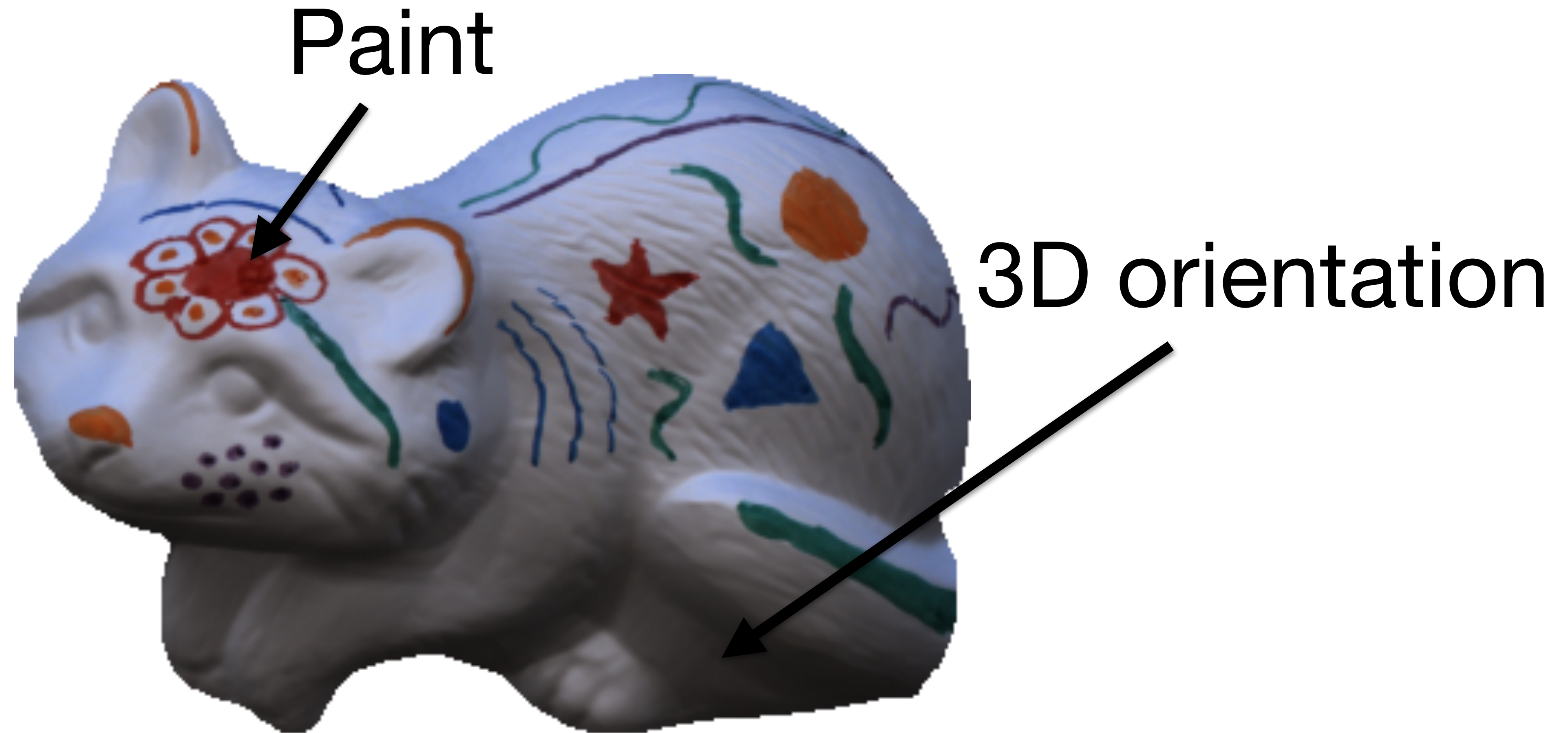


Lecture 21: Light, shading, and color

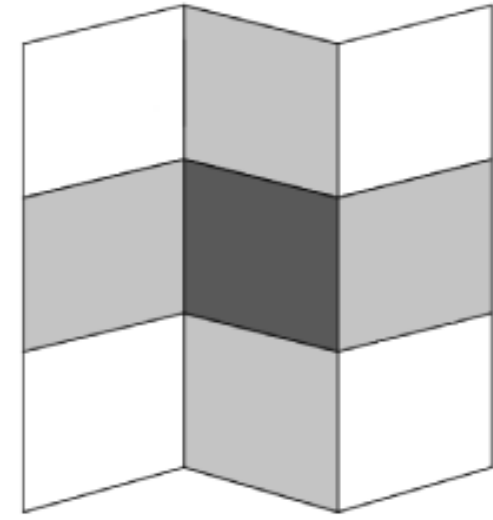
Announcements

- Class presentations 12/11 and 12/12
- Project report due on 12/13
- Grading rubric will be released on Monday

What can we infer from intensity changes?

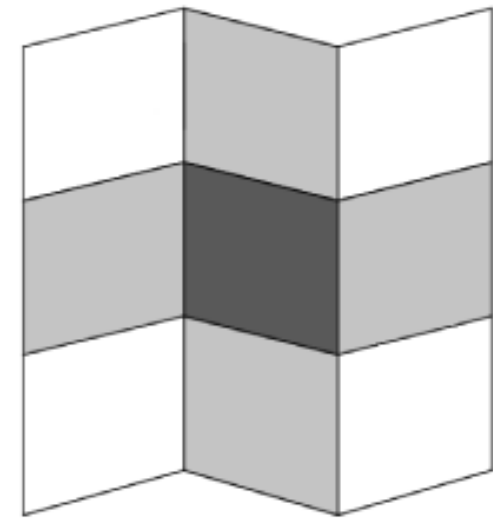


The Workshop Metaphor

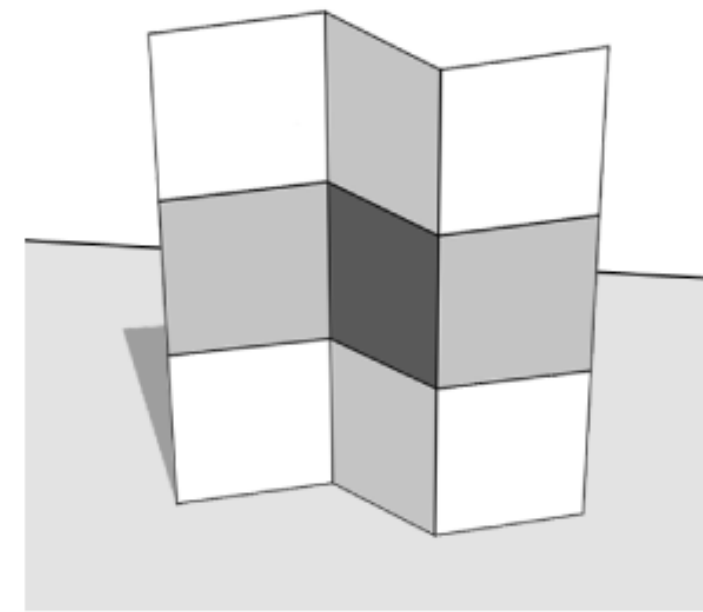


(a) an image

The Workshop Metaphor

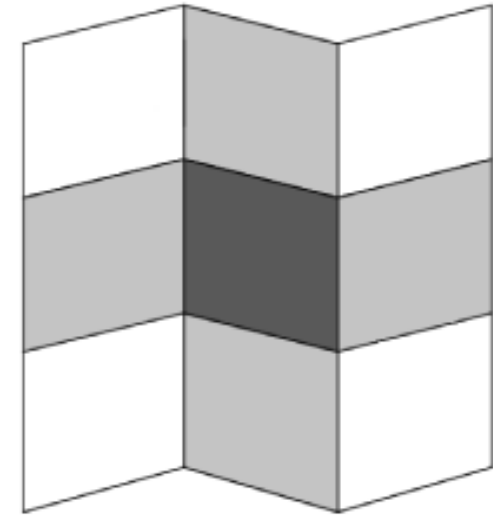


(a) an image

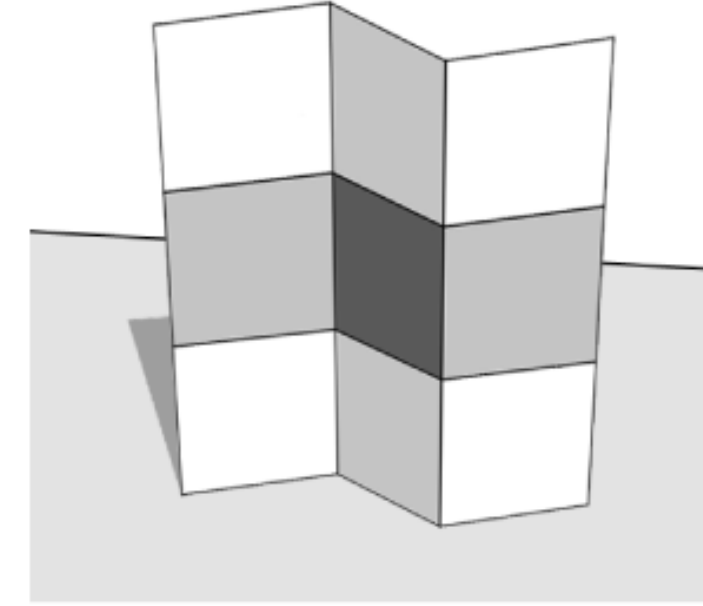


(b) a likely explanation

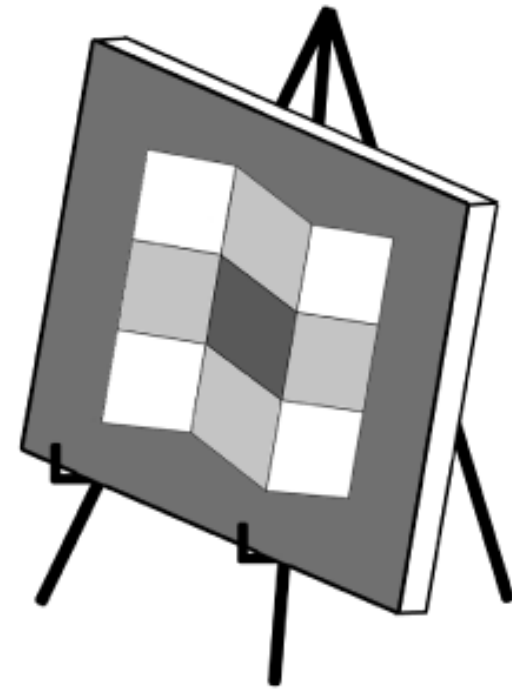
The Workshop Metaphor



(a) an image



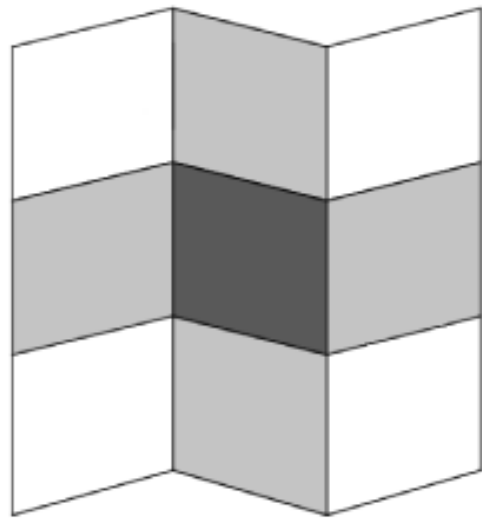
(b) a likely explanation



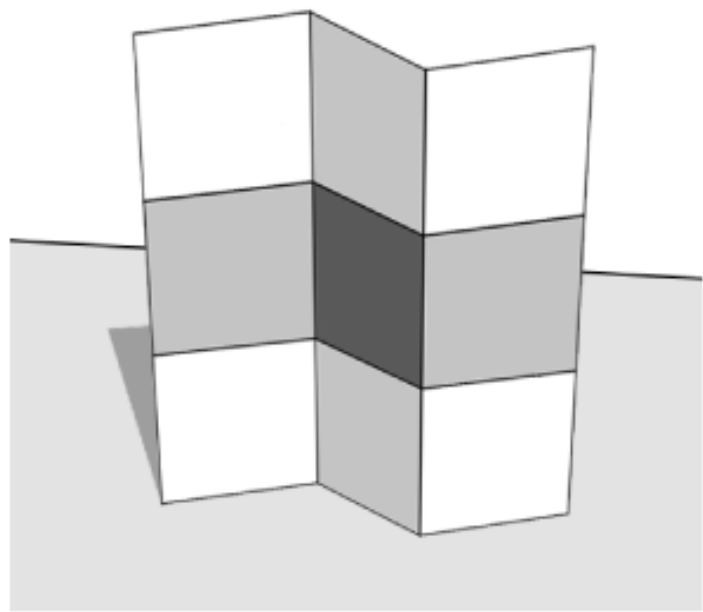
(c) painter's explanation

E. Adelson and A. Pentland, "The perception of shading and reflectance," *Perception as Bayesian inference*, 1996.

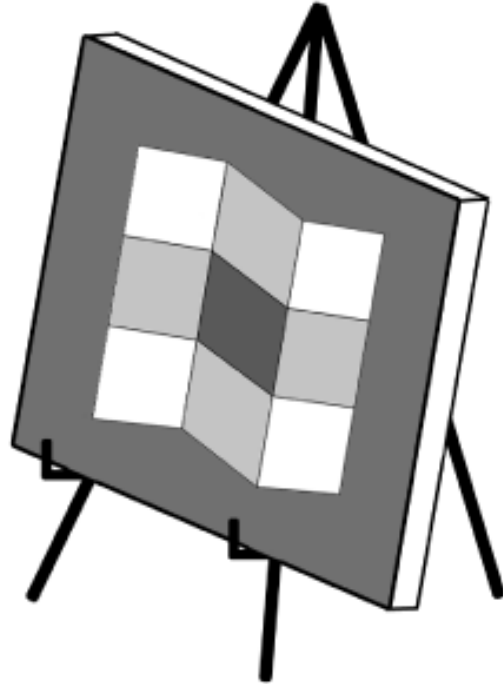
The Workshop Metaphor



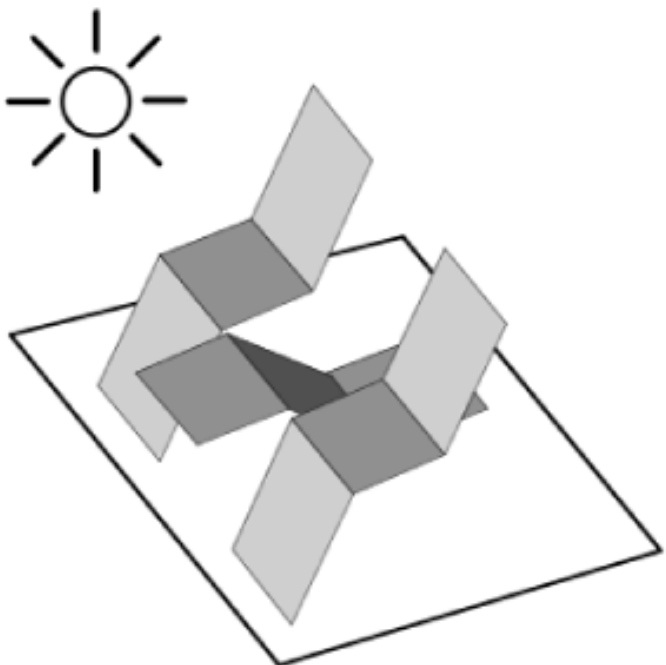
(a) an image



(b) a likely explanation



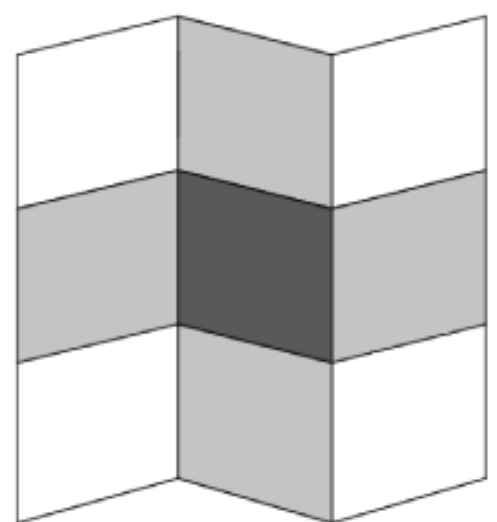
(c) painter's explanation



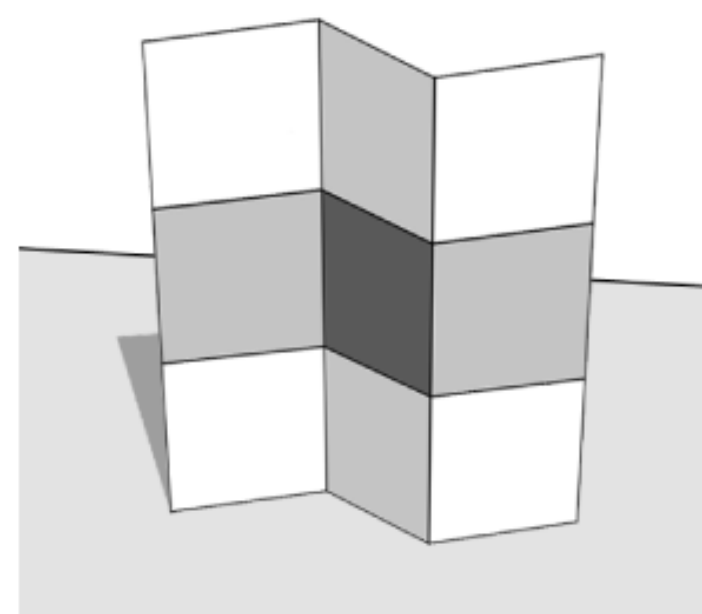
(d) sculptor's explanation

E. Adelson and A. Pentland, "The perception of shading and reflectance," *Perception as Bayesian inference*, 1996.

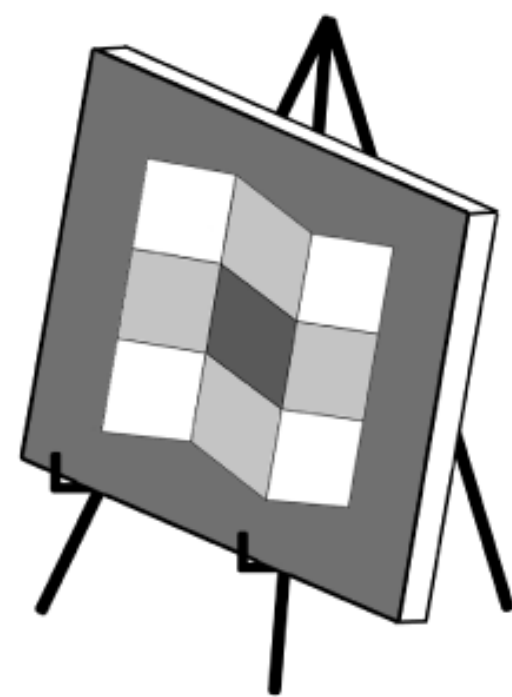
The Workshop Metaphor



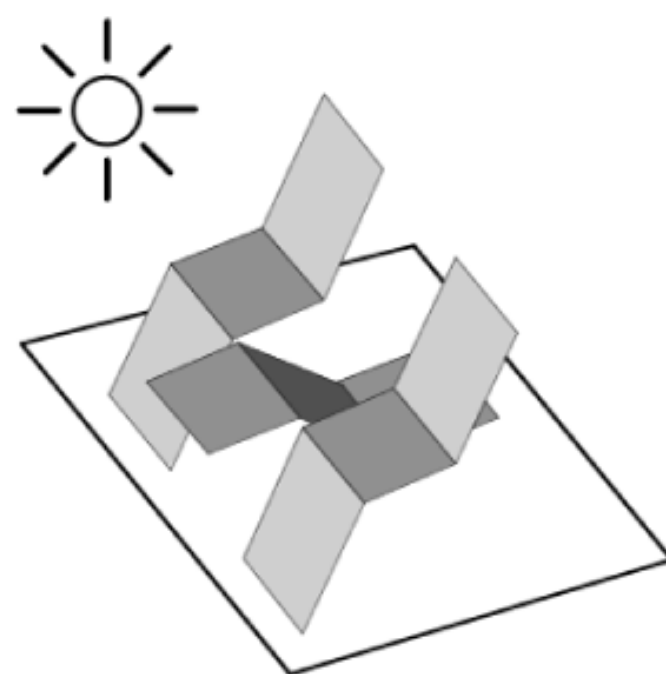
(a) an image



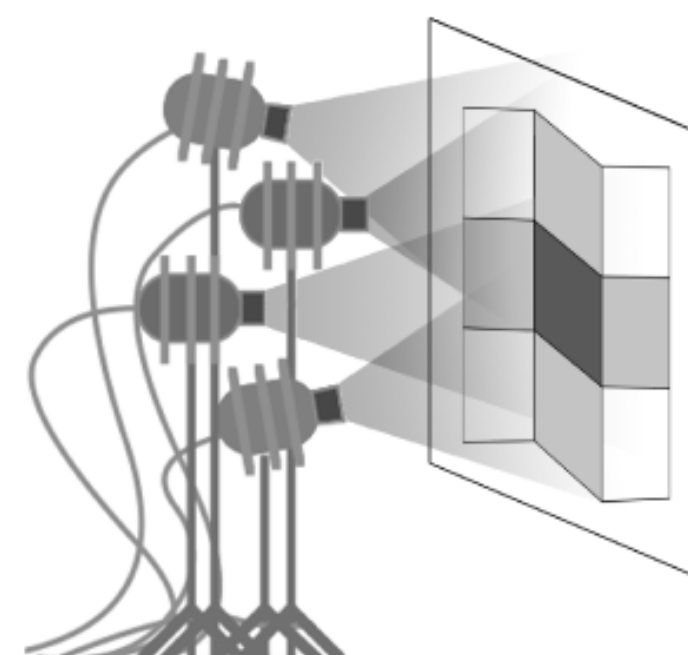
(b) a likely explanation



(c) painter's explanation



(d) sculptor's explanation



(e) gaffer's explanation

E. Adelson and A. Pentland, "The perception of shading and reflectance," *Perception as Bayesian inference*, 1996.

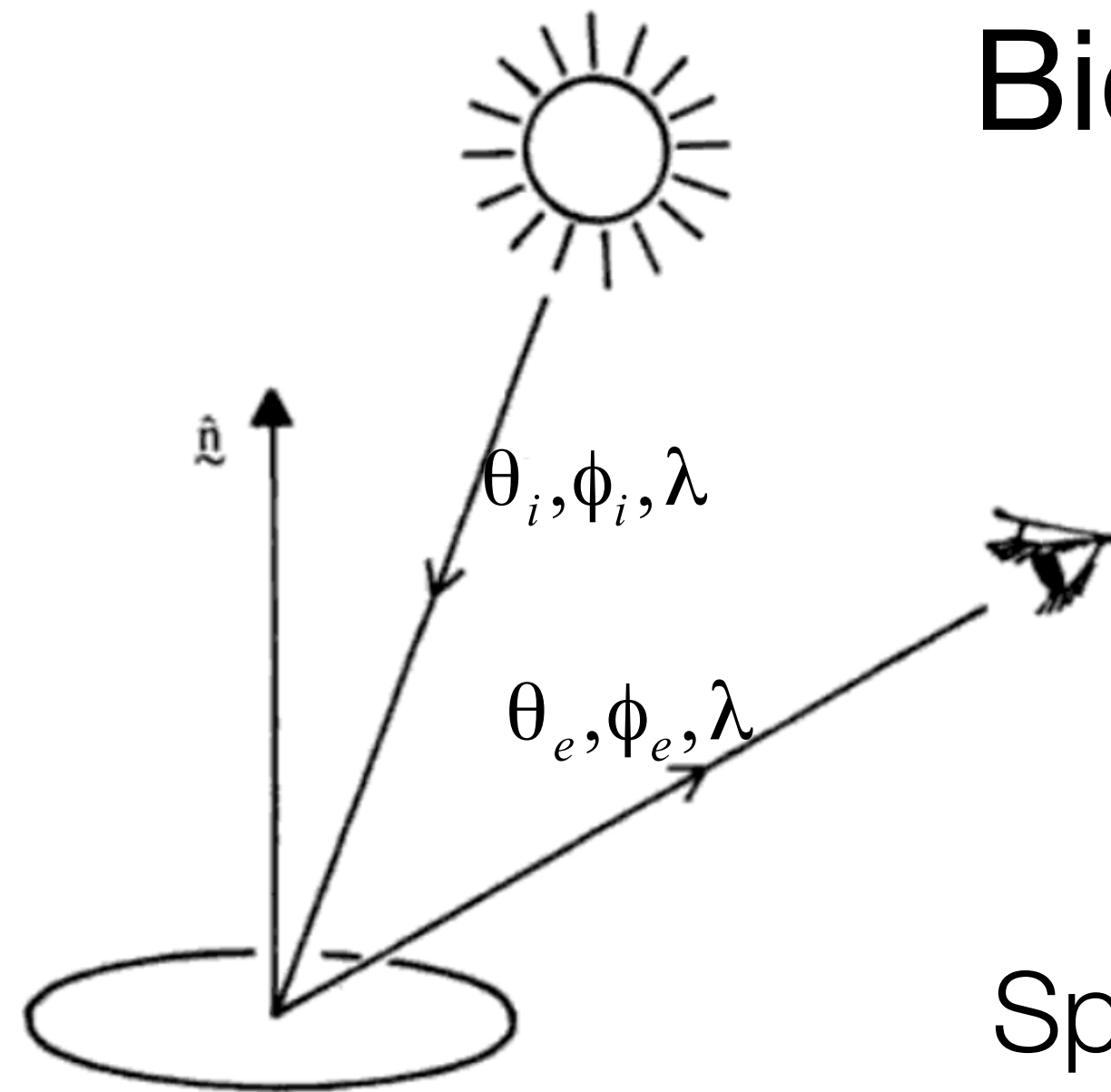
Today

- **Shape from shading**
- Intrinsic image decomposition
- Color perception

Shape perception



Interaction of light and surfaces



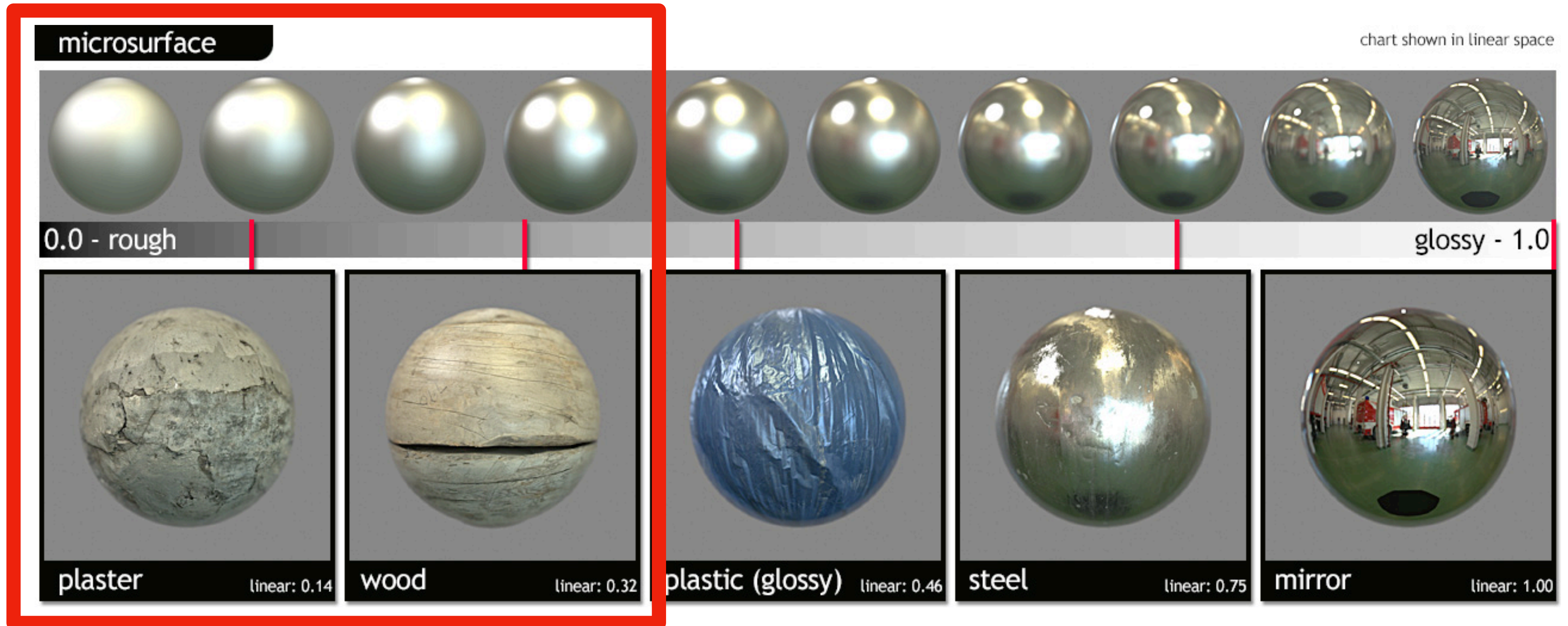
Bidirectional reflectance distribution function (BRDF)

$$BRDF = f(\theta_i, \phi_i, \theta_e, \phi_e, \lambda) = \frac{L(\theta_e, \phi_e, \lambda)}{E(\theta_i, \phi_i, \lambda)}$$

Spectral irradiance: incident power per unit area, per unit wavelength.

[Horn, 1986]

Effect of BRDF on sphere rendering



Diffuse reflection

For now, ignore specular reflection



And refraction...

