

Introduction

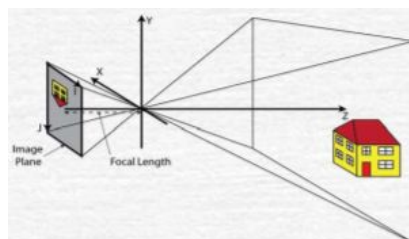
- Computer Vision is about understanding images
 - Greyscale, Colour, Multi-Spectral
 - Snapshots or Video
 - Taken by static or moving cameras
 - Taken of a static or moving scene
 - Taken with a calibrated or un-calibrated camera
- Can drive:
 - **Inspection** - e.g. industrial inspection
 - **Analysis** - e.g. Surveillance/Forensics
 - **Control** - e.g. biometrics, landmine detection, medical imaging
- *“What we experience, apparently directly, is actually very different from what is recorded by our sense organs”*
- Applications: AR, Gaming, AutoDriver, Robot Vision

Learning Goals

- **Understand**
 - **the broad subject of computer vision**
 - **the main algorithmic processes used to manipulate images**
 - **How information may be extracted from images, and the associated problems**
- **Be able to**
 - **Describe the various operations both algorithmically and mathematically**
 - **Code and test basic vision algorithms**
 - **Develop potential solutions to complex vision problems**

Images

- Camera Models
 - Components: a photosensitive image plane, housing and lenses
 - Mathematical model needed - simple pinhole model, distortions need to be considered



- 3D point translated to a 2D image $(x,y,z) \rightarrow (i,j)$

$$\begin{bmatrix} i \cdot w \\ j \cdot w \\ w \end{bmatrix} = \begin{bmatrix} f_i & 0 & c_i \\ 0 & f_j & c_j \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

- W is taken as the Scaling factor in the homogeneous coordinates being used to describe the image points
- F_i and f_j describe the combination of camera focal length and the size of the pixels in the I and J directions respectively

- (c_i, c_j) are the coordinates of the point at which the optical axis intersects the image plane (**optical centre**)
 - Note: this is the perpendicular line from the image plane which extends through the pinhole of the camera
- Digital Images
 - Images are (generally) a 2D projection of a 3D scene
 - Continuous 2D function
 - To process with a computer we need discrete representation
 - Conversion into an $M \times N$ matrix
 - Where each element is given an integer value - i.e. the continuous range (colour spectrum) is split into k intervals (where k is typically 256)
 - **Sampling**
 - Digital images are created with 2D arrays of photosensitive elements with small borders between them - can result in data loss
 - Big issue is that pixels represent an average value (luminance and chrominance) over a discrete area which in the real world could source from a single object, but also multiple objects
 - **Quantisation**
 - Each pixel in a digital image $f(i,j)$ is a function of scene brightness, the brightness values are continuous but need to be quantised
 - Typically the number of brightness levels per channel is $k=2^b$ where b is the number of bits (typically 8)
 - How many bits to use? The more you use the more memory occupied, the less you use the less information in the image
 - **We want enough samples to not waste space and time, and get exactly enough information**
- Colour Images
 - **Luminance only** - simple representation, humans can understand
 - **Colour images** (luminance + chrominance)
 - multiple channels (typically 3)
 - ~16.8 million colours - more complex to process
 - Facilitates more operations
 - **RGB images**
 - Red (700nm), Green (546nm), Blue (436nm)
 - Colours are combined on viewing
 - RGB \rightarrow GreyScale
 - **$Y = 0.299R + 0.587G + 0.114B$**
 - Camera photosensitive elements
 - Separate for red green blue - sometimes sensitive to all

