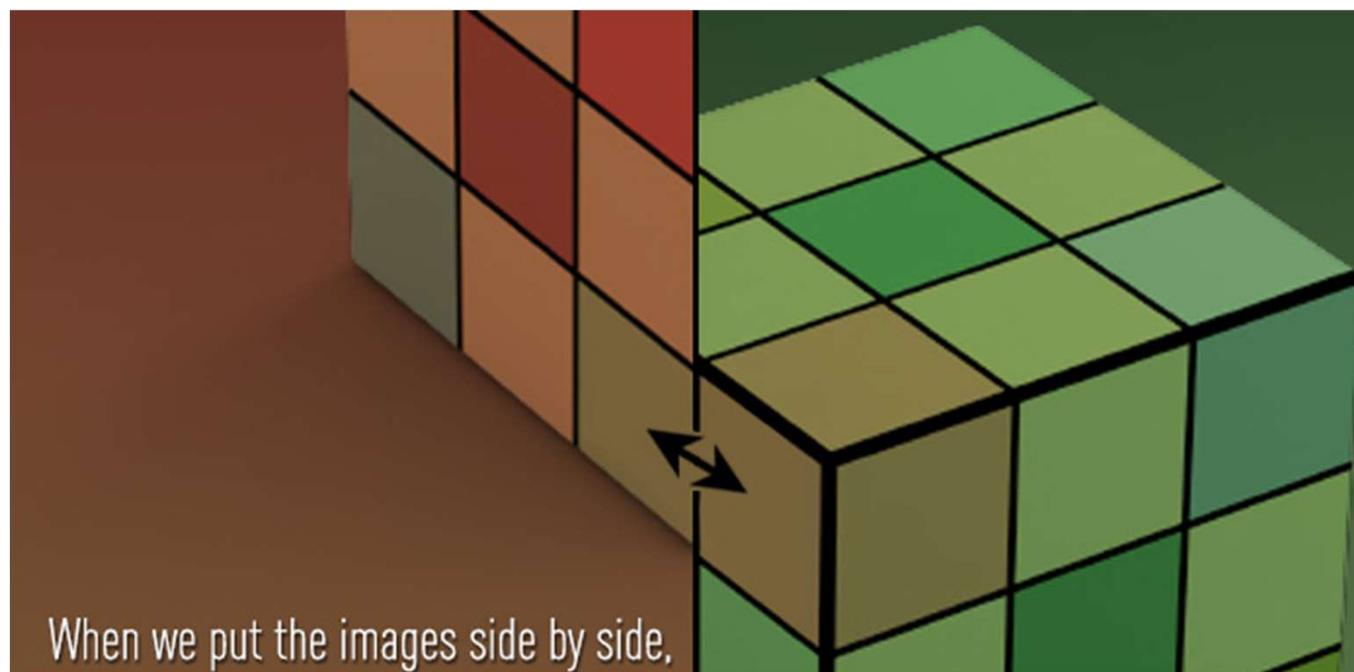






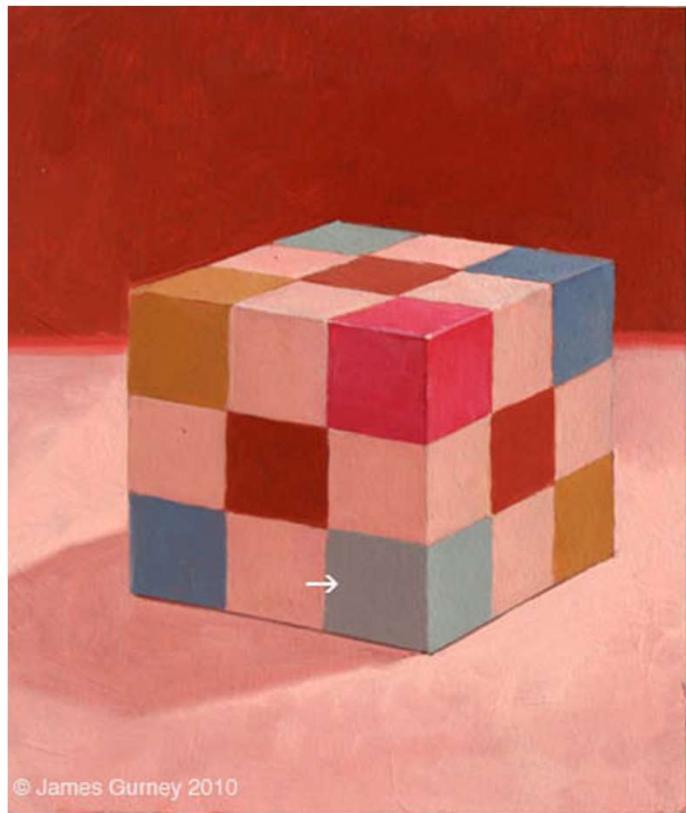






When we put the images side by side,





© James Gurney 2010



Modelling human colour constancy

Von Kries Law:

