MAIA - MedicAl Imaging and Applications

Advanced Image Analysis

Lectures on Advanced Color Image Processing

B1 - Human Vision System The Retina and the Brain

March/2018

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- **B1 - Human Vision System: The Retina and the Brain**
    1. **Basics of Human Perception.**
    2. Perception and Color. Measuring Color.
    3. Color Spaces. Perceptually Uniform Color Spaces.
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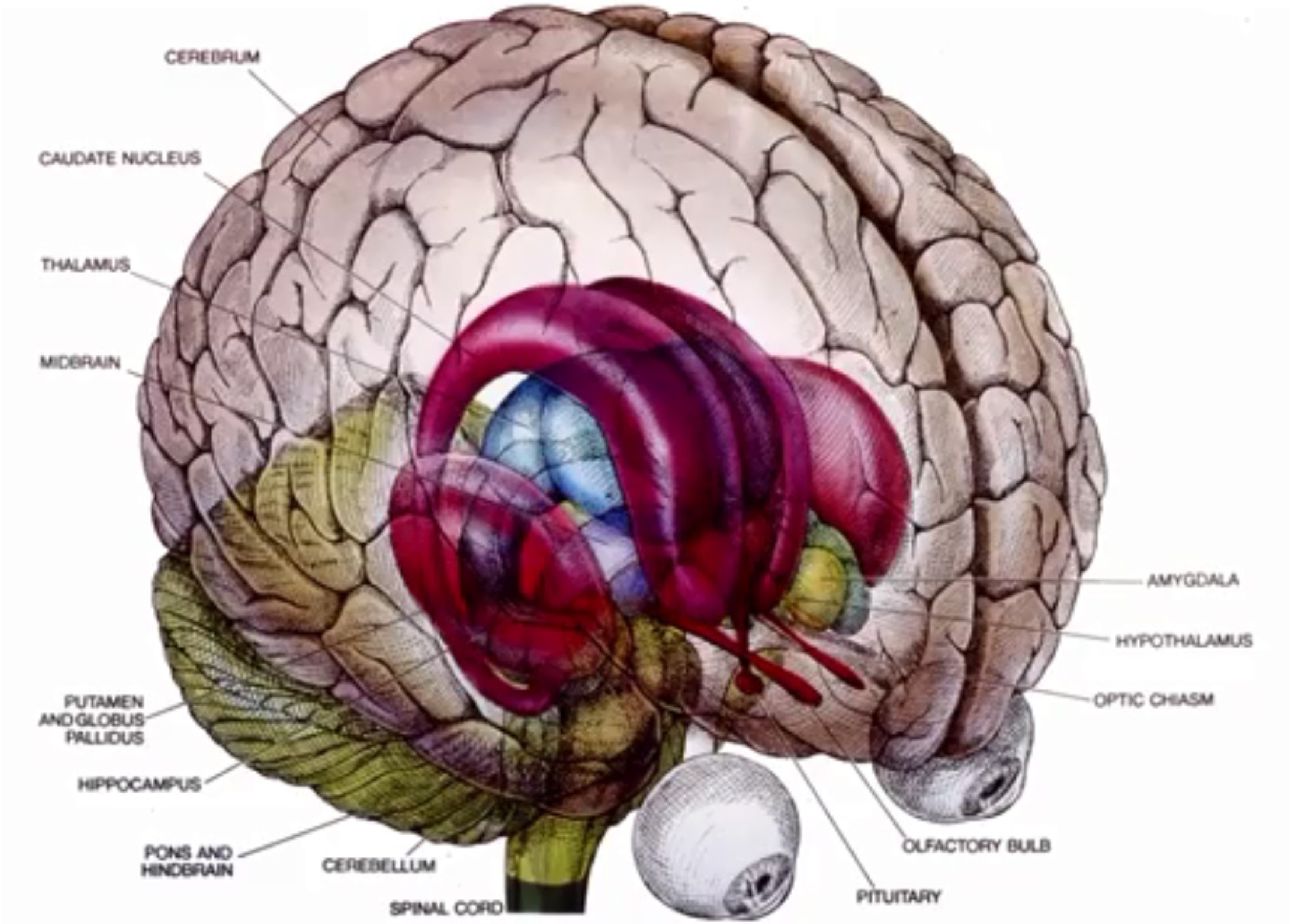
1 - Basics of Human Perception



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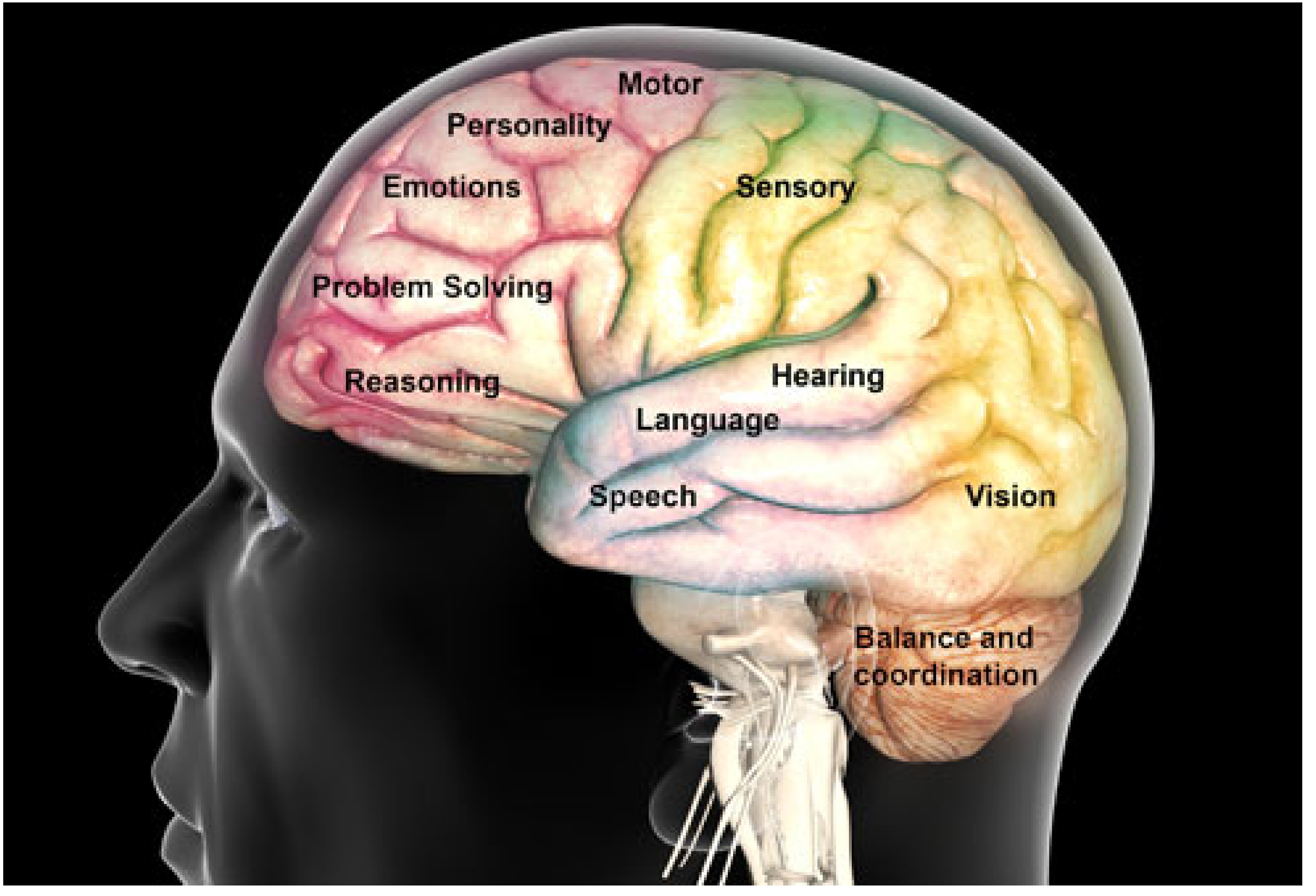

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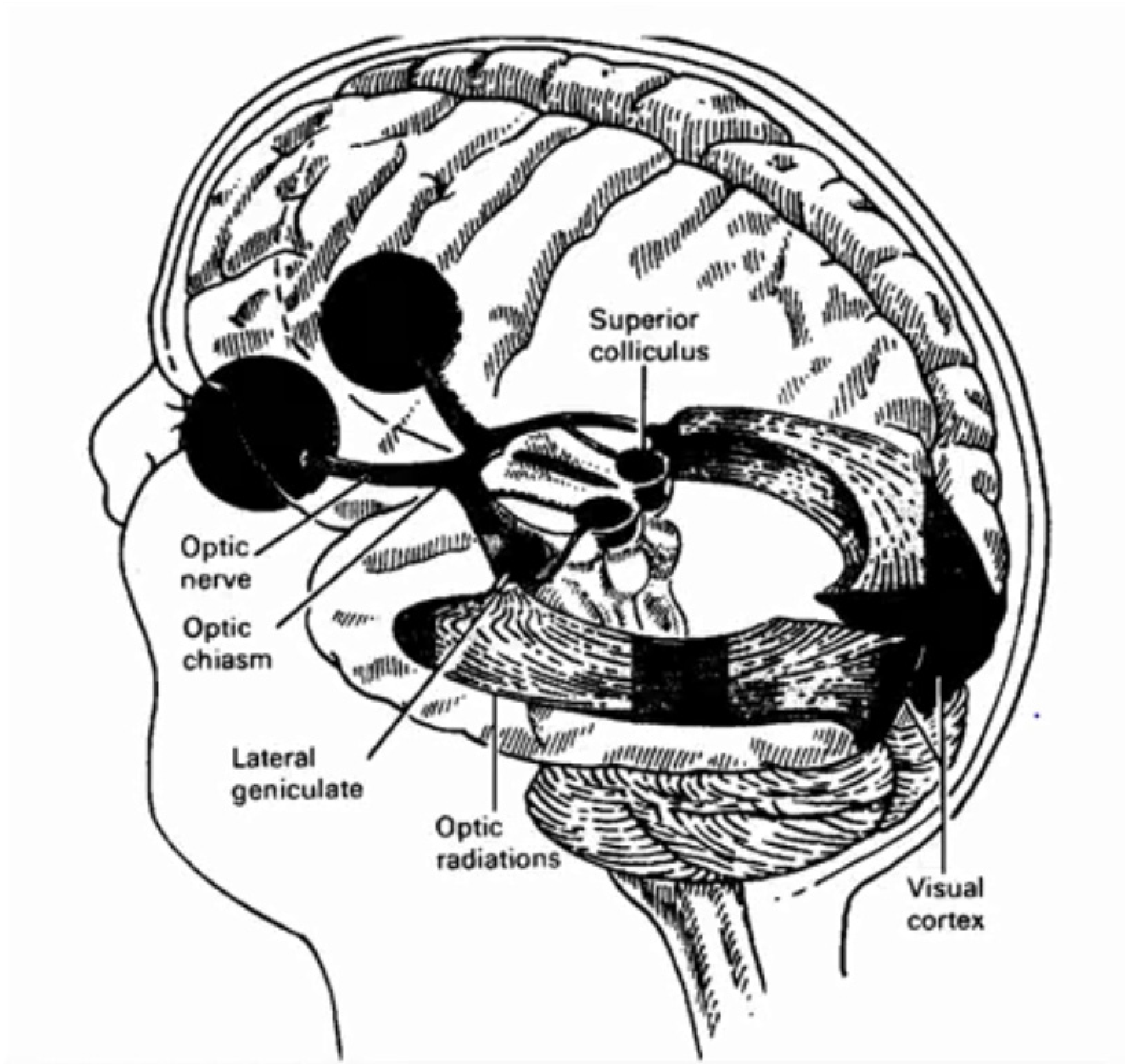


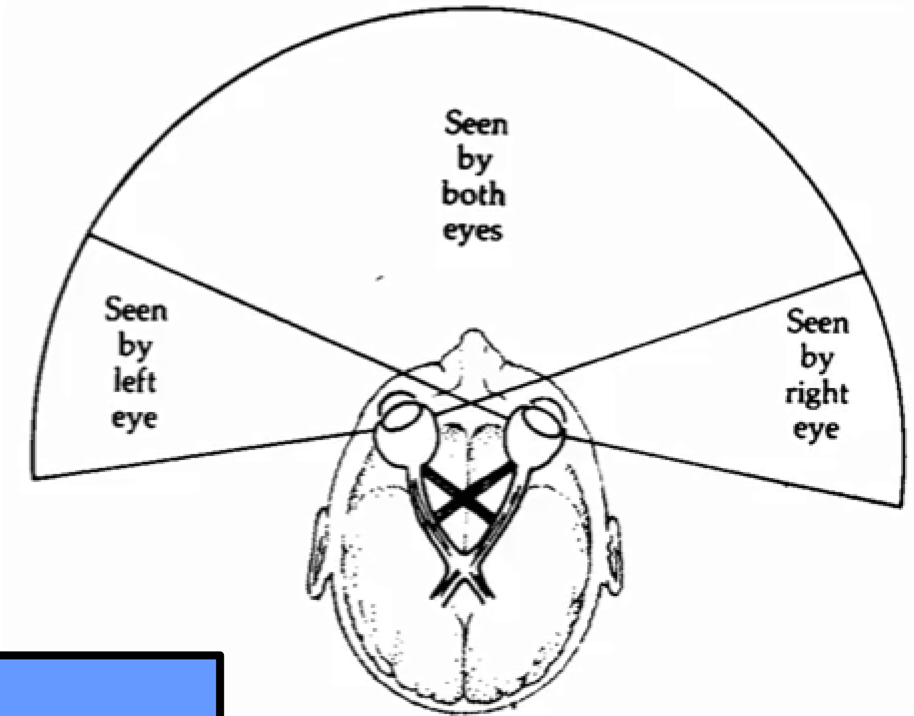
1 - Basics of Human Perception

Vision Field (degrees):

Each eye: 160º (**monocular**)

