

Light, colour, & shadow

Semester 2, 2022

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Outline

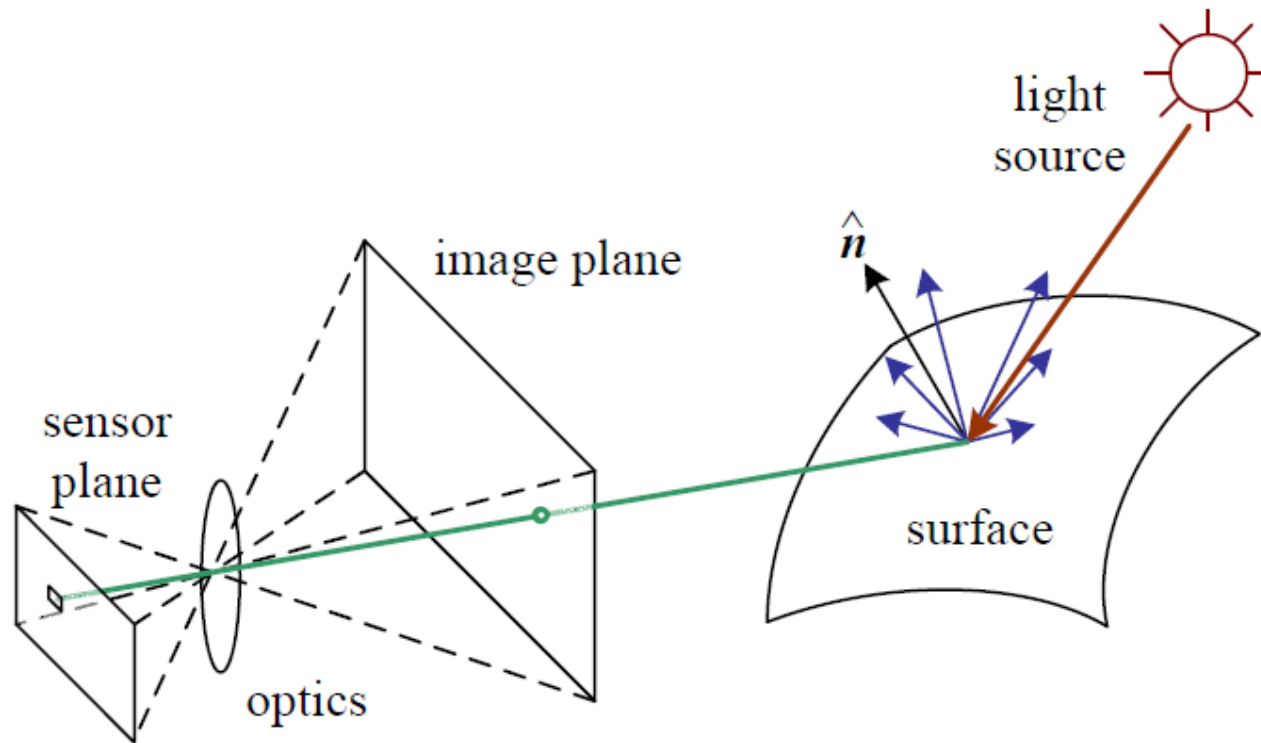
- Image formation, continued
- Colour
- Shading and surfaces

Learning outcomes

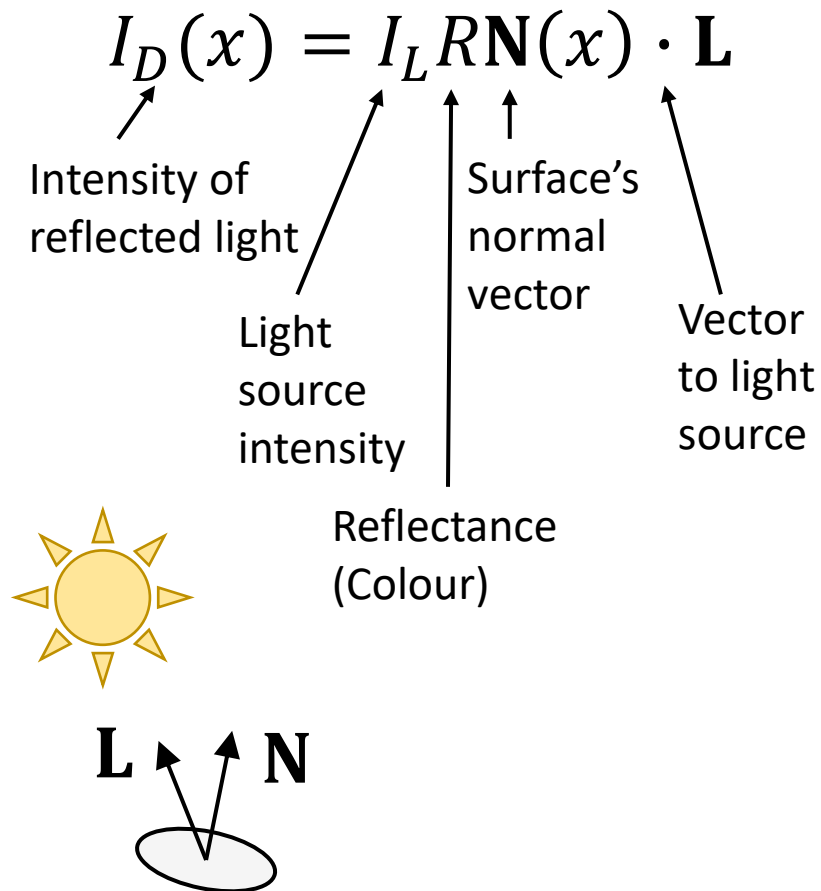
- Explain the diffuse reflectance model
- Explain how trichromatic colour values are computed and implement colour space transforms
- Explain the problems involved in recreating surface properties from a single image

Image formation

Image formation model



Diffuse (Lambertian) reflectance



Goal of vision

$$I_D(x) = I_L R \mathbf{N}(x) \cdot \mathbf{L}$$

Intensity of reflected light

Surface's normal vector

Reflectance (Colour)

