Light and Color



Computer Vision Jia-Bin Huang, Virginia Tech

Administrative stuffs

- Signed up <u>Piazza discussion board</u>?
- Sample final project ideas posted
- Installed MATLAB?
 - Akrit (TA) will hold a tutorial session next Friday
- Reviewed Linear Algebra?
- Questions about the course logistics?

Search for Teammates!

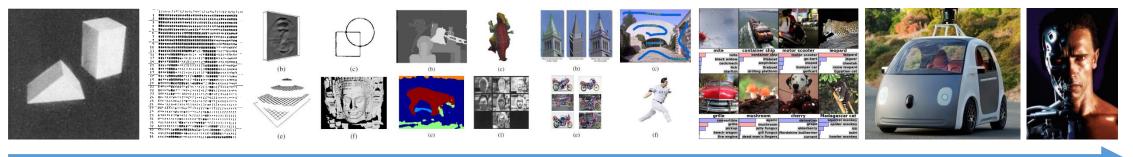
add new post:

- \mathcal{R} \odot I'm one student looking for more people to work with.
- l'm from a group looking for more students.

*Name	Jia-Bin Huang	*Email jbhuang@vt.edu						
*About Me	Introduce yourself. What kind of teammate(s) are you looking for?							
	(Things you could include: your location, grad/undergrad, when you're available help people get to know you!)							

Previous class: Introduction

• Overview of computer vision



• Examples of computer vision applications

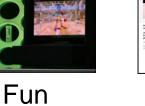




Security



Comfort



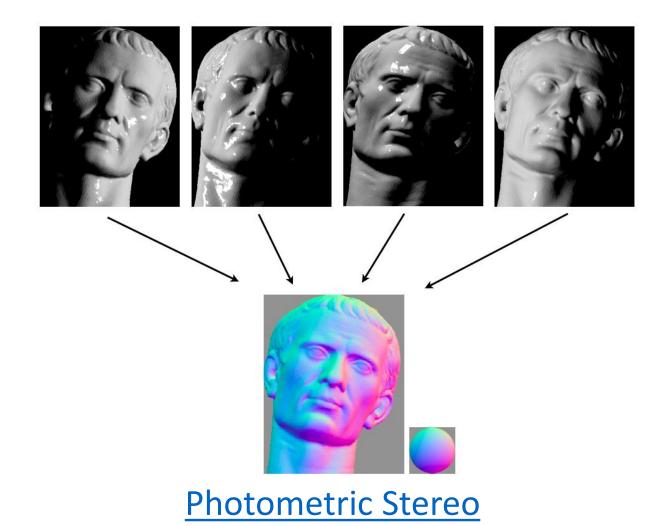
Access

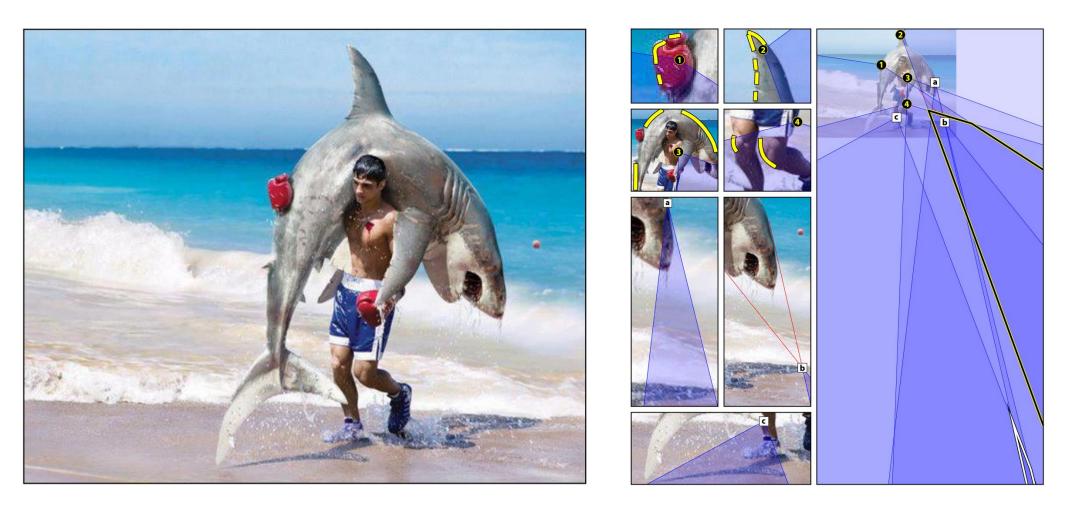
Today's class

• What determines pixels' brightness?

• What determines pixels' **color**?

• What can we infer about the scene from pixel intensities?



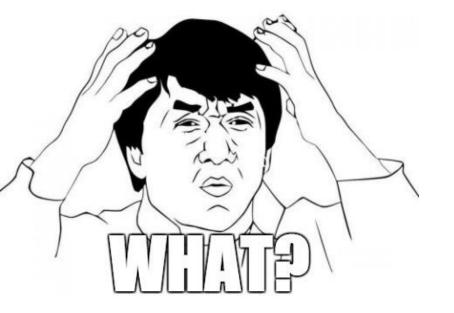


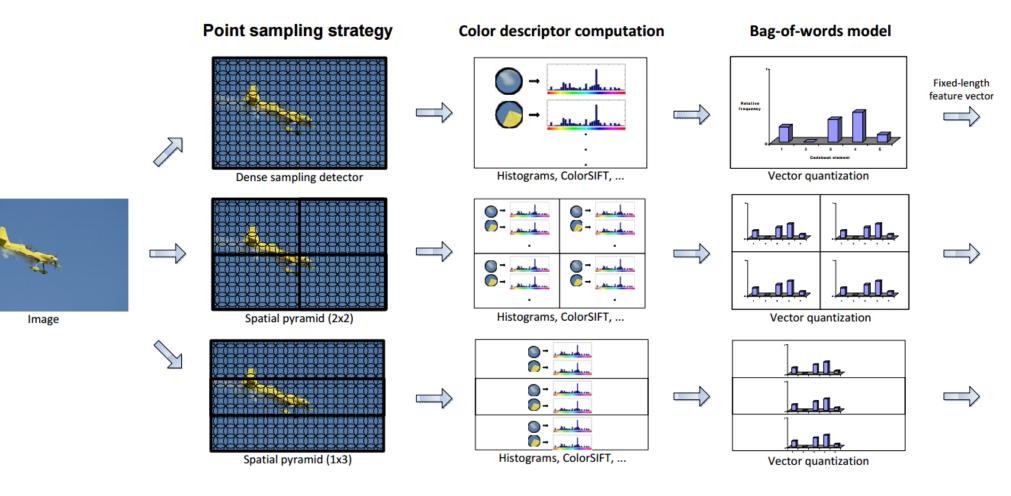
Exposing Photo Manipulation from Shading and Shadows [Kee et al. TOG 14]

White and gold?

Or

Black and blue?





Object and scene categorization [Sande et al. PAMI 2010]

What determines pixels' brightness?

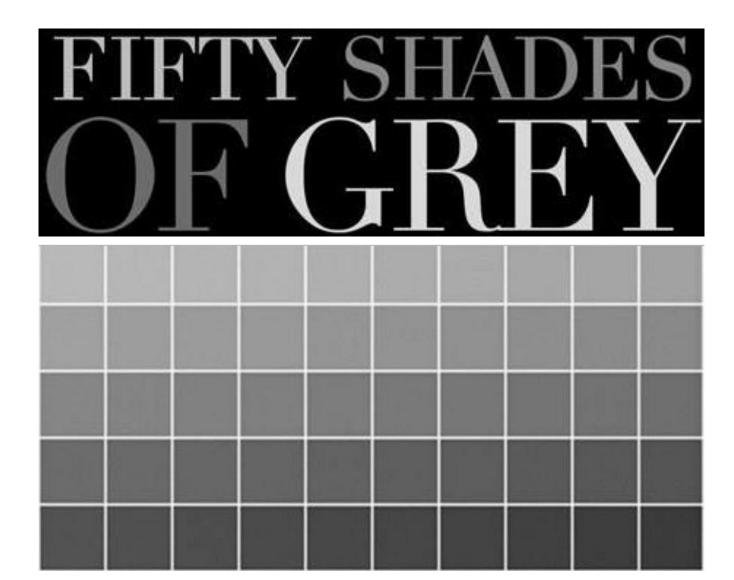
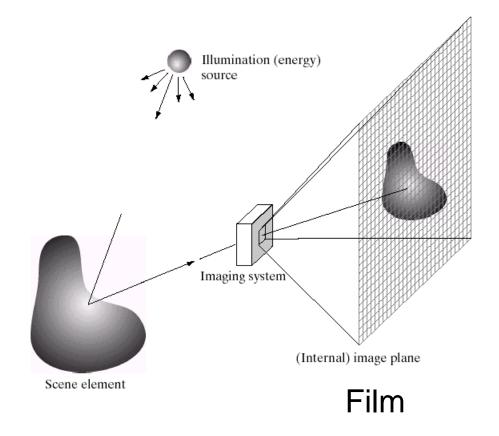
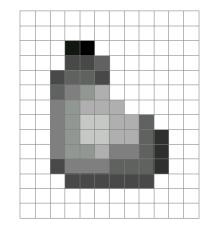
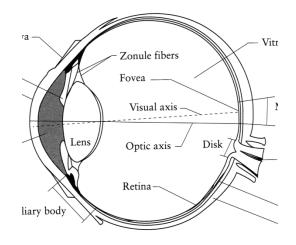


Image Formation



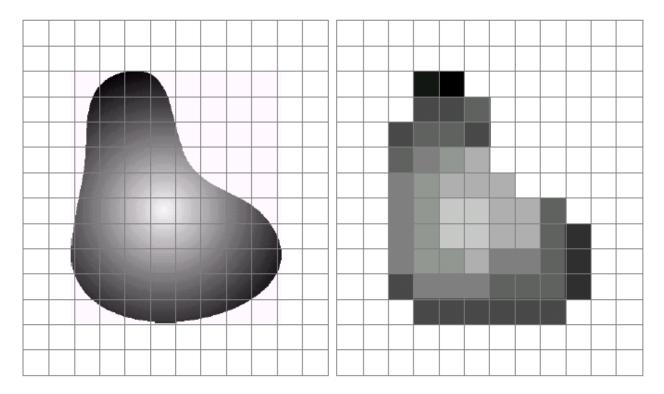


Digital Camera



The Eye

Sensor Array

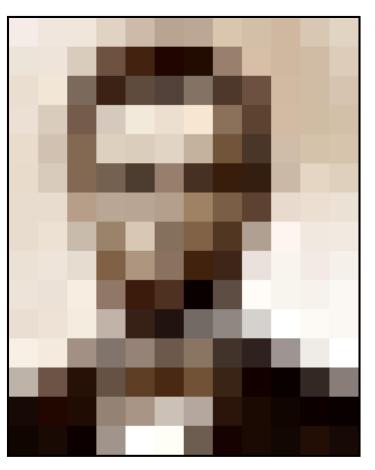


CMOS sensor

a b

FIGURE 2.17 (a) Continuos image projected onto a sensor array. (b) Result of image sampling and quantization.