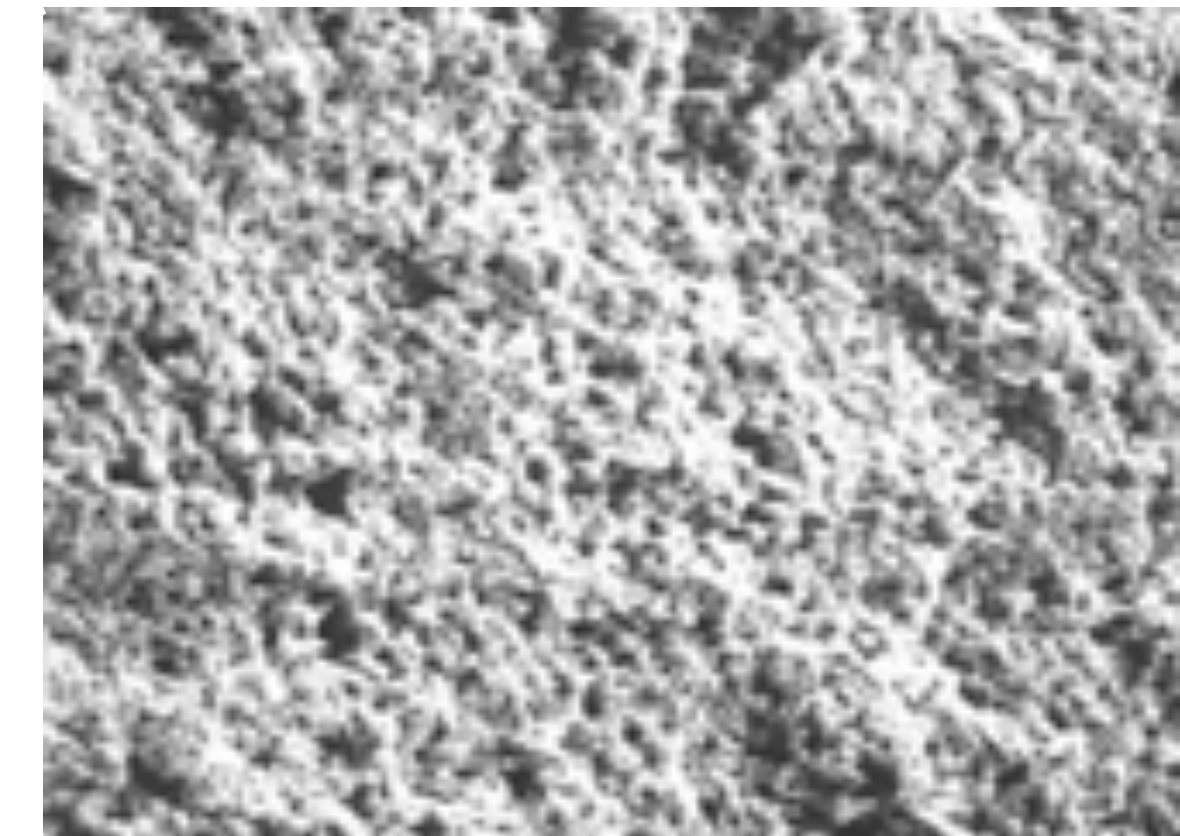
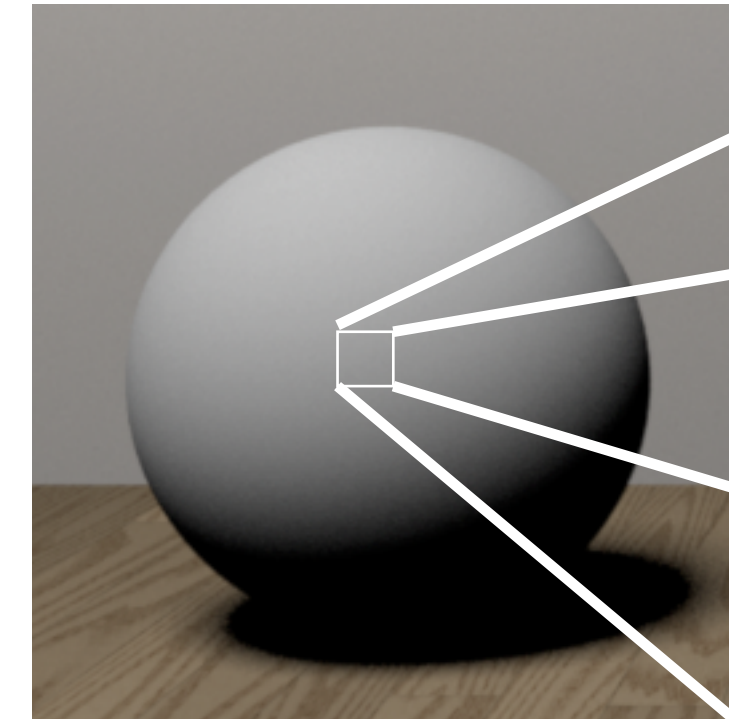
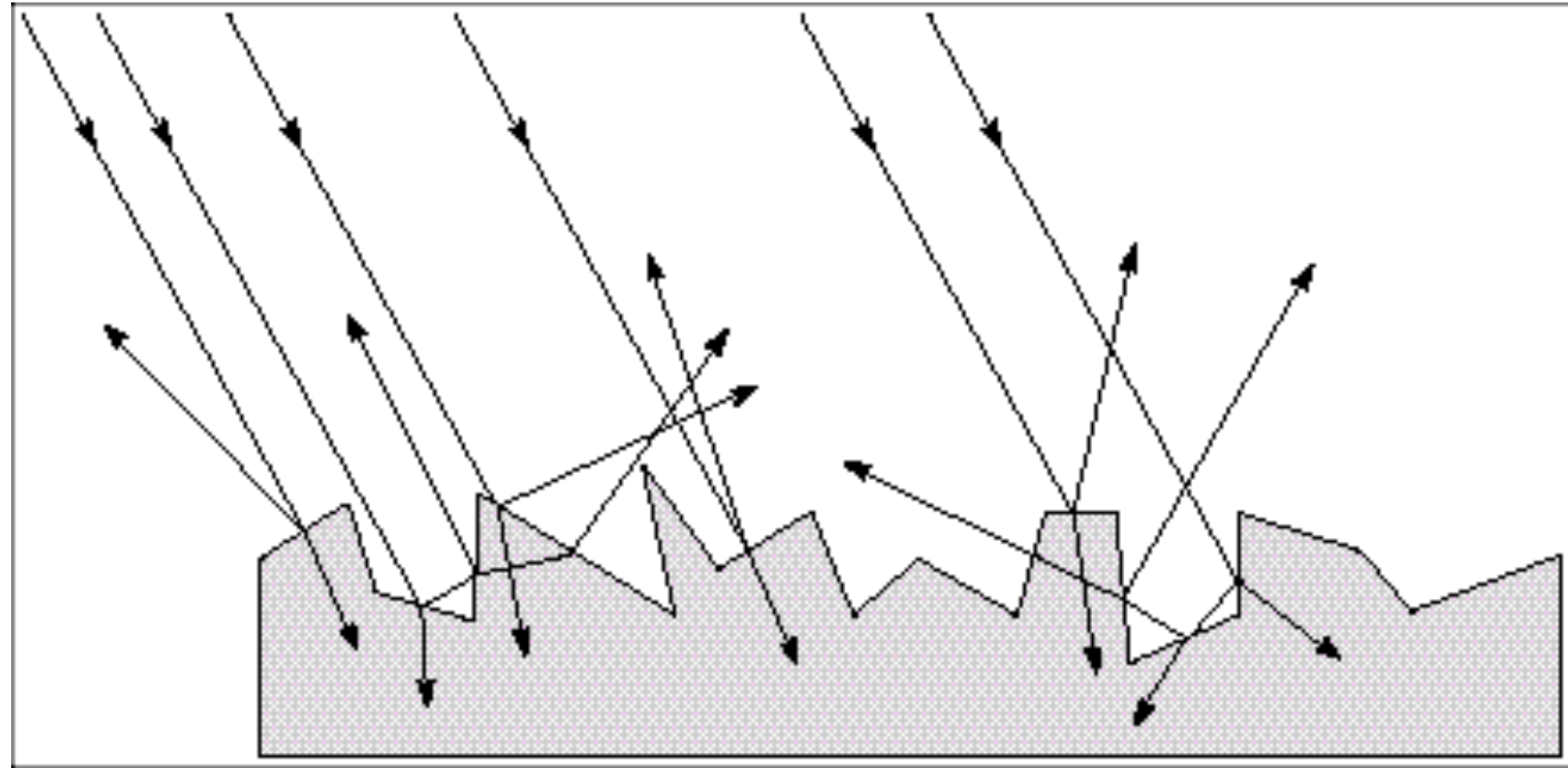


And interreflections...



Source: Photometric Methods for 3D Modeling, Matsushita, Wilburn, Ben-Ezra. Changes by N. Snavely

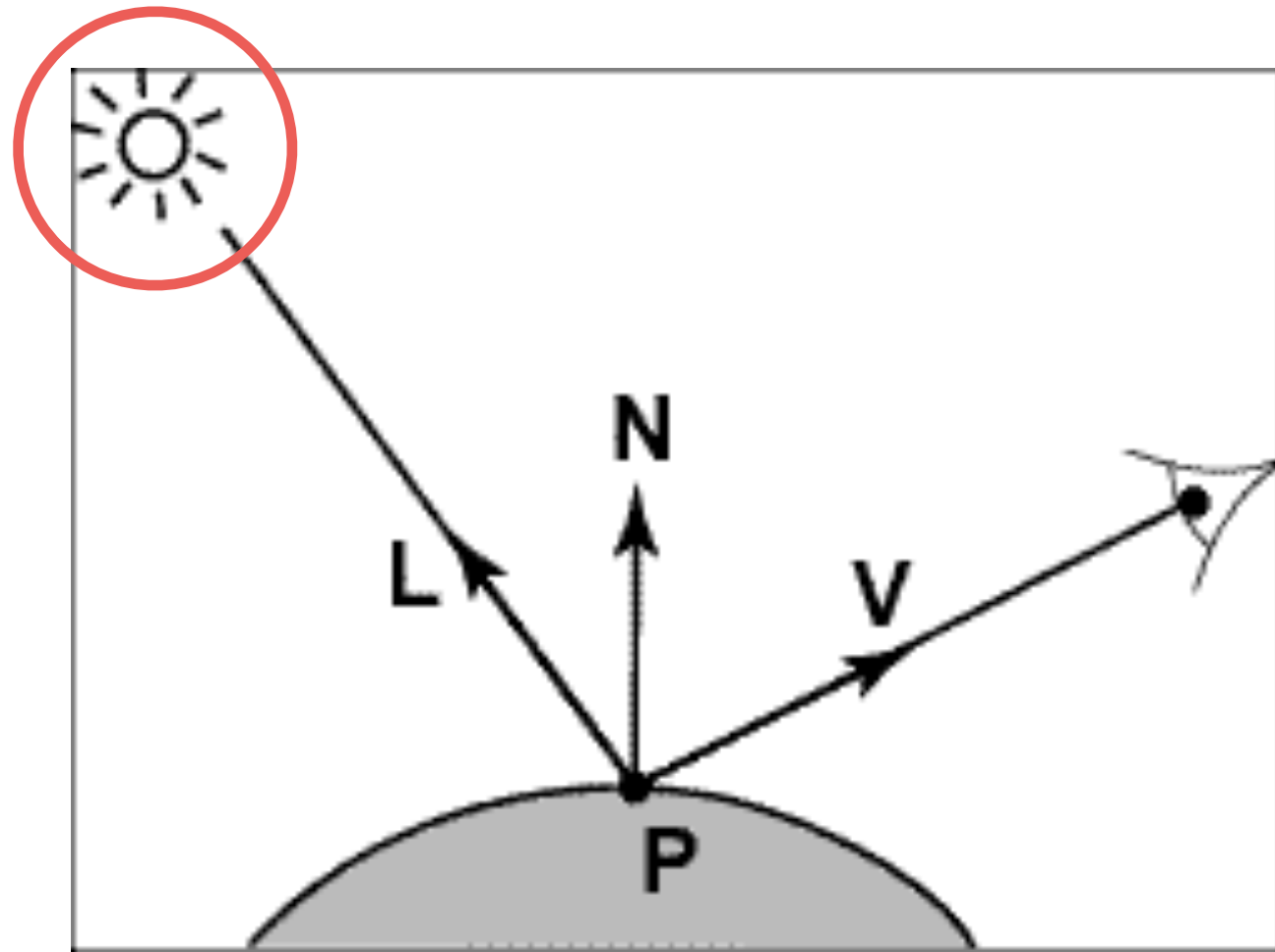
Diffuse reflection



Diffuse reflection

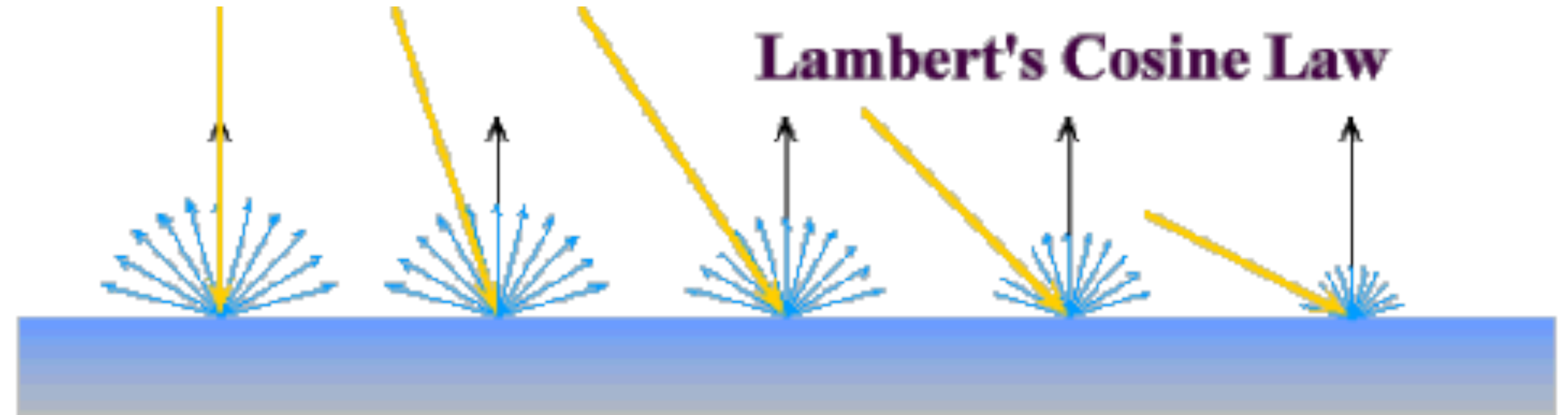
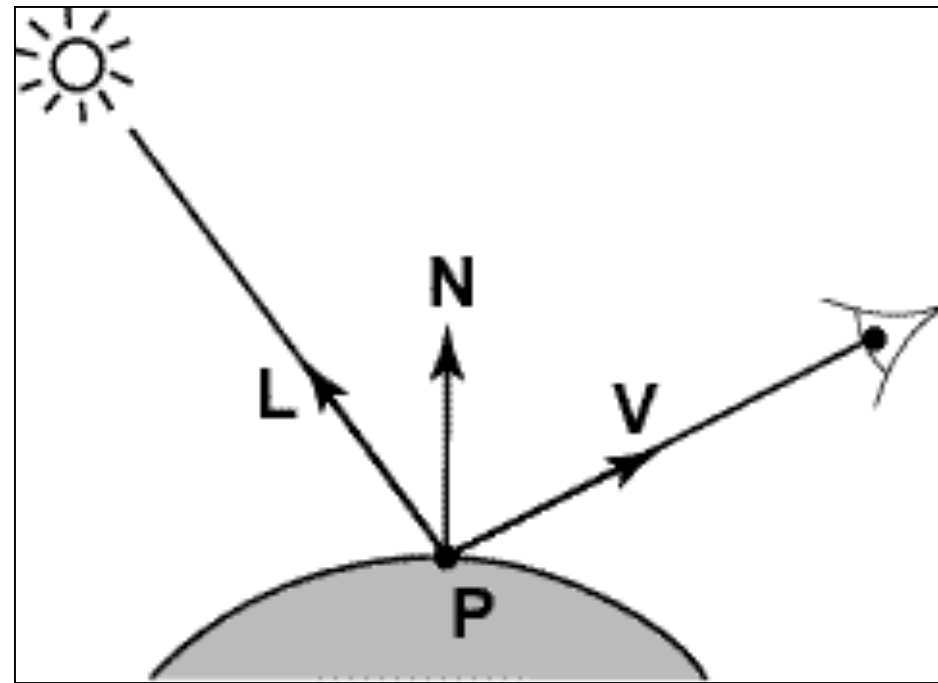
- Dull, matte surfaces like chalk or latex paint
- Microfacets scatter incoming light randomly
- Effect is that light is reflected equally in all directions

Directional lighting



- All rays are parallel
- Equivalent to an infinitely distant point source

Diffuse reflection

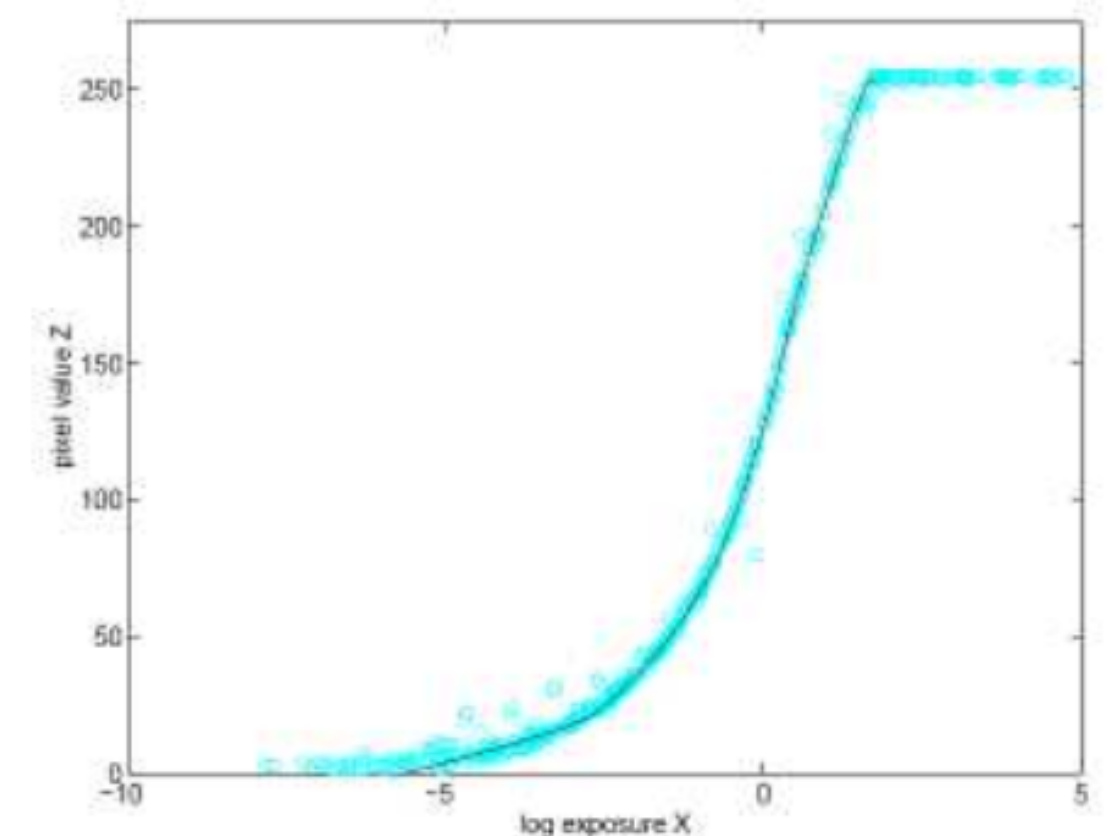


$$R_e = k_d \mathbf{N} \cdot \mathbf{L} R_i$$

image intensity of \mathbf{P} $\longrightarrow I = k_d \mathbf{N} \cdot \mathbf{L}$

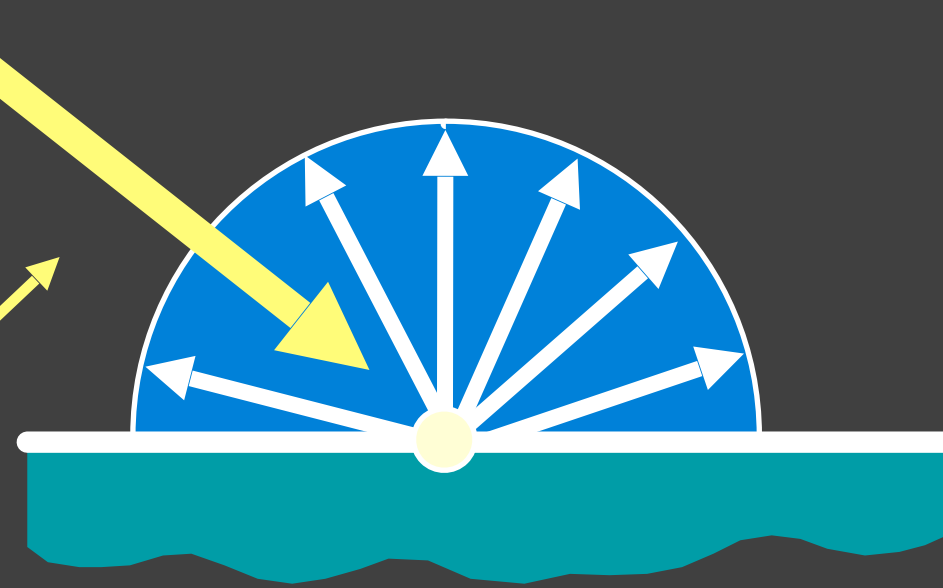
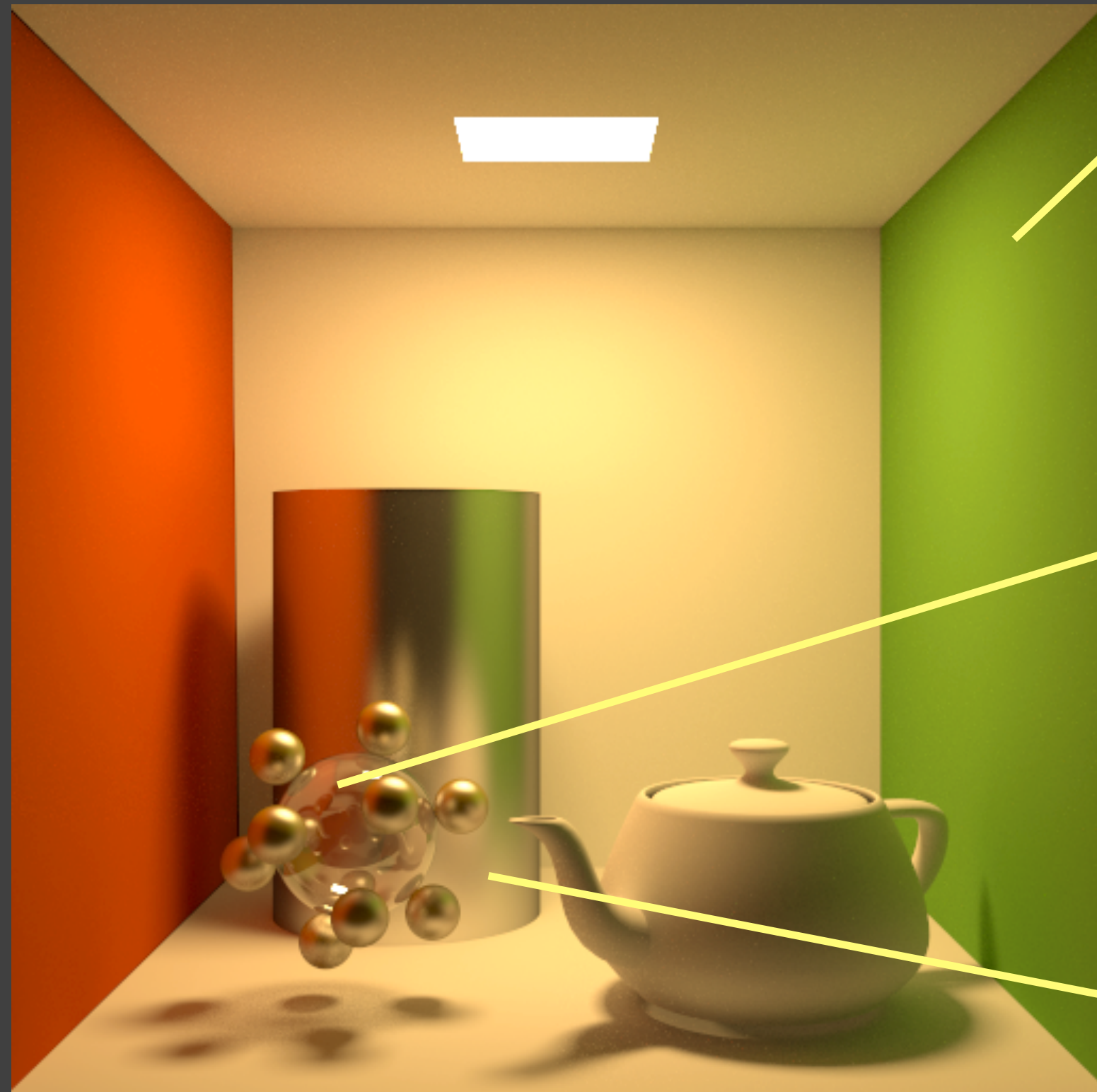
Simplifying assumptions we'll often make:

- $I = R_e$: "camera response function" is the identity
 - In actual cameras it is a nonlinear function
 - Can always achieve this in practice by inverting it
- $R_i = 1$: light source intensity is 1
 - can achieve this by dividing each pixel in the image by R_i

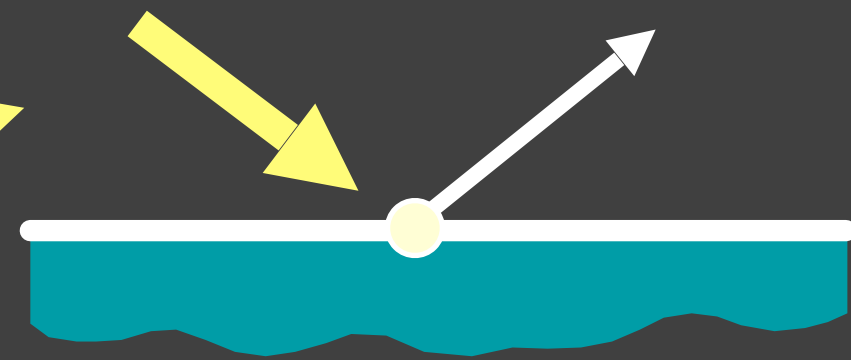


Source: [Debevec & Malik 1997]

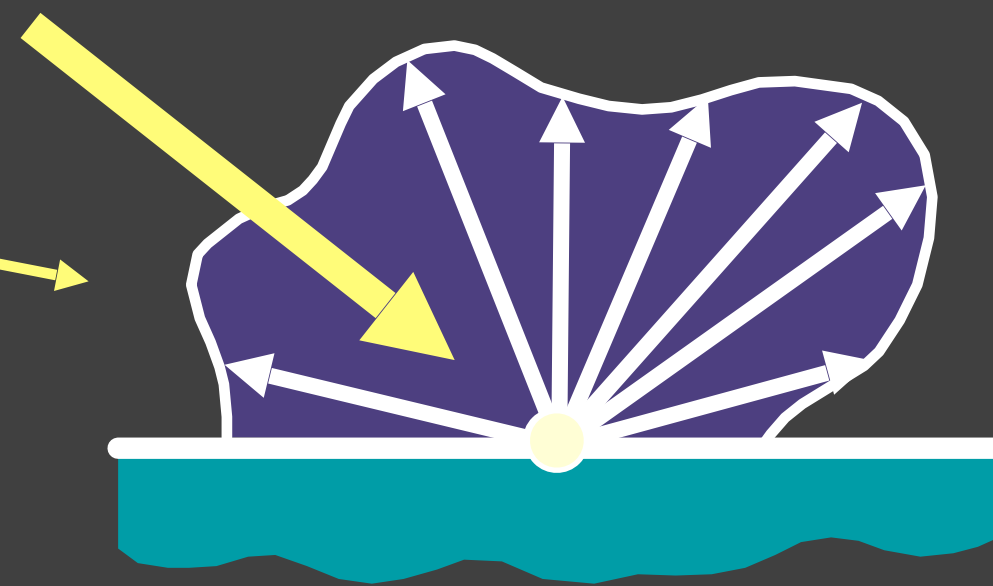
Other BRDFs



Ideal diffuse
(Lambertian)

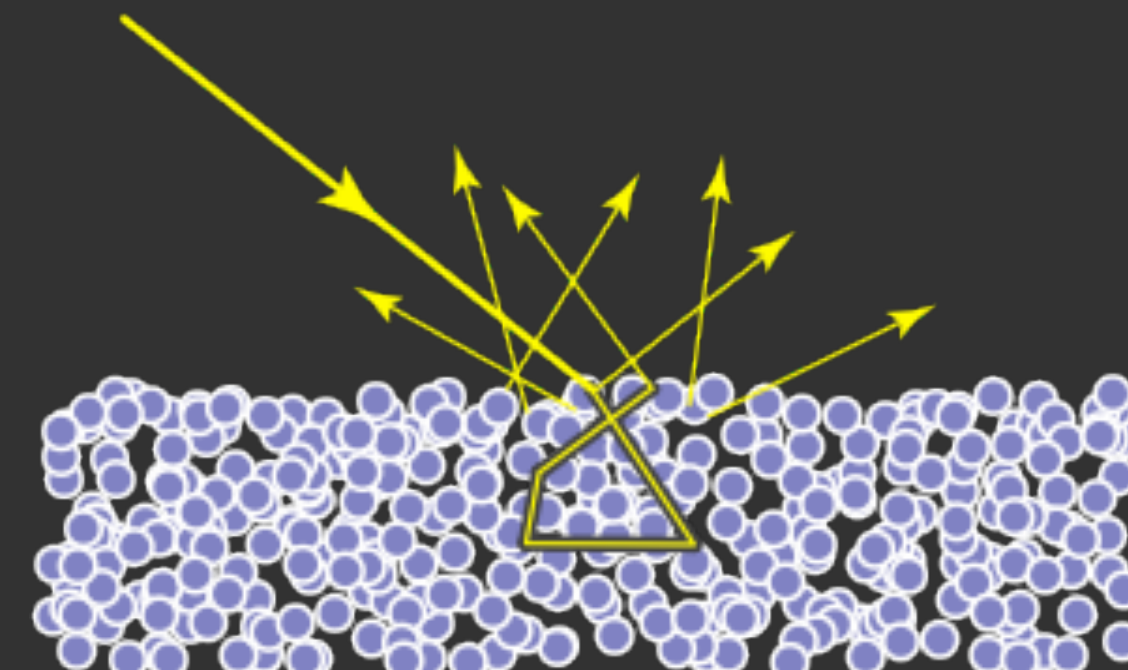
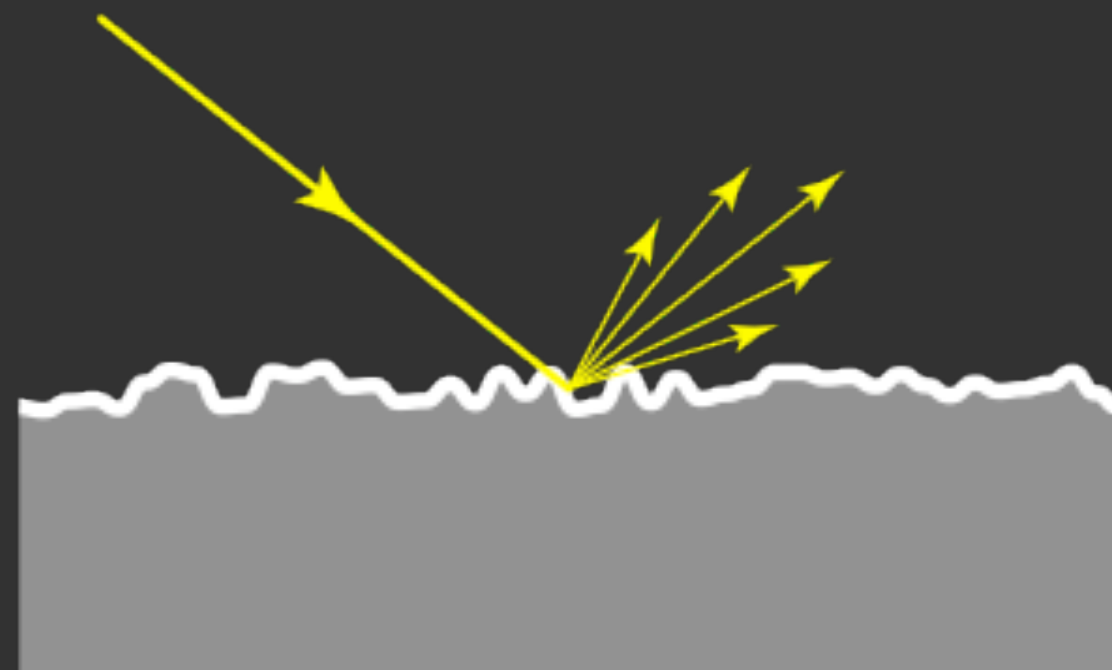