Recover surface colour and normal from reflected light



Colour

Visible light

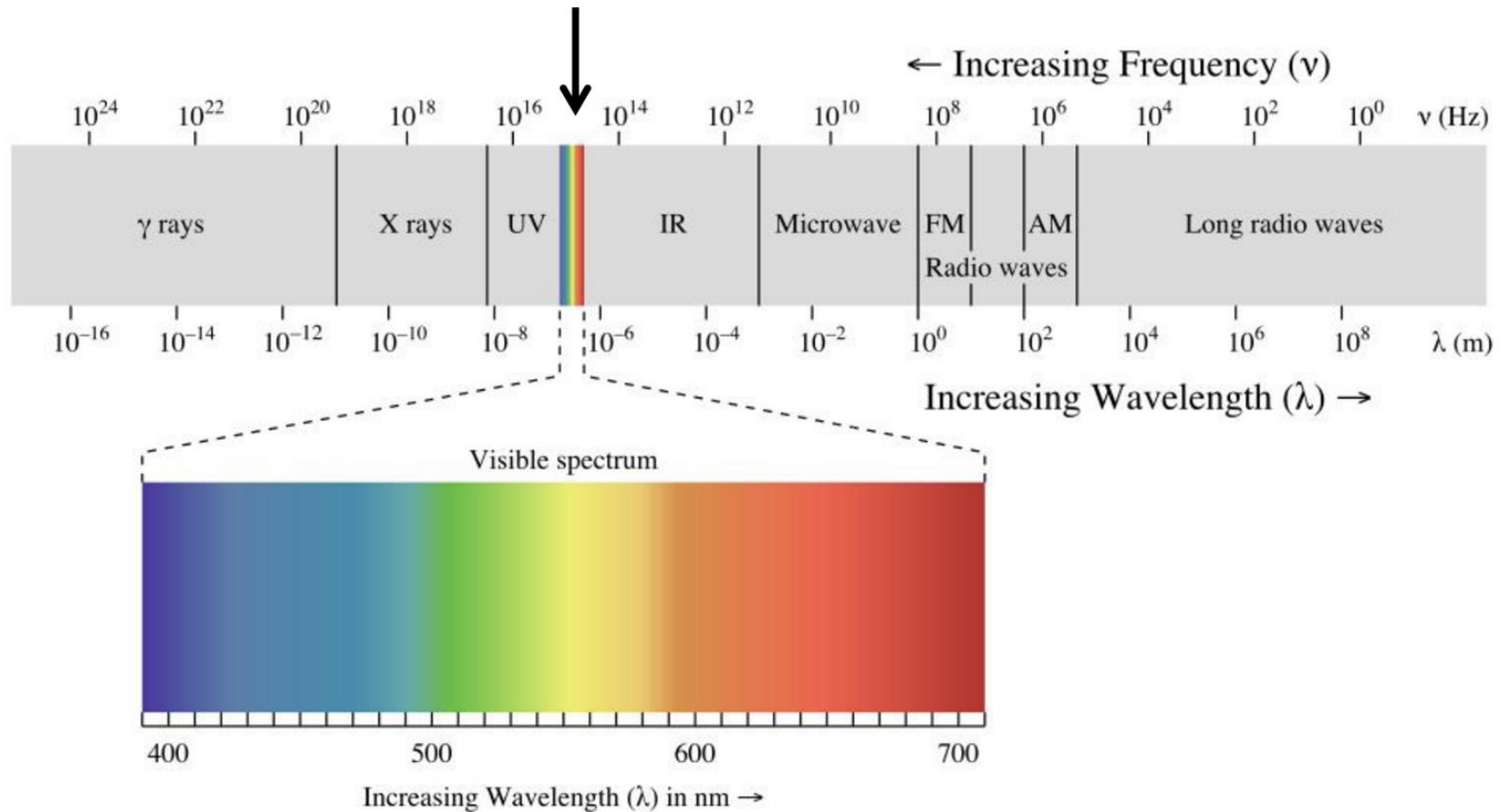


Figure: M. Brown

Visible light

- Spectral power distribution (SPD) = relative amount of each wavelength reflected by a surface (or produced by a light source)

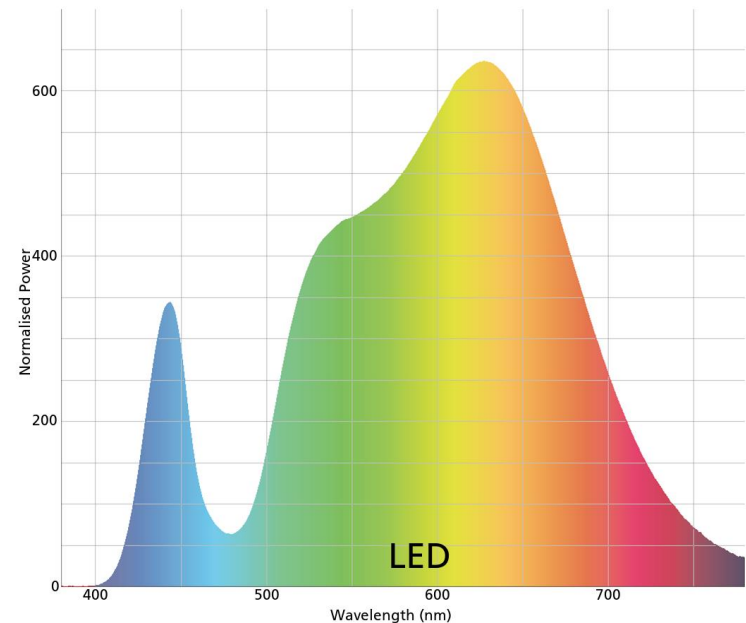
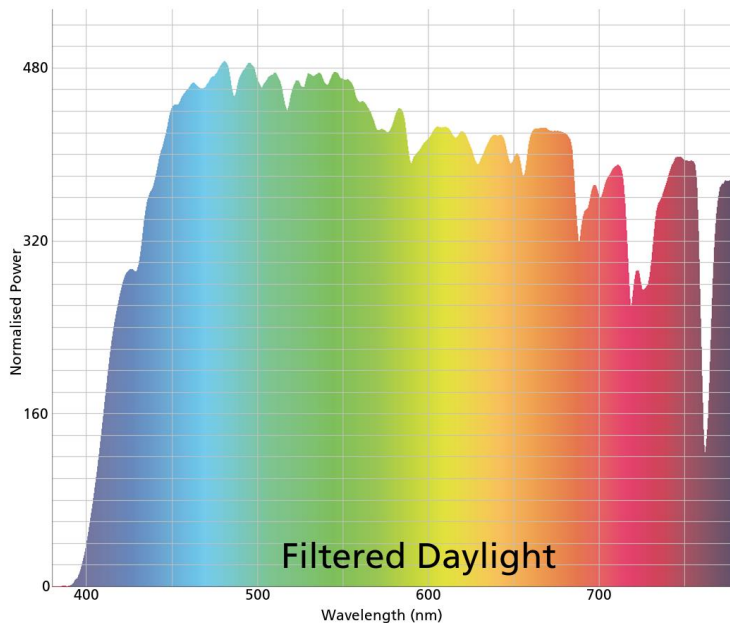


Figure: <https://research.ng-london.org.uk/scientific/spd/>

Perceived colour

- Human colour perception is based on 3 types of colour-sensitive cells (cones)

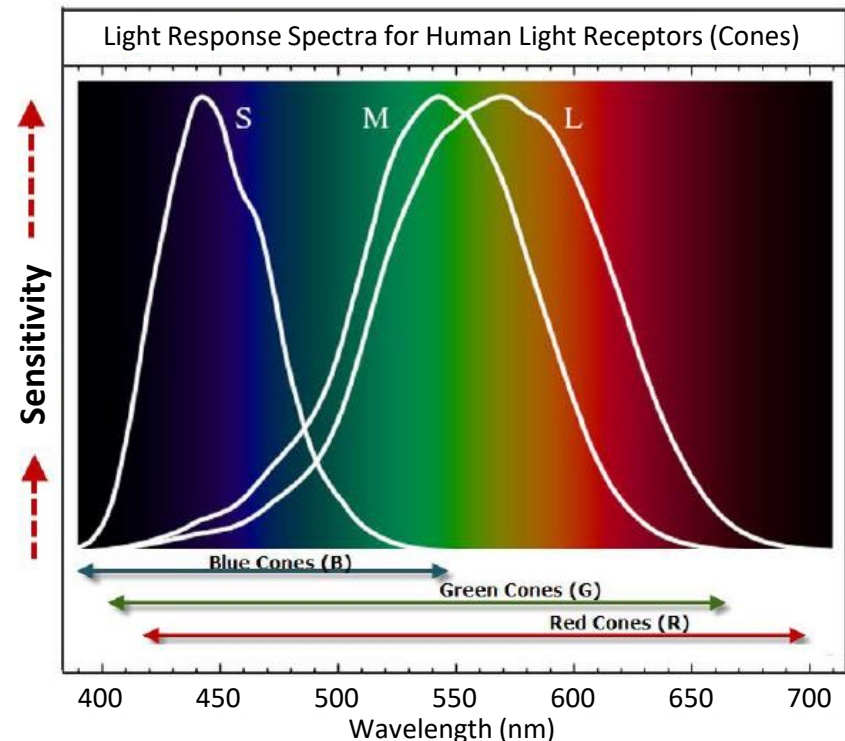
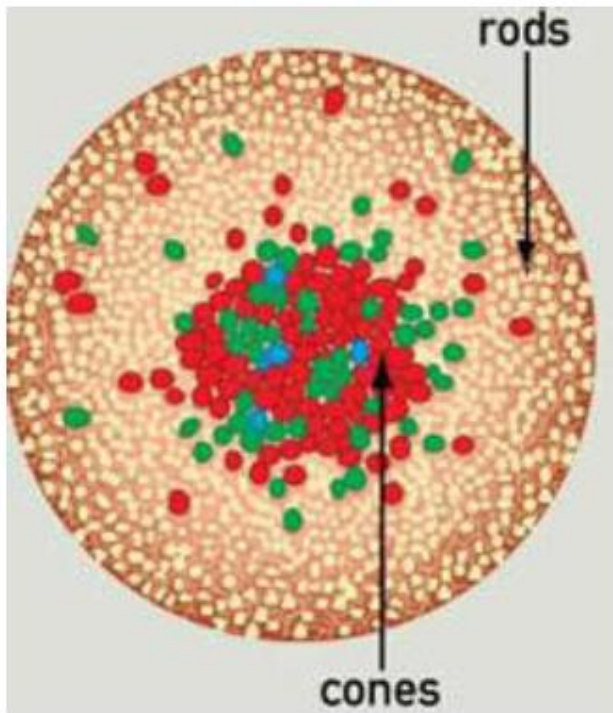