What humans see

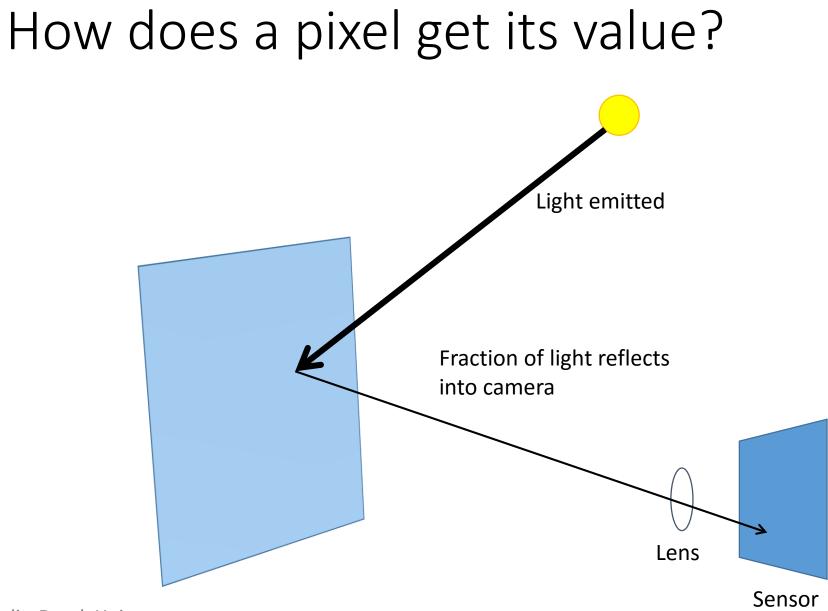


Slide credit: Larry Zitnick

What computers see

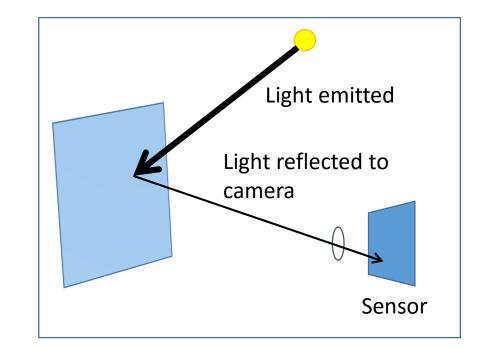
243	239	240	225	206	185	188	218	211	206	216	225
242	239	218	110	67	31	34	152	213	206	208	221
243	242	123	58	94	82	132	77	108	208	208	215
235	217	115	212	243	236	247	139	91	209	208	211
233	208	131	222	219	226	196	114	74	208	213	214
232	217	131	116	77	150	69	56		201	228	223
232	232	182	186	184	179	159	123	93	232	235	235
232	236	201	154	216	133	129	81	175	252	241	240
235	238	230	128	172	138	65	63	234	249	241	245
237	236	247	143	59	78		94	255	248	247	251
234	237	245	193			115	144	213	255	253	251
248	245	161	128	149	109	138	65	47	156	239	255
190	107	39	102	94	73	114			7	51	137
23			148	168	203	179					8
			160	255	255	109					

Slide credit: Larry Zitnick



How does a pixel get its value?

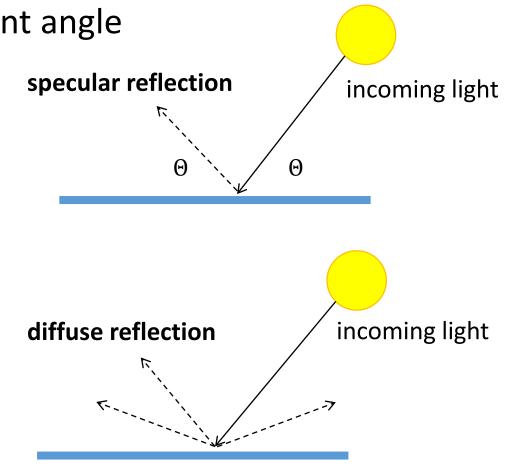
- Major factors
 - Illumination strength and direction
 - Surface geometry
 - Surface material
 - Nearby surfaces
 - Camera gain/exposure



Basic models of reflection

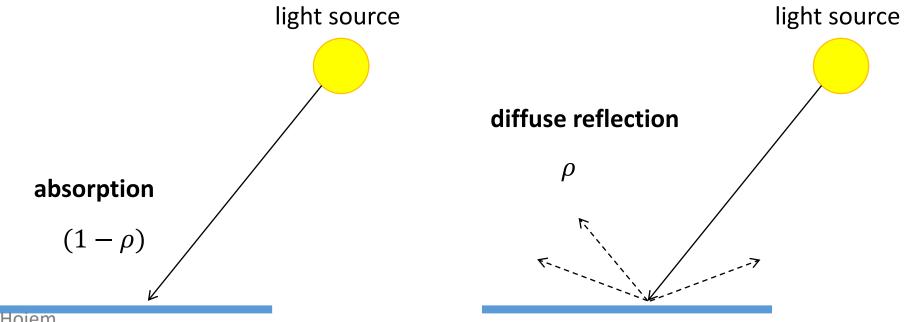
- Specular: light bounces off at the incident angle
 - E.g., mirror

- Diffuse: light scatters in all directions
 - E.g., brick, cloth, rough wood



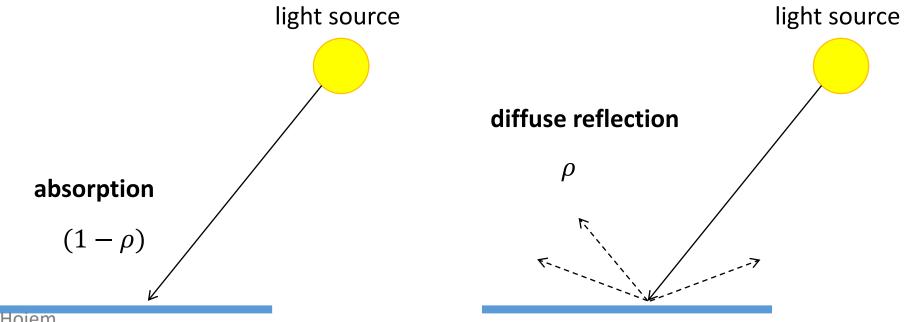
Lambertian reflectance model

- Some light is absorbed (function of albedo ρ)
- Remaining light is scattered (diffuse reflection)
- Examples: soft cloth, concrete, matte paints



Lambertian reflectance model

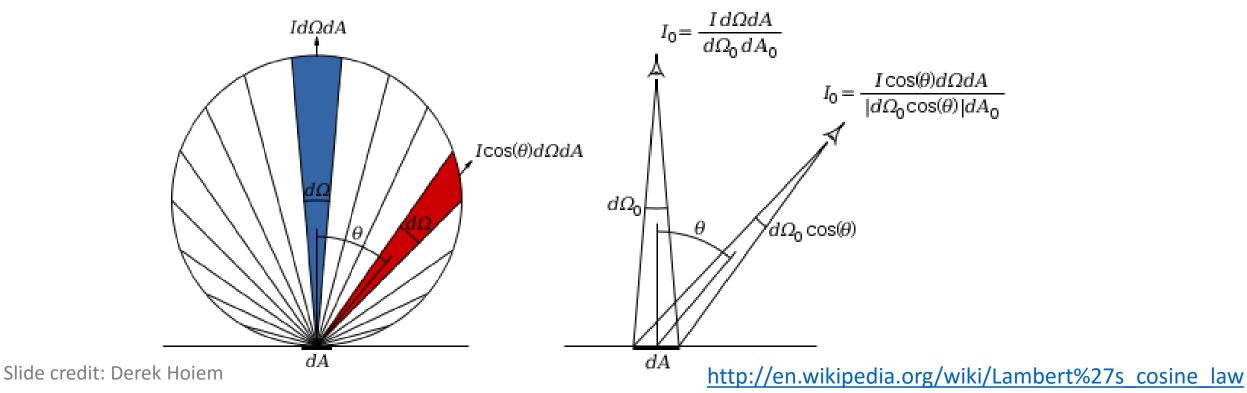
- Some light is absorbed (function of albedo ρ)
- Remaining light is scattered (diffuse reflection)
- Examples: soft cloth, concrete, matte paints



Diffuse reflection: Lambert's cosine law

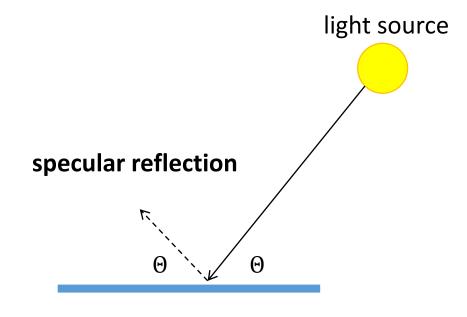
Intensity does *not* depend on viewer angle.

- Amount of reflected light proportional to $\cos(\theta)$
- Visible solid angle also proportional to $\cos(\theta)$



Specular Reflection

- Reflected direction depends on light orientation and surface normal
 - E.g., mirrors are fully specular
 - Most surfaces can be modeled with a mixture of diffuse and specular components





Flickr, by suzysputnik

Flickr, by piratejohnny

Most surfaces have both specular and diffuse components

 Specularity = spot where specular reflection dominates (typically reflects light source)





Typically, specular component is small

Slide credit: Derek Hoiem

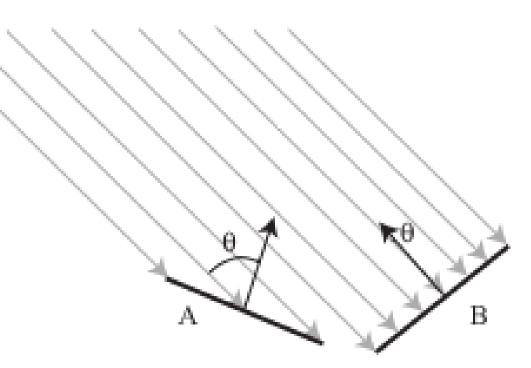
Photo: northcountryhardwoodfloors.com

Intensity and Surface Orientation

Intensity depends on illumination angle because less light comes in at oblique angles.

