Administrivia

- HW 3
  - I am planning to grade it on the weekend.
- Quiz one on Monday.
  - One piece of paper, both sides, allowed.
  - Details from this week excluded
    - But note that much of what we talked about on Monday was review
  - My quizzes tend to be conception and/or apply what you know
  - You need to be sure that you know
    - Spectra and sensor interaction
    - Camera geometry
    - Lambertian reflectance
    - Solving vision like problems by optimization
      - Homogenous least squares
      - Non-homogenous least squares

Naive Color Model (2)

Naive value for the color of the surface under a **different** light, (R_L, G_L, B_L) is given by:

$$(R,G,B) = (\rho_R R_L, \rho_G G_L, \rho_B B_L)$$

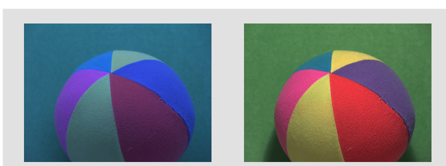
This is naïve because we assume that the part of the light that stimulates one channel, does **not** interact with the albedo of any other channel.

Alternatively, everything about the surface color can be captured in the three albedo numbers.

This is the "diagonal model" for illumination change.

Diagonal Model for Color

Light color (R_{L1}, G_{L1}, B_{L1})



Light color (R_{L2}, G_{L2}, B_{L2})

The albedos at a pixel are the same, so under the naive color model

$R_1 = \rho_R * R_{L1}$ (and similarly for green and blue)

so, consistent with our motivating definition, $\rho_R = \dfrac{R_1}{R_{L1}}$

and $R_2 = \rho_R * R_{L2} = \dfrac{R_1}{R_{L1}} * R_{L2} = R_1 * \left(\dfrac{R_{L2}}{R_{L1}}\right)$

Diagonal Model for Color

(Same scene, but different illuminant)

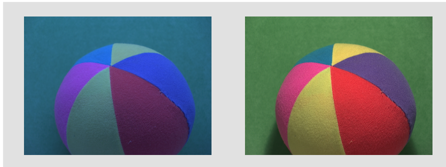
Light color (R_{L1}, G_{L1}, B_{L1})

Light color (R_{L2}, G_{L2}, B_{L2})

Diagonal model assumes that all the (R,G,B) in the left image change by the ratio of the lights

$$R_2 = \frac{R_{L2}}{R_{L1}} * R_1 \qquad G_2 = \frac{G_{L2}}{G_{L1}} * G_1 \qquad B_2 = \frac{B_{L2}}{B_{L1}} * B_1$$

Light color (R_{L1}, G_{L1}, B_{L1})



Light color (R_{L2}, G_{L2}, B_{L2})

Diagonal model assumes that all the (R,G,B) in the left image change by the ratio of the lights

$$R_2 = \frac{R_{L2}}{R_{L1}} * R_1 \qquad G_2 = \frac{G_{L2}}{G_{L1}} * G_1 \qquad B_2 = \frac{B_{L2}}{B_{L1}} * B_1$$

One way to understand the above equations

Estimates of the albedos for each channel

- In matrix form

$$\begin{pmatrix} R_2 \\ G_2 \\ B_2 \end{pmatrix} = \begin{vmatrix} \frac{R_{L2}}{R_{L1}} & & \\ & \frac{G_{L2}}{G_{L1}} & \\ & & \frac{B_{L2}}{B_{L1}} \end{vmatrix} \begin{pmatrix} R_1 \\ G_1 \\ B_1 \end{pmatrix}$$

(albedo estimate for R)

- Note that this says $\frac{R_2}{R_{L2}} = \frac{R_1}{R_{L1}}$ (etc, for G, B)

- The key point is that under the naive model you would get the same estimate of albedo

Diagonal Model for Color

- Note that this says $\frac{R_2}{R_{L2}} = \frac{R_1}{R_{L1}}$ (etc, for G, B)

- This would mean $\frac{\int E_2(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda}{\int E_2(\lambda)R^{(k)}(\lambda)d\lambda} = \frac{\int E_1(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda}{\int E_1(\lambda)R^{(k)}(\lambda)d\lambda}$!

- Or equivalently $\frac{\int E_2(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda}{\int E_1(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda} = \frac{\int E_2(\lambda)R^{(k)}(\lambda)d\lambda}{\int E_1(\lambda)R^{(k)}(\lambda)d\lambda}$! !