- Human color constancy can be modeled by a gain mechanism in each color channel

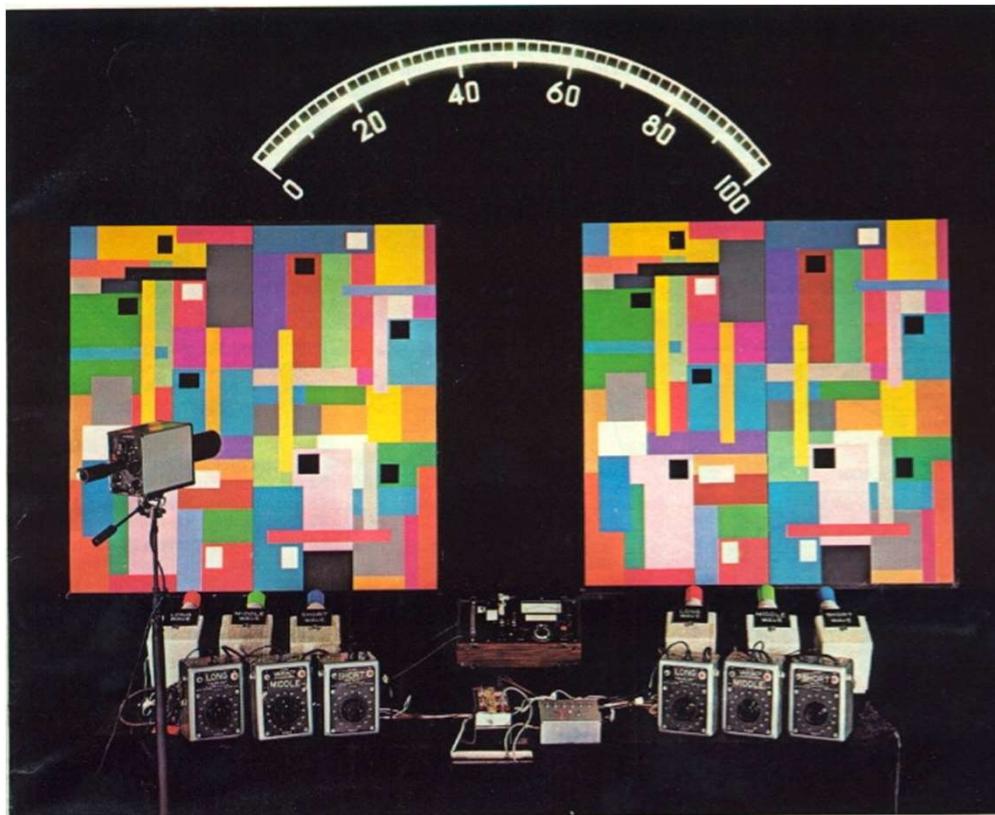
$$R' = k_r R, \quad G' = k_g G, \quad B' = k_b B,$$

Modelling human colour constancy

The Retinex Theory of Colour Vision:

- Portmanteau formed from "retina" and "cortex".

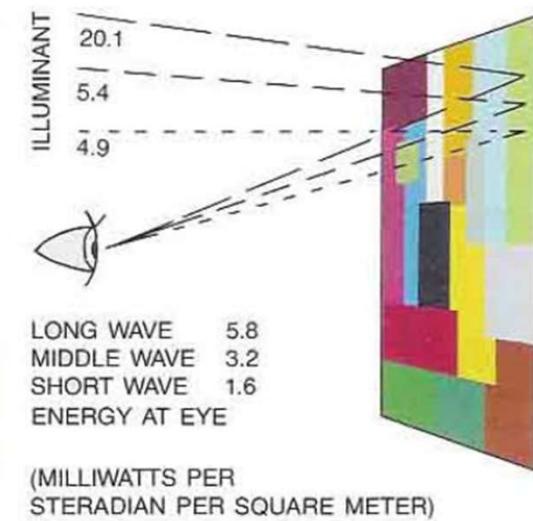
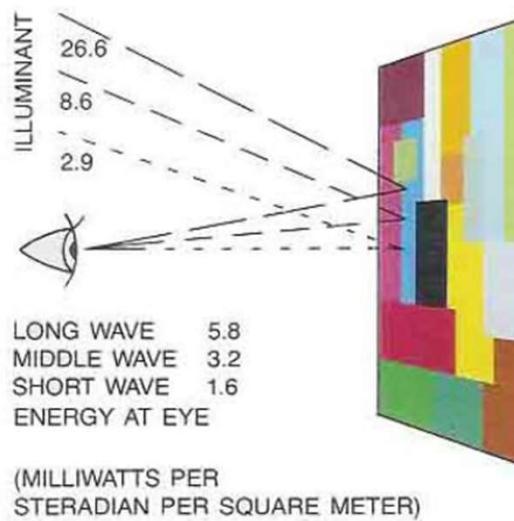
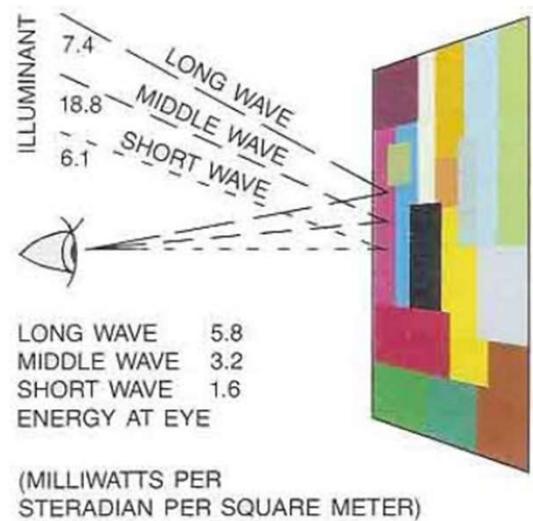
Modelling human colour constancy