- $\rho=\mbox{Albedo:}$ fraction of light that is reflected
- S = directional source
- N = surface normal
- I = reflected intensity

$$I(x) = \rho(x)(\boldsymbol{S} \cdot \boldsymbol{N}(x))$$

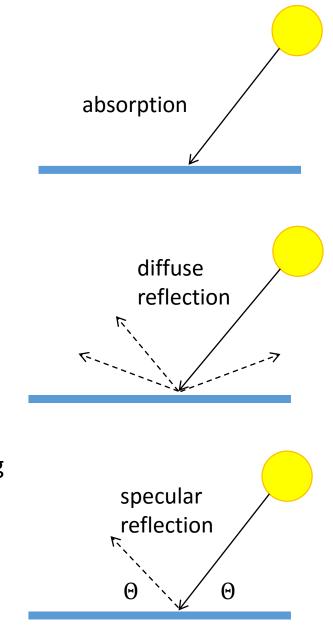


Slide credit: Forsyth

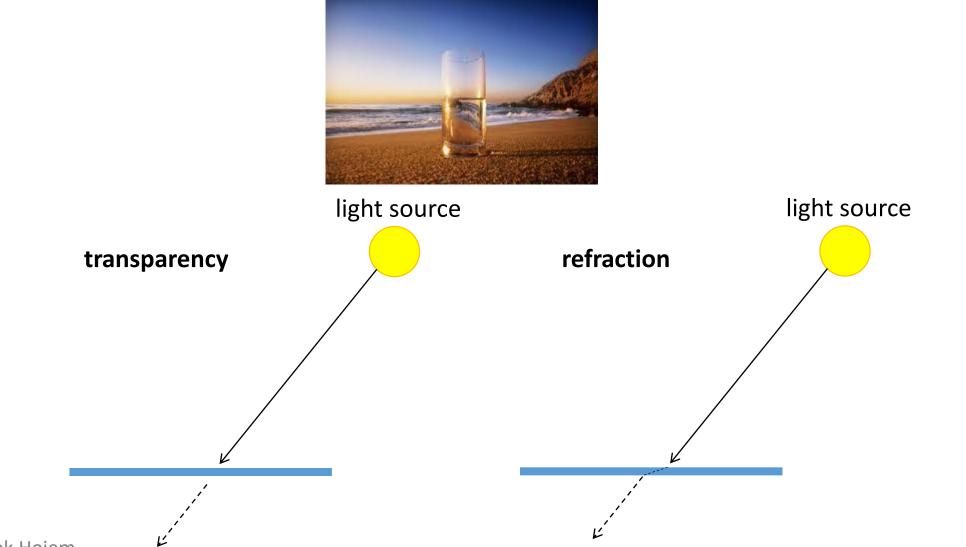


Recap

- When light hits a typical surface
 - Some light is absorbed (1-ho)
 - More absorbed for low albedos
 - Some light is reflected diffusely
 - Independent of viewing direction
 - Some light is reflected specularly
 - Light bounces off (like a mirror), depends on viewing direction

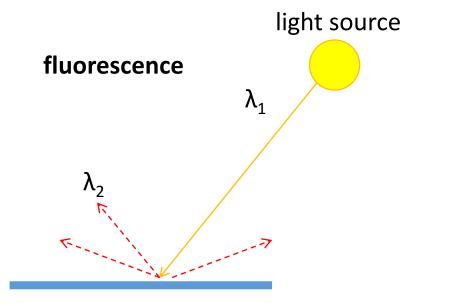


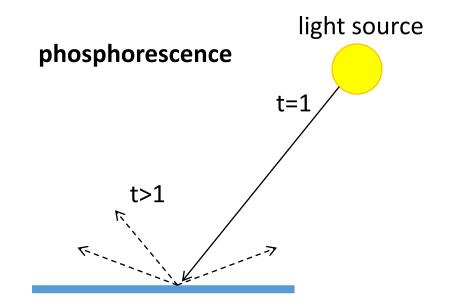
Other possible effects



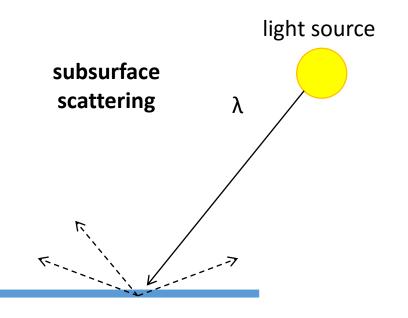






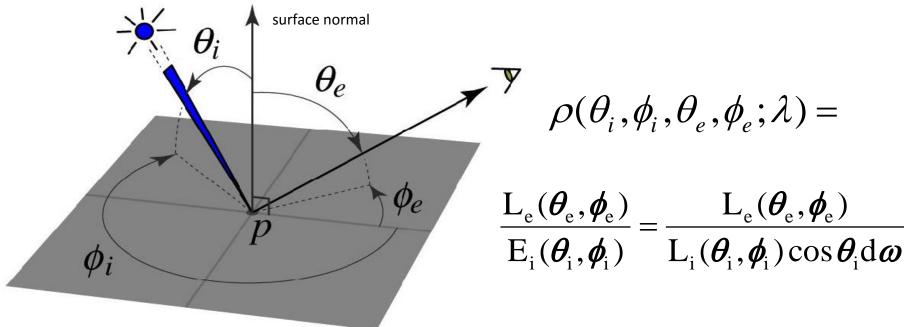






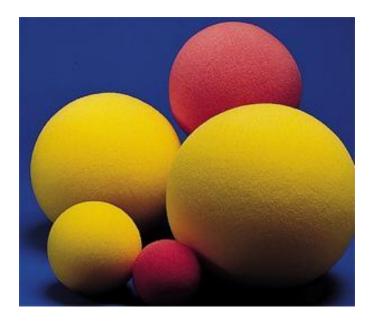
BRDF: Bidirectional Reflectance Distribution Function

• Model of local reflection that tells how bright a surface appears when viewed from one direction when light falls on it from another



Slide credit: S. Savarese

Reflection models







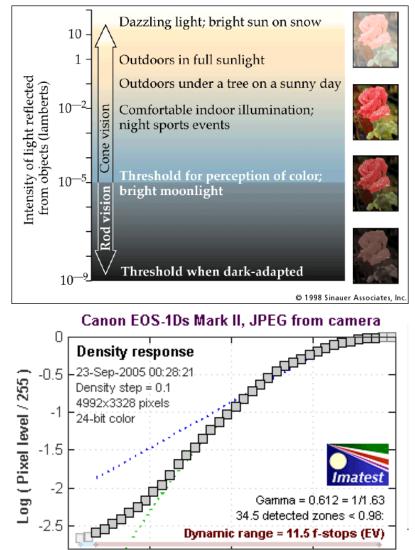
Lambertian: reflection all diffuse

Mirrored: reflection all specular

Glossy: reflection mostly diffuse, some specular

Dynamic range and camera response

- Typical scenes have a huge dynamic range
- Camera response is roughly linear in the mid range (15 to 240) but non-linear at the extremes
 - called saturation or undersaturation



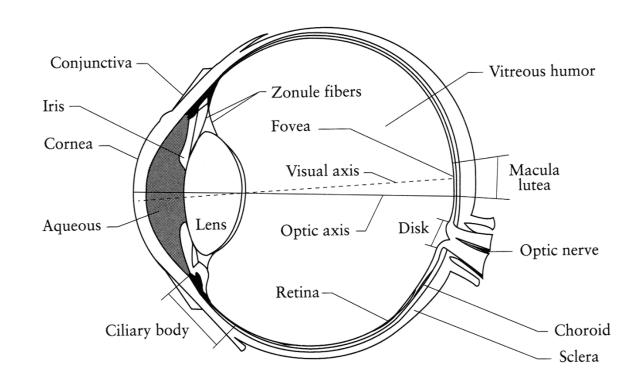
Log Exposure (-Target density)

What determines pixels' color?



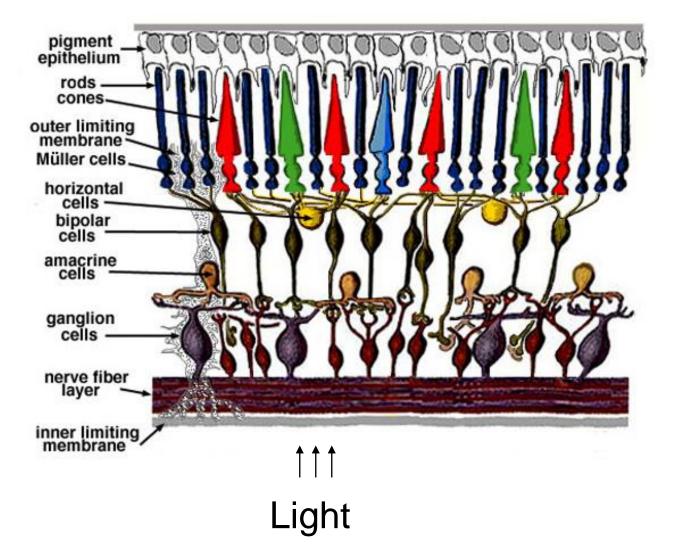
https://upload.wikimedia.org/wikipedia/commons/b/b1/Colouring_pencils.jpg

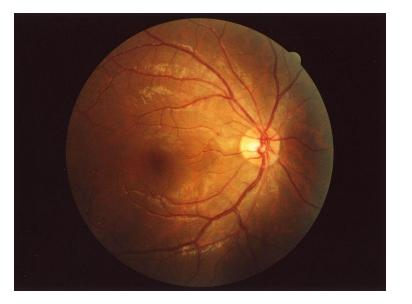
The Eye



- The human eye is a camera!
 - Iris colored annulus with radial muscles
 - **Pupil** the hole (aperture) whose size is controlled by the iris
 - What's the "film"?
 - photoreceptor cells (rods and cones) in the retina

Retina up-close





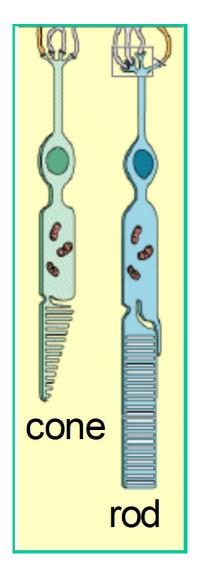
Two types of light-sensitive receptors

Cones

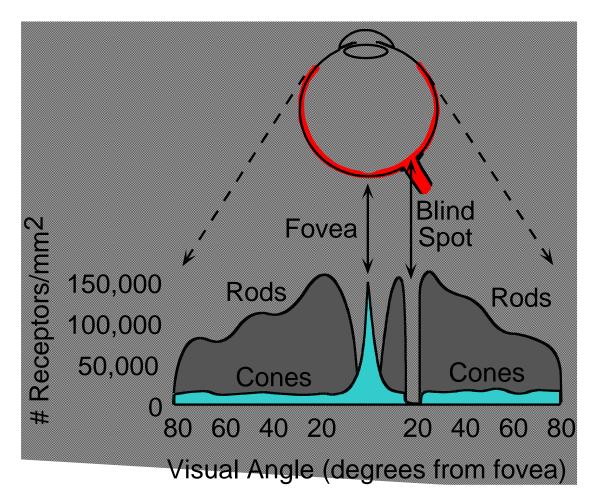
- cone-shaped
- less sensitive
- operate in high light color vision

Rods

- rod-shaped
- highly sensitive
- operate at night
- gray-scale vision
- slower to respond



Distribution of Rods and Cones



Night Sky: why are there more stars off-center?