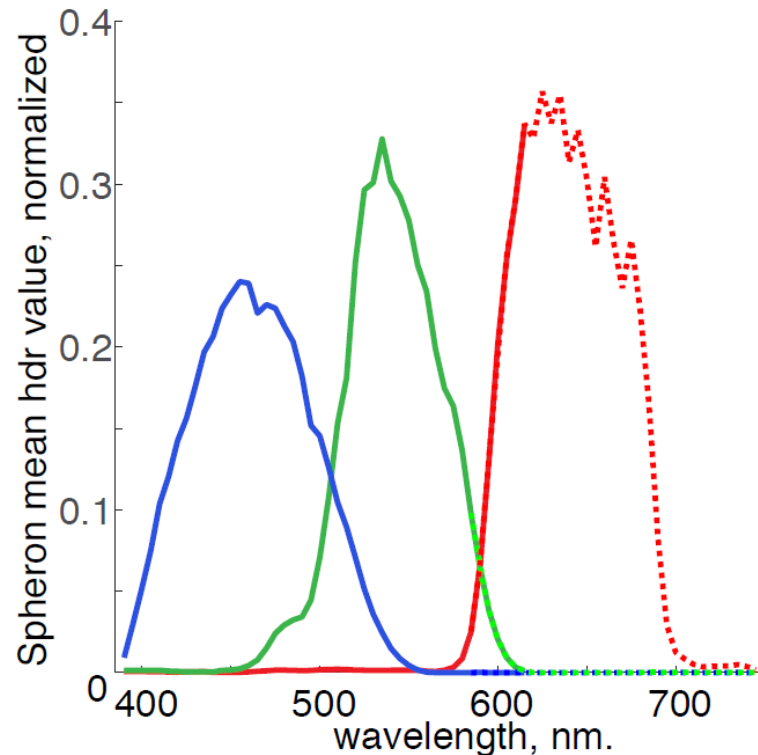
Figure: M. Brown

Perceived colour

- Standard cameras also have 3 colour sensors, each with a different spectral sensitivity



Spheron SpheroCam HDR



Adams, et al. (2016), <https://syns.soton.ac.uk/>

Perceived colour

- Most surfaces reflect a range of wavelengths, but perceived colour is a function of cone response

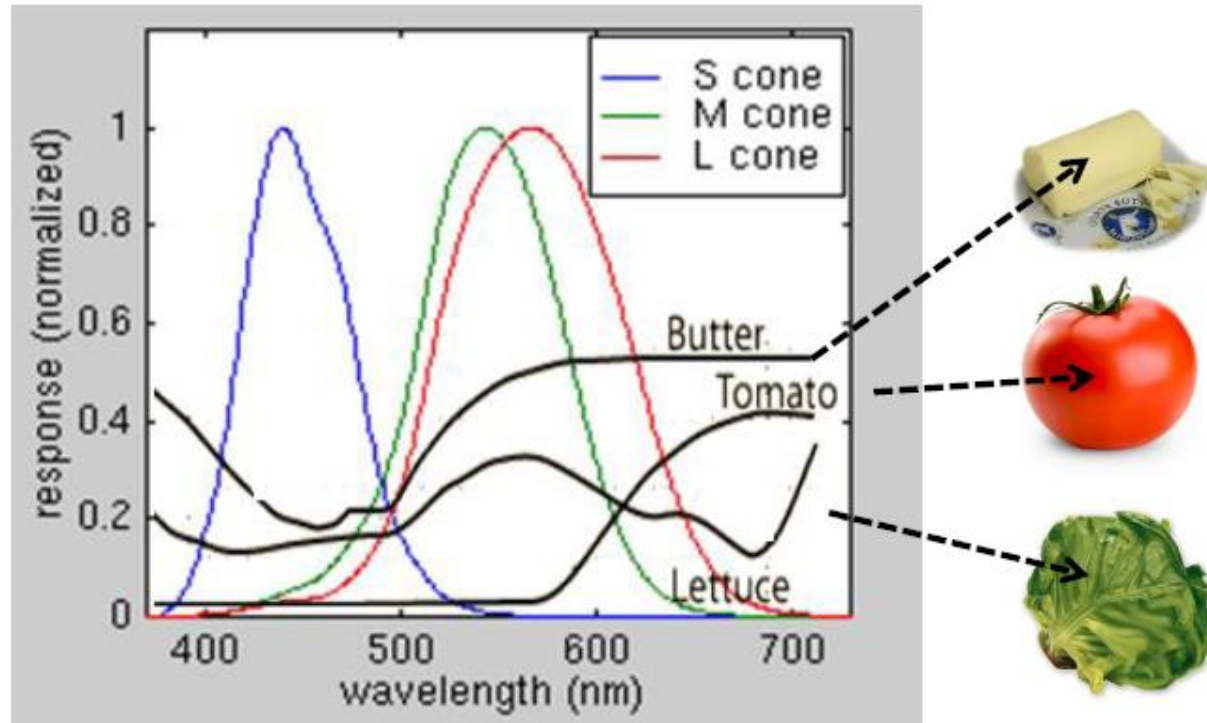
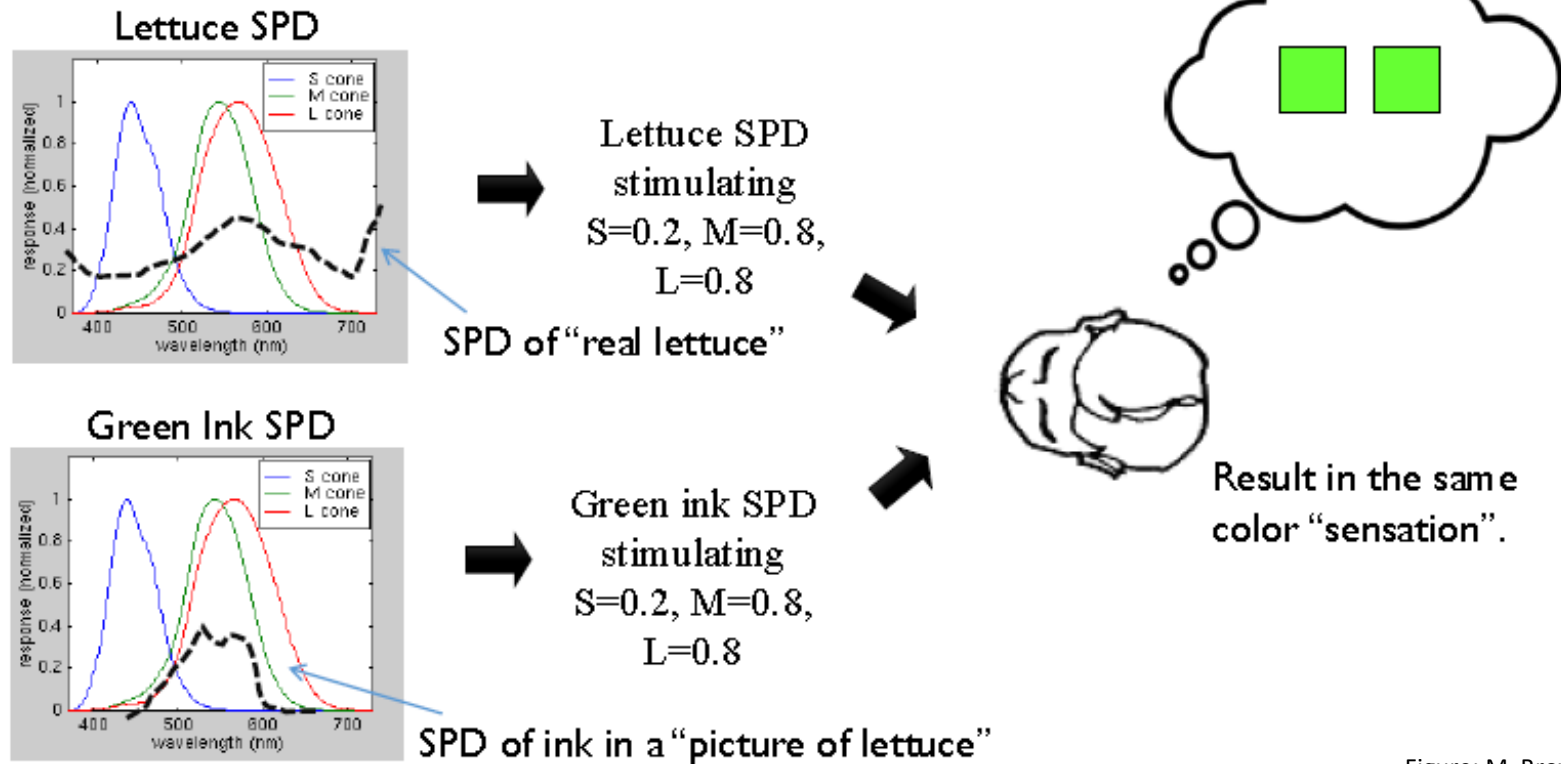


