

Image Processing and Computer Vision - Notes

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1 Image Acquisition

Proposition 1.1 - Common Challenges with Image Acquisition

Below are some common challenges that are faced/produced by image acquisition

Viewpoint Variation	Several images may be taken of the same object but will vary the angle
Illumination	Images may be taken in low/high light
Occlusion	Object may be partly obscured
Scale	Objects may look vary different when placed next to other objects due to their relative scale
Deformation	Objects may have slight variations on the perfect form
Background Clutter	Lots happening behind an object may work to obscure it
Object Intra-Class Variation	Some objects in the same class can vary a lot in shape (<i>e.g.</i> chairs)
Local Ambiguity	Certain regions of an image can be missinturpred without the rest of the scene being accounted for
World Behind the Image	Depth may need to be accounted for to make sense of an image.

Definition 1.1 - Dirac Delta-Function, δ

The *Dirac Delta-Function* is used to map continuous distributions to discrete distributions by sampling at particular intervals. Intuitively

$$\delta(t) = \begin{cases} 1 & , t = 0 \\ 0 & , t \neq 0 \end{cases} \implies \delta(t - \alpha) = \begin{cases} 1 & , t = \alpha \\ 0 & , t \neq \alpha \end{cases}$$

Definition 1.2 - Sifting Property

We can apply the *Dirac Delta-Function* to a function to sample a particular value

$$\int_{-\infty}^{\infty} f(t)\delta(t)dt = f(0) \implies \int_{-\infty}^{\infty} f(t)\delta(t - \alpha)dt = f(\alpha)$$

This can be applied to 2D objects (such as images) as

$$\int_{-\infty}^{\infty} f(a,b)\delta(a - x, b - y)dadb = f(x, y)$$

Definition 1.3 - Point Spread-Function

A *Point Spread-Function* is applied after sampling an image. It takes the value of a pixel & transforms pixels around it using this value in some way.

e.g.  (Should be a white dot on black background but ink).

2 Image Representation

Definition 2.1 - Colour Space

Colour Space are different techniques for representing colours. These are generally made up of 3D vectors.

Colour Space	Vector Description
RGB	(Red $\in [0, 255]$, Green $\in [0, 255]$, Blue $\in [0, 255]$)
HSI	(Hue $\in [0, 360]$, Saturation $\in [0, 1]$, Intensity $\in [0, 1]$) Hue gives the colour in degrees
YUV	(Brightness $\in [0, 255]$, Blue Projection $\in [0, 255]$, Red Projection $\in [0, 255]$)
La*b*	(Luminance $\in [0, 100]$, Red/Green $\in \{-a, +b\}$, Blue/Yellow $\in \{+b, -b\}$)

Remark 2.1 - Representing Video

To represent video each fixel is given a third parameter, *time* so we now have

$$f(x, y, t) \mapsto (R, G, B)$$

or any other *Colour Space*.

Definition 2.2 - Quantisation

Quantisation is representing a continuous single channel function with discrete single channel function that groups the continuous values into a set number of levels.

Example 2.1 - Quantisation

16 levels



6 levels



2 levels

Definition 2.3 - Aliasing

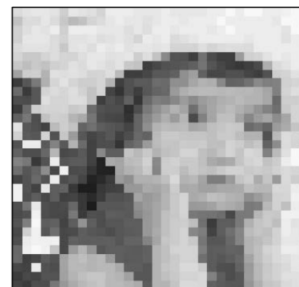
Aliasing is the result of sparse sampling since single pixels represent to large an area to get any detail out of it.

Example 2.2 - Aliasing

256 x 256



64x64



32x32

Definition 2.4 - Anti-Aliasing

Anti-Aliasing is the process for avoiding *Aliasing*. This can be achieved by using a sampling rate which is a critical limit defined by the *Shannon-Nyquist Theorem*.

Theorem 2.1 - Shannon-Nyquist Theorem

An analogue signal with maximum frequency x Hz may be completely reconstructed if regular samples are taken with frequency $2x$ Hz.

