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?

Paint

3D orientation
The Workshop Metaphor

(a) an image

Figure source: J. Barron

The Workshop Metaphor

(a) an image

(b) a likely explanation

The Workshop Metaphor

(a) an image

(b) a likely explanation

(c) painter’s explanation

Figure source: J. Barron

The Workshop Metaphor

(a) an image  (b) a likely explanation

(c) painter’s explanation  (d) sculptor’s explanation

The Workshop Metaphor

(a) an image  (b) a likely explanation

(c) painter’s explanation  (d) sculptor’s explanation  (e) gaffer’s explanation

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

https://marmoset.co/posts/physically-based-rendering-and-you-can-too/

Source: W. Freeman
For now, ignore specular reflection
And refraction…

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

Source: S. Lazebnik and K. Bala
Directional lighting

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

Source: N. Snavely
Diffuse reflection

\[ R_e = k_d N \cdot LR_i \]

\[ I = k_d N \cdot L \]

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]

Source: N. Snavely
Other BRDFs

Ideal diffuse (Lambertian)

Ideal specular

Directional diffuse

from Steve Marschner
Non-smooth-surfaced materials

from Steve Marschner
Shape from shading

\[ I = k_d N \cdot L \]

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.

Source: N. Snavely
An ambiguity that artists exploit!

Contours provide extra shape information

Consider points on the *occluding contour*:

\[ N_z = 0 \]

\[ N_z \text{ positive} \]

\[ N_z \text{ negative} \]


Source: S. Lazebnik
Application: finding the direction of the light source

\[ I(x,y) = N(x,y) \cdot S(x,y) \]

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


Source: S. Lazebnik
Application: detecting image splices

Fake photo

Real photo

[Johnson and Farid, 2005]

Source: S. Lazebnik
Photometric stereo

Source: N. Snavely
Photometric stereo

Can write this as a linear system, and solve:

\[
\begin{bmatrix}
I_1 \\
I_2 \\
I_3
\end{bmatrix} = k_d \begin{bmatrix}
L_1^T \\
L_2^T \\
L_3^T
\end{bmatrix} N
\]

Source: N. Snavely
Photometric Stereo

Input

Recovered albedo

Recovered normal field

Recovered surface model

Source: Forsyth & Ponce, S. Lazebnik
Photometric Stereo

- Input (1 of 12)
- Normals (RGB colormap)
- Normals (vectors)
- Shaded 3D rendering
- Textured 3D rendering

Source: N. Snavely
Video photometric stereo

Video Normals from Colored Lights
Gabriel J. Brostow, Carlos Hernández, George Vogiatzis, Björn Stenger, Roberto Cipolla

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.
But what if we don’t know the BRDF?

[Johnson and Adelson, 2009]
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**

\[ I = R + S(Z, L) \]

- **Z** (shape/depth)
- **S(Z, L)** (log-shading image of Z and L)
- **L** (illumination)
- **R** (log-reflectance)

Source: J. Barron [Barrow and Tenenbaum 1978]
Intrinsic image decomposition

Far
Near

$Z$
shape / depth

$S(Z, L)$
log-shading image of $Z$ and $L$

$L$
illumination

$R$
log-reflectance

$I = R + S(Z, L)$
Lambertian reflectance

Source: J. Barron

[Barrow and Tenenbaum 1978]
Retinex: keep only large magnitude edges

Input

Estimated reflectance

[Land & McCann 1978], figure from [Grosse et al. 2019]
CNN-based reflectance estimation

[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

- **Red**
- **Green**
- **Blue**
- **Cyan**
- **Magenta**
- **Yellow**

Source: W. Freeman
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

Source: A. Efros
Distribution of Rods and Cones

Source: A. Efros
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.

Source: W. Freeman
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

Subspace of sensor responses

Spectral sensitivities of L, M, and S cones

Source: W. Freeman
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

Source: W. Freeman
Color matching experiment

Source: W. Freeman
Color matching experiment

Source: W. Freeman
Color matching experiment

The primary color amounts needed for a match

Source: W. Freeman
"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 $\tilde{\bar{v}}_{10}(\lambda)$, $\tilde{\bar{g}}_{10}(\lambda)$, and $\tilde{\bar{b}}_{10}(\lambda)$.

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

Source: W. Freeman
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 \( x(\lambda) \), \( y(\lambda) \), and \( z(\lambda) \). 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.
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!

Source: F. Durand
Light sources

https://en.wikipedia.org/wiki/Color_temperature
Same scene under different illuminations

White balancing

Is this a green light and a white object, or a green object and a white light?
White balancing

\[ I = W \times L \]

our \( \hat{W}, \hat{L}, \text{err} = 0.13^\circ \)

baseline \( \hat{W}, \hat{L}, \text{err} = 5.34^\circ \)

[Barron, "Convolutional Color Constancy", 2015]
Color constancy

Dale Purves, R. Beau Lotto, Surajit Nundy, "Why We See What We Do."
The dress

Two interpretations
