MAIA - MedicAl Imaging and Applications

Advanced Image Analysis

Lectures on Advanced Color Image Processing

B7 – RETINEX AND COLOR CONSTANCY

March/2018

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Multi-Exposure Image Fusion

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).

HDR imaging requires to know the precise exposure time. The HDR image itself looks dark and is not pretty to look at. The minimum intensity in an HDR image is 0, but theoretically, there is no maximum. So we need to map its values between 0 and 255 so we can display it (**tone mapping**).

As you can see, assembling an HDR image and then doing tone mapping is quite tricky. Can't we just use the multiple images and create a tone mapped image **without ever going to HDR?**

The answer is yes, using **Exposure Fusion**.

Multiple Exposure Image Composition

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).

Exposure Fusion

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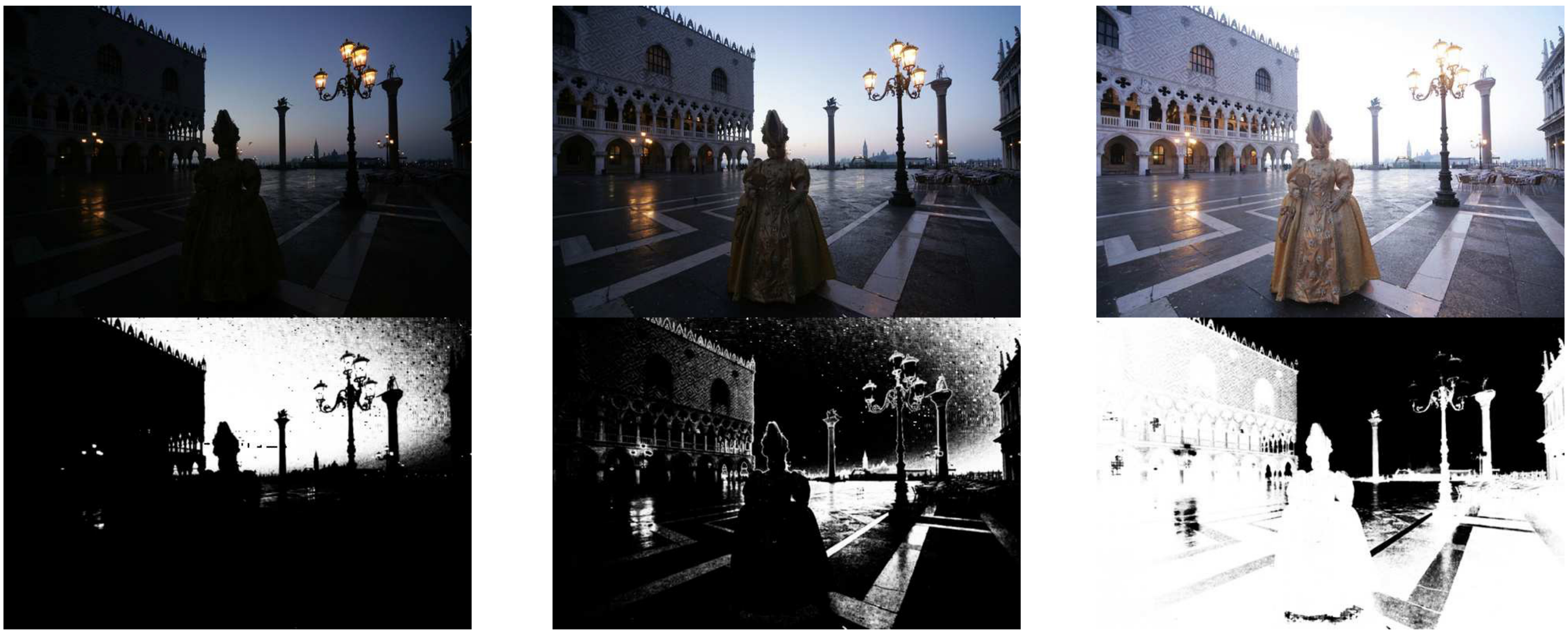
UK

Multiple Exposure Image Composition

$$C = W_1 \cdot I_1 + (1 - W_1) \cdot I_2 \longrightarrow C = W_1 \cdot I_1 + W_2 \cdot I_2 + \ldots W_n \cdot I_n$$

$$\sum_{i=1}^{n} W_i = 1$$



Multiple Exposure Image Composition

$$C = W_1 \cdot I_1 + 1 - W_2 \cdot I_2 \longrightarrow C = W_1 \cdot I_1 + W_2 \cdot I_2 + \ldots W_n \cdot I_n$$

$$\sum_{i=1}^{n} W_i = 1$$




Multiple Exposure Image Composition

- How do we compute W_i?

$$\boxed{C = W_1 \cdot I_1 + W_2 \cdot I_2 + \ldots W_n \cdot I_n}$$

Contrast:
Absolute Value of Laplacian Filter Response, $W^C = \mathcal{L}(I)$ $\mathcal{L} =$

0	1	0
1	−4	1
0	1	0

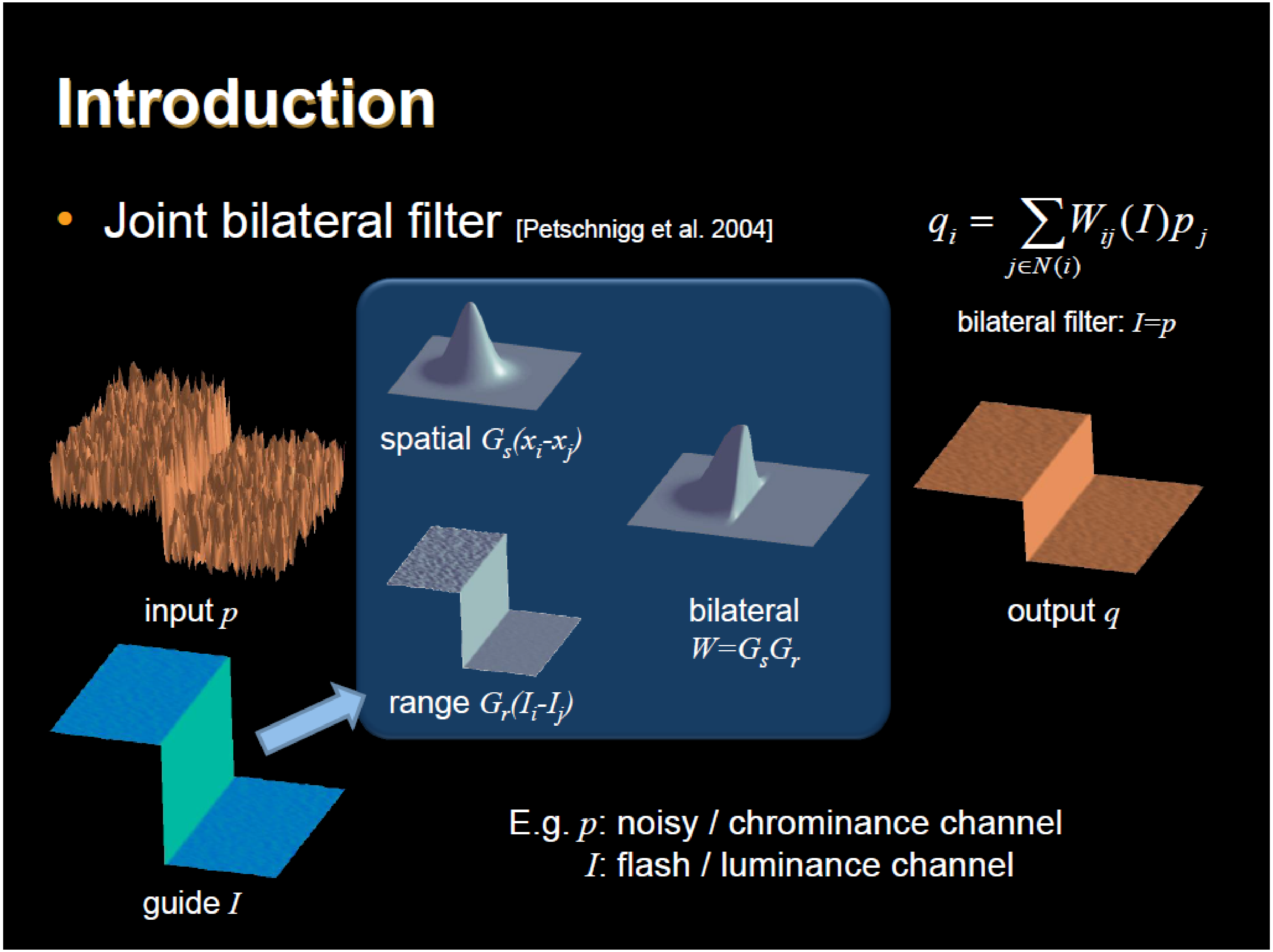
Saturation:
Standard Deviation between R, G, and B values in each pixel, $\mu = \frac{I_R(i)+I_G(i)+I_B(i)}{3}$

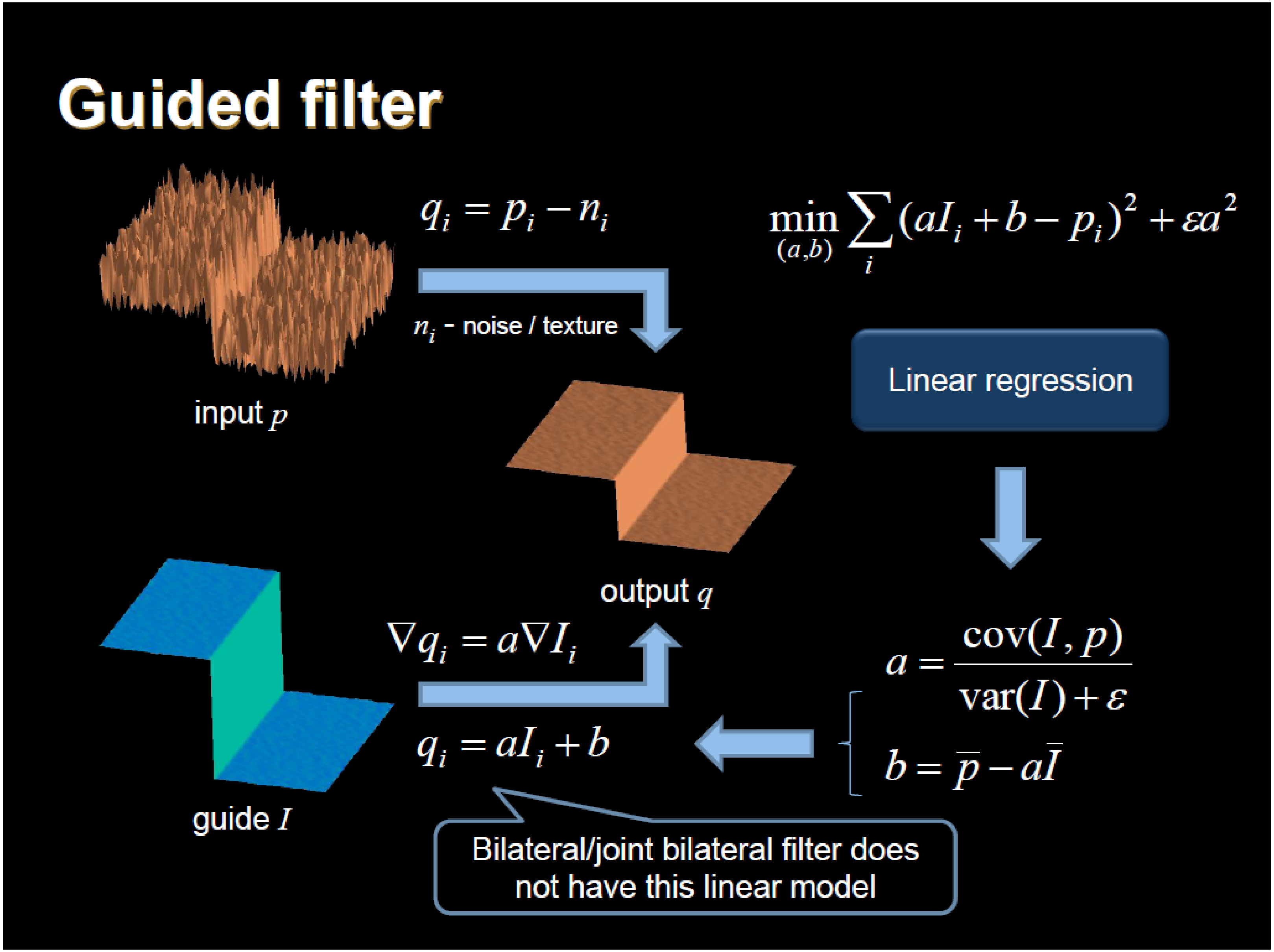
$$W^{sat}(i) = \sqrt{((I_R(i) - \mu)^2 + (I_G(i) - \mu)^2 + (I_B(i) - \mu)^2)/3}$$