Definition 2.5 - Convolution

Convolution is an operation which takes two functions & produces a third which describes how the shape of one of the two functions is changed by the other.

For functions f & g

$$(f * g)(x) := \int_{-\infty}^{\infty} f(x - t)h(x)\partial t$$

N.B. $*$ is the symbol for convolution.

Remark 2.2 - Convolution in Image Representation

Suppose you have a system, represented by kernel $g(x)$, & an input signal, represented by $f(x)$. Then $f * g(x)$ describes the effect of the system on the input signal. The resulting image is called the *Response of f to the kernel h* .

Proposition 2.1 - 2D Discrete Convolution

Since images are represented by discrete 2D functions $f : \mathbb{N} \times \mathbb{N} \rightarrow (\mathbb{N} \times \mathbb{N} \times \mathbb{N})$ it is pertinent to understand *2D Discrete Convolution*.

$$h(x, y) = \sum_{i \in I} \sum_{j \in J} f(x - i, y - j)g(i, j)$$

Often the kernel, $g(x, y)$, has negative indices so the pixel being acted upto is equivalent to the middle pixel in the matrix representation of $g(x, y)$.

N.B. A convolution whose kernel is symmetric on 180 degree rotation is called a *Correlation*.

Example 2.3 - 2D Discrete Convolution

Below is a representation of a grayscale image, $f(x, y)$, on the left & a kernel $g(x, y)$ on the

		$y-1$	y	$y+1$		
$x-1$		43	12	61		
x		44	45	60		
$x+1$		43	50	61		

	-1	0	1
-1	-1	0	1
0	-2	0	2
1	-1	0	1

right.

$$(f * g)(x, y) = f(x+1, y+1)g(-1, -1) + f(x+1, y)g(0-1, 0) + \dots + f(x-1, y-1)g(1, 1) = -68.$$

Example 2.4 - Kernels

Kernels can be defined with specific outcomes in mind.

Operation	Matrix
Identity	$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$
Edge Detection	$\begin{pmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{pmatrix}$ $\begin{pmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 1 \end{pmatrix}$ $\begin{pmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{pmatrix}$
Sharpen	$\begin{pmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{pmatrix}$
Box Blur	$\frac{1}{9} \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$
Gaussian Blur 3×3	$\frac{1}{16} \begin{pmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{pmatrix}$

Gaussian Blur 5×5	$\frac{1}{256} \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{pmatrix}$
Unsharp Masking 5×5	$\frac{-1}{256} \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{pmatrix}$

3 Frequency Domains & Image Transforms

Definition 3.1 - Image Transform

An *Image Transform* is deriving a new representation of the input data by encoding the image using another parameter space (e.g. Fourier, DCT, Wavelet, etc.).

Remark 3.1 - Purpose of Image Transforms

Image Transforms can be used in

- i) Image Filtering;
- ii) Image Compression;
- iii) Feature Extraction;
- iv) etc.

Definition 3.2 - Properties of a Signal

A *Signal* is a sinusoidal function over continuous time. They have the following properties

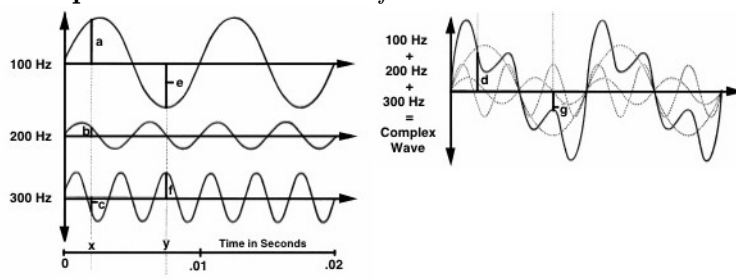
- i) Frequency - Number of cycles per second, Hz;
- ii) Period - Length of a cycle, s;
- iii) Amplitude - Peak intensity of the signal;
- iv) Phase - The shift of the trig wave from its default position, π .