Figure: M. Brown

Perceived colour

- Result: many different spectra appear to be the same colour



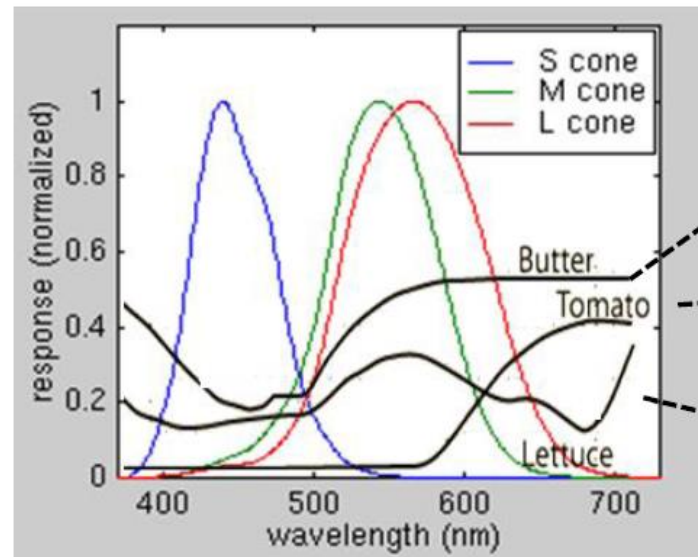
Trichromatic colour response

- Sensor response = sensitivity x spectrum, integrated over all wavelengths

$$I_R = \int_{400}^{700} I(\lambda) S_R(\lambda) d\lambda$$

$$I_G = \int_{400}^{700} I(\lambda) S_G(\lambda) d\lambda$$

$$I_B = \int_{400}^{700} I(\lambda) S_B(\lambda) d\lambda$$

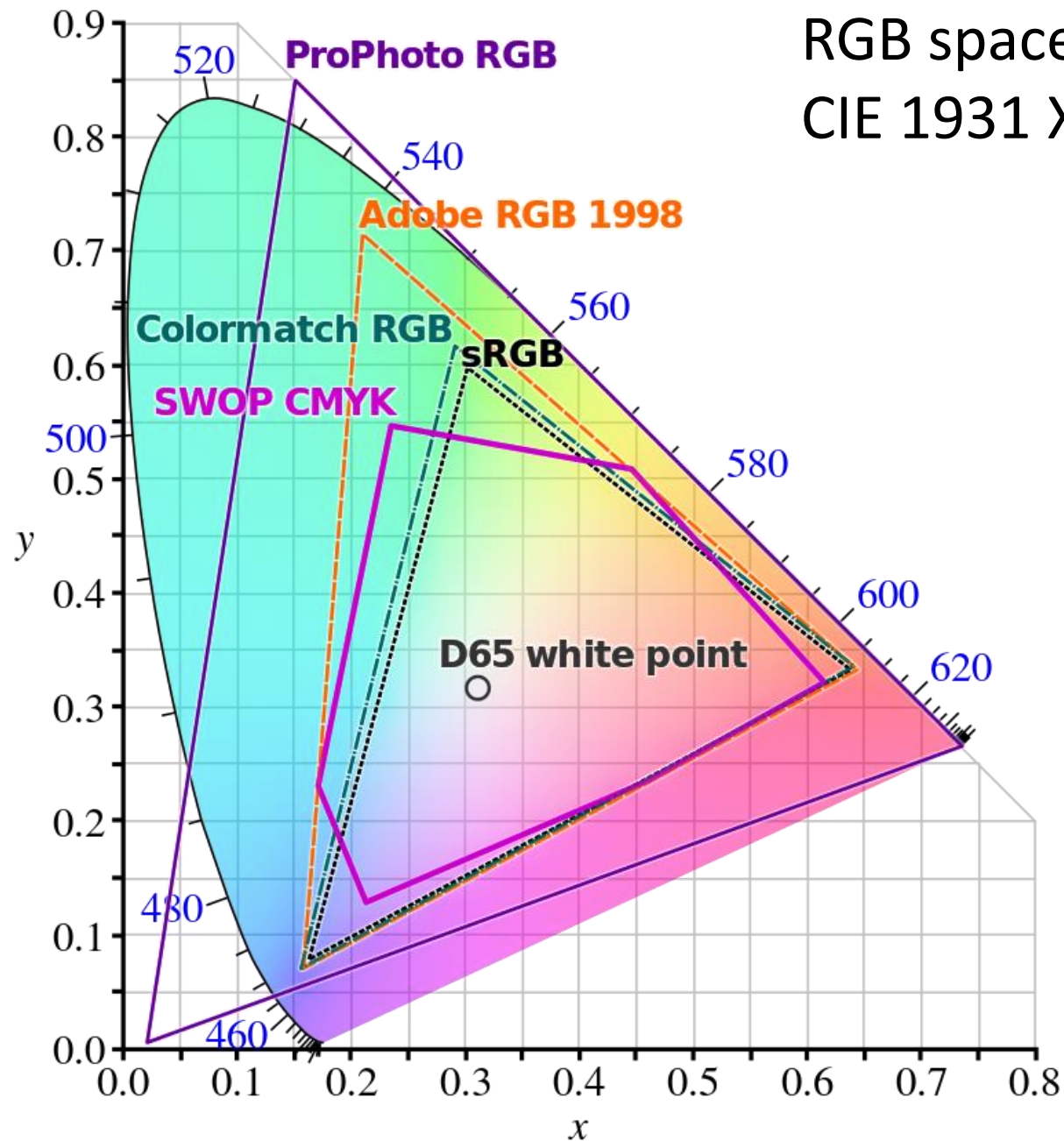


<https://csci1230.graphics/demos/metamers/index.html>

Colour representation

- Common colour spaces:
- RGB (red, green, blue)
 - Most common spaces for digital images
- HSL/HSV (hue, saturation, lightness/value)
 - Attempt to match human understanding of colour
- CIE 1931 XYZ
 - Based on human cone sensitivity, basis for other spaces
- LAB (luminance, a^* =red/green, b^* =blue/yellow)
 - Approximately perceptually uniform space

RGB spaces, plotted in CIE 1931 XYZ space



Colour transforms

- Converting between colour spaces is straightforward:
 - Linearize R, G, B values
 - Linear transform, e.g. $\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = M \begin{bmatrix} R \\ G \\ B \end{bmatrix}$
 - Values of M can be looked up for various colour spaces and white points (= the value defined to be “white” for a given colour space)
- Built-in functions in OpenCV, scikit-image

Example: colour swap

Swap R,G
channels in RGB



Invert red-green
axis in LAB



Summary

- Colour is not just three values, but human eye (and standard camera) depends on just three sensors
- Many trichromatic colour spaces
- RGB most common for image storage, other spaces may be more useful for colour manipulations

Shading and surfaces

Goal of vision

$$I_D(x) = I_L R \mathbf{N}(x) \cdot \mathbf{L}$$

Intensity of reflected light

Surface's normal vector

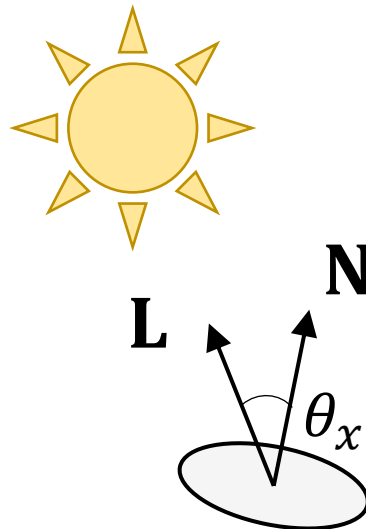
Reflectance (Colour)

