University of Porto – Faculty of Engineering

Computer-Aided Diagnosis (DACO)

TLX – Advanced Image Processing and Enhancement

Oct/2017

Adrian Galdran - Post-Doctoral Researcher
Biomedical Imaging Lab – INESC TEC Porto (Portugal)
http://bioimglab.inesctec.pt/

U.PORTO

0. Overview

1. **Introduction to the Image Acquisition Pipeline**
    1. The Human Visual System. Color Perception. Color Spaces
    2. How are Images built out of Light?
2. **Improving the Quality of Digital Images**
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    2. **Image Enhancement I**: Exposure Correction. Contrast Enhancement: Histogram Equalization, CLAHE.
    3. **Image Enhancement II:** Filtering & Image Restoration:
        1. Image Filtering
        2. Denoising, Deblurring, Illumination Correction
        3. Filtering in the Frequency Domain
4. **Project Description:**
    1. Skin Lesion Analysis
    2. Artery/Vein Classification

1. Introduction to the Image Acquisition Pipeline

1.1 The Human Visual System. Color Perception. Color Spaces

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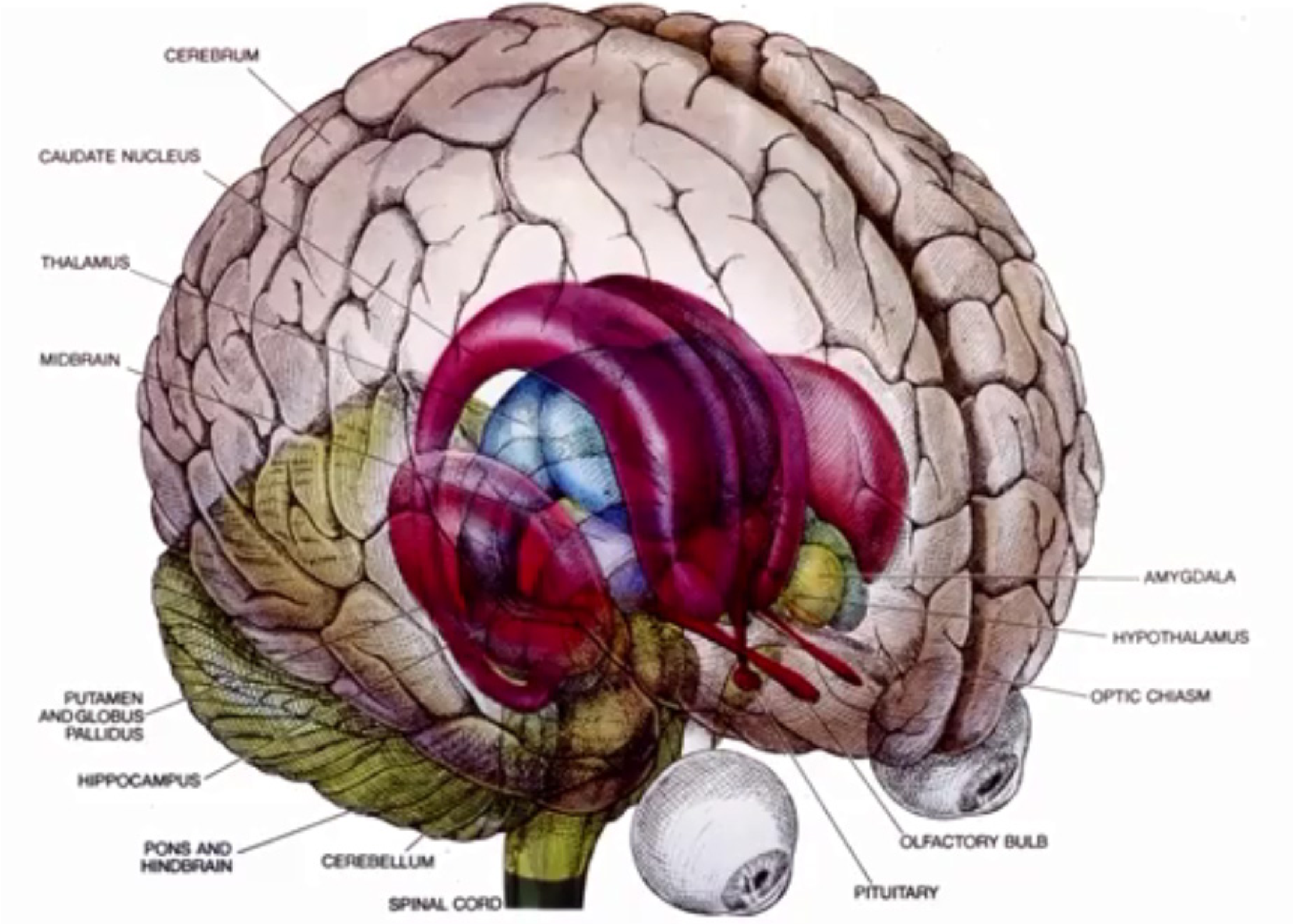
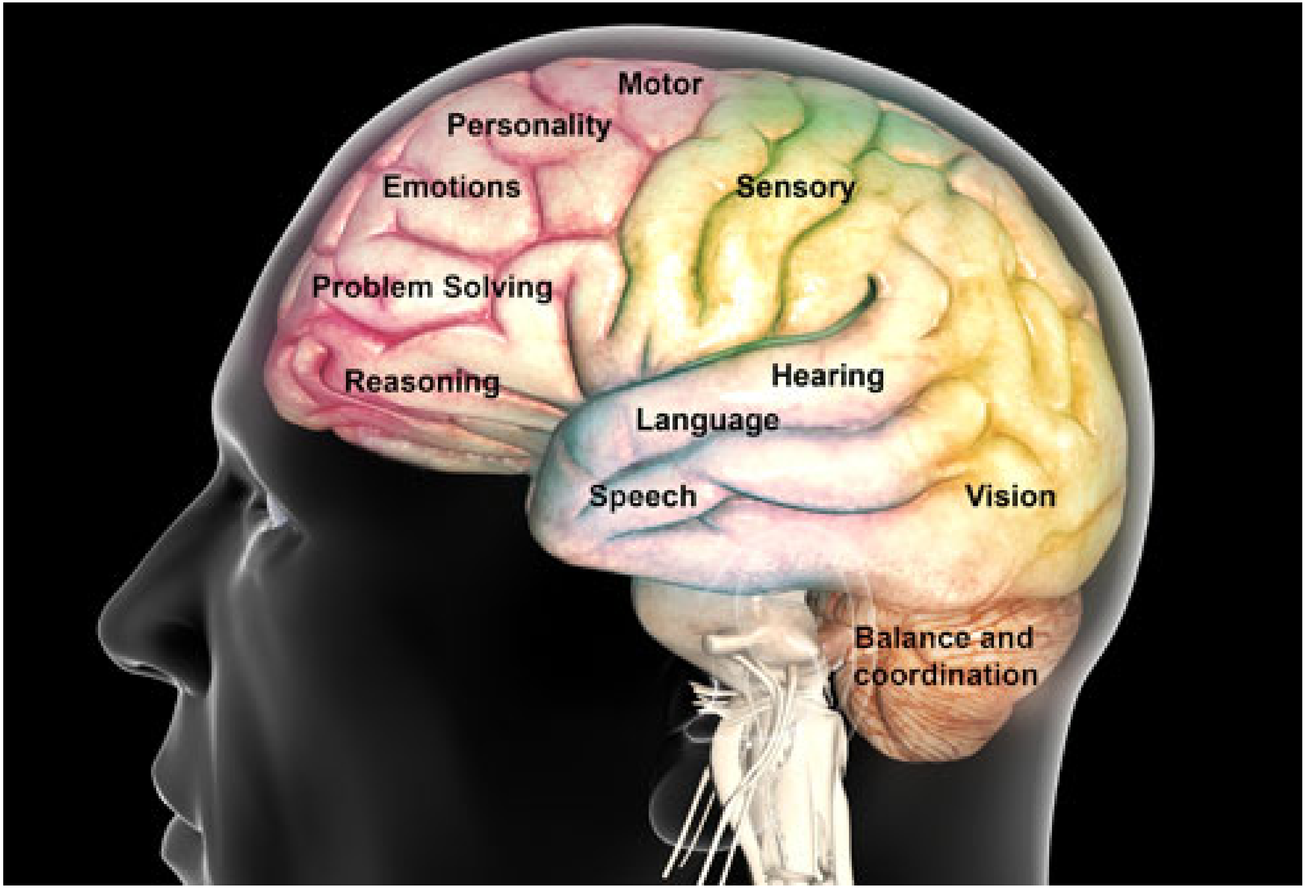
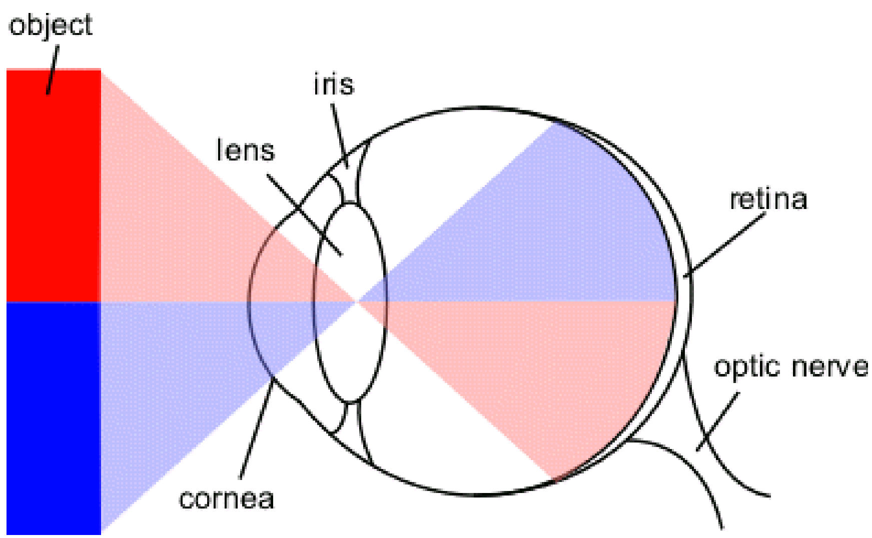
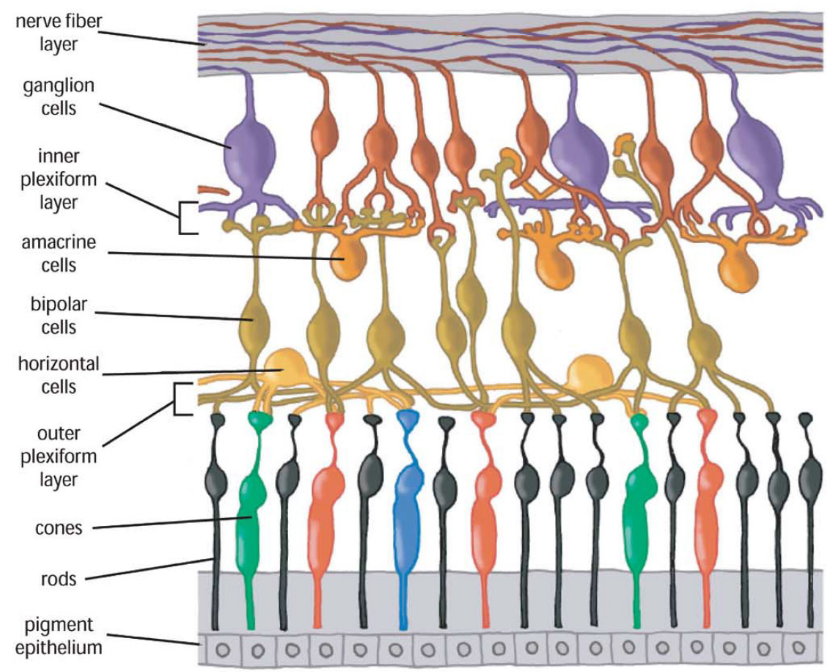



Motor
Personality
Emotions
Sensory
Problem Solving
Reasoning
Hearing
Language
Speech
Vision
Balance and coordination

Humans see colors thanks to photoreceptors cells present in the retina:

- **cones** (~7 millions): sensitive to colors; low overall sensitivity
- **rods** (~75-150 millions): not sensitive to colors; high overall sensitivity

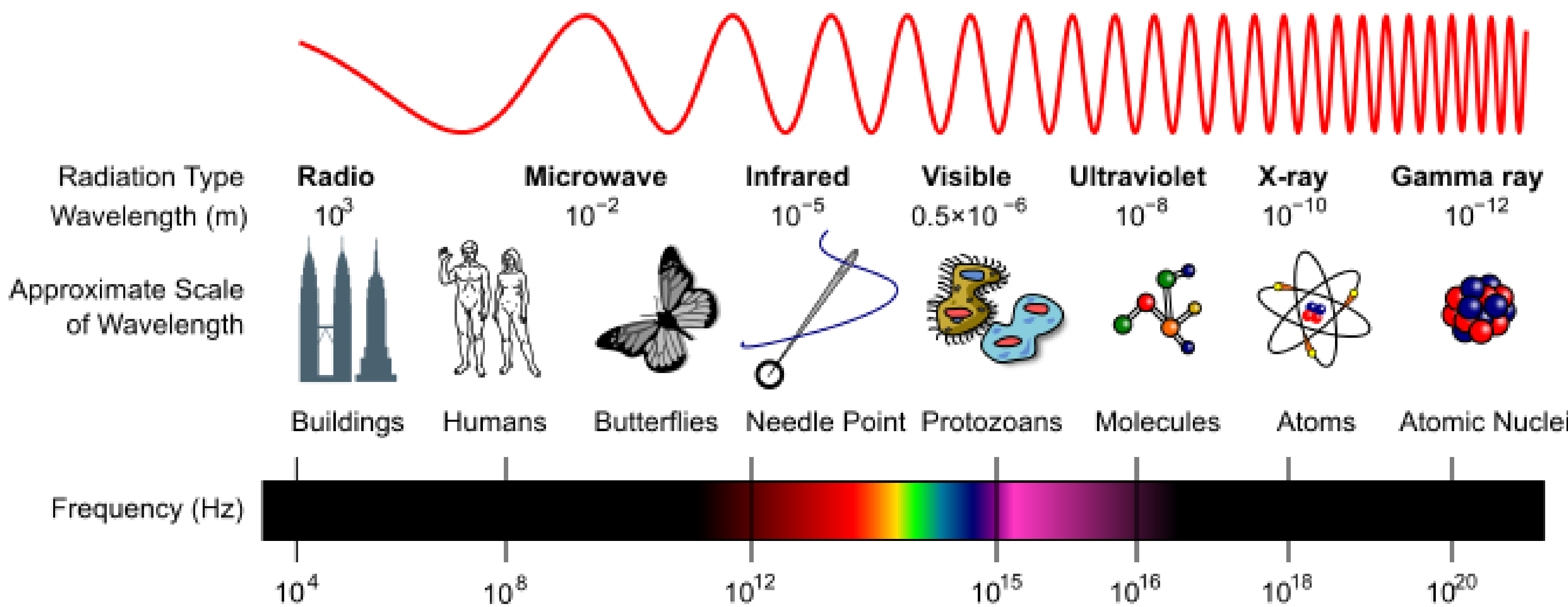




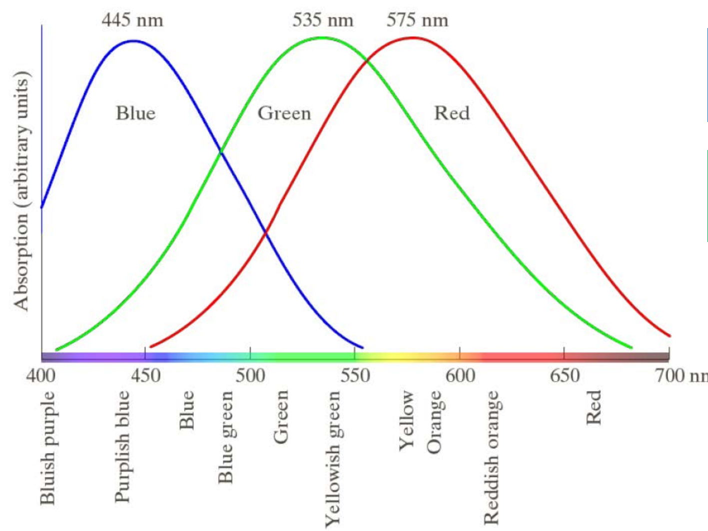
1.1 The Human Visual System. Color Perception. Color Spaces

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).