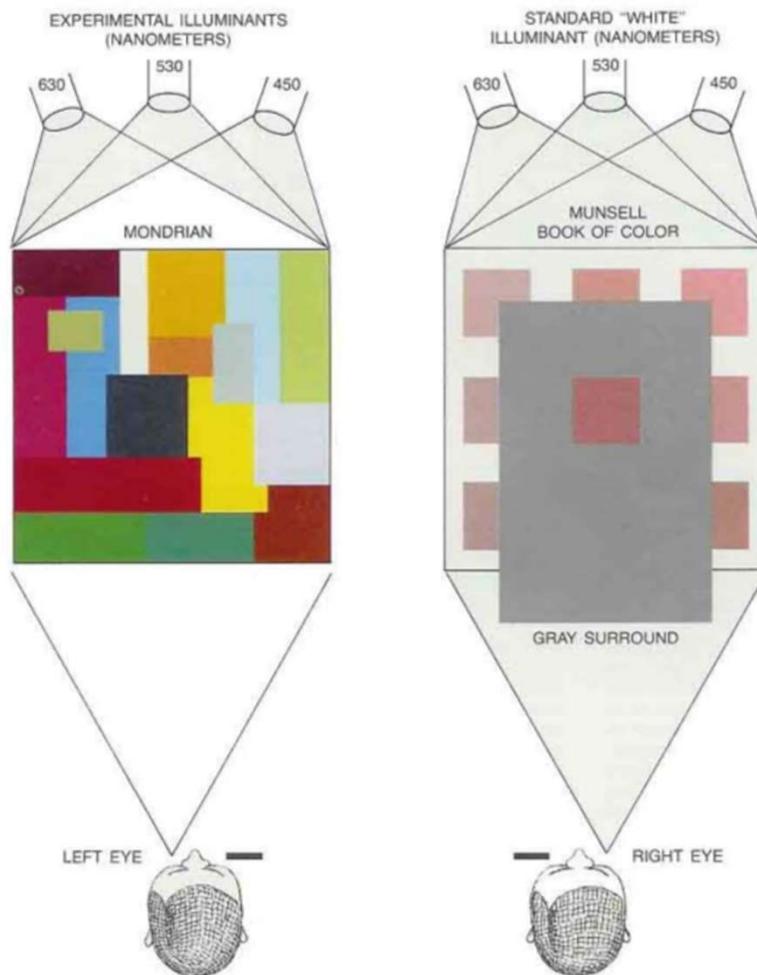
"COLOR MONDRIAN" EXPERIMENT employs two identical displays of sheets of colored paper mounted on boards four and a half feet square. The colored papers have a matte finish to minimize specular reflection. Each "Mondrian" is illuminated with its own set of three projector illuminators equipped with band-pass filters and independent brightness controls so that the long-wave ("red"), middle-wave ("green") and short-wave ("blue") illumination can be mixed in any desired ratio. A telescopic photometer can be pointed at any area to measure the flux, one wave band at a time, coming to the eye

from that area. The photometer reading is projected onto the scale above the two displays. In a typical experiment the illuminators can be adjusted so that the white area in the Mondrian at the left and the green area (or some other area) in the Mondrian at the right are both sending the same triplet of radiant energies to the eye. The actual radiant-energy fluxes cannot be re-created here because of the limitations of color reproduction. Under actual viewing conditions white area continues to look white and green area continues to look green even though the eye is receiving the same flux triplet from both areas.