Exposure:
Deviation from gray value, $W^{exp}(i) = \exp\left(-\frac{(I(i) - 0.5)^2}{\sigma^2}\right)$

$$\boxed{W = W^C \cdot W^{sat} \cdot W^{exp}} \Rightarrow \boxed{W_j = W_j^C \cdot W_j^{sat} \cdot W_j^{exp}} \quad \boxed{\sum_{j=1}^{n} W_j = 1}$$

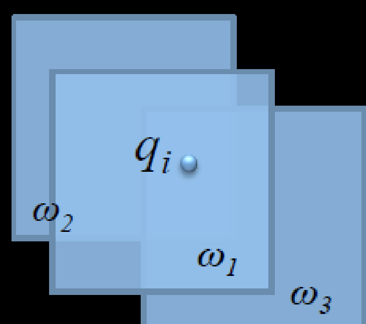
Let's see Multiple Exposure Image Fusion in action
Open mef.m files


Introduction
• Joint bilateral filter [Petschnigg et al. 2004]
$q_i = \sum_{j \in N(i)} W_{ij}(I) p_j$
bilateral filter: $I=p$
spatial $G_s(x_i\text{-}x_j)$
range $G_r(I_i\text{-}I_j)$
bilateral
$W=G_sG_r$
input p
output q
guide I
E.g. p: noisy / chrominance channel
I: flash / luminance channel


Guided filter
$q_i = p_i - n_i$
n_i - noise / texture
input p
output q
guide I
$\min_{(a,b)} \sum_i (aI_i + b - p_i)^2 + \varepsilon a^2$
Linear regression
$a = \frac{\mathrm{cov}(I,p)}{\mathrm{var}(I) + \varepsilon}$
$b = \bar{p} - a\bar{I}$
$\nabla q_i = a \nabla I_i$
$q_i = aI_i + b$
Bilateral/joint bilateral filter does not have this linear model

Guided filter

- Extend to the entire image
  - In all local windows ω_k, compute the linear coefficients
  - Compute the average of $a_k I_i + b_k$ in all ω_k that covers pixel q_i



Definition

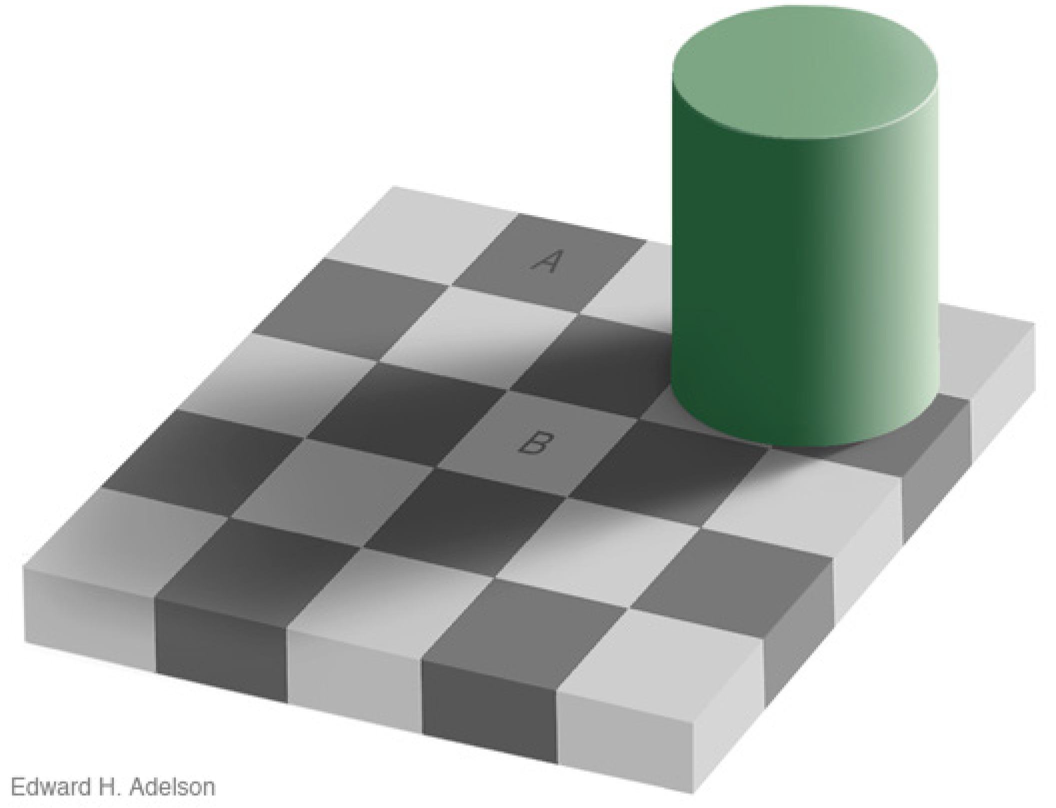
$$a_k = \frac{\mathrm{cov}_k(I,p)}{\mathrm{var}_k(I)+\varepsilon}$$

$$b_k = \bar{p}_k - a\bar{I}_k$$

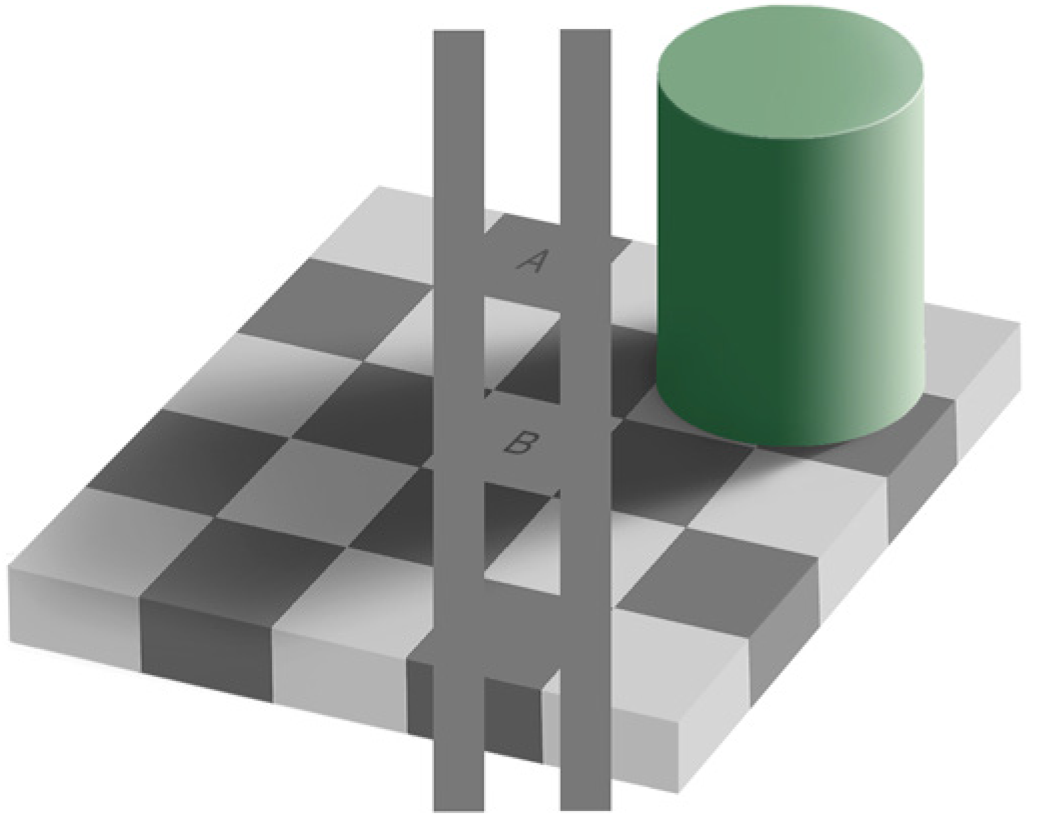
$$q_i = \frac{1}{|\omega|}\sum_{k|i\in\omega_k}(a_k I_i + b_k)$$