1.1 The Human Visual System. Color Perception. Color Spaces

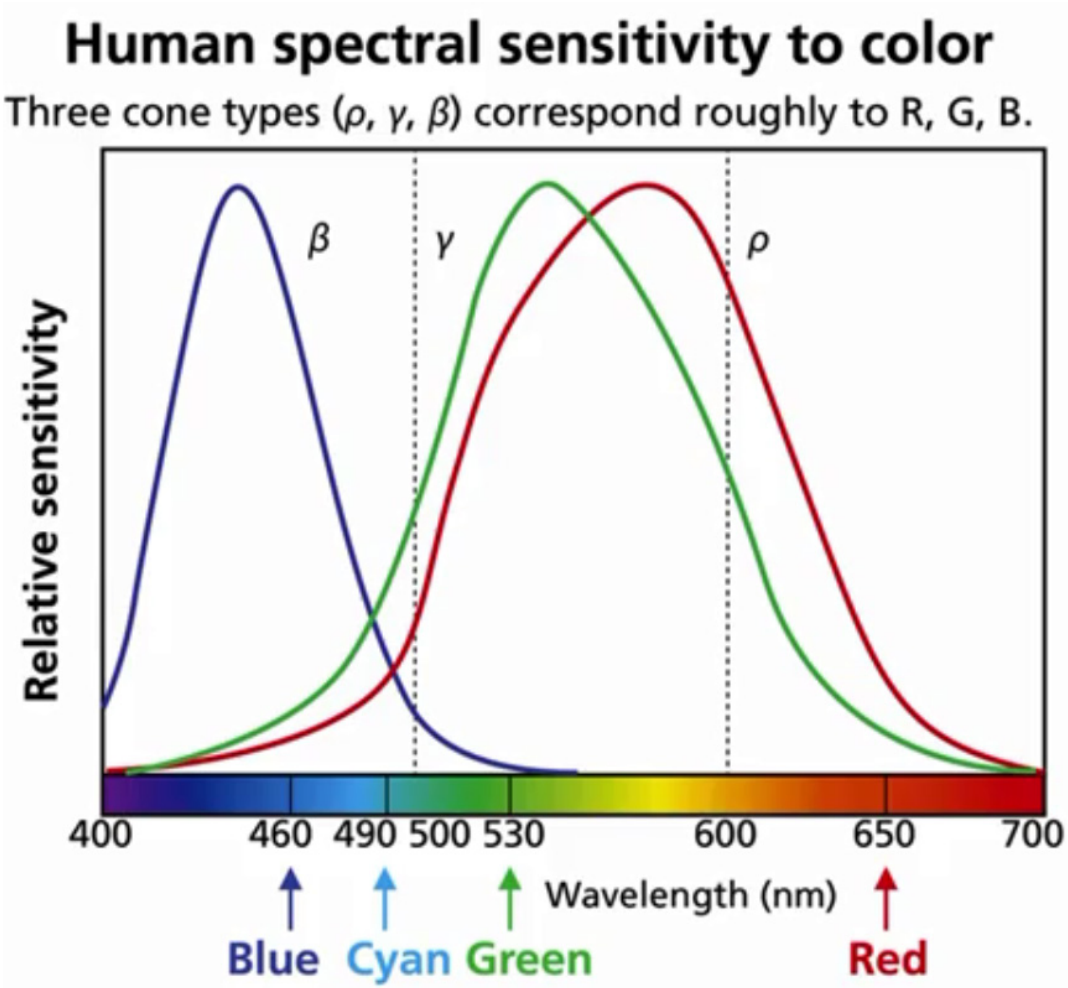


Each perceived color results from the activation of the cones belonging to the different types



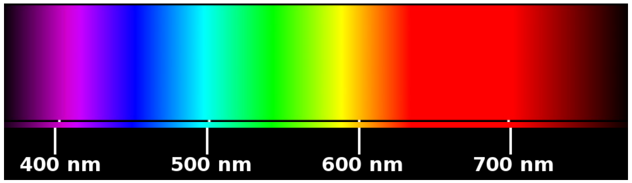
You do like this

You do not like this



Konig, XIX century

Use these three sensors to describe other colors

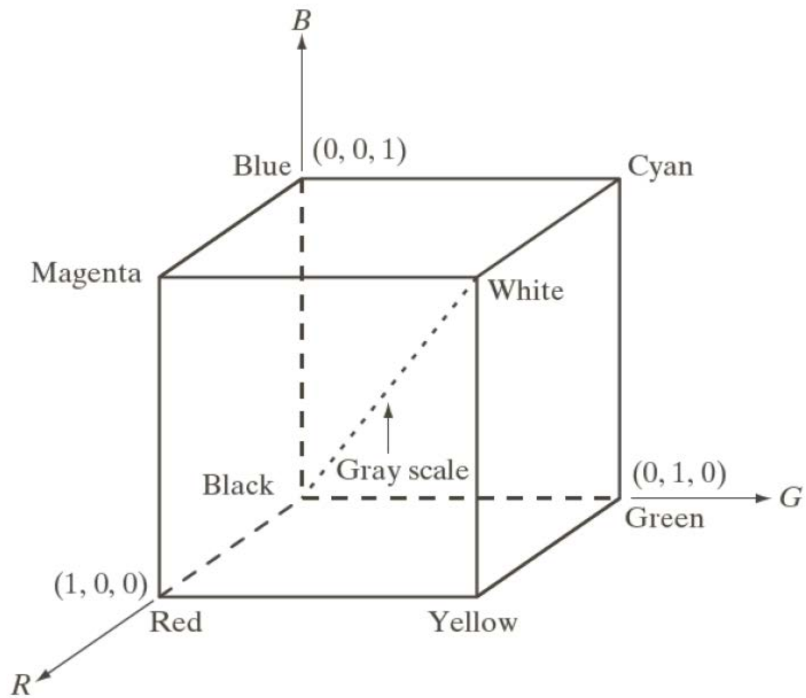


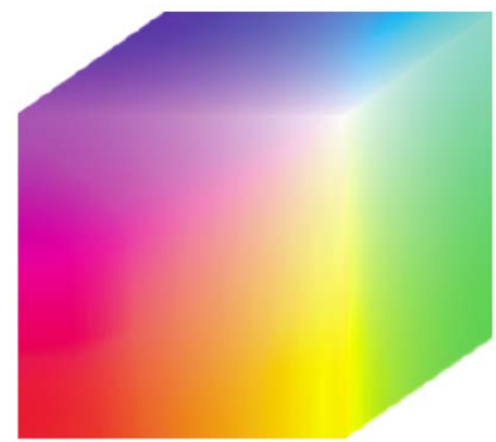
$$L = \int_{380}^{740} l(\lambda) \times E(\lambda)\, d\lambda$$

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

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

Each color can then be represented by its **primary** spectral components of R, G and B based on a **Cartesian** coordinate system





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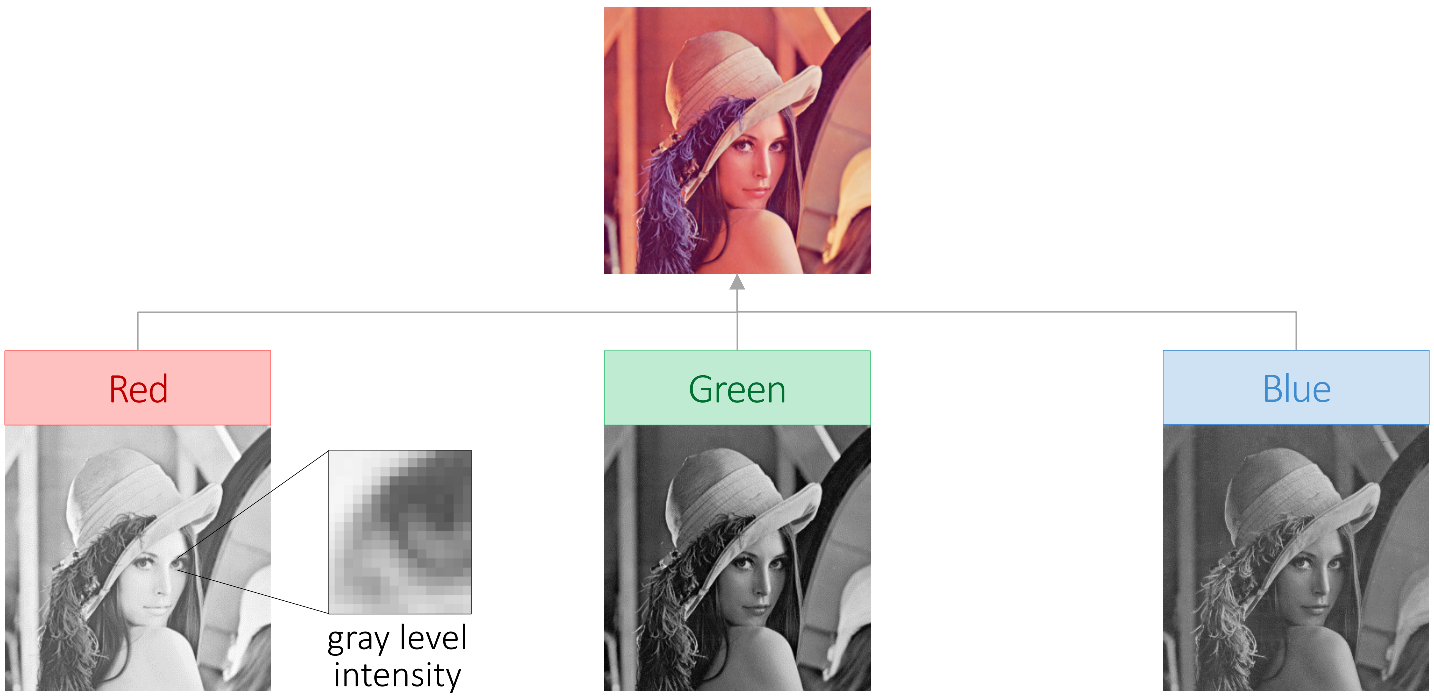


Perceptualy Uniform Color Spaces

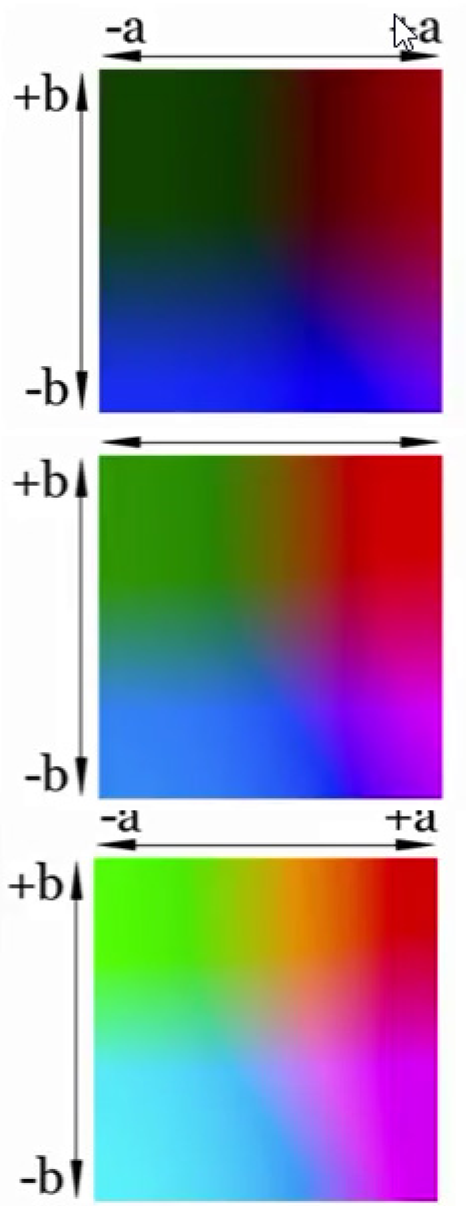
Humans do not refer to the color of an object by giving the percentage of each of the RGB components of its color

Perceptually Uniform Color Spaces separate brightness from chromaticity in a way that is consistent with human perception.

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.

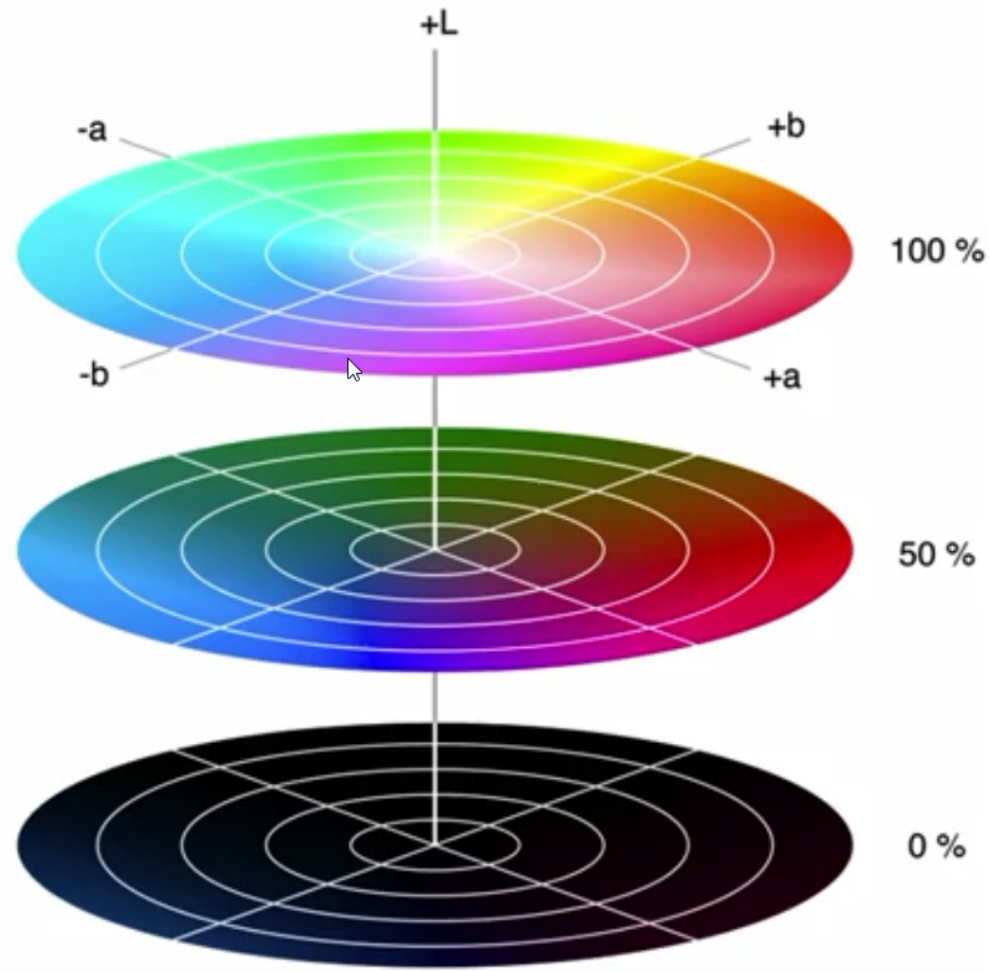
In CIELAB the chromaticity coordinates (a, b) can be positive or negative: $a > 0$ indicates redness, $a < 0$ greenness, $b > 0$ yellowness and $b < 0$ blueness.

1.1 The Human Visual System. Color Perception. Color Spaces



L increases

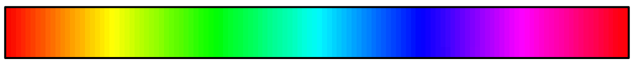
CIELAB COLOR SPACE



OTHER COLOR SPACES: HS*

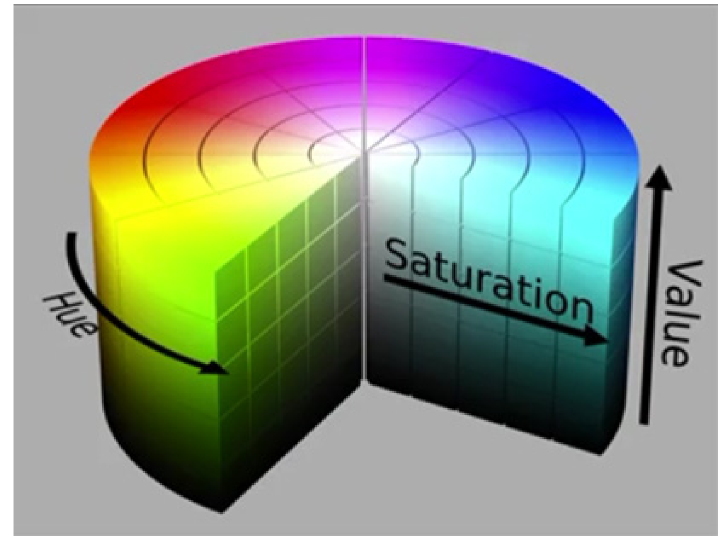
Describe a color through:

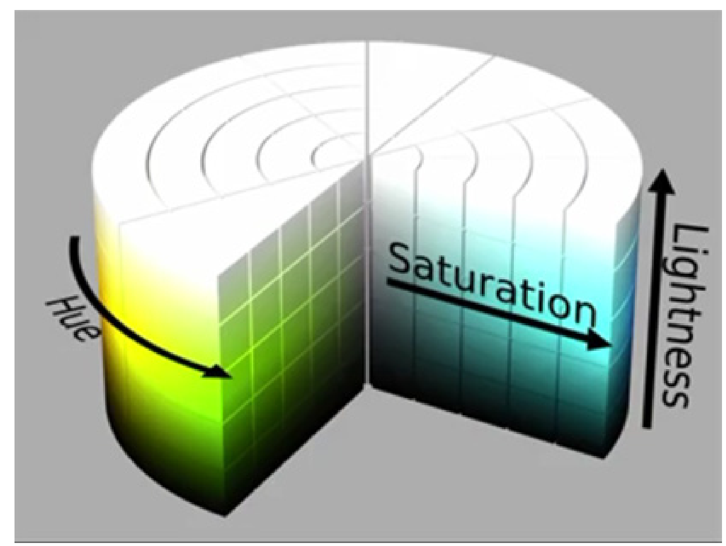
- **hue** (H): the dominant color



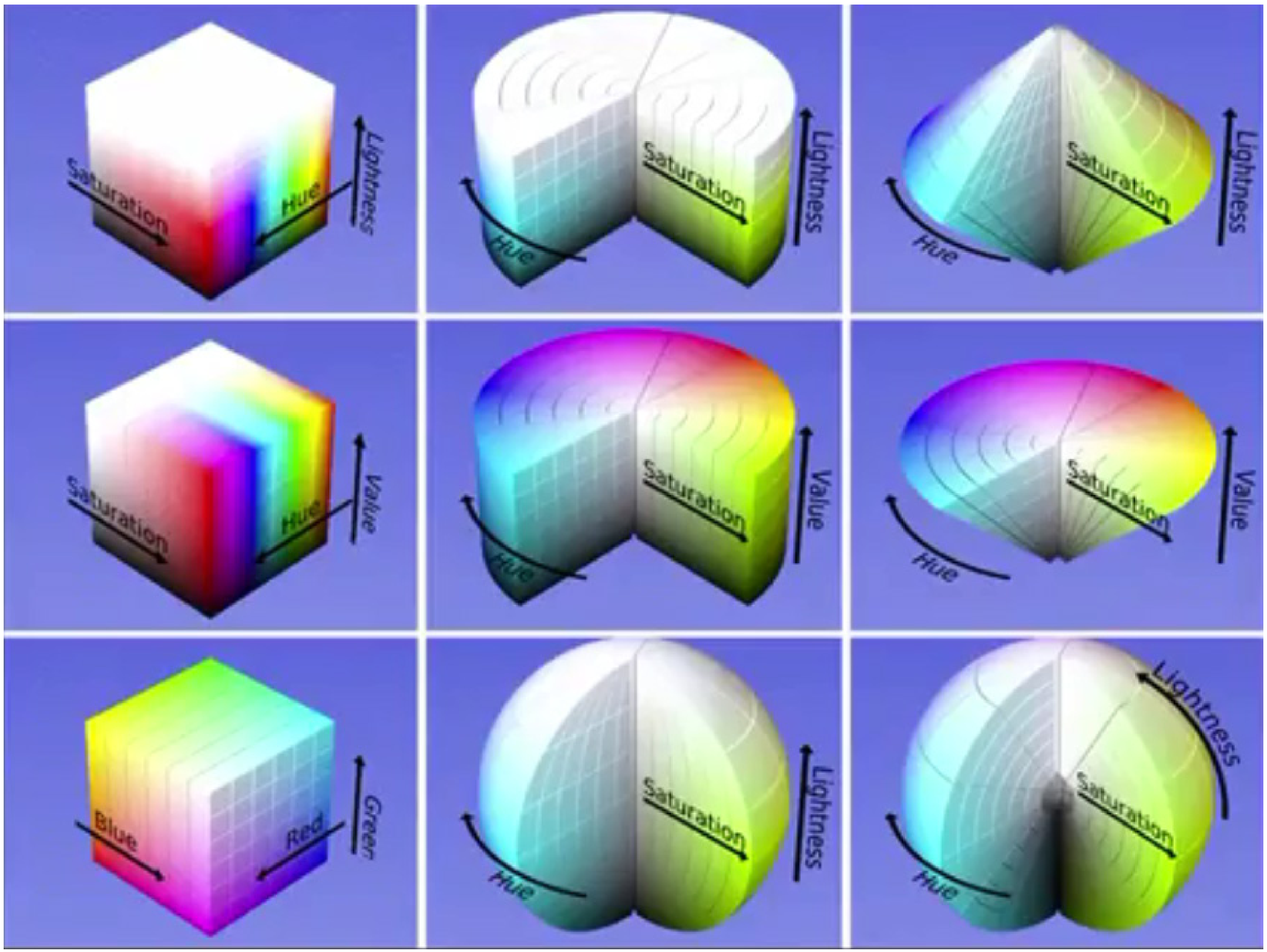
- **saturation** (S): color purity, quantity of white (pink is half saturated red)