- But this is not generally true!

Diagonal Model for Color

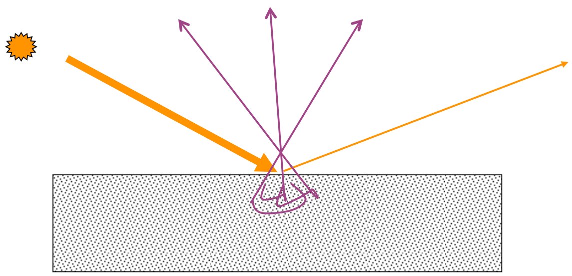
In general, $\frac{\int E_2(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda}{\int E_2(\lambda)R^{(k)}(\lambda)d\lambda} \neq \frac{\int E_1(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda}{\int E_1(\lambda)R^{(k)}(\lambda)d\lambda}$

- But expression holds when
  - Surface reflectance is uniform
  - Sensors are delta functions

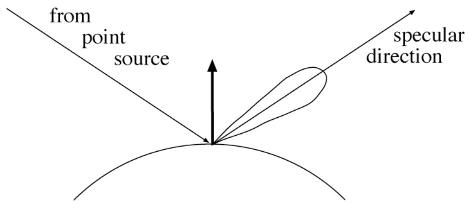
- Naïve approximation is relatively good when the camera sensors are “sharp” with minimal overlap.

Color and specularities

- Dielectric surfaces are well approximated by a specular part and a Lambertian body part.

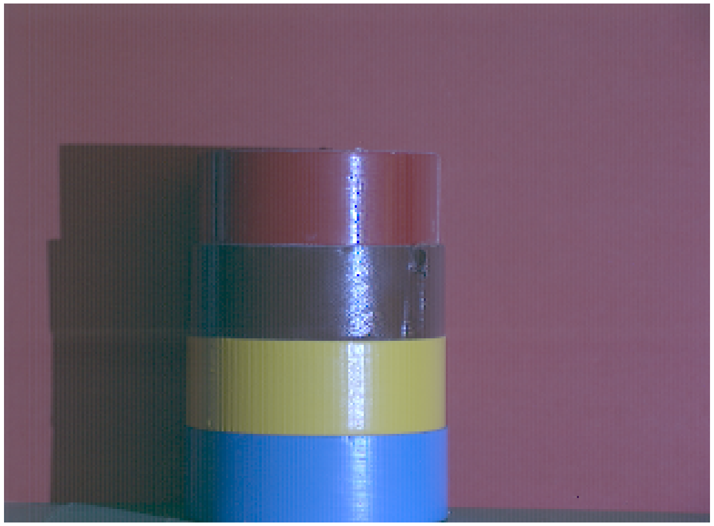


Specular surfaces

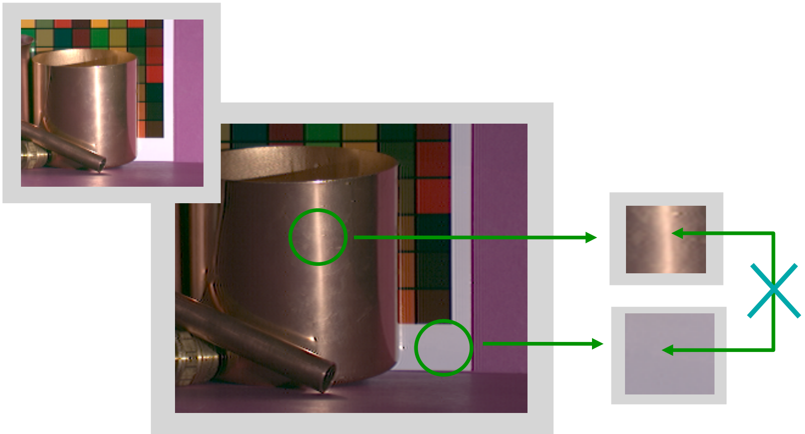


- Important point: The specular part of the reflected light usually carries the color of the **light**
- Technically, this is the case for dielectrics--plastics, paints, glass.
- Important exception is metals (e.g. gold, copper)