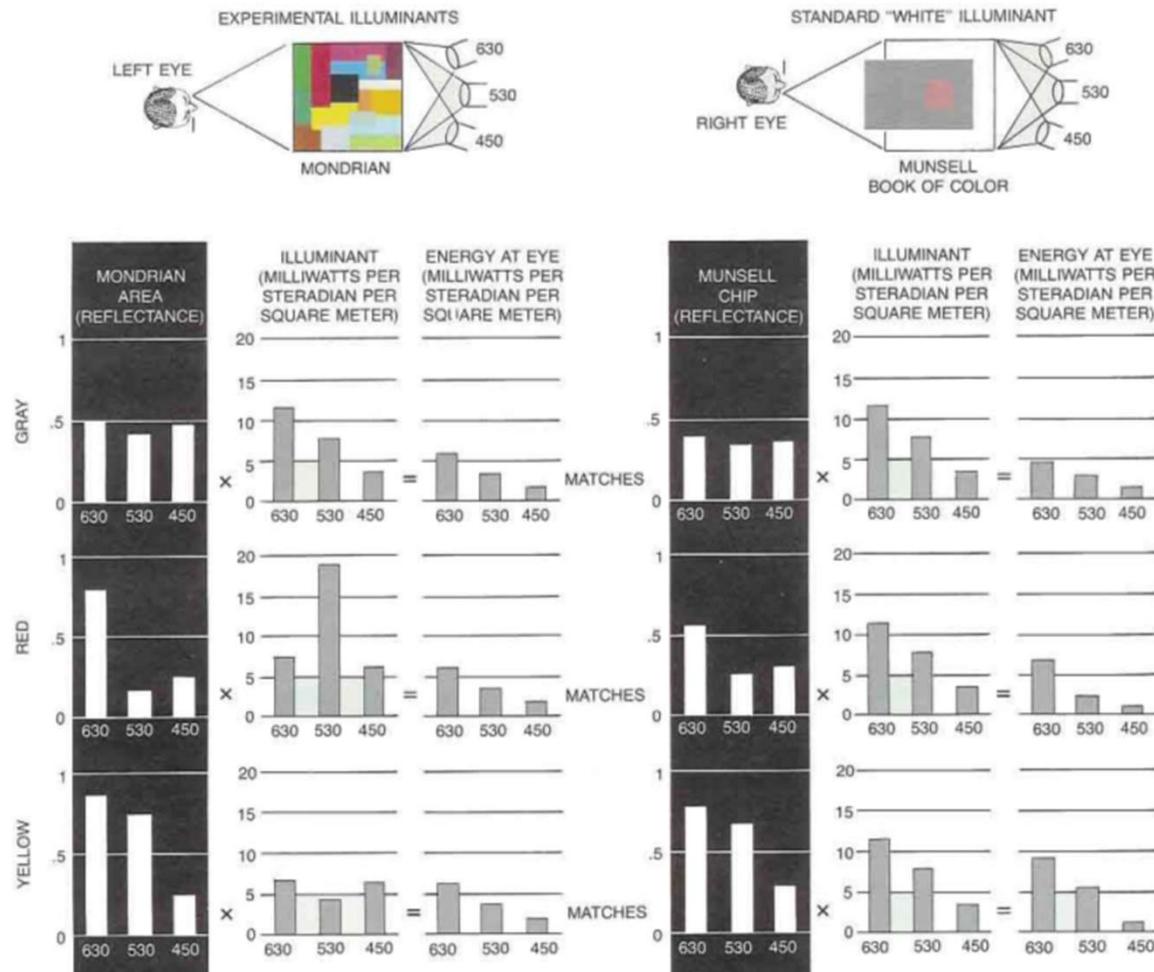
Modelling human colour constancy



Modelling human colour constancy



Modelling human colour constancy



Brightness perception

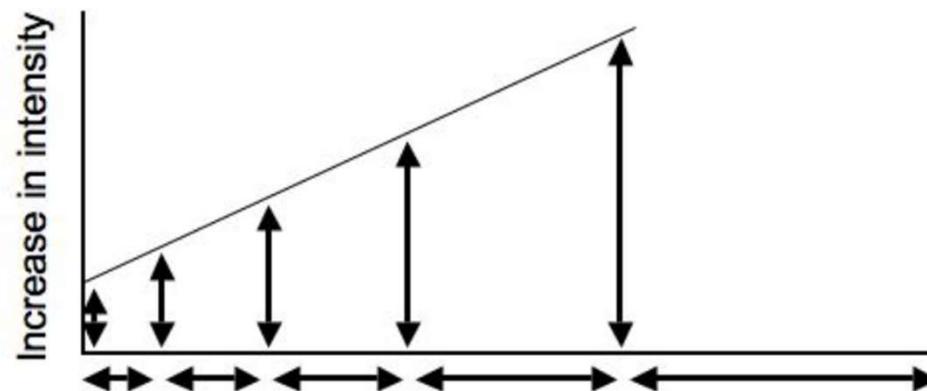
Weber's law

The smallest change in stimuli that can be perceived (dS , known as Just Noticeable Difference (JND)) is proportional to the initial intensity S . Mathematically,