Theorem 3.1 - Fourier's Theorem

All periodic functions over continuous time can be expressed as a sum of sin & cos terms, each with their own amplitude & shift.

$$f(t) = a_0 \sin(t + \theta_0) + a_1 \cos(t + \theta_1) + \dots$$

Example 3.1 - Fourier Transform



Proposition 3.1 - Frequency in Images

Frequency in Images is measured as the rate of change in intensity along a given line on the image.

Remark 3.2 - Fourier Transform on Frequency in Images

If we read the intensity values along a single row or column we can produce a sinusoidal wave which generalises the distribution & then perform a *Fourier Transform*.

Definition 3.3 - 2D Discrete-Space Fourier Transform

Images can be considered as 2-Dimensional discrete space. Let $f(x, y)$ be the intensity of the pixel at position (x, y) . 2D Discrete-Space Fourier Transforms have two variables: $u \in [-\pi, \pi)$ for the vertical frequency; and, $v \in [-\pi, \pi)$ for the horizontal frequency.

$$\begin{aligned} \underbrace{F(u, v)}_{\text{Fourier Space}} &= \sum_{y=0}^{m-1} \sum_{x=0}^{n-1} f(x, y) e^{i(ux+vy)} \\ &= \sum_{y=0}^{m-1} \sum_{x=0}^{n-1} f(x, y) [\cos(ux + vy) + i \sin(ux + vy)] \end{aligned}$$

N.B. $F(u, v)$ is a complex number.

Proposition 3.2 - Interpretations of 2D Fourier Transform

Since $F(u, v)$ is a complex number we cannot plot it exactly. Thus we consider

i) Magnitude, $|F(u, v)| := \sqrt{F_r(u, v)^2 + F_i(u, v)^2}$, and

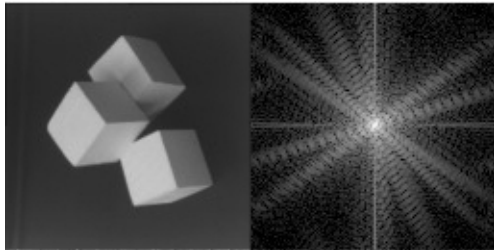
ii) Phase Angles, $\theta(u, v) := \tan^{-1} \left(\frac{F_i(u, v)}{F_r(u, v)} \right)$

Remark 3.3 - Expressing $F(u, v)$ in Polar Coordinates

$$F(u, v) = |F(u, v)| e^{i\theta(u, v)}$$

Remark 3.4 - Plotting Magnitude, $|F(u, v)|$

On the left we have a gray scale image & on the right we have the magnitude of a fourier transform on this image. On the right hand image the y -axis is $u \in [-\pi, \pi)$ and the x -axis is $v \in [-\pi, \pi)$. We see lots of straight lines since a linear transformation on $F(u, v) = F(au, av) \forall a \in \mathbb{R}$. Each line can be interpreted as the frequency of intensity for lines in the left hand image which are parallel to it.

**Theorem 3.2 - Convolution Theorem**

Let f be an image, g be a kernel, F be the result of a fourier transform on f and G be a kernel. Then

$$h = f * g \iff H = FG$$

Proof 3.1 - Convolution Theorem

$$\begin{aligned}
h(x) &= f(x) * g(x) \\
&= \sum_y f(x-y)g(y) \\
H(u) &= \sum_x \left(\sum_y f(x-y)g(y) \right) e^{iux} \\
&= \sum_x g(y) \sum_x f(x-y) e^{iux} \\
&= \sum_y g(y) (F(u) e^{iuy}) \\
&= \sum_y g(y) e^{iuy} F(u) \\
&= G(u) \cdot F(u) \\
&= F(u) \cdot G(u)
\end{aligned}$$

Definition 3.4 - Butterworth's Low Pass Filter

Butterworth's Low Pass Filter is a *Signal Processing Filter* designed to have a frequency response which is as flat as possible. It appears to soften an image

$$H(u, v) = \frac{1}{1 + \left(\frac{r(u, v)}{r_0} \right)^{2n}} \text{ of order } n$$