Slide credit: Efros

Find your blind spot

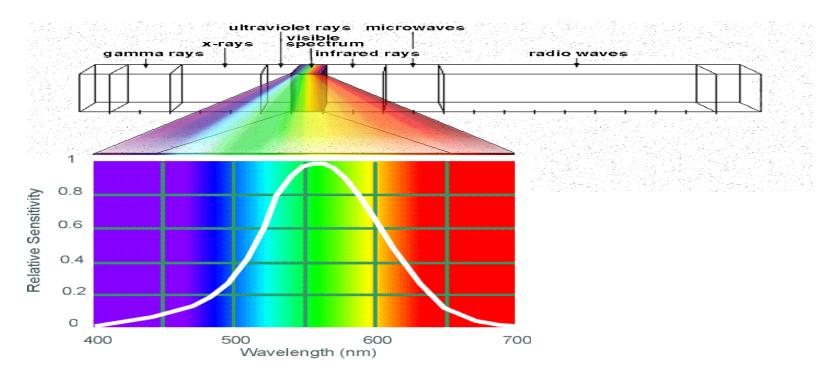


www.jolyon.co.uk



The Physics of Light

Light: Electromagnetic energy whose wavelength is between 400 nm and 700 nm. (1 nm = 10 -9 meter)

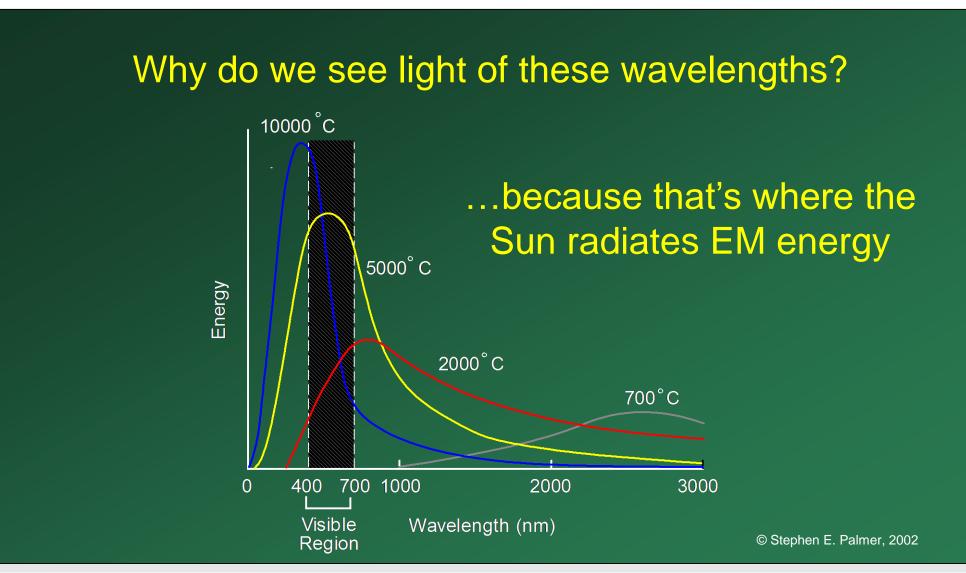


Human Luminance Sensitivity Function

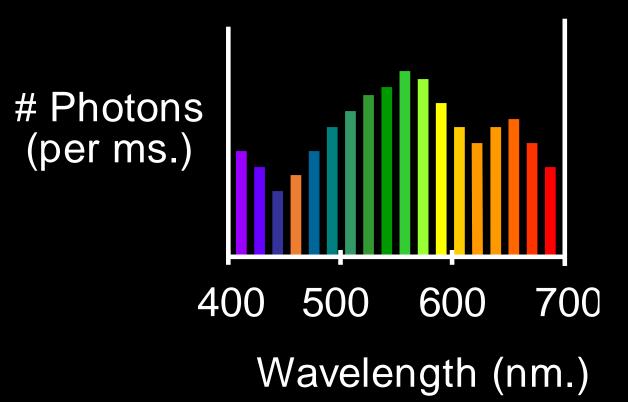
http://www.yorku.ca/eye/photopik.htm

Slide Credit: Efros

Visible Light

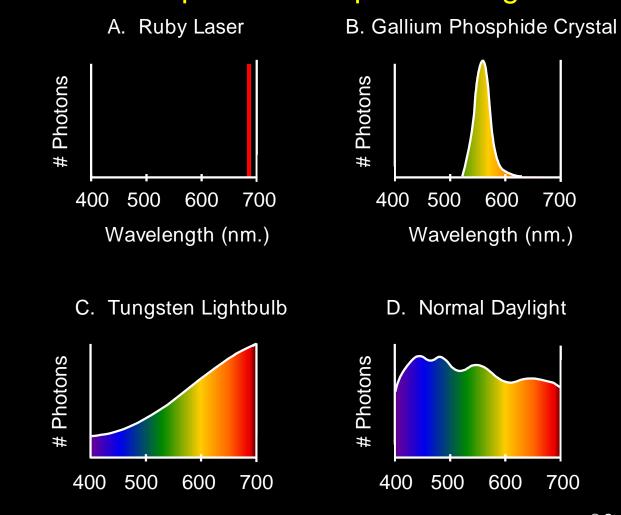


Any patch of light can be completely described physically by its spectrum: the number of photons (per time unit) at each wavelength 400 - 700 nm.





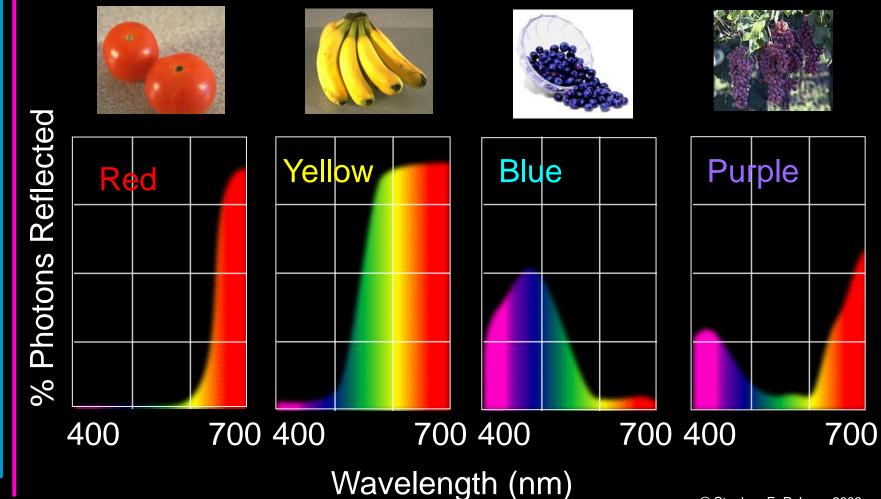
Some examples of the spectra of light sources



© Stephen E. Palmer, 2002

The Physics of Light

Some examples of the <u>reflectance</u> spectra of <u>surfaces</u>



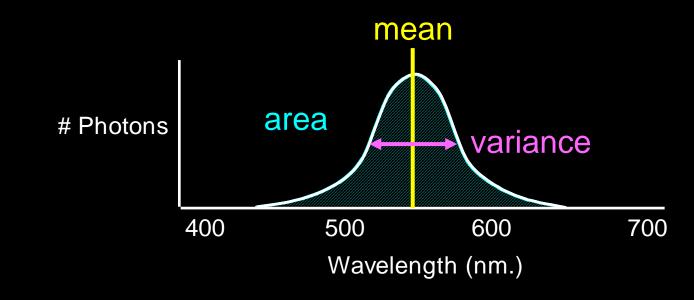
© Stephen E. Palmer, 2002

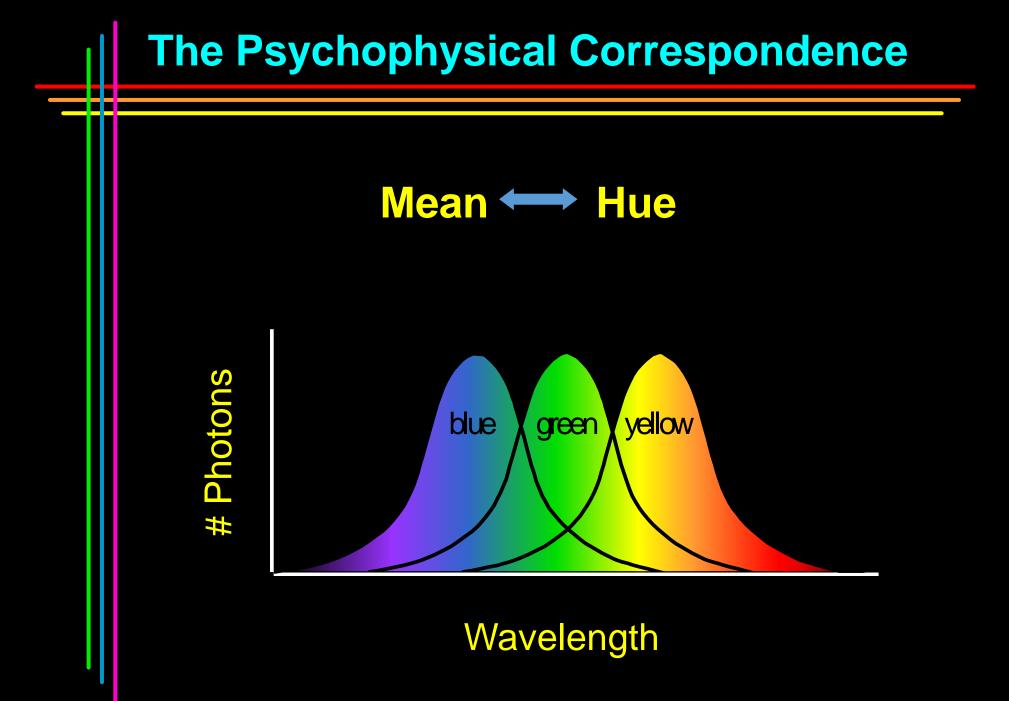
The Psychophysical Correspondence

There is no simple functional description for the perceived color of all lights under all viewing conditions, but