Recover surface colour and normal from reflected light



Recovering surface normal

- Assume no changes in surface colour/reflectance (constant albedo)
- Can you recover surface normal from image?
- $I_D(x) = \mathbf{N}(x) \cdot \mathbf{L} = \cos \theta_x$



Recovering surface normal

- Can recover *angle* between surface normal and light source, but not normal
- However, can add additional assumptions:
 - Normals along boundary of object are known
 - Neighbouring normal are similar

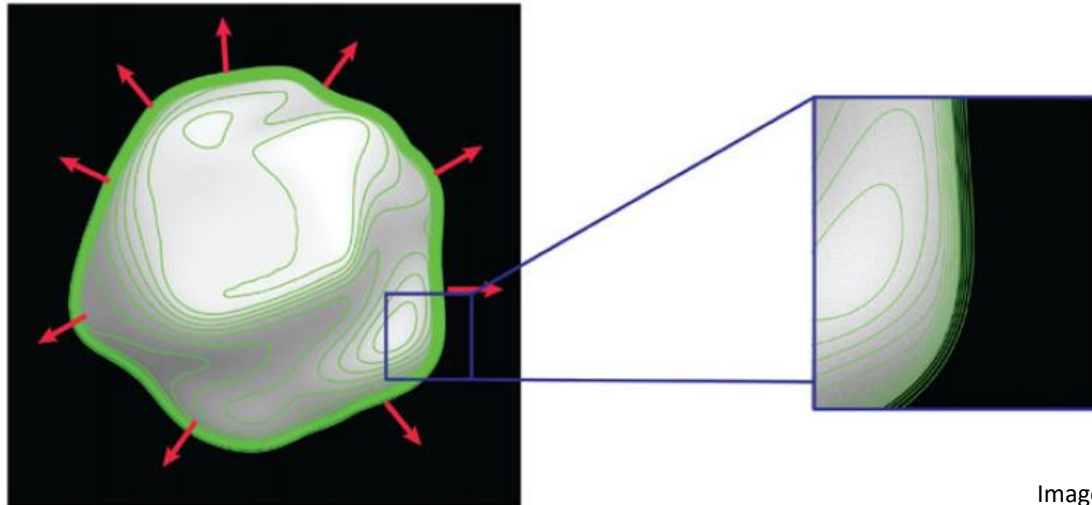
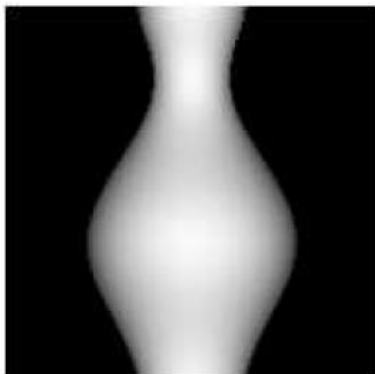


Image: Kunsberg, et al. (2018)

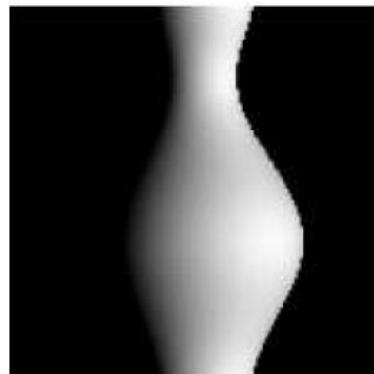
“Shape from shading”



(a)



(b)



(c)



(d)

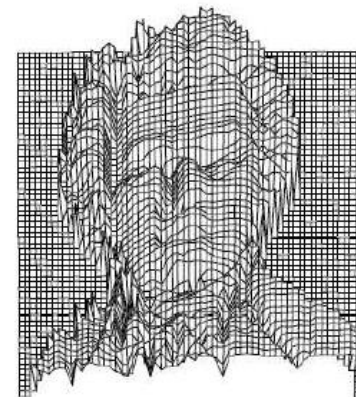
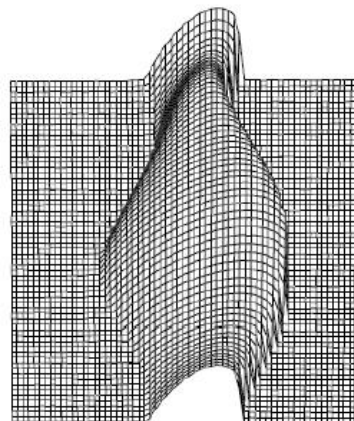
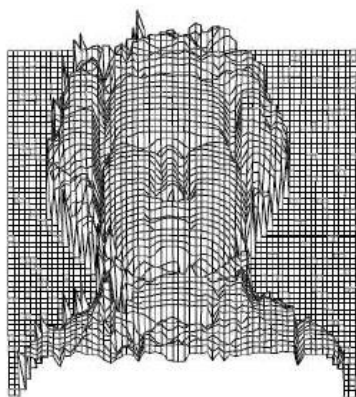
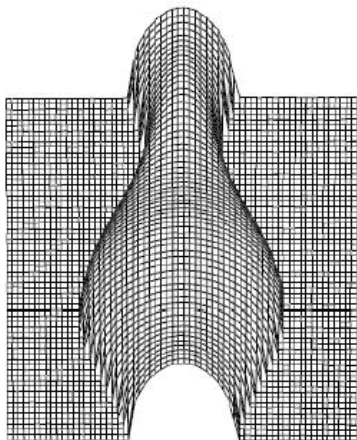
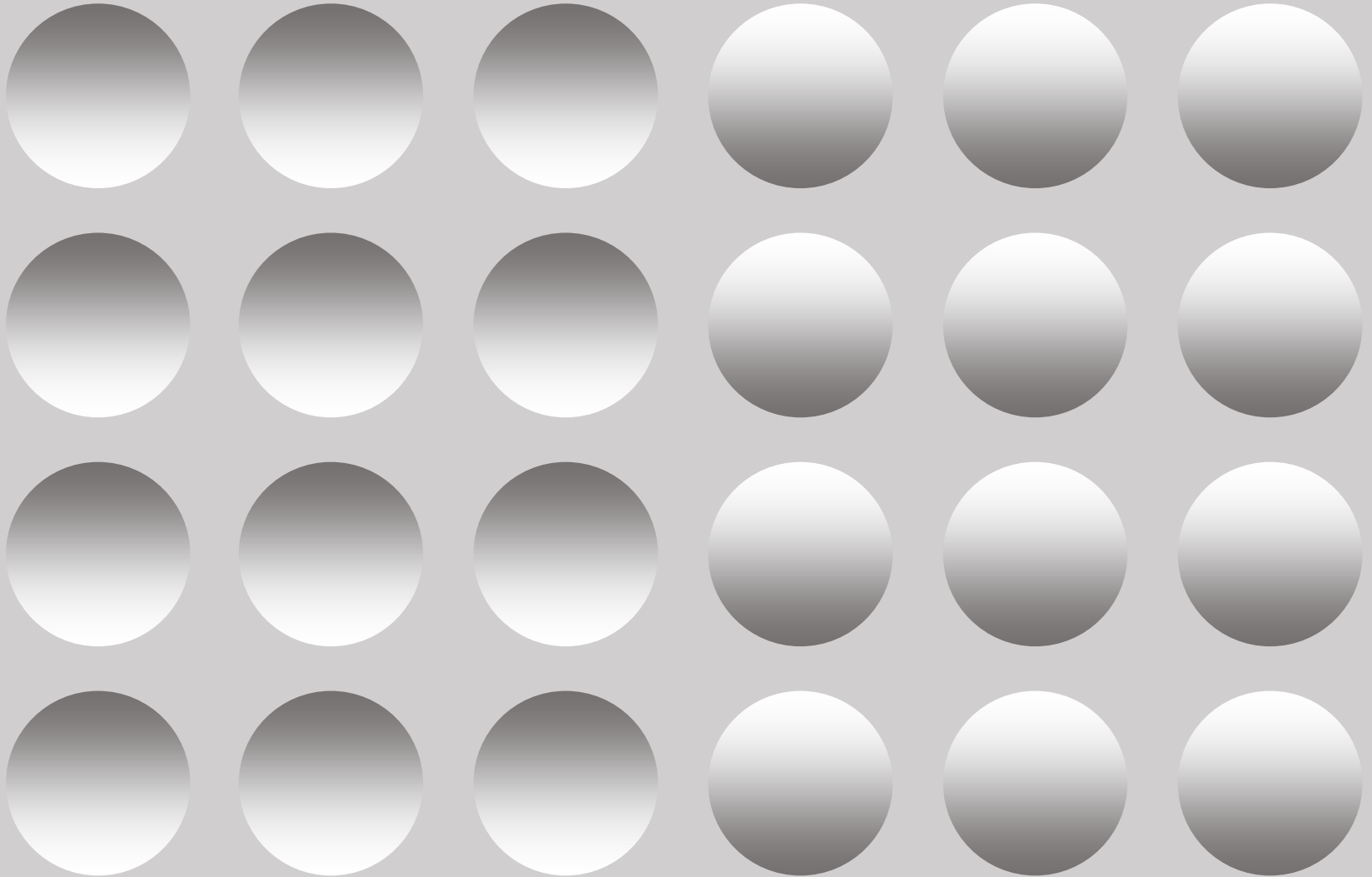