- Bayer pattern
- **CMY Images**
 - Cyan-Magenta-Yellow
 - Secondary colours, subtractive scheme
 - **$C = 255 - R$**
 - **$M = 255 - G$**
 - **$Y = 255 - B$**
- **YUV**
 - Previously used for analogue tv signals
 - Conversion from RGB
 - **$Y = 0.299R + 0.587G + 0.114B$**
 - **$U = 0.492 * (B-Y)$**
 - **$V = 0.877 * (R-Y)$**
- **HLS**
 - Hue, luminance, saturation
 - Separation of luminance and chrominance
 - Hue = 0...360 (circular)
 - Luminance = 0...1
 - Saturation = 0...1

$$V_{max} \leftarrow \max(R, G, B)$$

$$V_{min} \leftarrow \min(R, G, B)$$

$$L \leftarrow \frac{V_{max} + V_{min}}{2}$$

$$S \leftarrow \begin{cases} \frac{V_{max} - V_{min}}{V_{max} + V_{min}} & \text{if } L < 0.5 \\ \frac{V_{max} - V_{min}}{2 - (V_{max} + V_{min})} & \text{if } L \geq 0.5 \end{cases}$$

$$H \leftarrow \begin{cases} 60(G - B)/(V_{max} - V_{min}) & \text{if } V_{max} = R \\ 120 + 60(B - R)/(V_{max} - V_{min}) & \text{if } V_{max} = G \\ 240 + 60(R - G)/(V_{max} - V_{min}) & \text{if } V_{max} = B \end{cases}$$

- Noise

- Affects most images, degrades them, interferes with processing
- Measuring noise
 - Signal to Noise ratio

$$S/N \text{ ratio} = \frac{\sum_{(i,j)} f^2(i,j)}{\sum_{(i,j)} v^2(i,j)}$$

- Types of noise:
 - Gaussian
 - Good approximation to real noise - distribution is Gaussian (has mean and std. dev.)
 - Salt and Pepper
 - Impulse noise - noise is maximum or minimum values

- Smoothing

- Removing or reducing noise

- Linear smoothing transformations
 - Image averaging - average on n images (**assumes static camera & scene, statistical independence**)
 - Local averaging and Gaussian smoothing
 - Filtering / Convolution
 - Linear transformation
 - Convolution mask
 - Non-linear: some logical operation performed on a local region
 - Averaging filters
 - Local neighbourhood
 - Different masks available: local average, gaussian

$$h = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$h = \frac{1}{10} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$f(i,j) = \sum_{(m,n) \in O} h(i-m, j-n) \cdot g(m,n) \quad h = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

- How to determine acceptable results: Size of noise, blurring of edges
- **Issues with smoothing: blurring sharp edges, quality degradation?**

- Non-Linear Transformations

- Rotating mask
 - Define a number of masks/regions
 - Mask size and shape
 - Use the average of one of the masks - which? **Most homogeneous**
 - Algorithm
 - For each point: calculate dispersions, assign output point average of mask with minimum dispersion

$$\sigma^2 = \frac{1}{n} \sum_{(i,j) \in R} \left[g(i,j) - \frac{1}{n} \sum_{(i',j') \in R} g(i',j') \right]^2$$

- Iterative application: Convergence; Effects of mask size
- Effects: **noise suppression and image sharpening**
- Median filter
 - Use the median value, not affected by noise (ignores average)
 - **Doesnt blur edges and can be applied iteratively**
 - Damages thin lines and sharp corners (can change shape to mitigate this)
 - Computationally expensive
- Bilateral filter

- Weight local pixels
 - Distance from centre
 - Difference in colour/intensity space

$$f(i, j) = \frac{1}{W_p} \sum_{(m, n) \in \Omega} g(m, n) f_R(\|g(m, n) - f(i, j)\|) f_S\left(\sqrt{(m-i)^2 + (n-j)^2}\right)$$

$$W_p = \sum_{(m, n) \in \Omega} f_R(\|g(m, n) - f(i, j)\|) f_S\left(\sqrt{(m-i)^2 + (n-j)^2}\right)$$

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- Preserves edges
- **Causes staircase effect, introduction of false edges**

- Image Pyramids

- Process images at multiple scales efficiently
- Technique
 - Smooth image (regularly gaussian)
 - Sub-sample (usually by a factor of 2)