$$dS = S \cdot K$$

S is the reference stimulus
 K is a constant

Weber's law



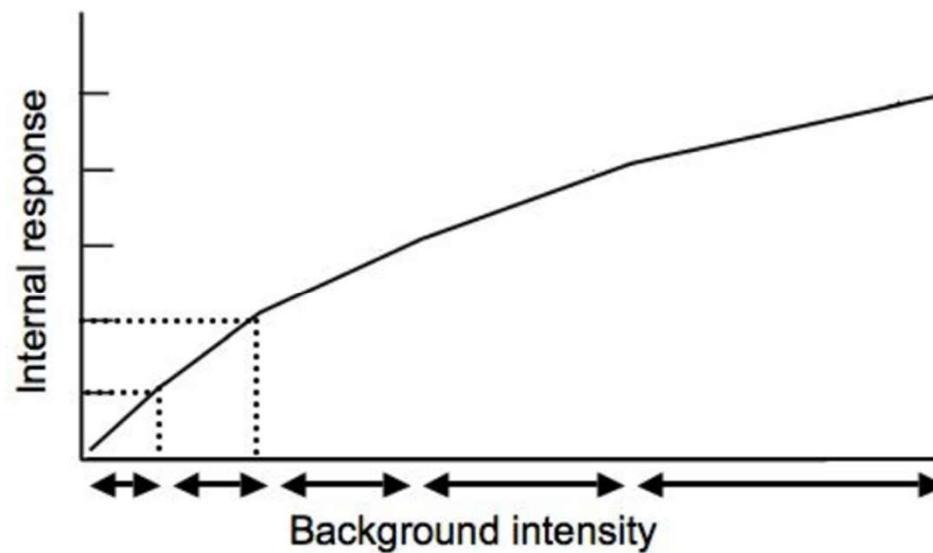
Fechner's law

Perceived brightness is proportional to the logarithm of the actual intensity

$$p = K \ln(S)$$

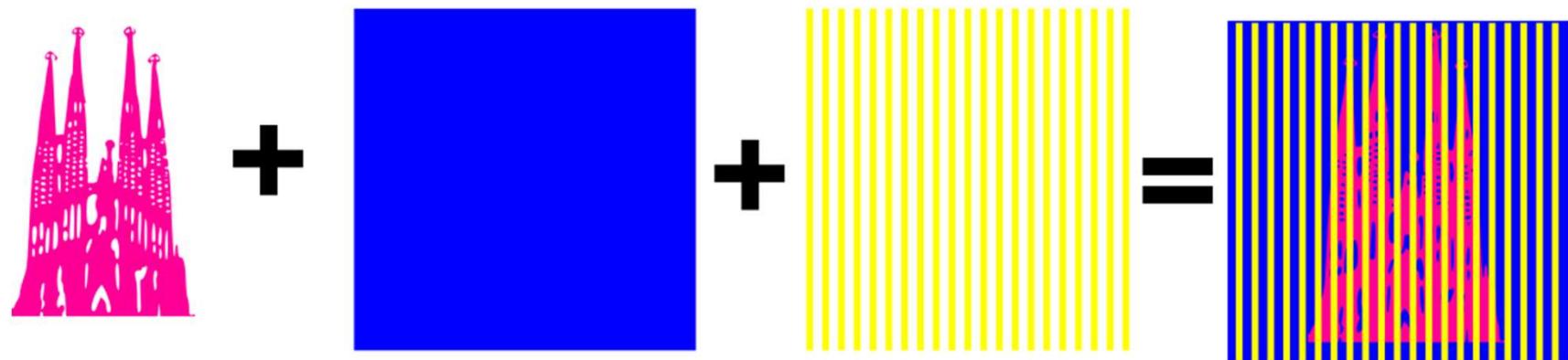
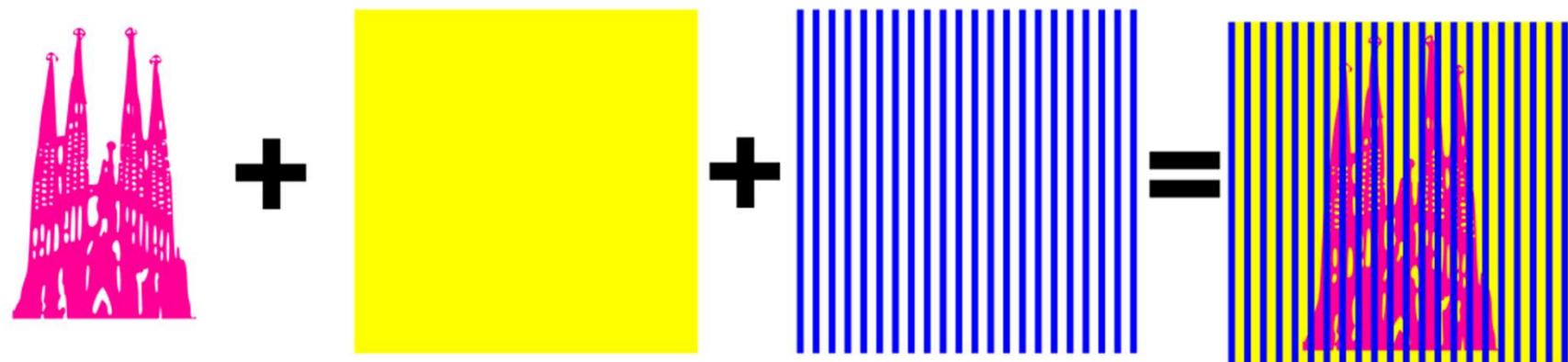
S is the reference stimulus
K is a constant

