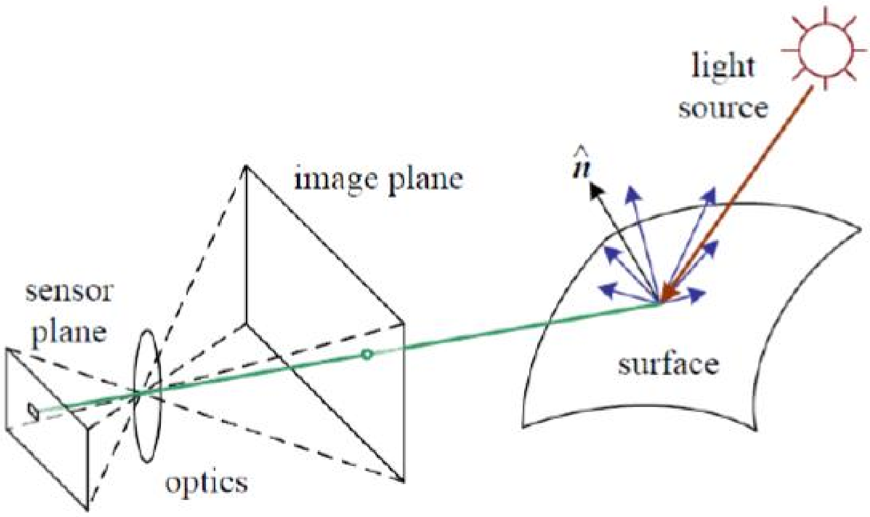
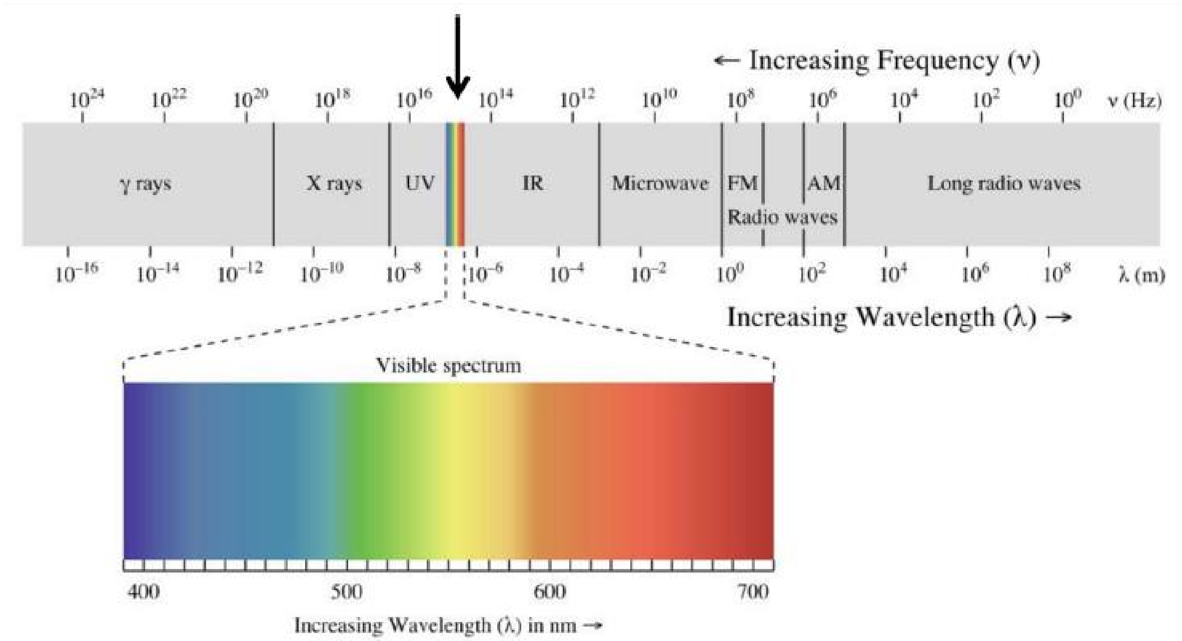
3 - Light, shadow, and edges