Ideal
specular



Directional
diffuse

Non-smooth-surfaced materials



20

from Steve Marschner

Shape from shading



$$I = k_d \mathbf{N} \cdot \mathbf{L}$$

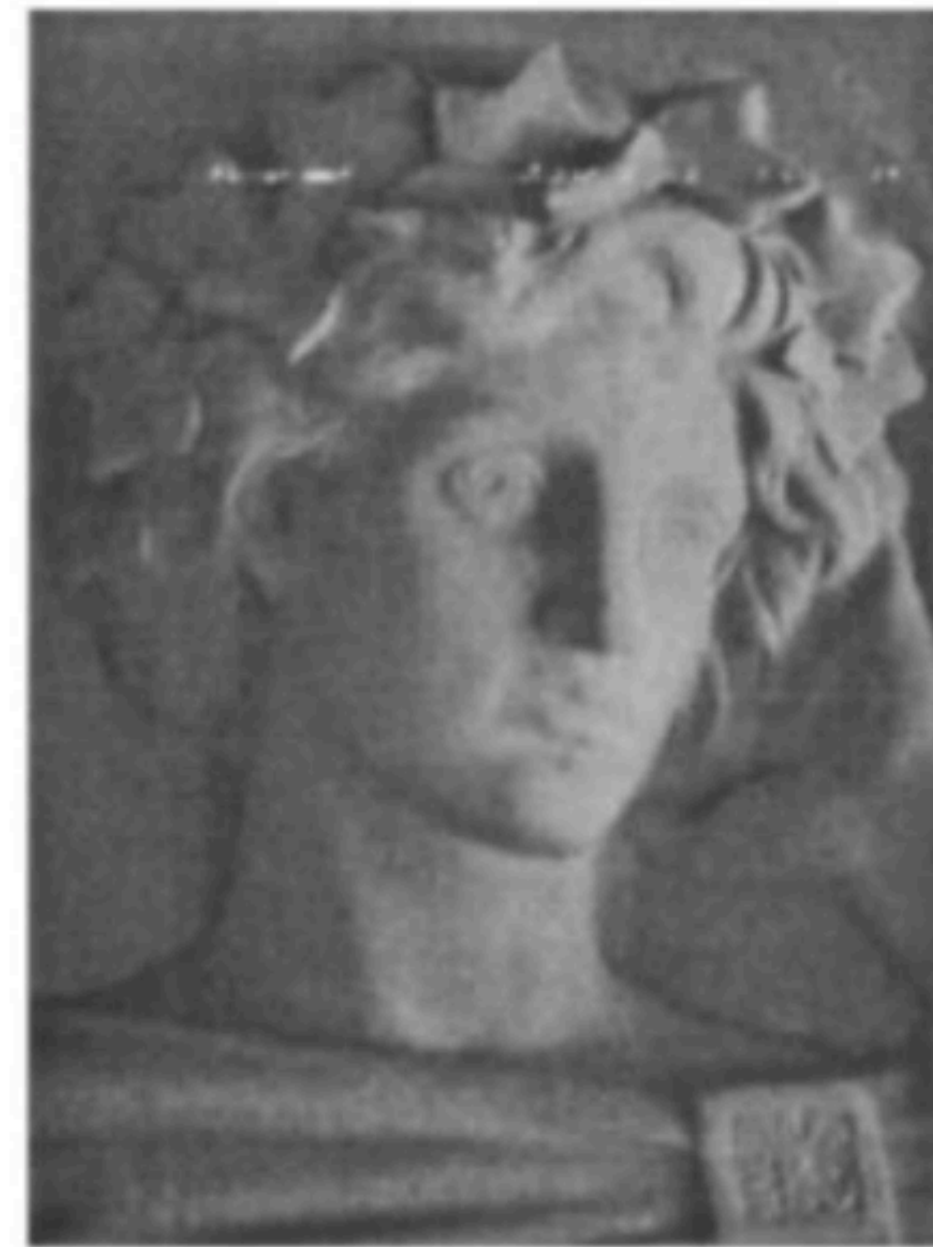
Assume k_d is 1 for now.

What can we measure from one image?

- $\cos^{-1}(I)$ is the angle between N and L
- Add assumptions:
 - Constant albedo
 - A few known normals (e.g. silhouettes)
 - Smoothness of normals

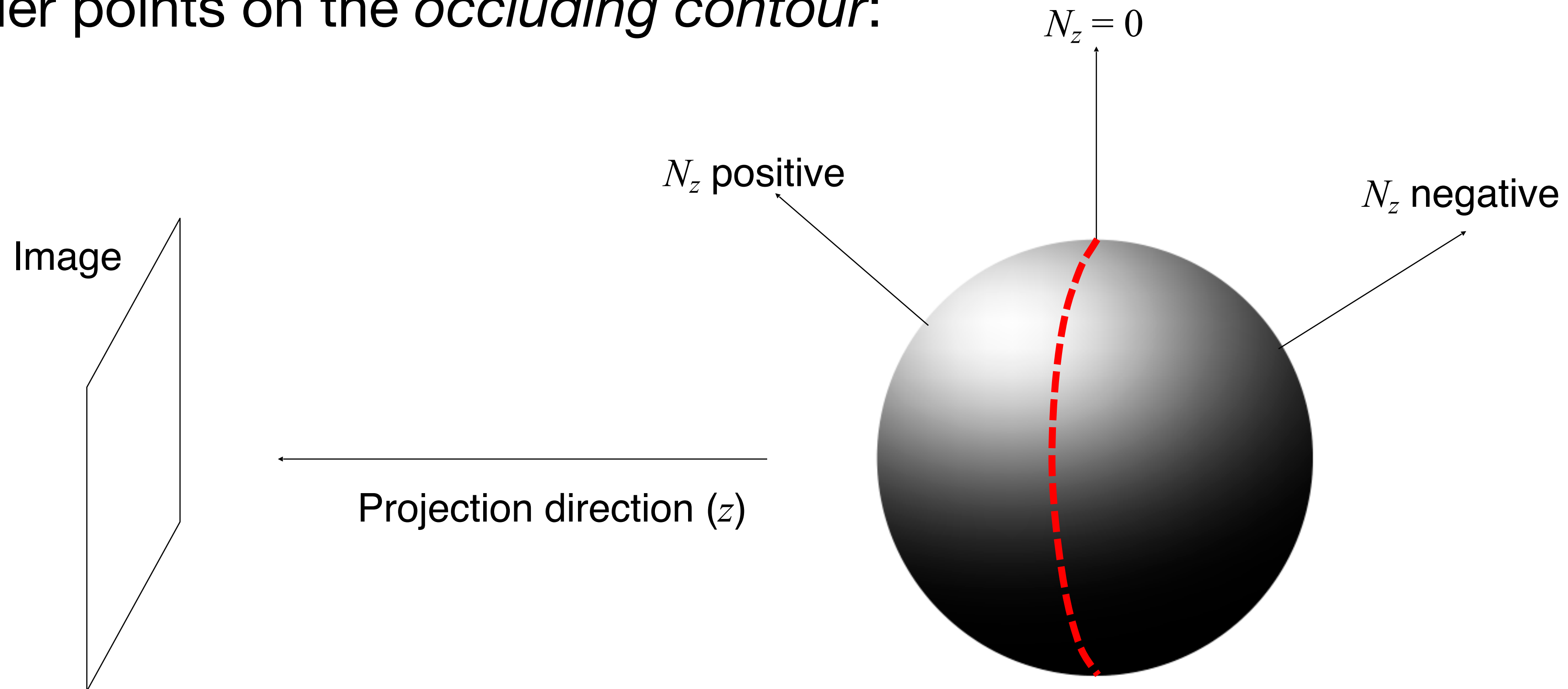
In practice, this doesn't work well: assumptions are too restrictive, too much ambiguity in nontrivial scenes.

An ambiguity that artists exploit!



Contours provide extra shape information

Consider points on the *occluding contour*:

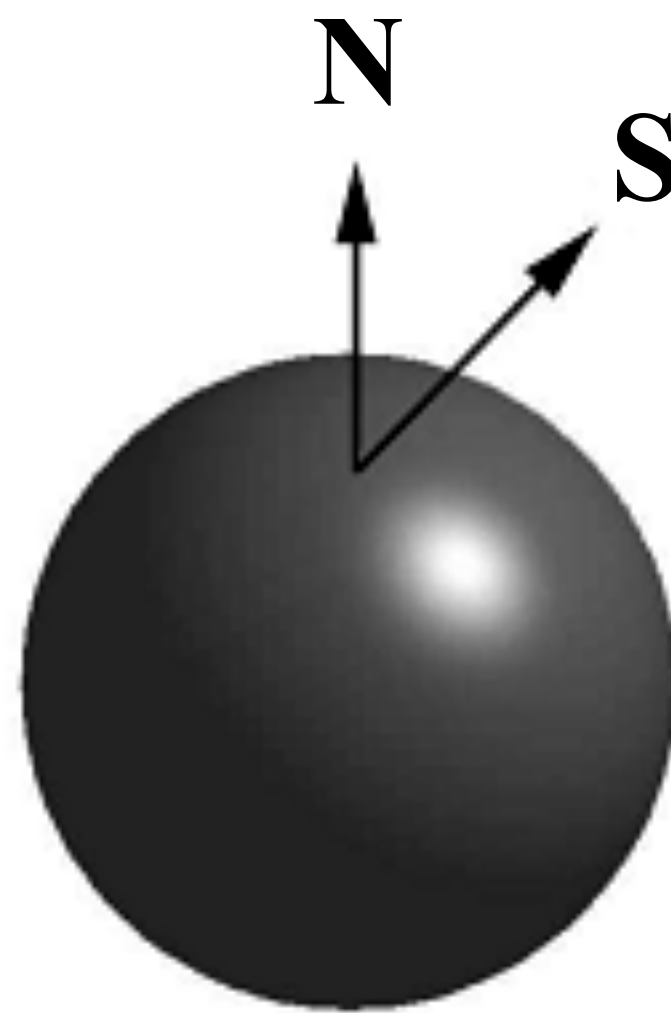


Application: finding the direction of the light source

$$I(x,y) = \mathbf{N}(x,y) \cdot \mathbf{S}(x,y)$$

Full 3D case:

$$\begin{pmatrix} N_x(x_1, y_1) & N_y(x_1, y_1) & N_z(x_1, y_1) \\ N_x(x_2, y_2) & N_y(x_2, y_2) & N_z(x_2, y_2) \\ \vdots & \vdots & \vdots \\ N_x(x_n, y_n) & N_y(x_n, y_n) & N_z(x_n, y_n) \end{pmatrix} \begin{pmatrix} S_x \\ S_y \\ S_z \end{pmatrix} = \begin{pmatrix} I(x_1, y_1) \\ I(x_2, y_2) \\ \vdots \\ I(x_n, y_n) \end{pmatrix}$$



For points on the occluding contour, $N_z = 0$:

$$\begin{pmatrix} N_x(x_1, y_1) & N_y(x_1, y_1) \\ N_x(x_2, y_2) & N_y(x_2, y_2) \\ \vdots & \vdots \\ N_x(x_n, y_n) & N_y(x_n, y_n) \end{pmatrix} \begin{pmatrix} S_x \\ S_y \end{pmatrix} = \begin{pmatrix} I(x_1, y_1) \\ I(x_2, y_2) \\ \vdots \\ I(x_n, y_n) \end{pmatrix}$$

Finding the direction of the light source



Application: detecting image splices

Real photo



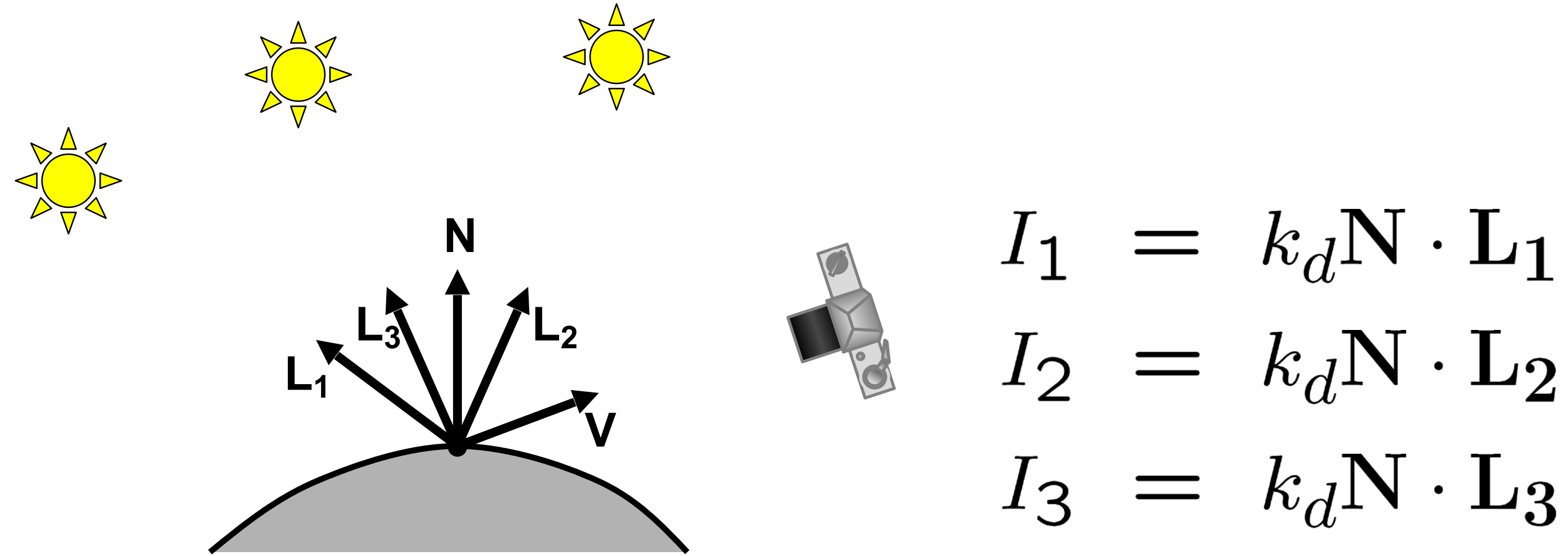
Fake photo



Photometric stereo



Photometric stereo



Can write this as a linear system, and solve:

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = k_d \begin{bmatrix} \mathbf{L}_1^T \\ \mathbf{L}_2^T \\ \mathbf{L}_3^T \end{bmatrix} \mathbf{N}$$

Photometric Stereo

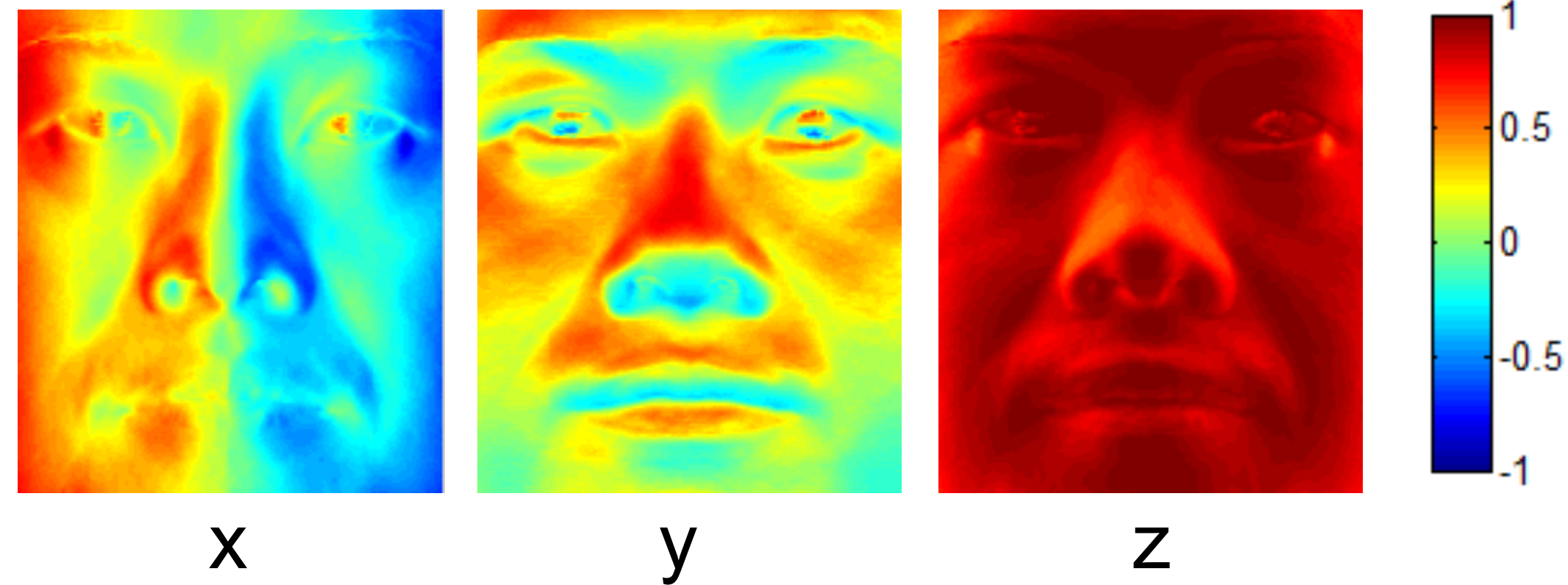
Input



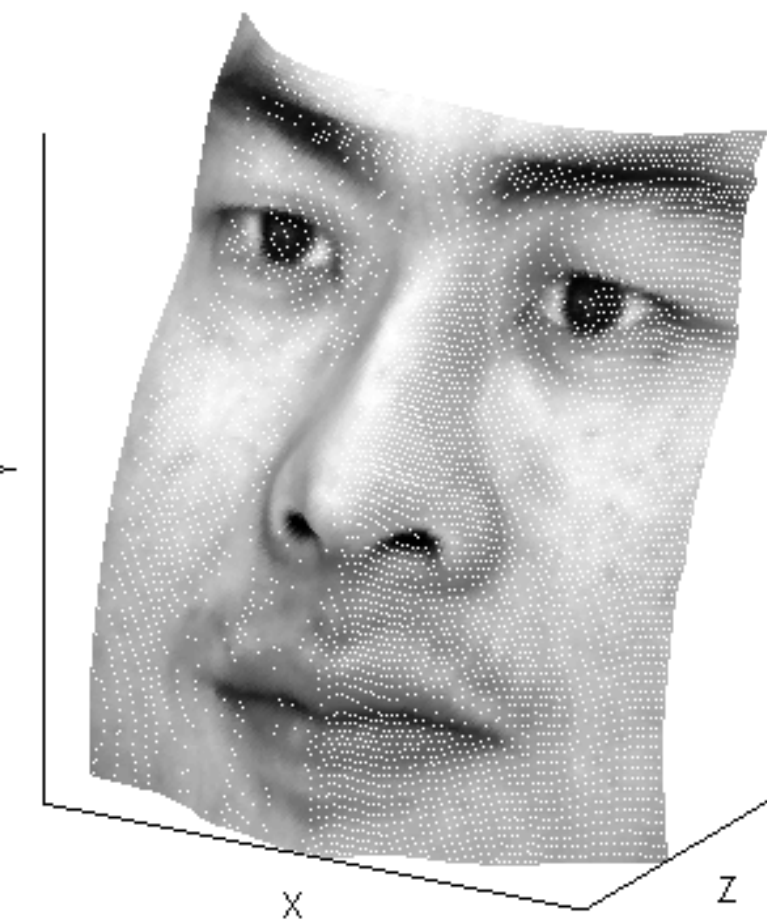
Recovered albedo



Recovered normal field



Recovered surface model



Photometric Stereo



Input
(1 of 12)



Normals (RGB
colormap)



Normals (vectors)



Shaded 3D
rendering



Textured 3D
rendering

Video photometric stereo

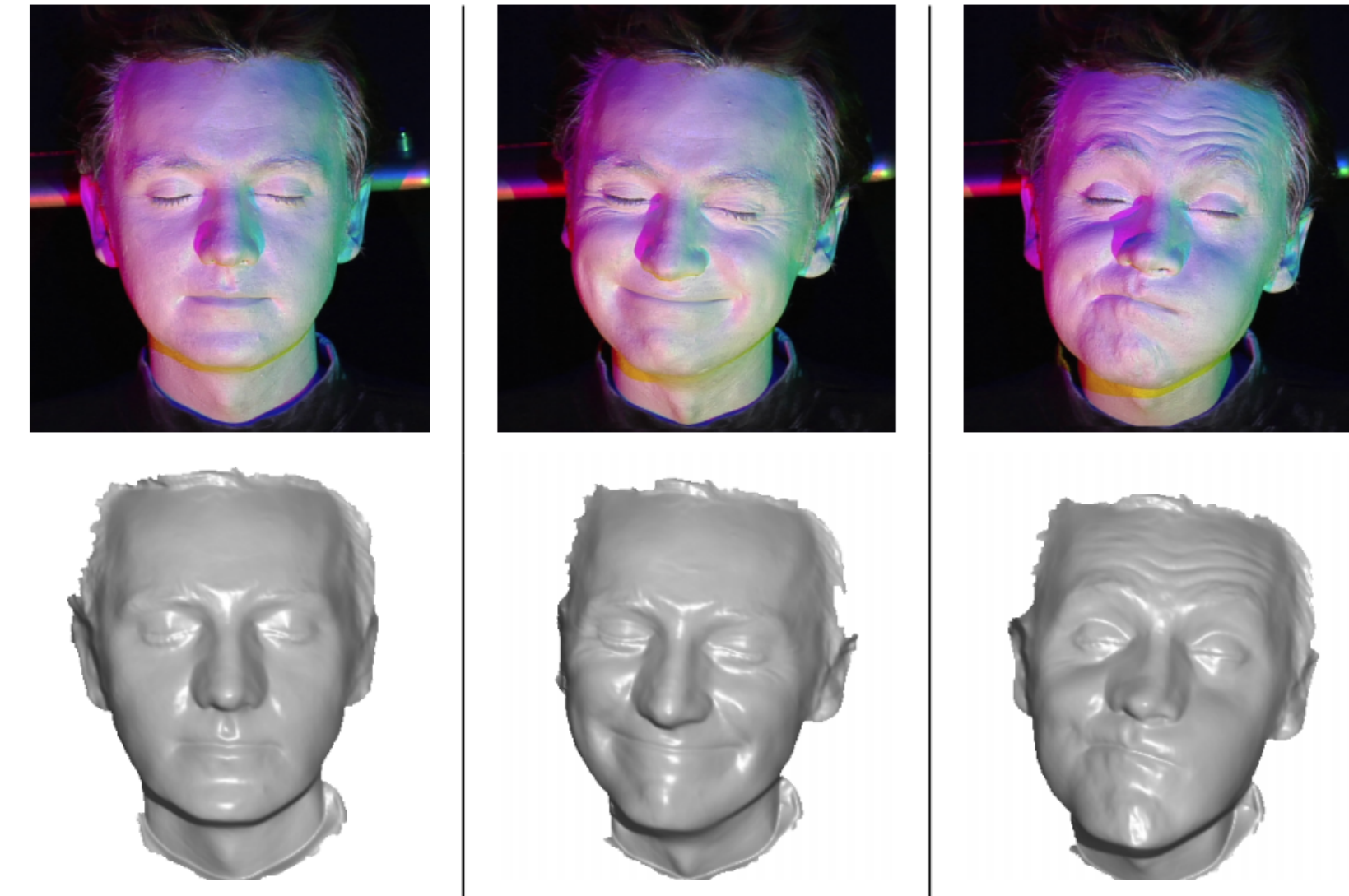
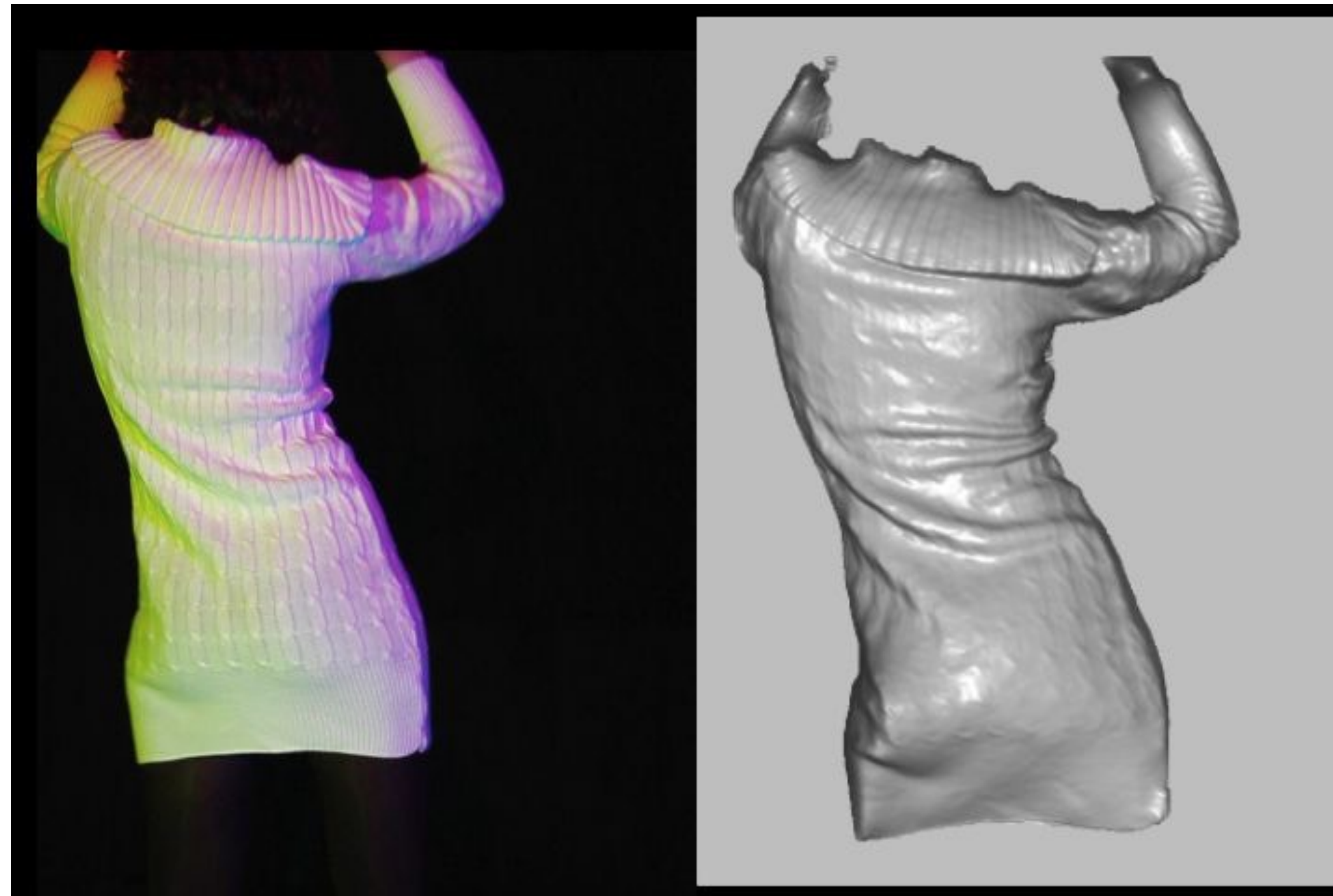


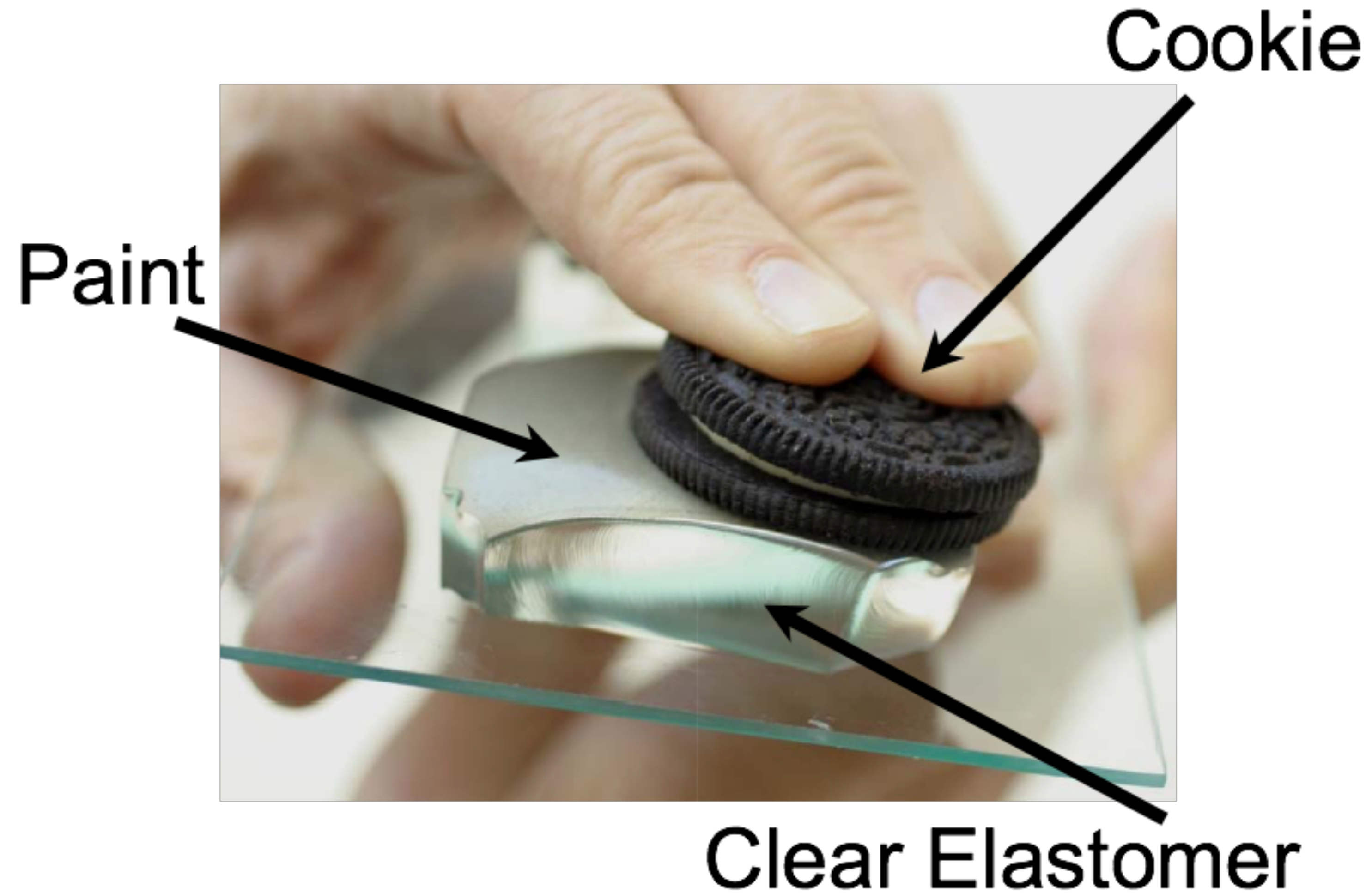
Fig. 2. Applying the original algorithm to a face with white makeup. Top: example input frames from video of an actor smiling and grimacing. Bottom: the resulting integrated surfaces.