Definition 3.5 - Butterworth's High Pass Filter

Butterworth's High Pass Filter is a *Signal Processing Filter* designed to have a frequency response which is as flat as possible. It appears to sharpen an image

$$H(u, v) = \frac{1}{1 + \left(\frac{r_0}{r(u, v)} \right)^{2n}} \text{ of order } n$$

4 Edges & Shapes

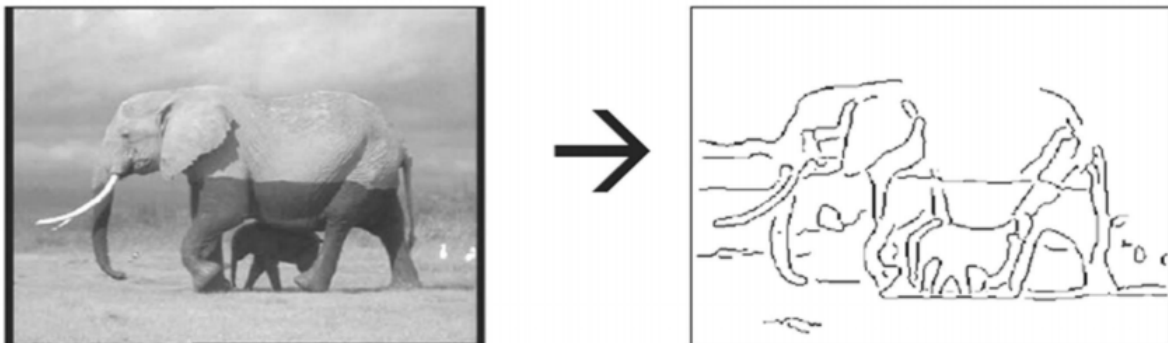
4.1 Edge Detection

Remark 4.1 - Edges are Useful

Edges are one of the best features to identify an object with. This *Edge-Detection* is a useful thing to be able to do.

Definition 4.1 - Edge

An *Edge* is a sharp change in image brightness. Edges are produced by object boundaries, patterns & shadows, this can lead to us finding *Nuisance Edges* which do not help achieve our goal.

Example 4.1 - Edge Detection**Remark 4.2 - Uses of Edges**

Edges are used for

- i) Segmentation - Finding object boundaries;
- ii) Recognition - Extracting patterns;
- iii) Motion Analysis - Finding reliable tracking regions.

Remark 4.3 - Edge Detection Strategy

In order to find edges we want to determine the *rate of change* in a pixel's neighbourhood

Definition 4.2 - Image Gradient

Image Gradient is a vector which gives the direction of greatest change in intensity at a specific pixel. For a pixel at (x, y) with $f : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$ mapping to the intensity the *Image Gradient* is

$$\nabla f(x, y) := \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix}$$

N.B. Generally denoted by Ψ .

Definition 4.3 - Angle of Gradient

$$\Psi := \tan^{-1} \left(\frac{\partial f / \partial y}{\partial f / \partial x} \right)$$

Definition 4.4 - Edge Direction

Edge Direction for a specific pixel is the direction of an edge, it is perpendicular/orthogonal to the *Image Gradient*.

N.B. Generally denoted by Φ .

$$\Phi := \Psi - \frac{\pi}{2} = \tan^{-1} \left(\frac{\partial f / \partial y}{\partial f / \partial x} \right) - \frac{\pi}{2}$$

Definition 4.5 - Image Gradient Magnitude

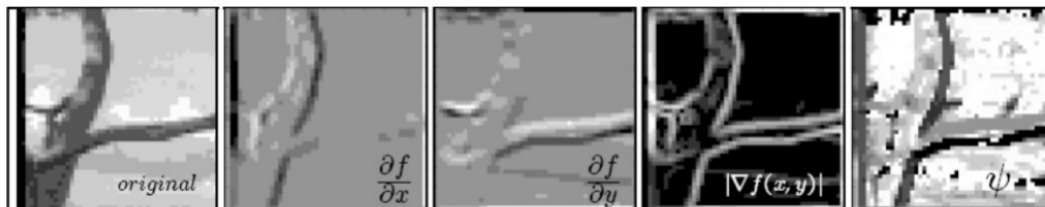
Magnitude measures the magnitude of the growth.