Image: R. Szeliski, *Computer Vision*, Figure 13.2

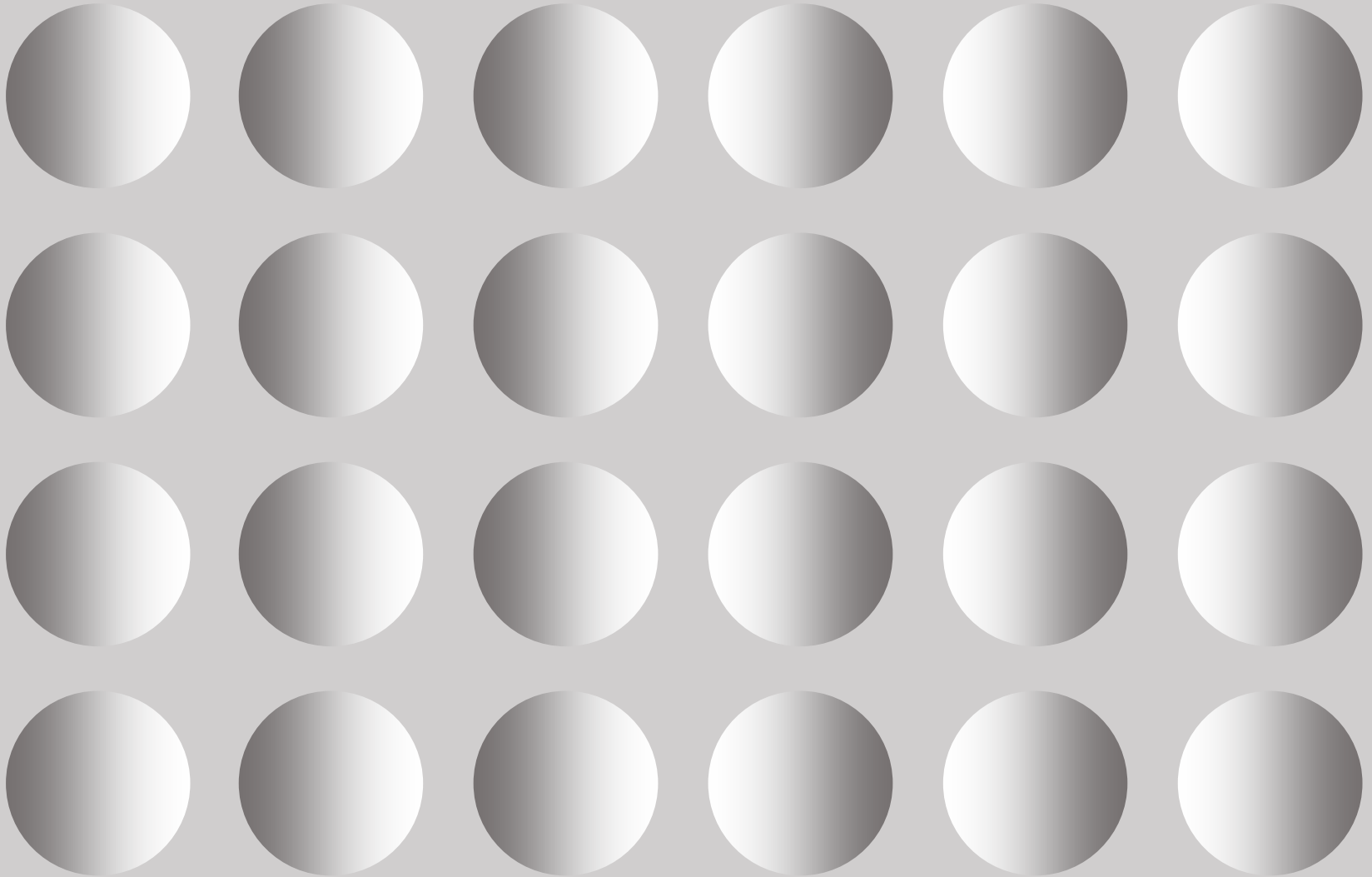
“Shape from shading”

- Recover 3D shape from 2D image based only on surface brightness (shading)
- Requires additional assumptions, no algorithm works for all cases
- How does the human visual system do it?