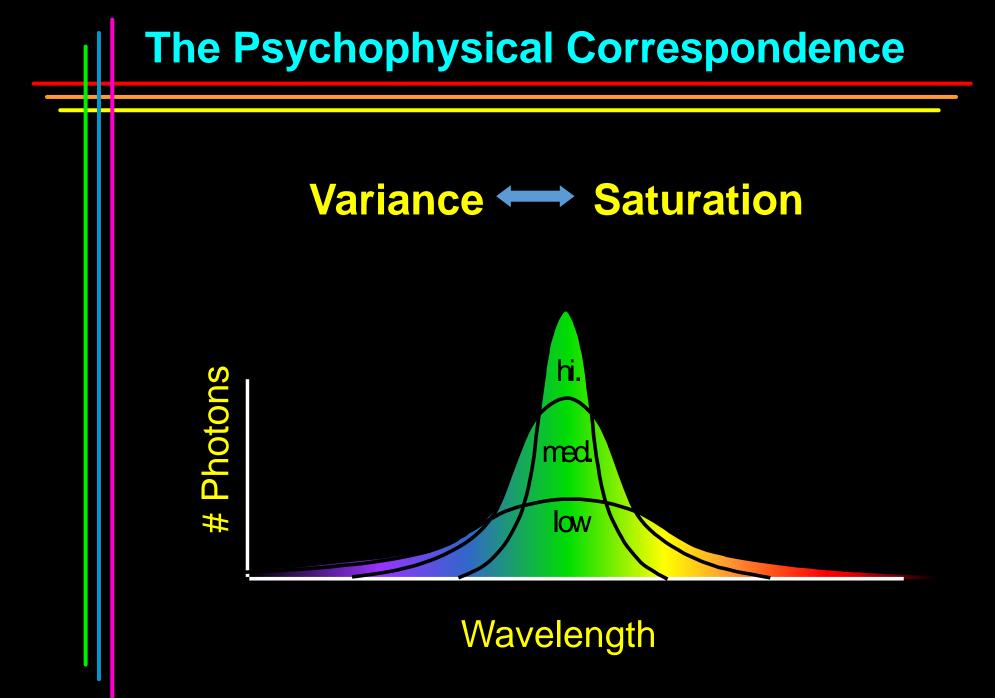
A helpful constraint:

Consider only physical spectra with normal distributions

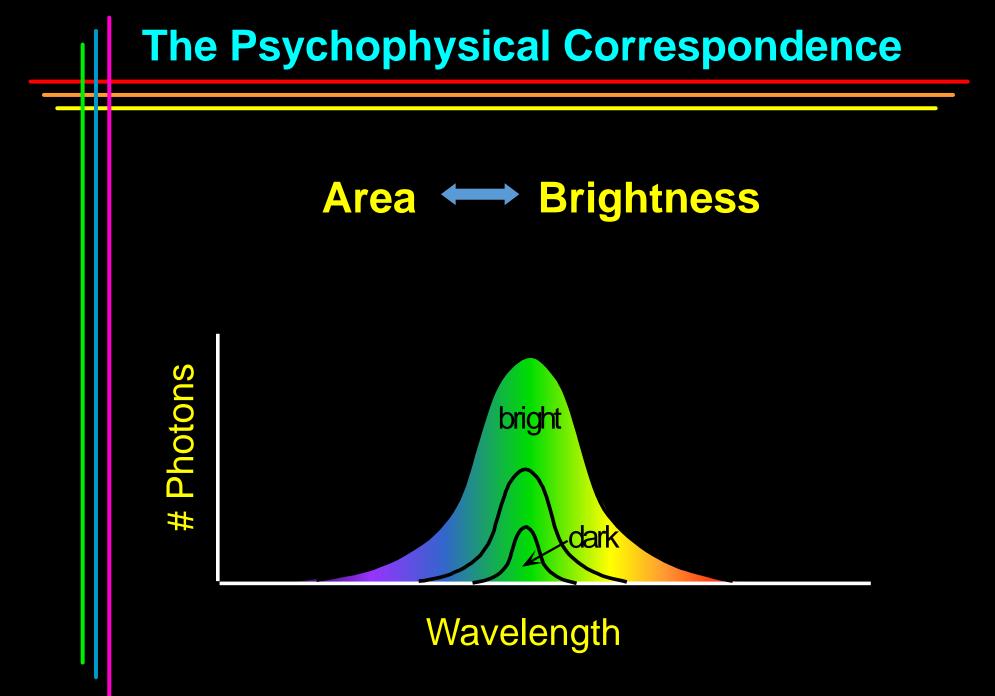




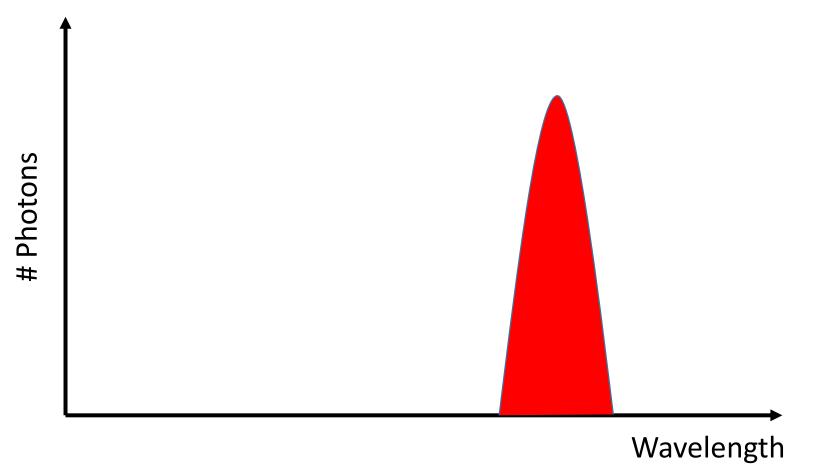
© Stephen E. Palmer, 2002



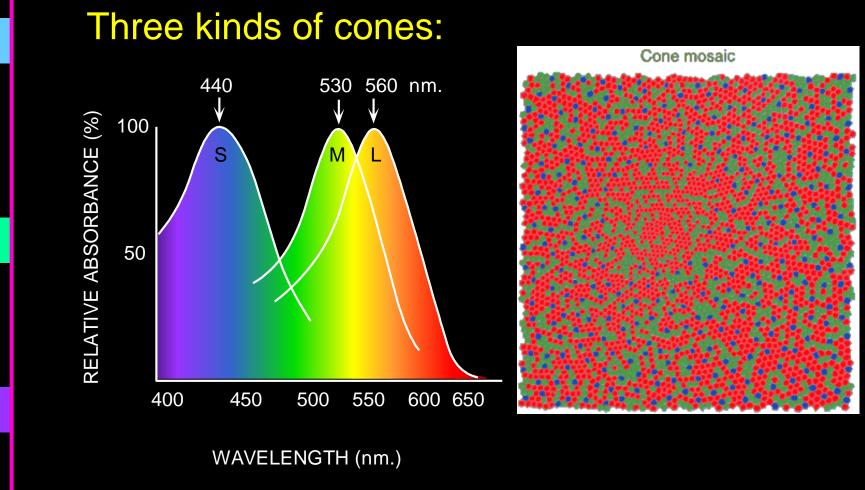
© Stephen E. Palmer, 2002



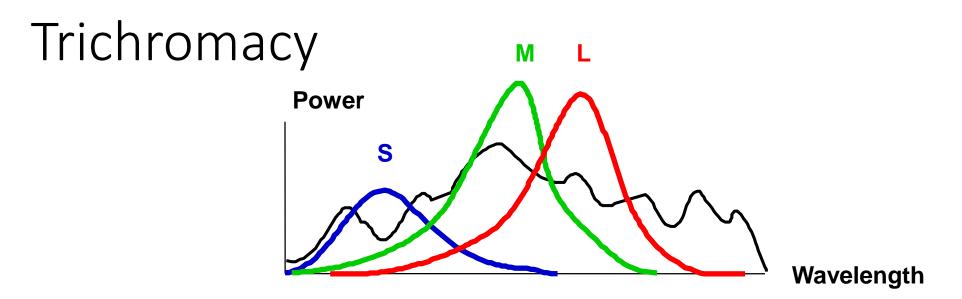
Question: draw a "pink" light



Physiology of Color Vision



- Why are M and L cones so close?
- Why are there 3?

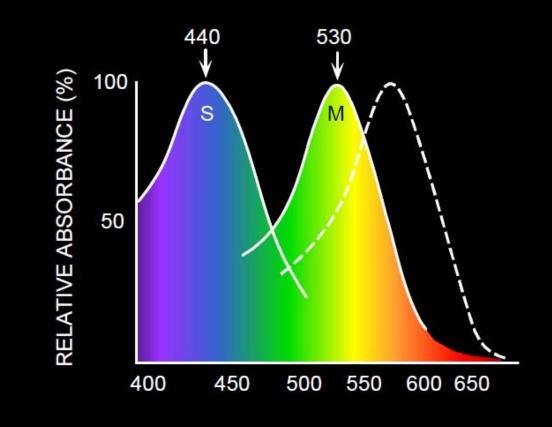


Rods and cones act as *filters* on the spectrum

- To get the output of a filter, multiply its response curve by the spectrum, integrate over all wavelengths
 - Each cone yields one number
- How can we represent an entire spectrum with 3 numbers?
- We can't! Most of the information is lost
 - As a result, two different spectra may appear indistinguishable
 - » such spectra are known as metamers

Physiology of Color Blindness

Protanopia: Lack of L-cones



WAVELENGTH (nm.)

Normal Trichromat





Physiology of Color Blindness

Deuteranopia: Lack of M-cones

560 440 RELATIVE ABSORBANCE (%) 100 S 50 400 450 500 550 600 650

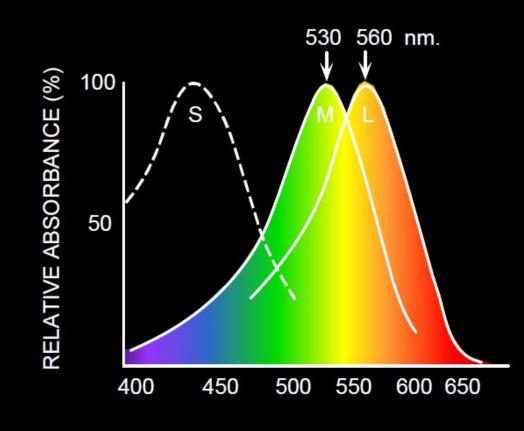
WAVELENGTH (nm.)

Normal Trichromat



Physiology of Color Blindness

Tritanopia: Lack of S-cones



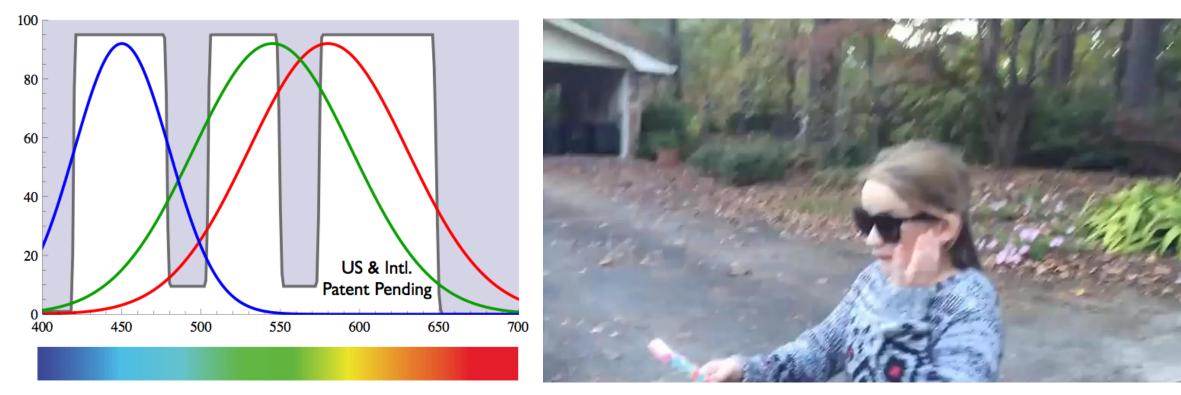
WAVELENGTH (nm.)