Dielectric Specularities

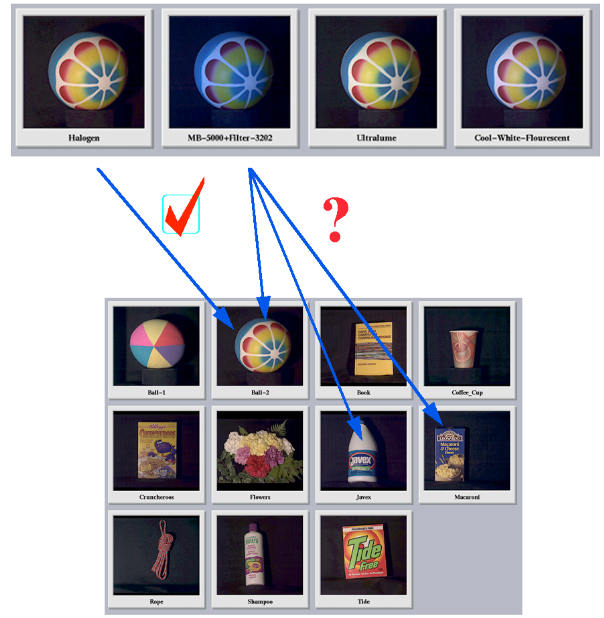


Metallic Specularities

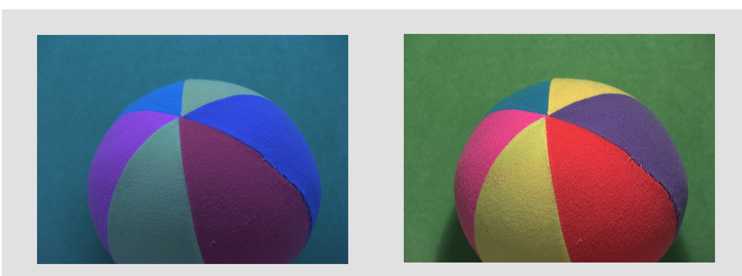


Color for recognition

- It seems natural to use color (as opposed to grays in a B&W image) to recognize things--why?
  - Color has more information than grays
  - Grays in a B&W image are subject to shading
  - Light varies greatly in intensity--less so in chromaticity
  - Chromaticity is color without magnitude. For example
    - $r=R/(R+G+B)$ and $g=G/(R+G+B)$
  - BUT the ambiguity between what part of the signal is due to light and what part is due to the world **remains**.

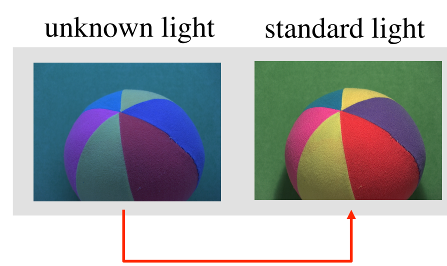


The Computational Color Constancy Problem



(Same scene, but different illuminant)

Color constancy

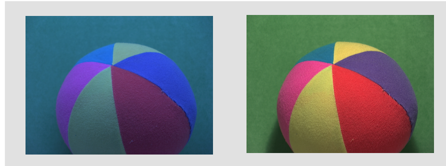


Color constancy algorithms strive to map image pixels to useful illuminant invariant values. One example is the image as if it was taken under the known standard light.

Often done by estimating the illuminant, followed by color correction (but there are other ways).

unknown light standard light

Color Correction



Suppose that the image on the right was how the scene on the left would look under a known, “standard” light.

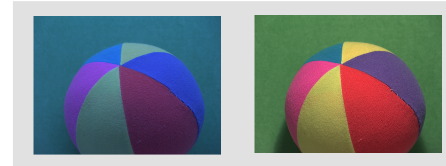
Under that light a uniform reflective surface (white) is $\left(R_W^S, G_W^S, B_W^S\right)$

So, to correct the image on the left, we can estimate the color of white, under the unknown light. Suppose it is: $\left(R_W^U, G_W^U, B_W^U\right)$

Then we can correct the image using the diagonal matrix from a few slides back.

unknown light standard light

Estimating the color of the light



The hard part is to estimate the color of the light (i.e., $\left(R_W^U, G_W^U, B_W^U\right)$)

Many interesting algorithms have been developed. Two simple ones:

Max RGB: $R_W^U = \max_{pix}(R)$ (Similarly for G and B)

Gray world: $\left(\frac{1}{2}\right) R_W^U = \underset{pix}{ave}(R)$ (Similarly for G and B)