Fechner's analysis



Visual illusions and CNNs

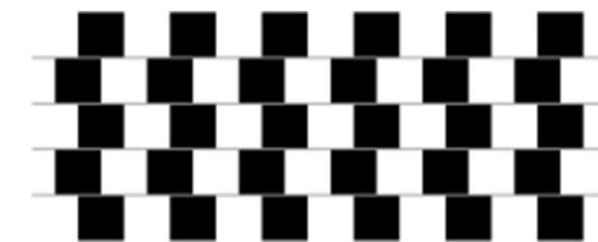
Visual Illusions



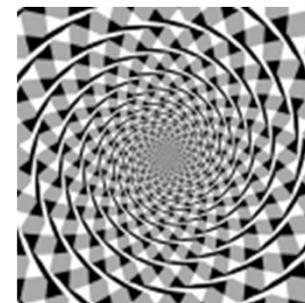
Visual Illusions



Müller-Lyer illusion



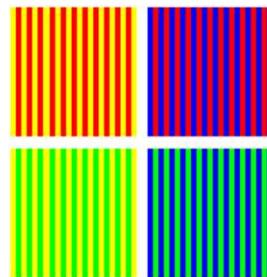
Cafe Walls illusion



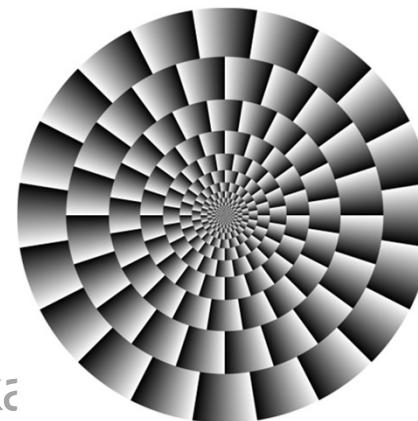
Fraser's spiral illusion



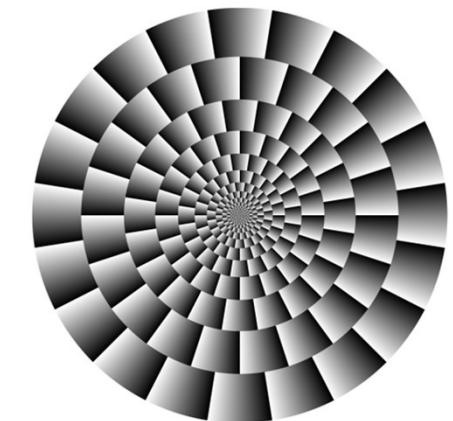
Brightness contrast



Color assimilation



Fraser-Wilcox illusion

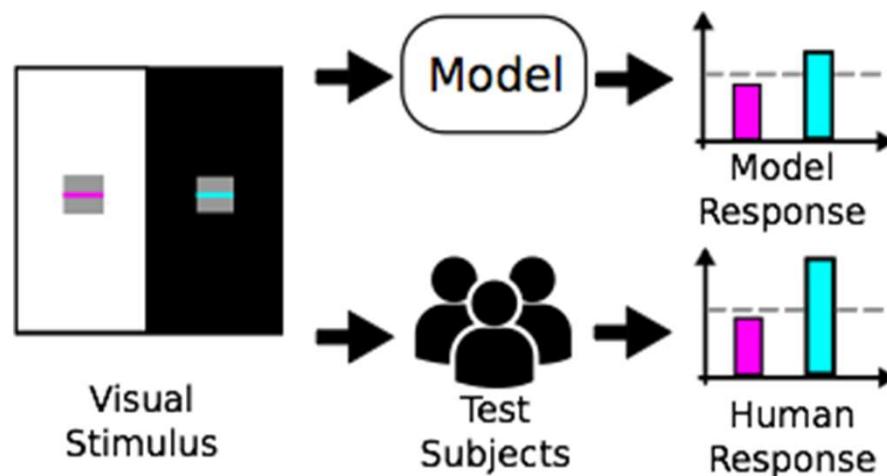


'A Catalogue of illusions' from Prof. Akitaoka

<http://www.psy.ritsumei.ac.jp/~akitaoka/catalogue.html>

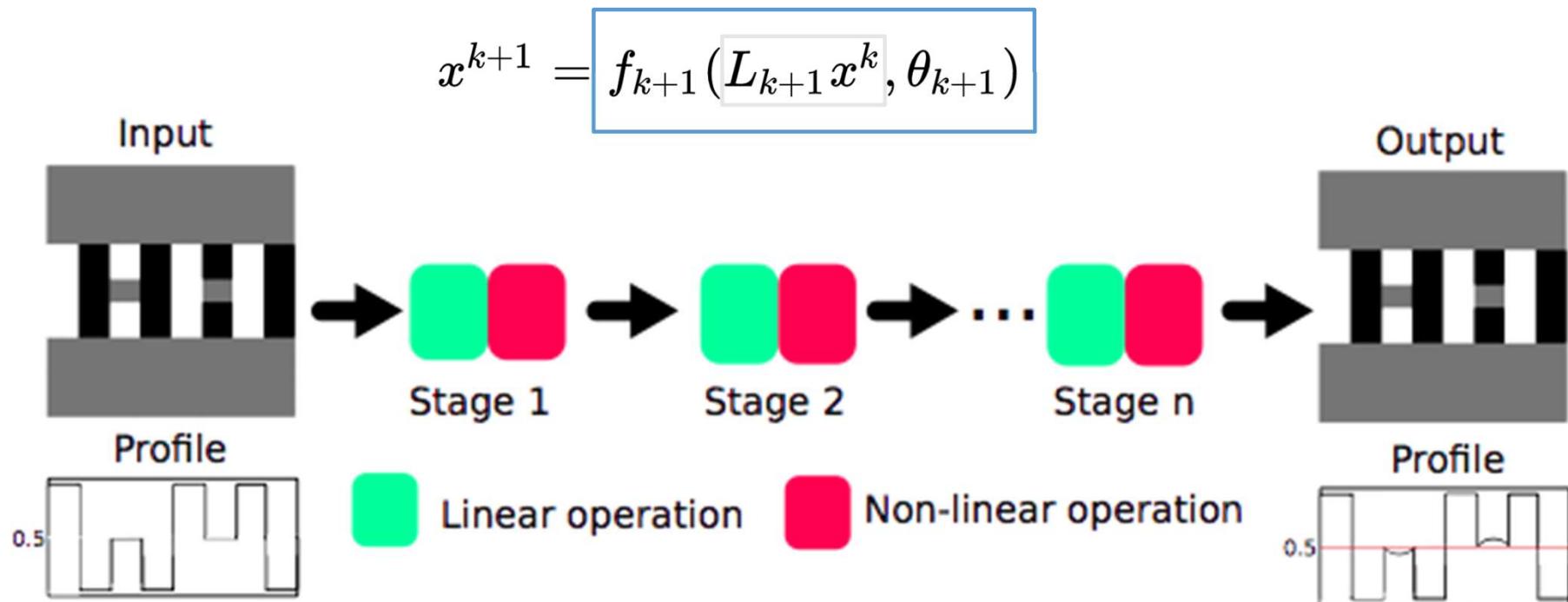
Why are Visual illusions important in vision science?

- Reveal differences between perception and reality.
- These *perception errors* are key to understand how vision works.
- Good vision models should reproduce human perception of visual illusions.



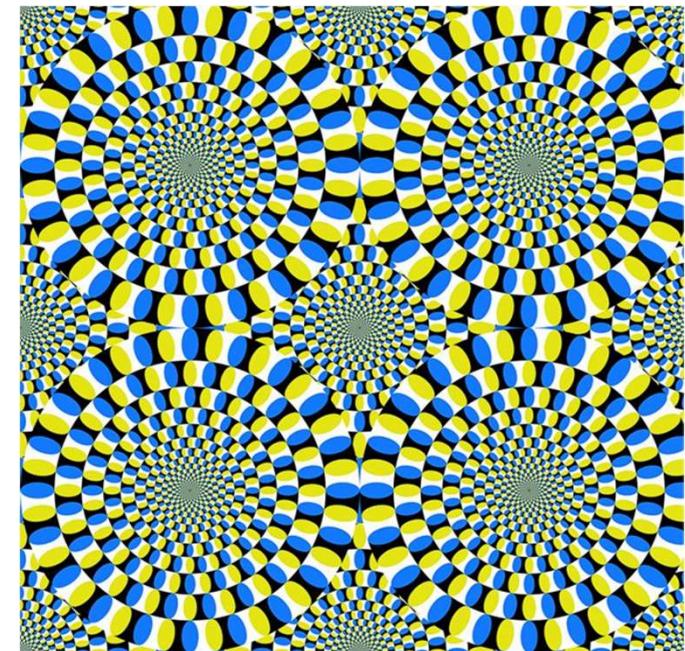
Cascade of Linear + Non Linear Operations

Perception is explained in many models of vision science and neuroscience as a cascade of modules composed by a linear operation followed by a nonlinearity.



Other works linking CNNs and Visual Illusions

- *E. Watanabe et al. Illusory motion reproduced by deep neural networks trained for prediction. Frontiers in psychology, 9:345, 2018.* 2
- Kim, B., Reif, E., Wattenberg, M. and Bengio, S., 2019. Do Neural Networks Show Gestalt Phenomena? An Exploration of the Law of Closure. arXiv preprint arXiv:1903.01069.
- Sun, E.D. and Dekel, R., 2019. ImageNet-trained deep neural network exhibits illusion-like response to the Scintillating Grid. arXiv preprint arXiv:1907.09019.
- Ward, E.J., 2019. Exploring perceptual illusions in deep neural networks. bioRxiv, p.687905.
- Anonymous (ICLR 2020 submission). The function of contextual illusions.<https://openreview.net/forum?id=H1gB4RVKvB>
- Jacob, G., Pramod, R. T., Katti, H., Arun, S. P. Do deep neural networks see the way we do?