$$|\nabla f(x, y)| := \sqrt{\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2}$$

Proposition 4.1 - Estimating ∇f

We can define $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$ to be matrices, rather than typical derivatives, in order to produce estimates for the *Image Gradient* which can be used to analyse an image by convolution. We can then combine the results in order to analyse *Image Gradient Angle* and *Magnitude*. Consider

$$\frac{\partial f}{\partial x} = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix} \text{ and } \frac{\partial f}{\partial y} = \begin{pmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}$$

**Definition 4.6 - Prewitt Operator**

Prewitt Operators are a set of 3×3 kernels used for estimating the *Image Gradient*. There are 8 *Prewitt Operators*, each in a different direction

$\begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{pmatrix}$	$\begin{pmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{pmatrix}$	$\begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix}$	$\begin{pmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{pmatrix}$
$\begin{pmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 0 & -1 & -1 \\ 1 & 0 & -1 \\ 1 & 1 & 0 \end{pmatrix}$	$\begin{pmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{pmatrix}$	$\begin{pmatrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{pmatrix}$

Remark 4.4 - *Alternative estimates of ∇f*

Instead of weighting all pixels in a given direction equally, we may want to weight central ones more heavily. This is since the central pixels are geometrically closer to the pixel which is being acted upon & such should better describe it.

$$\frac{\partial f}{\partial x} = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \quad \frac{\partial f}{\partial y} = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}$$

N.B. This is called the *Sobel Filter*.

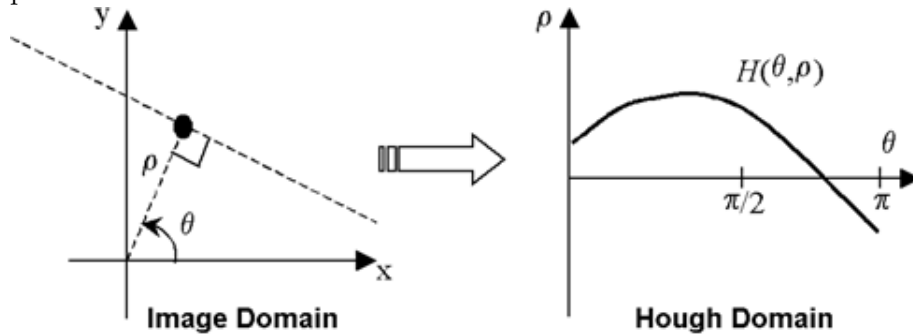
4.2 Shapes

Definition 4.7 - *Hough Transform*

A *Hough Transform* is used to find lines which best explain the set of edge points given to it.

Hough Transforms are centred around the premise that lines can be described by $\rho = x \cos \theta + y \sin \theta$ where either (x, y) is fixed, or (ρ, θ) is fixed.

Suppose we are given an edge point (x_0, y_0) , we are now dealing with the case where (ρ, θ) are variable. Plot all the combinations of (ρ, θ) than produce lines which pass through (x_0, y_0) produces a sinusoidal wave.



Proposition 4.2 - *Line Detection Algorithm*

Below is an algorithm which uses the *Hough Transform* on a set of edge points in order to detect lines in an image

- i) Make available an $n = 2$ dimensional array, $H(\rho, \theta)$, to be used for the parameter space;
- ii) Find the *Gradient Image*, $G(x, y)$;
- iii) For any pixel (x_0, y_0) where $|G(x_0, y_0)| > T_s$ (some threshold value) increment all values of $H(\rho, \theta)$ where (ρ, θ) satisfy $\rho = x_0 \cos \theta_0 + y_0 \sin \theta_0$.

$$\forall \rho, \theta \text{ where } \rho = x_0 \cos \theta_0 + y_0 \sin \theta_0 \text{ do } H(\rho, \theta) + 1$$

- iv) Any (ρ, θ) where $H(\rho, \theta) \geq T_h$ (another threshold value) represent a straight line which has been detected in the image.