Image formation

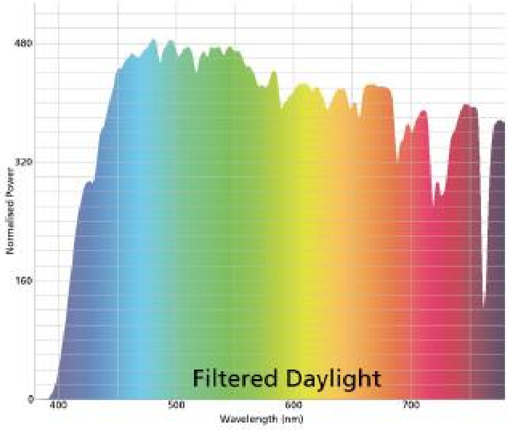


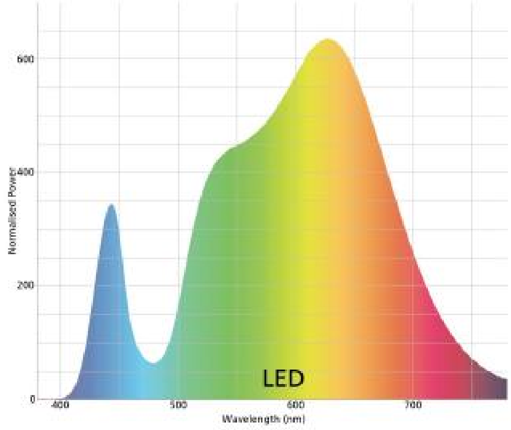
Color

Visible light



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





Perceived colour:

- Human colour perception is based on 3 types of colour-sensitive cells (cones 视锥细胞)
- Standard cameras also have 3 colour sensors, each with a different spectral sensitivity
- Most surfaces reflect a range of wavelengths, but perceived colour is a function of cone response
- Result: Many different spectra appear to be the same colour

Trichromatic colour response

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

Colour representation: Common colour spaces

- RGB (red, green, blue)
  - Most common spaces for digital images
- HSL/HSV (hue (色彩), 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

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

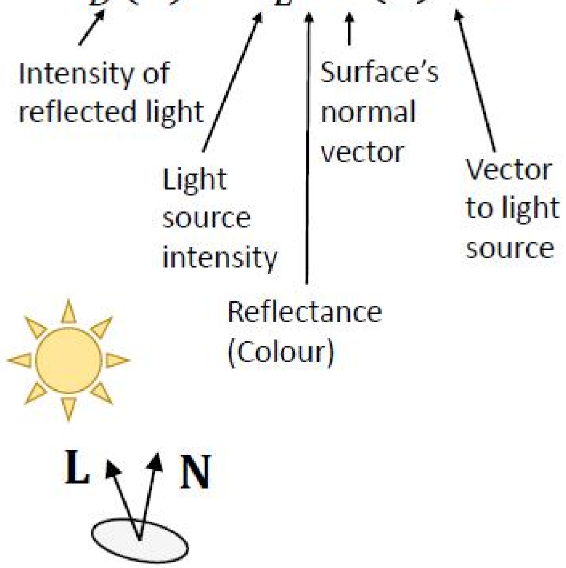
Summary

- 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 L3.1 P22

Diffuse (Lambertian) reflectance

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



Goal of vision: Recover surface colour and normal from reflected light

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

Shape from shading

- Recover 3D shape from 2D image based only on surface brightness (shading)
- Requires additional assumptions, no algorithm works for all cases

Recovering surface reflectance

- Luminance = Reflectance * Illumination

Reflectance from frequency

- Simple approach: assume illumination variation produces low-spatial-frequency changes in image, remove illumination in frequency domain
- $L = R \times I$
- $\ln(L) = \ln(R) + \ln(I)$
- $FT(\ln(L)) = FT(\ln(R)) + FT(\ln(I))$
- Apply a high-pass filter g in the frequency domain
- $Image = e^{FT^{-1}(g \times FT(\ln(L)))}$

- Separating reflectance and illumination in the frequency domain:

Recovering surface properties

- Problems with the simple approach?
  - Some reflectance edges are smooth
  - Some lighting edges are not smooth (texture, corners)
- More sophisticated approaches (e.g., based on partial differential equations) can give better results but have similar problems
- Even more complicated in practice!
  - Lighting usually isn't uniform
  - Most surfaces aren't matte/Lambertian

Examples:

- Cast shadows: Change in illumination, not change in surface
- Specularity (镜面反射): Specular (mirror-like) reflection
- Anisotropy (各向异性): Anisotropic reflection caused by tiny grooves (凹槽) in surface
- Transparency: Light passes through surface
- Translucency (半透明): 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

Edges

Edge detection

Causes of edges

- Surface normal discontinuity
- Depth discontinuity
- Surface discontinuity
- Illumination discontinuity

Characterising edges: change in intensity L3.2 P8-9

- Gradient of a function over x,y:
- $\nabla f = \frac{\partial f}{\partial x}\mathbf{i} + \frac{\partial f}{\partial y}\mathbf{j}$

  $\mathbf{i}$ = unit vector in the x direction
  $\mathbf{j}$ = unit vector in the y direction
- Gradient at a single point (x,y) is a vector:
  - Direction is the direction of maximum slope:
  - $\theta = \tan^{-1}(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x})$
  - Length is the magnitude (steepness) of the slope
  - $\|\nabla f\| = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2}$

Partial derivatives: x->vertical edges y->horizontal edges

Issue: noise L3.2 P13-15

- Smooth (blur) first
- More efficient: Associative property of convolution

Sobel L3.2 P16-18

Canny edge detection L3.2 P21

- Foundational approach to edge detection
- Detect edges based on image gradient, then do additional processing to improve the edge map
- Filter with derivative of Gaussian filters
- Get magnitude, orientation of all the edges
- You really only need two oriented filters (dx and dy)

Non-maximum suppression L3.2 P28

- If nearby pixels claim to be part of the same edge, only keep the one with maximum gradient.

- Bin edges by orientation

- For each edge pixel

    - Check the two neighbour pixels orthogonal to this edge pixel
    - If either neighbour has same edge orientation AND higher magnitude, this pixel is not an edge

Thresholding with hysteresis (滞后) L3.2 P31

Problems: low-contrast edge/shadow

No single threshold will work: use hysteresis

- Two thresholds T1, T2 with T1 > T2
- Strong edges: magnitude > T1
- Weak edges: T1 > magnitude > T2
- For each weak edgy:
    - Check the 8-pixel neighbourhood around this pixel
    - If any neighbour is a strong edge, relabel the weak edge pixel as a strong edge
- Final edge map = strong edges

Summary

- Canny edge detector: commonly used algorithm to detect edges in images
- Defines edges based on image gradient
- Post-processing of gradient to better localise edges (non maximum suppression) and preserve faint/broken edges (thresholding with hysteresis)

Edges for image recognition L3.2 P35

Compression

- Edge = discontinuity
- Efficient way to represent images: only represent points where the signal changes

Invariance

- Edge-based features are invariant or tolerant to many irrelevant image changes

Invariant to X

- Response/representation does not vary with X, is insensitive to changes in X

Tolerant to X

- Response is mostly insensitive to X

Different situations

- Light intensity
    - Image derivative is invariant to intensity shift (I' = I + b)
    - Tolerant to contrast change (I'= aI), but depends on thresholds
- Light direction
    - Nicely tolerant
- Translation

    - Completely invariant
- Rotation
    - Same collection of edges. However not invariant, e.g. horizontal edge become vertical edge.
- Scale
    - Not invariant. Number of edges depend on scale of the image.
    - e.g. Corner in small scale may become edge in large scale.
- 3D rotation / pose
    - Somewhat tolerant. Not invariant.

Image recognition

- To recognize objects across variations in lighting, position, size, pose, etc.
- Learn invariant features and compare them to image
- Learn a separate set of features for each variation (e.g. 8 different rotations) and compare each one to image
- Recognition algorithms often use a mixture of both strategies

Summary

- Edge detection is the first step for most visual processing systems
- Edge based features have desirable properties for visual recognition
    - Compress information
    - Invariant or tolerant to irrelevant changes in the images