- **brightness** (B/V), or *lightness* (L), or *intensity* (I): amount of light





EXTENSIONS


Saturation
Hue
Lightness
Saturation
Lightness
Hue
Saturation
Lightness
Hue
Saturation
Hue
Value
Saturation
Value
Hue
Saturation
Value
Hue
Blue
Red
Green
Saturation
Lightness
Hue
Lightness
Saturation
Hue

1.2 How are Images built out of Light?

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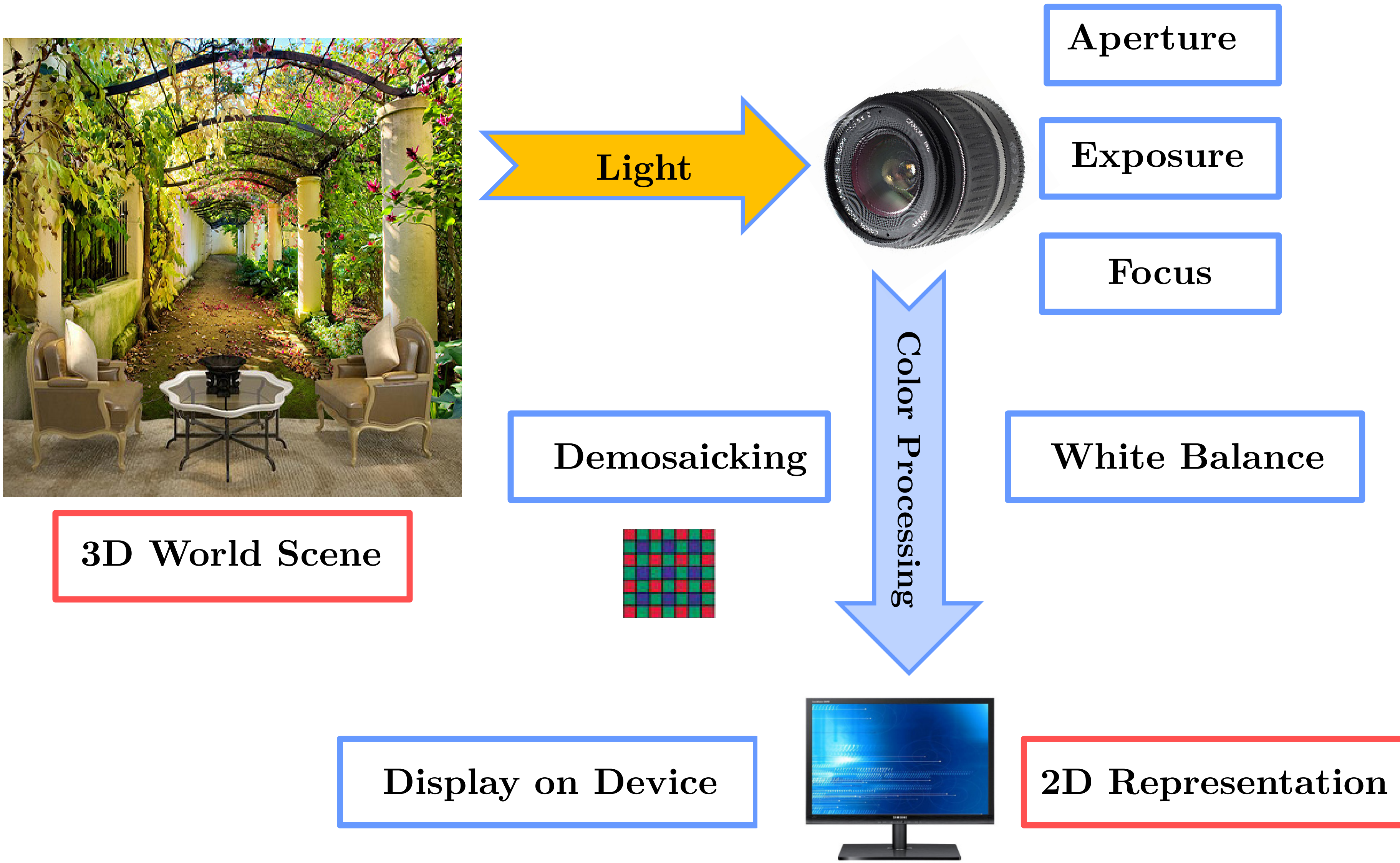
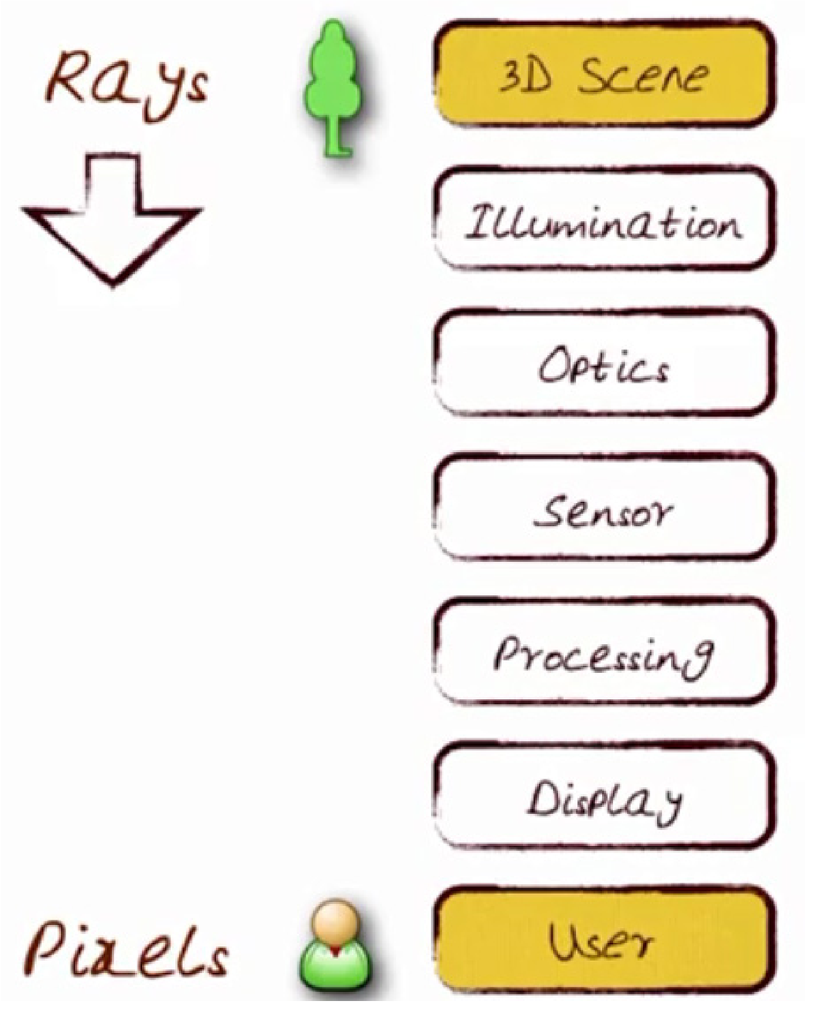
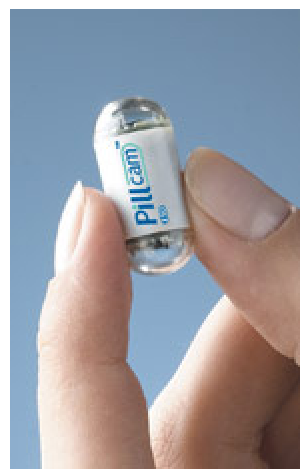
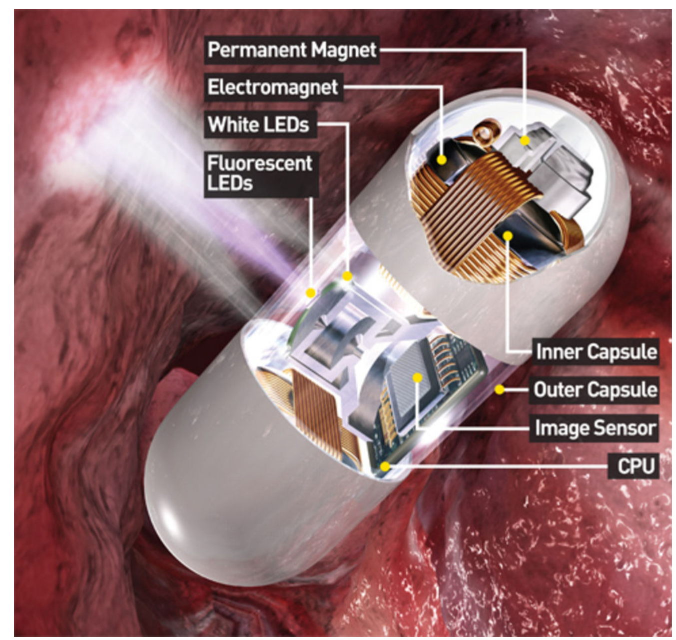


From Light Rays to Pixels

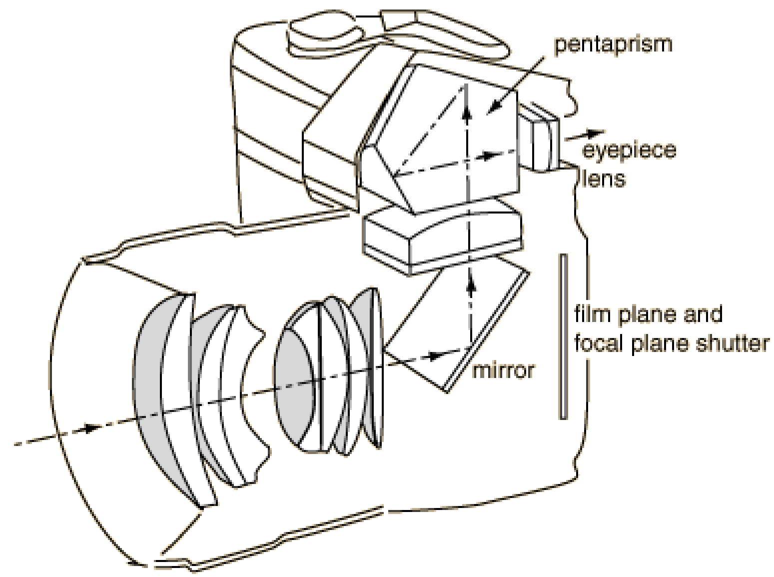


Cameras and their evolution





Single Lens Reflex Cameras



1.2 How are Images built out of Light?

Exposure = Irradiance X Time

$$H = E \times T$$

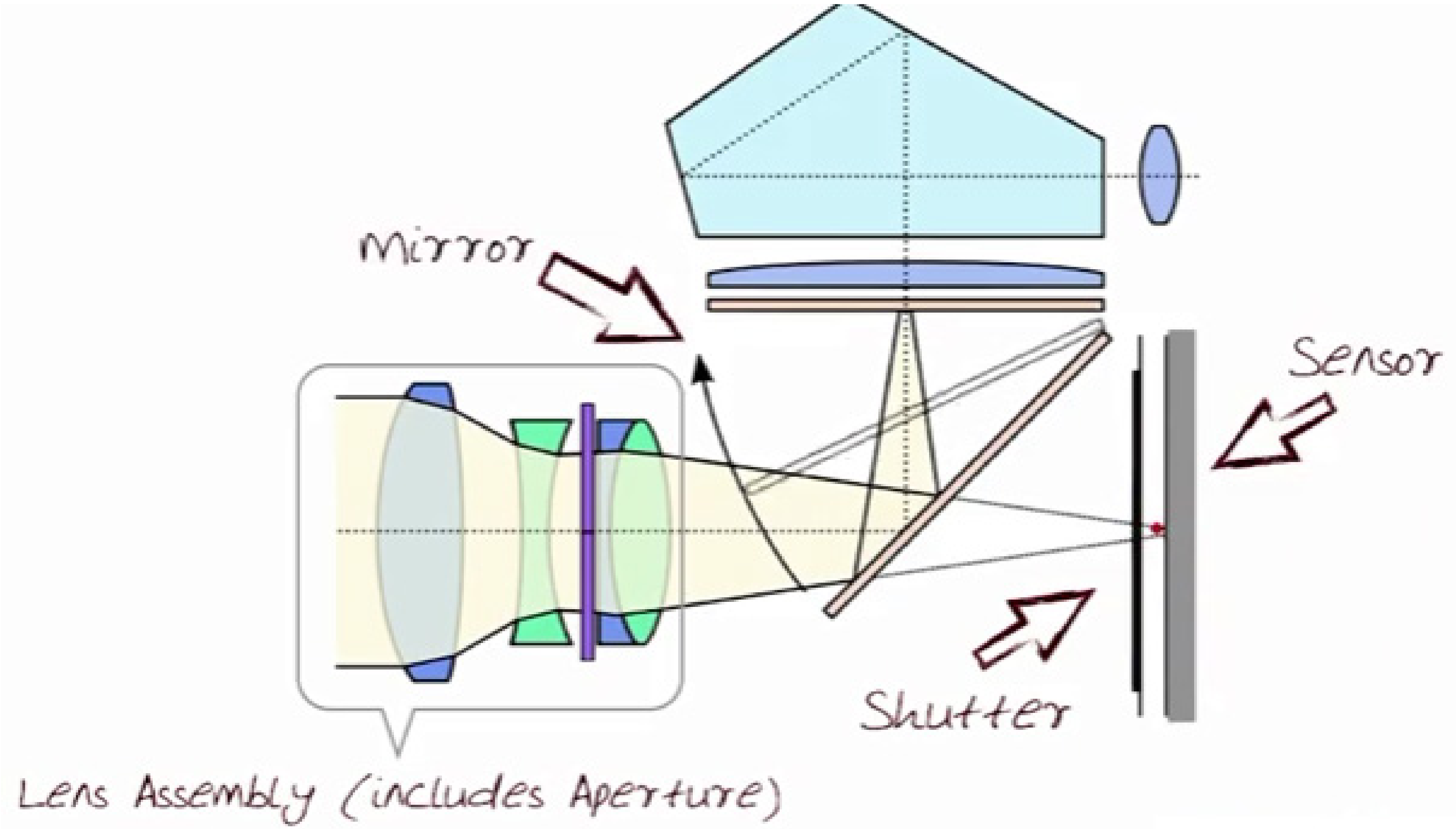
Irradiance (E)

* Amount of light falling on a unit area of sensor per second
* Controlled by lens **aperture**

Exposure Time (T)

* How long the **shutter** is kept open

1.2 How are Images built out of Light?



https://www.youtube.com/watch?v=ptfSW4eW25g

Shutter Speed

Amount of time the sensor is exposed to light

https://www.youtube.com/watch?v=yr3ngmRuGUc

Sensors and Storage

Photographic Film

External Flash Disk

* Film and Digital Cameras are the same
  * There have been significant improvements in actuators, and lenses
* Difference is how light is trapped and preserved
* Chemical process for Film, and Electronic for Digital capture the moment in Time and Space

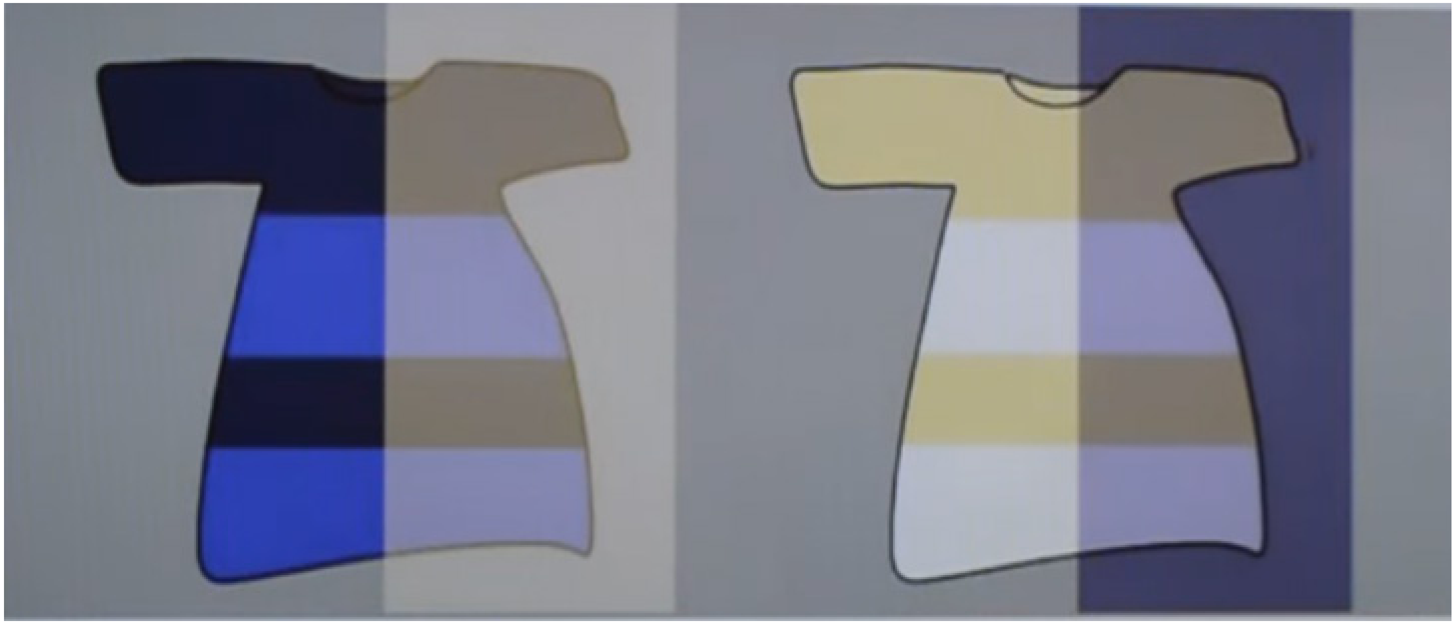
2. Improving the Quality of Digital Images