$$= \bar{a}_i I_i + \bar{b}_i$$

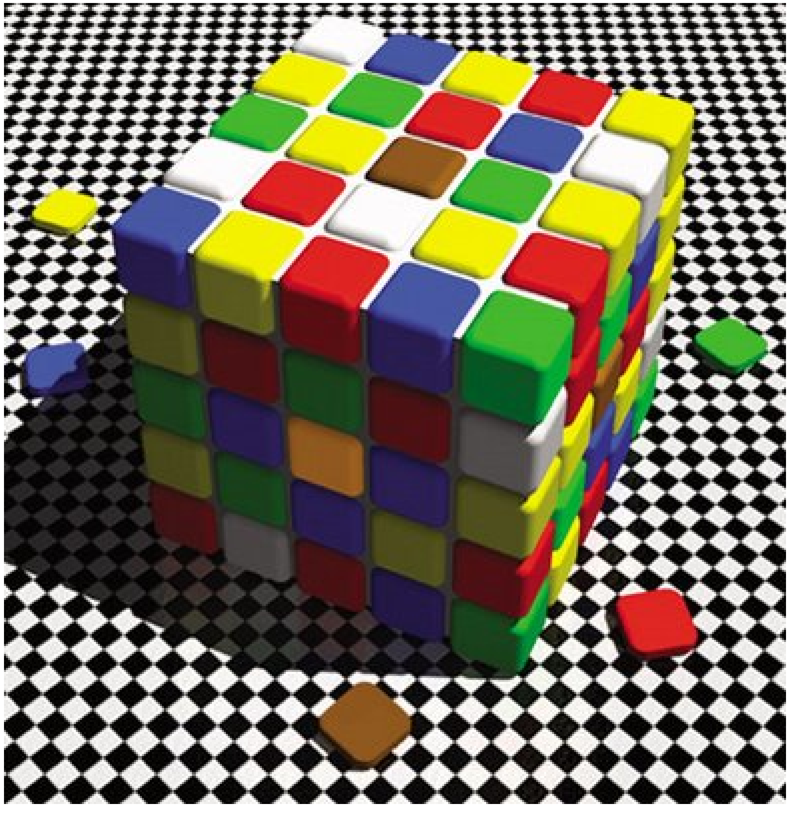
Recap on Color Constancy



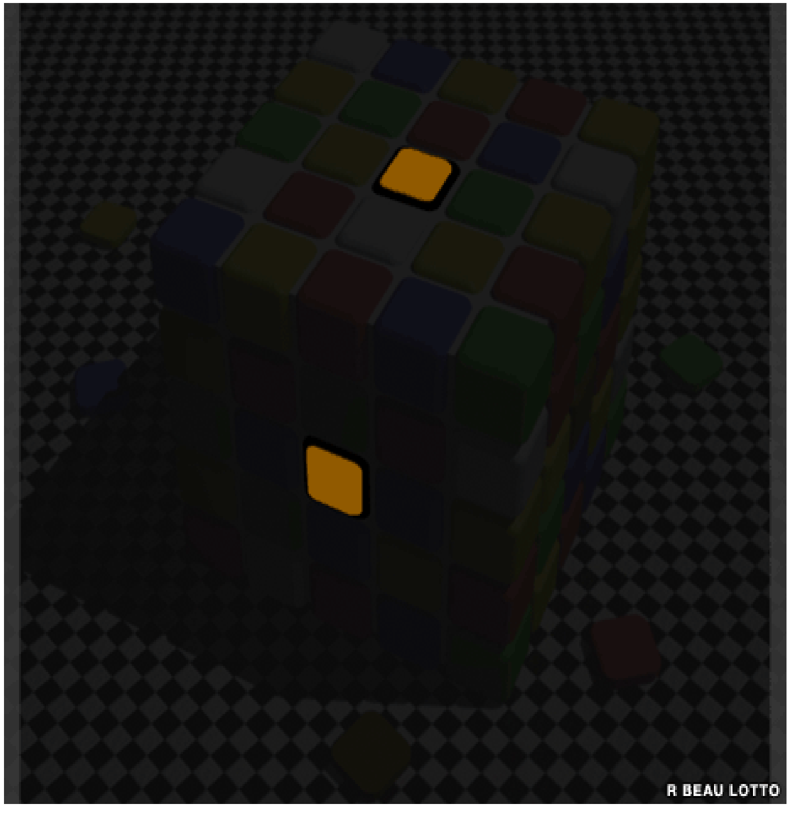
Recap on Color Constancy



Recap on Color Constancy



Recap on Color Constancy



Recap on Color Constancy

Light Perception is not simpy a matter of light acquisition

Colors **perceived different** can be “**radiometrically**” **equal**

Color Constancy:

QUIZ!
How would you define color constancy?

Recap on Color Constancy

Light Perception is not simpy a matter of light acquisition

Colors **perceived different** can be “**radiometrically**” **equal**

Color Constancy:

QUIZ!
How would you define 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**

Recap on Color Constancy

Colors **perceived different** can be “**radiometrically**” **equal**

“**Radiometrically**” **different** colors can be **perceived the same**

Recap on Color Constancy

Colors **perceived different** can be “**radiometrically**” **equal**

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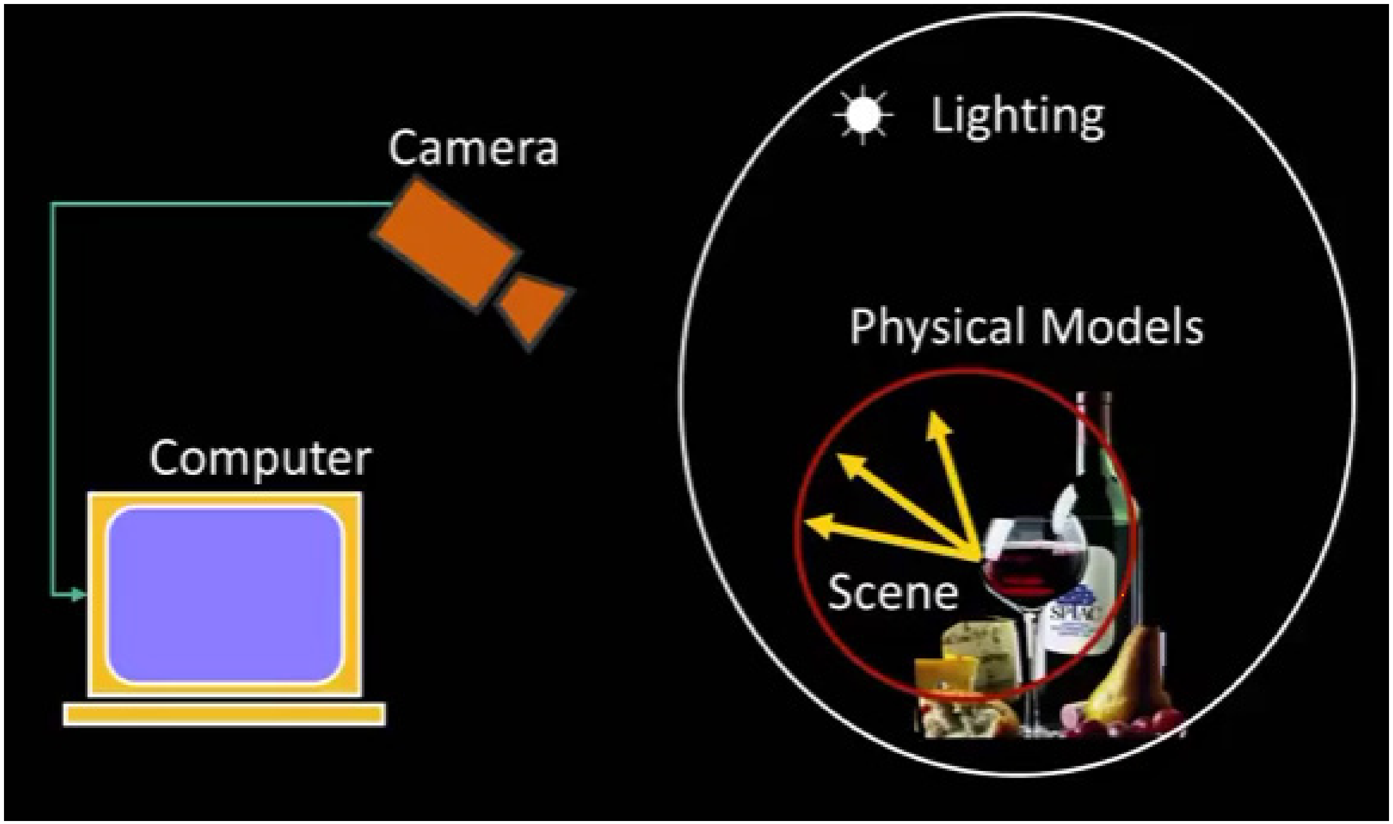
Photometry: Measuring Light



Photometry: Measuring Light

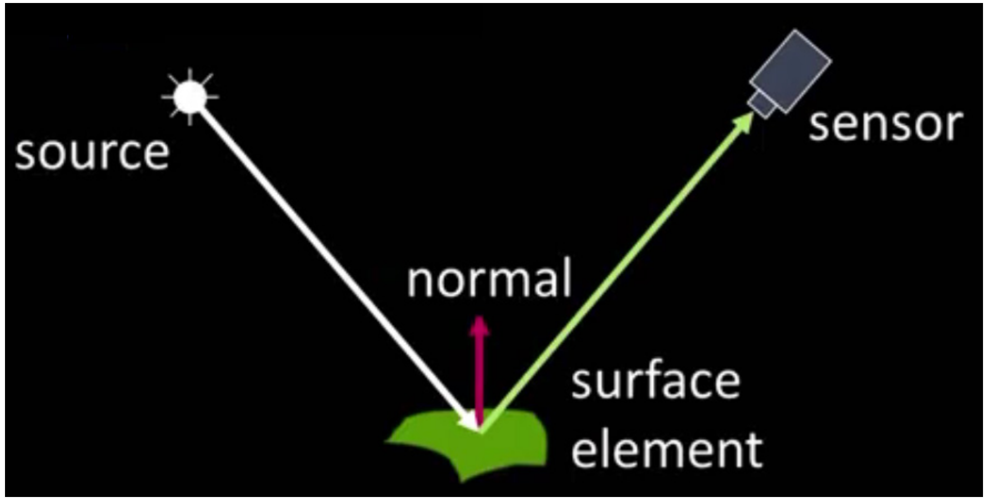
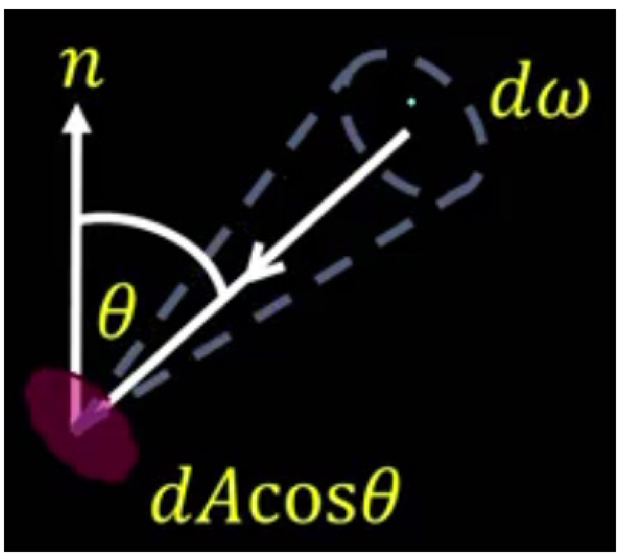


Image Intensity = F(normal, surface reflectance, illumination)