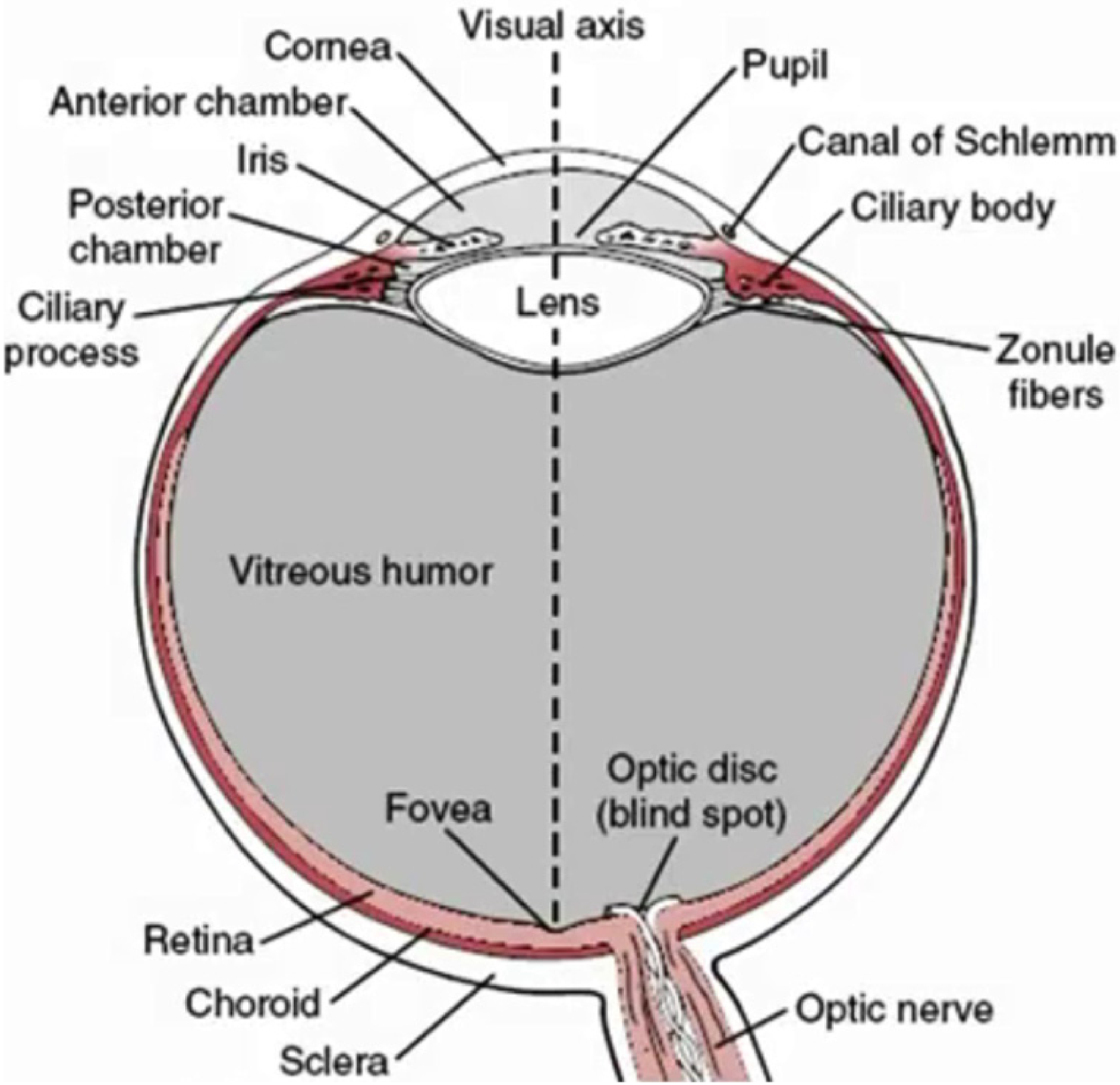
Both eyes: 160º+160º = 320º?

No, because there is overlap:
120º (**binocular**)



QUIZ!
What is our total visual field?
Link: https://goo.gl/forms/zX8xLDuz6lXOVatg2

1 - Basics of Human Perception



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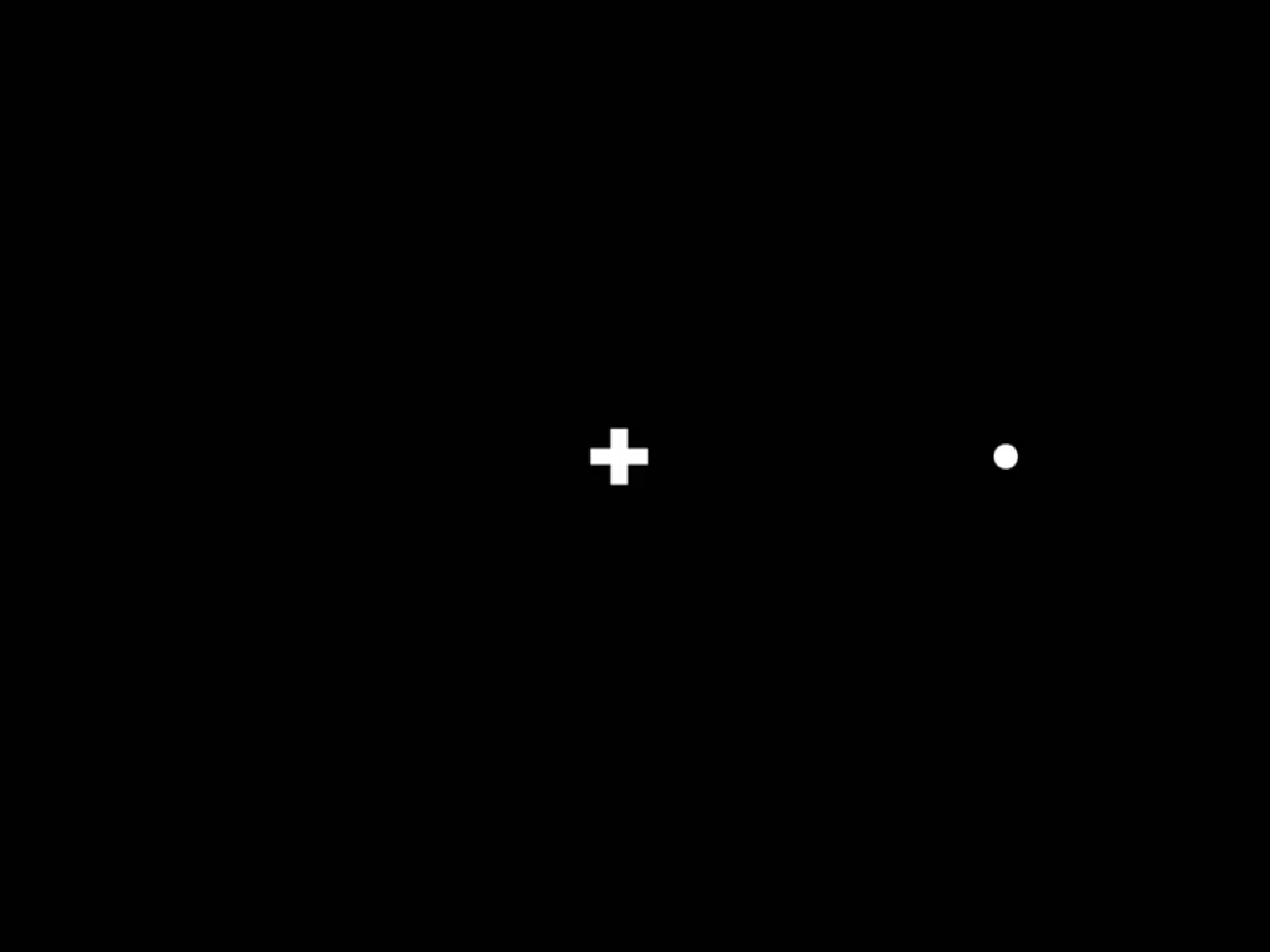