Normal Trichromat





Correcting Colorblind?



EnChroma Cx

http://enchroma.com/

<u>The "photometer metaphor" of color perception</u>: Color perception is determined by the spectrum of light on each retinal receptor (as measured by a photometer).



<u>The "photometer metaphor" of color perception</u>: Color perception is determined by the spectrum of light on each retinal receptor (as measured by a photometer).



Color Constancy

<u>The "photometer metaphor" of color perception</u>: Color perception is determined by the spectrum of light on each retimal receptor (as measured by a photometer).



Color Constancy

Do we have constancy over all global color transformations?





60% blue filter

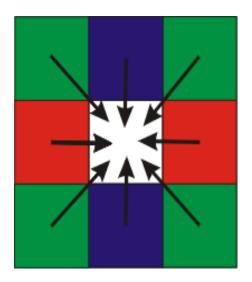
Complete inversion

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Color Constancy: the ability to perceive the invariant color of a surface despite ecological Variations in the conditions of observation.

Another of these hard inverse problems: Physics of light emission and surface reflection <u>underdetermine</u> perception of surface color

Practical Color Sensing: Bayer Grid



 Estimate RGB at 'G' cels from neighboring values Image: state state

http://www.cooldictionary.com/ words/Bayer-filter.wikipedia

Color Image





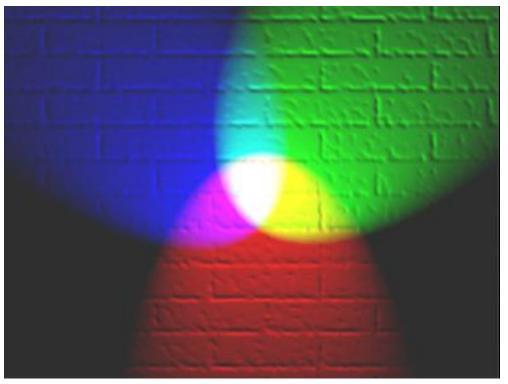
Images in Matlab

- Images represented as a matrix
- Suppose we have a NxM RGB image called "im"
 - im(1,1,1) = top-left pixel value in R-channel
 - -im(y, x, b) = y pixels down, x pixels to right in the bth channel
 - im(N, M, 3) = bottom-right pixel in B-channel
- imread(filename) returns a uint8 image (values 0 to 255)
 - Convert to double format (values 0 to 1) with im2double

Cun							vvic		2000								
ro		CO	um	<u>n</u> –													
10	vv	0.92	0.93	0.94	0.97	0.62	0.37	0.85	0.97	0.93	0.92	0.99	R				
- I.		0.95	0.89	0.82	0.89	0.56	0.31	0.75	0.92	0.81	0.95	0.91			•		
		0.89	0.72	0.51	0.55	0.51	0.42	0.57	0.41	0.49	0.91	0.92	0.92	0.99	ı G		
		0.96	0.95	0.88	0.94	0.56	0.46	0.91	0.87	0.90	0.97	0.95	0.92	0.91			
		0.71	0.81	0.81	0.87	0.57	0.37	0.80	0.88	0.89	0.79	0.85	0.91	0.91			B
		0.49	0.62	0.60	0.58	0.50	0.60	0.58	0.50	0.61	0.45	0.33	0.91	0.95	0.92	0.99	
		0.86	0.84	0.74	0.58	0.51	0.39	0.73	0.92	0.91	0.49	0.74	0.79	0.85	0.95	0.91	
		0.96	0.67	0.54	0.85	0.48	0.37	0.88	0.90	0.94	0.82	0.93	0.45	0.33	0.91	0.92	
		0.69	0.49	0.56	0.66	0.43	0.42	0.77	0.73	0.71	0.90	0.99	0.49	0.74	0.97	0.95	
		0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97	0.82	0.93	0.79	0.85	
V		0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93	0.90	0.99	0.45	0.33	
				0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97	0.49	0.74	
				0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93	0.82	0.93	
				0.51	0.54	0.05	0.45	0.41	0.70	0.70	0.77	0.05	0.55	<u> </u>	0.90	0.99	
						0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97	
						0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93	

Color spaces

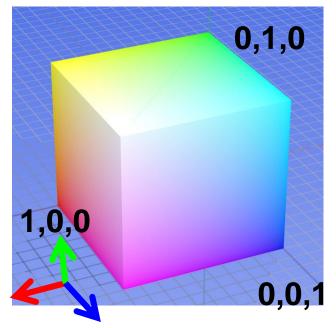
• How can we represent color?



http://en.wikipedia.org/wiki/File:RGB_illumination.jpg

Color spaces: RGB

Default color space



RGB cube

- Easy for devices
- But not perceptual
- Where do the grays live?
- Where is hue and saturation?

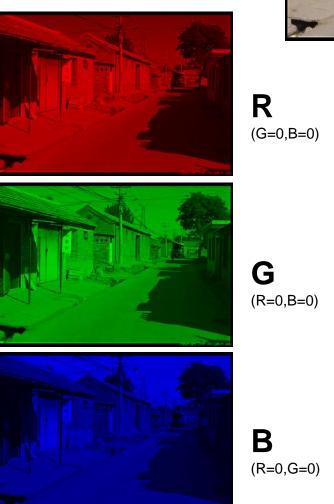
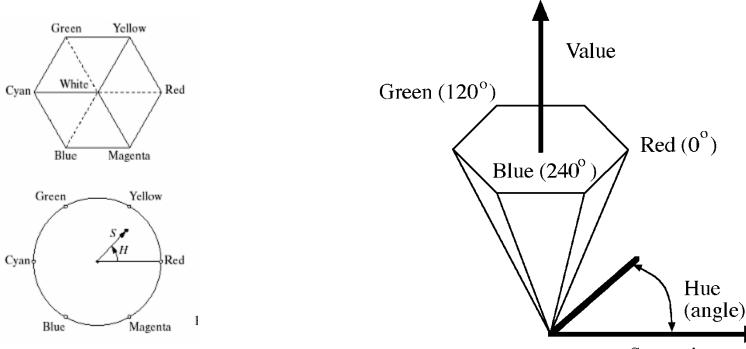




Image from: http://en.wikipedia.org/wiki/File:RGB_color_solid_cube.png



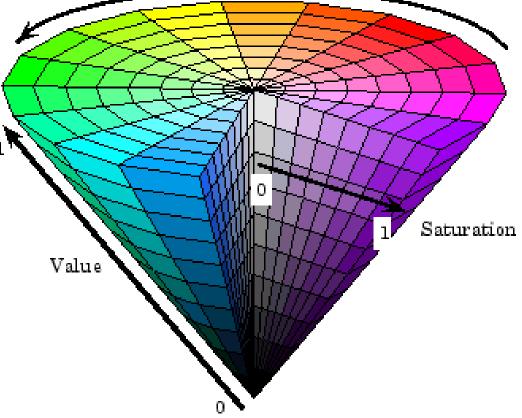


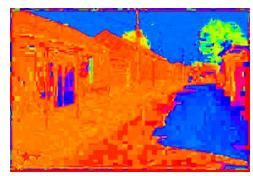
Saturation

- Hue, Saturation, Value (Intensity)
 - RGB cube on its vertex
- Decouples the three components (a bit)
- Use rgb2hsv() and hsv2rgb() in Matlab

Color spaces: HSV Intuitive color space

Hue





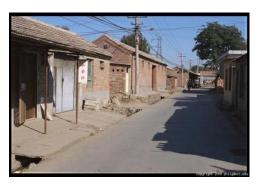
H (S=1,V=1)





(H=1,V=1)

S

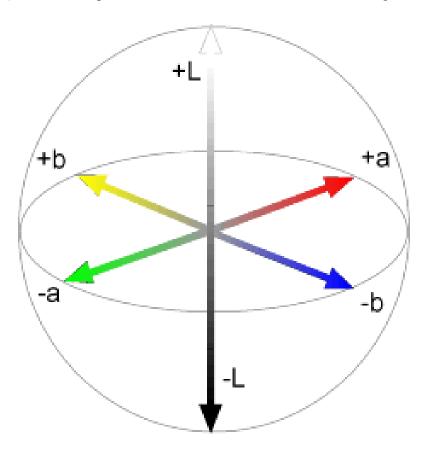


(H=1,S=0)

V

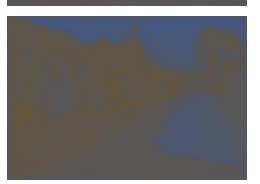
Color spaces: L*a*b*

"Perceptually uniform" color space











(a=0,b=0)

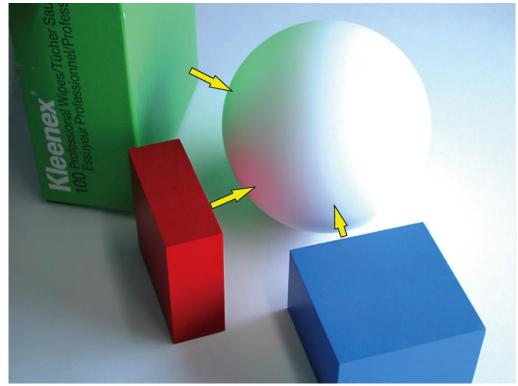
a (L=65,b=0)

b

(L=65,a=0)

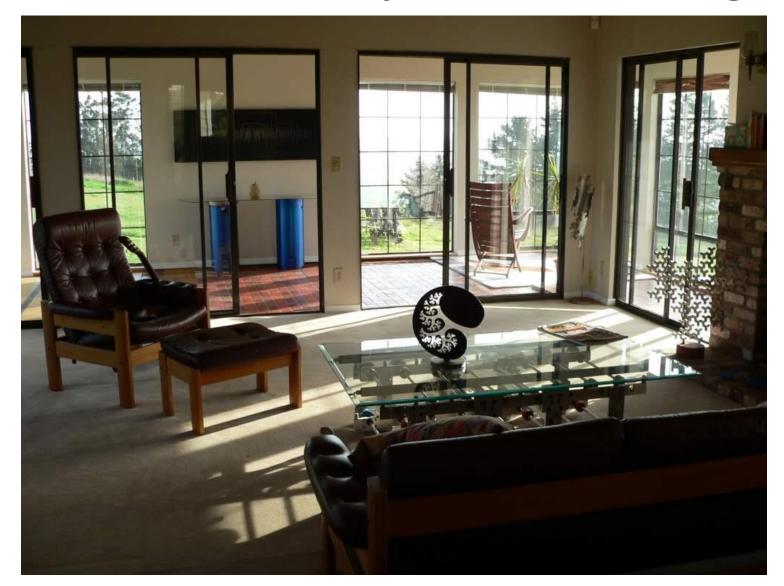
So far: light→surface→camera

- Called a local illumination model
- But much light comes from surrounding surfaces