Video Normals from Colored Lights

Gabriel J. Brostow, Carlos Hernández, George Vogiatzis, Björn Stenger, Roberto Cipolla

[IEEE TPAMI](#), Vol. 33, No. 10, pages 2104-2114, October 2011.

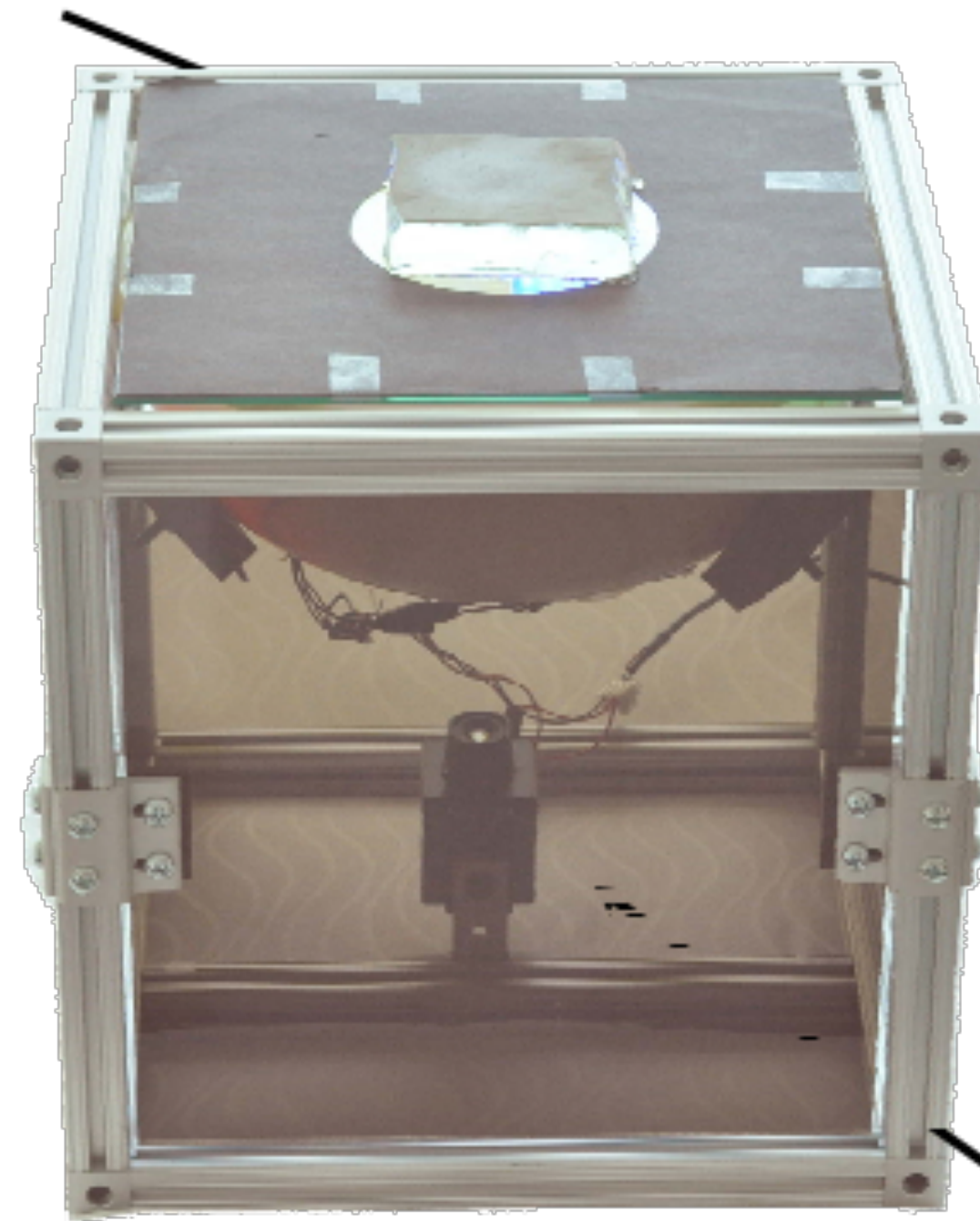
But what if we don't know the BRDF?



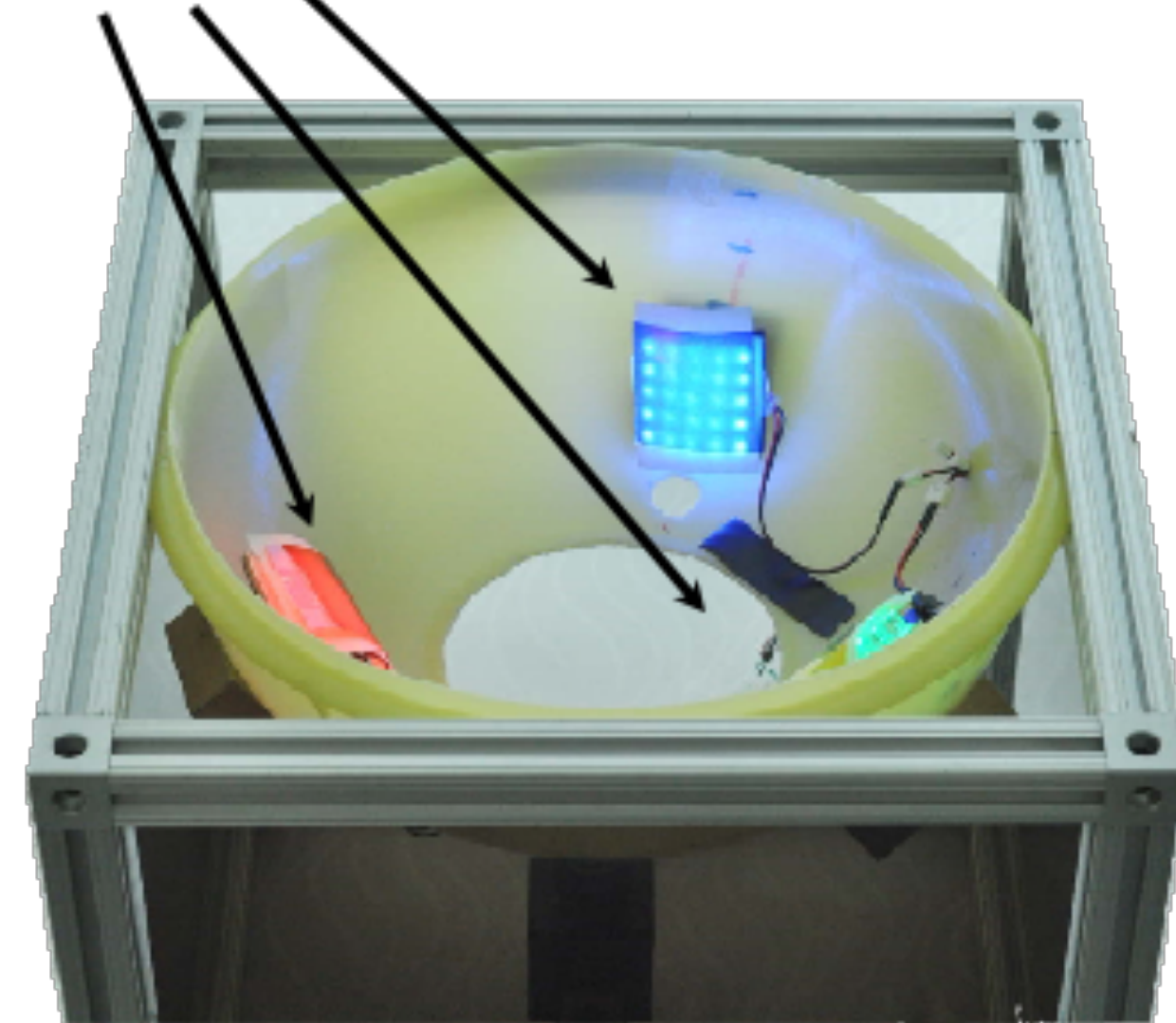
[Johnson and Adelson, 2009]



Sensor

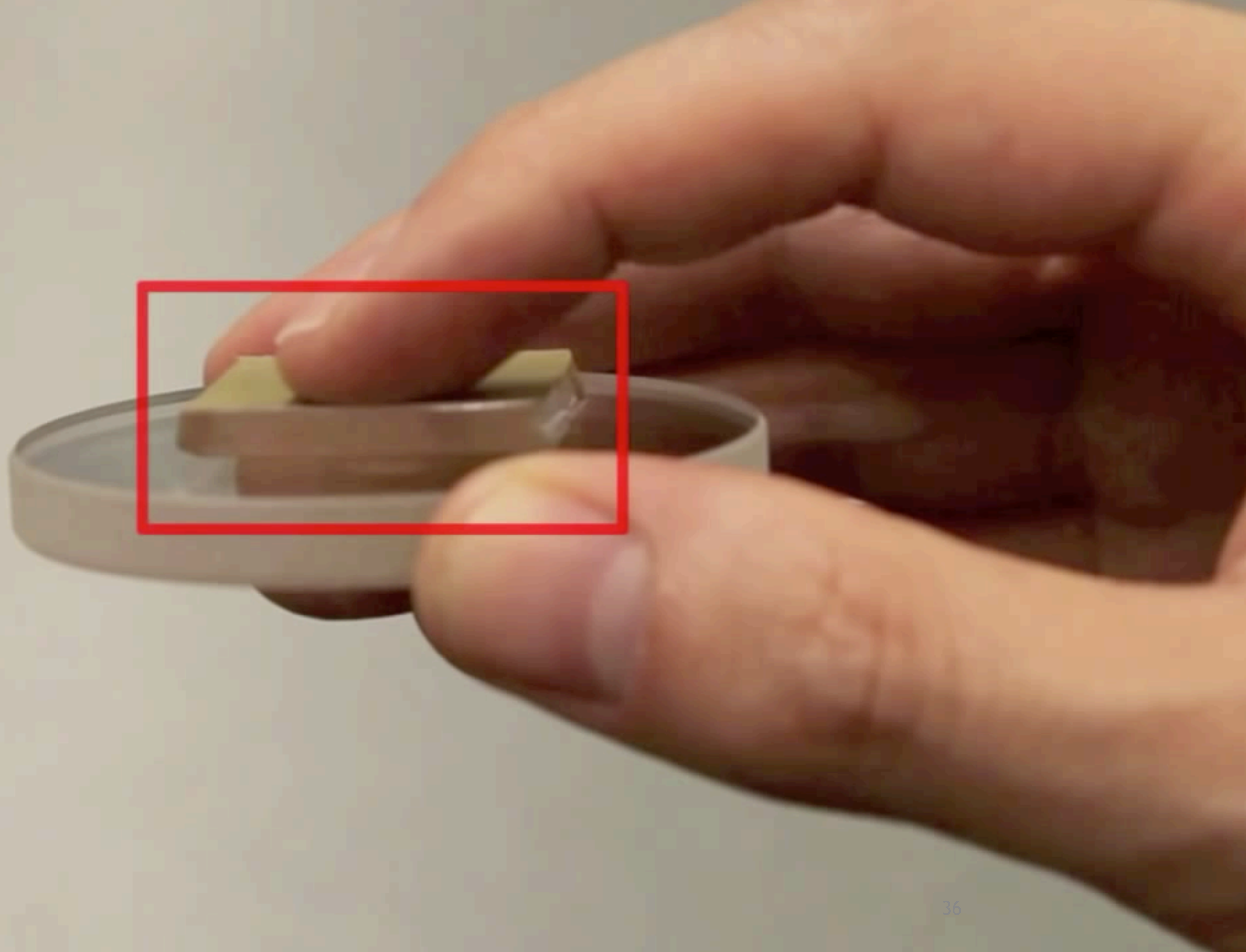


Lights



Camera





Today

- Shape from shading
- **Intrinsic image decomposition**
- Color perception

What about paint?



$$I = k_d \mathbf{N} \cdot \mathbf{L}$$

k_d is **reflectance** or **albedo**

Intrinsic image decomposition

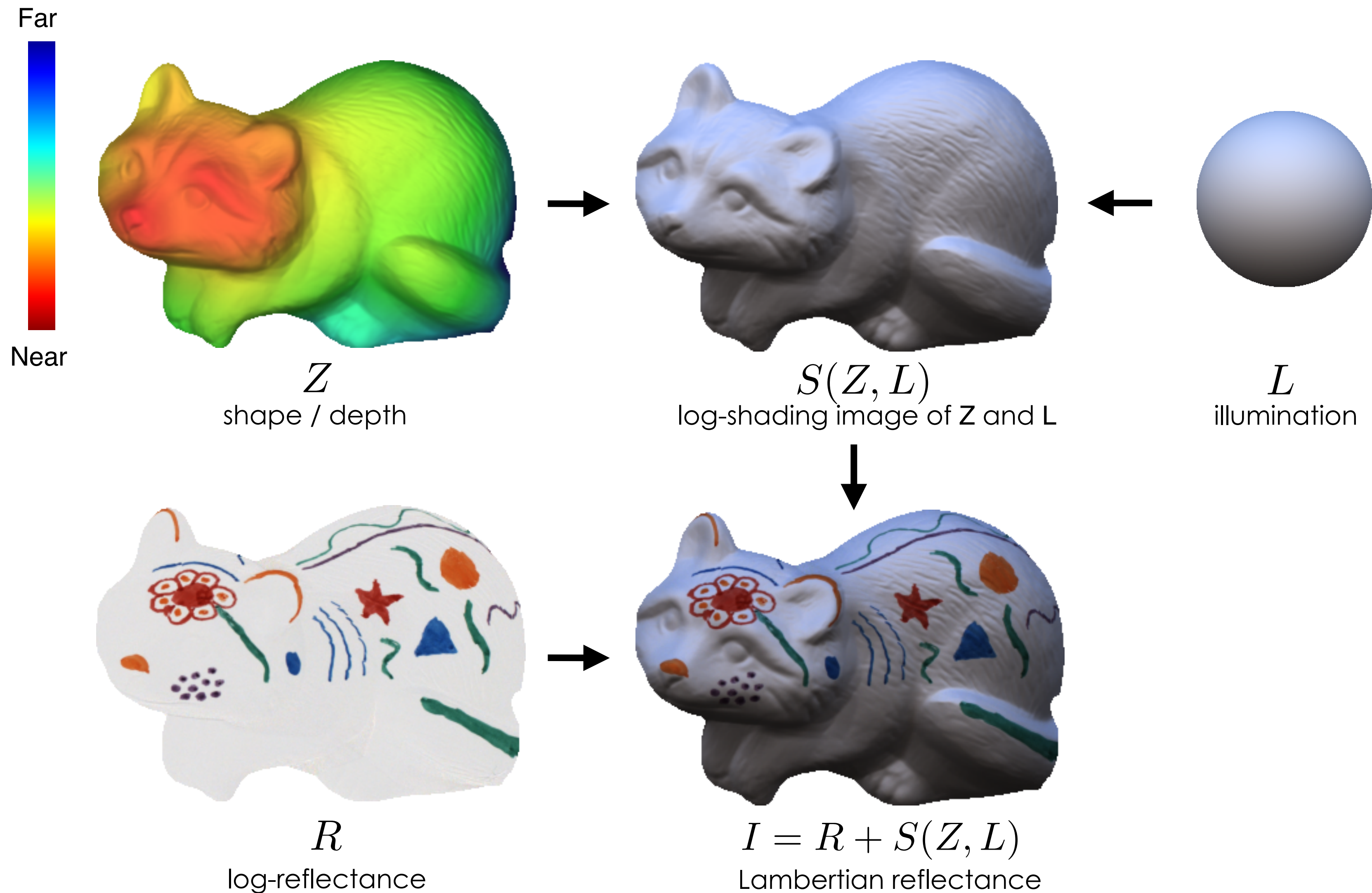


Reflectance

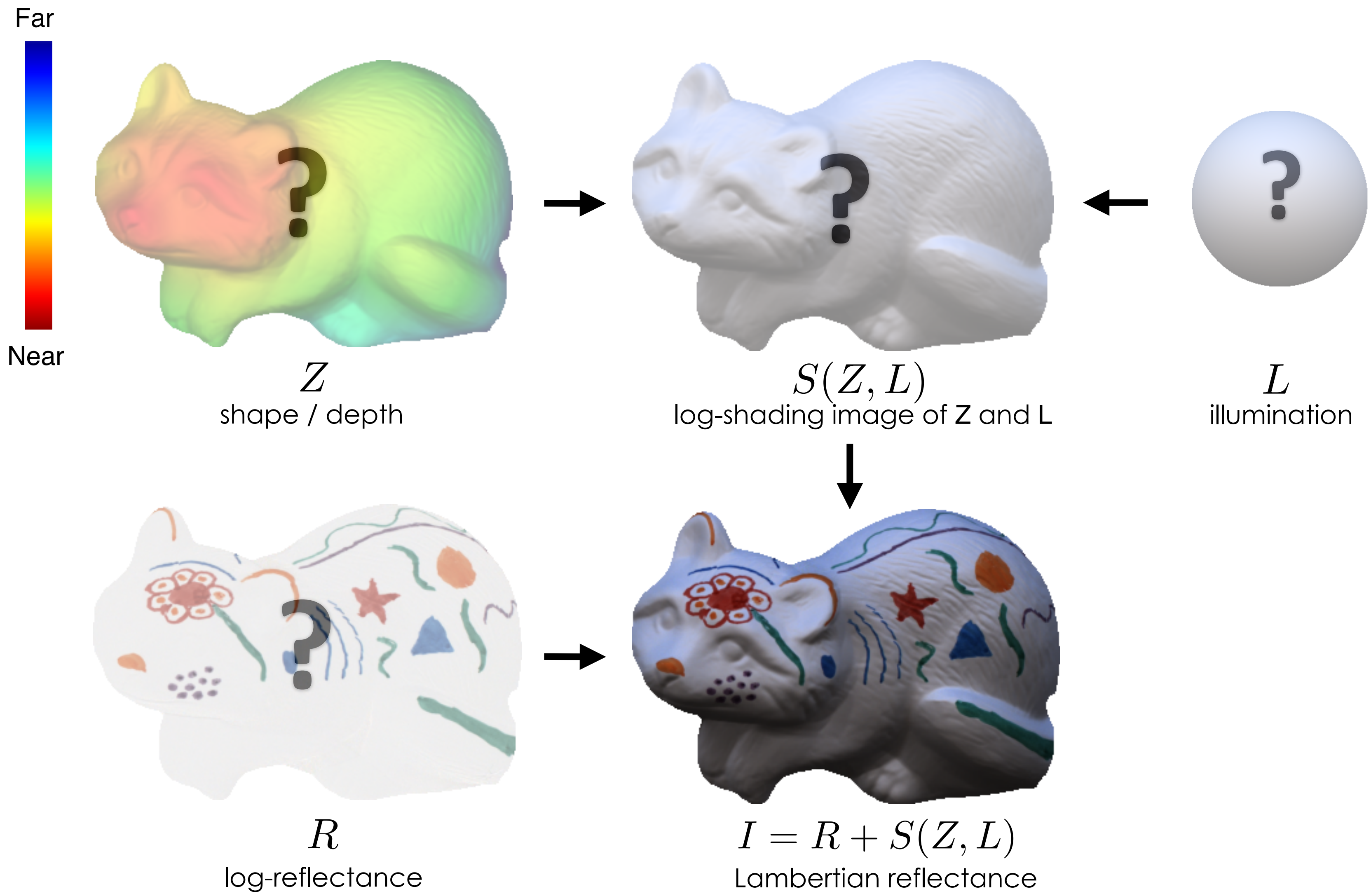


Shading

Intrinsic image decomposition



Intrinsic image decomposition



Retinex: keep only large magnitude edges



Input



Estimated reflectance

CNN-based reflectance estimation

Input



Reflectance



Shading



[Bell et al., "Intrinsic images in the wild", 2014]

Applications of intrinsic image decomposition

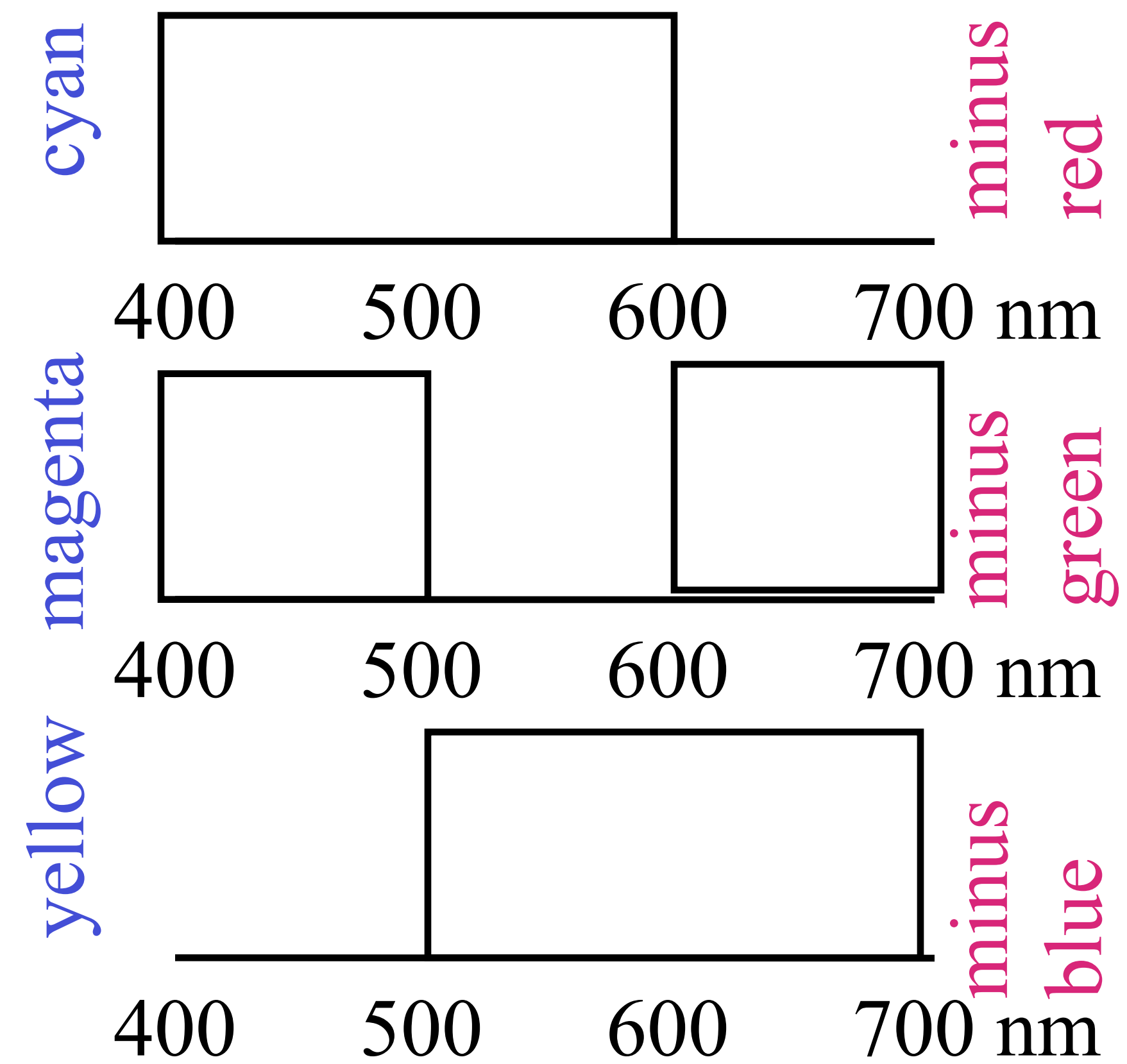
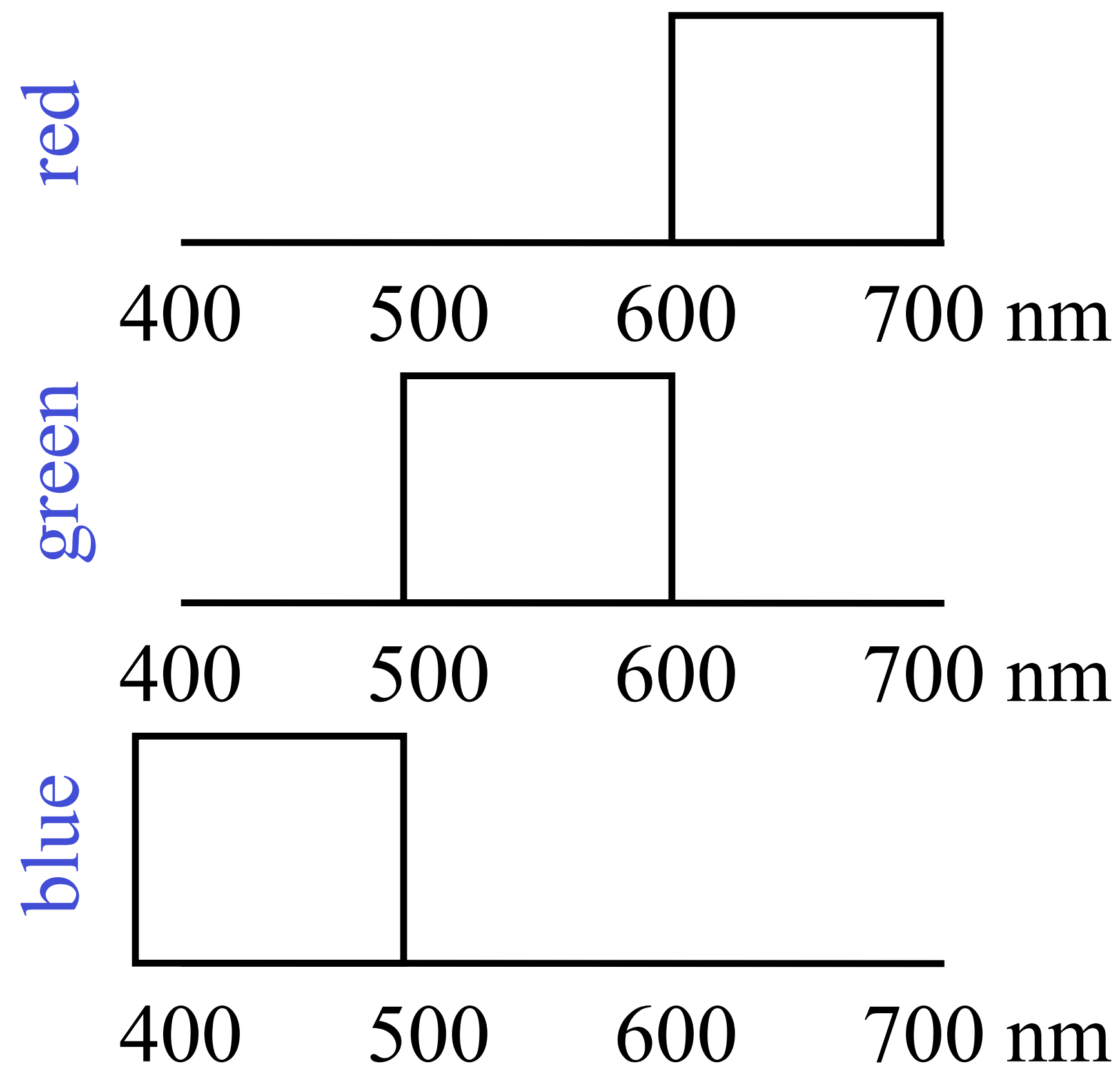
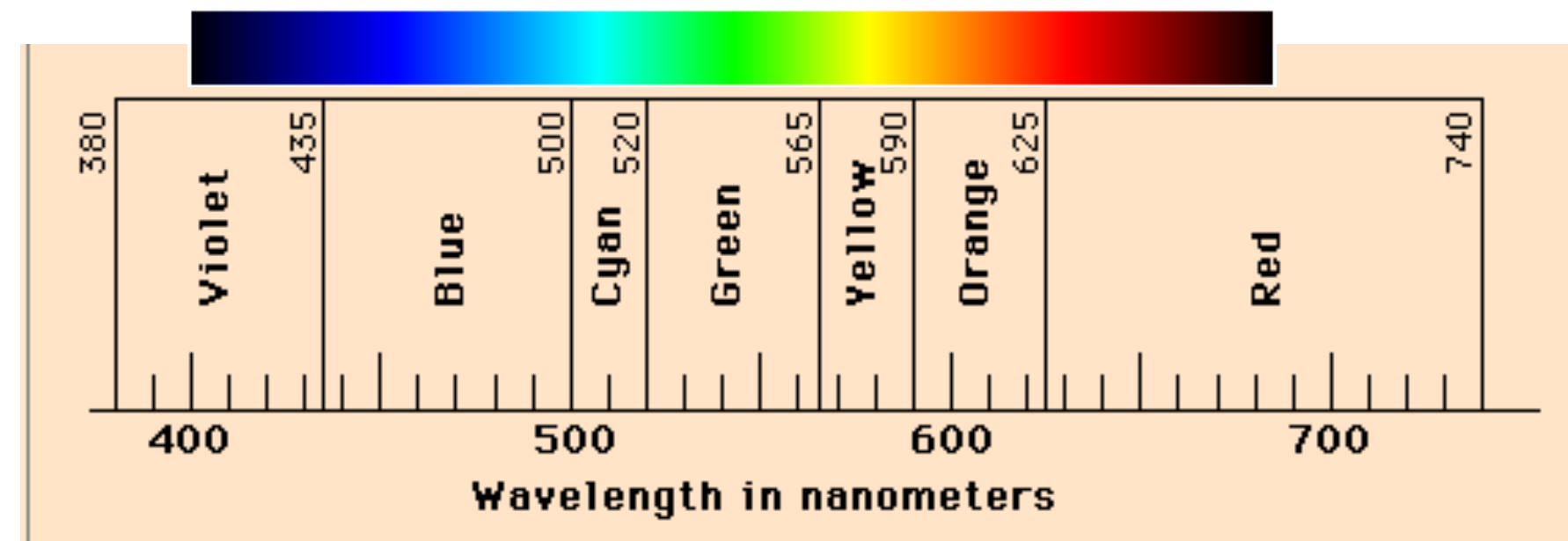