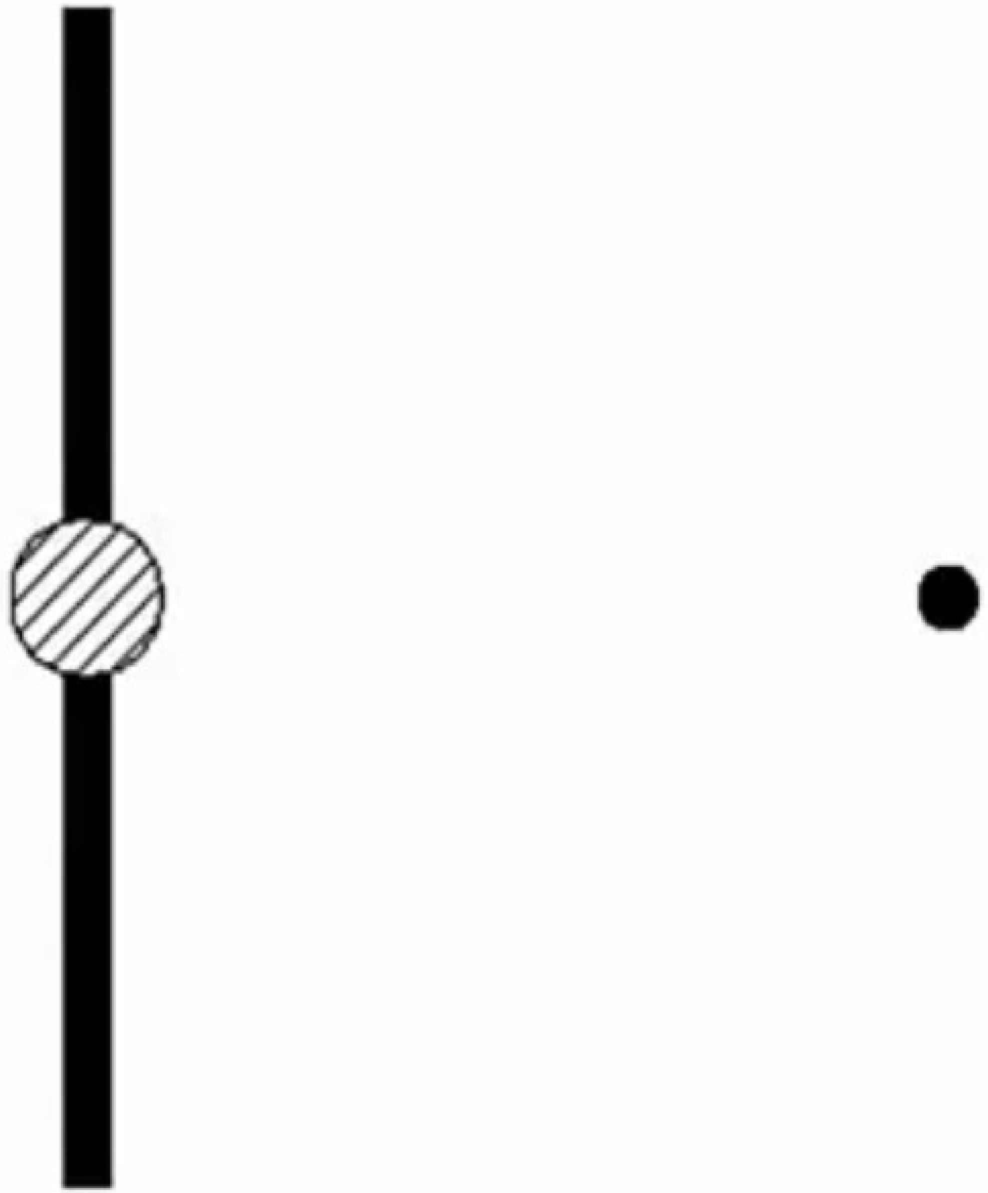

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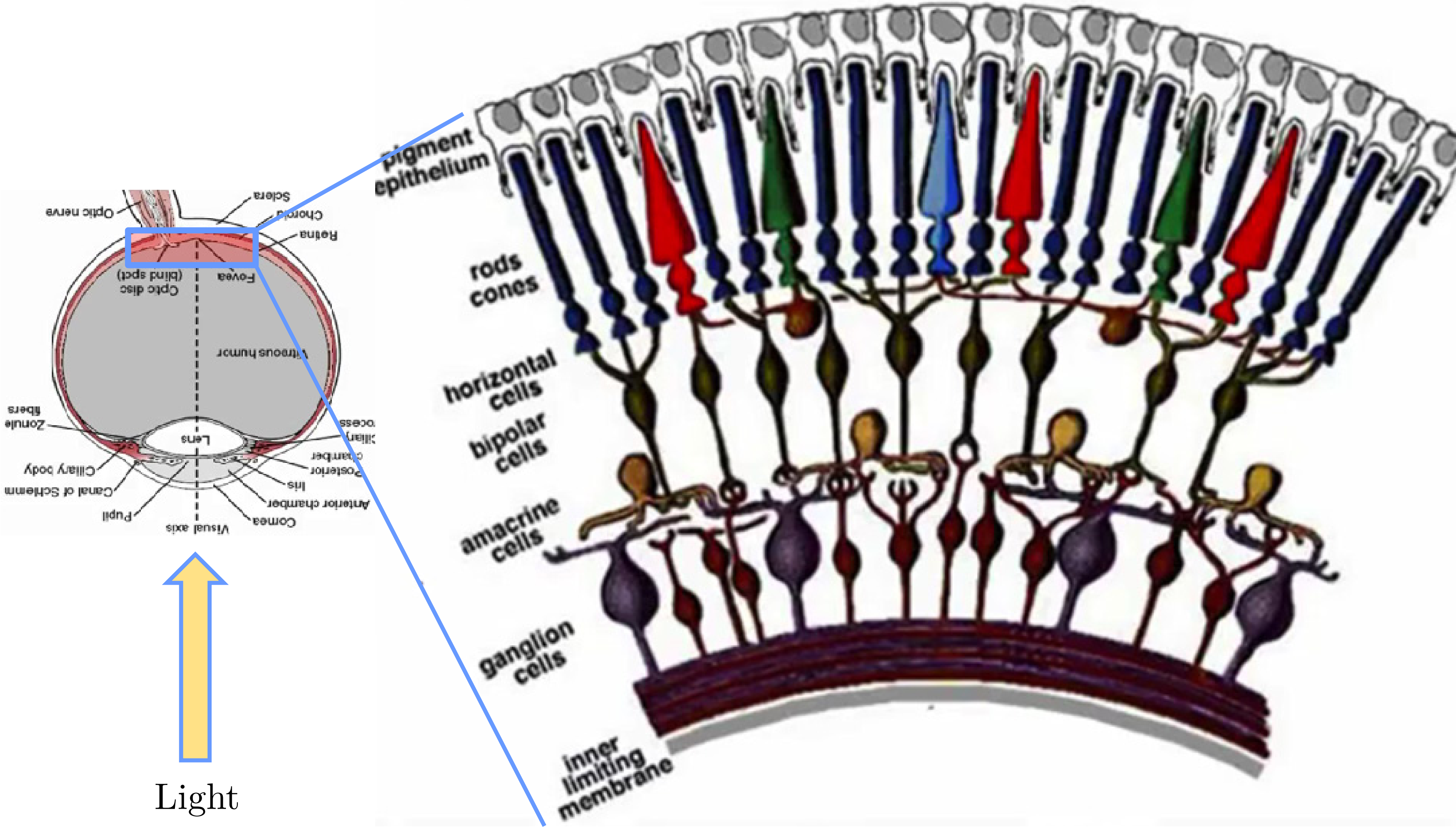
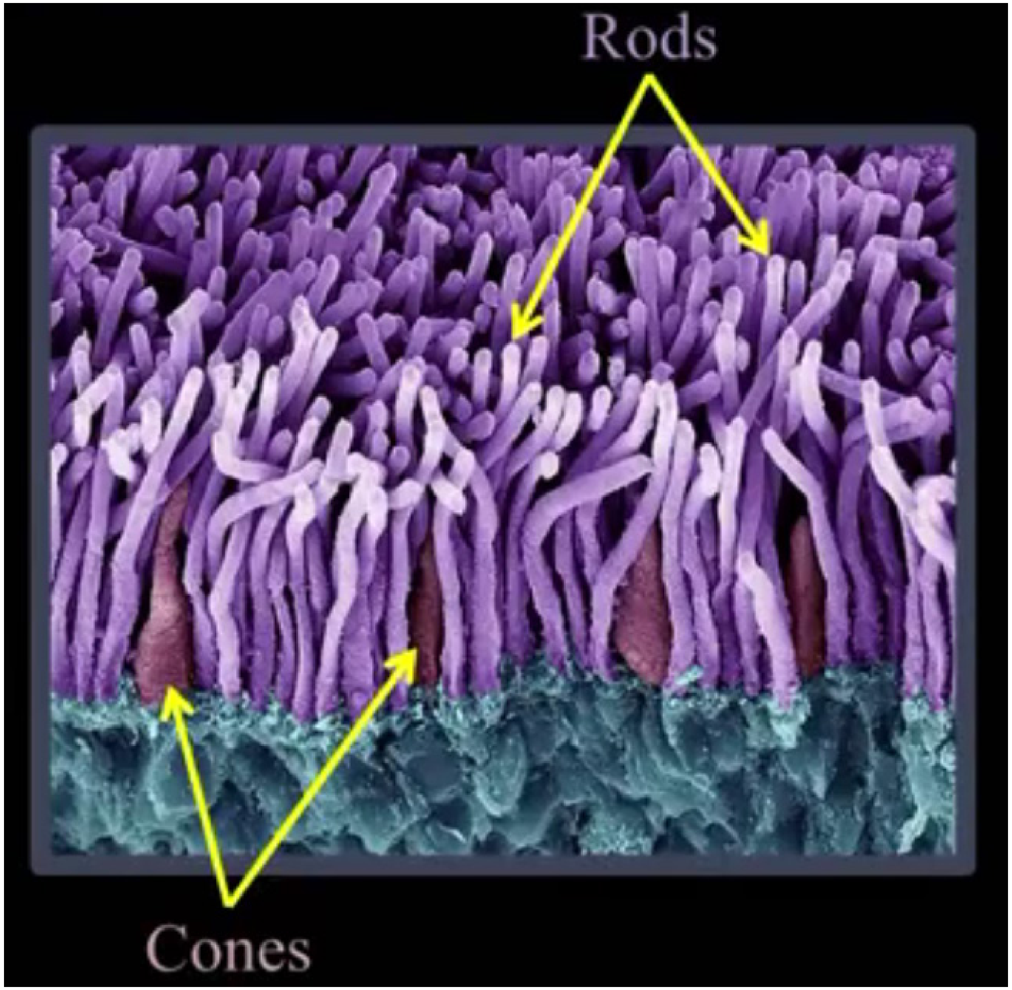
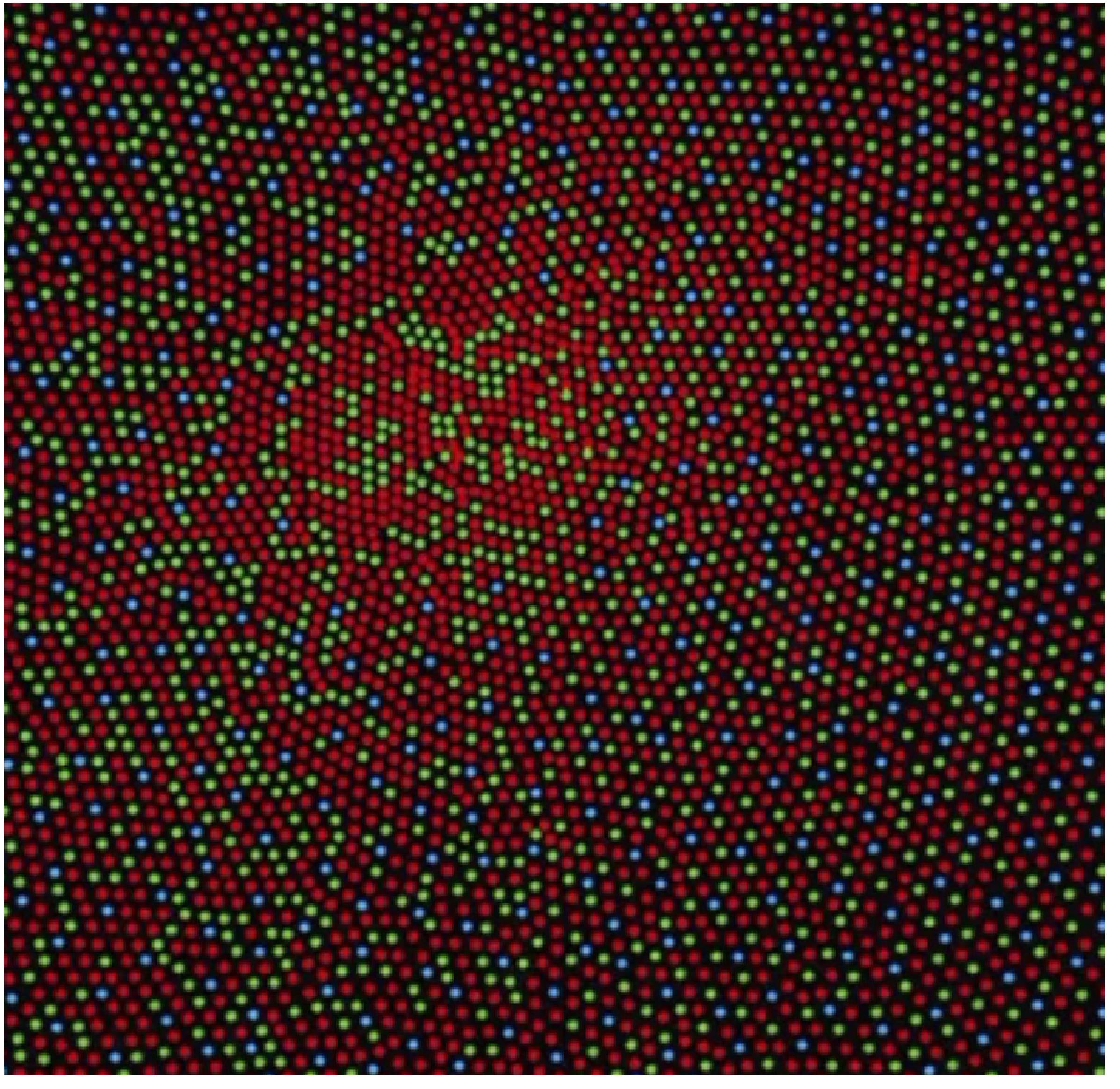


1 - Basics of Human Perception

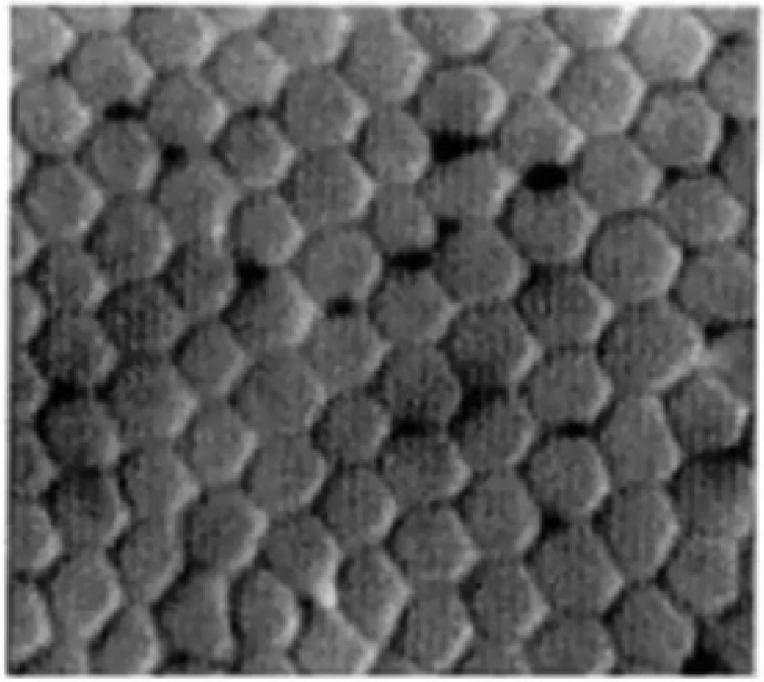
Rods & Cones:

- **120 million rods**
- **6-7 million cones.**
- **Rods are 1000x more light sensitive than cones.**
- **Rods discriminate brightness levels when there is low illumination.**
- **Cones discriminate colors.**