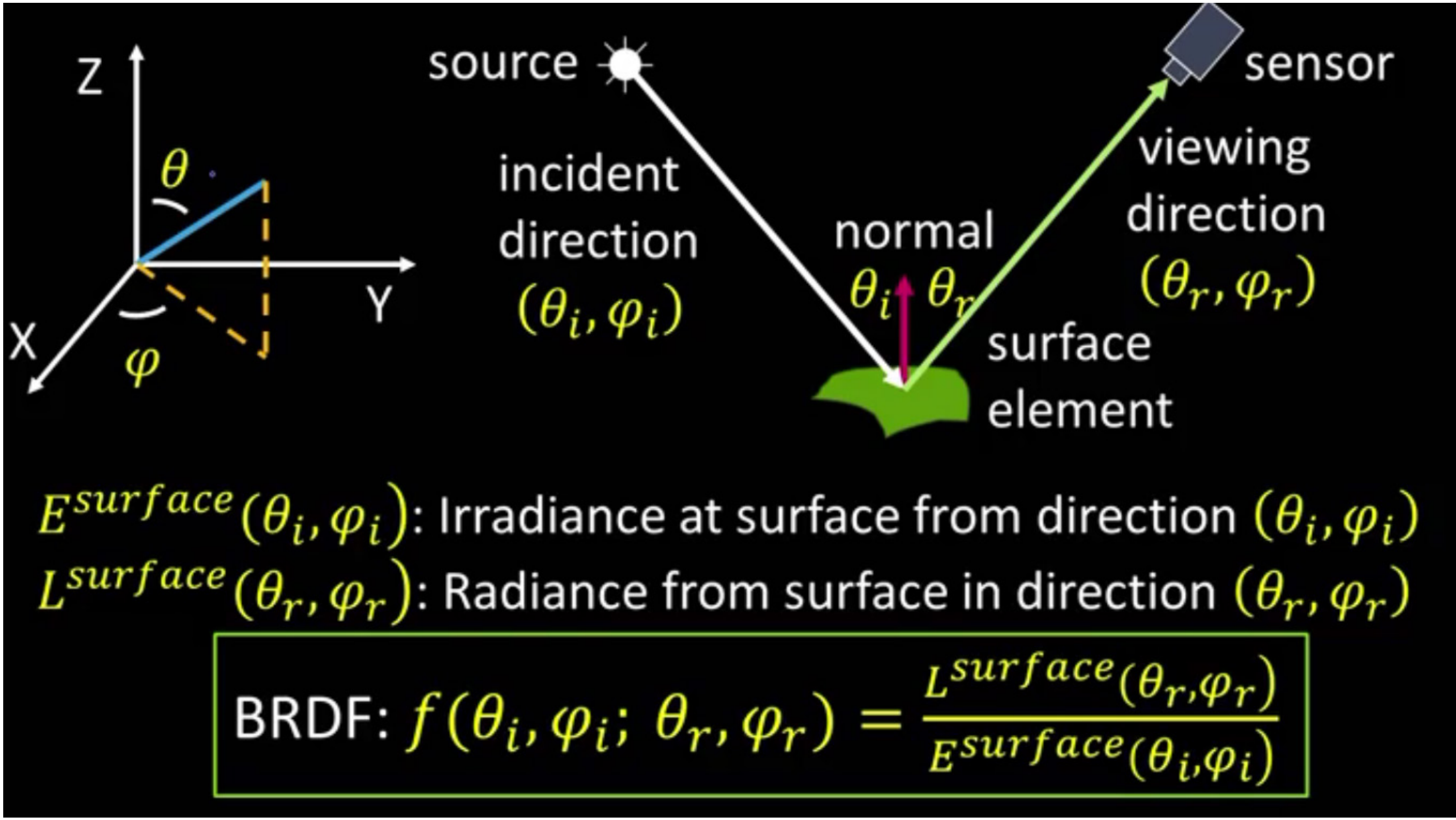
Irradiance: Energy emitted from light source

Describes the amount of light
that **arrives to** the surface

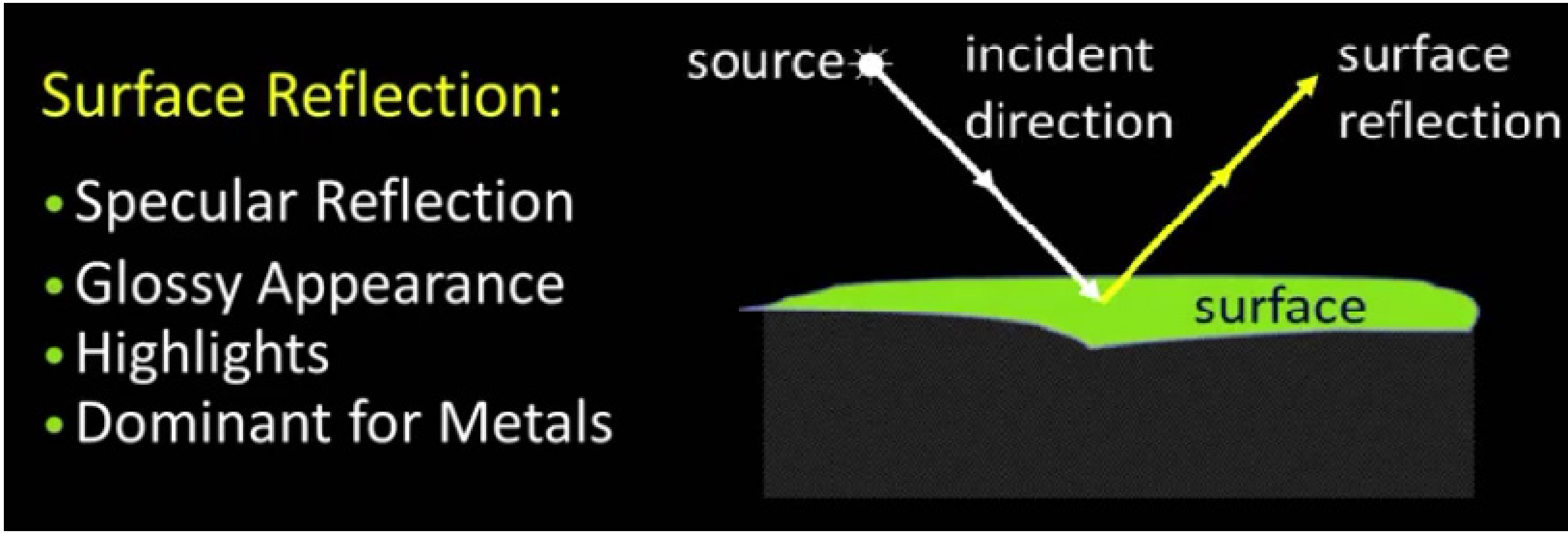
Radiance: Light that goes from the surface towards sensors

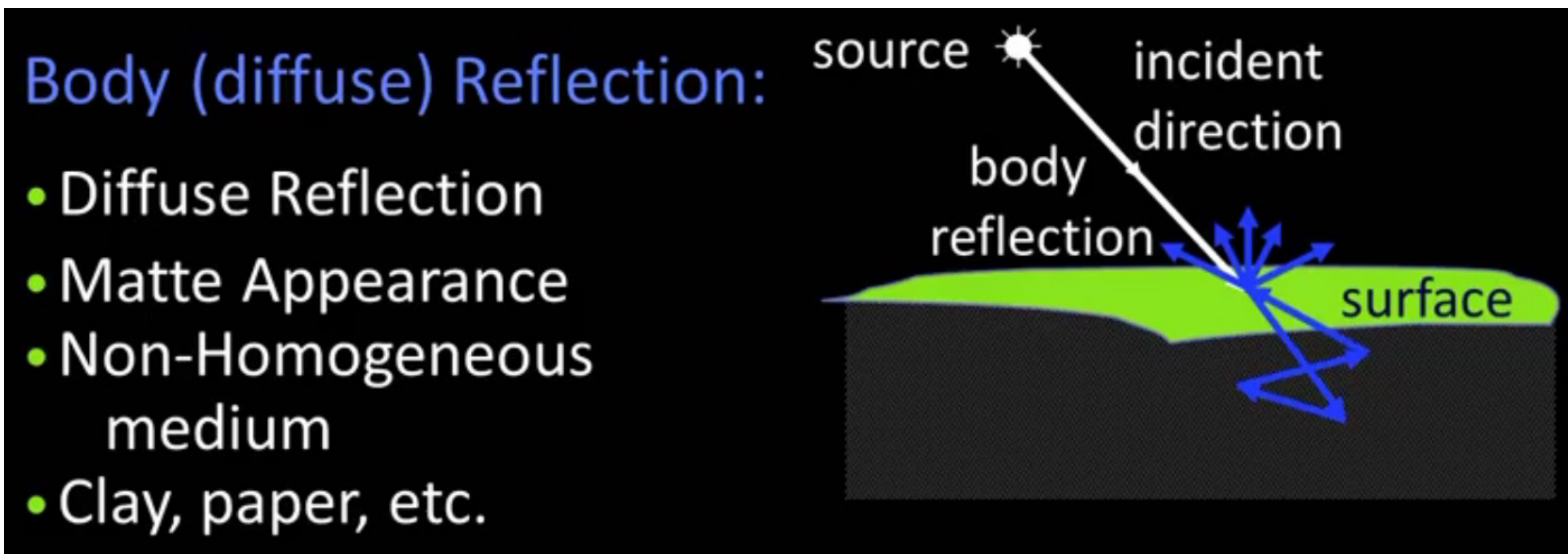
Describes the amount of light
that **goes out** of to the surface