2.1 Color Image Processing: Color Constancy

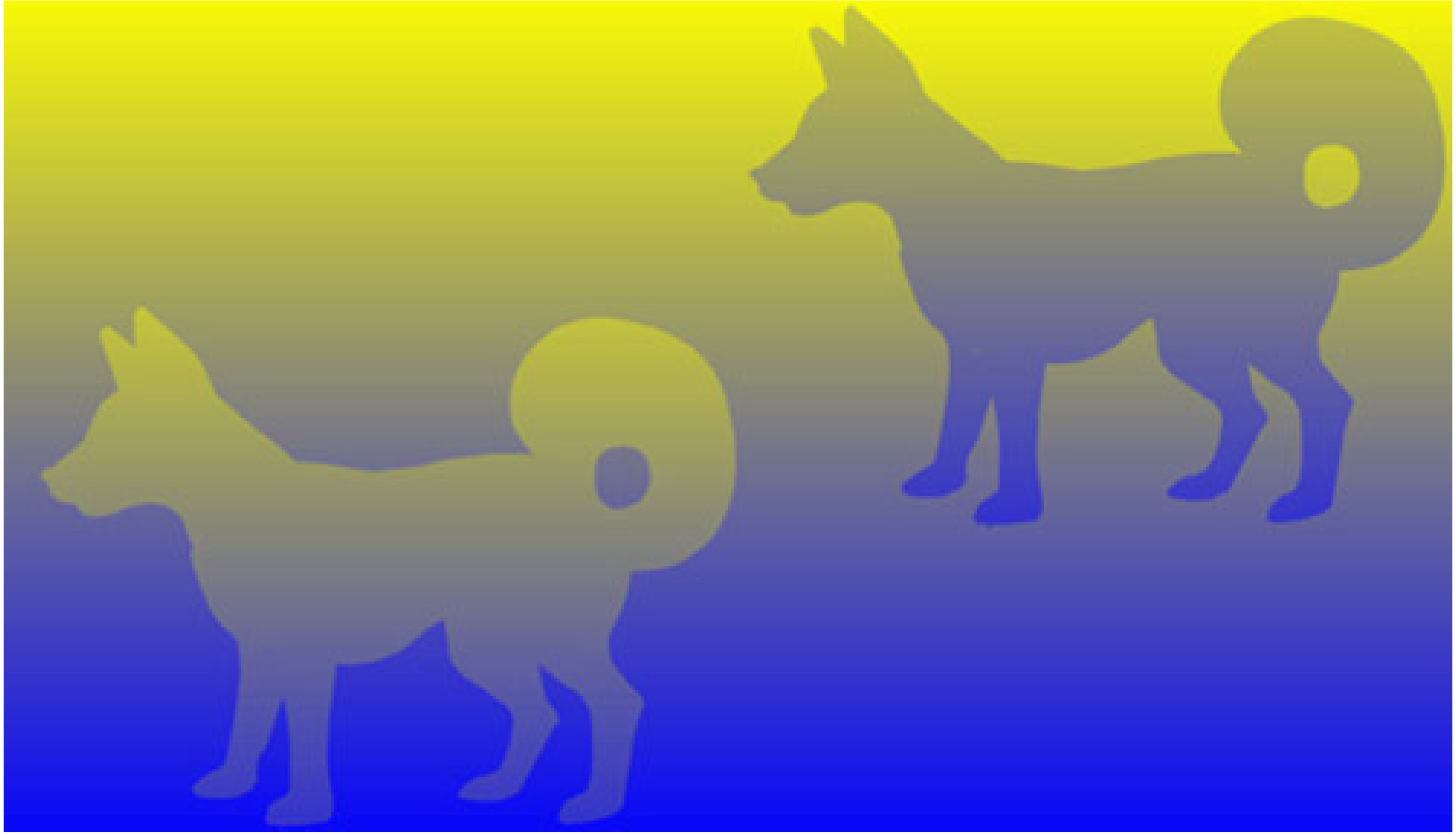
The Need for Illumination Invariance

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**.

A related phenomenon is the fact that two colors that we perceive as different can be exactly the same! Link



How Does Colored Light Affect Perception



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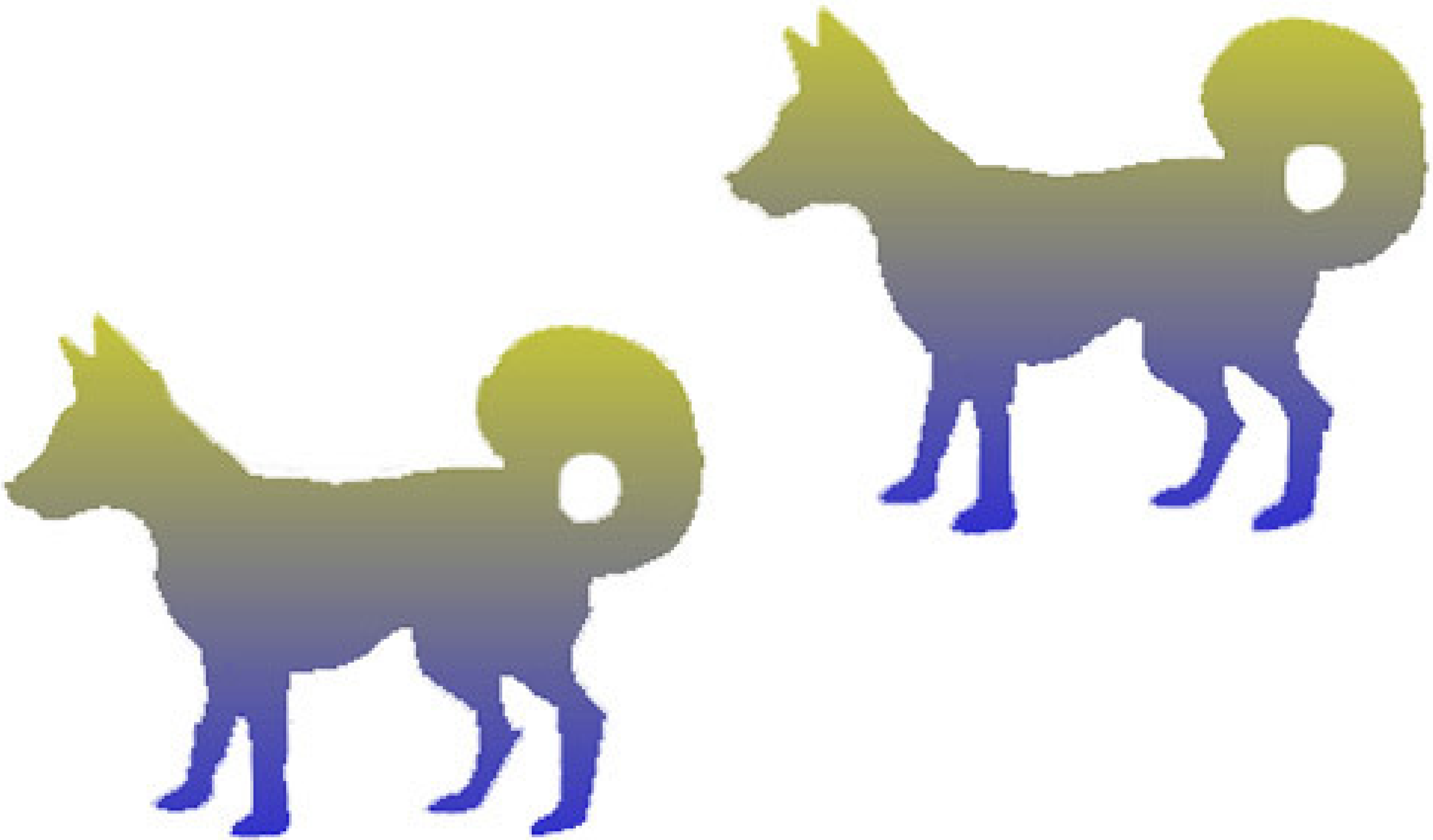


Light Perception is not simpy a matter of light acquisition

Colors **perceived different** can be "**radiometrically**" **equal**

Color Constancy:

Ability of the human to perceive colors robustly independently of changes in illumination.

What does that mean?

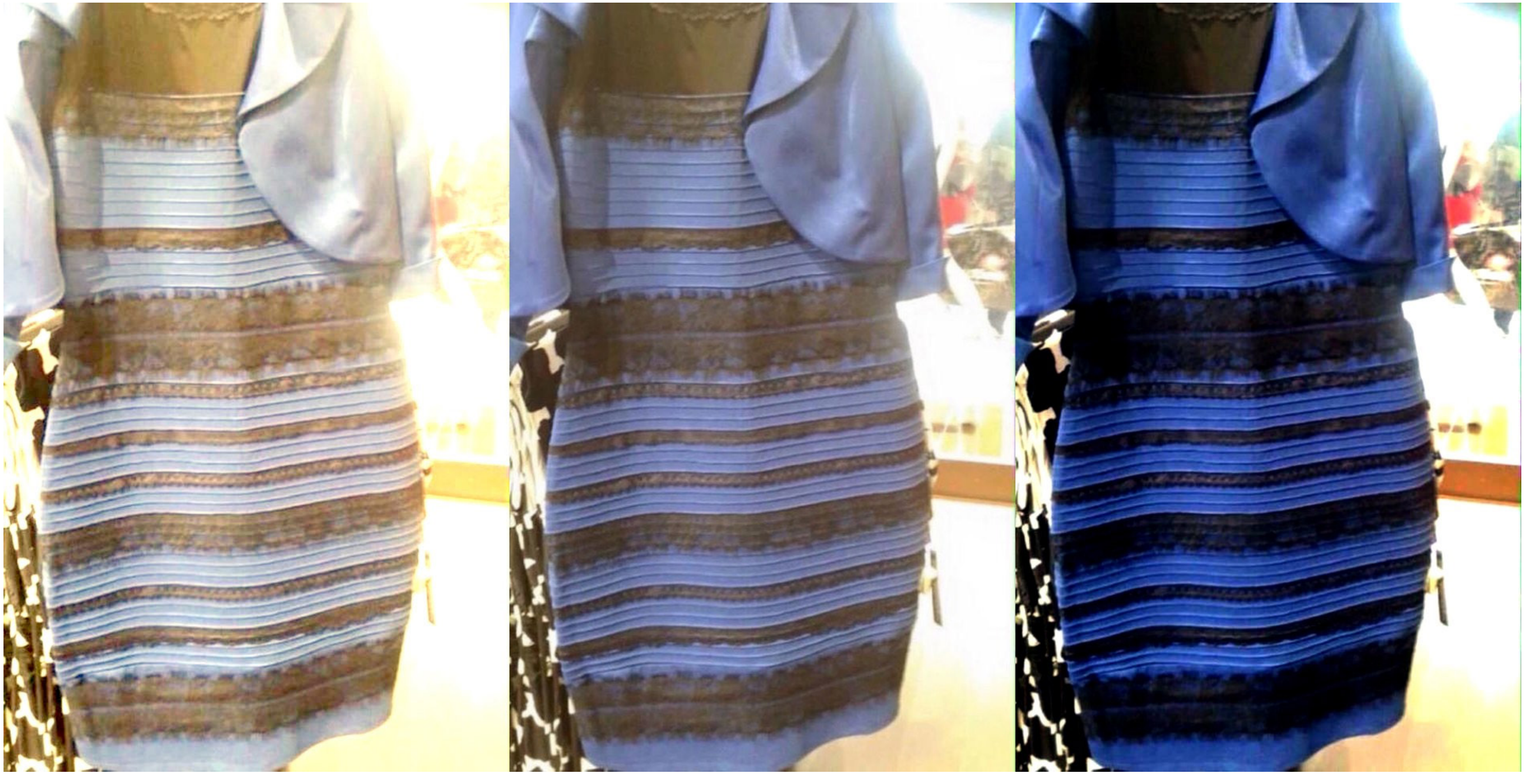
"**Radiometrically**" **different** colors can be **perceived the same**

Colors **perceived different** can be "**radiometrically**" **equal**

"**Radiometrically**" **different** colors can be **perceived the same**

The Infamous Dress

The Infamous Dress



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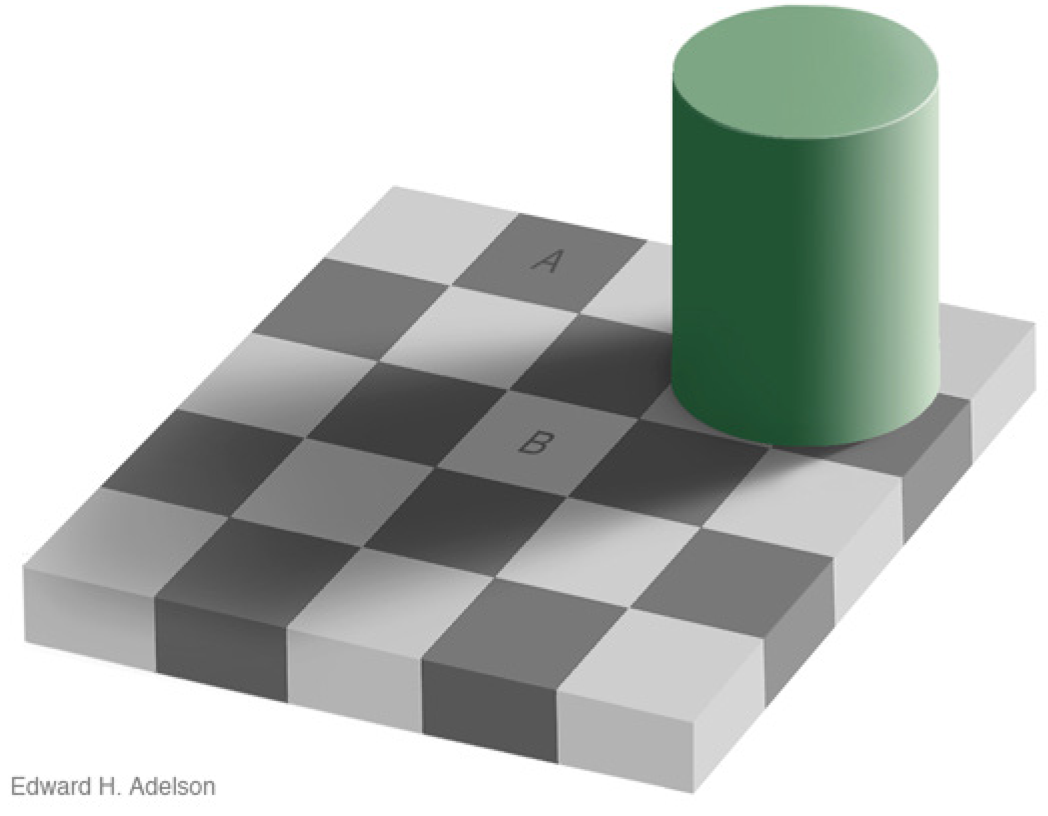

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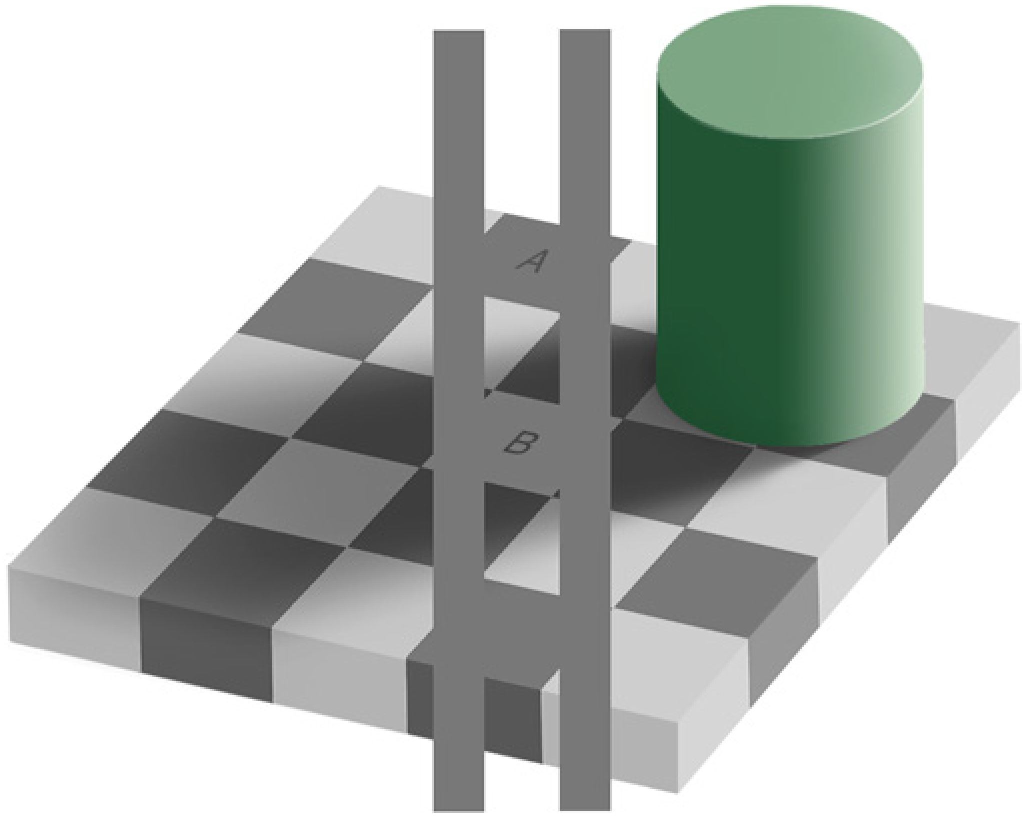