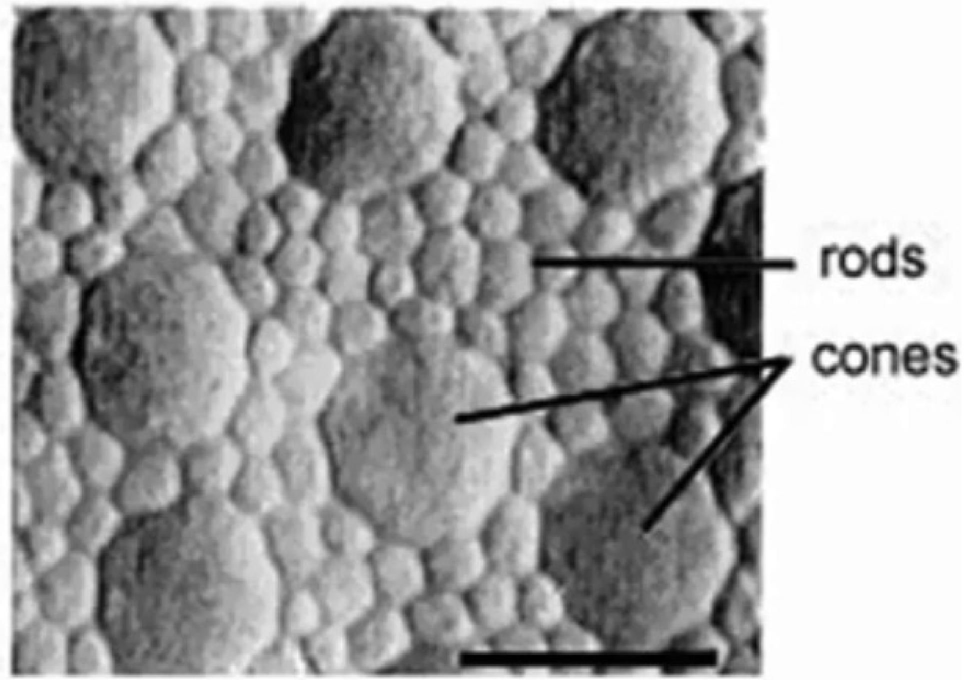


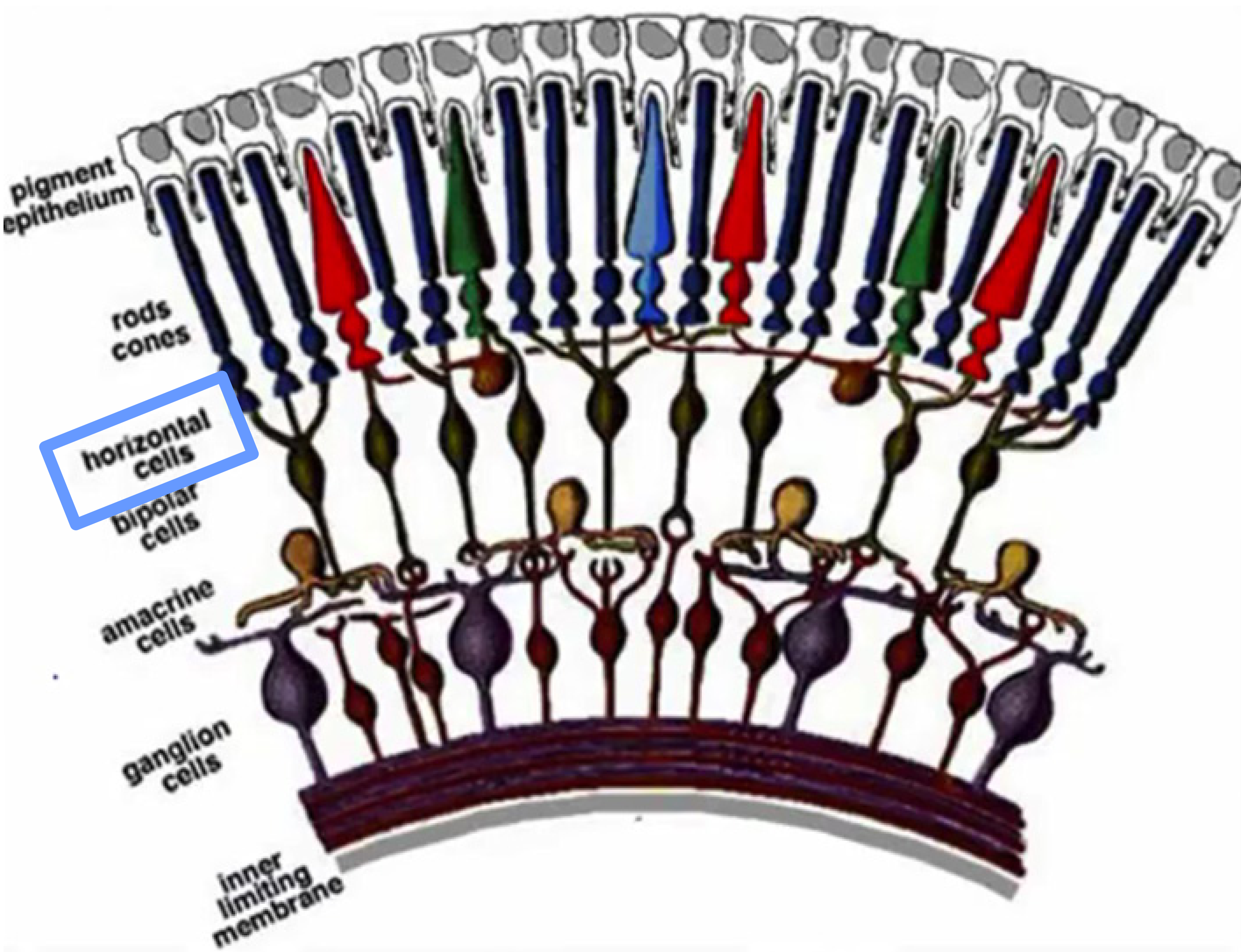


Fovea



Periphery

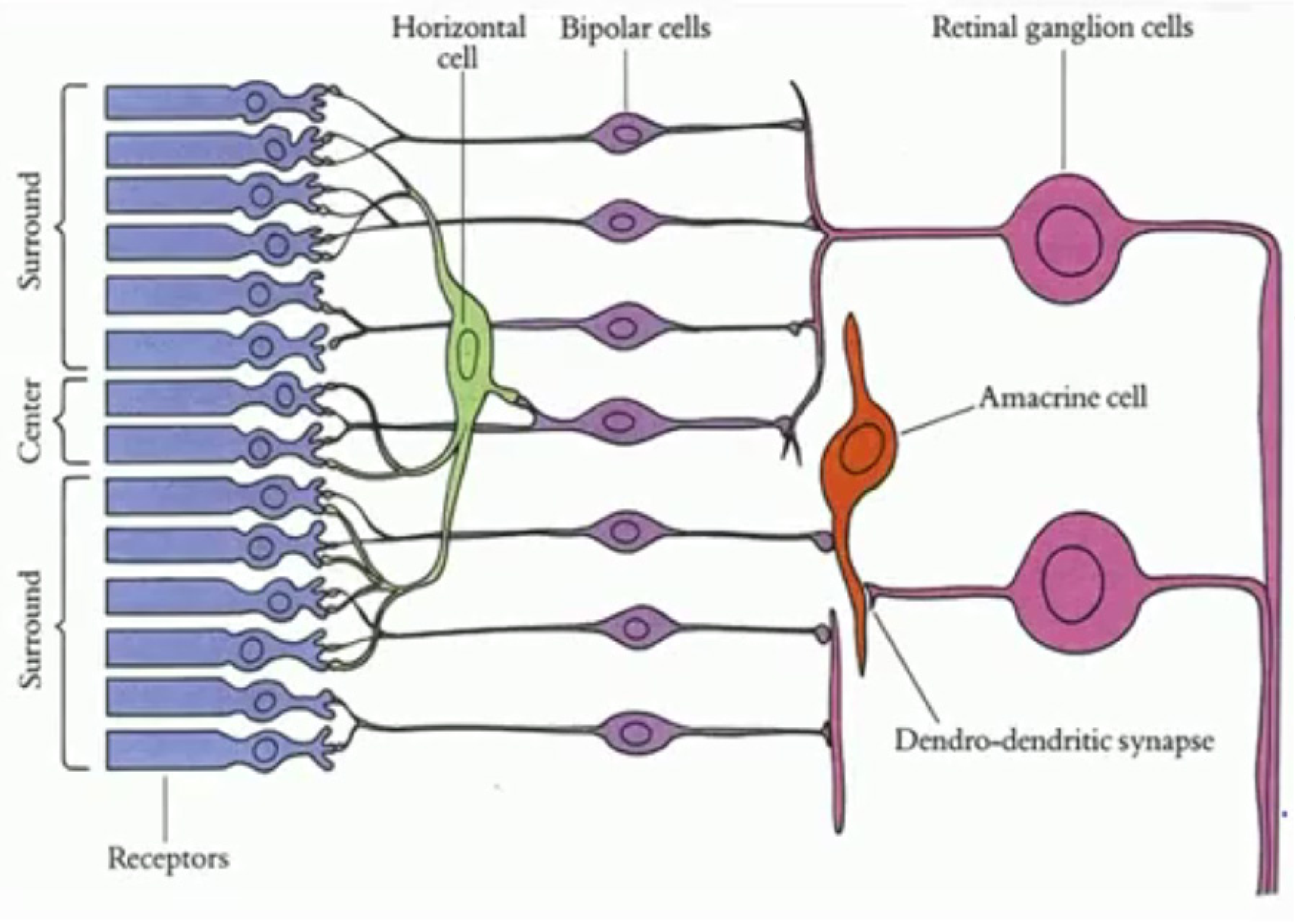


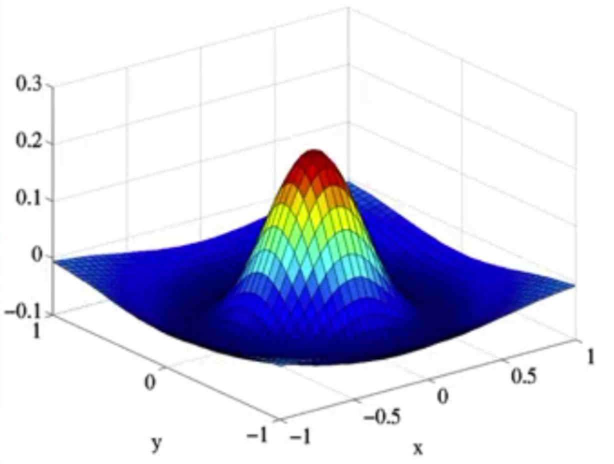

pigment epithelium
rods
cones
horizontal cells
bipolar cells
amacrine cells
ganglion cells
inner limiting membrane

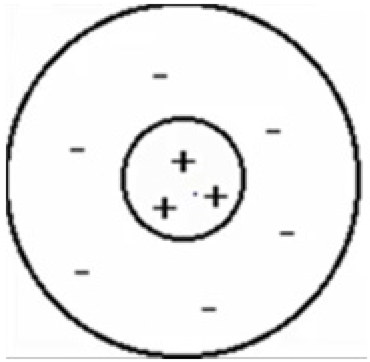
1 - Basics of Human Perception

Figure 1: A series of five photographs. The exposure is increasing from left (1/1000 of a second) to right (1/4 of a second).

1 - Basics of Human Perception







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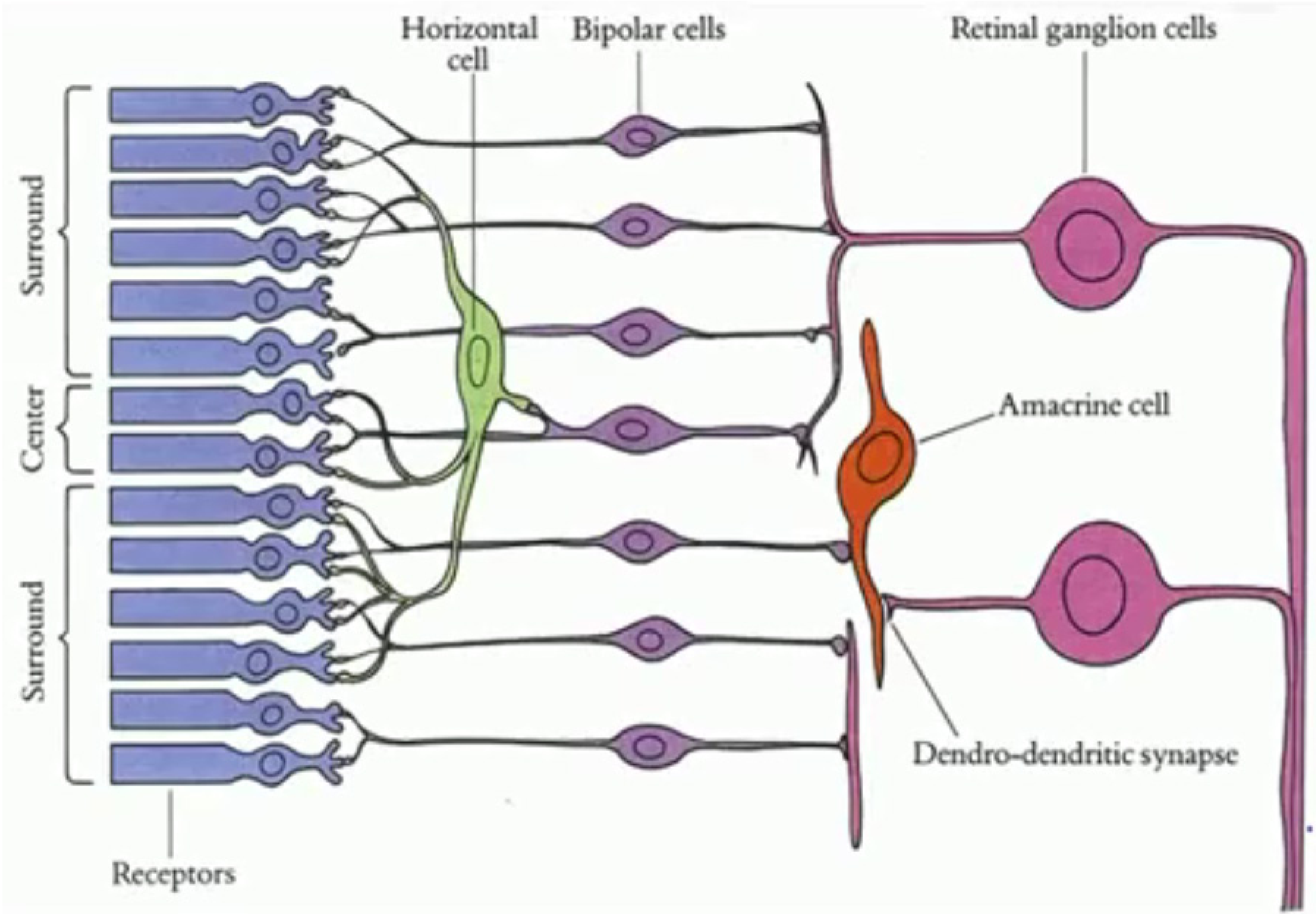

2 - Perception and Color. Measuring Color

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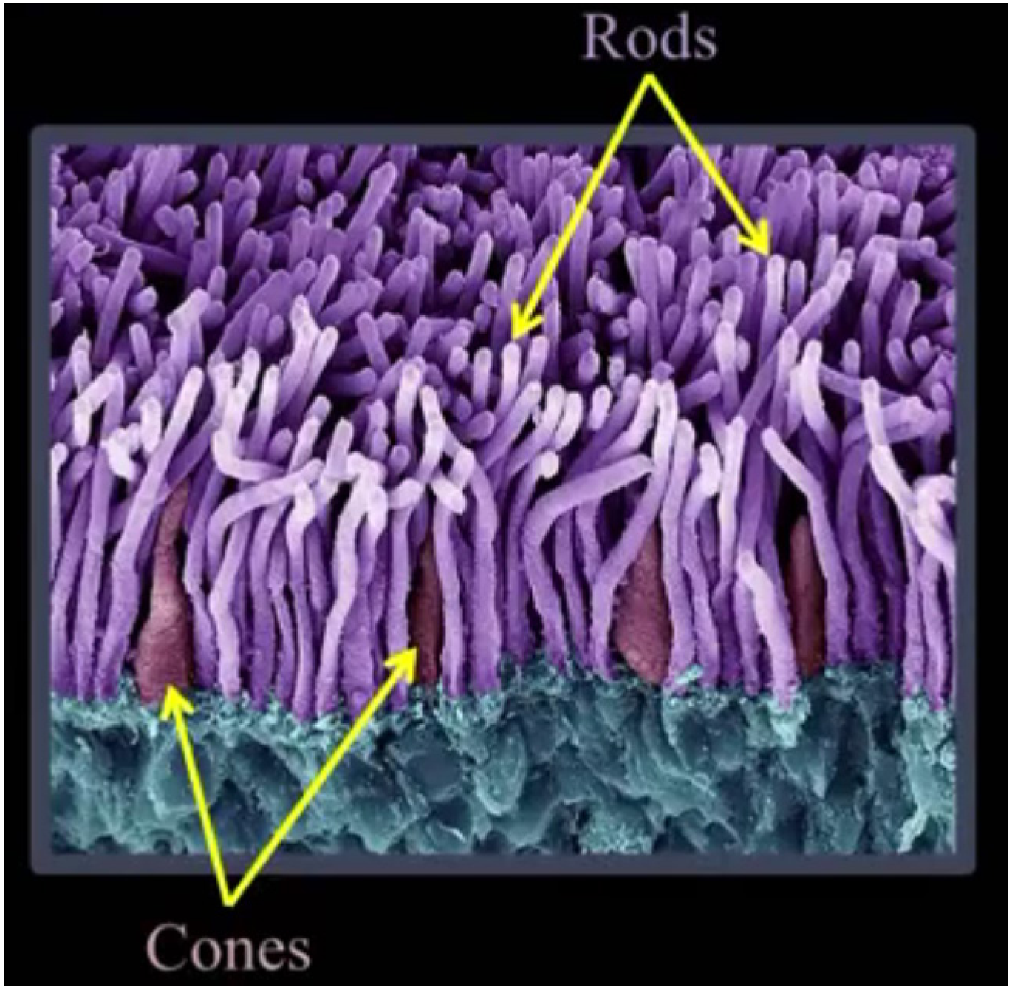
QUIZ!
Which photoreceptor is responsible for color discrimination?
Link: https://goo.gl/forms/IPkIQSYPsFCu5JIU2

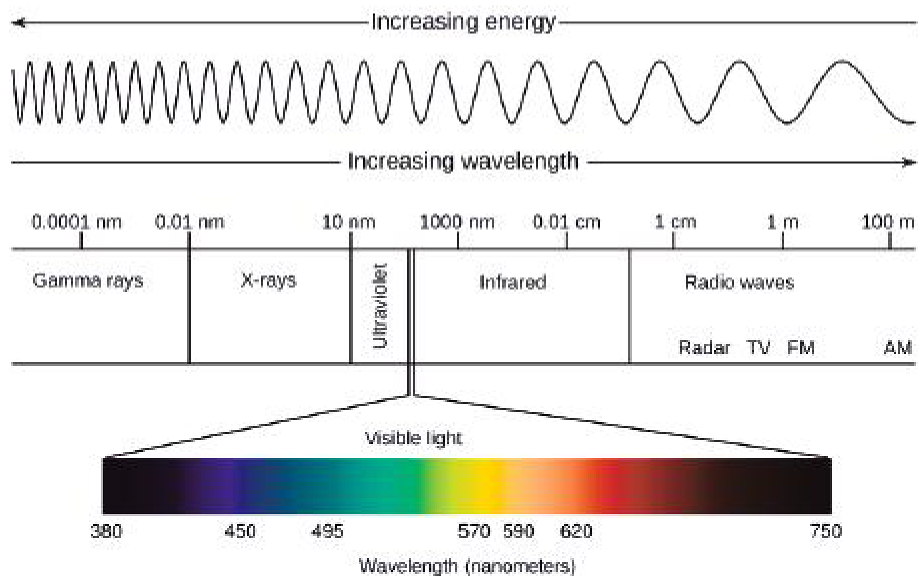


Cones:

- 6-7 Million cones in the retina
- High-resolution (details) vision
- Packed into the fovea
- Color Discrimination
- Three types of cones:
  1. **Red Cones (64%)**
  2. **Green Cones (32%)**
  3. **Blue Cones (2%)**

QUIZ!
Which photoreceptor is responsible for color discrimination?
Link: https://goo.gl/forms/IPkIQSYPsFCu5JIU2

How to measure color?