Bidirectional Reflectance Distribution Model

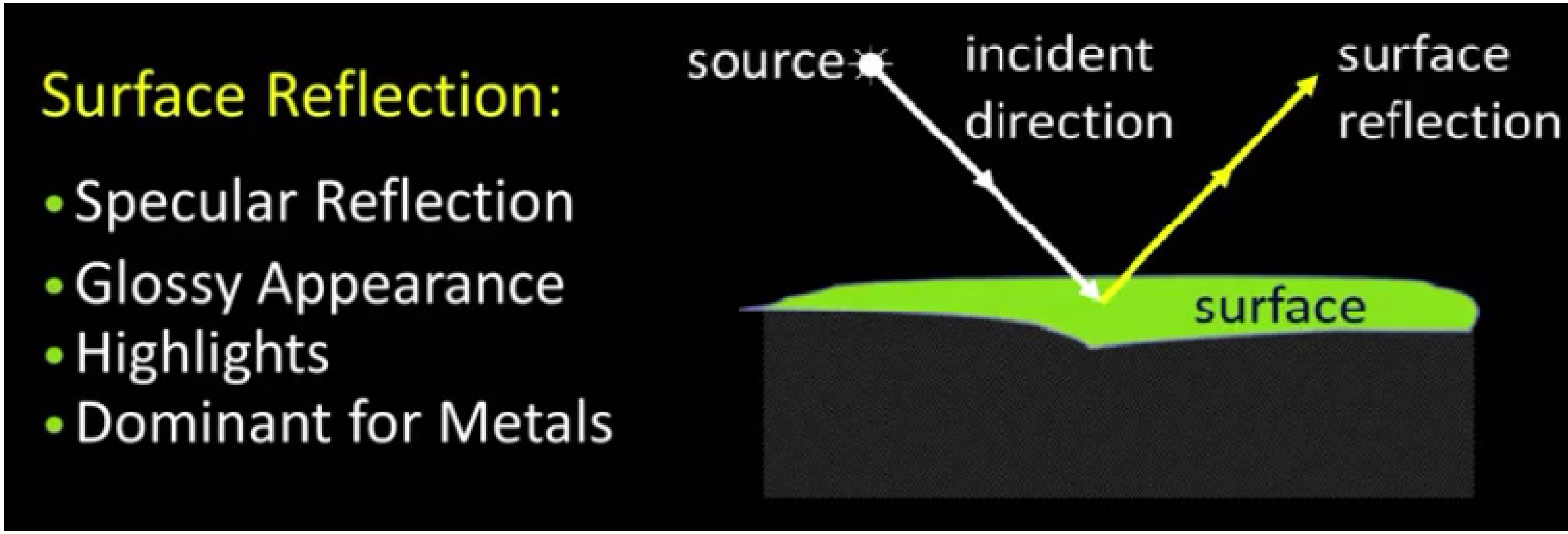


Photometry: Measuring Light



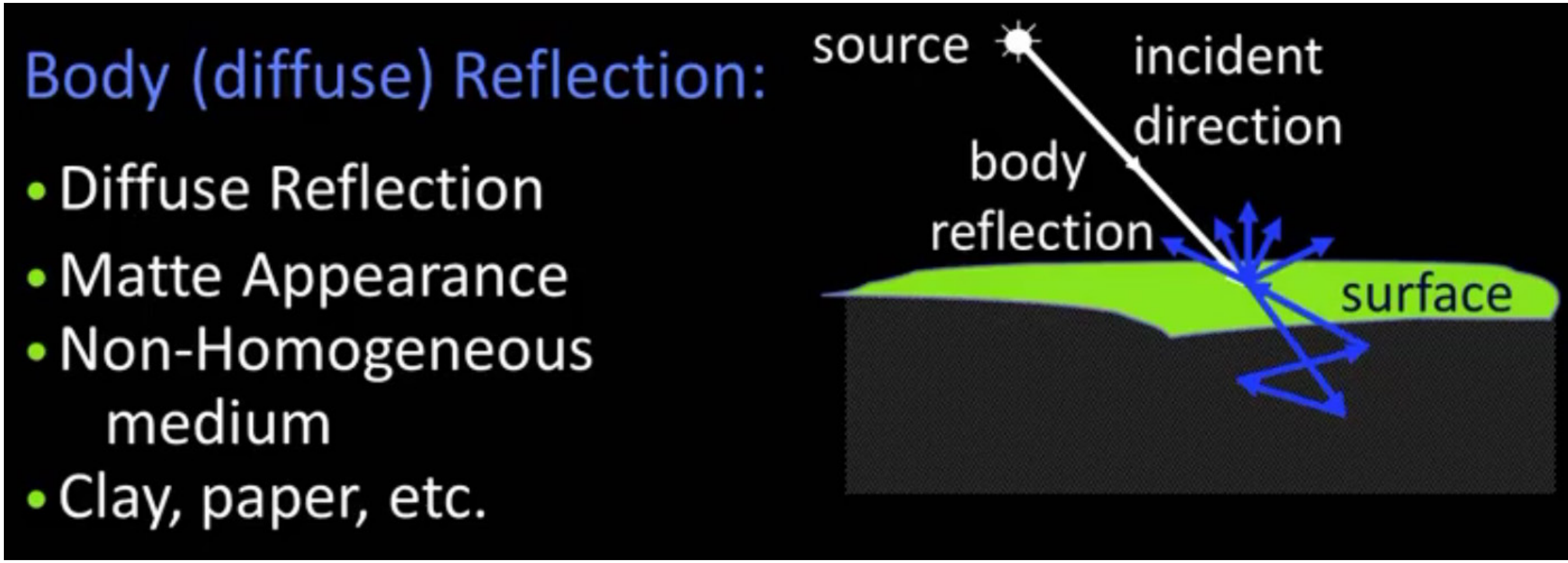


Photometry: Measuring Light



Specular Reflection: Really Hard to model, we ignore it (useful for graphics)

Photometry: Measuring Light



Lambertian Reflection Model: All light rays are reflected in the same way. Brightness is the same independenlty of the point of view.

Image Intensity = F(~~normal~~, surface reflectance, illumination)

Machine 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!

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

FIRST APPROACH TO MACHINE COLOR CONSTANCY

Assumptions:

- All objects in the scene are **flat**.
- All objects are considered **Lambertian** (no specularities, diffuse reflection)
- Scene uniformly illuminated with a **single global (uniform) illuminant**.

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

Irradiance $I(\lambda)$ **Reflectance** $R(\lambda)$ **Radiance** $E(\lambda)$

FIRST APPROACH TO MACHINE COLOR CONSTANCY

$$R = \int_{380}^{740} r(\lambda) \times I(\lambda) \times S(\lambda)\, d\lambda$$

$$G = \int_{380}^{740} g(\lambda) \times I(\lambda) \times S(\lambda)\, d\lambda$$

$$B = \int_{380}^{740} b(\lambda) \times I(\lambda) \times S(\lambda)\, d\lambda$$

$$\longrightarrow$$

$$R = I(\lambda_R)S(\lambda_R)$$

$$G = I(\lambda_G)S(\lambda_G)$$

$$B = I(\lambda_B)S(\lambda_B)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} I(\lambda_R) & 0 & 0 \\ 0 & I(\lambda_G) & 0 \\ 0 & 0 & I(\lambda_B) \end{bmatrix} \begin{bmatrix} S(\lambda_R) \\ S(\lambda_G) \\ S(\lambda_B) \end{bmatrix}$$

$$S(\lambda_R) = \frac{R}{I(\lambda_R)}, \; S(\lambda_G) = \frac{G}{I(\lambda_G)}, \; S(\lambda_B) = \frac{B}{I(\lambda_B)}$$

Machine Color Constancy

FIRST APPROACH TO MACHINE COLOR CONSTANCY

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} \frac{1}{I(\lambda_R)} & 0 & 0 \\ 0 & \frac{1}{I(\lambda_G)} & 0 \\ 0 & 0 & \frac{1}{I(\lambda_B)} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

1. **Estimate illuminant components**
2. **Invert for white-balanced triplet**

Simplest Color Constancy

Gray World

Colors in the scene are sufficiently varied, and the average of reflectances is gray. In other words, reflectances are uniformly distributed over [0, 1]. For each waveband, **impose average 0.5**.

White Patch

The brightest object in a scene becomes the reference white, it is perceived as white. An estimate of illuminant color is obtained by finding the brightest pixel in the scene. **Impose white presence**.

FIRST APPROACH TO MACHINE COLOR CONSTANCY

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- All objects in the scene are **flat**.
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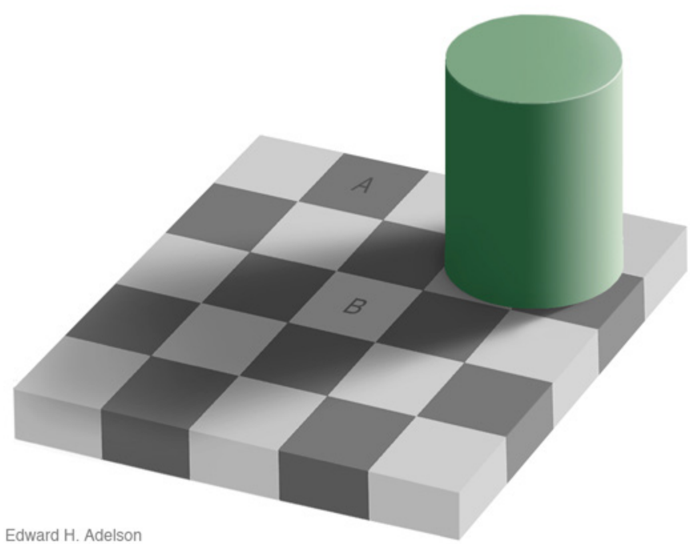
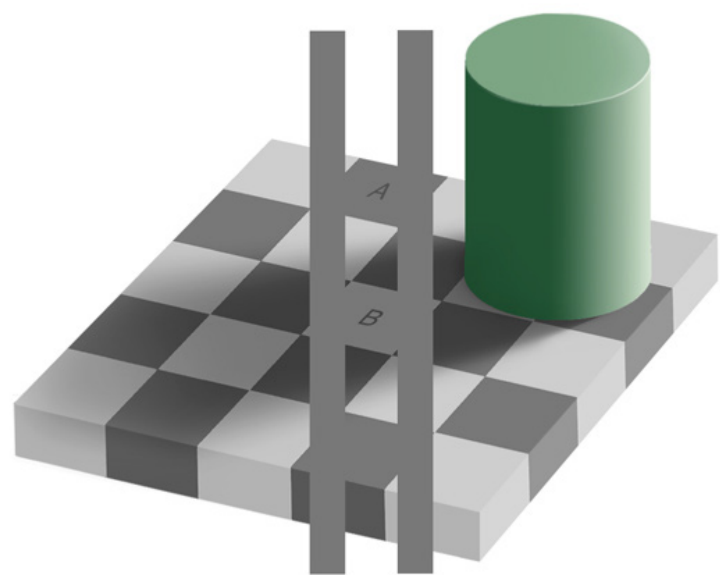
COLOR CONSTANCY UNDER NON-UNIFORM ILLUMINATION

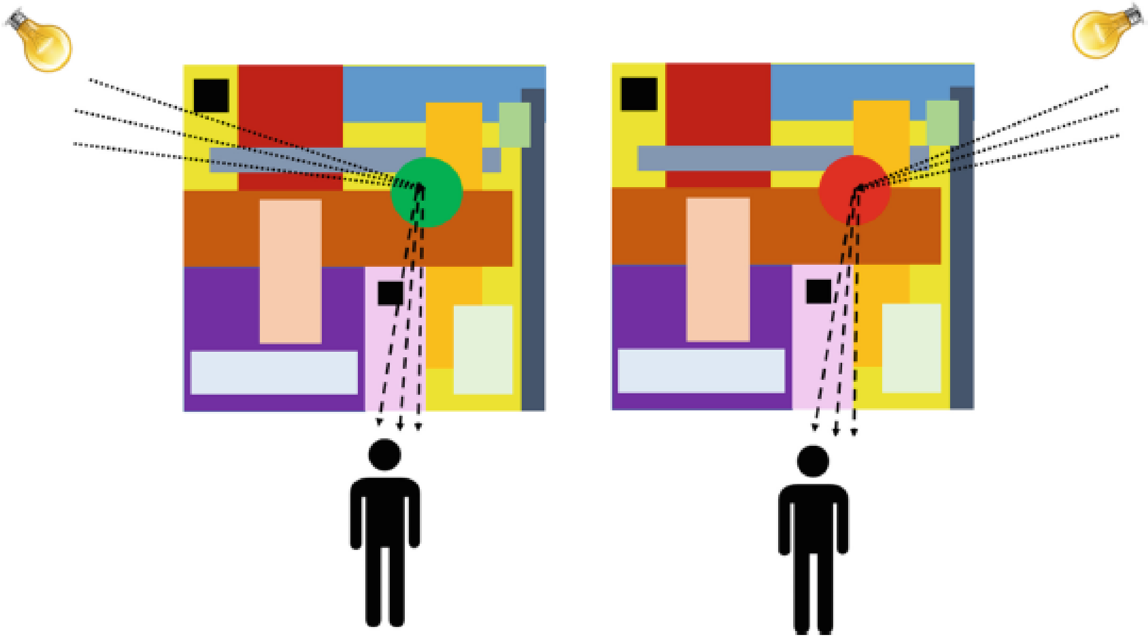
$$E(\lambda, x) = I(\lambda, x) \times R(\lambda, x)$$