[Barron and Malik "SIRFS", 2012]

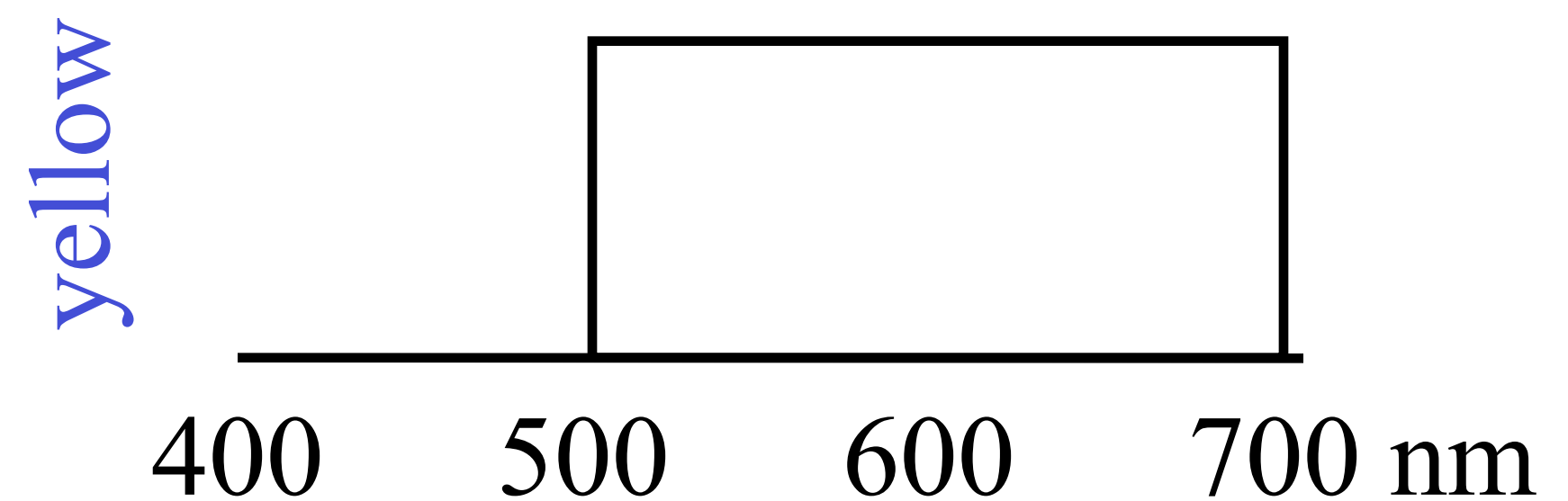
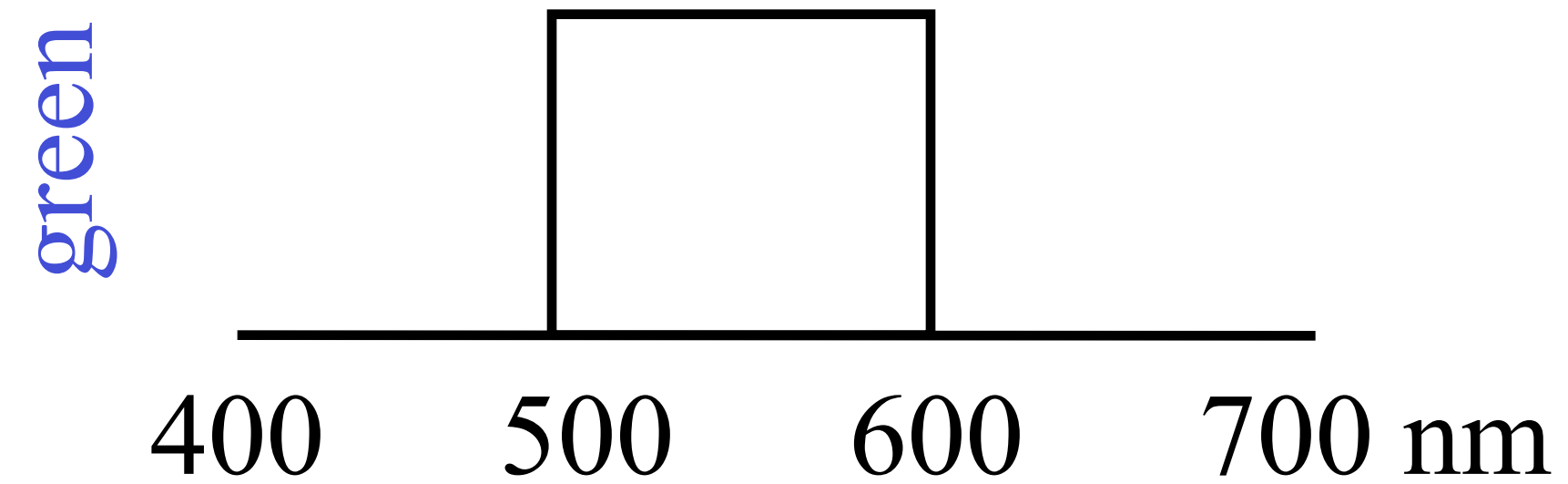
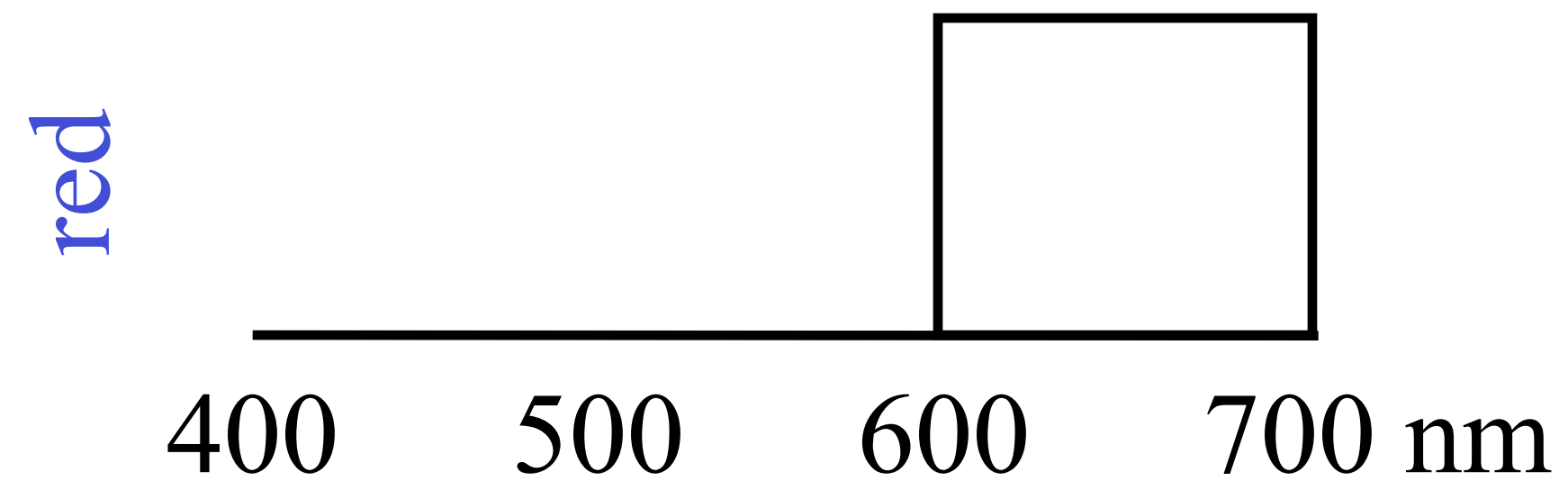
Today

- Shape from shading
- Intrinsic image decomposition
- **Color perception**

Color names for cartoon spectra



Additive color mixing



When colors combine by *adding* the color spectra. Example color displays that follow this mixing rule: CRT phosphors, multiple projectors aimed at a screen.

Red and green make...

Yellow!

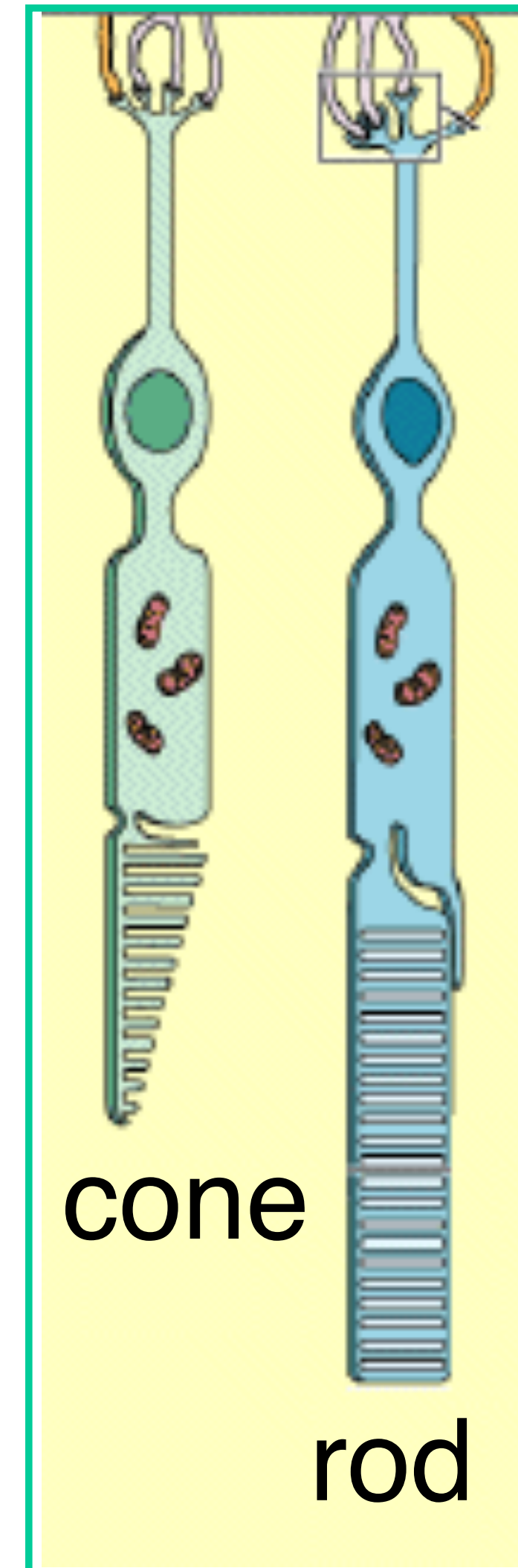
How is color perceived in the eye?

Cones

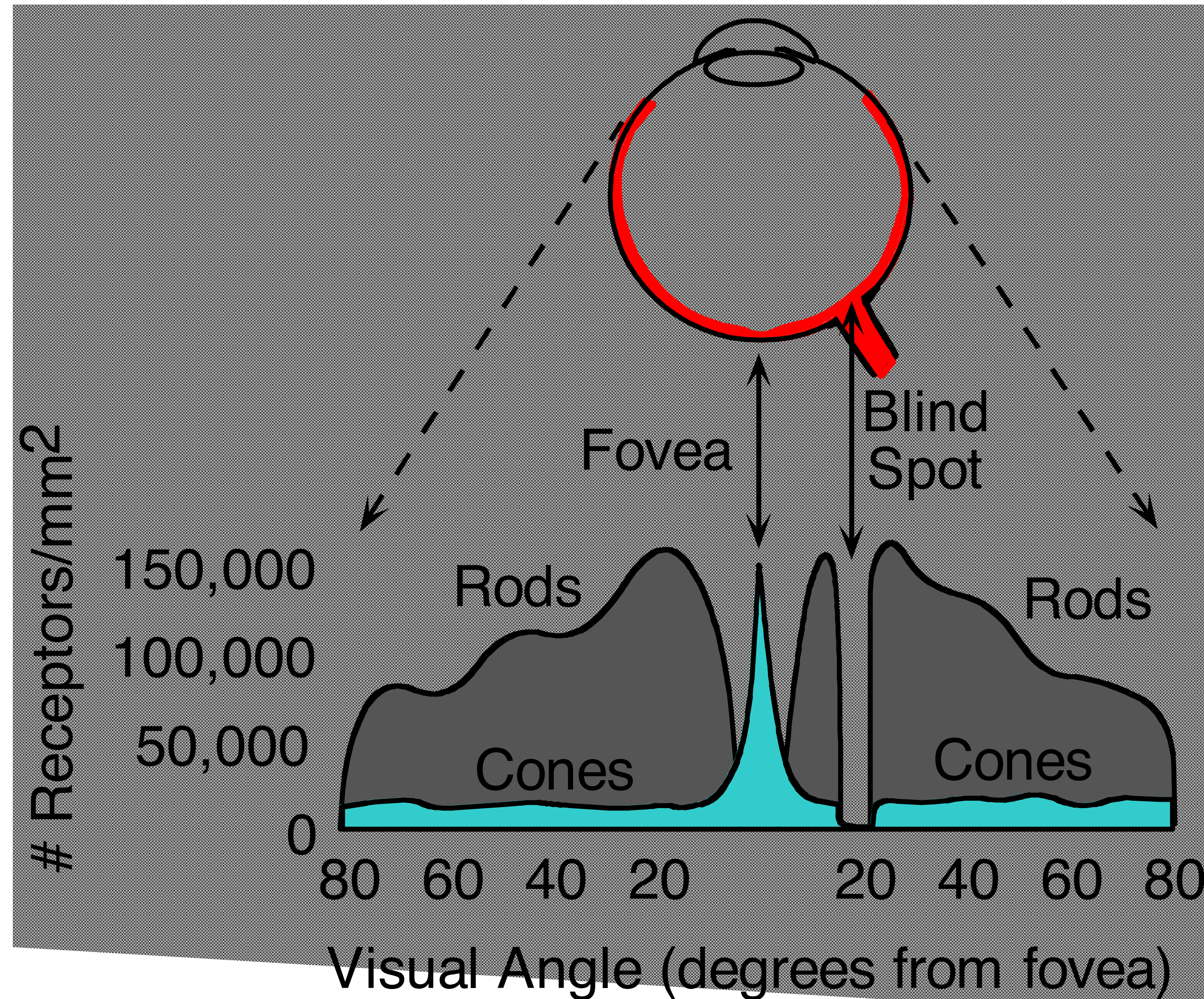
cone-shaped
less sensitive
operate in high light
color vision

Rods

rod-shaped
highly sensitive
operate at night
gray-scale vision

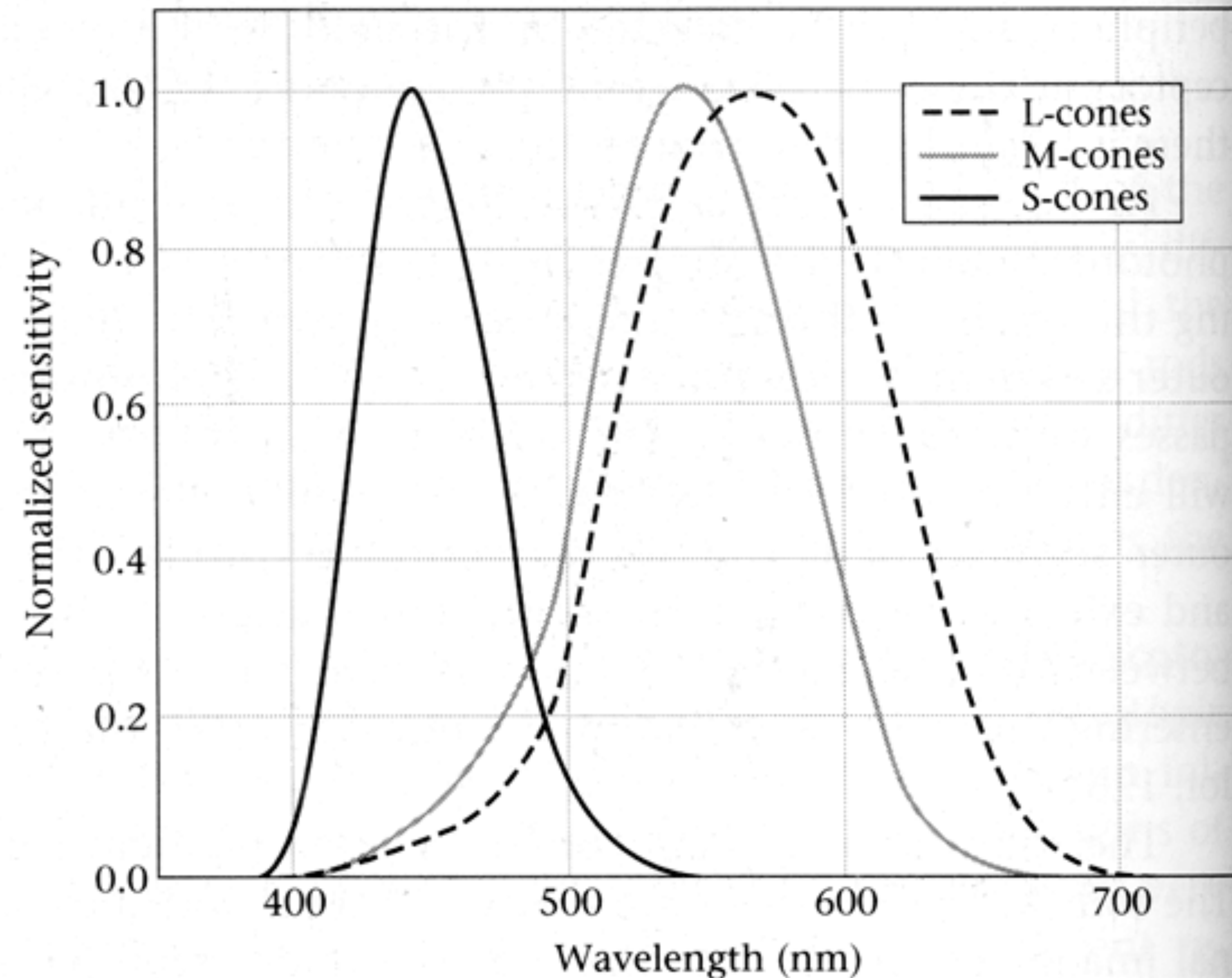


Distribution of Rods and Cones

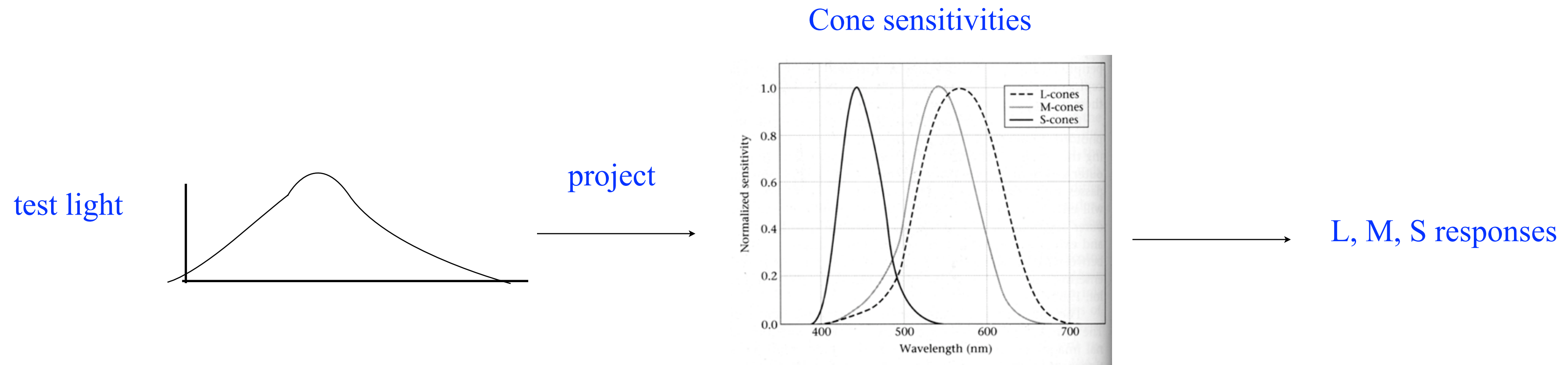


Human eye photoreceptor spectral sensitivities

3.3 SPECTRAL SENSITIVITIES OF THE L-, M-, AND S-CONES in the human eye. The measurements are based on a light source at the cornea, so that the wavelength loss due to the cornea, lens, and other inert pigments of the eye plays a role in determining the sensitivity. Source: Stockman and MacLeod, 1993.



How we sense light spectra



Biophysics: integrate the response over all wavelengths, weighted by the photosensor's sensitivity at each wavelength.

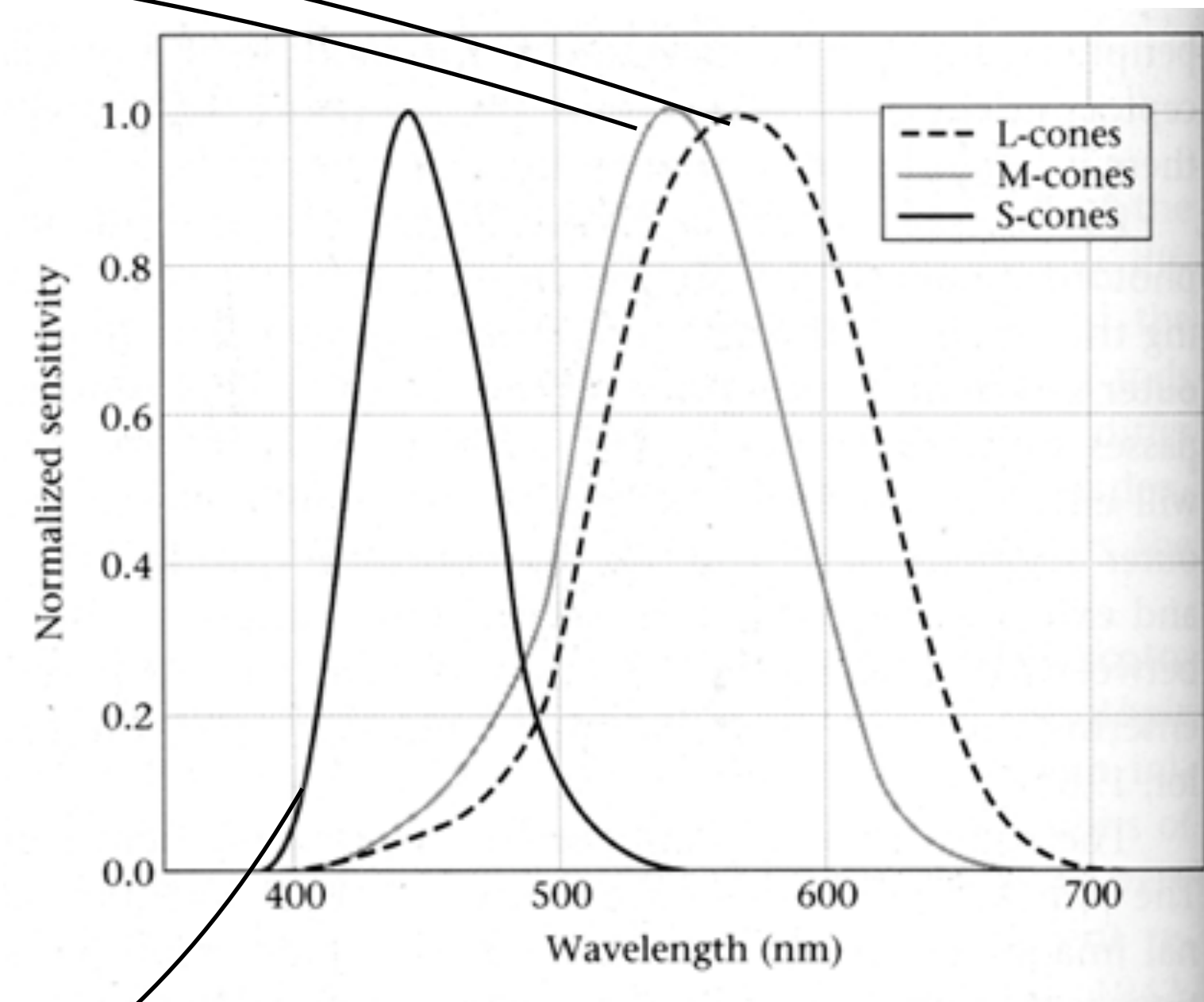
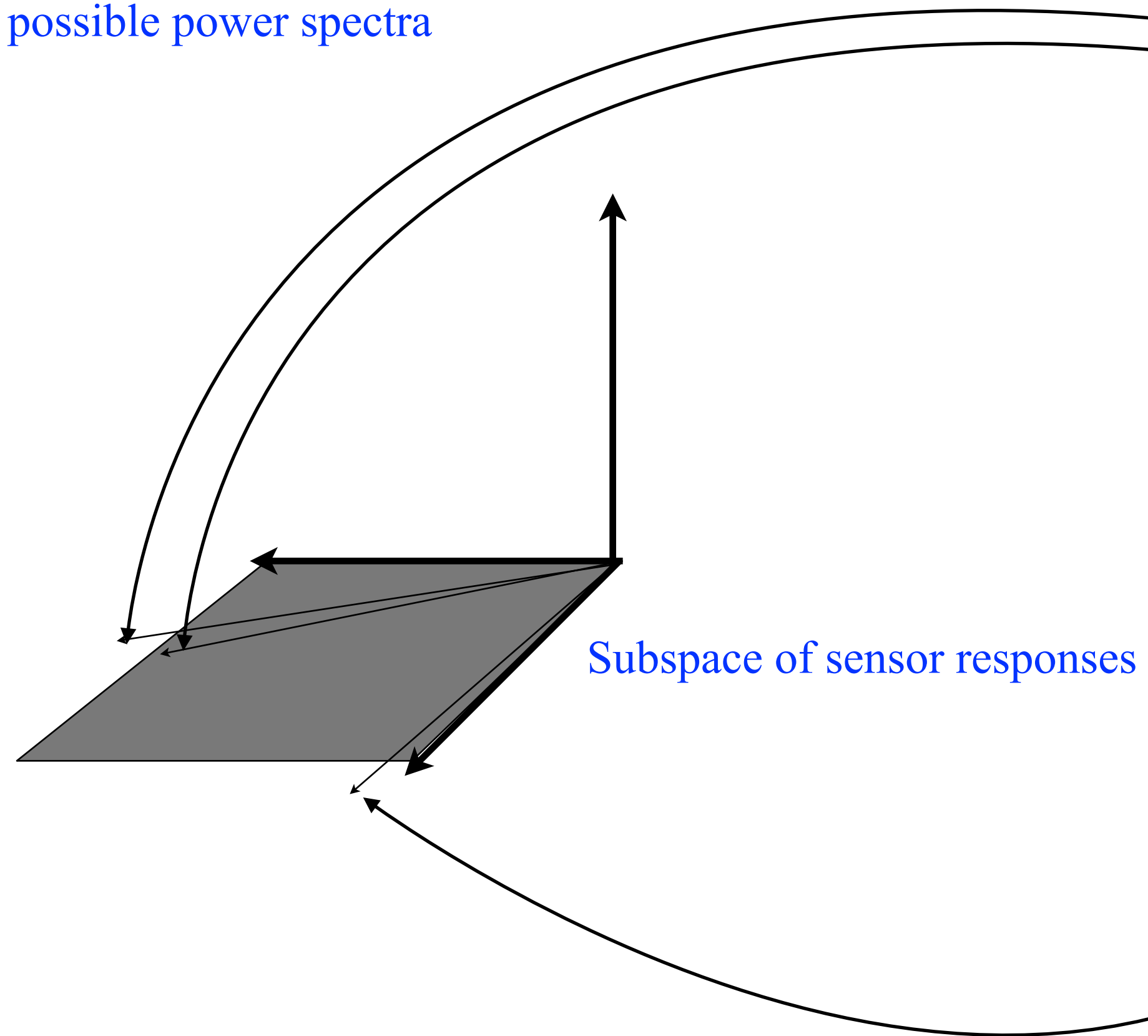
Mathematically: take dot product of input spectrum with the cone sensitivity basis vectors. Project the high-dimensional test light into a 3D space.

$$\mathbf{R} = \mathbf{C} \mathbf{t}$$

\mathbf{R} = cone responses
 \mathbf{C} = cone sensitivities
 \mathbf{t} = input spectrum