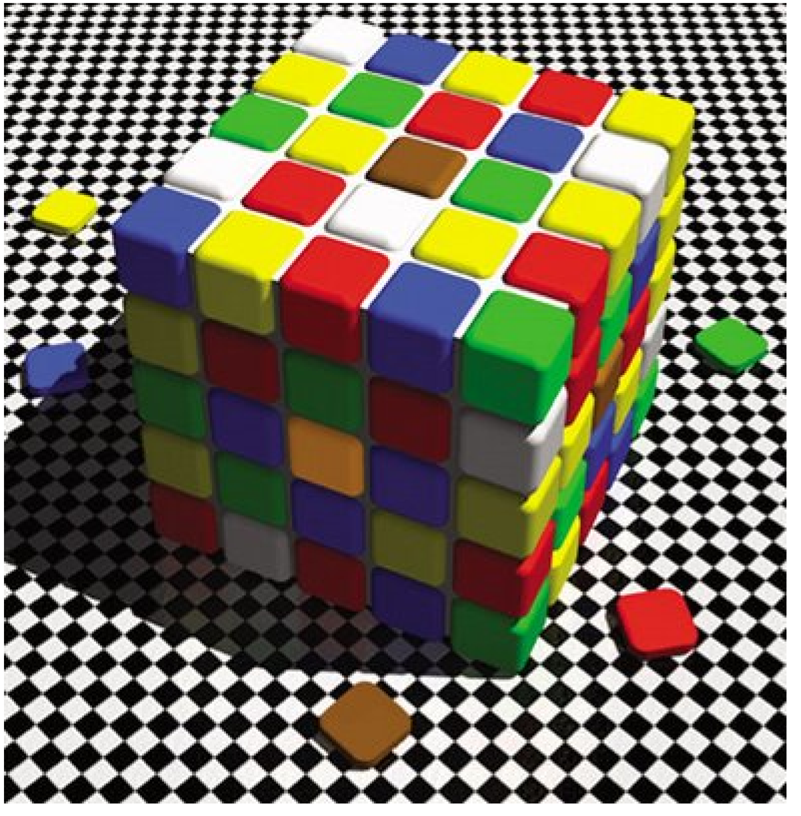

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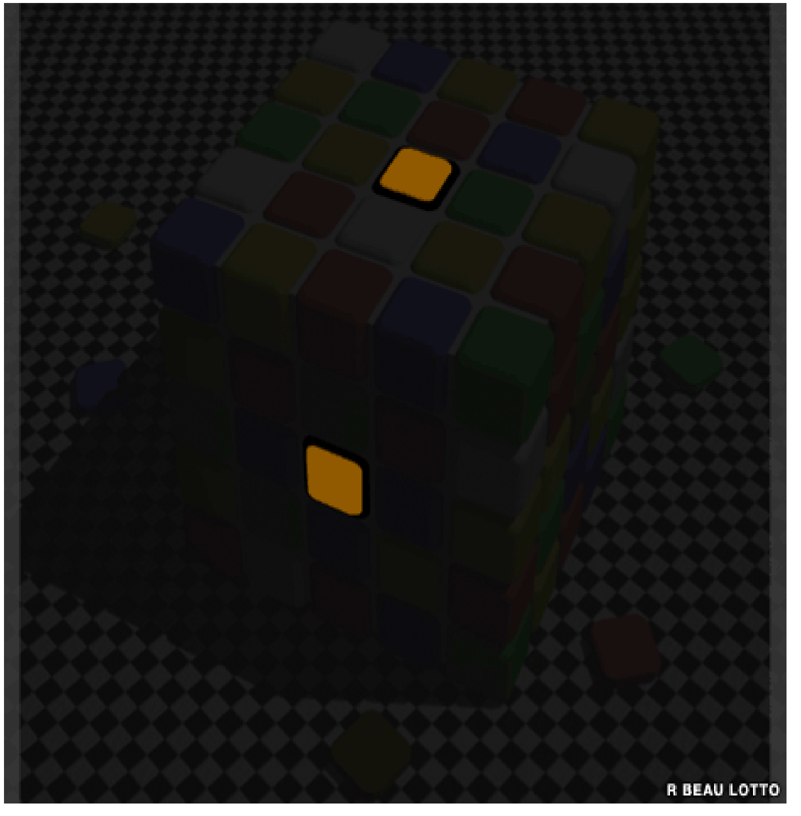


2.1 Color Image Processing: Color Constancy

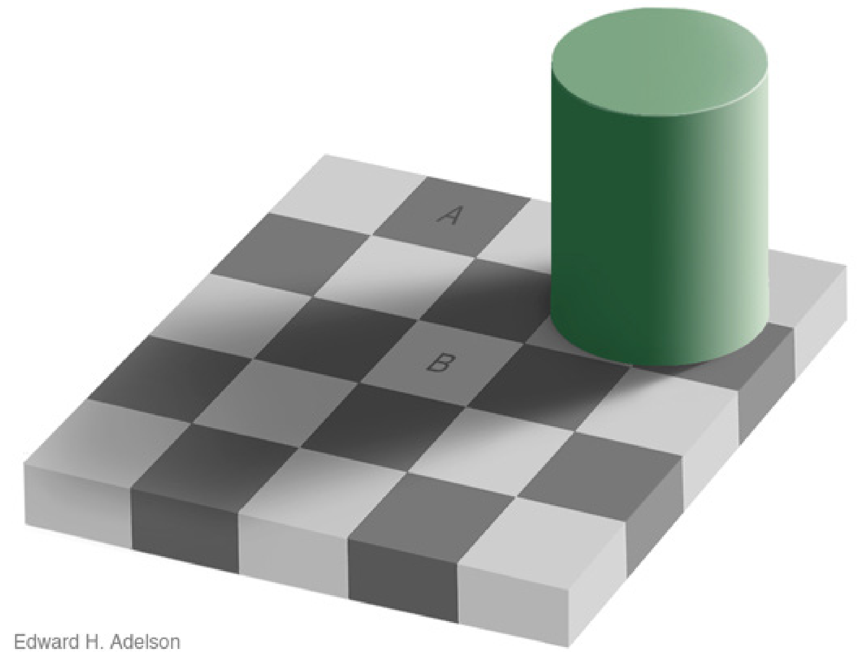
Color Constancy: **Ability of the human to perceive colors robustly independently of changes in illumination.**

Reproducing this in our cameras is a problem called **Machine Color Constancy**

But wait!

If humans have color constancy, why trying to reproduce it in digital devices?

Both squares have the same intensity, but **look different**.



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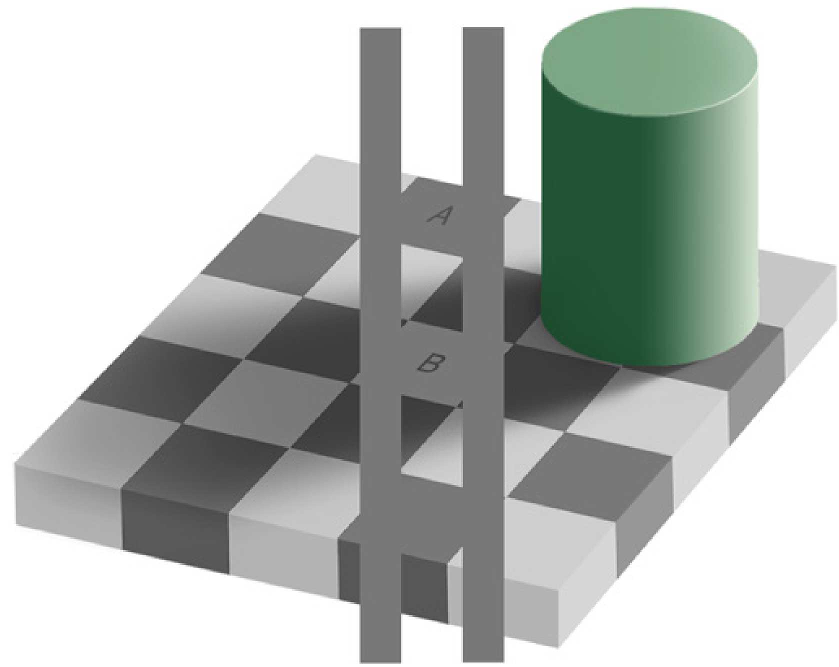
The output of a color constancy algorithm should be an image in which intensities **are different**.



3. Image Enhancement and Restoration

3.1 Image Enhancement I: Exposure Correction. Contrast Enhancement: Histogram Equalization, CLAHE

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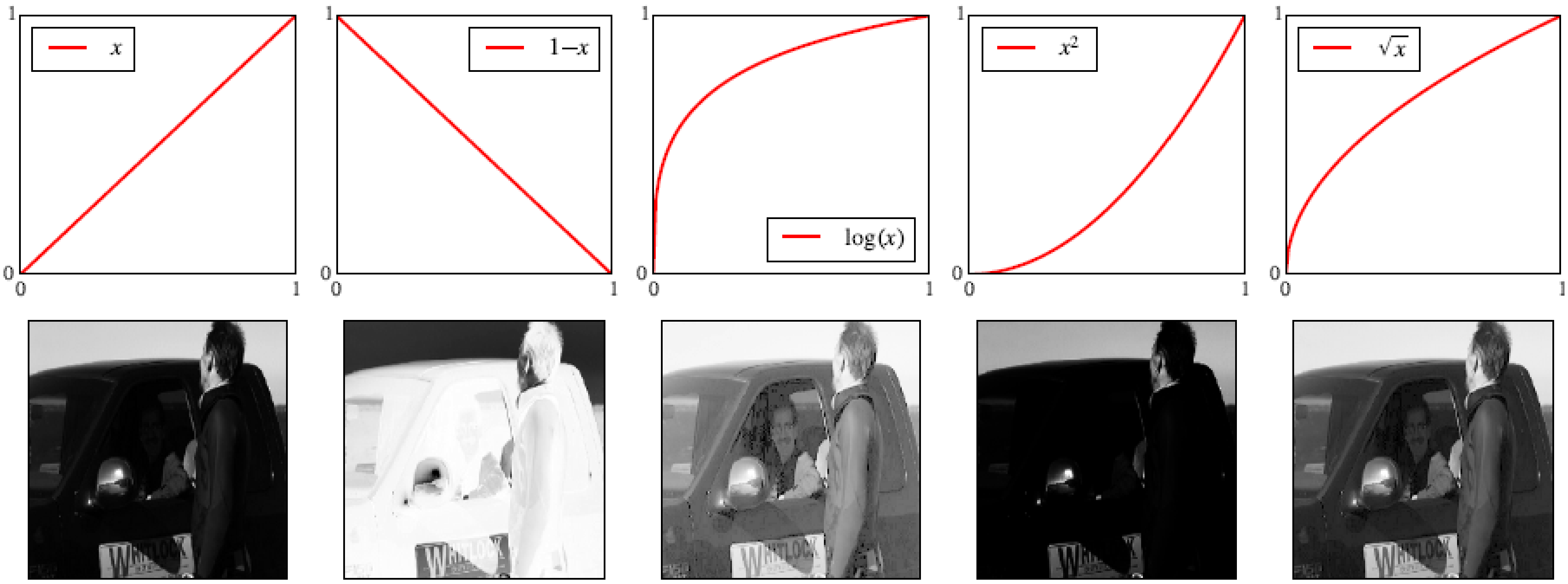
Intensity Manipulations: We can correct the aspect of some images by mapping the intensities to a different range in several ways. Note, this are global transformation that do not take into account neighboring pixel values

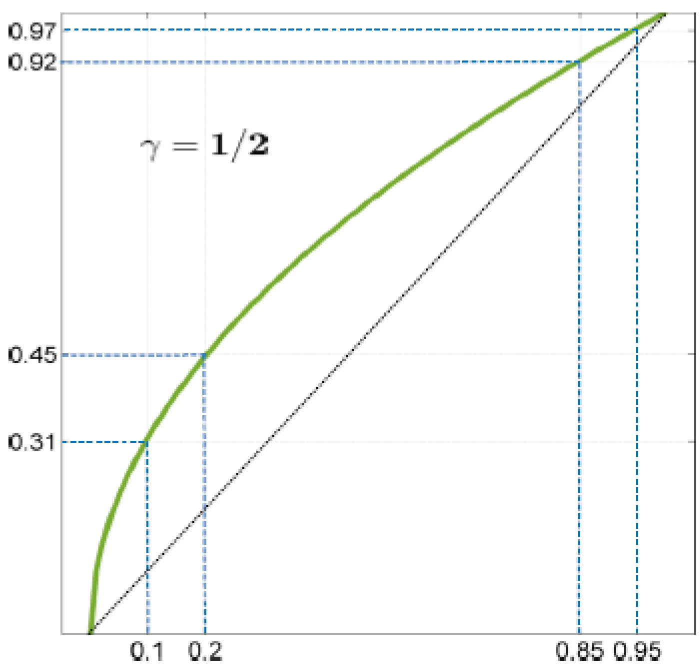


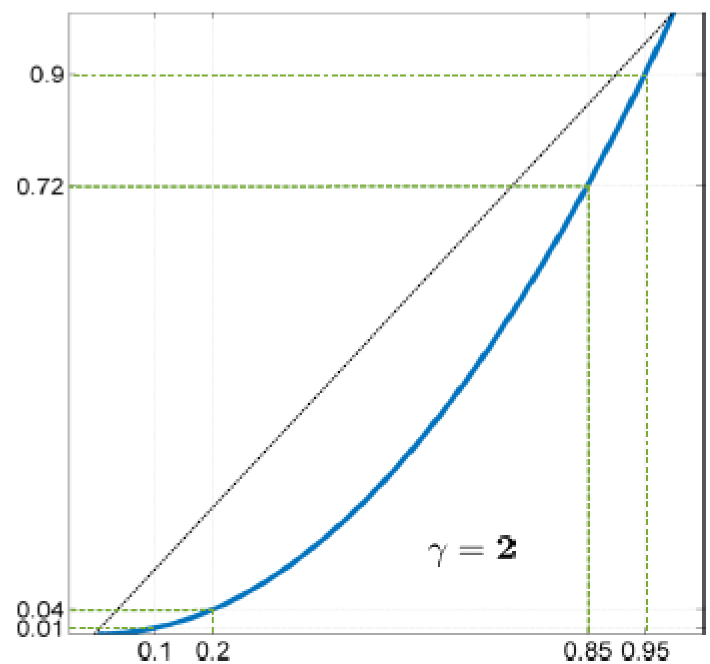
3.1 Image Enhancement I: Exposure Correction. Contrast Enhancement: Histogram Equalization, CLAHE

Exposure Correction: if not enough light reached the imaging system, objects can appear too dark. In the opposite situation, objects can appear too bright

Gamma Correction: A simple technique to scale up or down intensities and solve that situation.

$$\boxed{I(x) \Rightarrow I(x)^{\gamma}}$$





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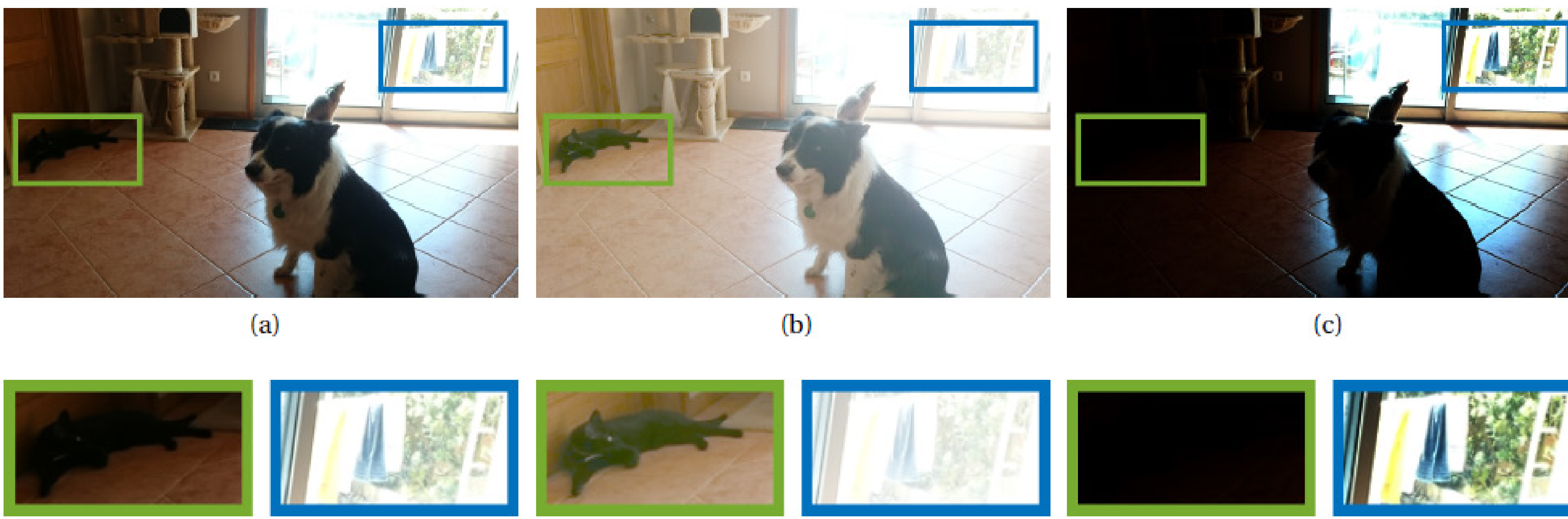

(a) (b) (c)

(d) (e) (f)

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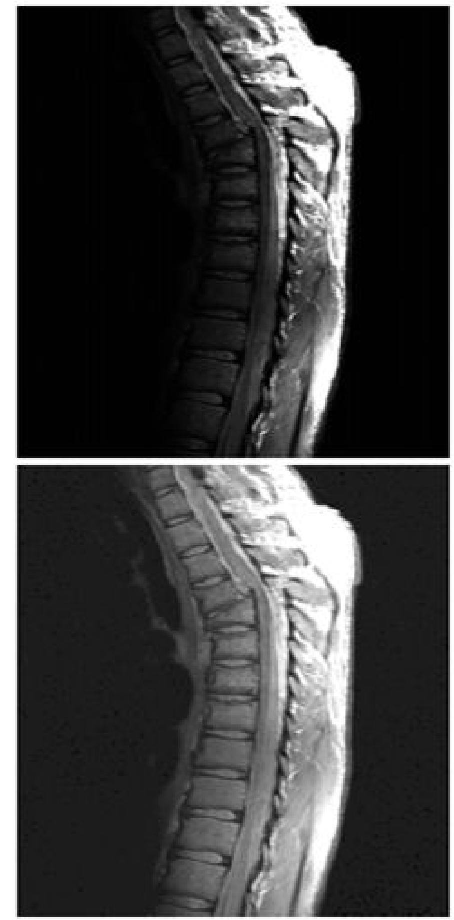
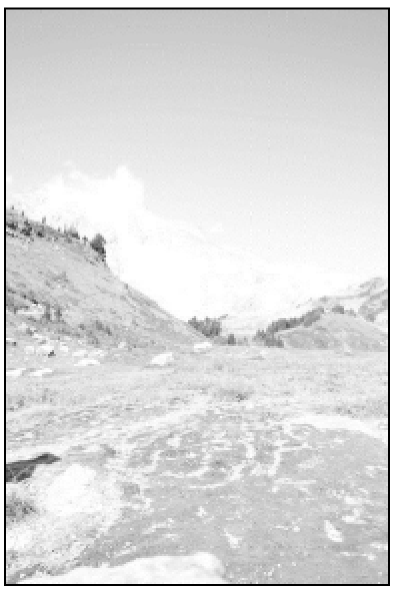
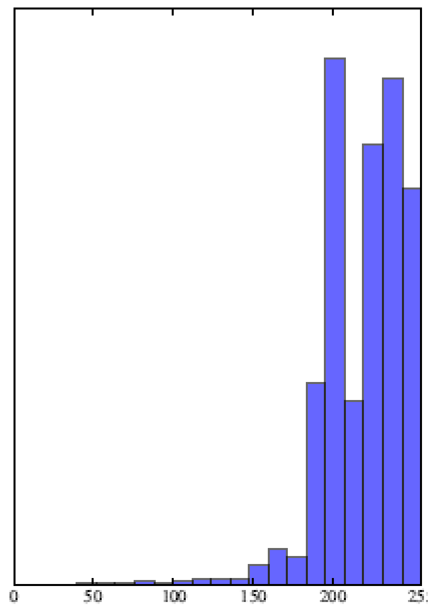