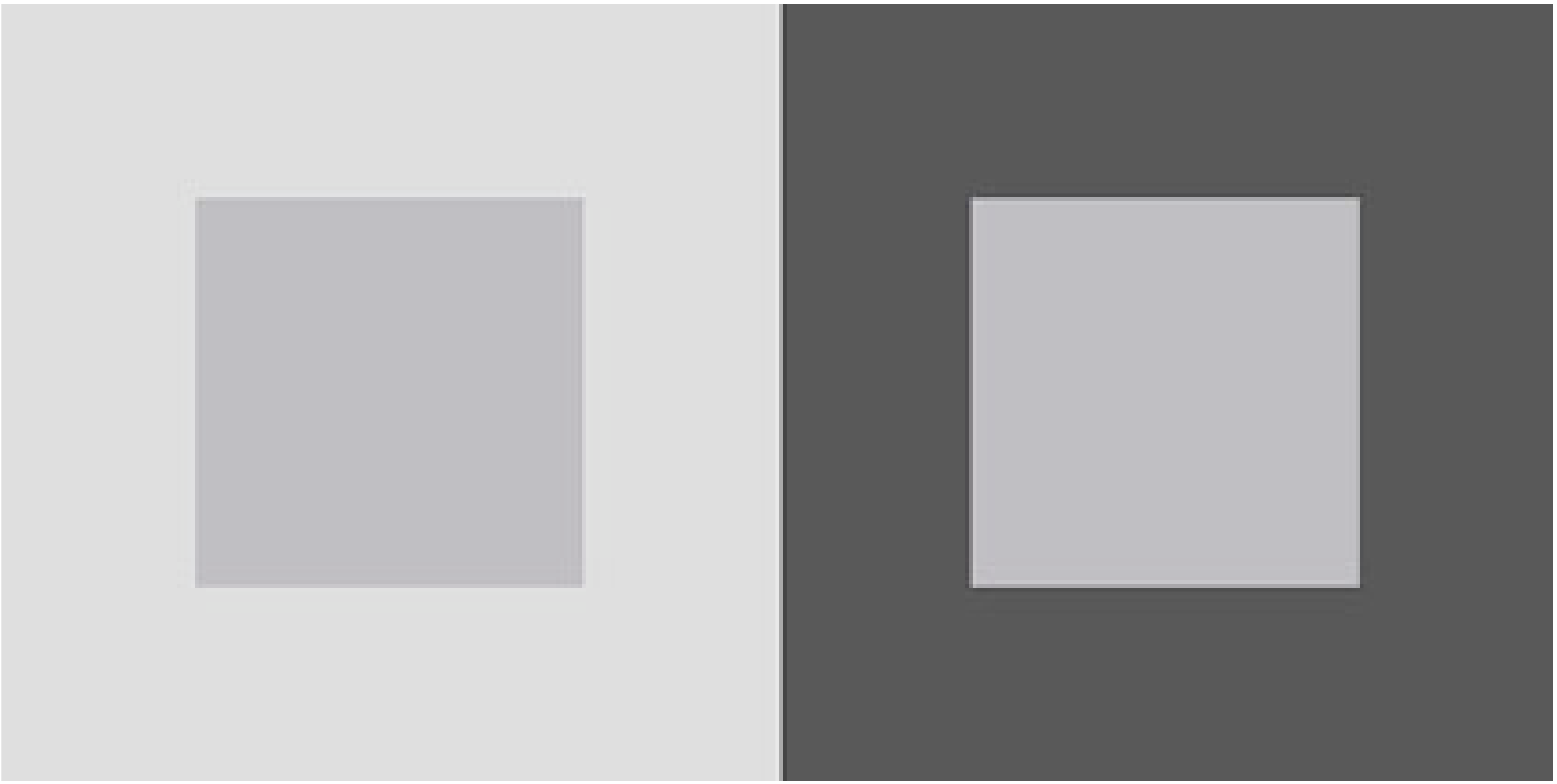
RETINEX THEORY OF COLOR VISION

1950 - A series of experiments by Land & McCann demonstrating that the process of color formation done by a camera and a human are different. Empirically demonstrate the above statements with psychophysical experiments



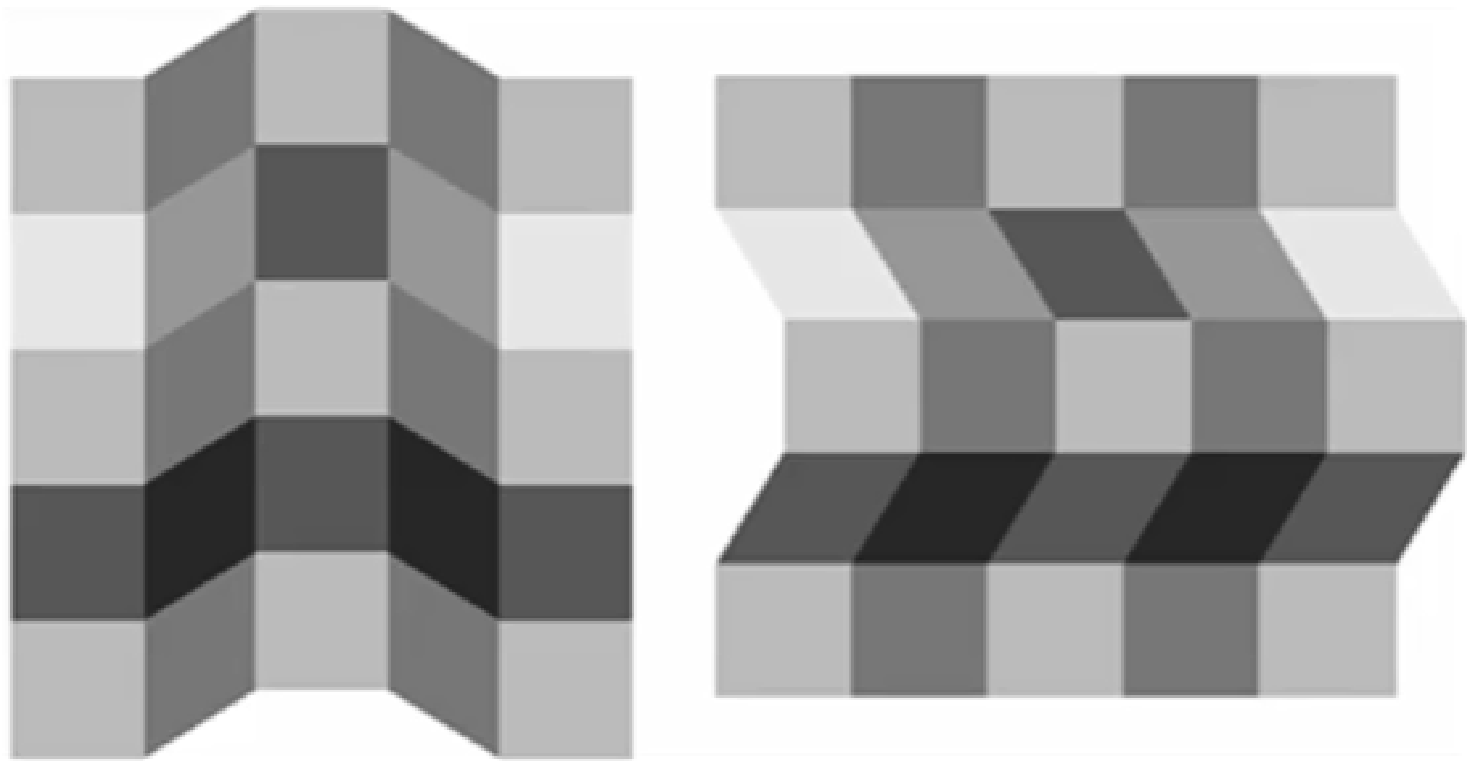
(Light sources tuned so that both look the same)

RETINEX



Machine Color Constancy

Color sensation is a ***spatial process***, related to surrounding visual information, edges and other relative spatial relationships



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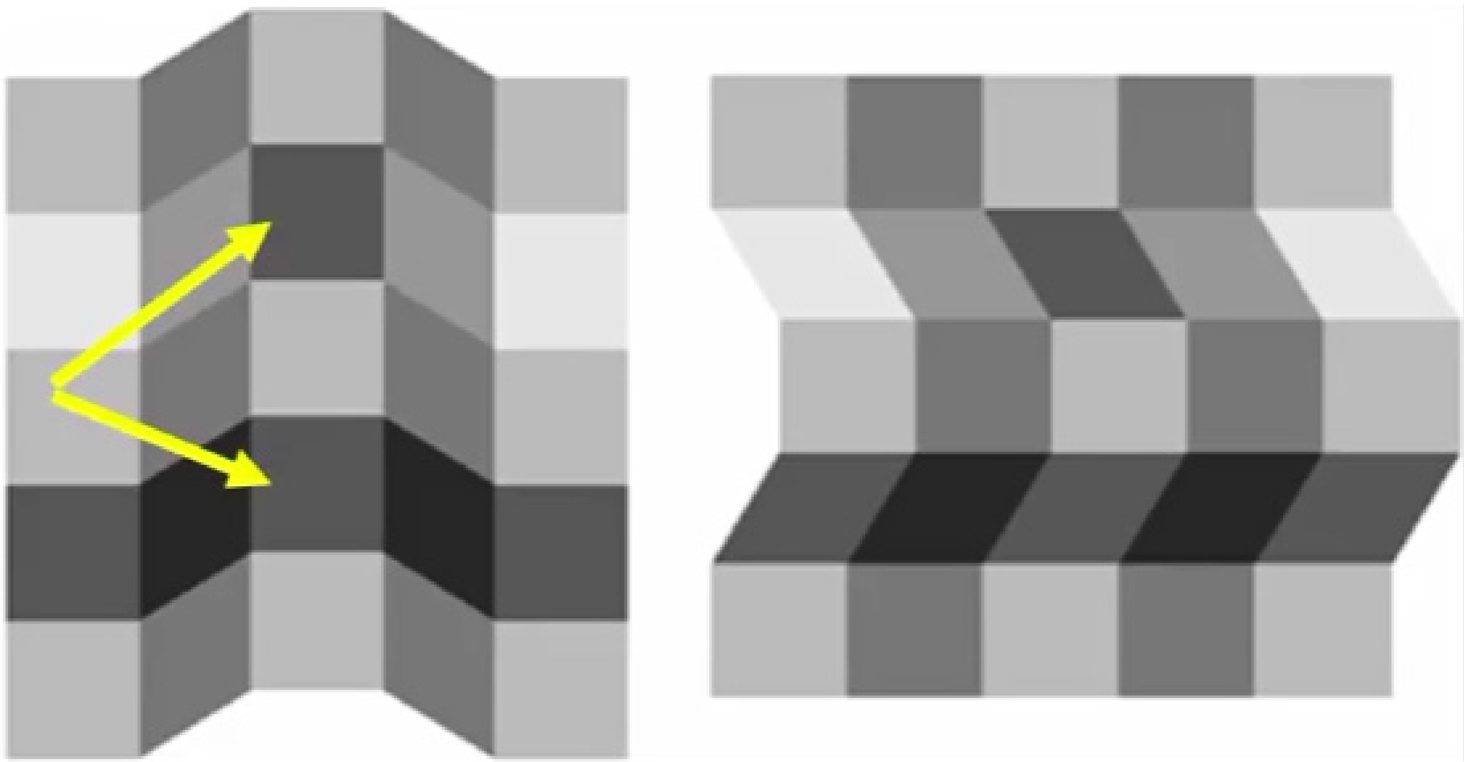