Radiometric Approach:

(independent of HVS)

Irradiance $I(\lambda)$

Reflectance $R(\lambda)$

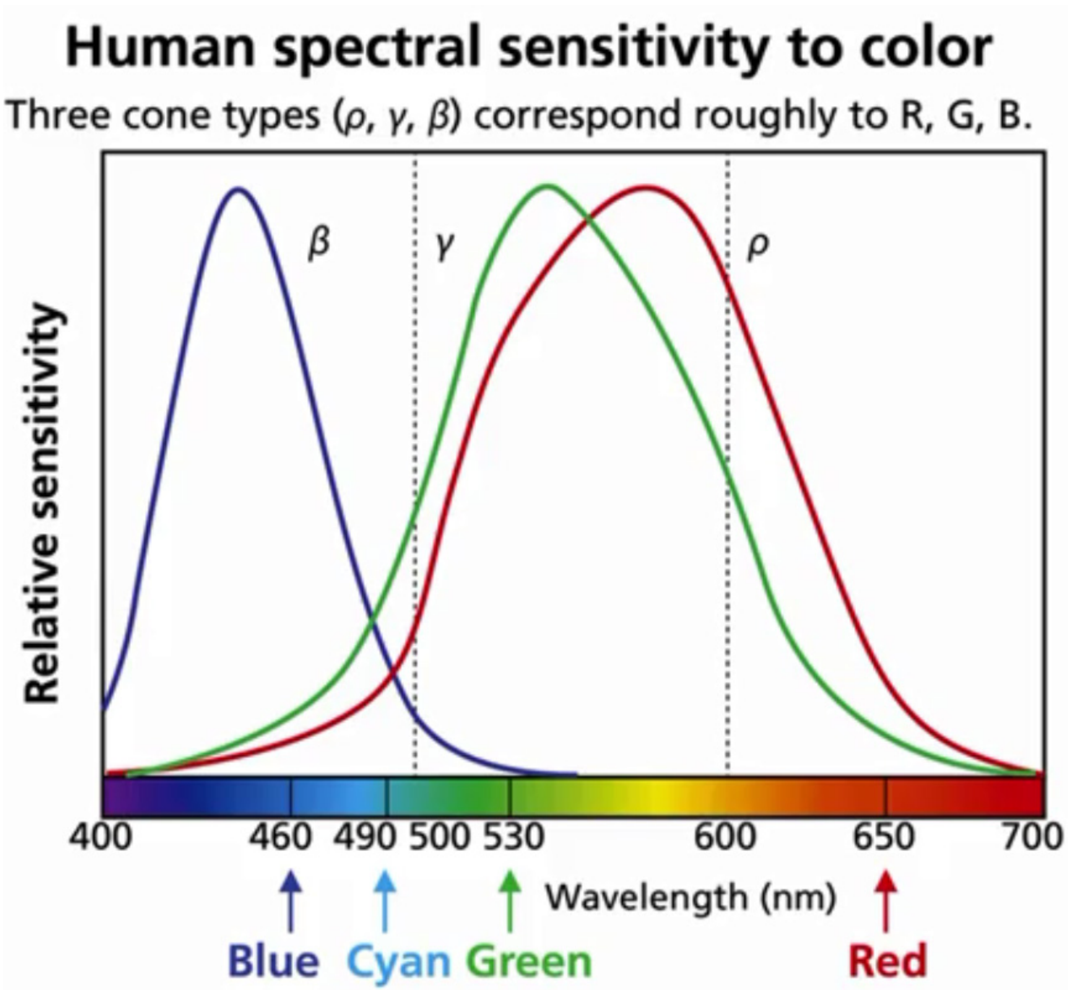
Radiance $E(\lambda)$

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

Colorimetric Approach:

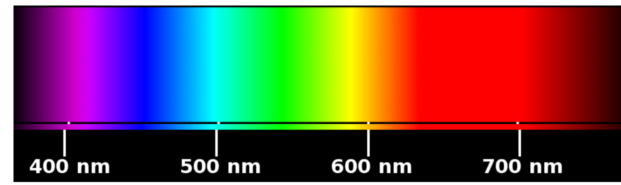
(takes into account the HVS)

Colorimetric Point of View



Konig, XIX century

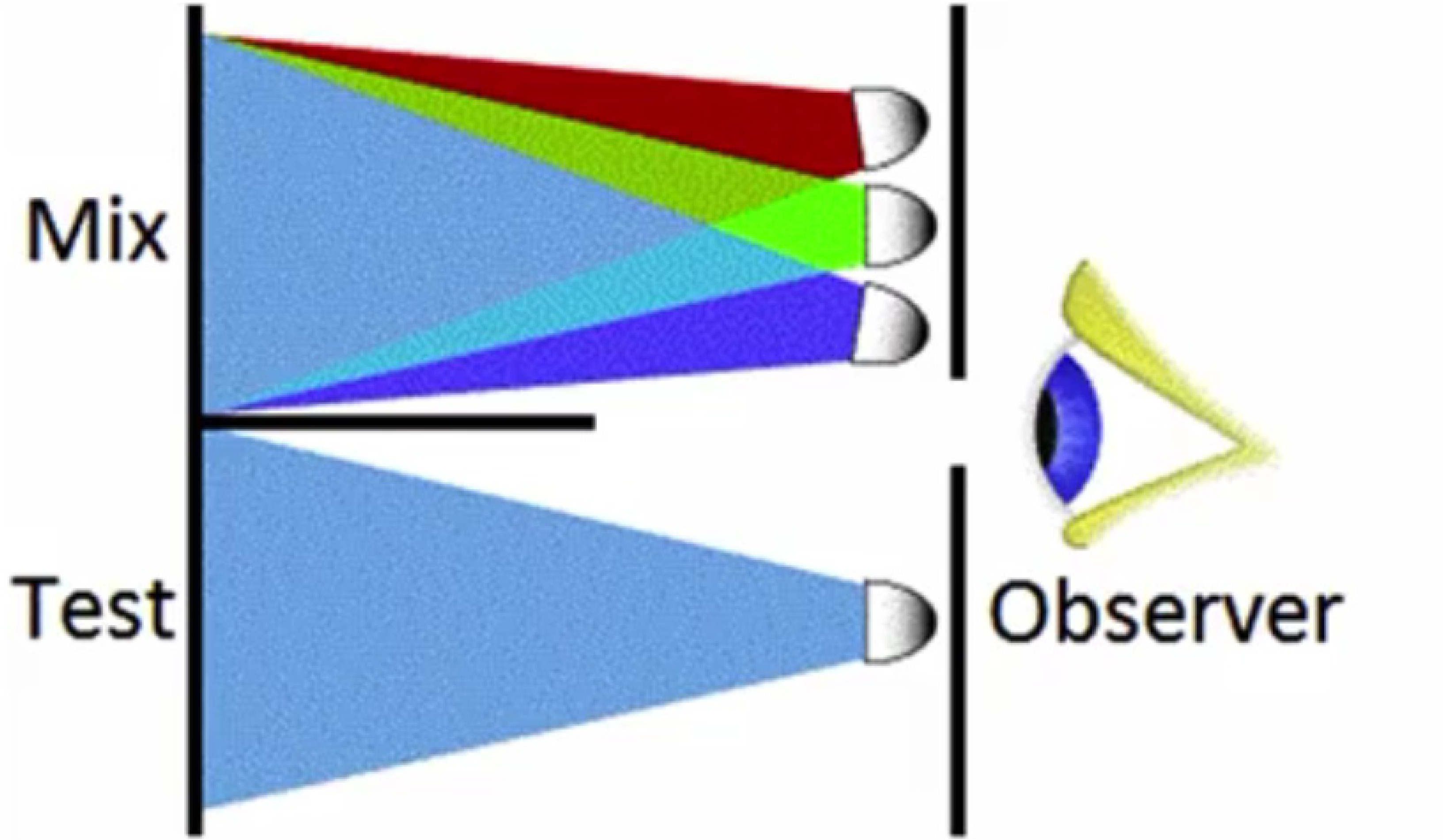
Use these three sensors to describe other colors?



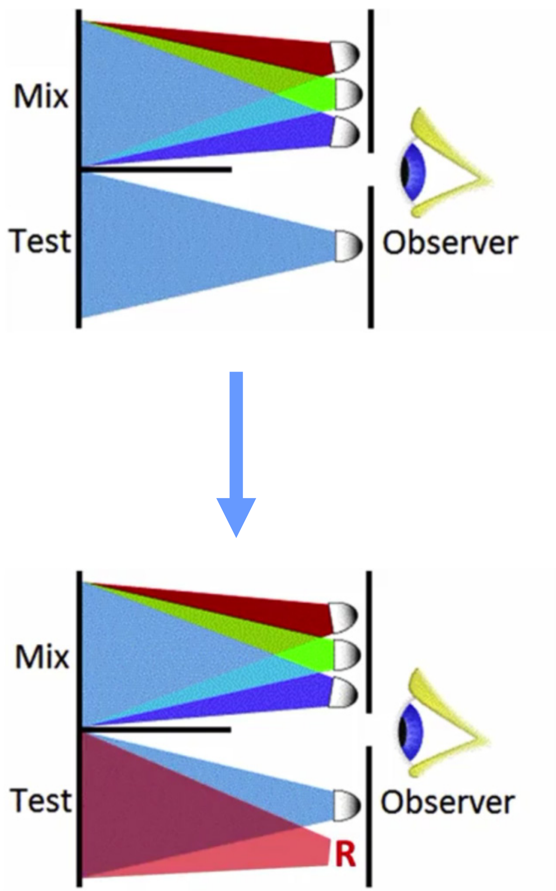
$$L = \int_{380}^{740} l(\lambda) \times E(\lambda)\, d\lambda$$

$$M = \int_{380}^{740} m(\lambda) \times E(\lambda)\, d\lambda$$

$$S = \int_{380}^{740} s(\lambda) \times E(\lambda)\, d\lambda$$



Wright & Guild, 1920



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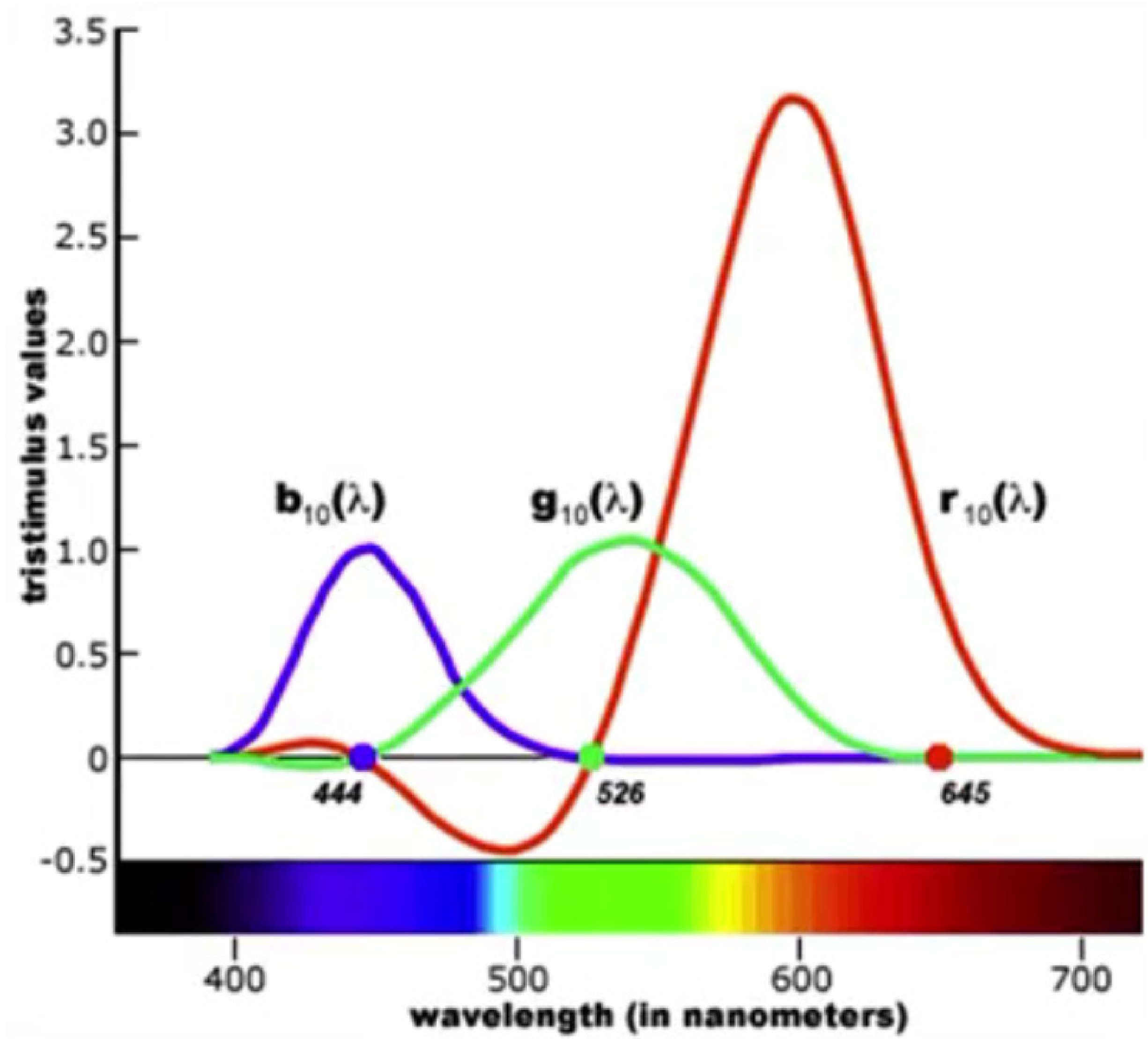