Cone response curves as basis vectors in a 3D subspace of light power spectra

3D depiction of the high-dimensional space of all possible power spectra



Spectral sensitivities of L, M, and S cones

UNITED STATES DEPARTMENT OF AGRICULTURE

COLOR STANDARDS

for

FROZEN

FRENCH FRIED POTATOES

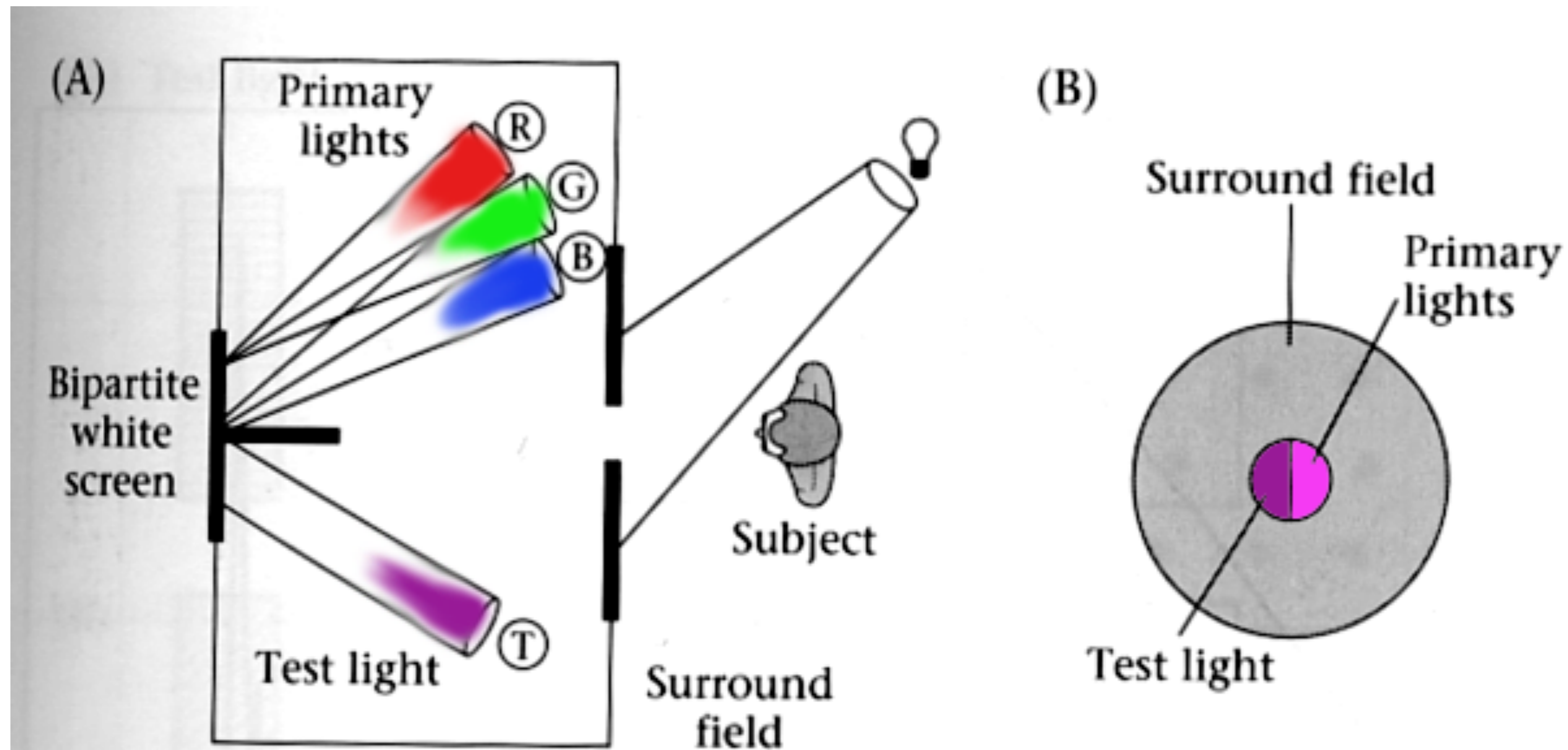


FOURTH EDITION, 1988
© 1988 KOLLMORGEN CORPORATION

MUNSELL COLOR
BALTIMORE, MARYLAND
64-1

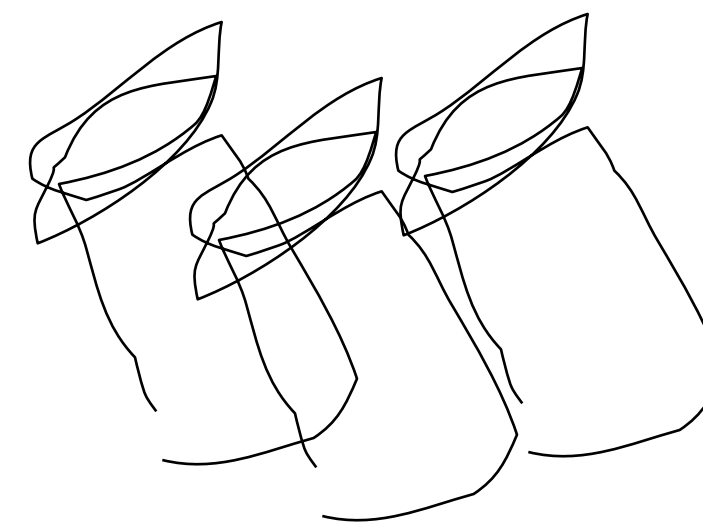
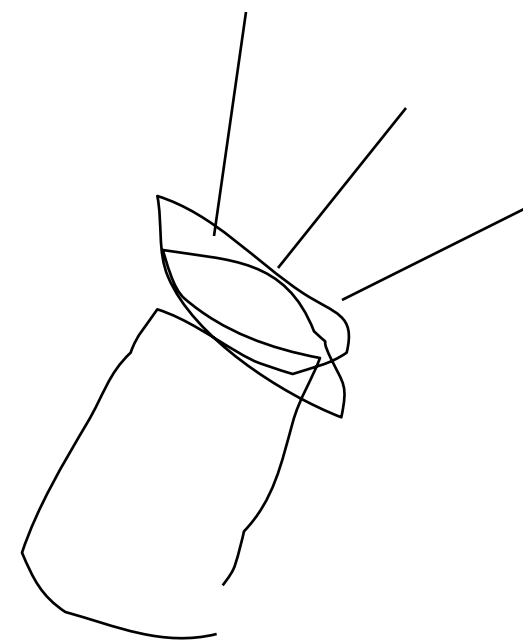
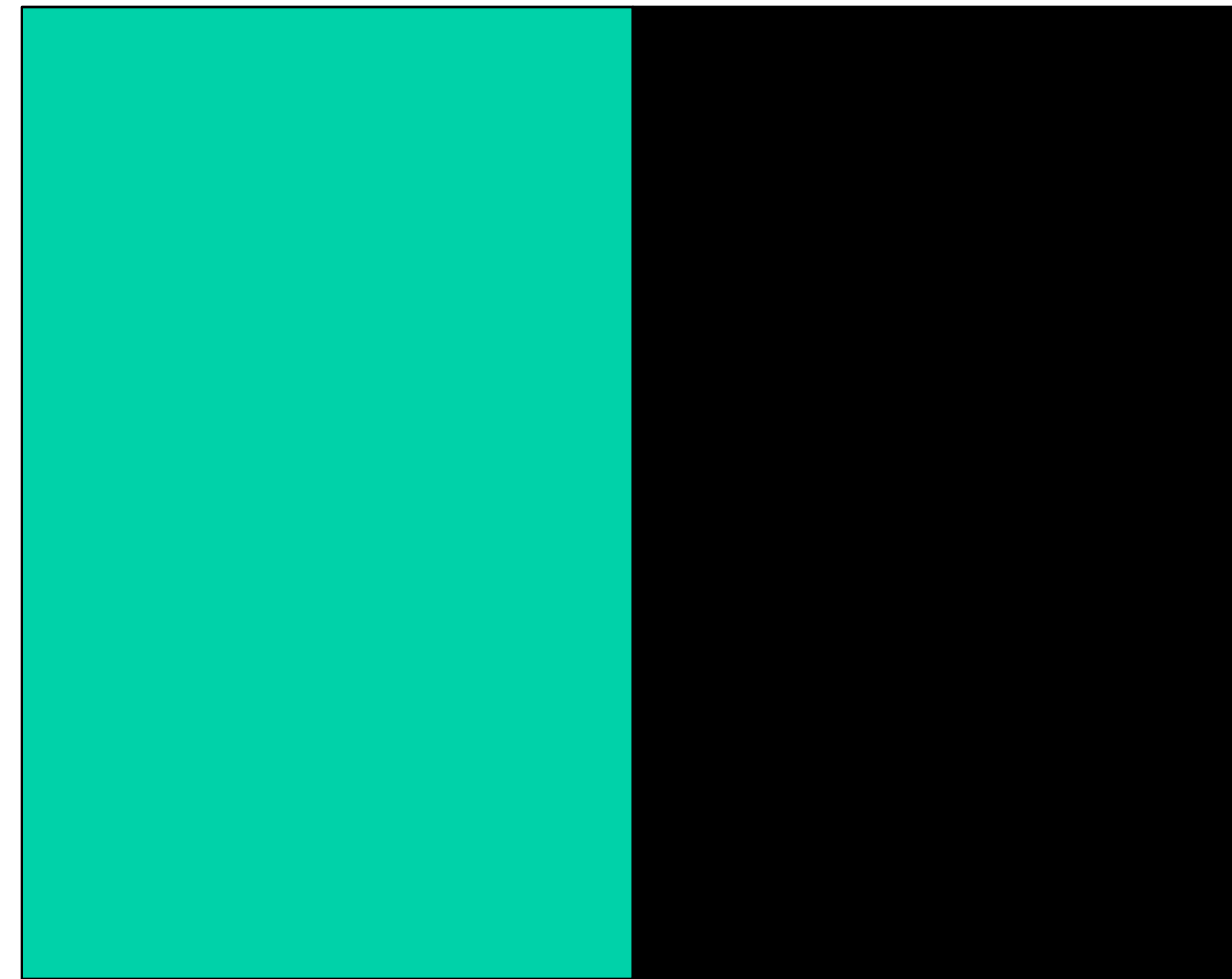


Color matching experiment

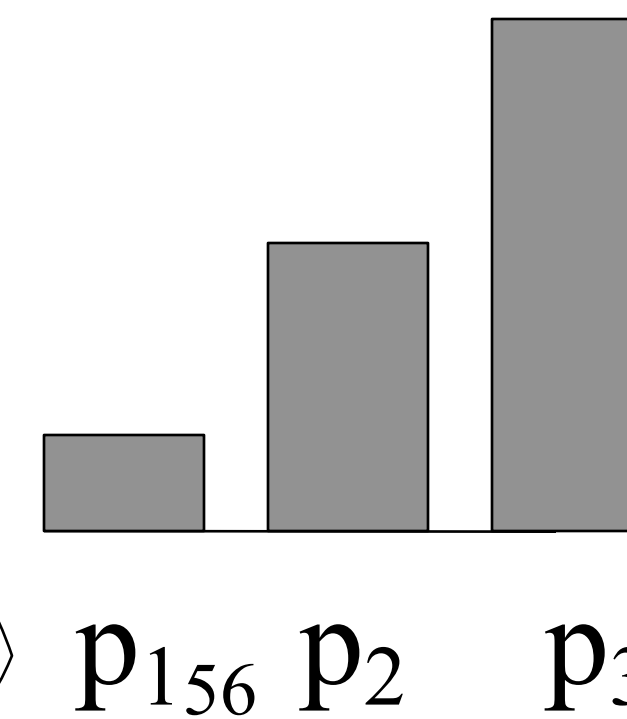
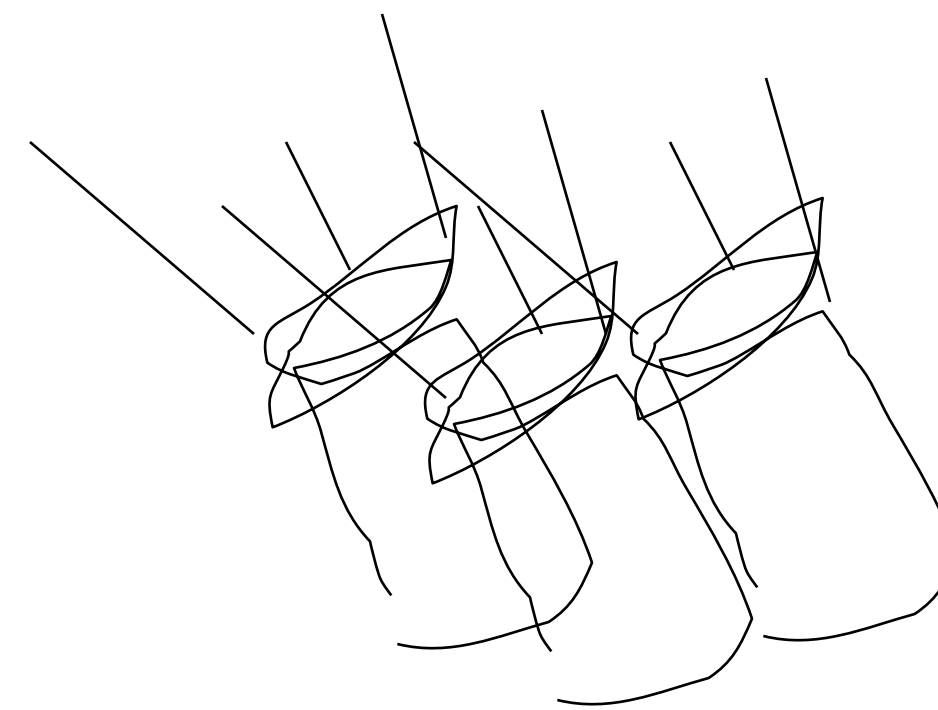
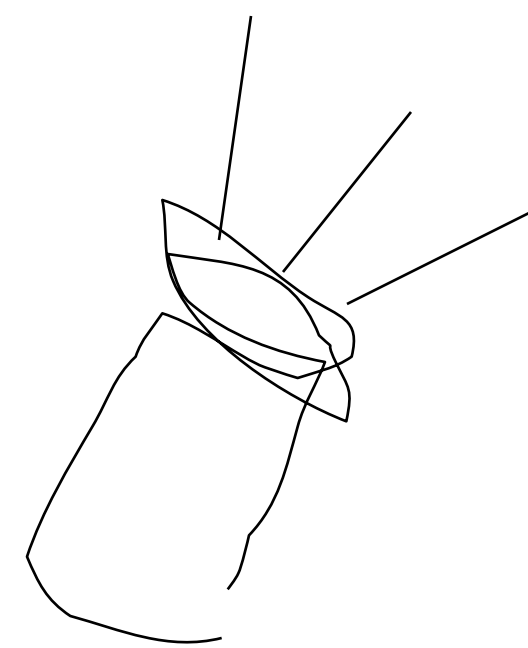
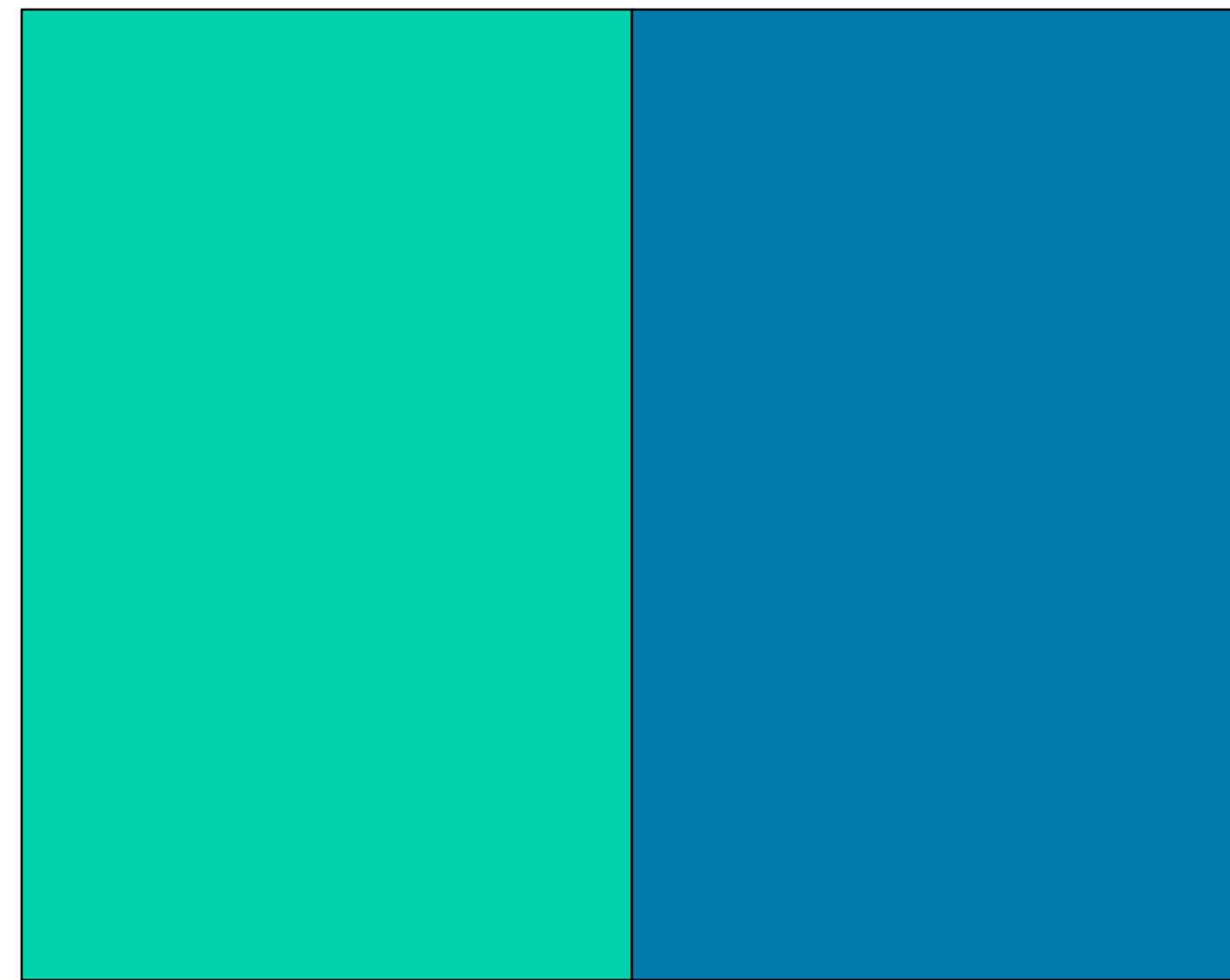


4.10 THE COLOR-MATCHING EXPERIMENT. The observer views a bipartite field and adjusts the intensities of the three primary lights to match the appearance of the test light. (A) A top view of the experimental apparatus. (B) The appearance of the stimuli to the observer. After Judd and Wyszecki, 1975.

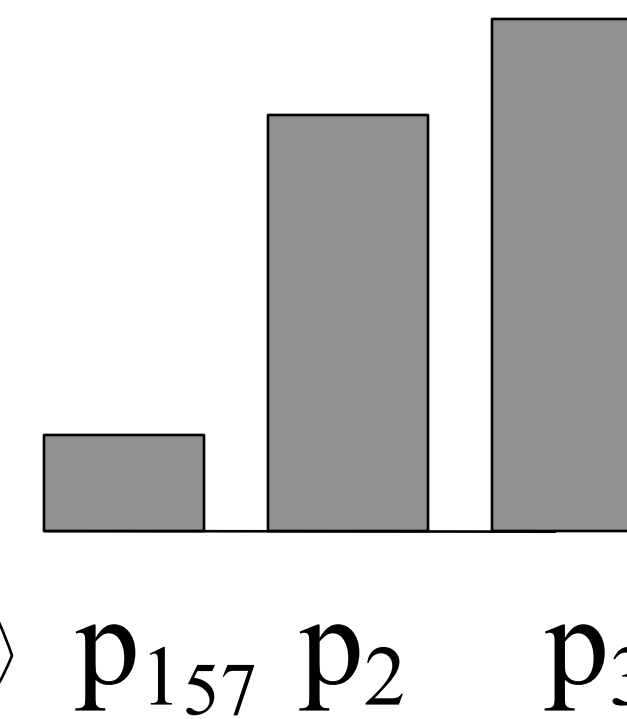
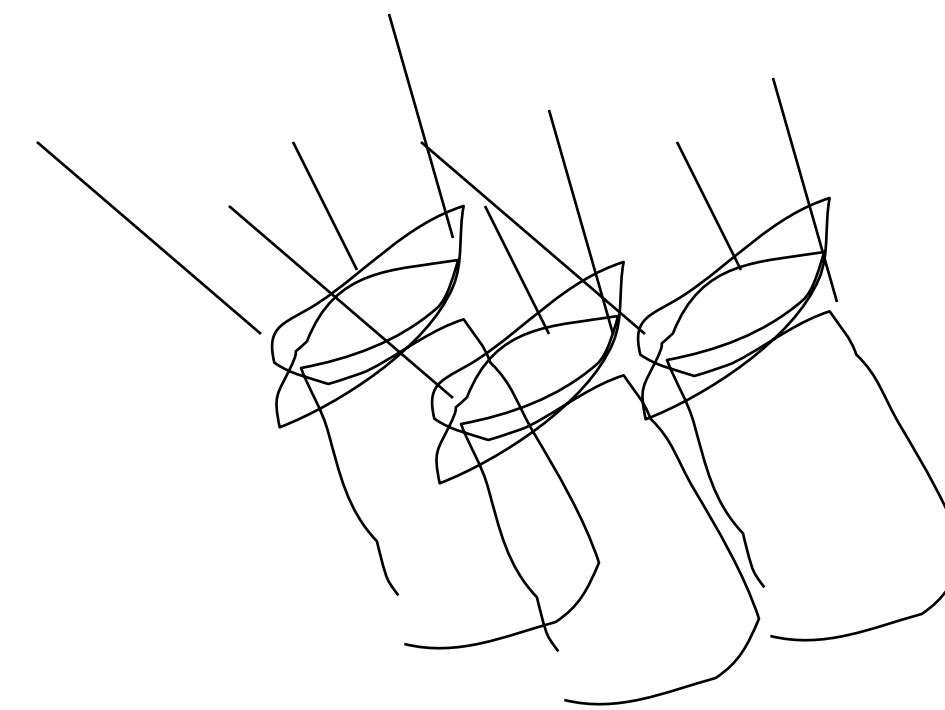
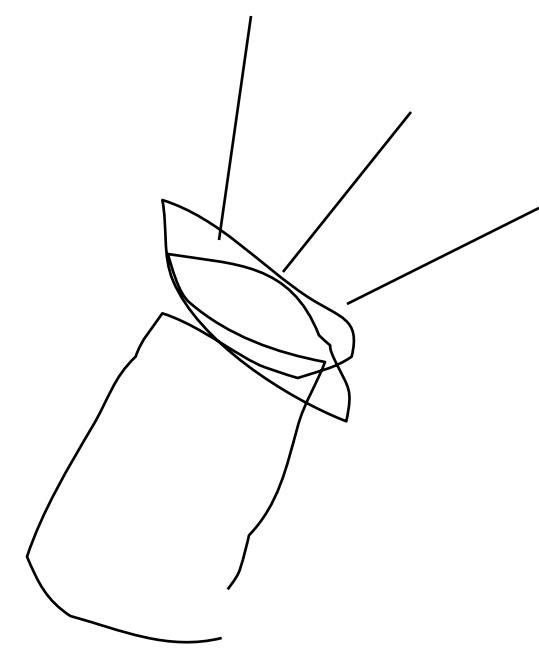
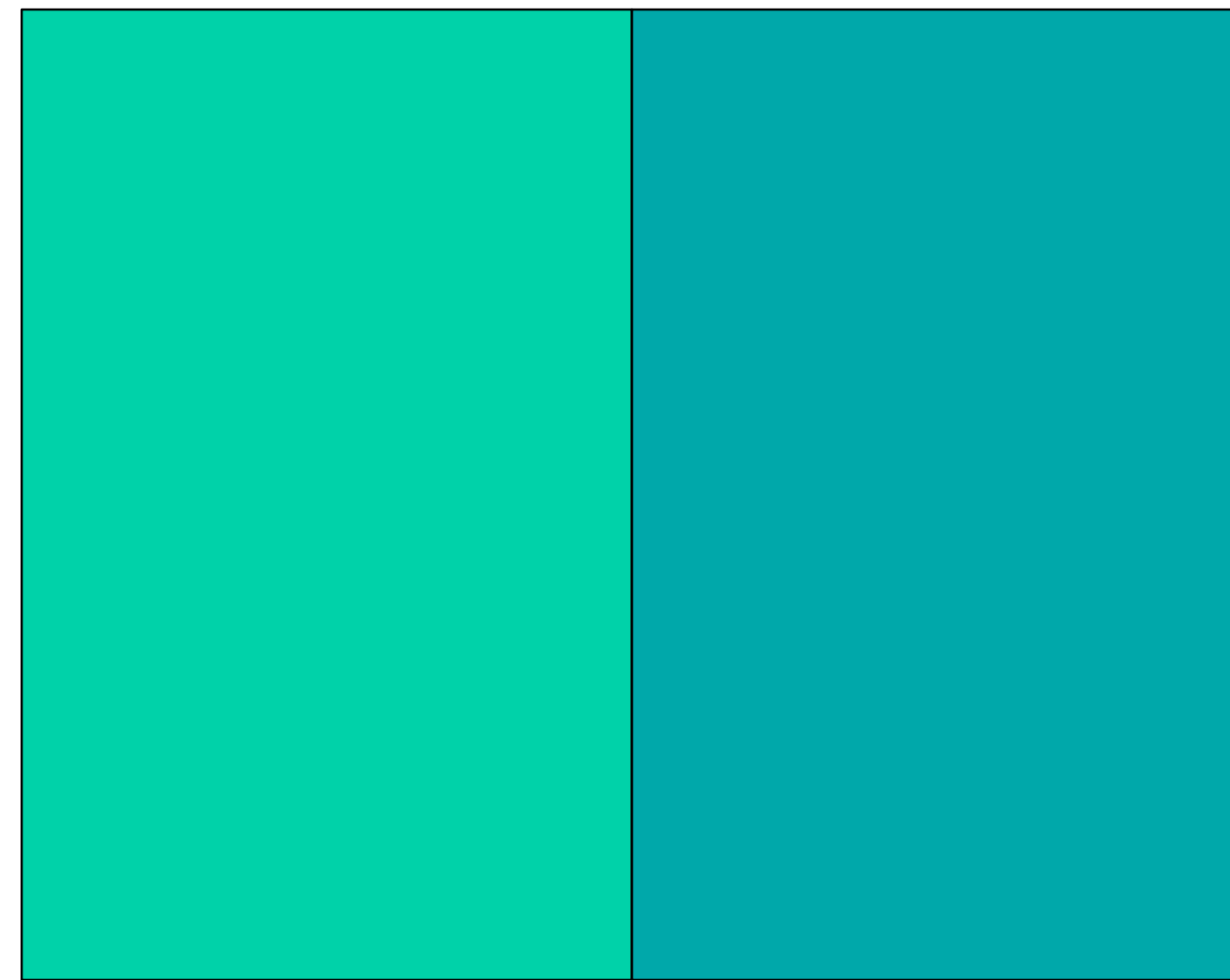
Color matching experiment