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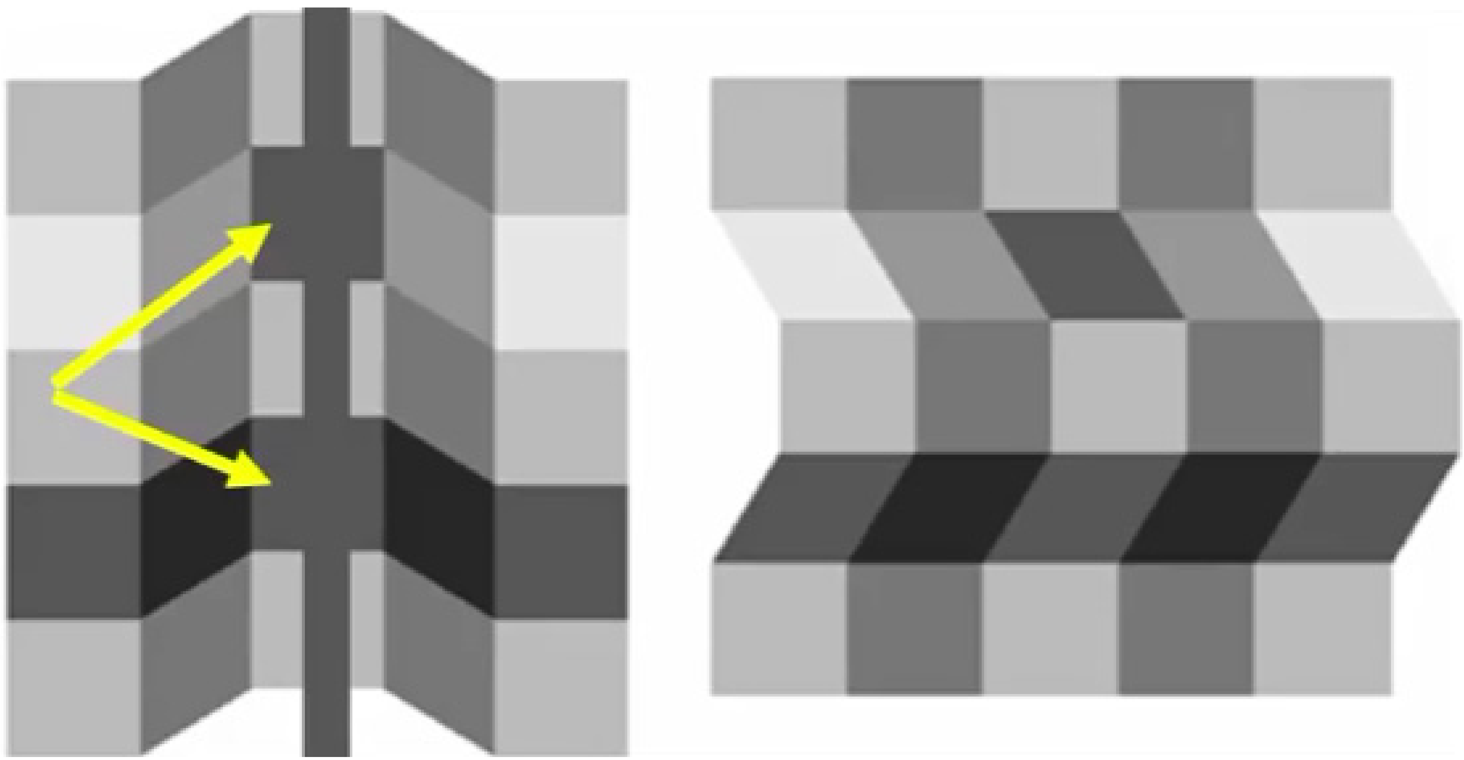

RETINEX

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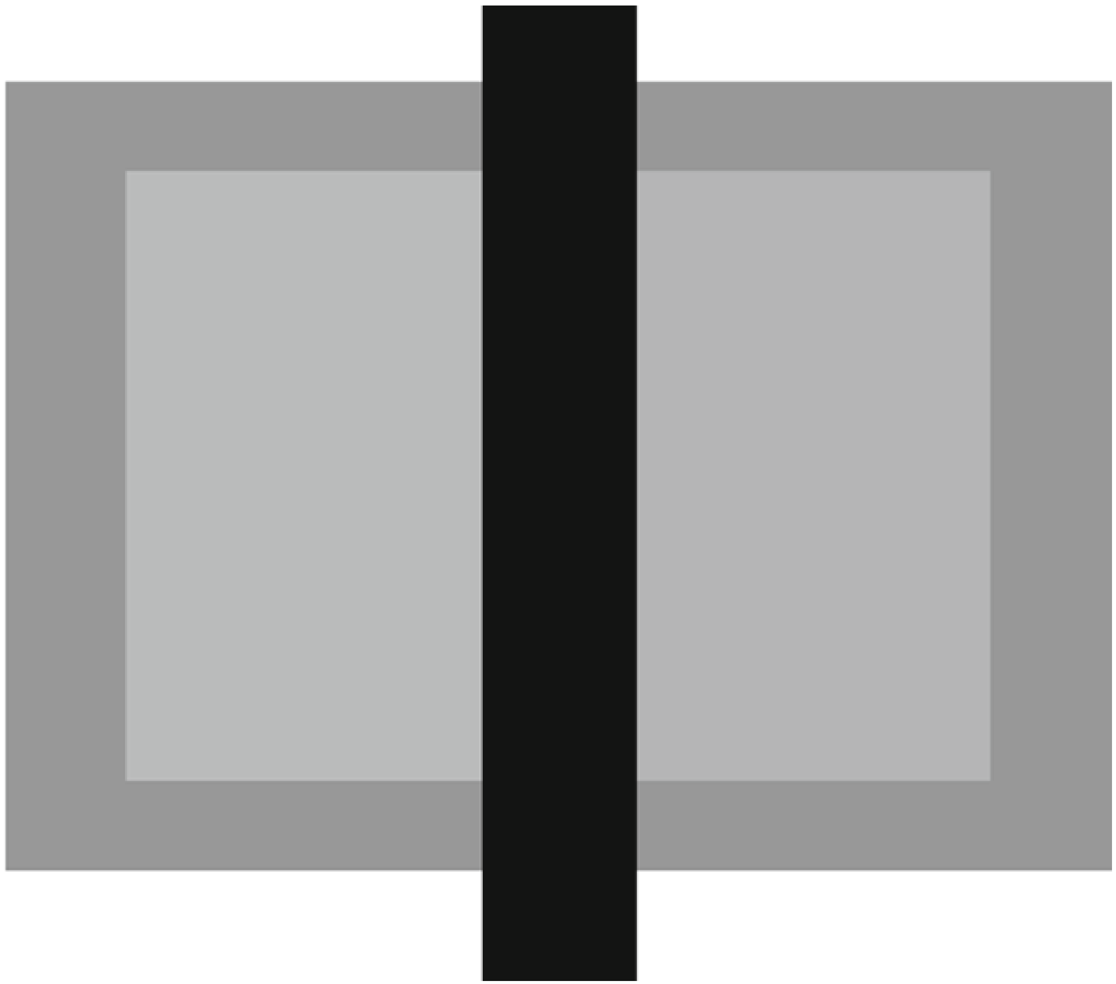


RETINEX

Color sensation is a ***spatial process***, related to surrounding visual information, edges and other relative spatial relationships

Retinex theory states that the human color sensation is a process that involves a ***local***, ***spatial*** comparison among different areas of an observed scene.

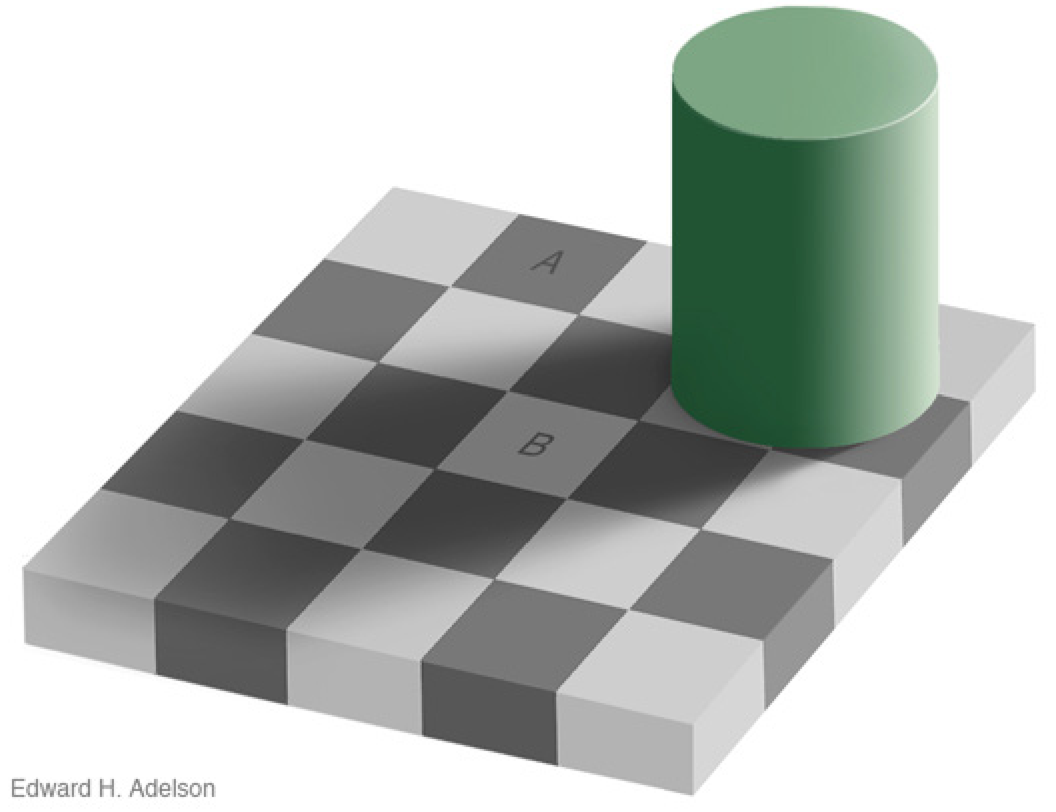
RETINEX ALGORITHMICALLY

First: What do we really want to accomplish?