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CIE RGB Color Space:

- CIE = Comission International de l'Eclairage
- CIE amalgamated Wright & Guilt results mapped wavelengths with perceived color.
- **Result**: CIE RGB color space.

$$R = \int_{380}^{740} r(\lambda) \times E(\lambda)\ d\lambda \qquad G = \int_{380}^{740} g(\lambda) \times E(\lambda)\ d\lambda \qquad B = \int_{380}^{740} b(\lambda) \times E(\lambda)\ d\lambda$$

CIE XYZ Color Space:

- **Easy Computation:** Linear Transform of RGB
- **Decouples Color:** Y= Luminance, X,Z = Perceived Color
- Represents a **wide range** of colors

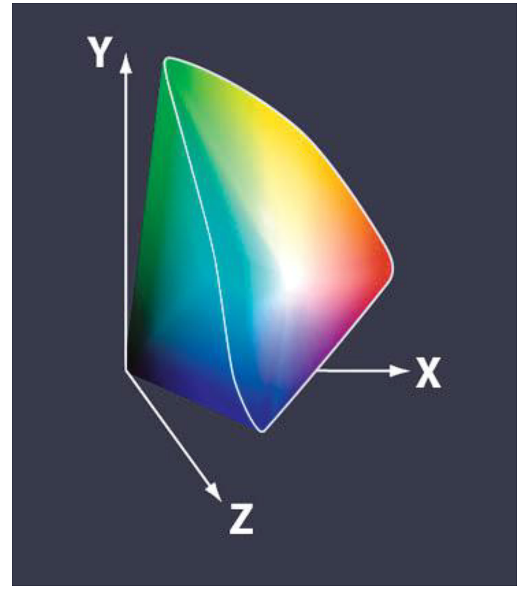
$$X = \int_{380}^{740} x(\lambda) \times E(\lambda)\ d\lambda \qquad Y = \int_{380}^{740} y(\lambda) \times E(\lambda)\ d\lambda \qquad Z = \int_{380}^{740} z(\lambda) \times E(\lambda)\ d\lambda$$

Chromaticity Coordinates

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

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

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



QUIZ!

Given two colors with CIEXYZ coordinates:

$$C_1 = (X_1, Y_1, Z_1) \qquad C_2 = (2 \cdot X_1, 2 \cdot Y_1, 2 \cdot Z_1)$$

How are their chromaticity coordinates related?

https://goo.gl/forms/dhVSV3IobbbiSyJM2

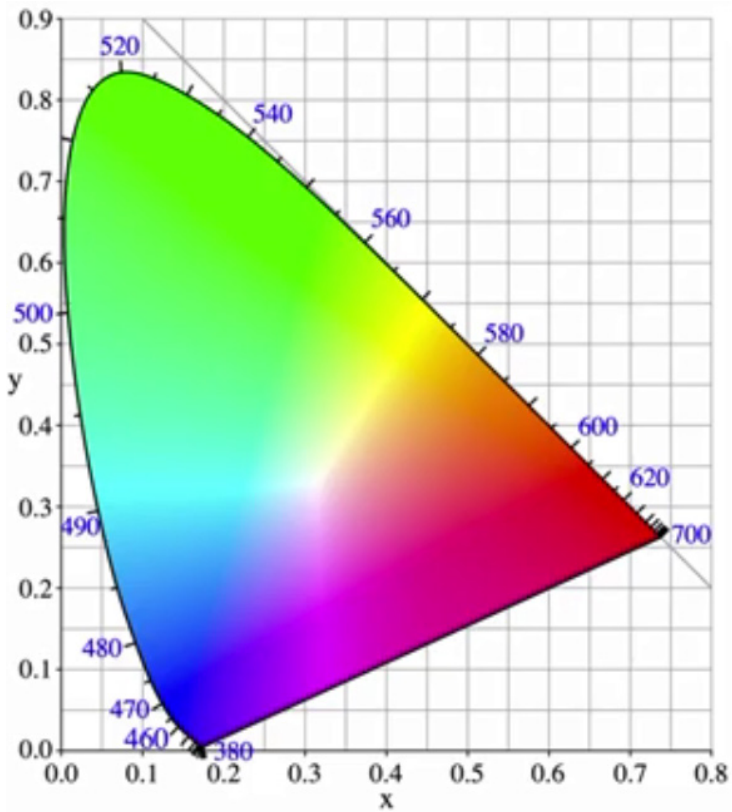
Chromaticity Diagram

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

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

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

$$\Rightarrow \quad x + y + z = 1 \quad \Rightarrow \quad z = 1 - (x + y)$$



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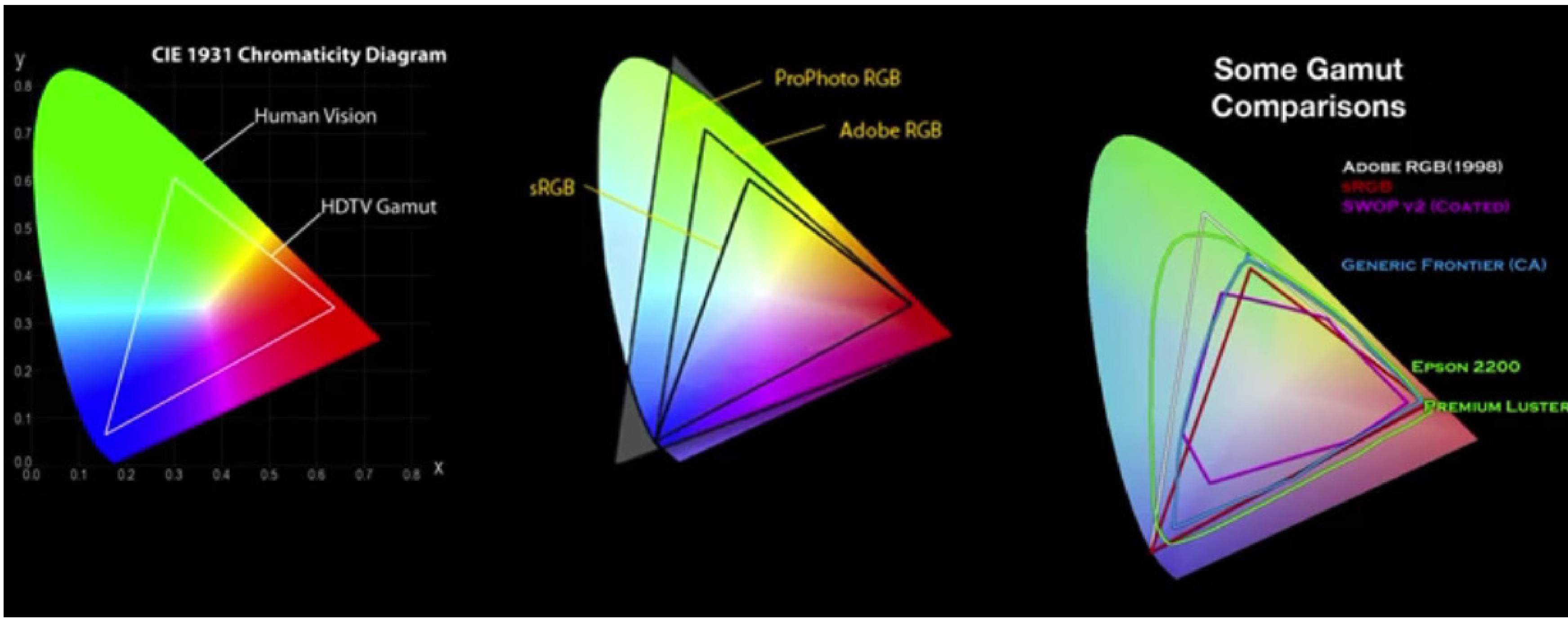


Limitations of CIExyz – Perceptualy Uniform Color Spaces

- Distance between two points in XYZ space or in the xy diagram is **not proportional** to the perceived difference between the colors corresponding to the points.
- A mixture of two lights in equal proportions will have chromaticity coordinates that **do not lie exactly at the middle** of the segment joining the chromaticities of the original two lights

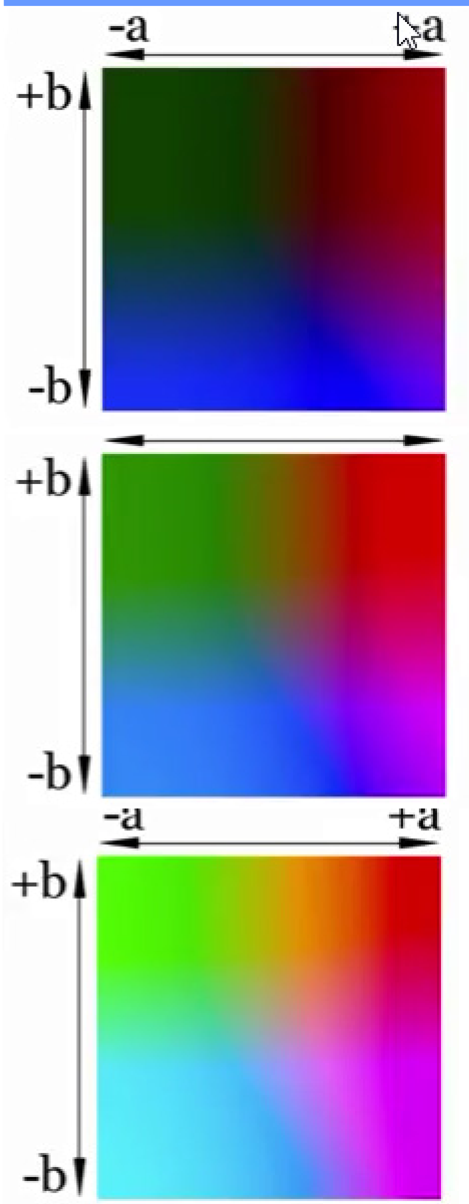
But we want Perceptual Uniformity!

In 1976, CIE introduced the **Lab color space**. Euclidean distance between two points in CIELAB space becomes proportional to the perceptual difference between the colors corresponding to those points.

You go from CIExyz to Lab through a complex non-linear transformation.

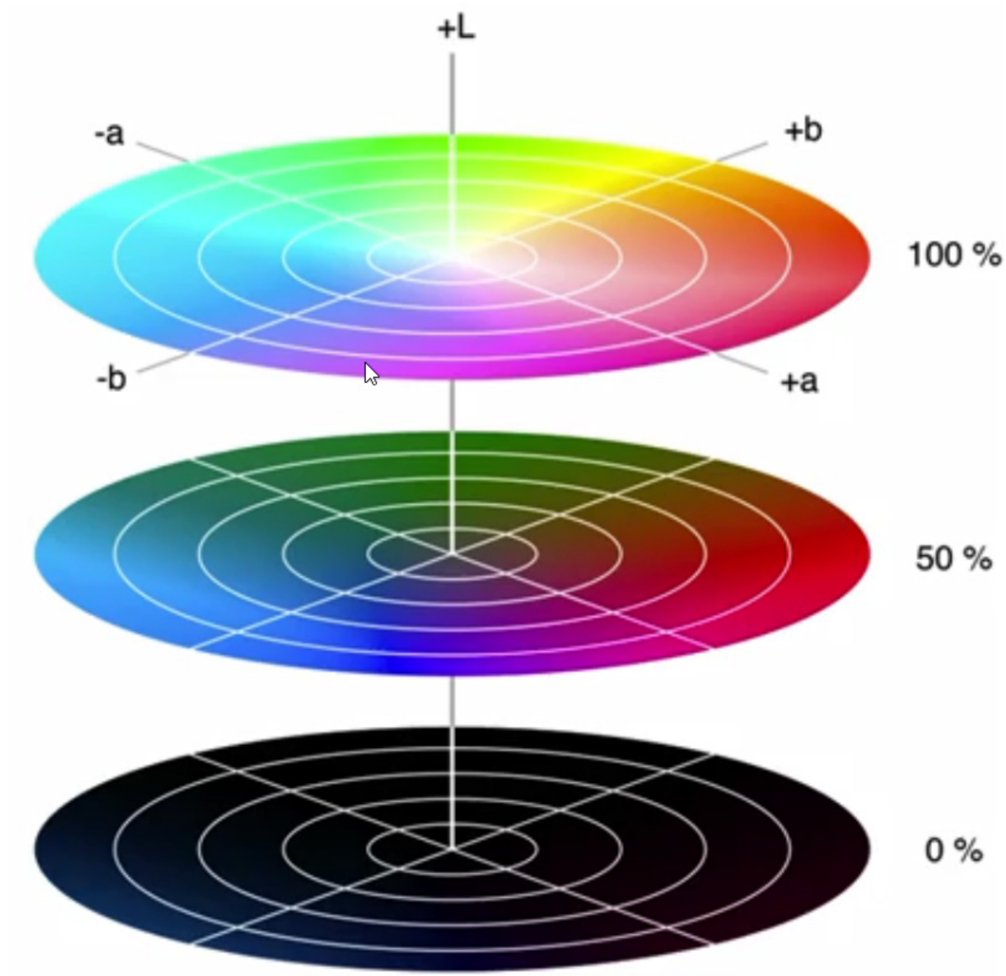
In CIELAB the chromaticity coordinates (a, b) can be positive or negative: $a > 0$ indicates redness, $a < 0$ greenness, $b > 0$ yellowness and $b < 0$ blueness.