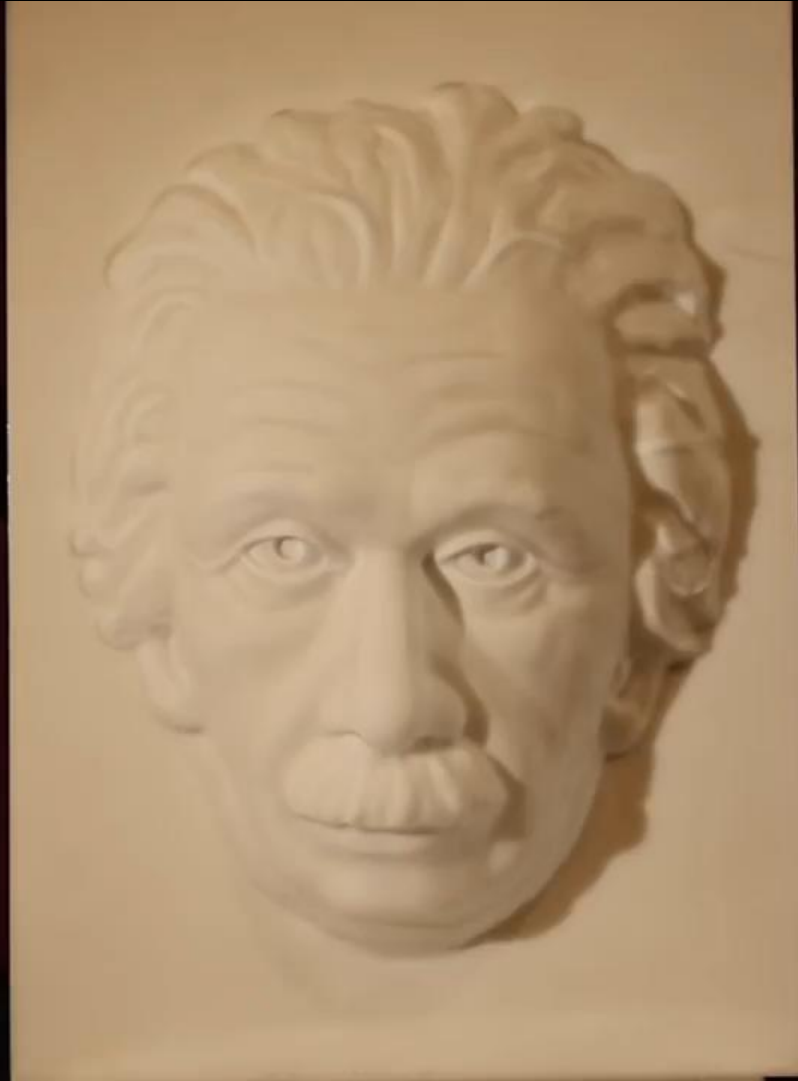
Lighting priors



Lighting priors



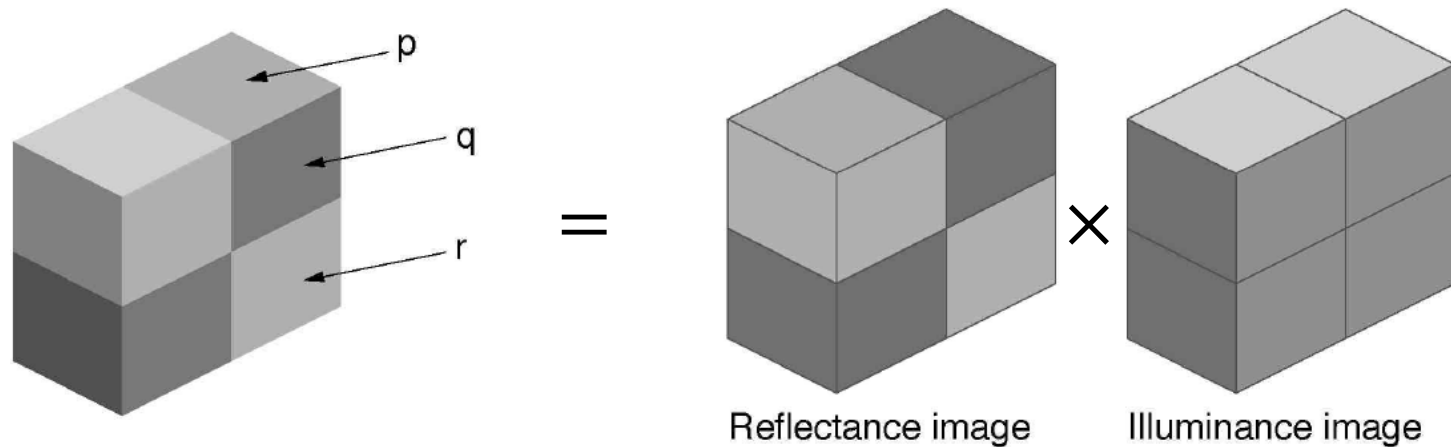
Shape priors



“Shape from shading”

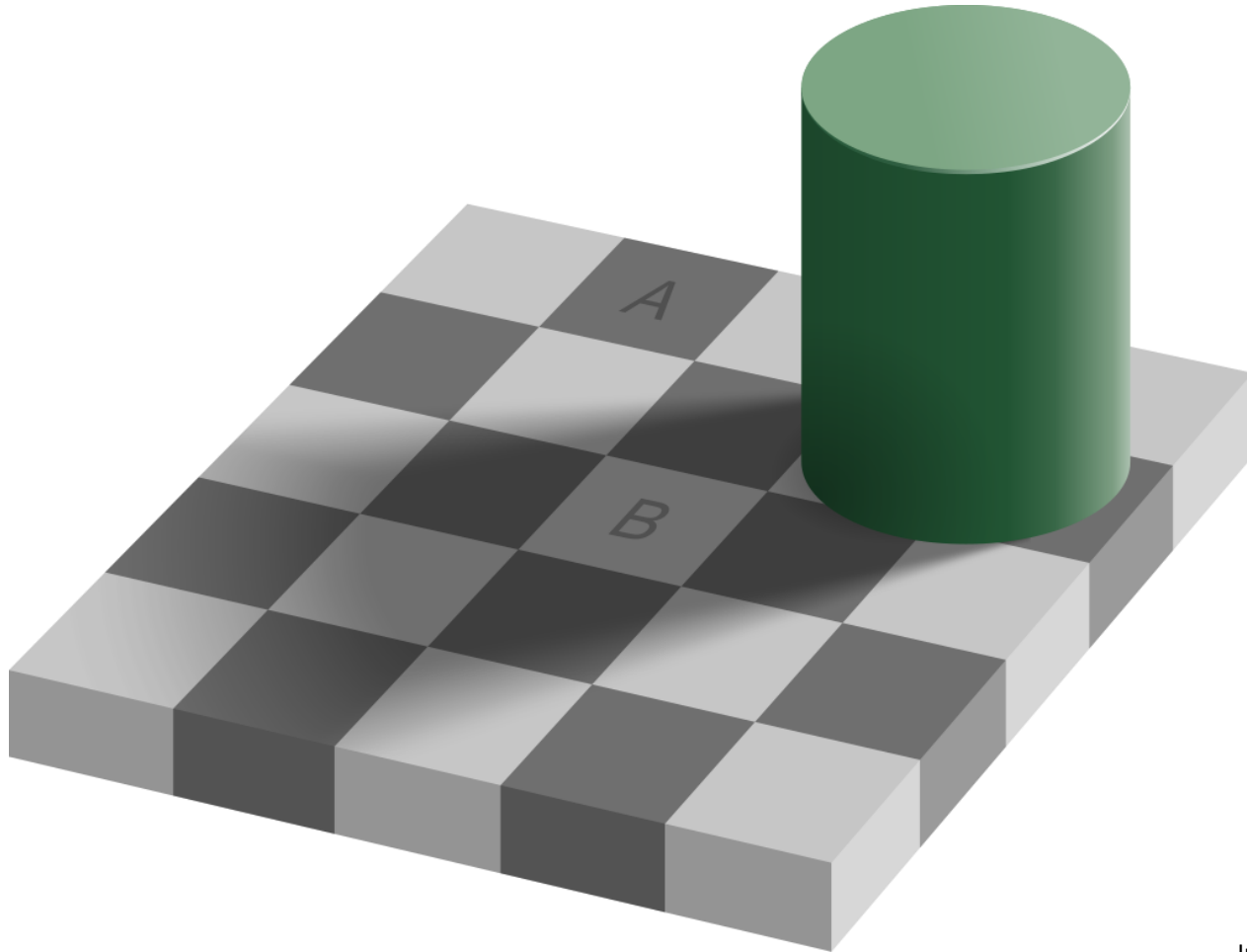
- Recover 3D shape from 2D image based only on surface brightness (shading)
- Requires additional assumptions, no algorithm works for all cases
- What if surface isn't constant albedo?