Goal: An algorithm that estimates (predicts) the color sensation of objects in an image out of their RGB values

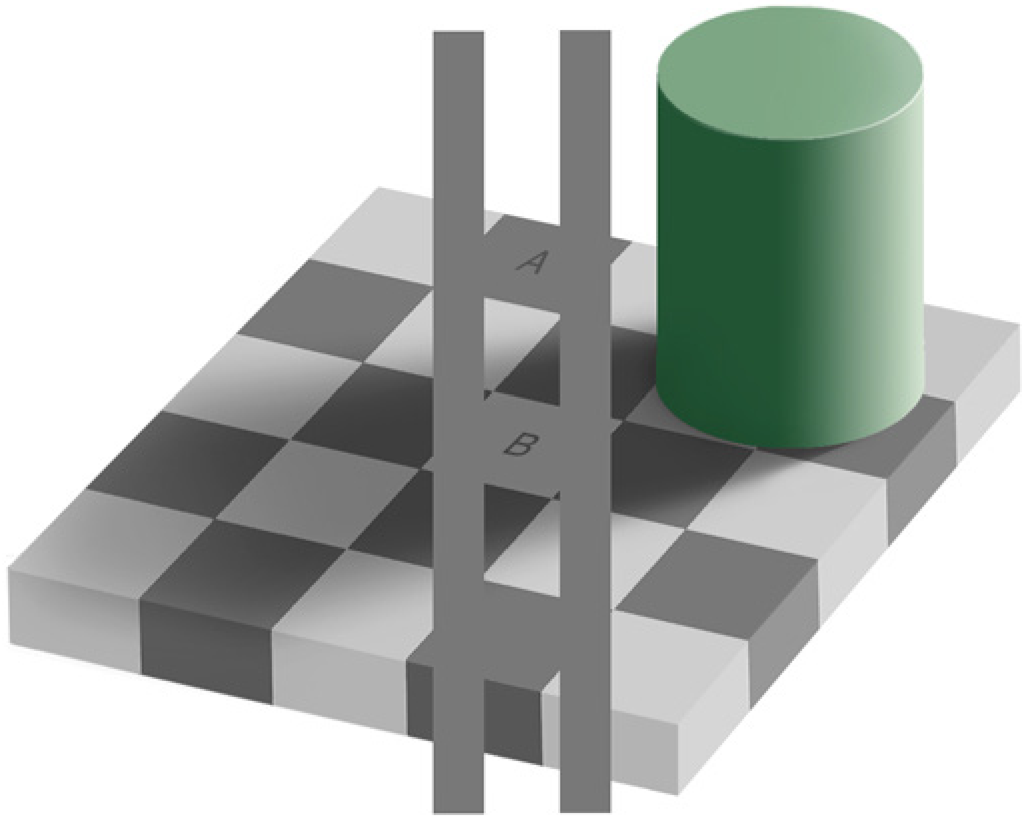
$$E(x) = I(x) \times R(x) \quad \Rightarrow \quad R(x)$$

RETINEX



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

RETINEX



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

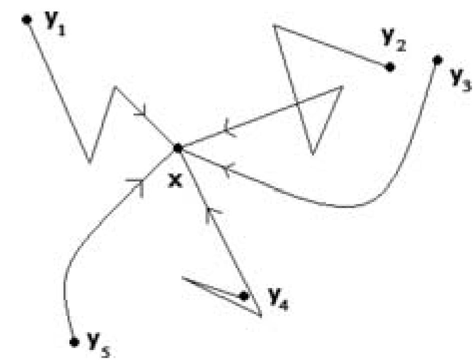
The output of Retinex should be an image in which intensities **are different**.

RETINEX ALGORITHMICALLY

A set of paths randomly chosen over the image is used to explore and compare the image intensities of different regions.

$$\gamma = \{y = z_0, z_1, \ldots, z_{n-1}, x = z_n\}$$

$$l^{\gamma}(x) = \frac{\mathrm{I}(x)}{\mathrm{I}(y)} = \underbrace{\frac{\mathrm{I}(z_1)}{\mathrm{I}(y)}}_{r_1} \cdot \underbrace{\frac{\mathrm{I}(z_2)}{\mathrm{I}(z_1)}}_{r_2} \cdots \underbrace{\frac{\mathrm{I}(z_{n-1})}{\mathrm{I}(z_{n-2})}}_{r_{n-1}} \underbrace{\frac{\mathrm{I}(x)}{\mathrm{I}(z_{n-1})}}_{r_n}$$



This unfolding of the I(x)/I(y) computation is not trivial due to the addition of two supplementary mechanisms, called **threshold** and **reset**.

RETINEX ALGORITHMICALLY

$$\gamma = \{y = z_0, z_1, \ldots, z_{n-1}, x = z_n\}$$

$$l^{\gamma}(x) = \frac{\mathrm{I}(x)}{\mathrm{I}(y)} = \underbrace{\frac{\mathrm{I}(z_1)}{\mathrm{I}(y)}}_{r_1} \cdot \underbrace{\frac{\mathrm{I}(z_2)}{\mathrm{I}(z_1)}}_{r_2} \cdots \underbrace{\frac{\mathrm{I}(z_{n-1})}{\mathrm{I}(z_{n-2})}}_{r_{n-1}} \underbrace{\frac{\mathrm{I}(x)}{\mathrm{I}(z_{n-1})}}_{r_n}$$

The **threshold** mechanism sets ratios in the above equation that are close to 1 to 1:

$$|1 - r_i| < \tau \Rightarrow r_i = 1$$

This disregards unwanted effects in lightness estimation due to smooth slowly varying illumination.

RETINEX ALGORITHMICALLY

$$\gamma = \{y = z_0, z_1, \ldots, z_{n-1}, x = z_n\}$$

$$l^{\gamma}(x) = \frac{\mathrm{I}(x)}{\mathrm{I}(y)} = \underbrace{\frac{\mathrm{I}(z_1)}{\mathrm{I}(y)}}_{r_1} \cdot \underbrace{\frac{\mathrm{I}(z_2)}{\mathrm{I}(z_1)}}_{r_2} \cdots \underbrace{\frac{\mathrm{I}(z_{n-1})}{\mathrm{I}(z_{n-2})}}_{r_{n-1}} \underbrace{\frac{\mathrm{I}(x)}{\mathrm{I}(z_{n-1})}}_{r_n}$$

The **reset** mechanism does the following: when the chain of computations reaches a pixel z_j having an intensity greater than every other previous point in γ the sequential product up to z_j is reset to 1, and lightness computation restarts from it:

$$l^{\gamma}(x) = \frac{\mathrm{I}(x)}{\mathrm{I}(y)} = \overbrace{r_1 \cdot r_2 \ldots r_{j+1}}^{1} \cdot r_j \ldots r_{n-1} \cdot r_n = \frac{\mathrm{I}(z_{j+1})}{\mathrm{I}(z_j)} \cdot \frac{\mathrm{I}(z_{j+2})}{\mathrm{I}(z_{j+1})} \cdots \frac{\mathrm{I}(x)}{\mathrm{I}(z_{n-1})} = \frac{\mathrm{I}(x)}{\mathrm{I}(z_j)}$$

This is a local White Patch!

The chain of rations simplifies to $I(x)/I(z_{max})$ where z_{max} is the pixel with maximum intensity along γ.

RETINEX AND DEHAZING

$$t(x) = 1 - \min_{y \in \Omega(x)} (\mathrm{I}(x))$$

$$\min_{y \in \Omega(x)} y = 1 - \max_{y \in \Omega(x)} (1 - y)$$

$$t_{1-\mathrm{I}}(x) = 1 - \min_{y \in \Omega(x)} (1 - \mathrm{I}(x)) = \max_{y \in \Omega(x)} (\mathrm{I}(x))$$

RETINEX AND DEHAZING

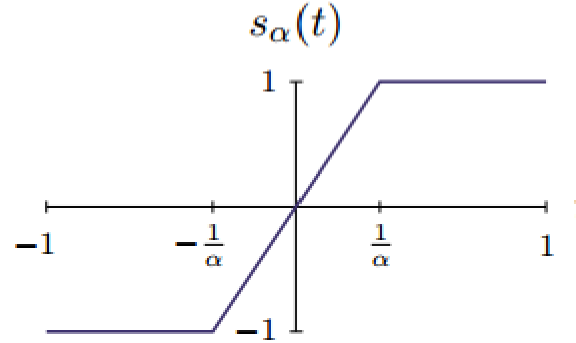
$$\mathrm{t}(x) = 1 - \min_{y \in \Omega(x)} (\mathrm{I}(x))$$

$$\min_{y \in \Omega(x)} y = 1 - \max_{y \in \Omega(x)} (1 - y)$$

$$\mathrm{t}_{1-\mathrm{I}}(x) = 1 - \min_{y \in \Omega(x)} (1 - \mathrm{I}(x)) = \max_{y \in \Omega(x)} (\mathrm{I}(x))$$

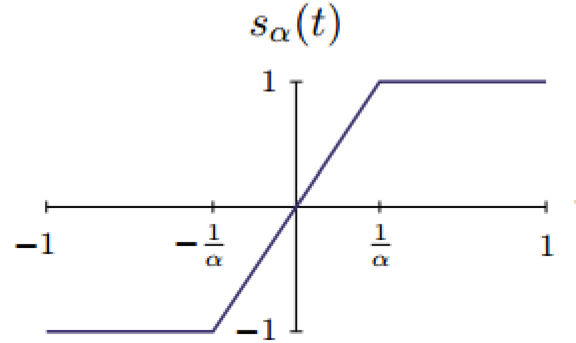
AUTOMATIC COLOR ENHANCEMENT - ACE

$$R(x) = \sum_{y \in \Omega \setminus x} \frac{s_\alpha\big(I(x) - I(y)\big)}{\|x - y\|}, \quad x \in \Omega,$$



AUTOMATIC COLOR ENHANCEMENT - ACE

$$R(x) = \sum_{y \in \Omega \setminus x} \frac{s_\alpha\big(I(x) - I(y)\big)}{\|x - y\|}, \quad x \in \Omega,$$



Look into IPOL!