3 - Color Spaces. Perceptually Uniform Color Spaces

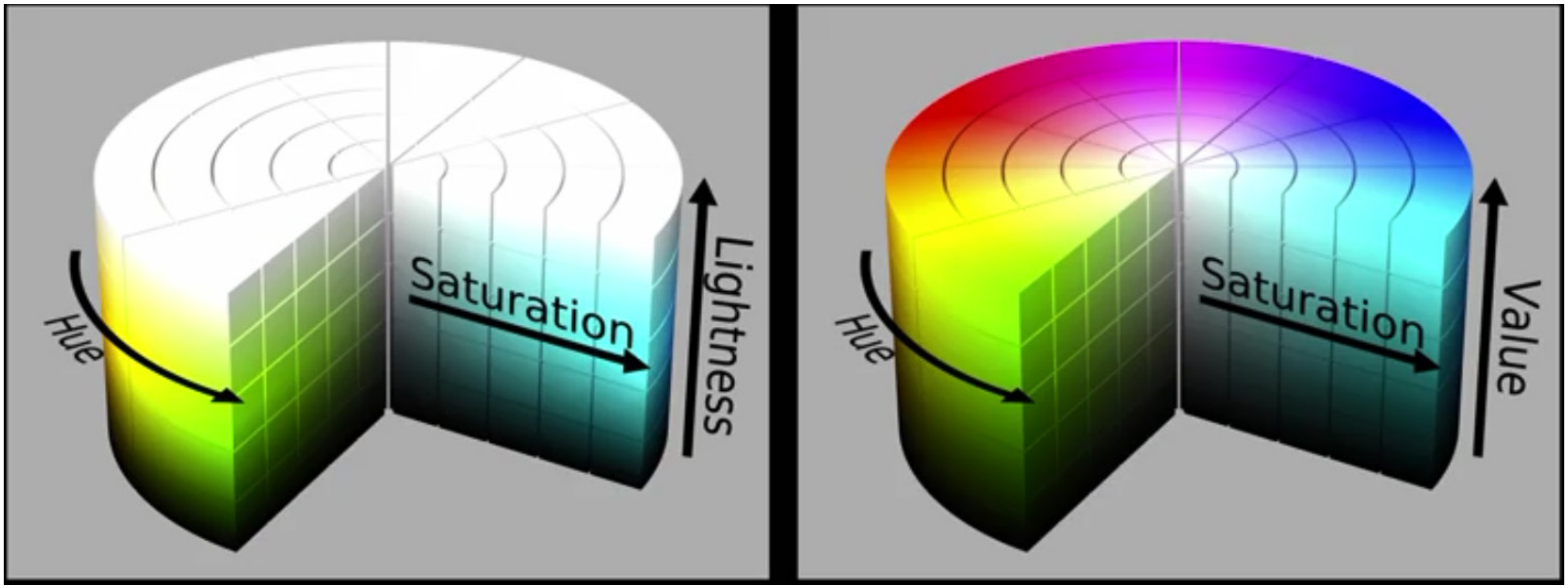


L increases

CIELAB COLOR SPACE

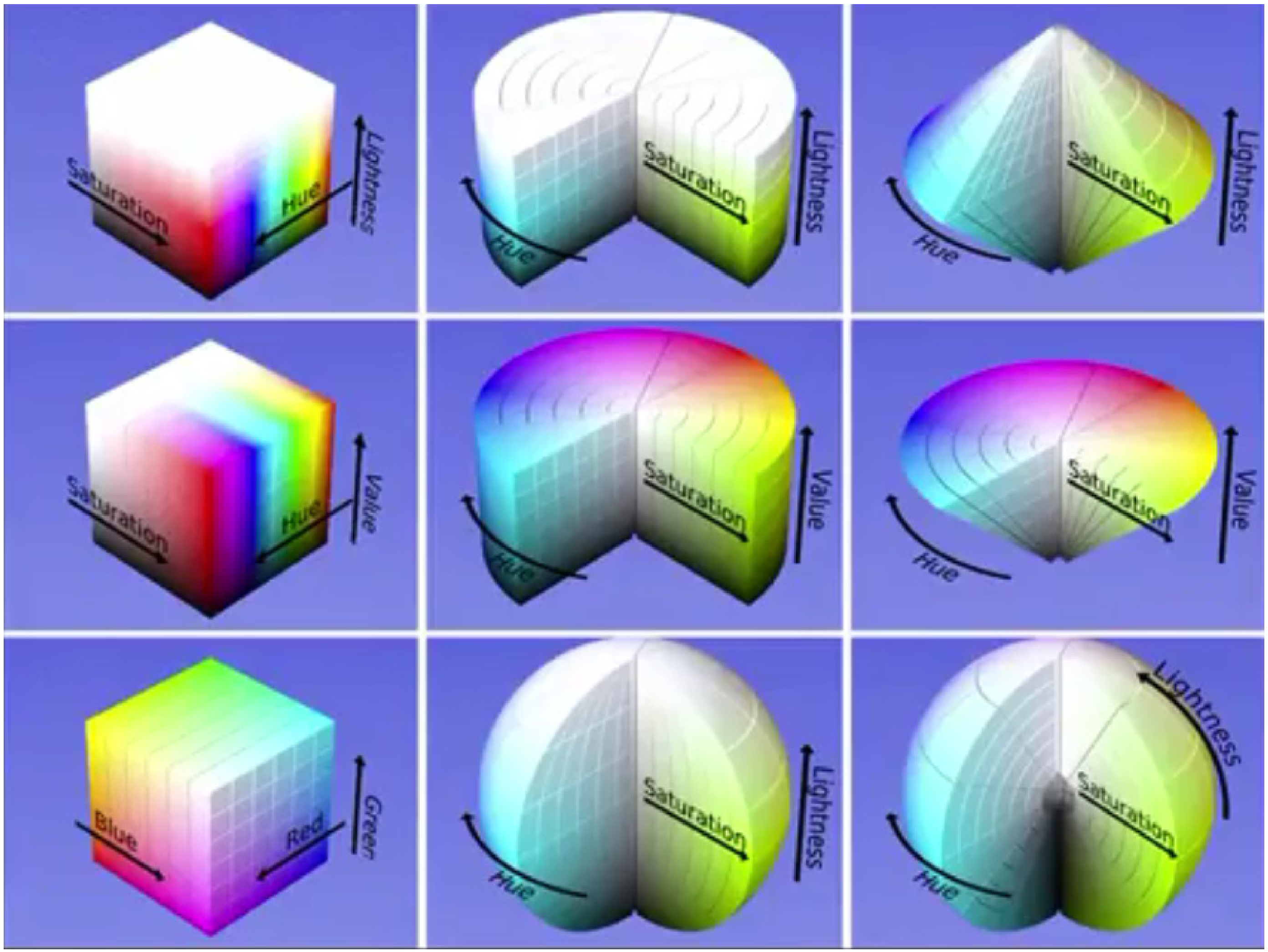


OTHER COLOR SPACES: HS*



QUIZ!
How would you expect a color with HSV coordinates (h,s,v) to change if we multiply h by 2?
Link: https://goo.gl/forms/6Ny9LfxONAf8CCPq2

EXTENSIONS


Saturation
Hue
Lightness
Saturation
Hue
Lightness
Saturation
Hue
Lightness
Saturation
Hue
Value
Saturation
Hue
Value
Saturation
Hue
Value
Blue
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Hue

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From pixels to superpixels

From pixels to superpixels

From pixels to superpixels

From pixels to superpixels

Clear your mind for a moment, and consider how we represent images.

Why pixels? Why square unitary regions within a rectangular grid?

It is a **limitation** of our HW/SW, but it does not come from the HVS.

Pixels do not carry any kind of semantic information with them.

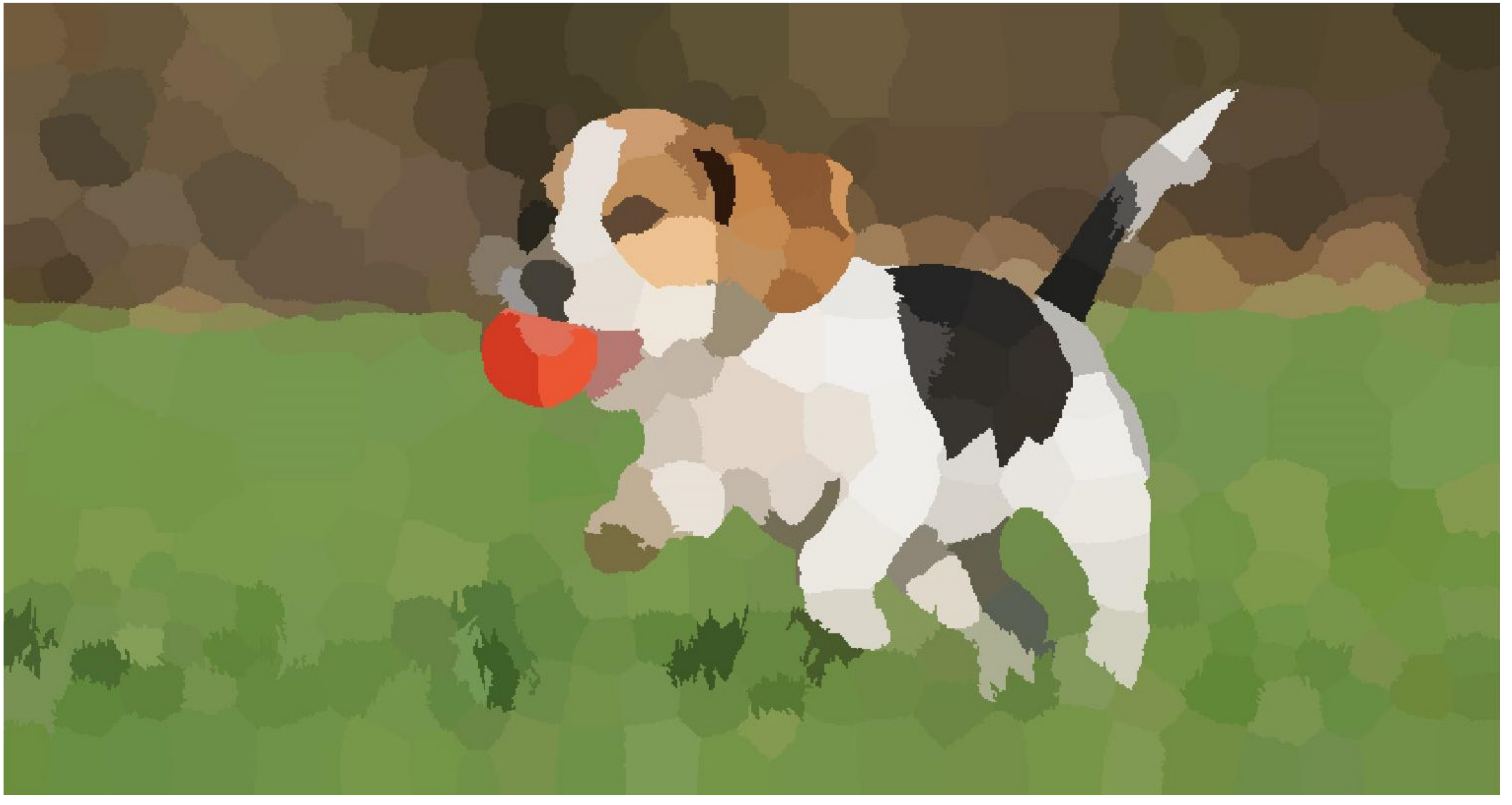
Superpixels are methods for locally grouping pixels such that the resultiug super-atomic representations contain perceptually meaningful information.

Superpixels capture image redundancy, provide a convenient primitive from which to compute image features, and reduce the complexity of subsequent image processing tasks.

There are many approaches to generating superpixels. You have already studied some of them! mean shift, quick shift, watershed.

From pixels to superpixels

From pixels to superpixels



SLIC superpixels

SLIC stands for Simple Linear Iterative Clustering, quite a descriptive name!

Simple to use: only one parameter (number of wanted superpixels)

Perceptually meaningful: it clusters pixels in the xy-Lab color space

Memory-efficient: The complexity of SLIC is linear in the number of pixels in the image, O(n)

Let's see the algorithm:

$$d_c = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}$$

$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2},$$

$$D' = \sqrt{\left(\frac{d_c}{N_c}\right)^2 + \left(\frac{d_s}{N_s}\right)^2}.$$

Algorithm 1. SLIC superpixel segmentation

```
/* Initialization */
Initialize cluster centers C_k = [l_k, a_k, b_k, x_k, y_k]^T by sampling
pixels at regular grid steps S.
Move cluster centers to the lowest gradient position in a 3 × 3
neighborhood.
Set label l(i) = −1 for each pixel i.
Set distance d(i) = ∞ for each pixel i.

repeat
  /* Assignment */
  for each cluster center C_k do
    for each pixel i in a 2S × 2S region around C_k do
      Compute the distance D between C_k and i.
      if D < d(i) then
        set d(i) = D
        set l(i) = k
      end if
    end for
  end for
  /* Update */
  Compute new cluster centers.
  Compute residual error E.
until E ≤ threshold
```

Color Constancy

When we light a surface of reflectance $R(\lambda)$ with an illuminant of spectrum $I(\lambda)$, we receive a radiance $E(\lambda)$. However, we can usually tell apart colors regardless of the color of the illuminant. This ability is **Color Constancy**. Link

Land's Experiments

Reminder

Irradiance $I(\lambda)$

Reflectance $R(\lambda)$

Radiance $E(\lambda)$

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

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6 - Introduction to Computational Image Processing