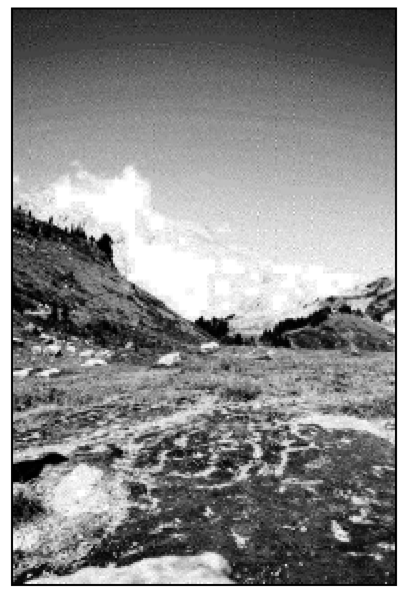
3.1 Image Enhancement I: Exposure Correction. Contrast Enhancement: Histogram Equalization, CLAHE

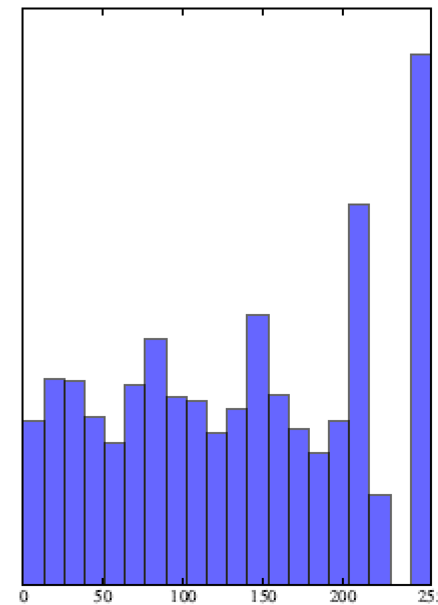
Contrast Enhancement: Contrast is the difference between the lowest and the largest intensity value in an image, or in a region of it

Histogram Equalization: Lack of contrast is sometimes characterized by an "inefficient" use of the available dynamic range (we do not use all the intensities we can). We can impose that the histogram is as flat as possible:

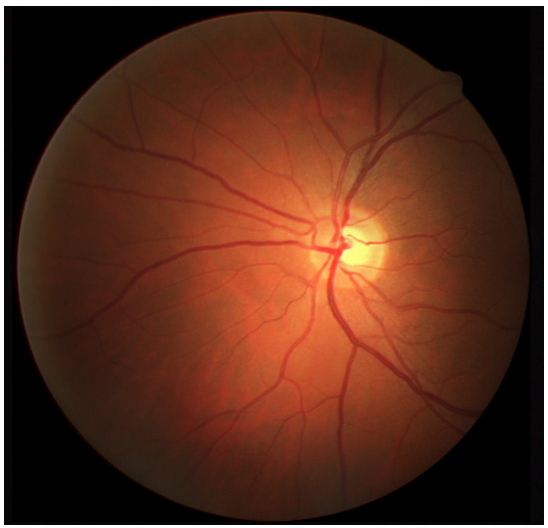




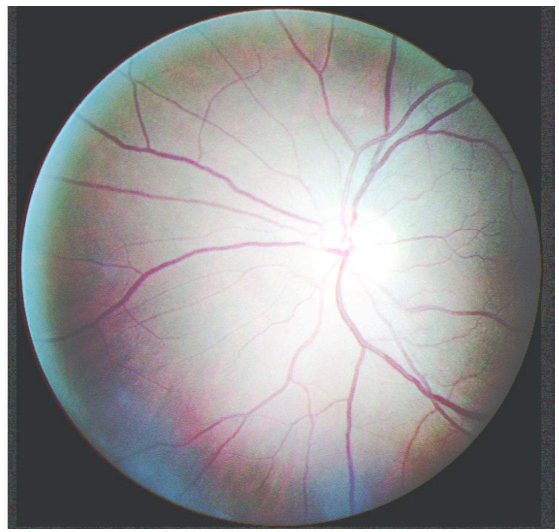




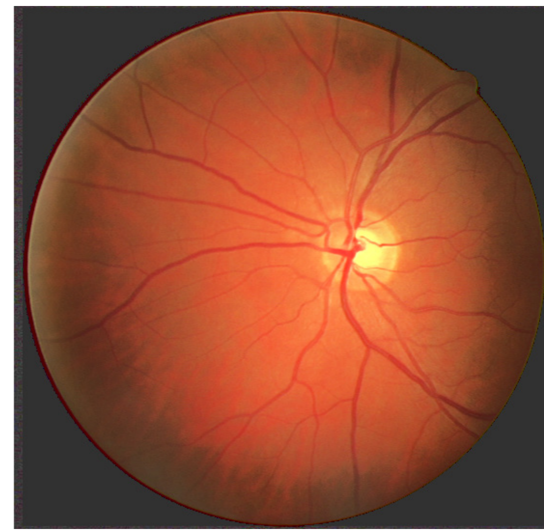
Histogram Equalization in Color: It can modify aggresively the aspect of an image. Sometimes it can be better to process only V in an HSV representation:



original image

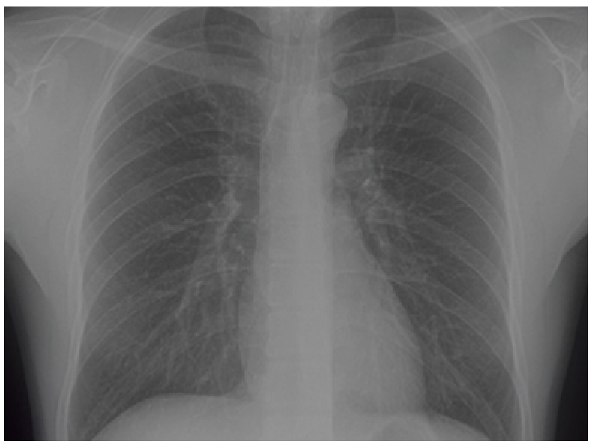


histogram equalization in R,G,B



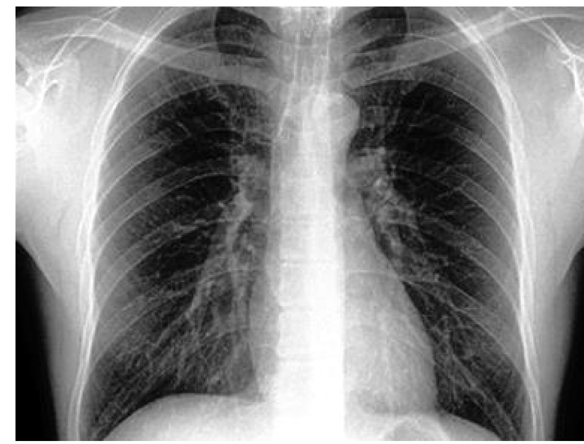
histogram equalization in V

Contrast-Limited Adaptive Histogram Equalization (CLAHE):
Sometimes the loss of contrast is specific to a given image location, but the rest of the image is correctly contrasted. In those cases, applying a global histogram equalization can produce **over-enhancement**.



original image

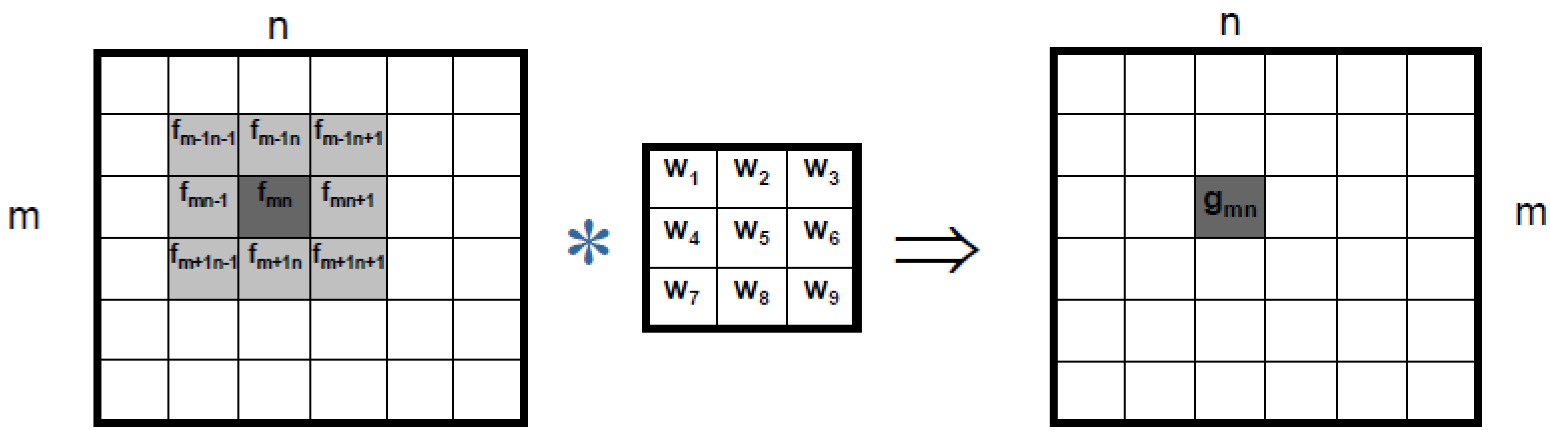
histogram equalization



CLAHE

3.2 Image Enhancement II: Image Filtering

Linear filtering involves the convolution of the input image with a specific mask to enhance the image:



$$\boxed{\begin{aligned} g_{mn} = {} & w_9 f_{m-1n-1} + w_8 f_{m-1n} + w_7 f_{m-1n+1} \\ & + w_6 f_{mn-1} + w_5 f_{mn} + w_4 f_{mn+1} \\ & + w_3 f_{m+1n-1} + w_2 f_{m+1n} + w_1 f_{m+1n+1} \end{aligned}}$$

3.2 Image Enhancement II: Image Filtering

There are many types of kernels/masks, useful for different tasks: Link

Linear filter masks

Based on sums
(all mask weights with identical signs)

$$\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}\quad \frac{1}{5}\begin{bmatrix}0&1&0\\1&1&1\\0&1&0\end{bmatrix}\quad \frac{1}{16}\begin{bmatrix}1&2&1\\2&4&2\\1&2&1\end{bmatrix}\quad \frac{1}{25}\begin{bmatrix}1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\end{bmatrix}\quad \frac{1}{256}\begin{bmatrix}1&4&6&4&1\\4&16&24&16&4\\6&24&36&24&6\\4&16&24&16&4\\1&4&6&4&1\end{bmatrix}$$

Image smoothing

Based on differences
(mask weights with different signs)

$$\begin{bmatrix}0&-1&0\\0&0&0\\0&1&0\end{bmatrix}\quad \begin{bmatrix}-1&0&1\\-2&0&2\\-1&0&1\end{bmatrix}\quad \begin{bmatrix}0&-1&0\\-1&4&-1\\0&-1&0\end{bmatrix}\quad \begin{bmatrix}-1&-1&-1\\-1&8&-1\\-1&-1&-1\end{bmatrix}\quad \begin{bmatrix}1&1&1&1&1\\1&1&1&1&1\\0&0&0&0&0\\-1&-1&-1&-1&-1\\-1&-1&-1&-1&-1\end{bmatrix}$$

$$\begin{bmatrix}0&-1&0\\-1&4&-1\\0&-1&0\end{bmatrix}\longrightarrow\begin{bmatrix}0&-1&0\\-1&5&-1\\0&-1&0\end{bmatrix}\qquad \begin{bmatrix}-1&-1&-1\\-1&8&-1\\-1&-1&-1\end{bmatrix}\longrightarrow\begin{bmatrix}-1&-1&-1\\-1&9&-1\\-1&-1&-1\end{bmatrix}$$

Edge enhancement

and

image sharpening

Filtering in the Frequency Domain

Represent the signal as an infinite weighted sum of an infinite number of sinusoids:

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi ux} dx$$

Again: $e^{ik} = \cos k + i \sin k \qquad i = \sqrt{-1}$

Spatial Domain (x) $\longrightarrow$ Frequency Domain (ω or u or *even* s)
(Frequency Spectrum $F(u)$ or $F(\omega)$)

Inverse Fourier Transform (IFT) – add up all the sinusoids at x:

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{i2\pi ux} du$$

3.2 Image Enhancement II: Image Filtering

Filtering in the Frequency Domain

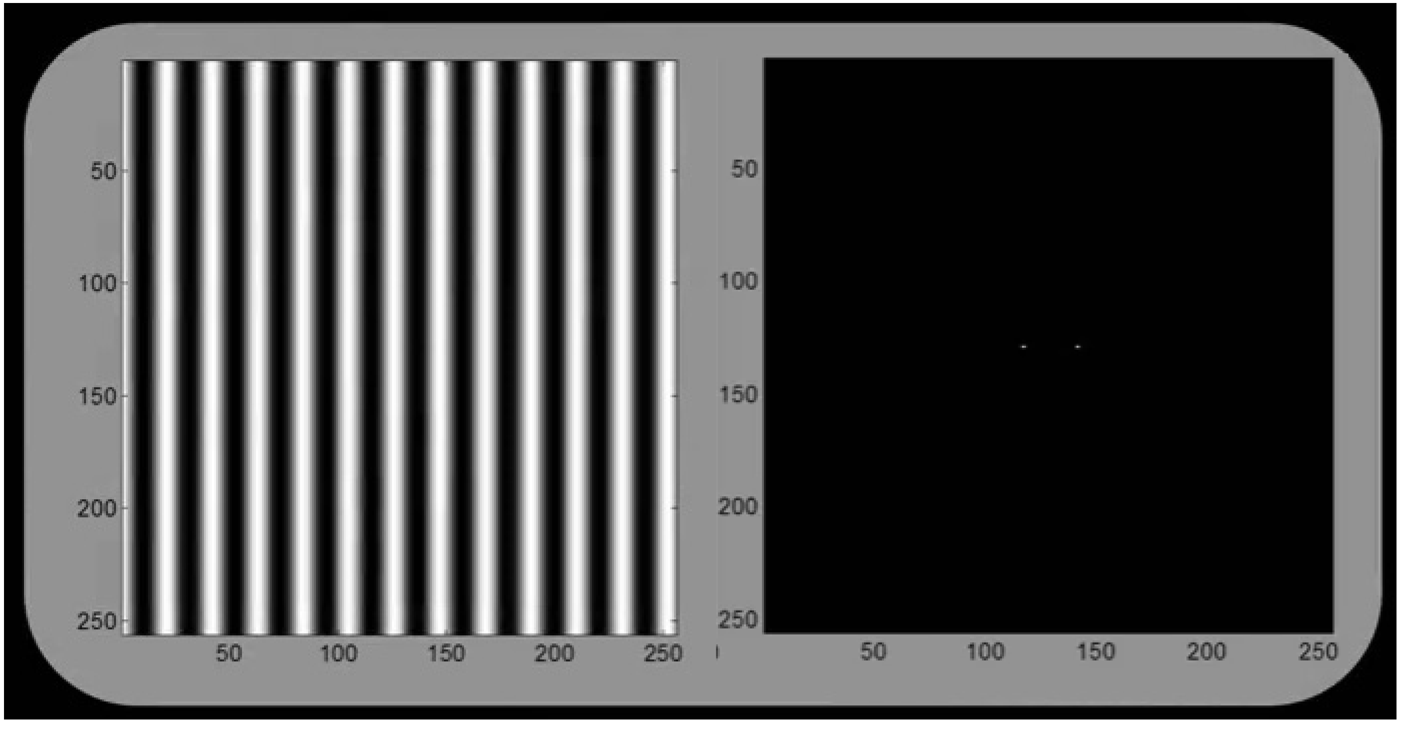
- The two dimensional version: .

$$F\left(u,v\right)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f\left(x,y\right)e^{-i2\pi\left(ux+vy\right)}dx\,dy\,\frac{1}{2}$$

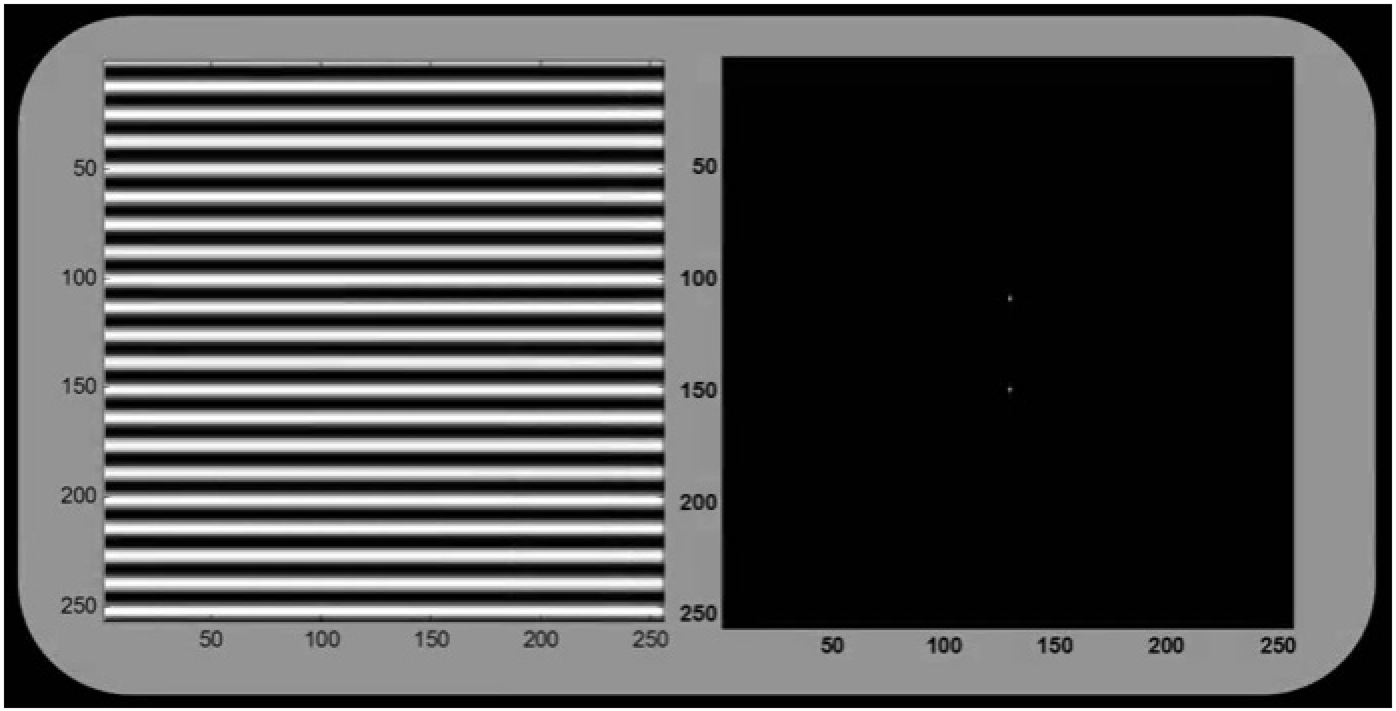
- And the 2D ***Discrete FT***:

$$F(k_x,k_y)=\frac{1}{N}\sum_{x=0}^{x=N-1}\sum_{y=0}^{y=N-1} f(x,y)e^{-i\frac{2\pi(k_x x+k_y y)}{N}}$$