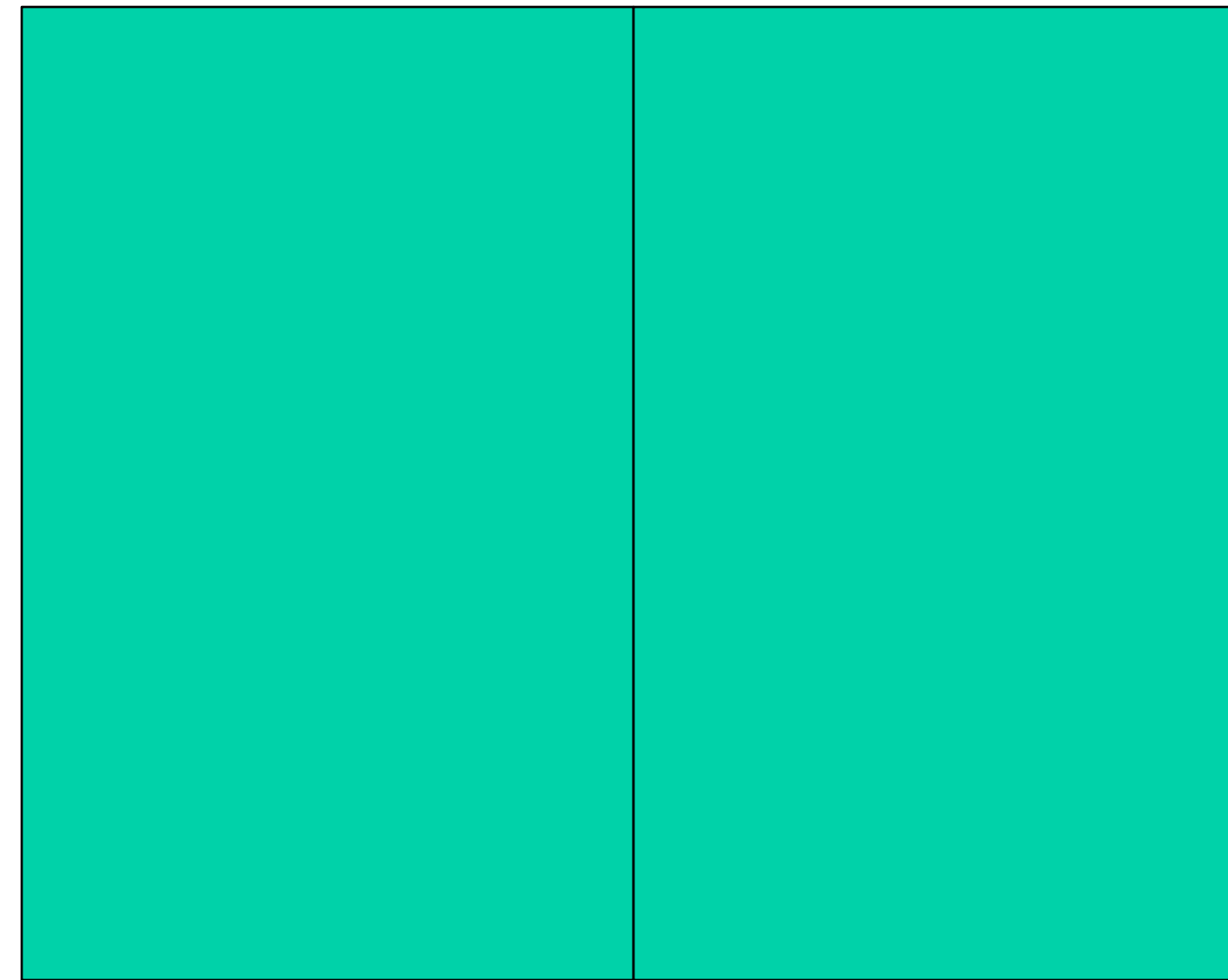
Color matching experiment



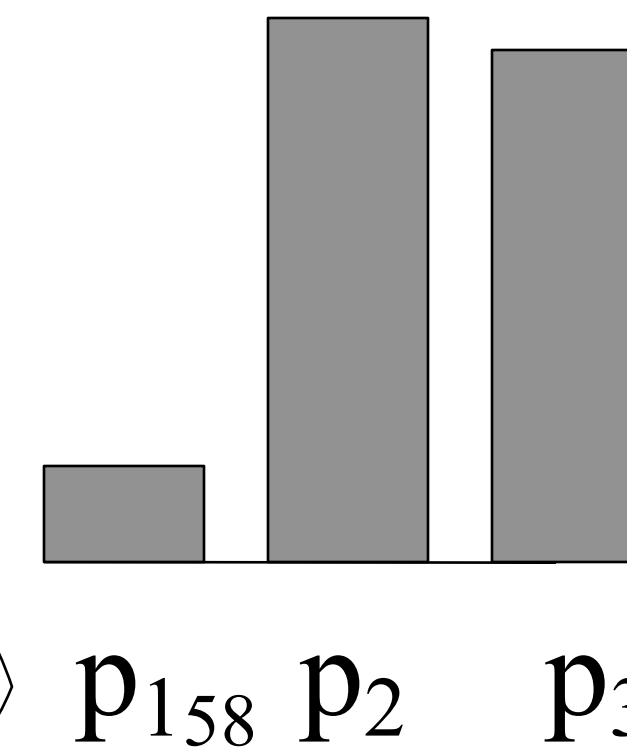
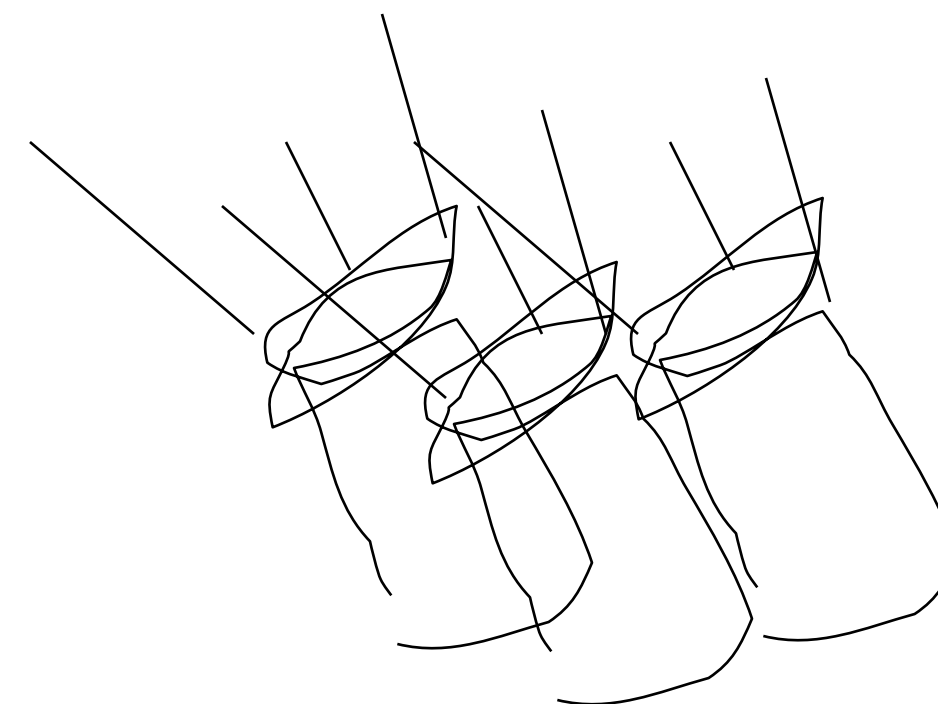
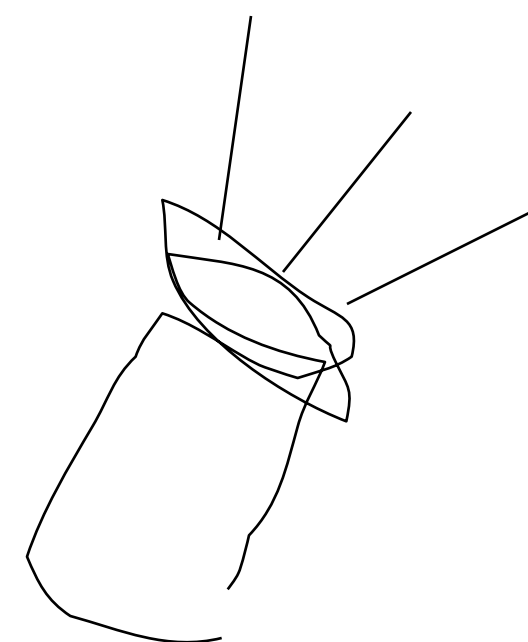
Color matching experiment



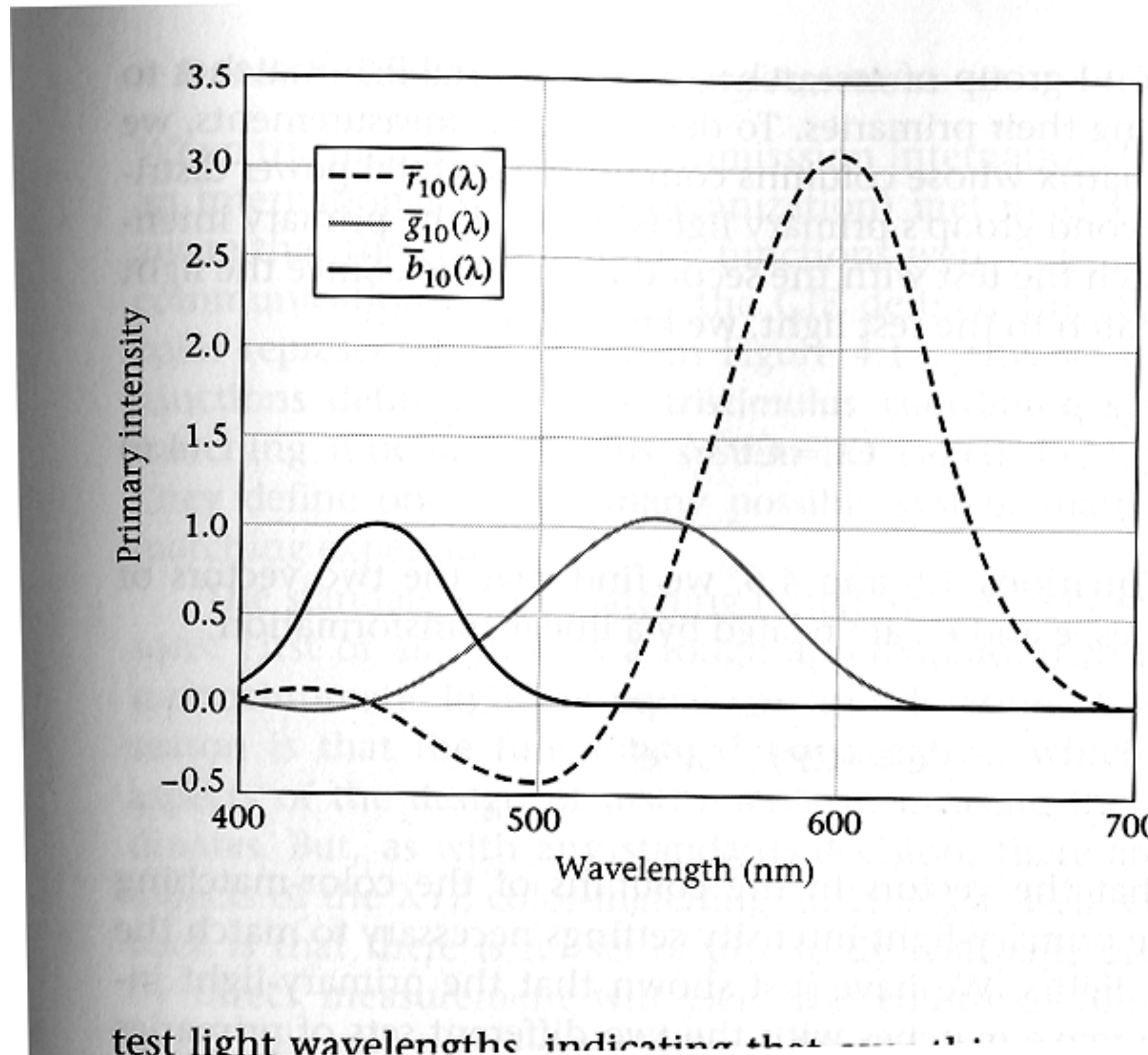
Color matching experiment



The primary color amounts needed for a match



“Color matching functions” let us find other basis vectors for the eye response subspace of light power spectra

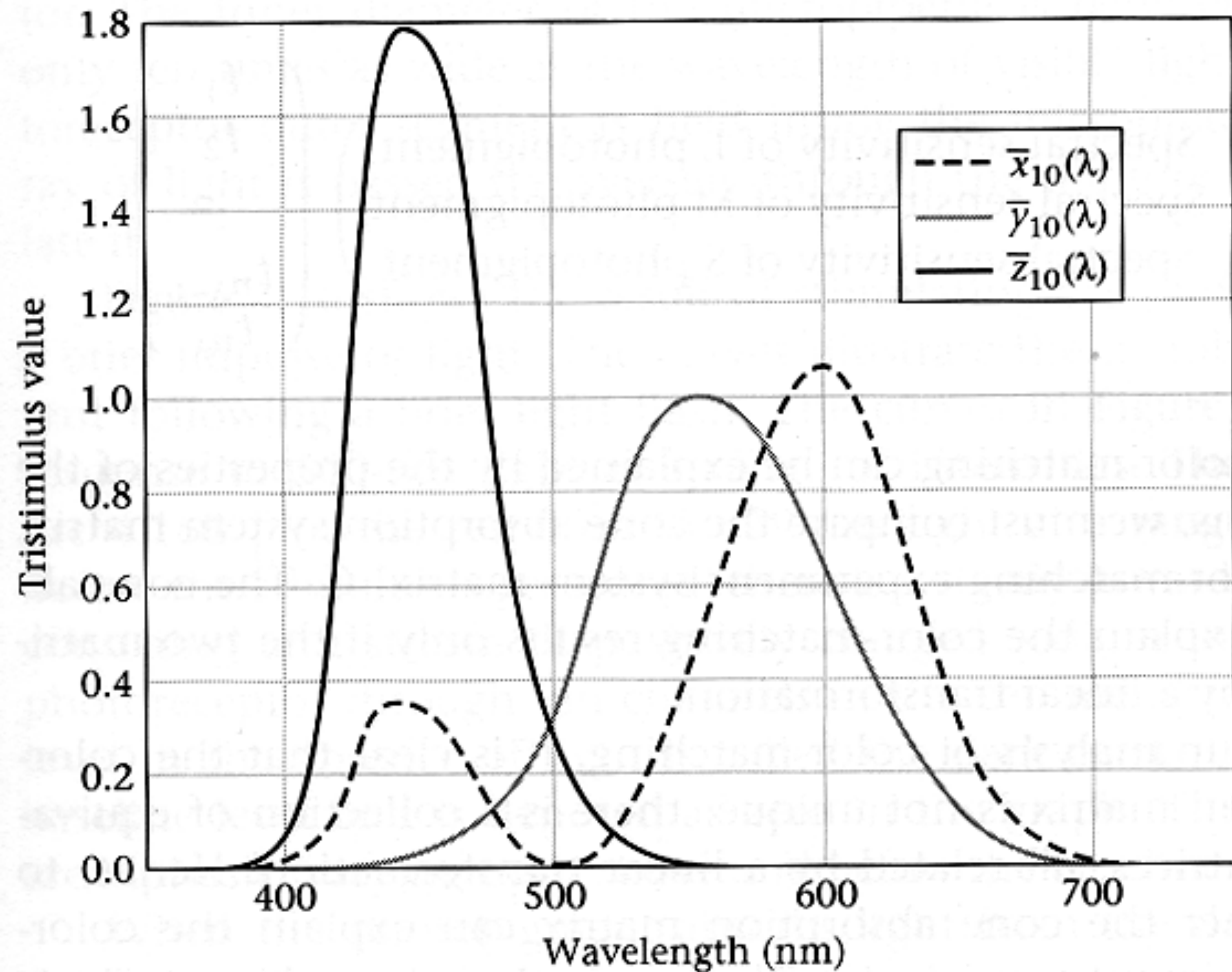


- $p_1 = 645.2 \text{ nm}$
- $p_2 = 525.3 \text{ nm}$
- $p_3 = 444.4 \text{ nm}$

4.13 THE COLOR-MATCHING FUNCTIONS ARE THE ROWS OF THE COLOR-MATCHING SYSTEM MATRIX. The functions measured by Stiles and Burch (1959) using a 10-degree bipartite field and primary lights at the wavelengths 645.2 nm, 525.3 nm, and 444.4 nm with unit radiant power are shown. The three functions in this figure are called $\bar{r}_{10}(\lambda)$, $\bar{g}_{10}(\lambda)$, and $\bar{b}_{10}(\lambda)$.

test light wavelenoths indicating that ...

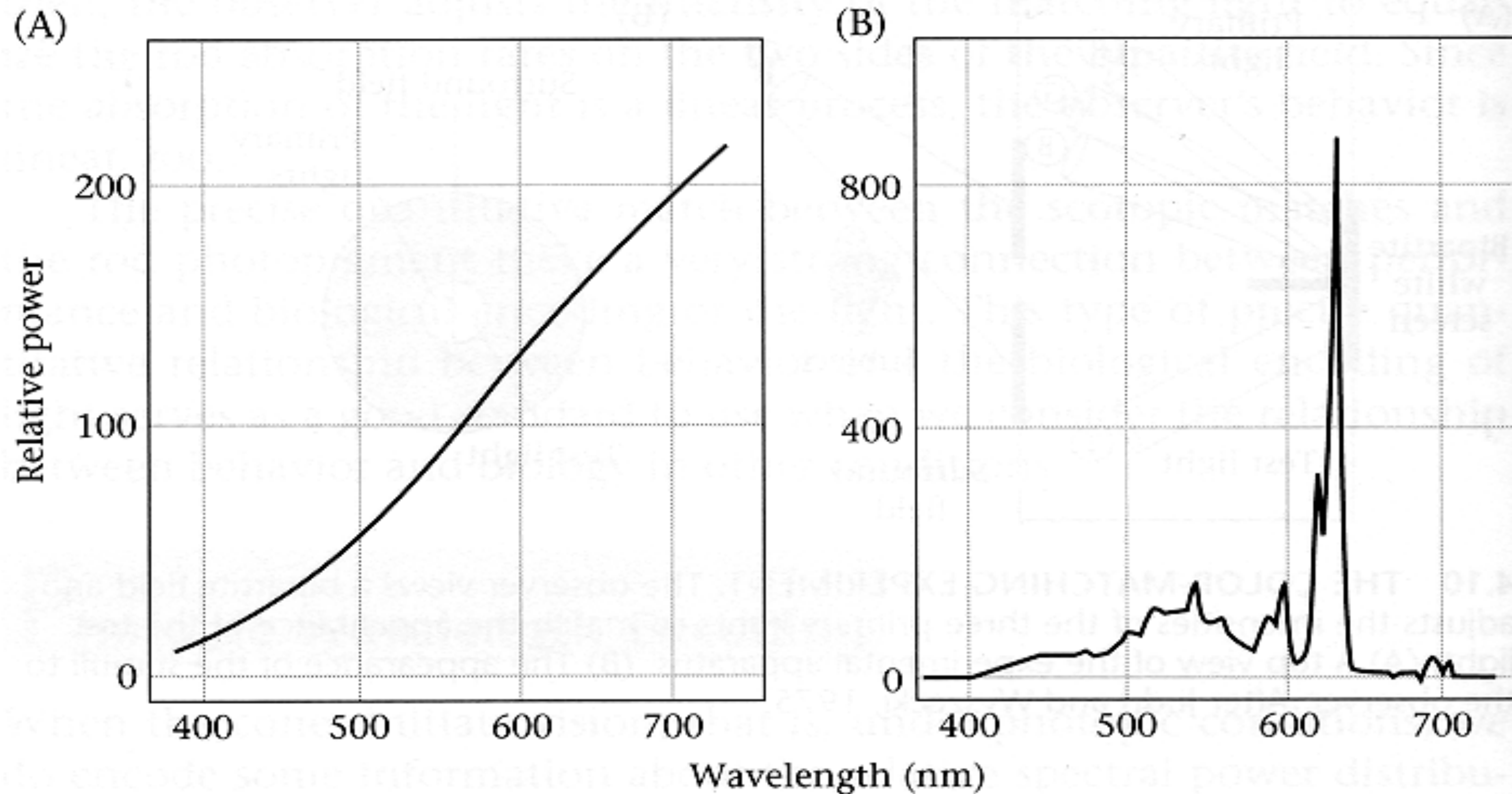
Other color matching functions



4.14 THE XYZ STANDARD COLOR-MATCHING FUNCTIONS. In 1931 the CIE standardized a set of color-matching functions for image interchange. These color-matching functions are called $\bar{x}(\lambda)$, $\bar{y}(\lambda)$, and $\bar{z}(\lambda)$. Industrial applications commonly describe the color properties of a light source using the three primary intensities needed to match the light source that can be computed from the XYZ color-matching functions.

Metameric lights

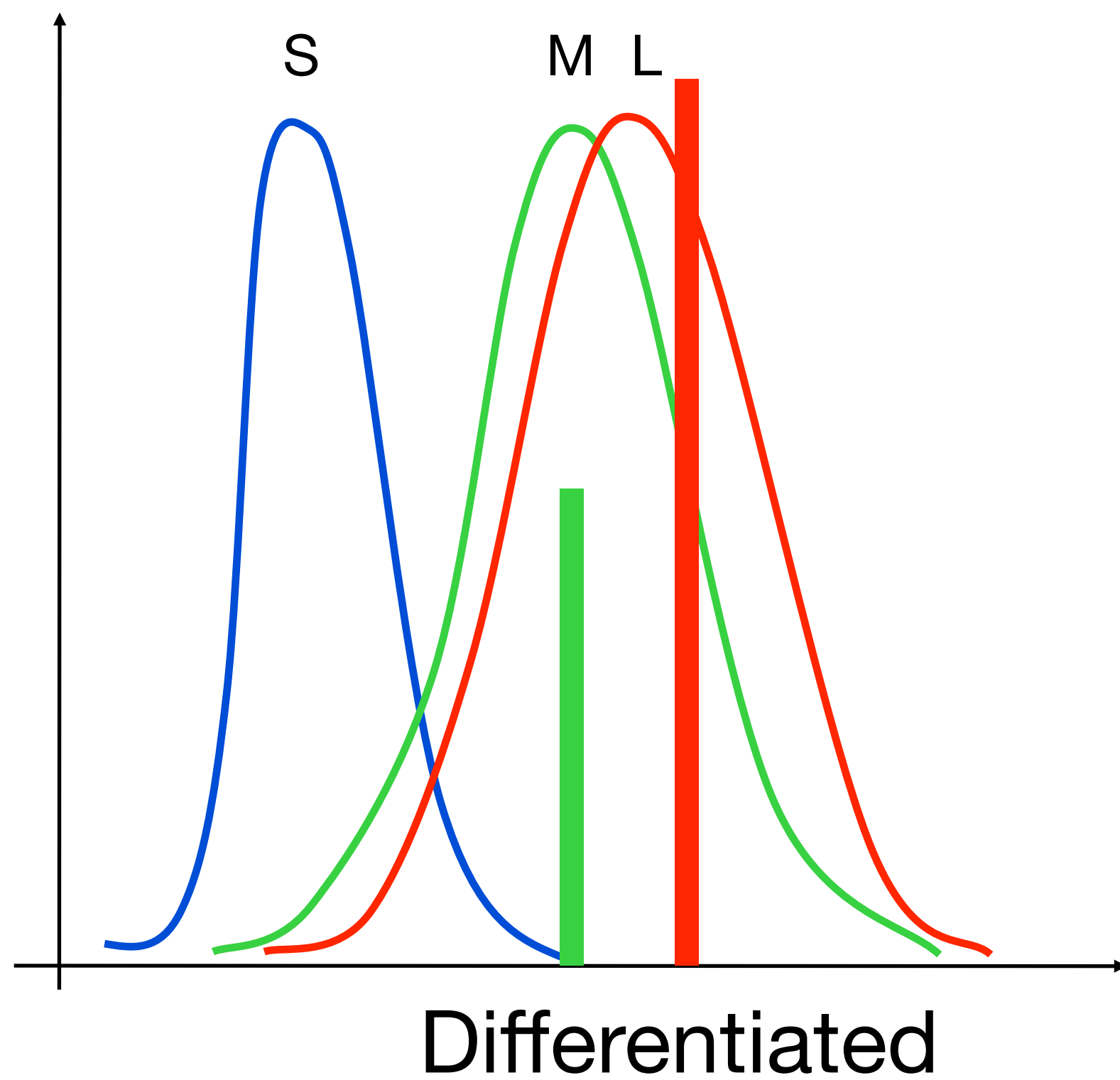
Foundations of Vision, by Brian Wandell, Sinauer Assoc., 1995



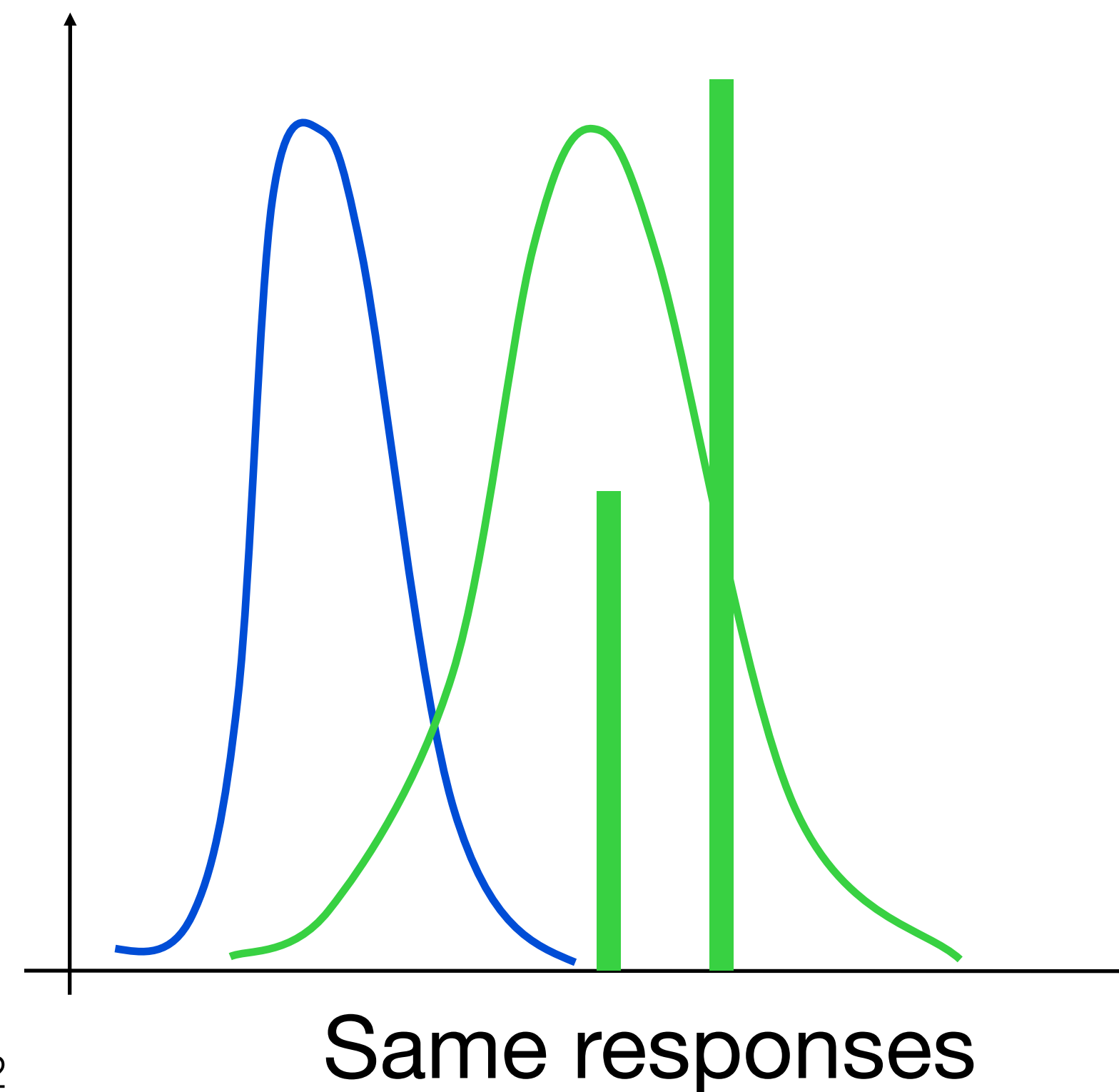
4.11 METAMERIC LIGHTS. Two lights with these spectral power distributions appear identical to most observers and are called metamers. (A) An approximation to the spectral power distribution of a tungsten bulb. (B) The spectral power distribution of light emitted from a conventional television monitor whose three phosphor intensities were set to match the light in panel A in appearance.

Color blindness

- Classical case: 1 type of cone is missing (e.g. red)
- Makes it impossible to distinguish some spectra
- There are also tetrachromats, who have 4 cones!