Recovering surface reflectance

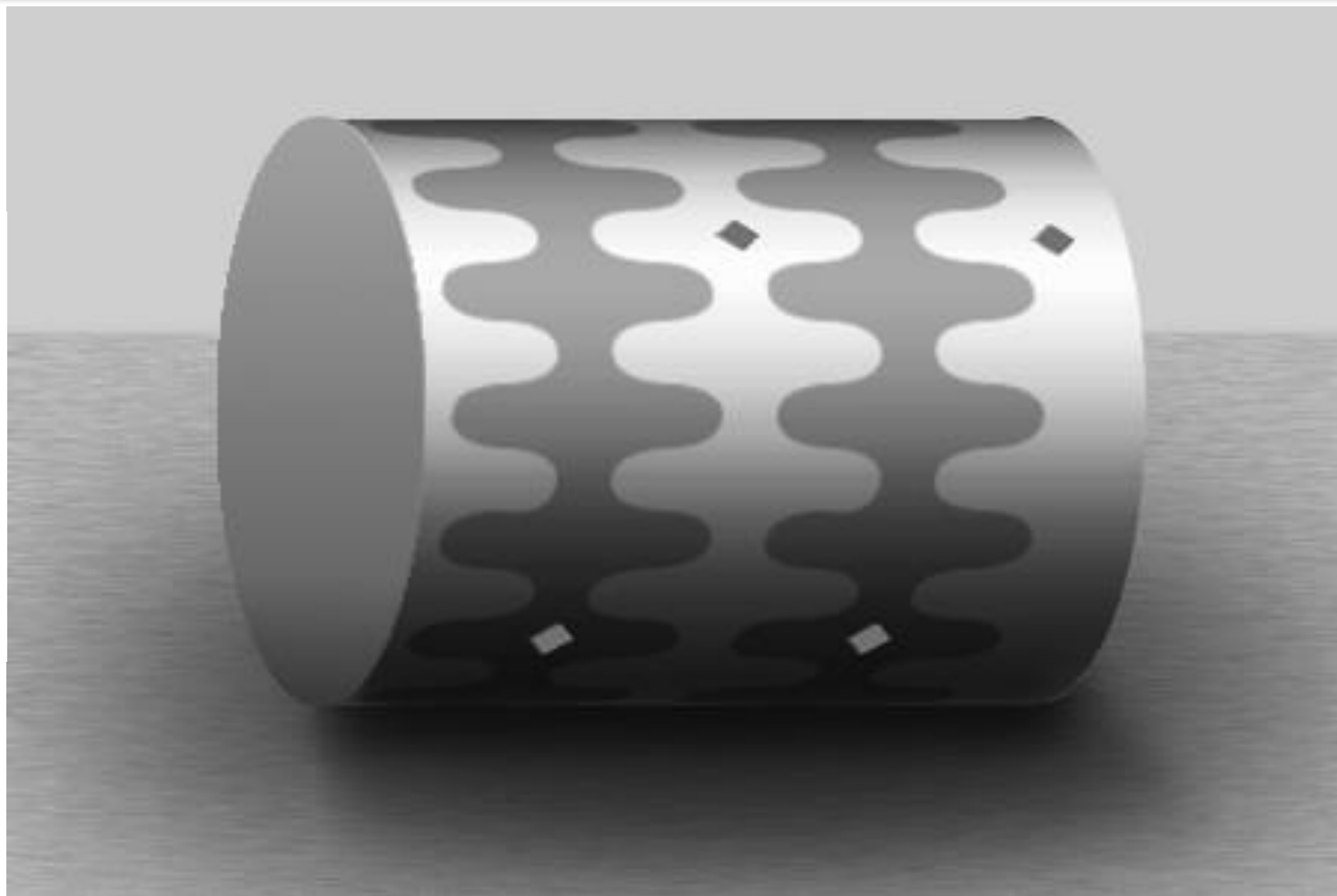


$$Luminance = Reflectance \times Illumination$$

Recovering surface reflectance



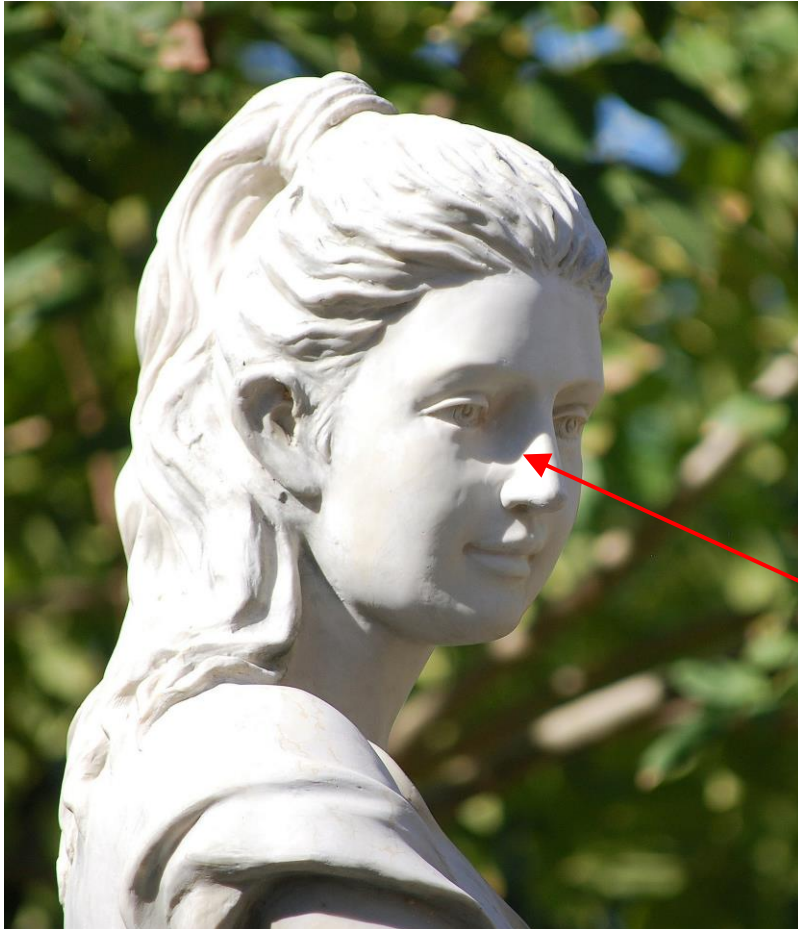
Global shape and context



Recovering surface properties

- Simple approach: assume lighting is blurry/smooth and hard edges are always due to reflectance
 - Some reflectance edges are smooth
 - Some lighting edges are not smooth (textures, corners)
- Even more complicated in practice!
 - Lighting usually isn't uniform
 - Most surfaces aren't matte/Lambertian

Cast shadows



Cast shadow – change in illumination, not change in surface

Specularity

Specular (mirror-like)
reflection



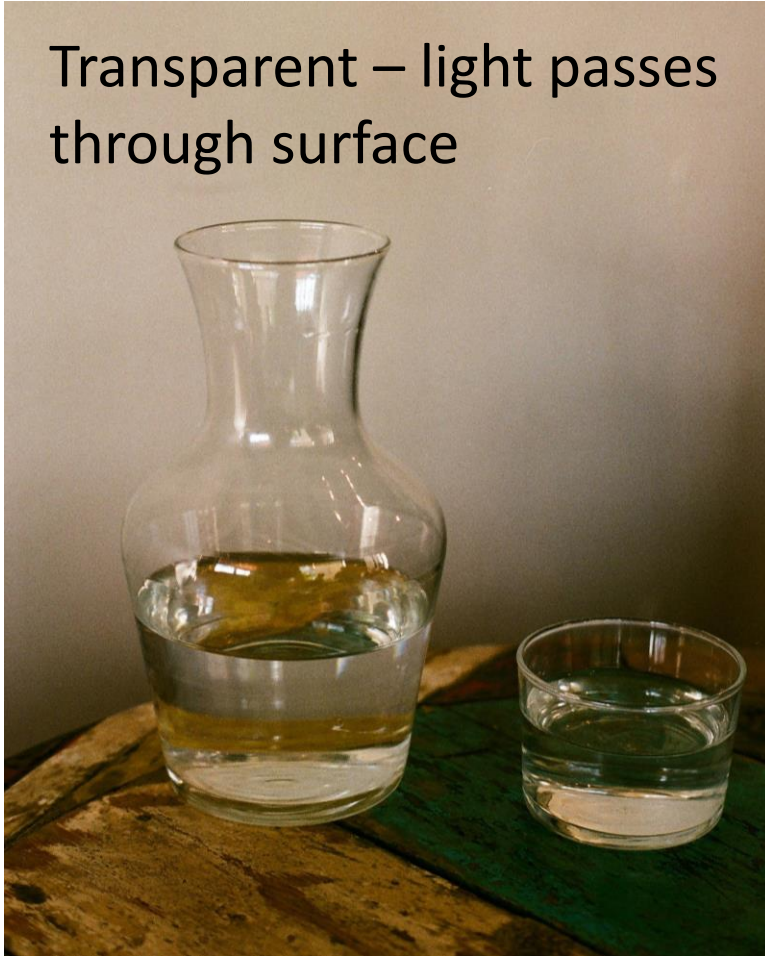
Anisotropy



Anisotropic
reflection
caused by
tiny grooves
in surface

Transparency / translucency

Transparent – light passes through surface



Translucent – light passes through but is scattered



Summary

- Recovering surface shape and reflectance from a single image is difficult
- Generally requires additional assumptions or constraints:
 - Assumptions about surface (e.g., matte, smooth)
 - Shape and/or lighting priors
- Images contain a lot of information, and it's not easy to separate out sources

Application: Photometric stereo

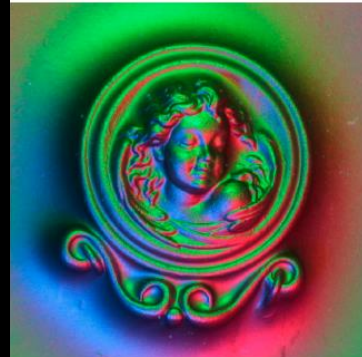
SIGGRAPH 2011 paper

M.K. Johnson, F. Cole, A. Raj, and E.H. Adelson,
Microgeometry Capture using an Elastomeric Sensor,
ACM Transactions on Graphics (Proc. of SIGGRAPH),
Volume 30, Issue 4, Article 46, 2011.

Object



Camera view



Johnson & Adelson (2009)

<https://www.youtube.com/watch?v=ste7l2OvVHs>

Application: Using reflections

Computational Mirrors: Blind Inverse Light Transport by Deep Matrix Factorization

Miika Aittala Prafull Sharma Lukas Murmann Adam B. Yedidia
Gregory W. Wornell William T. Freeman¹ Frédo Durand

Massachusetts Institute of Technology

¹ Google Research



Contains Audio Narration

NeurIPS 2019

<https://www.youtube.com/watch?v=bzsfREU2dDM>

Summary

- Images contain a lot of information, and if you understand the principles of image formation, you can find ways to extract it!