Proposition 4.3 - *Circle Detection Algorithm*

- i) Make available an $n = 3$ dimensional array, $H(x, y, r)$, to be used for the parameter space;

- ii) Find the *Gradient Image*, $G(x, y)$;
- iii) For any pixel (x_0, y_0) where $|G(x_0, y_0)| > T_s$ increment all $H(x, y, r)$ which satisfy

$$\forall r \text{ where } x_0 = x + r \cos \Phi \text{ and } y_0 = y + r \sin \Phi$$

- iv) Any (x, y, r) where $H(x, y, r) > T_h$ represents a circle with radius r and centre (x_0, y_0)

Definition 4.8 - General Hough Transform

A *General Hough Transform* is used to describe general shapes.

- i) Find the *Gradient Image*, $G(x, y)$.
- ii) Define a set of points $\phi_i := \frac{p_i}{i}$ for $i \in [1, k]$ and create a table using ϕ_1, \dots, ϕ_k as indexes.
- iii) Define a reference point (x_c, y_c) to act as a *centre of mass*.
- iv) For any given edge point (x_0, y_0) find

$$r = \sqrt{(x_0 - x_c)^2 + (y_0 - y_c)^2}, \beta = \tan^{-1} \left(\frac{y_0 - y_c}{x_0 - x_c} \right) \text{ and } \Phi_{(x_0, y_0)} \text{ in } G(x, y)$$

- v) Round $\Phi_{(x_0, y_0)}$ to the nearest ϕ_i and insert (r, β) into the table at ϕ_i

Proposition 4.4 - General Shape Detection Algorithm

- i) Prepare 2 dimensional array $H(x_c, y_c)$ for the parameter space (Set of all possible centre of masses).
- ii) $\forall (x_0, y_0)$ where $|G(x_0, y_0)| > T_s$ find the table entry, ϕ_i , closest to $\Phi_{(x_0, y_0)}$.
- iii) $\forall (r_j, \beta_j)$ in the table entry find

$$x_c = x + r \cos \beta \text{ and } y_c = y + r \sin \beta$$

Increment $H(x_c, y_c)$.

- iv) All (x_c, y_c) where $H(x_c, y_c) > T_h$ represents the locations of centre of masses for occurrences of the shape, in the image.

Remark 4.5 - Issues with Proposition 4.4

The algorithm defined in **Proposition 4.4** only detects shapes of the same *scale* and *orientation* as the original image. To counter this we introduce two new variables to the parameter space: S , a scaling factor; and, θ , an orientation factor.

- i) Prepare 4 dimensional array $H(x_c, y_c, S, \theta)$ for the parameter space (Set of all possible centre of masses, scales & orientations).
- ii) $\forall (x_0, y_0)$ where $|G(x_0, y_0)| > T_s$ find the table entry, ϕ_i , closest to $\Phi_{(x_0, y_0)}$.
- iii) $\forall (r_j, \beta_j)$ in the table entry find

$$x_c = x + rS \cos(\beta + \theta) \text{ and } y_c = y + rS \sin(\beta + \theta)$$

Increment $H(x_c, y_c, S, \theta)$.

- iv) All (x_c, y_c) where $H(x_c, y_c, S, \theta) > T_h$ represents the locations of centre of masses, scaling factors & orientations for occurrences of the shape in the image.