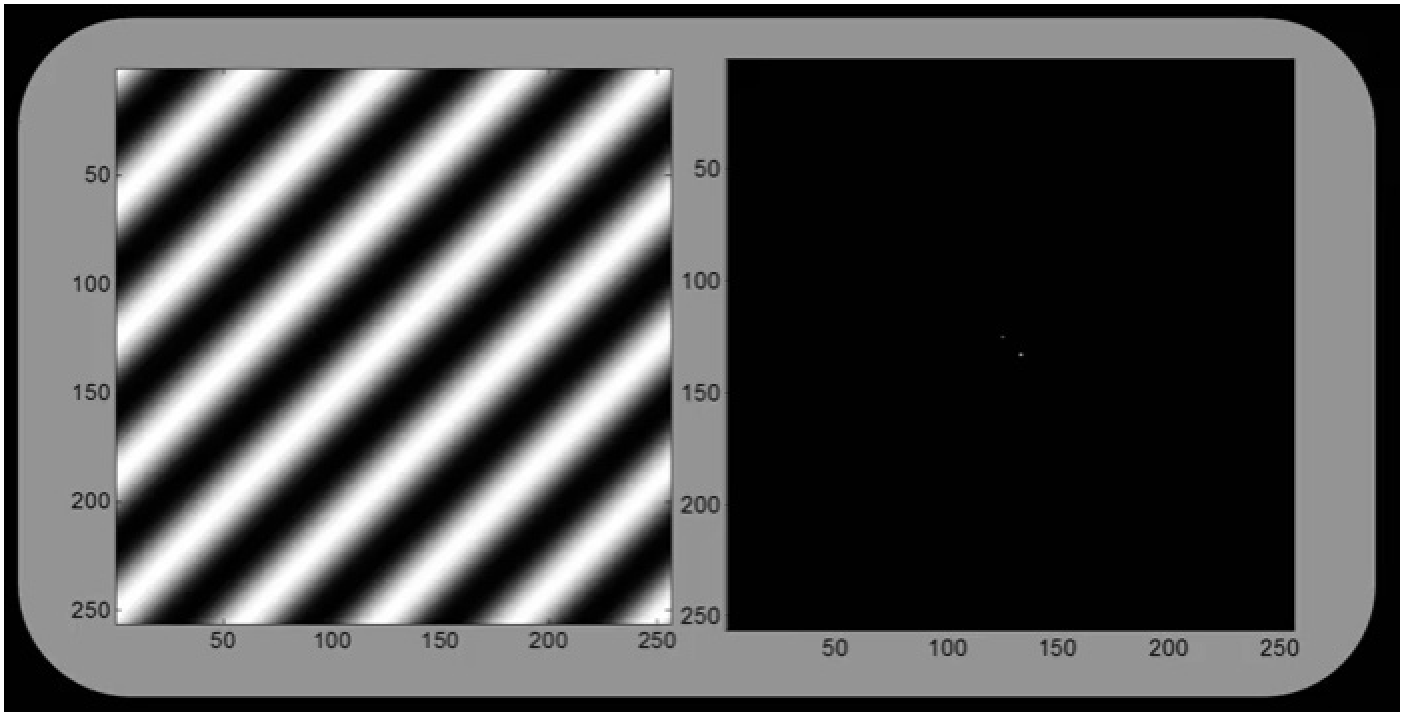
Filtering in the Frequency Domain



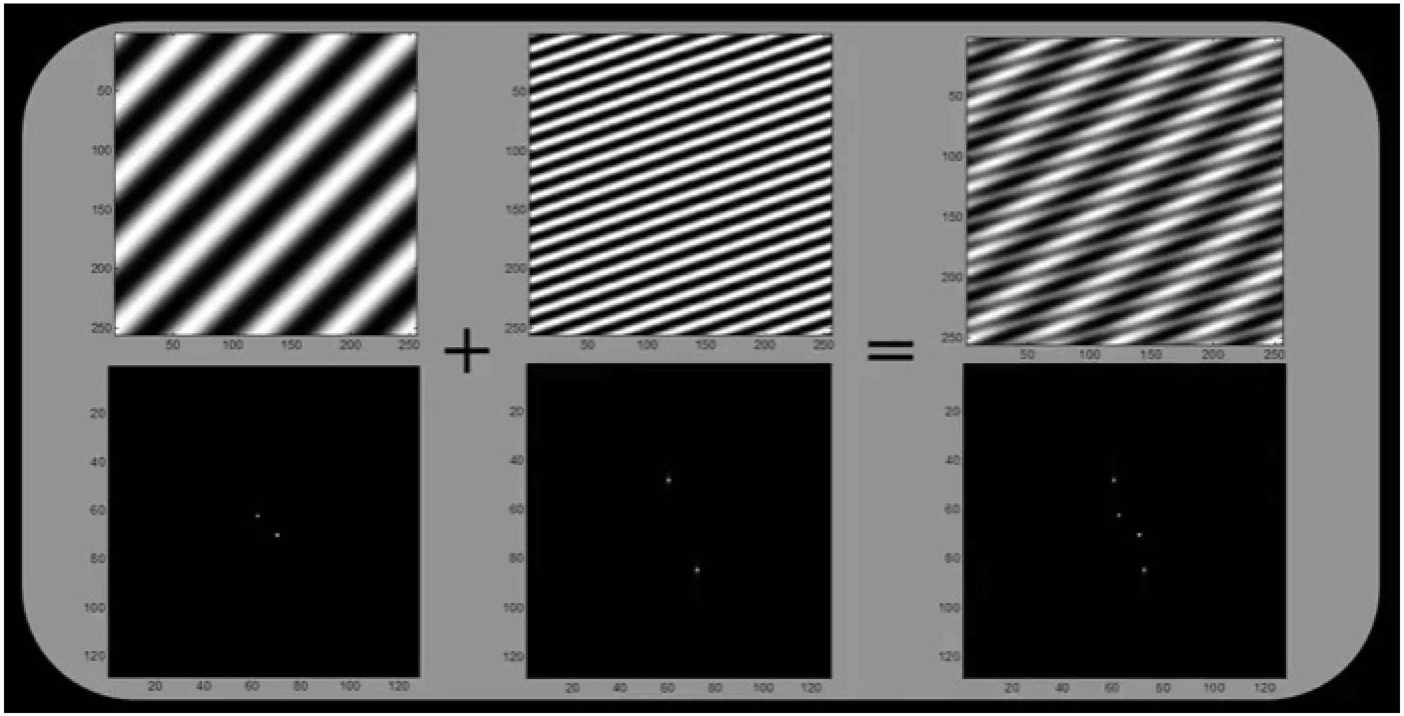
Filtering in the Frequency Domain



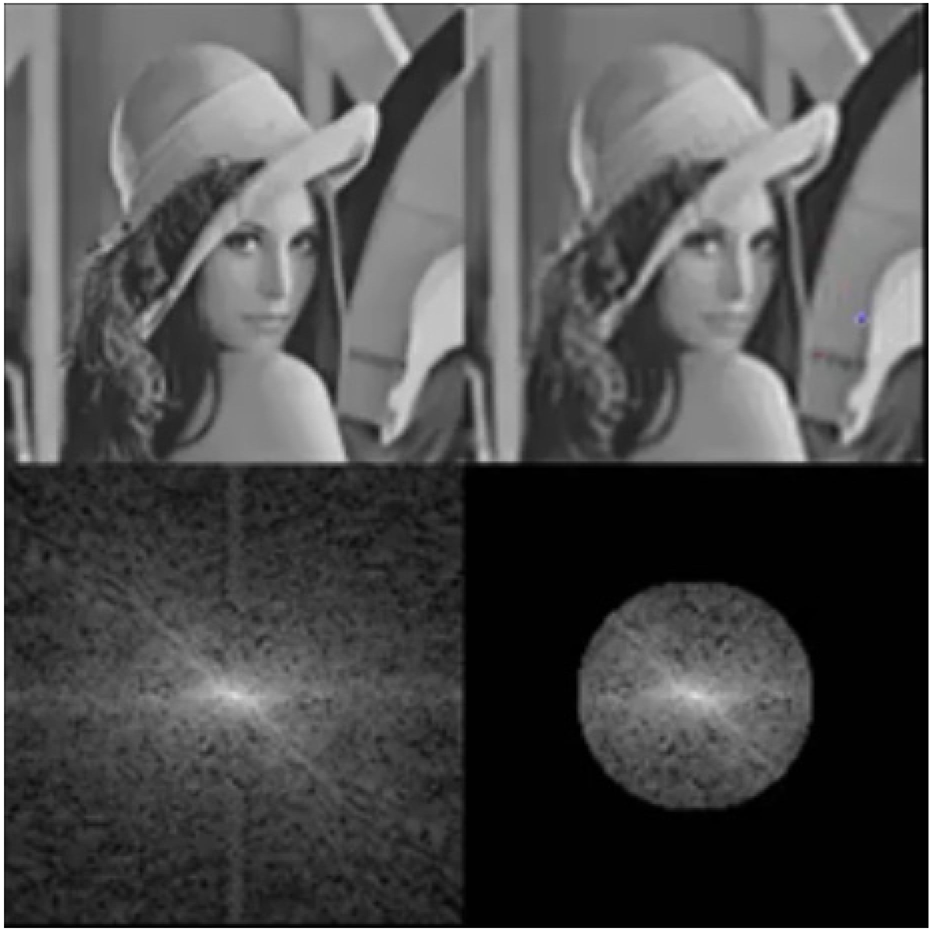
Filtering in the Frequency Domain



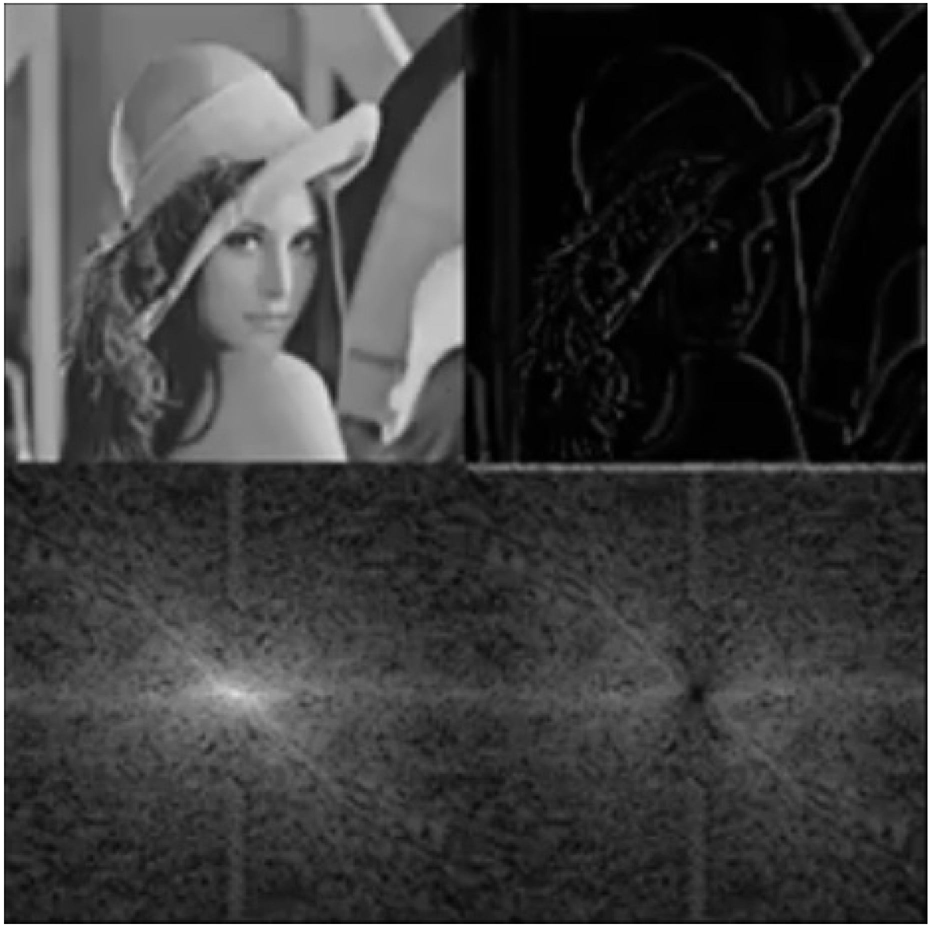
Filtering in the Frequency Domain



Filtering in the Frequency Domain



Filtering in the Frequency Domain



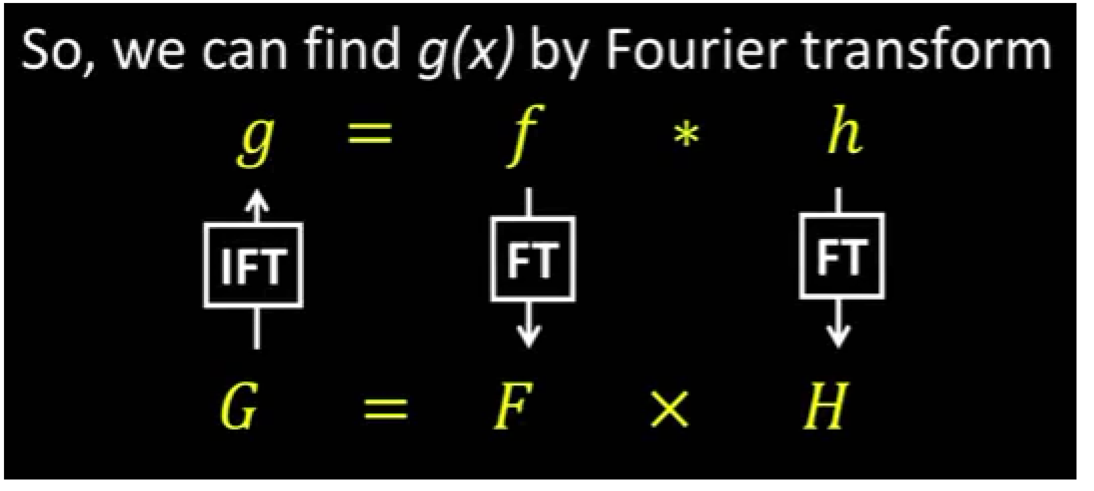
Filtering in the Frequency Domain

Let $g = f * h$

Then $$G(u) = \int_{-\infty}^{\infty} g(x) e^{-i2\pi ux} dx$$
$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\tau) h(x-\tau) e^{-i2\pi ux} d\tau dx$$
$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[f(\tau) e^{-i2\pi u\tau} d\tau \right] \left[h(x-\tau) e^{-i2\pi u(x-\tau)} dx \right]$$
$$= \int_{-\infty}^{\infty} \left[f(\tau) e^{-i2\pi u\tau} d\tau \right] \int_{-\infty}^{\infty} \left[h(x') e^{-i2\pi ux'} dx' \right]$$
$$= F(u) H(u)$$

Convolution in spatial domain
$\Leftrightarrow$ *Multiplication in frequency domain*

Filtering in the Frequency Domain



This is only useful (computationally) for large kernels

Application: Homomorphic Filtering for Illumination Correction

Assume an image is non-uniformly illuminated. If the image is the pixel-wise product of an undegraded image and the illumination field, it can be expressed as:

$$I(x) = i(x) \cdot r(x)$$

Where the first term (illumination field) is slowly-varying, i.e. low-frequency. We can turn the multiplicative relation into an additive one with a logarithm:

$$\log(I(x)) = \log(i(x)) + \log(r(x))$$

Take Fourier Transforms (which are linear):

$$\mathcal{F}(\log(I(x))) = \mathcal{F}(\log(i(x) + \log(r(x))) = \mathcal{F}(\log(i(x))) + \mathcal{F}(\log(r(x)))$$

Rewrite the last equation as: $\widetilde{I}(u) = \widetilde{i}(u) + \widetilde{r}(u)$

Since $\widetilde{i}(u)$ only contains low-frequency content, a high-pass filter $H(u)$ will cancel it.