Choosing three imaging tasks related with HVS

Denoise



Deblur



Restoration



|

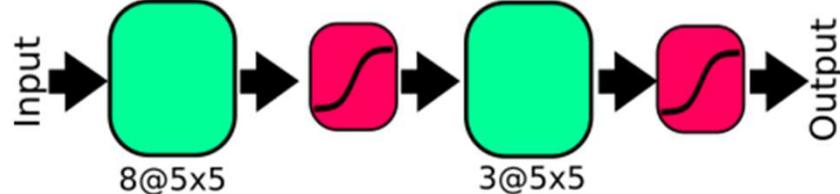
$I + \text{noise}$

$I + \text{blur}$

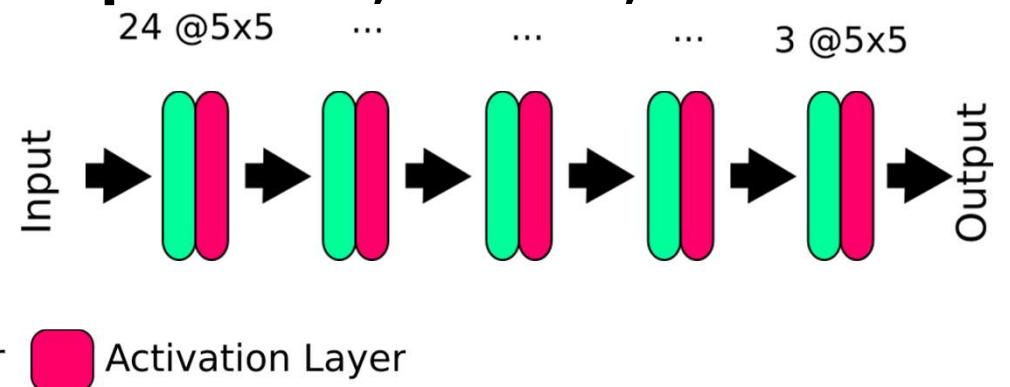
$I + \text{blur} + \text{noise}$

CNN Implementation details

DN-NET, DB-NET, Restore-Net



Deep DN-NET, DB-NET, and Restore-Net



Convolution Layer Activation Layer

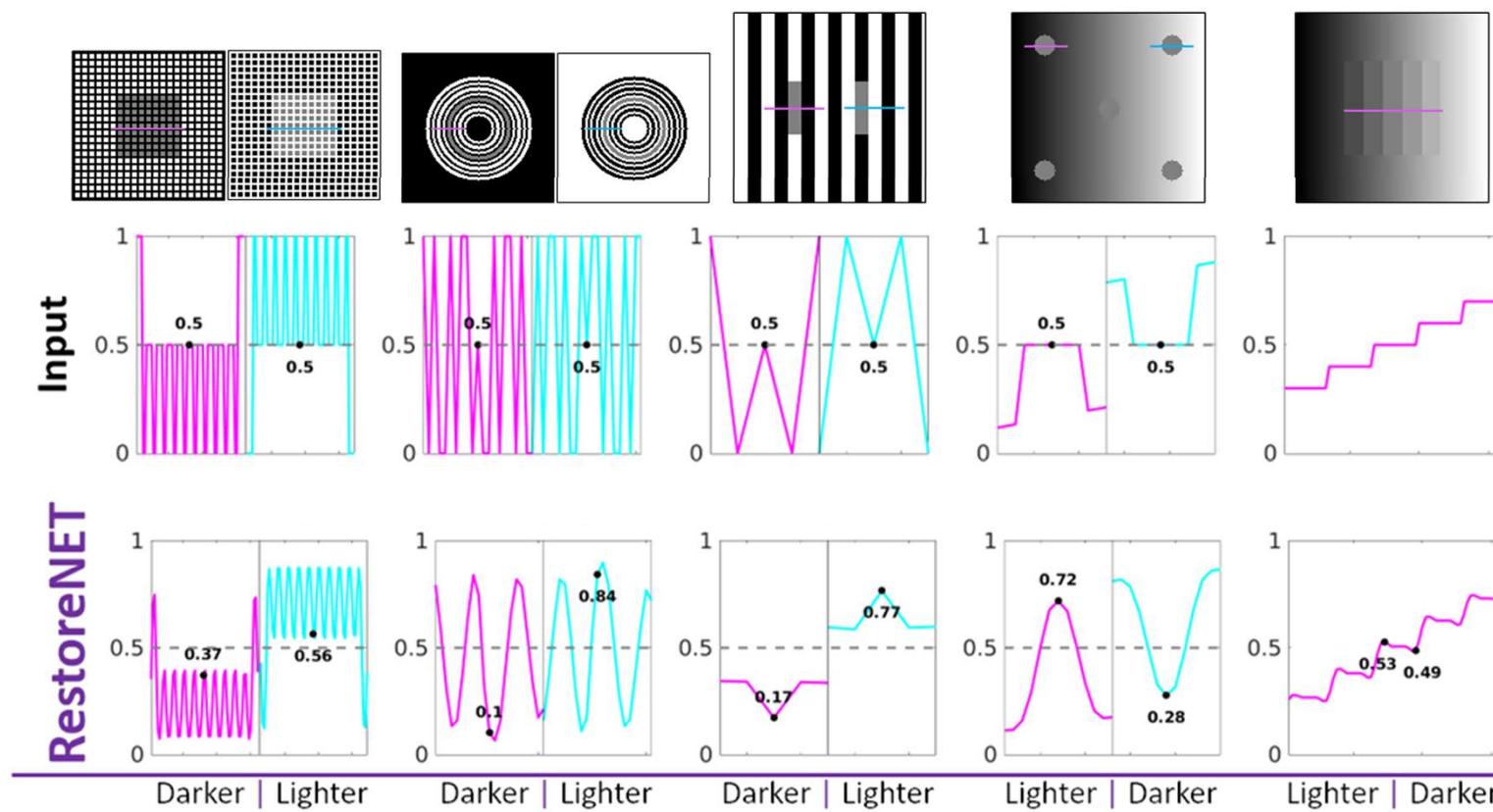
Zhang et al: Denoising deep CNN with state-of-the-art performance

Zhang, K., Zuo, W., Chen, Y., Meng, D. and Zhang, L., 2017. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. *IEEE Transactions on Image Processing*, 26(7), pp.3142-3155.