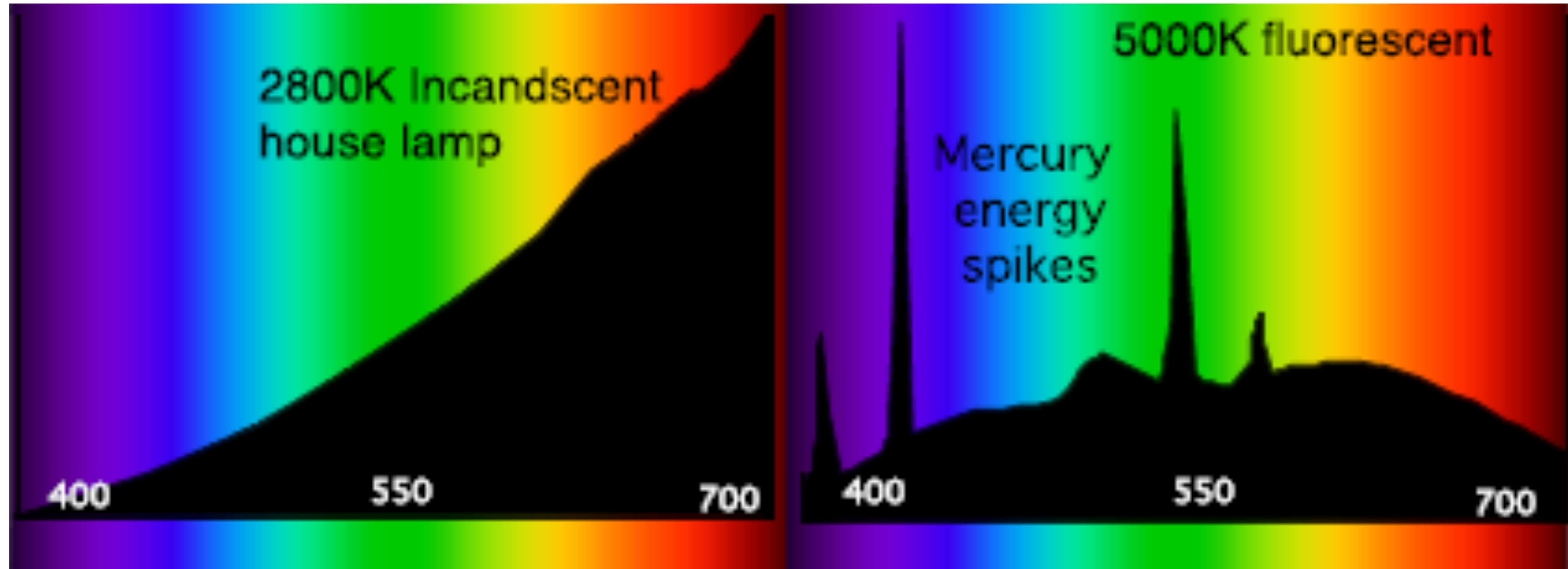


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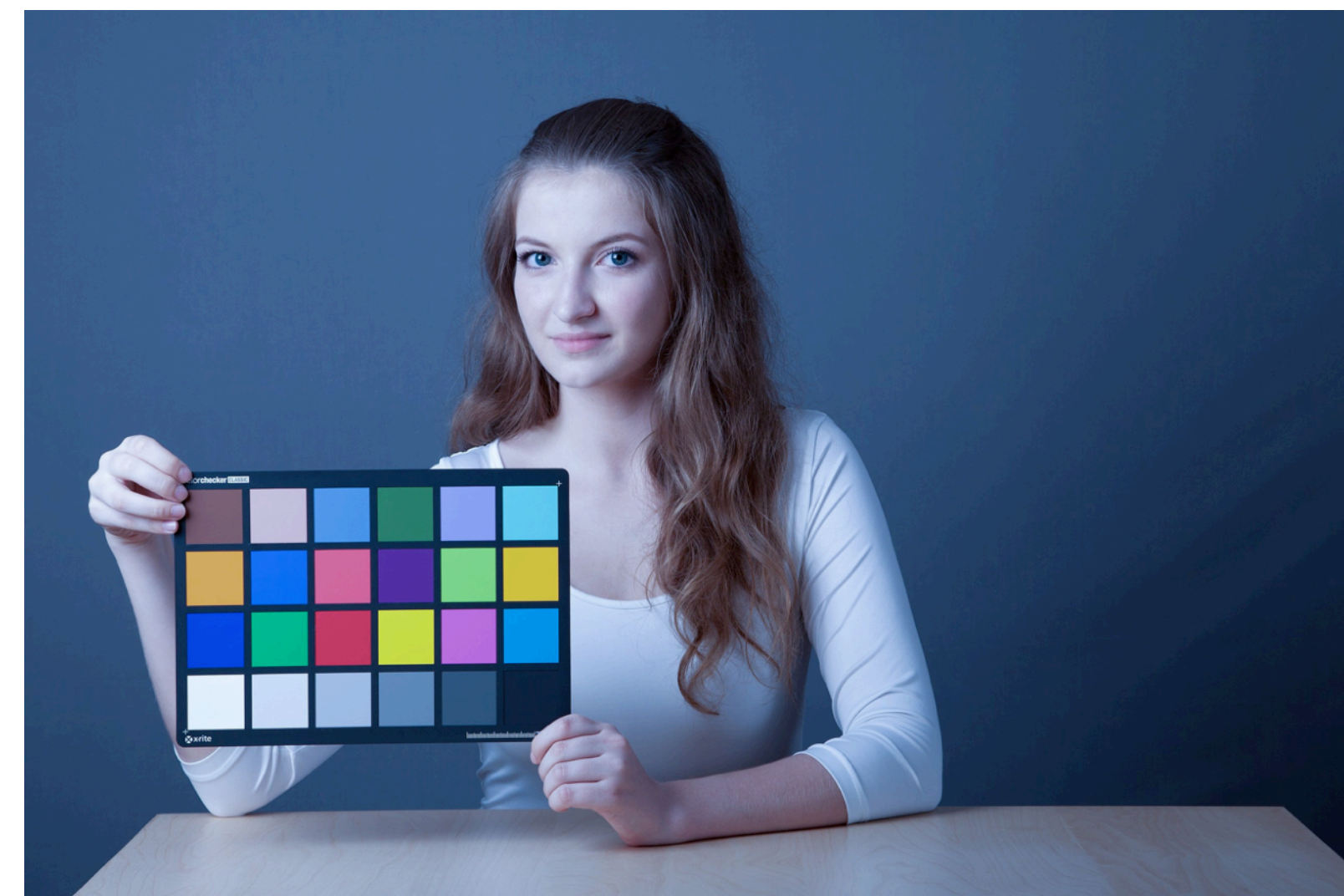
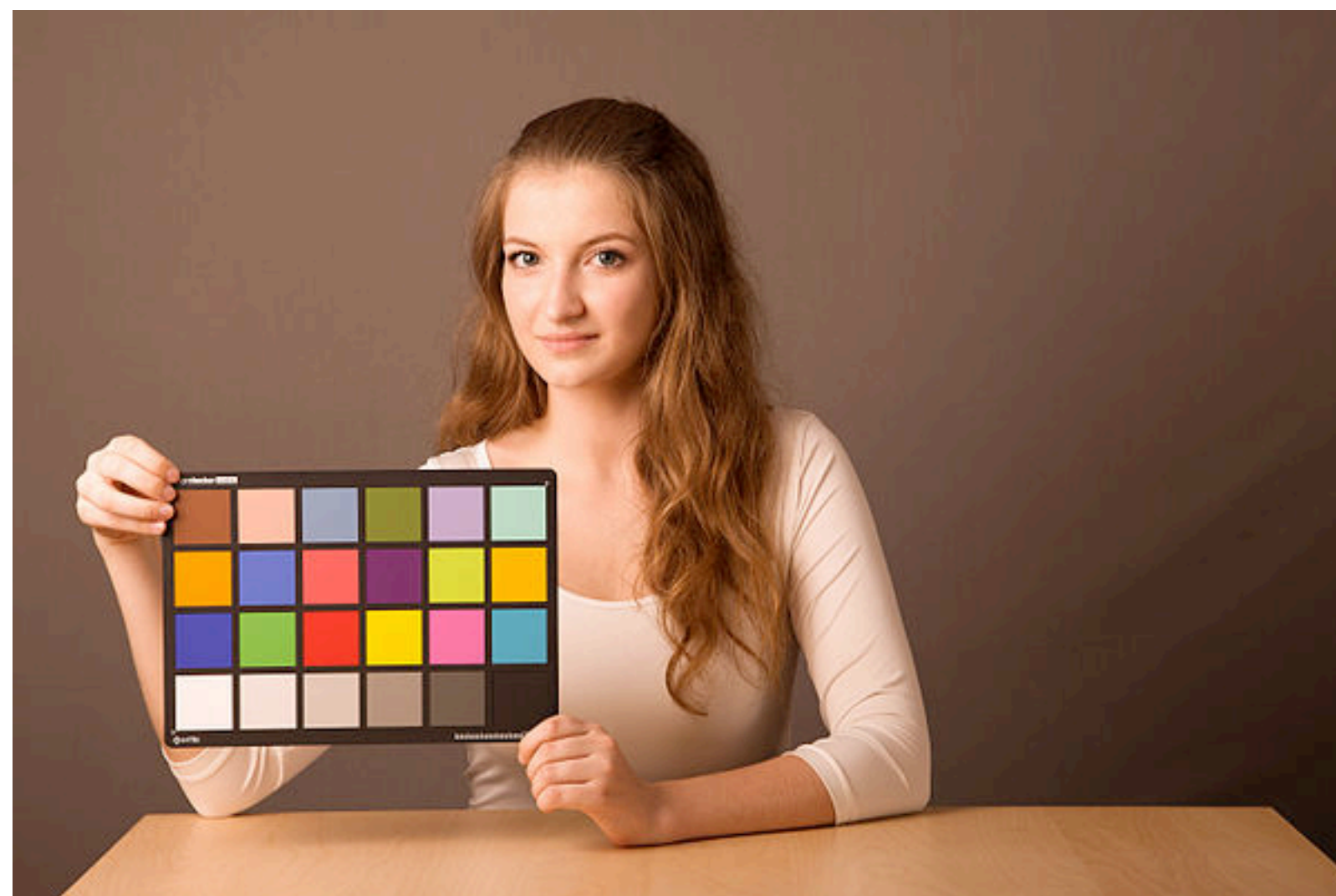
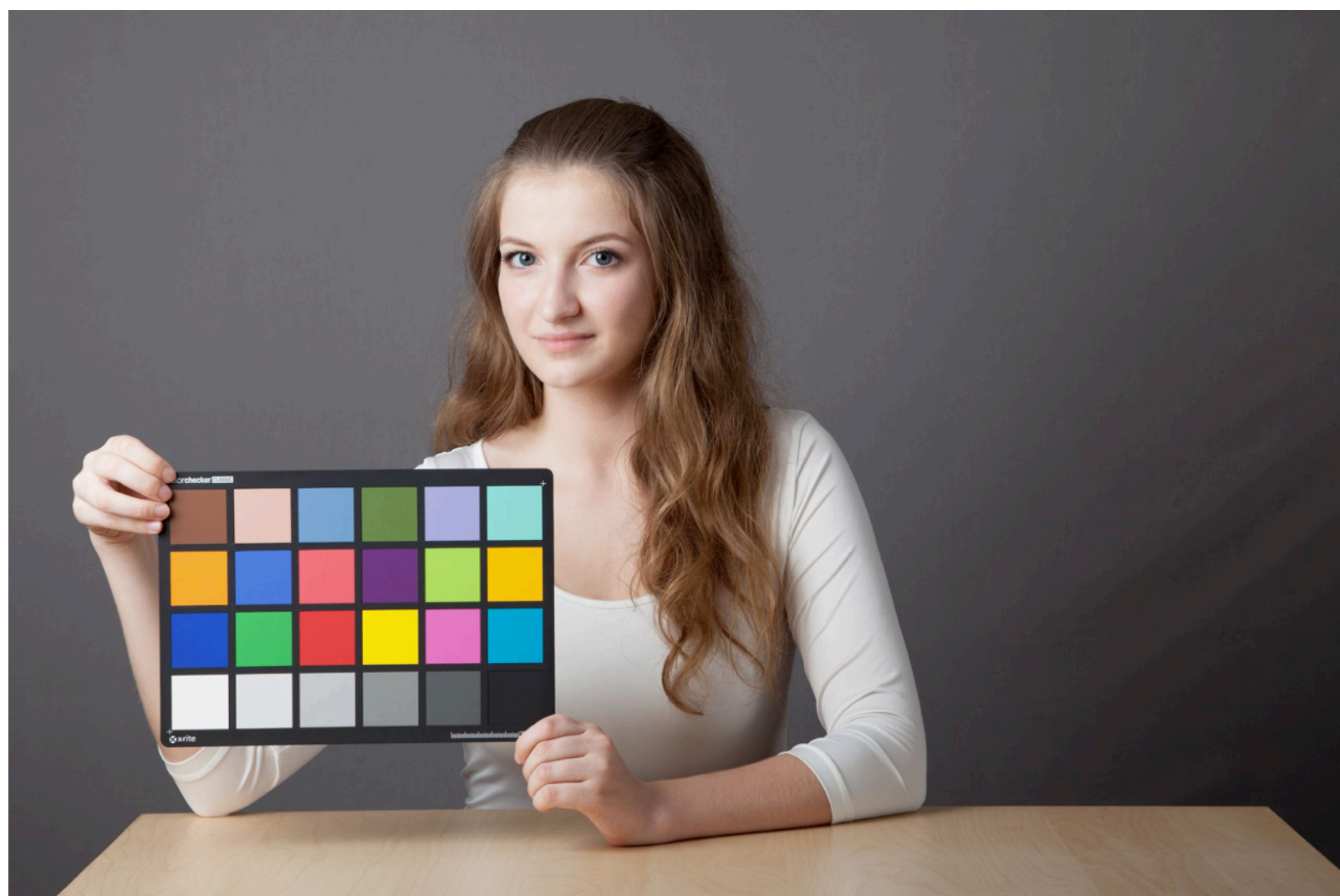
Source: F. Durand

Light sources



https://en.wikipedia.org/wiki/Color_temperature

Same scene under different illuminations



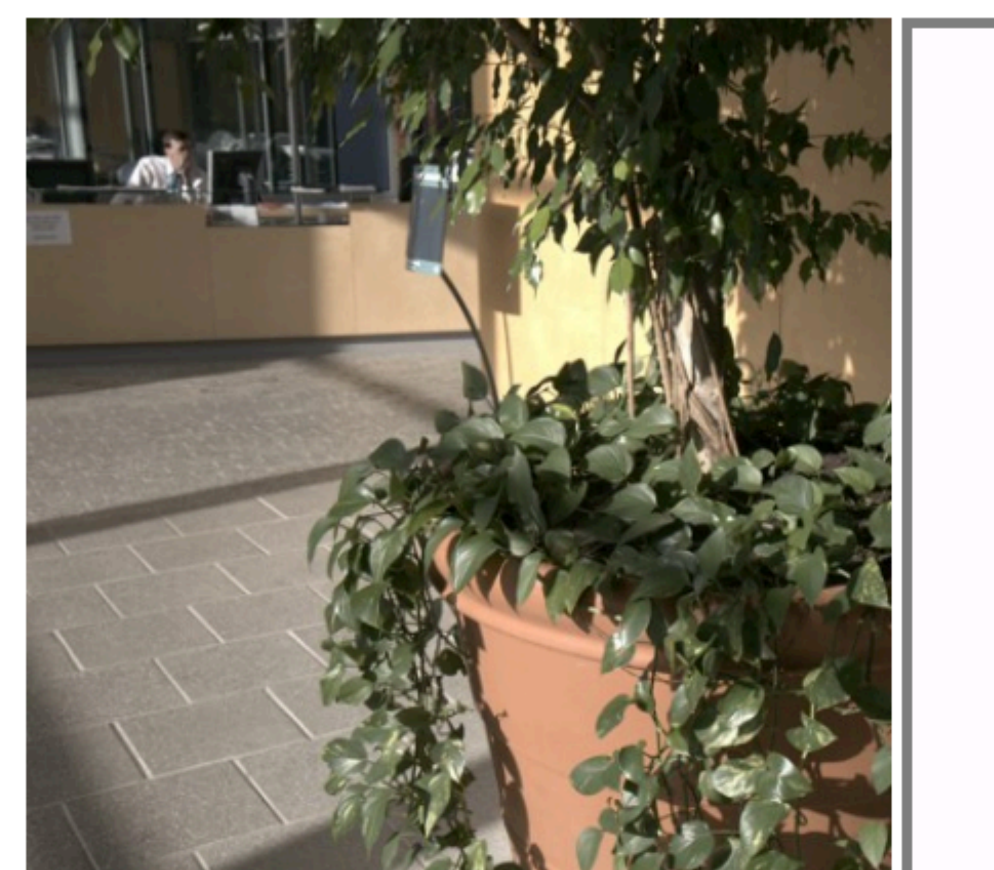
https://en.wikipedia.org/wiki/Color_balance

White balancing

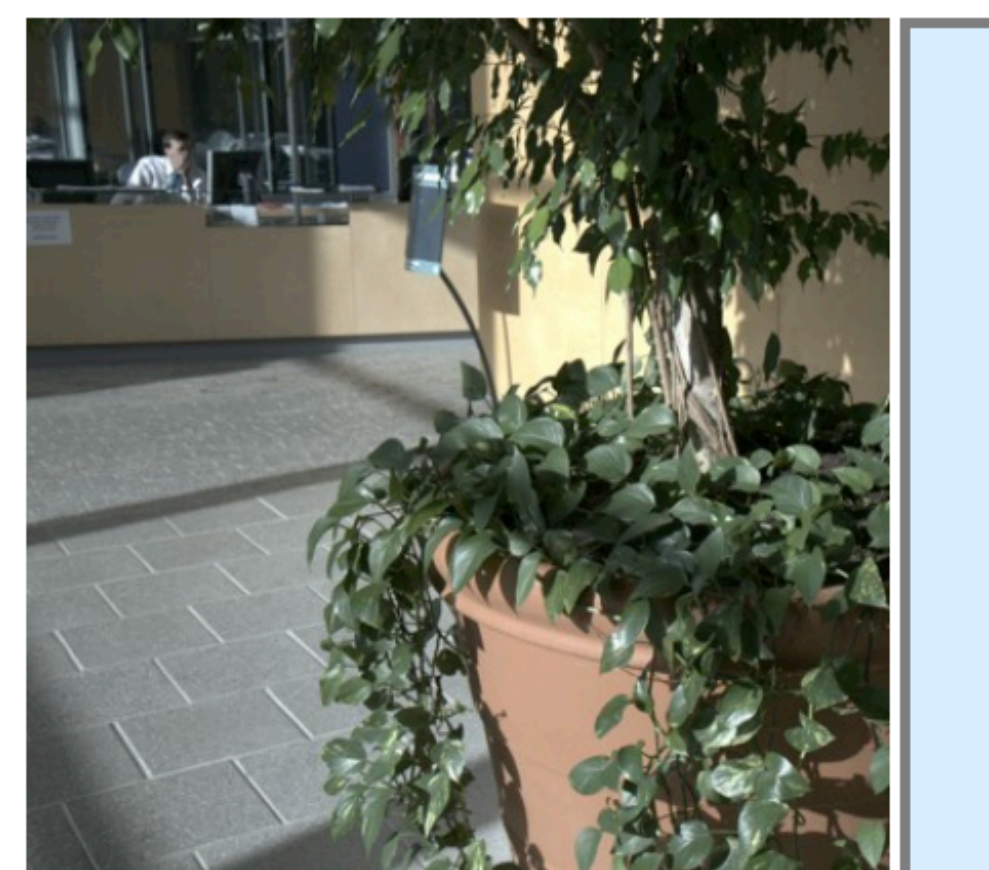


Is this a green light and a white object, or a green object⁶⁵ and a white light?

White balancing



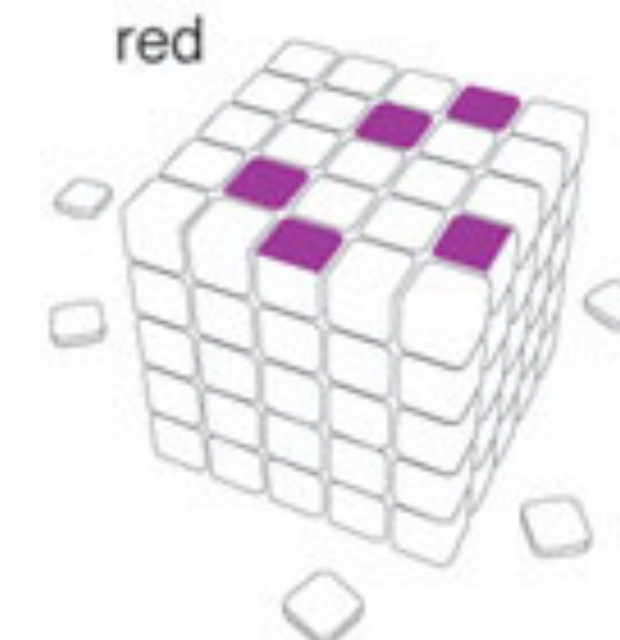
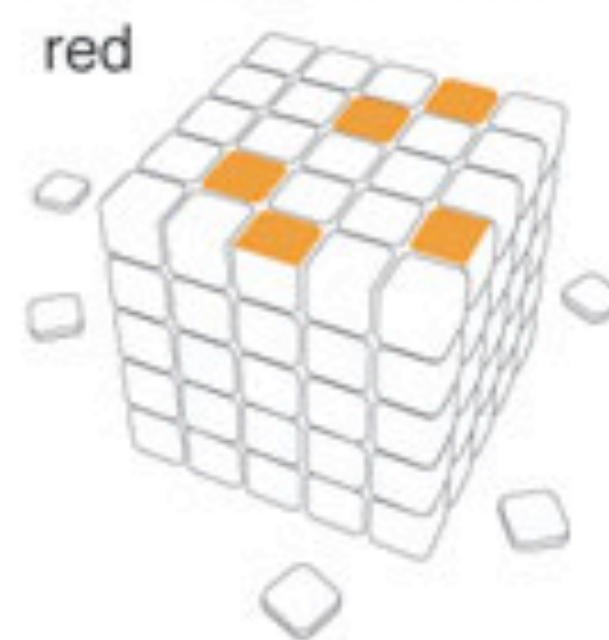
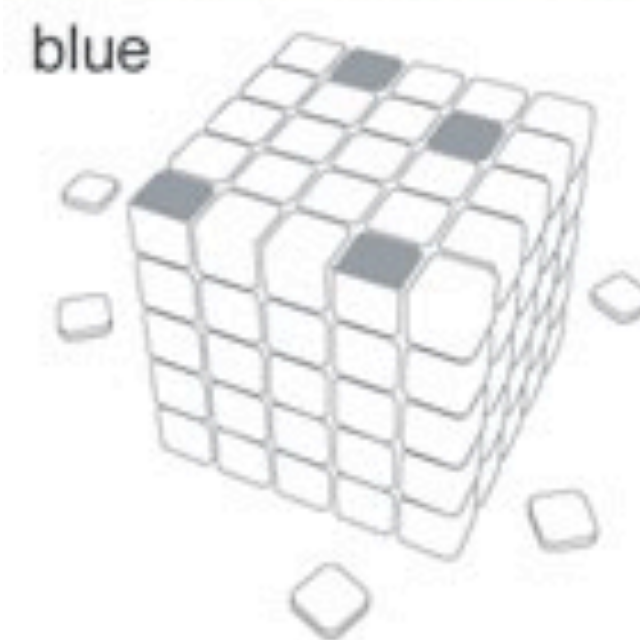
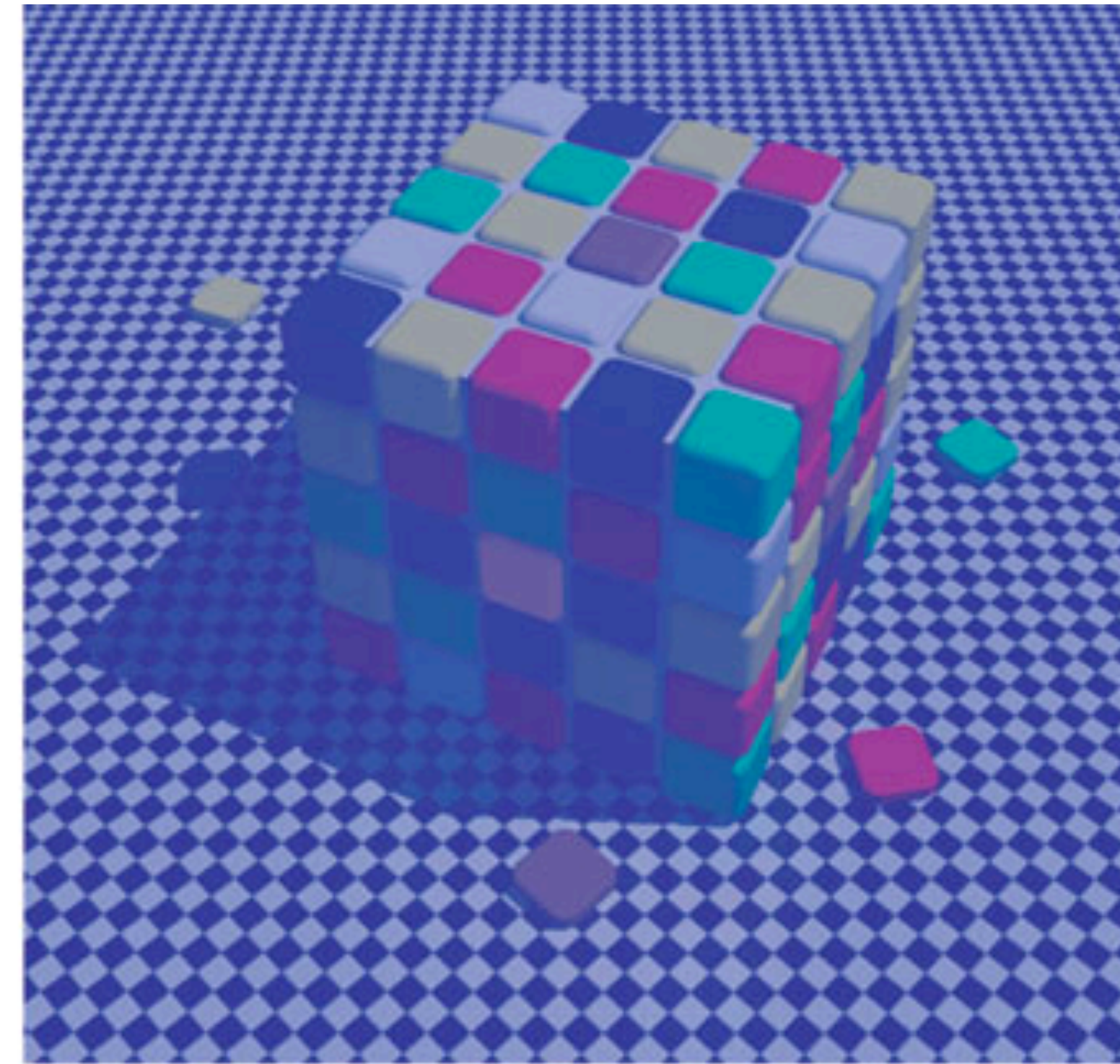
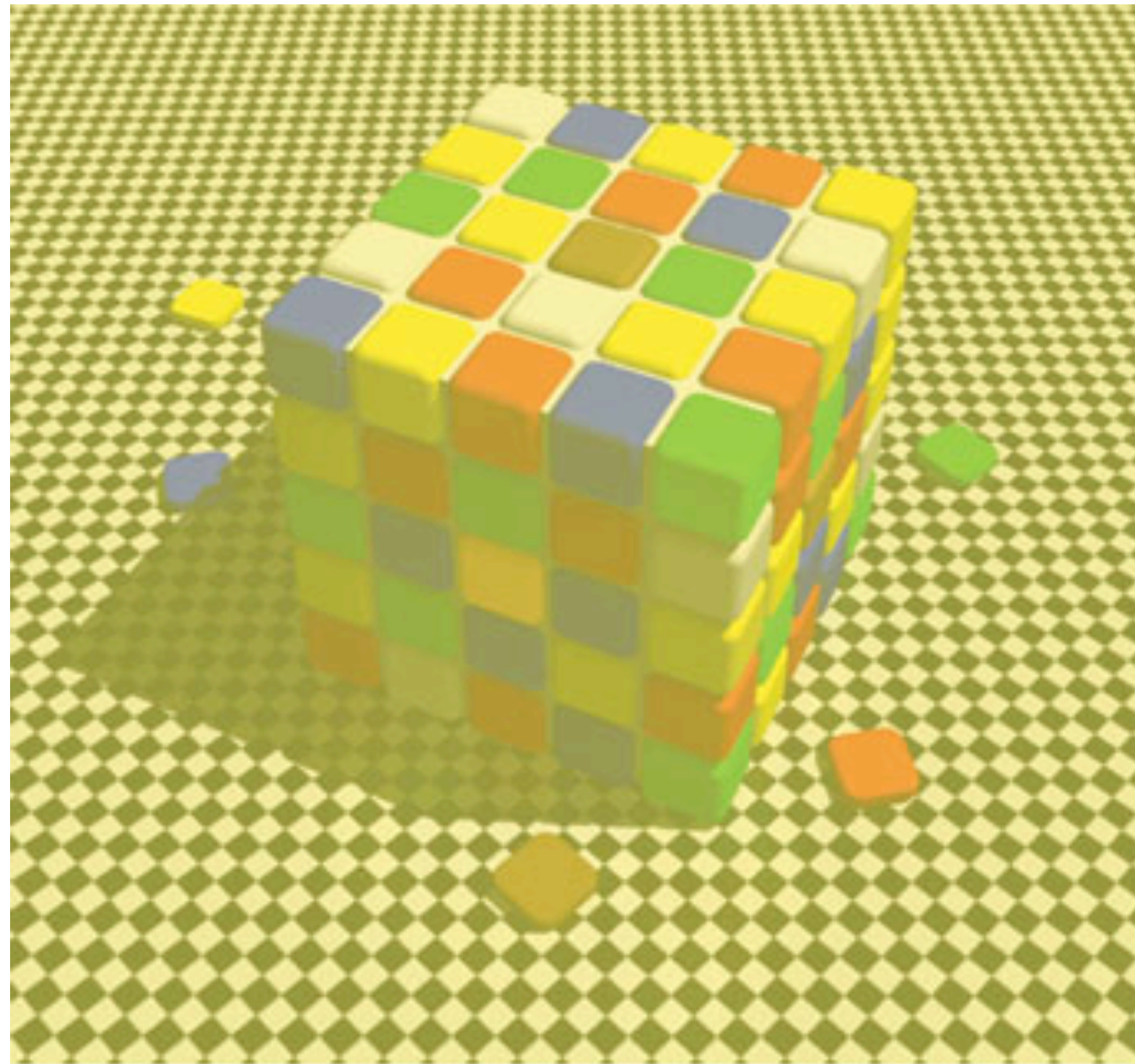
our \hat{W} , \hat{L} , err = 0.13°



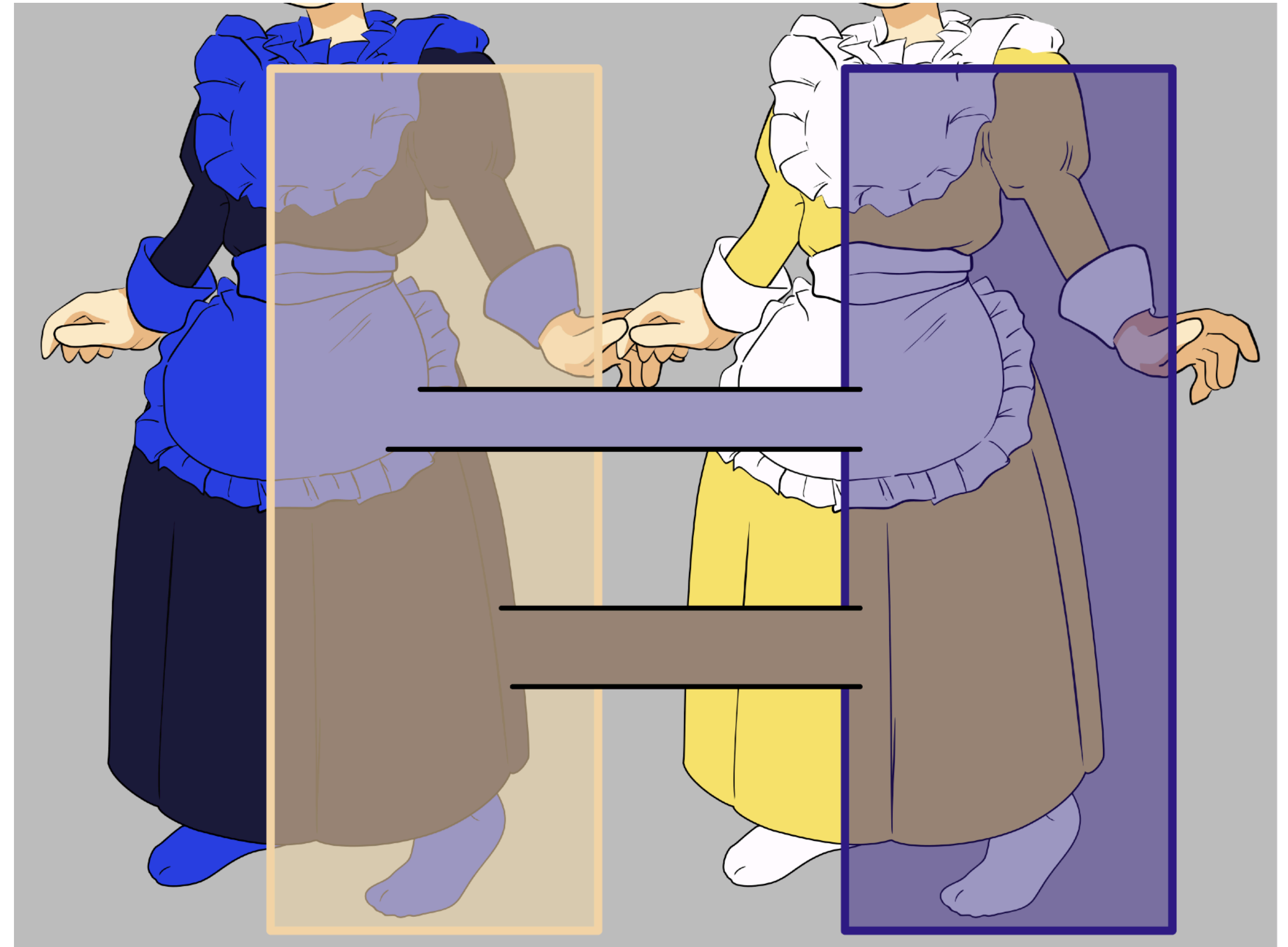
baseline \hat{W} , \hat{L} , err = 5.34°

[Barron, "Convolutional Color Constancy", 2015]

Color constancy



The dress



Two interpretations
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