3D World Scene

Light

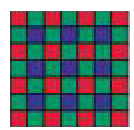
Aperture

Exposure

Focus

Color Processing

Demosaicking



White Balance

Display on Device

2D Representation

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Image Composition

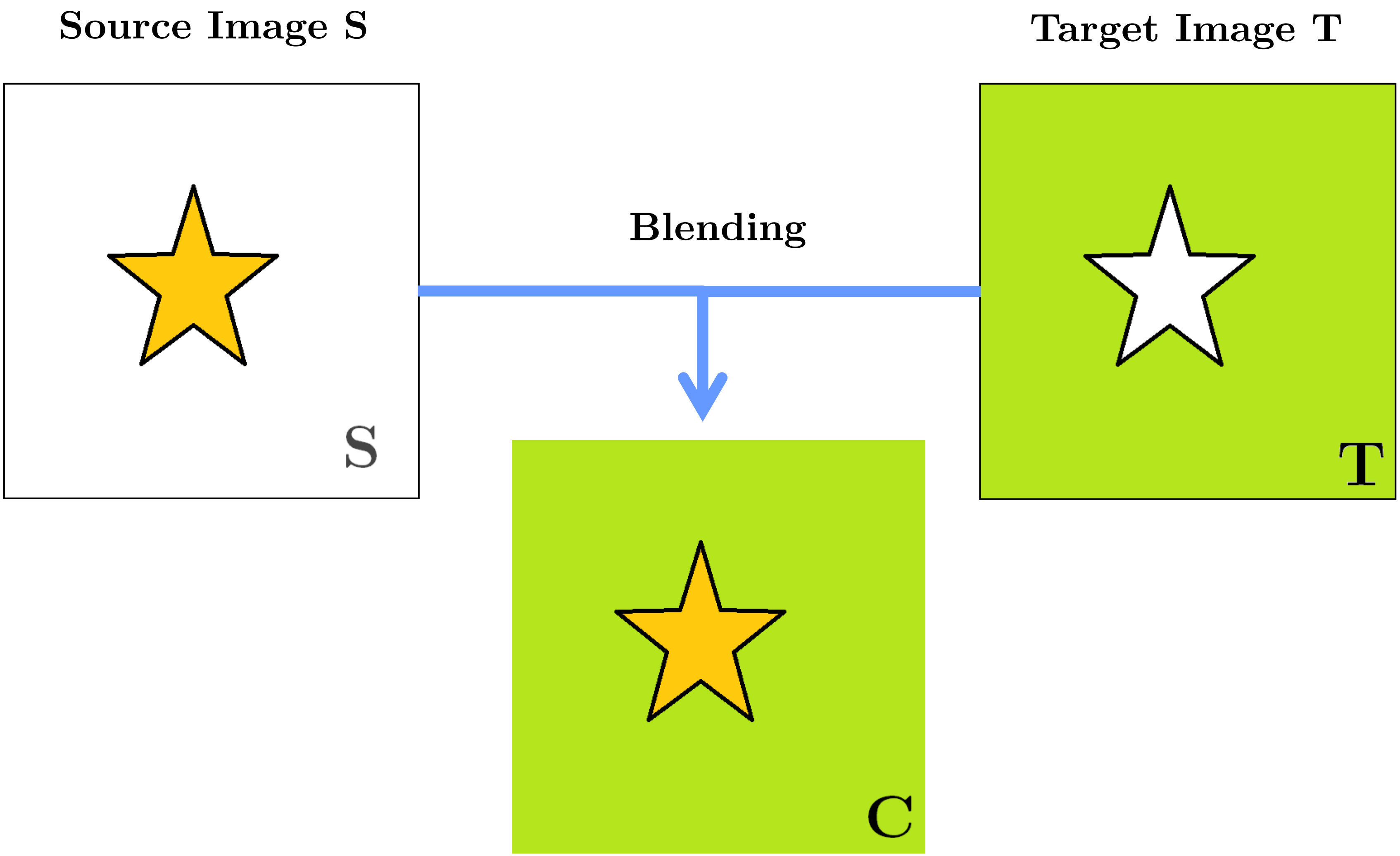
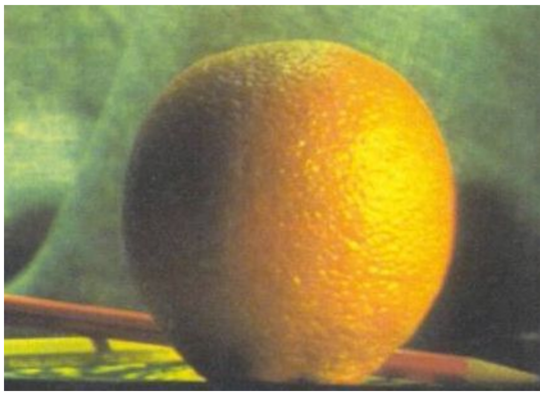


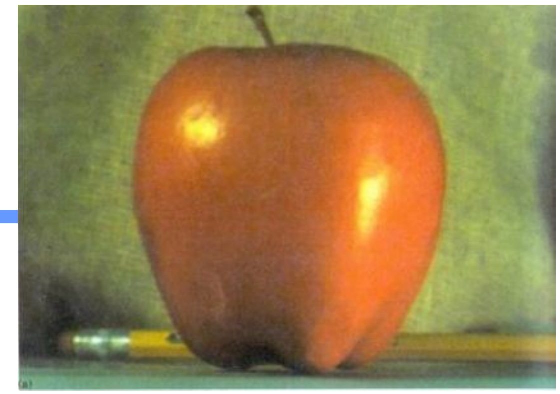
Image Composition

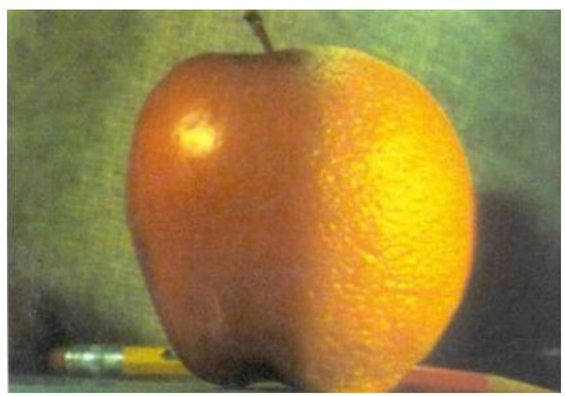
Source Image S

Target Image T



Blending





The Orangapple!

Image Composition

- **Naive Approach**: Given a binary mask **M**, compute **C** $=$ **M** $\cdot$ **S** $+$ **(1-M)** $\cdot$ **T**

This gives bad results, since the seam between **S** and **T** will be visible

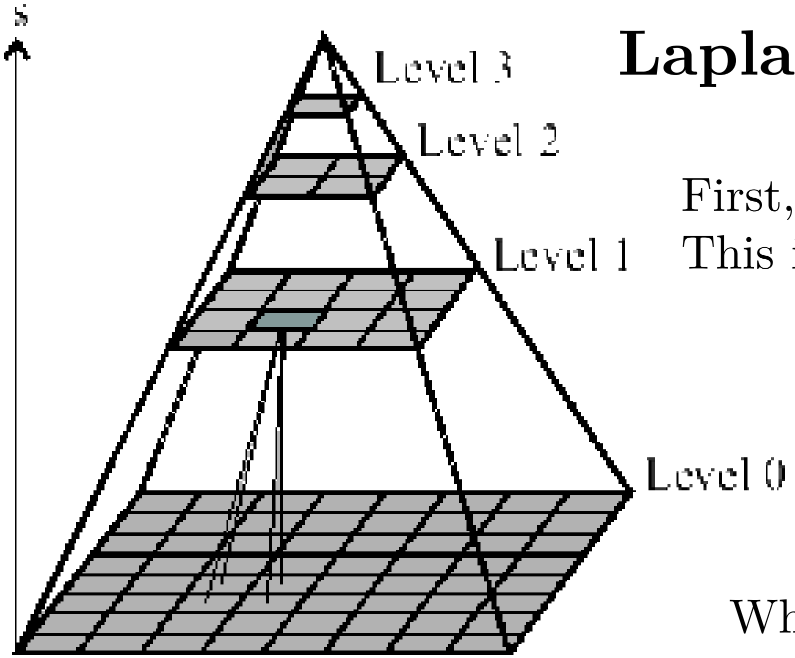
How to **"hide"** that seam?

- **2nd Naive Approach**: Given a binary mask **M**, blur its edges and then blend:

$$\mathrm{C} = \mathbf{G}_{\sigma} * M \cdot \mathrm{S} + (1 - \mathbf{G}_{\sigma} * M) \cdot \mathrm{T}$$

- **Better Approach**: Multi-resolution blending with **Laplacian Pyramids**

Merge different frequencies separately



Laplacian Pyramids

First, imagine you want to build a **Gaussian pyramid**. This is a hierarchy of images. Given a kernel K_σ,

$$\boxed{\begin{aligned} G_0 &= \text{Image at original resolution} \\ G_i &= (K_\sigma * G_{i-1}) \searrow 2 \end{aligned}}$$

Which is basically a series of blurrier, smaller images

Now you want to find relevant edges at different scales.
Look at the DoG (Difference of Gaussians = Laplacian) at each scale.
Which means you need to build the **Laplacian Pyramid**:

$$\boxed{L_i = G_i - K_\sigma * G_i}$$

Laplacian Pyramids

Reconstruction : From the Laplacian decomposition, you can come back to the original image by upsampling and adding back edges iteratively to the smallest image:

$$\boxed{I = \sum_{i=1}^{N} L_i \nearrow^{2}, \qquad L_N = G_N \qquad \mathbf{(1)}}$$

Laplacian Image Blending

We compute a Gaussian Pyramid for the target and the source, $L_i^T,\, L_i^S,\;\; i = 1, ..., N$

We compute a Gaussian Pyramid for the mask, G_i^M

We compute a Laplacian Pyramid for the composite image,

$$L_i^T = G_i^M \cdot L_i^S + (1 - G_i^M) \cdot L_i^T, \quad i = 1, ..., N$$

Apply the reconstruction formula **(1)** to the composite Laplacian Pyramid

Image Matting

Image Matting

Image Matting

Image Matting

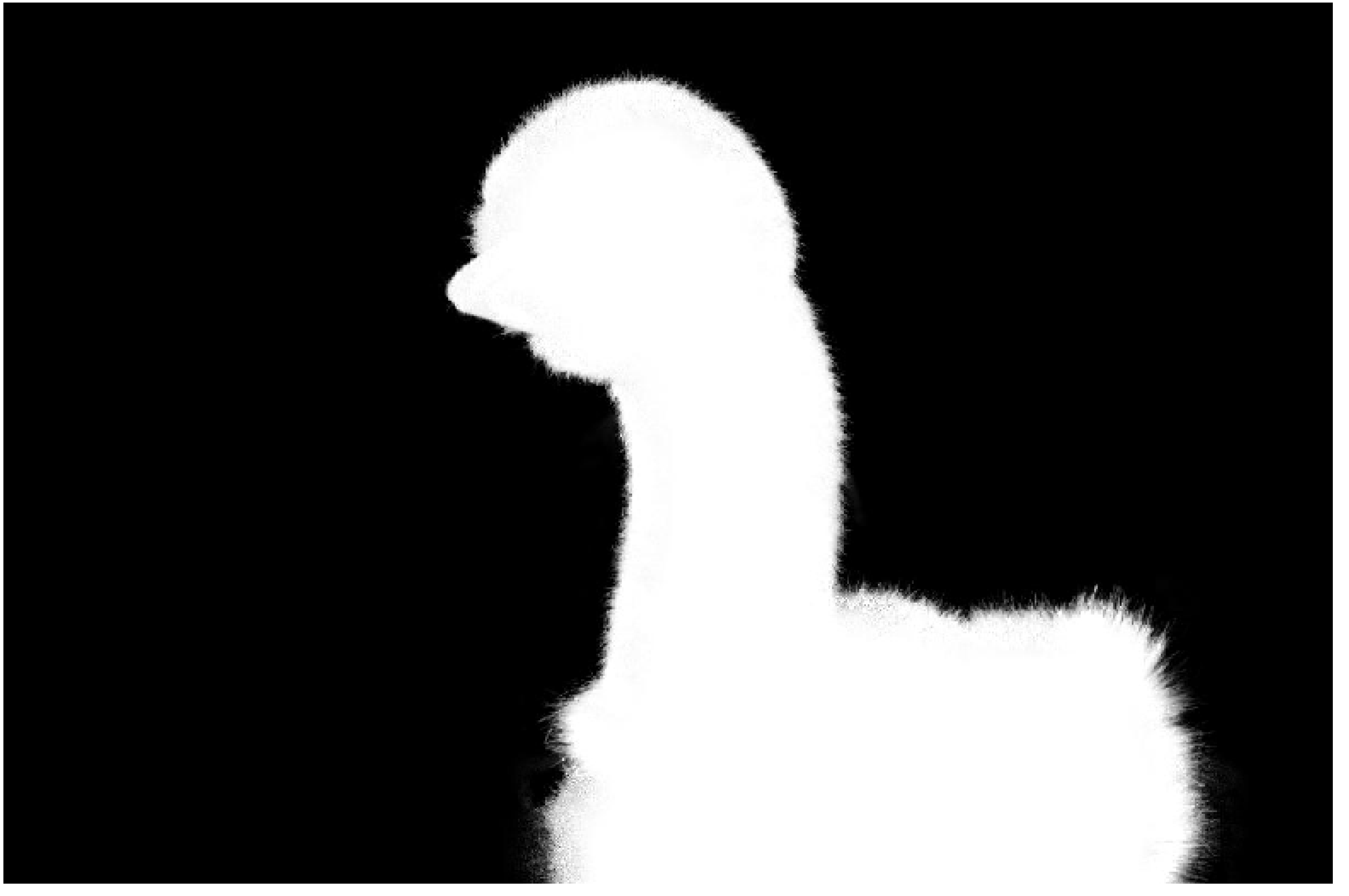
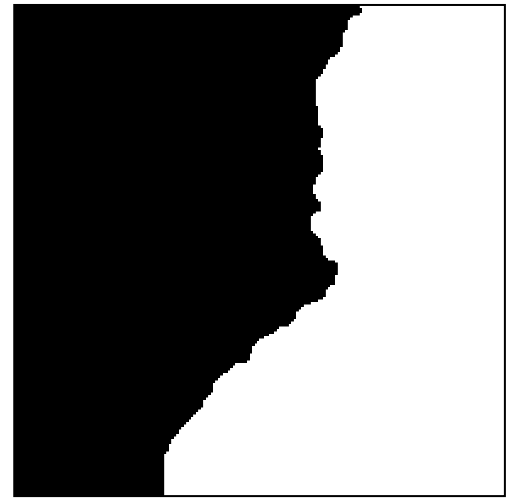


Image Matting



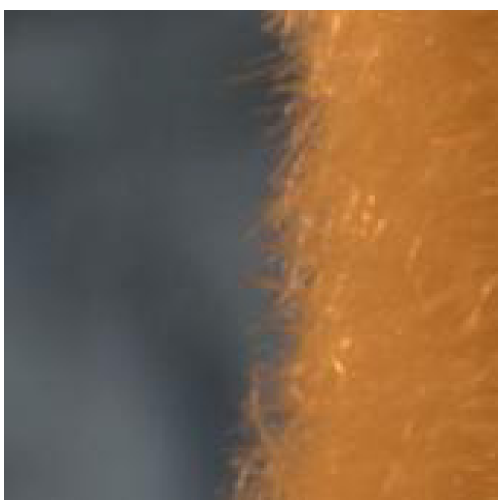


Image Matting