3.2 Image Enhancement II: Image Filtering

Application: Homomorphic Filtering for Illumination Correction

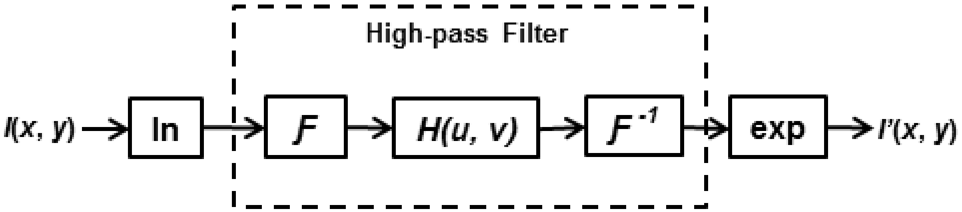
Since $\widetilde{i}(u)$ only contains low-frequency content, a high-pass filter $H(u)$ will cancel it. In addition, the high-pass filter will not affect the high-frequency content of $r(x)$

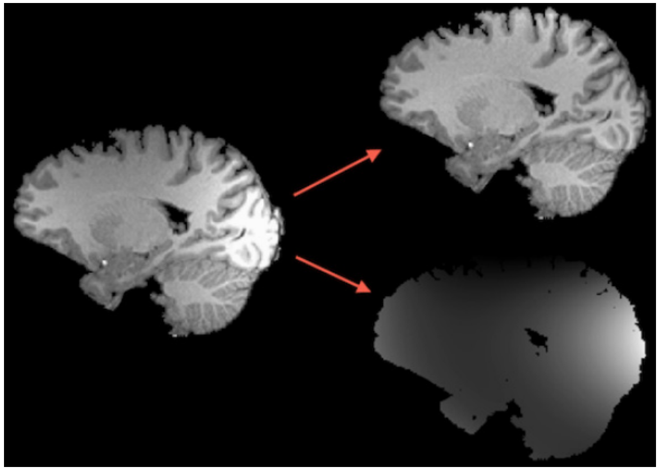
$$S(u) = H(u)\widetilde{I}(u) = H(u)\widetilde{i}(u) + H(u)\widetilde{r}(u) = \widetilde{r}(u)$$

Now we need to apply inverse Fourier transform, and exponentiation to obtain the undegraded image (with no illumination field):

$$\mathcal{F}^{-1}(S(u)) = \mathcal{F}^{-1}(\widetilde{r}(u)) = \log(r(x)) \longrightarrow r(x) = \exp\left(\mathcal{F}^{-1}(S(u))\right)$$

Summary of the operations:





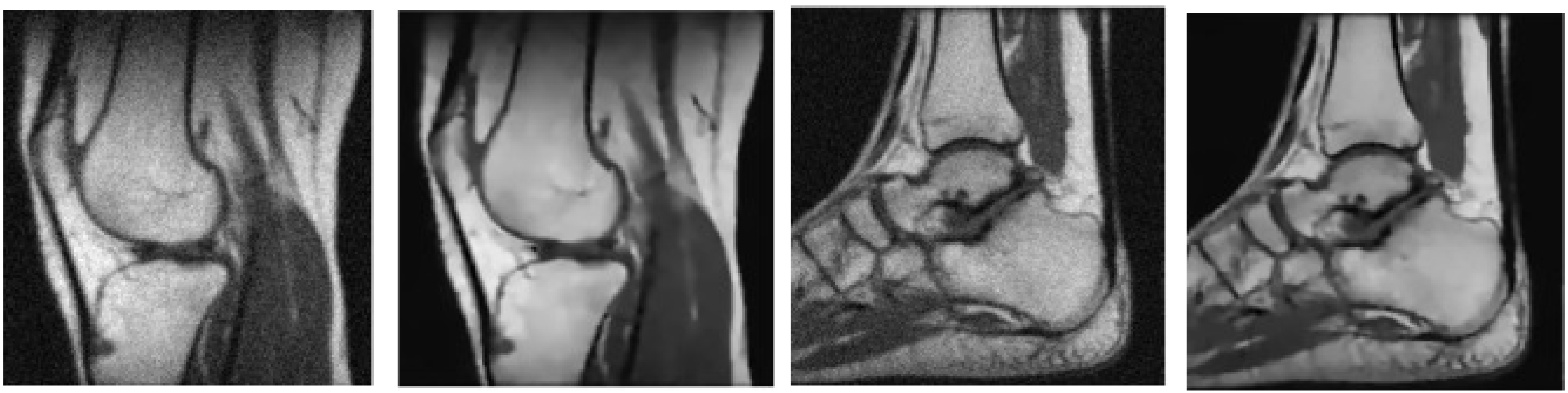
3.3 Image Restoration: Denoising, Deblurring, Illumination Correction

3.3 Image Restoration: Denoising, Deblurring, Illumination Correction

Image Denoising: Any acquisition system senses quantities of interest together with noise at different scales. Image Denoising is performed by modeling this noise and then removing it.

Simplest model of Image Noise: Gaussian

$$I(x) = J(x) + G_\sigma(x)$$



More sophisticated noise models exist: The way we model noise is the way we decide what to consider noise and what to consider signal!

3.3 Image Restoration: Denoising, Deblurring, Illumination Correction

Image Denoising: Any acquisition system senses quantities of interest together with noise at different scales. Image Denoising is performed by modeling this noise and then removing it.

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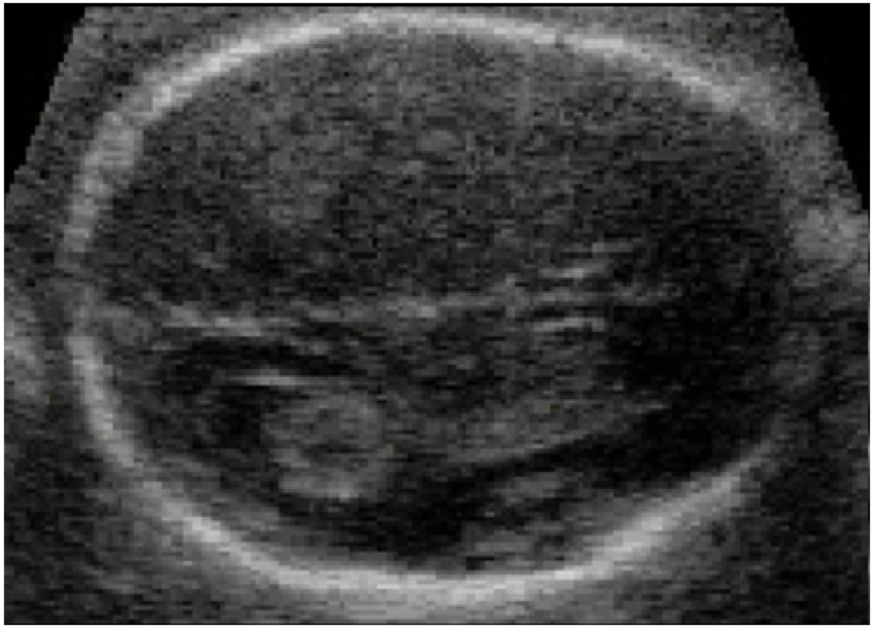
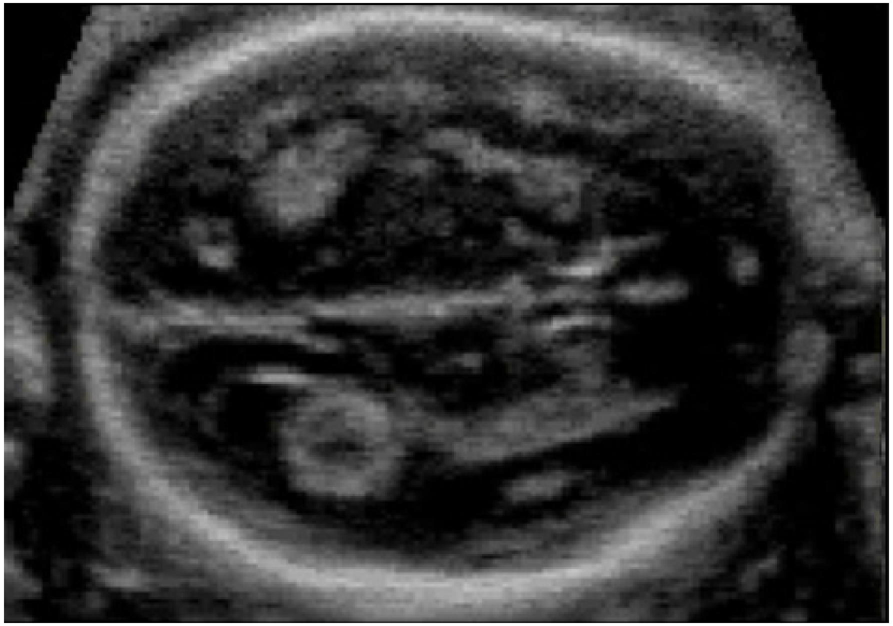


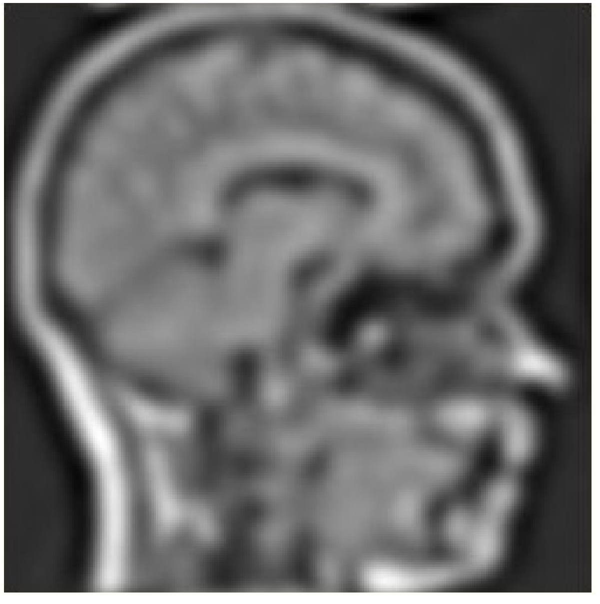


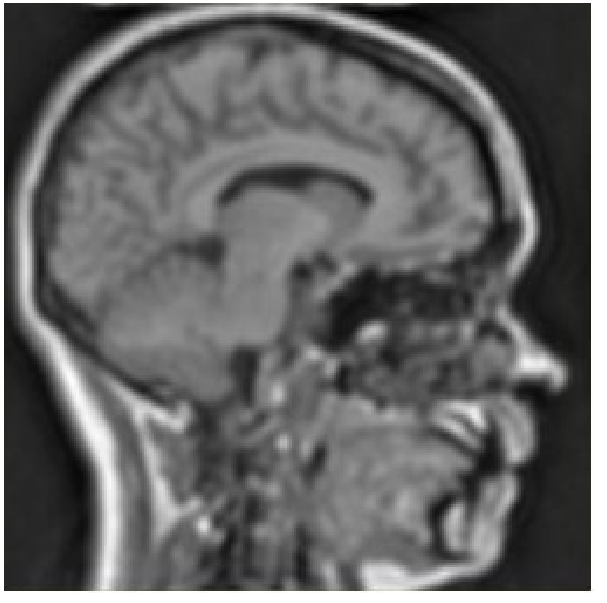
More sophisticated noise models exist: The way we model noise is the way we decide what to consider noise and what to consider signal!

Image Deblurring: Another typical problem with image acquisition is the presence of blur, or defocus. In this case, it is a much harder problem, since degradation is not additive.

Simplest model of Image Blur: **Gaussian**

$$I(x) = J(x) * G_\sigma(x)$$





Notice this is not only lack of contrast, or noise.

Image Dehazing: This is the task of fog removal.

Image Acquisition Model:

$$\boxed{\mathrm{I}(x) = \mathrm{J}(x)\mathrm{t}(x) + \mathrm{A}(1 - \mathrm{t}(x))} \qquad \boxed{\mathrm{t}(x) = e^{-\beta d(x)}}$$

J(x), the haze-free image, is what we want to retrieve. According to the model, it undergoes a **multiplicative** degradation depending on depth, and an **additive** degradation depending on depth and haze color.

As distance goes to 0, t(x) $\longrightarrow$ 1. Near the observer, haze has no effect and we have:

$$\lim_{t(x)\to 1} \mathrm{I(x)} = \mathrm{J(x)}$$

As distance increases, haze takes over the scene, and we have:

$$\lim_{t(x)\to 0} \mathrm{I(x)} = \mathrm{A}$$

Image Dehazing: This is the task of fog removal.

Image Acquisition Model:

$$\boxed{\mathrm{I}(x) = \mathrm{J}(x)\mathrm{t}(x) + \mathrm{A}(1 - \mathrm{t}(x))} \qquad \boxed{\mathrm{t}(x) = e^{-\beta d(x)}}$$

Hazy image

Image Dehazing: This is the task of fog removal.

Image Acquisition Model:

$$\boxed{\mathrm{I}(x) = \mathrm{J}(x)\mathrm{t}(x) + \mathrm{A}(1 - \mathrm{t}(x))}$$

$$\boxed{\mathrm{t}(x) = e^{-\beta d(x)}}$$

Histogram Equalization

Image Dehazing: This is the task of fog removal.

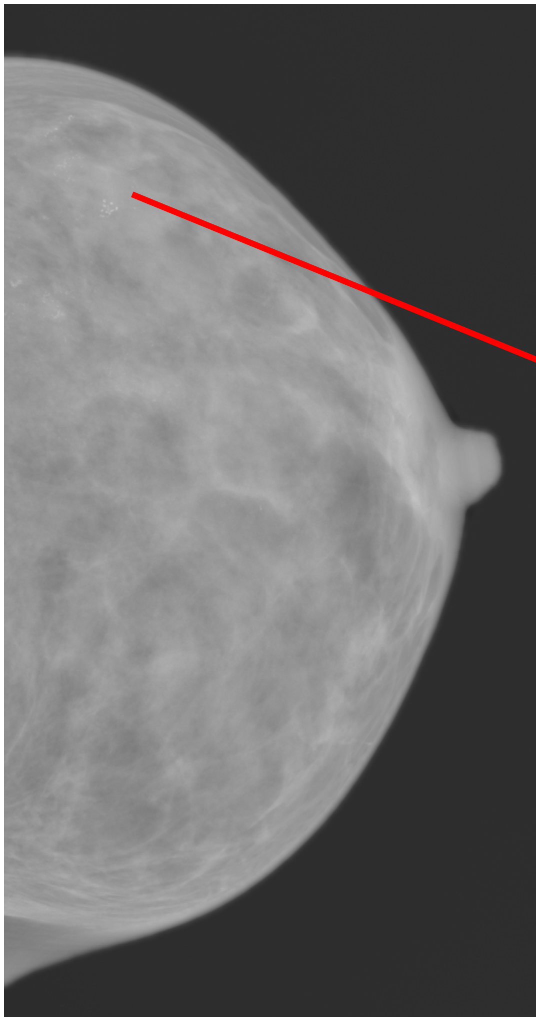
Image Acquisition Model:

$$\boxed{\mathrm{I}(x) = \mathrm{J}(x)\mathrm{t}(x) + \mathrm{A}(1 - \mathrm{t}(x))}$$

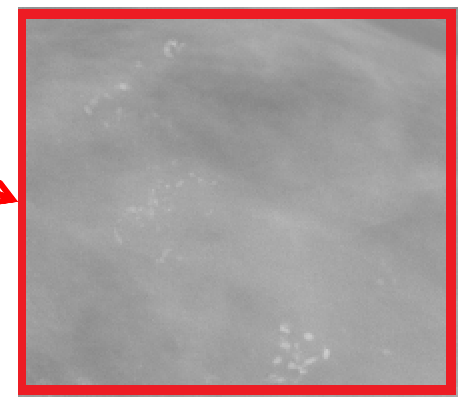
$$\boxed{\mathrm{t}(x) = e^{-\beta d(x)}}$$

Dehazed image

Image Dehazing: Applications for Medical Imaging



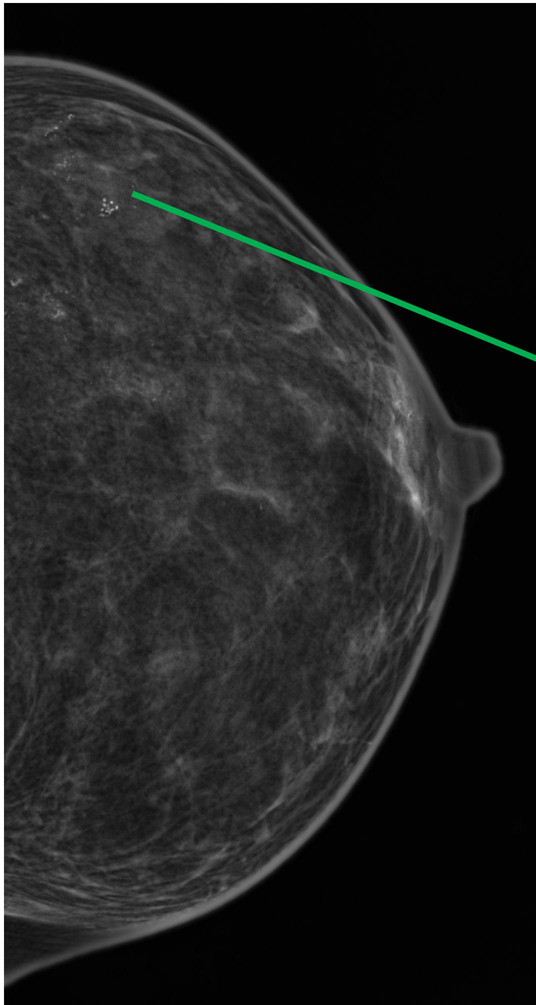
Digital Mammogram



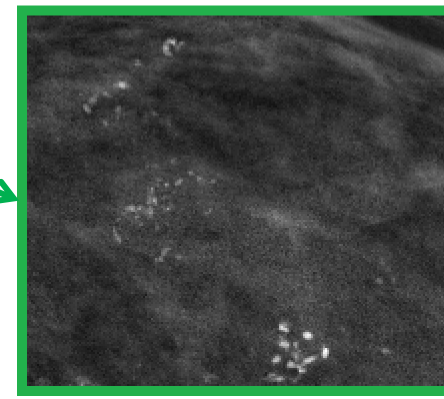
Micro-calcification Cluster

3.3 Image Restoration: Denoising, Deblurring, Illumination Correction

Image Dehazing: Applications for Medical Imaging



Digital Mammogram



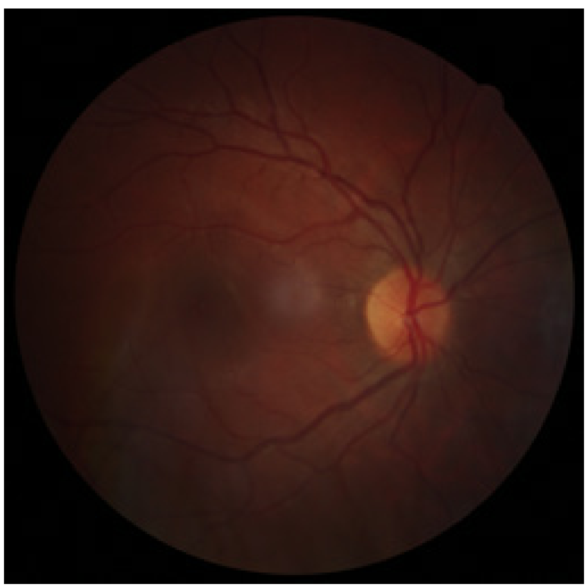
Micro-calcification Cluster

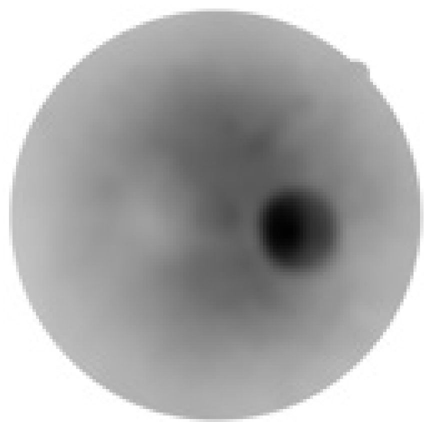
3.3 Image Restoration: Denoising, Deblurring, Illumination Correction

Illumination Correction by Dehazing:

- Think of shadows as the inverse of fog.
- They drive intensities towards white instead of towads dark.

$$\text{Shadow Removal}(I(x,y)) \rightsquigarrow \mathbb{1} - \text{Dehazing}(\mathbb{1} - I(x,y))$$





Shadow Map Estimate

Illumination Correction by Dehazing:

- Think of shadows as the inverse of fog.
- They drive intensities towards white instead of towads dark.

$$\text{Shadow Removal}(I(x,y)) \rightsquigarrow \mathbb{1} - \text{Dehazing}(\mathbb{1} - I(x,y))$$

Illumination Correction by Dehazing:

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4. Project Description

4.1 Skin Lesion Analysis

4.1 Skin Lesion Analysis

See moodle

4.2 Artery/Vein Classification

4.2 Artery/Vein Classification

See moodle