5 Image Segmentation

Definition 5.1 - Image Segmentation

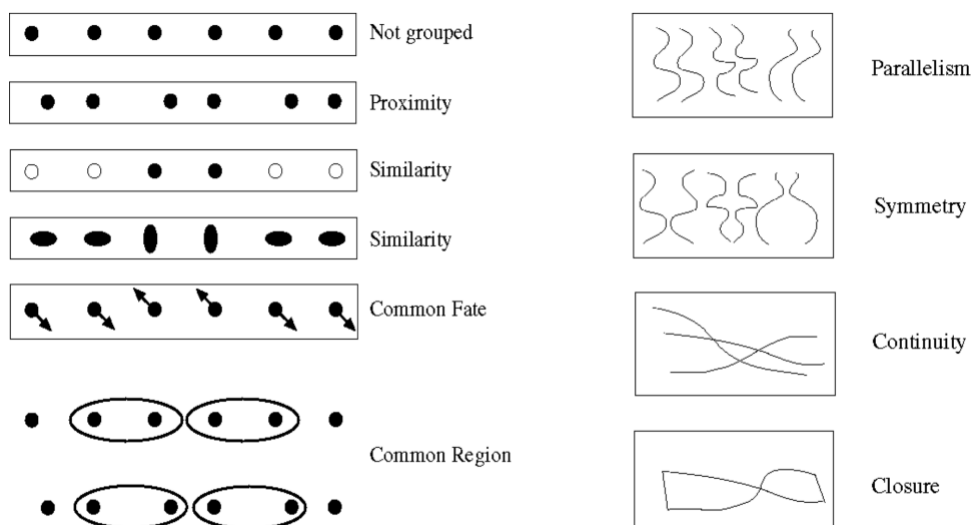
Image Segmentation is the process of partitioning the pixels in an image into homogenous regions. This may wrt colour, texture, object.

Remark 5.1 - Usefulness of Image Segmentation

Image Segmentation is useful since it simplifies an image from millions of pixels into a few regions making computation much easier.

Definition 5.2 - Gestalt Rules for Grouping & Segmentation

It is useful to consider the different ways in which we can group objects.



Remark 5.2 - Perfect Image Segmentation is hard

It is hard to achieve perfect *Image Segmentation* since pixels may straddle the boundary of objects & thus not truly belong to any object. Noise, non-uniform illumination, occlusions etc. will also cause problems.

Definition 5.3 - Over-Segmentation

Over-Segmentation is when an image is segmented into too many regions & loses the efficiencies gained by the simplification of *Image Segmentation*.

Example 5.1 - Over-Segmentation



Definition 5.4 - Under-Segmentation

Under-Segmentation is when an image is segmented into too few regions & too much information is lost.

Example 5.2 - Under-Segmentation



Proposition 5.1 - Segmentation Technique Types

There are several groups of techniques that can be used for *Image Segmentation*

- i) Thresholding. Categorise pixels wrt intensity.
- ii) Edge-Based. Region boundaries are produced using an edge map.
- iii) Region-Based. Regions are grown from seed pixels or using split-merge techniques.
- iv) Clustering & Statistical. Global partitioning, often based around histograms. (*e.g.* K-means).
- v) Topographic (OUT OF SCOPE). Stepwise simplifications that take spatially wider image configurations into account.

Proposition 5.2 - Thresholding Image Segmentation

Thresholding is a good technique when trying to distinguish dark objects(background) from bright objects (foreground). One possible algorithm is

- i) Choose a threshold value T .
- ii) For each pixel:
 - (a) If the brightness is less than T map to 0 (black).
 - (b) else, map to 255 (white).

Remark 5.3 - Choosing Threshold Value

Choosing a value for *Thresholding* is important since if it is too high then the background pixels are classified as the foreground. And visa-versa for too low.

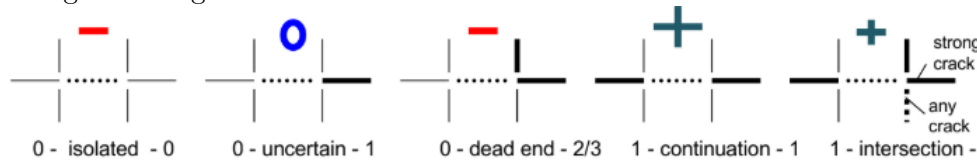
Proposition 5.3 - Choosing Threshold Value

There are several techniques used for choosing *Threshold Value*. By consider the histogram of an image's intensity we can produce regions for classification.