Dataset: All of them trained on a subset of ImageNet

Loss: Mean squared error

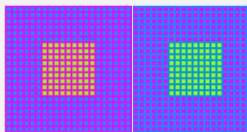
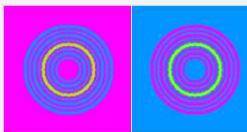
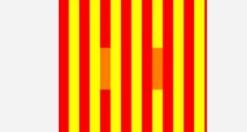
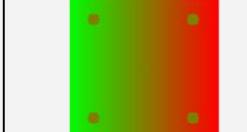
Results



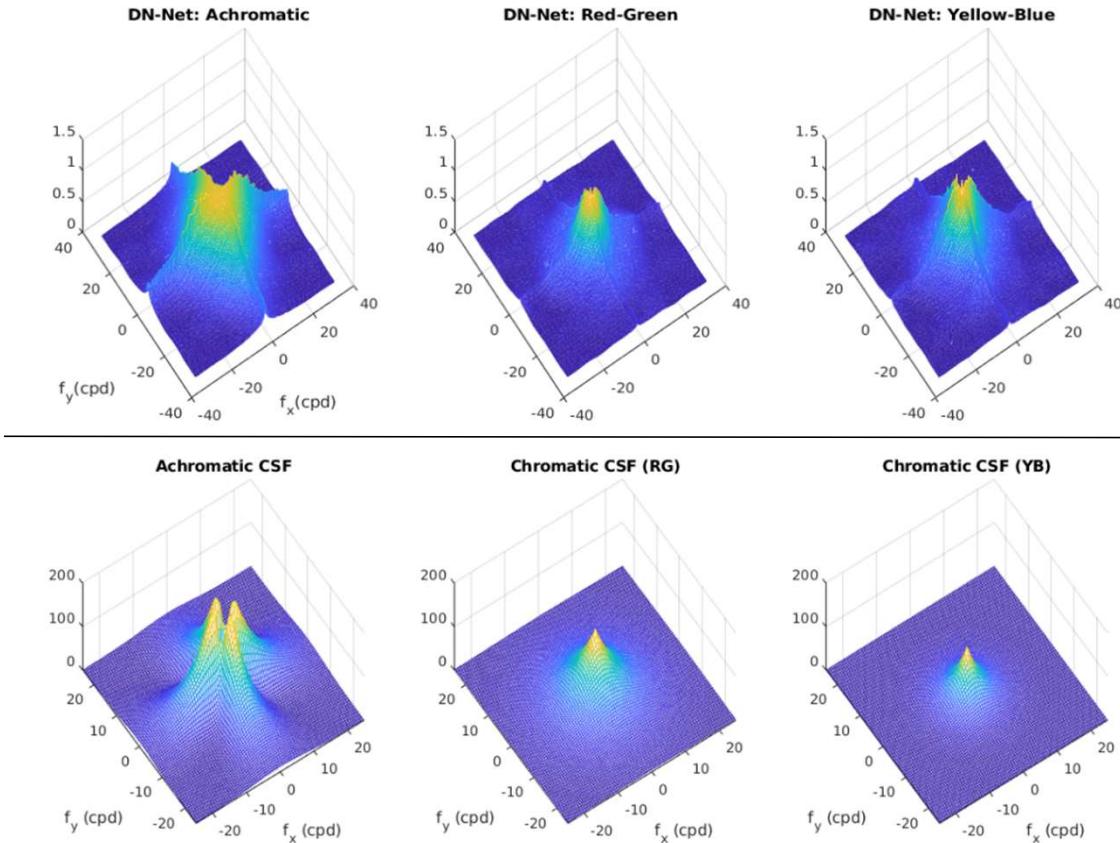
Summary of replication of grayscale VIs

Visual Illusion					
DN-NET	✓	✓	✓	✓	✗
DB-NET	✓	✓	✓	✓	✓
Restore-Net	✓	✓	✓	✓	✓
Deep DN-NET	✓	✓	✓	✗	✗
Deep DB-NET	✗	✓	✓	✓	✓
Deep RestoreNet	✓	✓	✓	✓	✓
Zhang et al.	✓	✗	✗	✓	✗

Summary of replication of color VIs

Visual Illusion						
DN-NET	✓	✓	✓	✗	✓	
DB-NET	✓	✓	✓	✗	✓	
Restore-Net	✓	✓	✓	✗	✓	
Deep DN-NET	✓	✓	✓	✗	✓	
Deep DB-NET	✓	✓	✓	✓	✓	
Deep RestoreNet	✓	✓	✓	✗	✓	
Zhang et al.	✓	✗	✗	✓	✗	

A comparison with human perception



Contrast sensitivity function of DB-NET

Gomez-Villa, A., Martín, A., Vazquez-Corral, J., Bertalmío, M. and Malo, J., 2019. Visual Illusions Also Deceive Convolutional Neural Networks: Analysis and Implications. arXiv preprint arXiv:1912.01643.

Human contrast sensitivity functions

Mullen, K. T. (1985). The contrast sensitivity of human colour vision to red-green and blue-yellow chromatic gratings. *The Journal of physiology*, 359(1), 381-400.

Watson, A. B., & Malo, J. (2002, September). Video quality measures based on the standard spatial observer. In *Proceedings. International Conference on Image Processing*(Vol. 3, pp. III-III). IEEE.

Human visual system and perception

Javier Vazquez-Corral
Universitat Autònoma de Barcelona

javier.vazquez@cvc.uab.cat

Slide credits: Marcelo Bertalmío and David Kane