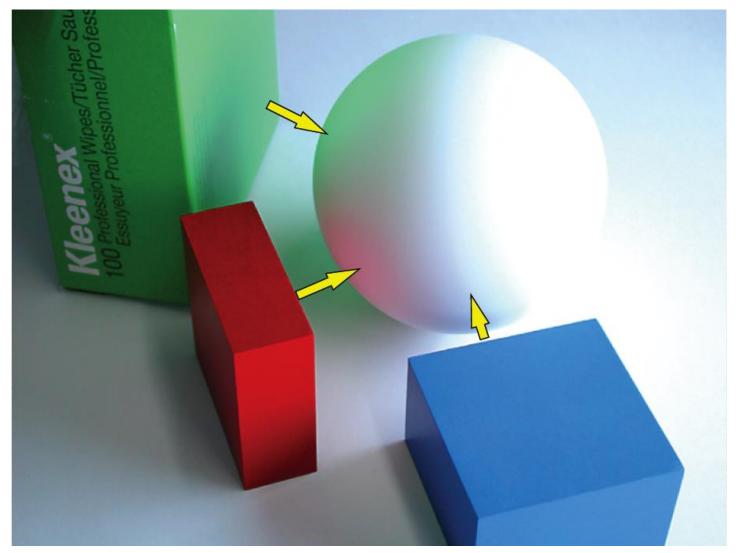


From Koenderink slides on image texture and the flow of light

Inter-reflection is a major source of light



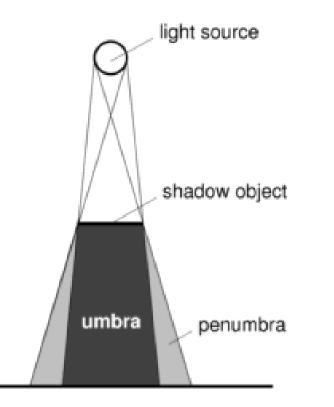
Inter-reflection affects the apparent color of objects



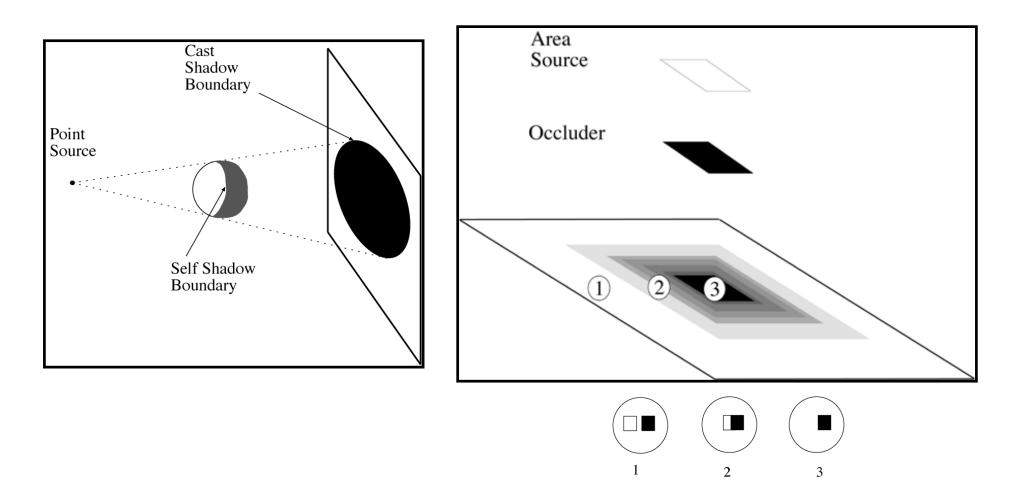
From Koenderink slides on image texture and the flow of light

Scene surfaces also cause shadows

• Shadow: reduction in intensity due to a blocked source



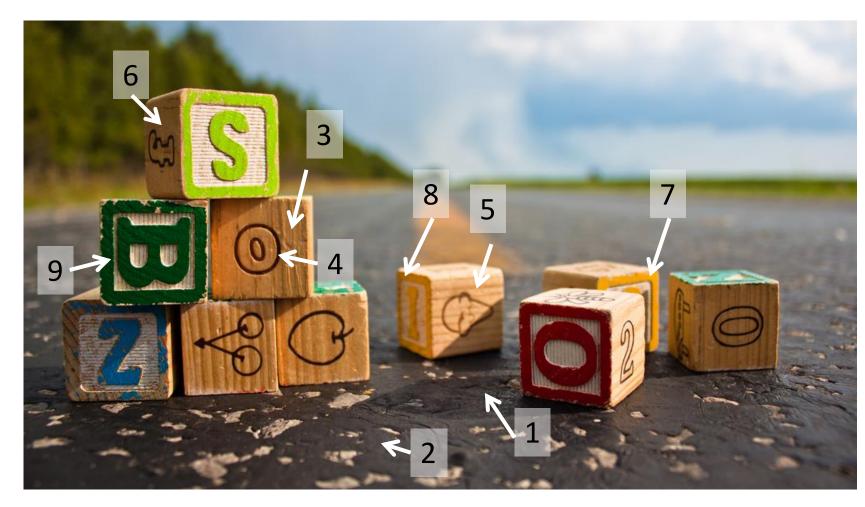
Shadows



Models of light sources

- Distant point source
 - One illumination direction
 - E.g., sun
- Area source
 - E.g., white walls, diffuser lamps, sky
- Ambient light
 - Substitute for dealing with interreflections
- Global illumination model
 - Account for interreflections in modeled scene

Questions



- A. Why is (2) brighter than (1)? Each points to the asphalt.
- B. Why is (4) darker than (3)?(4) points to the marking.
- C. Why is (5) brighter than (3)?Each points to the side of the wooden block.
- D. Why isn't (6) black, given that there is no direct path from it to the sun?
- E. Why (7) brighter than (8)?Both point to the yellow paints.
- F. Why is (9) green, given that the sun light contains all visible wavelengths?

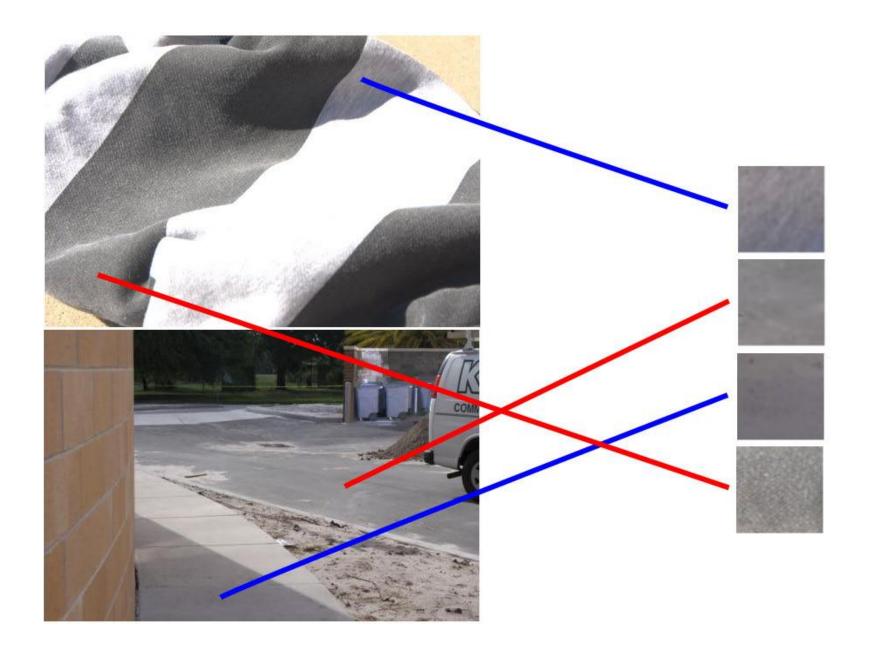
What does the intensity of a pixel tell us?

0.92 0.93 0.94 0.97 0.62 0.37 0.85 0.97 0.93 0.92 0.99 0.95 0.89 0.82 0.89 0.50 0.31 0.75 0.92 0.81 0.95 0.91 0.89 0.72 0.51 0.55 0.51 0.42 0.57 0.41 0.49 0.91 0.92 0.94 0.56 0.87 0.96 0.95 0.88 0.46 0.91 0.90 0.97 0.95 0.71 0.81 0.81 0.87 0.57 0.80 0.88 0.89 0.79 0.85 0.37 0.49 0.62 0.60 0.58 0.50 0.58 0.50 0.61 0.45 0.33 0.60 0.86 0.84 0.58 0.51 0.73 0.92 0.49 0.74 0.39 0.91 0.74 0.96 0.67 0.85 0.48 0.37 0.88 0.90 0.94 0.82 0.54 0.93 0.66 0.73 0.90 0.69 0.49 0.56 0.43 0.42 0.77 0.71 0.99 0.79 0.73 0.90 0.67 0.33 0.61 0.69 0.79 0.73 0.93 0.97 0.94 0.89 0.41 0.78 0.77 0.89 0.99 0.49 0.78 0.93 0.91

im(234, 452) = 0.58

The plight of the poor pixel

- A pixel's brightness is determined by
 - Light source (strength, direction, color)
 - Surface orientation
 - Surface material and albedo
 - Reflected light and shadows from surrounding surfaces
 - Gain on the sensor
- A pixel's brightness tells us nothing by itself

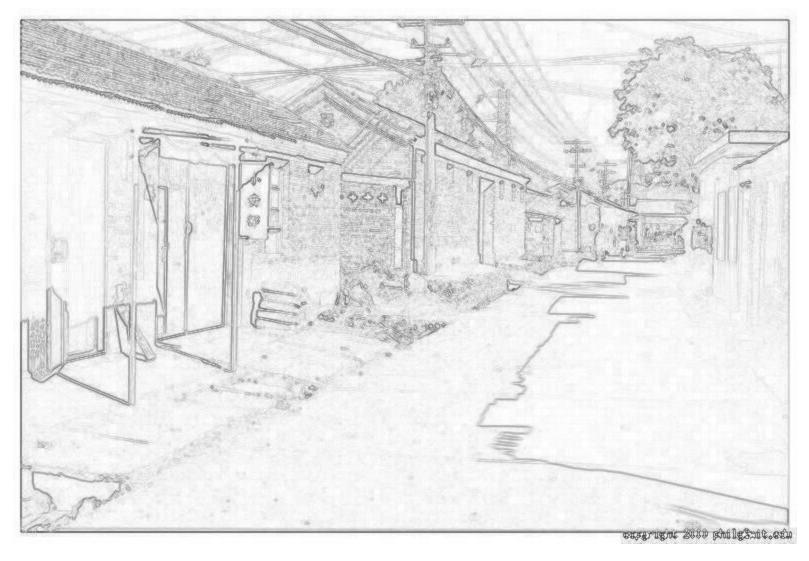


And yet we can interpret images...



- Key idea: for nearby scene points, most factors do not change much
- The information is mainly contained in *local differences* of brightness

Darkness = Large Difference in Neighboring Pixels



What is this?





What differences in intensity tell us about shape?

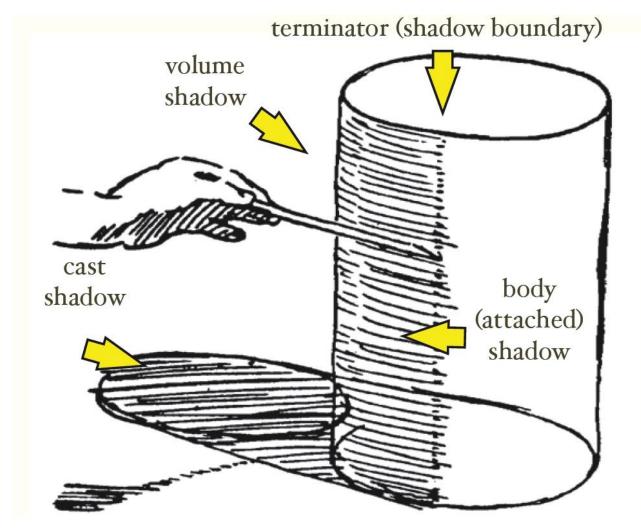
- Changes in surface normal
- Texture
- Proximity
- Indents and bumps
- Grooves and creases





Photos Koenderink slides on image texture and the flow of light

Shadows as cues

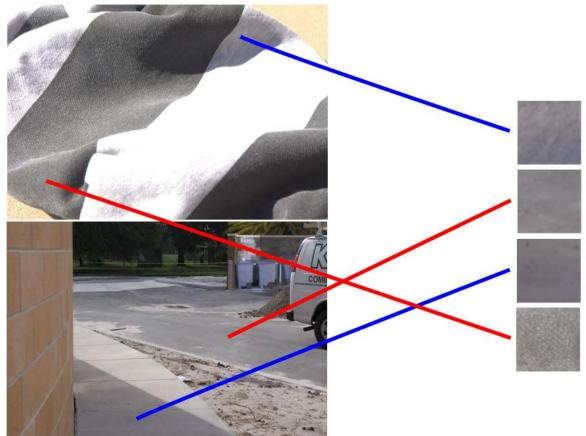


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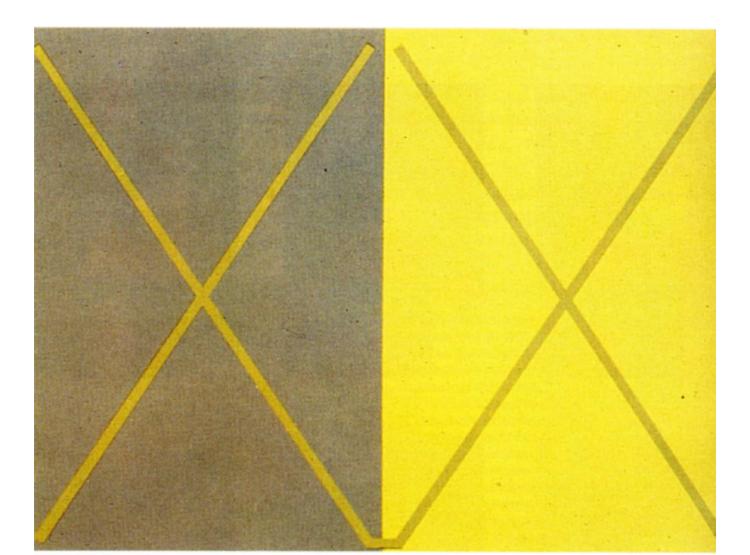
Slide: Forsyth

Color constancy

- Interpret surface in terms of albedo or "true color", rather than observed intensity
 - Humans are good at it
 - Computers are not nearly as good



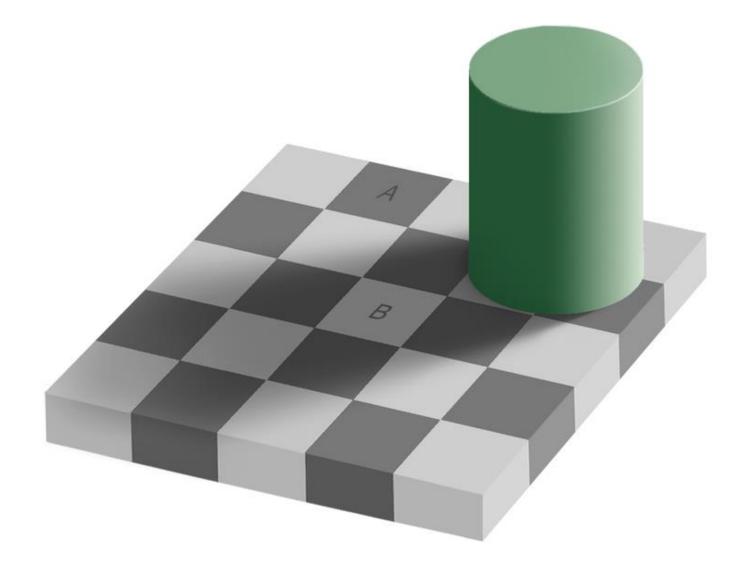
One source of constancy: local comparisons



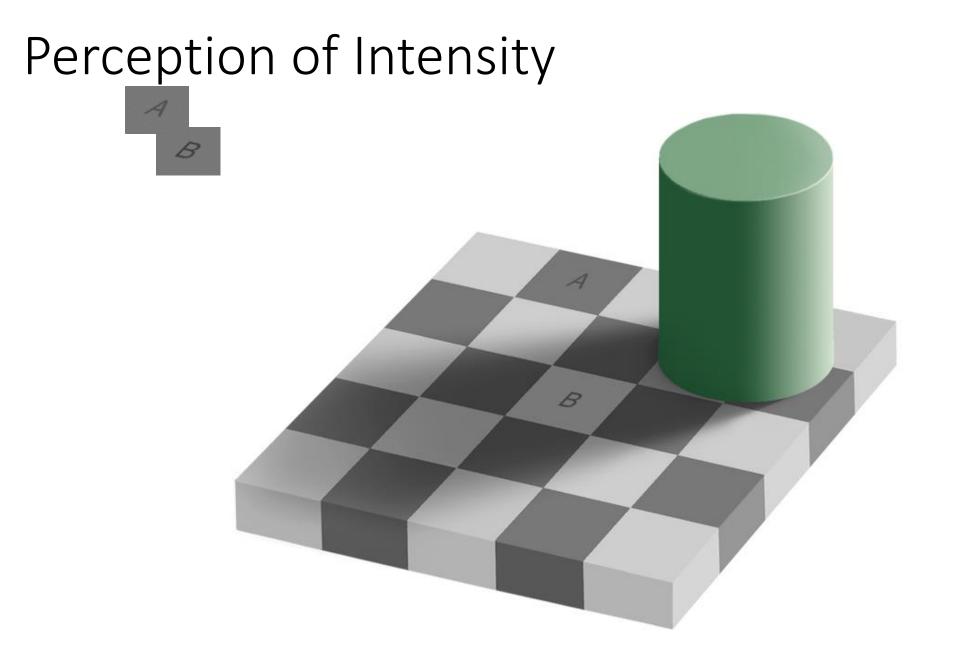


http://www.echalk.co.uk/amusements/OpticalIllusions/colourPerception/colourPerception.html

Perception of Intensity



from Ted Adelson



from Ted Adelson

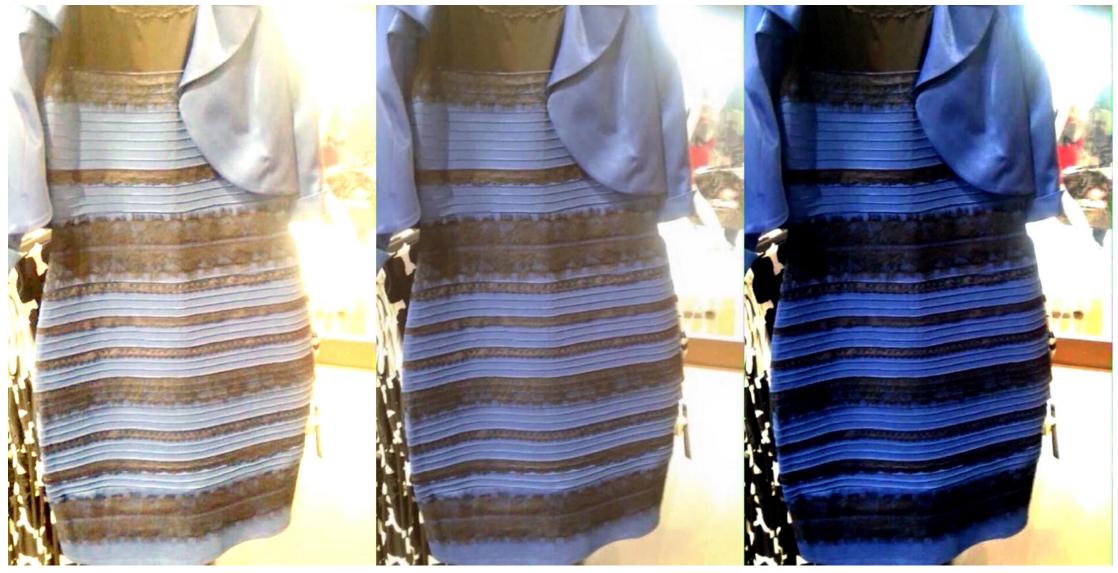
Color Correction

• Simple idea: multiply R, G, and B values by separate constants

$$\begin{bmatrix} \tilde{r} \\ \tilde{g} \\ \tilde{b} \end{bmatrix} = \begin{bmatrix} \alpha_r & 0 & 0 \\ 0 & \alpha_g & 0 \\ 0 & 0 & \alpha_b \end{bmatrix} \begin{bmatrix} r \\ g \\ b \end{bmatrix}$$

- How to choose the constants?
 - "White world" assumption: brightest pixel is white
 - Divide by largest value
 - "Gray world" assumption: average value should be gray
 - E.g., multiply r channel by avg(r) /avg((r+g+b)/3)
 - White balancing: choose a reference as the white or gray color



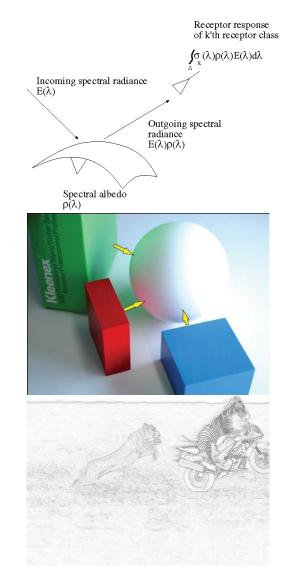


Discount the gold side



Things to remember

- Important terms: diffuse/specular reflectance, albedo
- Color vision: physics of light, trichromacy, color consistency, color spaces (RGB, HSV, Lab)
- Observed intensity depends on
 - light sources,
 - geometry/material of reflecting surface,
 - surrounding objects,
 - camera settings
- Objects cast light and shadows on each other
- Differences in intensity are primary cues for shape



Thank you

• Next class: Image Filters