- i) Make an initial estimate for threshold T .
- ii) Segment the image using T : Let G_1 be the pixels with intensity $> T$; and G_2 be the pixels with intensity $< T$.
- iii) Compute the average intensity values m_1 & m_2 for G_1 & G_2 respectively.
- iv) Compute a new threshold value $T = \frac{1}{2}(m_1 + m_2)$.
- v) Repeat **ii)-iv)** until convergence.

Proposition 5.4 - Edge-Based Segmentation

When performing *Edge-Based Image Segmentation* we want to detect strong edges that are relevant to the object we wish to detect. There are several techniques for assessing the strength of an edge, but generally we wish to remove edges that are isolated or irrelevant to an object. One valid technique is edge relaxation where we change the strength of an edge depending upon its 6 neighbour edges.

**Proposition 5.5 - Region Growing-Seed Pixel**

A function is required to analyse the homogeneity of two pixels $(s, p) \rightarrow \{0, 1\}$.

- i) Choose an initial seed pixel;
- ii) Consider the neighbouring pixels:
 - (a) If it is close to seed pixel, add to region & to queue to be analysed.
 - (b) Else, do nothing with it.
- iii) Repeat ii) until there are no pixels left in the queue to be analysed.

N.B. You may wish to add a final step to remove small regions.

Proposition 5.6 - Split & Merge Segmentation

Let H be a function to analyse the homogeneity of a region $(R) \rightarrow \{0, 1\}$

- i) Let R_0 represent the entire image.
- ii) If $H(R_i) = 0$ (*i.e.* is inhomogenous) then split it into four regions.
- iii) Repeat ii) until all regions are homogenous.
- iv) Merge all subregions that satisfy $H(R_i \cup R_j) = 1$ (*i.e.* are homogeneous)

Proposition 5.7 - Clustering Segmentation

If we map the RGB values of an image into the 3D real space we can use clustering algorithms to produce k clusters. We then map back to the pixel space using each cluster as a segment.

N.B. Look at k-means clustering.

6 Classical Object Detection

Remark 6.1 - Classical Object Detection

In this course we only cover *Classical Object Detection*. This technique came to prominence with the 2001 paper *First Real-Time Detection Method: Viola & Jones' - 2001* and was the industry standard for 10+ years. Now there are methods which use deep learning techniques.

Definition 6.1 - Object Detection

Object Detection bridges the semantic gap between pixel values & meaningful objects by grouping pixels and classifying. This is a difficult problem.

Remark 6.2 - Failings of Shape Detection for Object Detection

Typically using classical *Shape Detection & Segmentation* does not work for real world applications of *Object Detection* due

- i) High Intra-Class & Low Inter-Class variance;
- ii) Classes are rarely well defined;
- iii) Variations in illumination, scale, pose, deformation, occlusion etc.

Remark 6.3 - Shift-Scale Invariance

We require *Object Detection* algorithms to be shift & scale invariant so it can detect objects of any size at any point in the image.

Definition 6.2 - Sliding Window Detectors

Sliding Window Detectors ensure shift & scale invariance by setting a minimum size to check (say 20×20 px) and shifts the region it checks by 1px right-to-left, top-to-bottom until the whole is checked. They then increase the size of the region it checks (say 10%) and repeats the shifting. It does this until the size of the region it checks exceeds the size of the image.

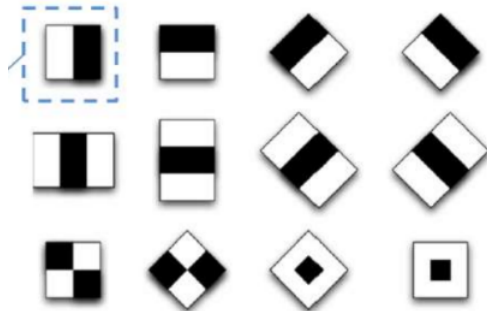
N.B. This technique does not work in real-time due to its high computation complexity.

Definition 6.3 - Haar-Like Features

Haar-Like Features are features of digital images used in *Object Detection*. They define a set of adjacent rectangles and assigns them to either be *light* or *dark* regions. It then returns a value, the average gray value of the light region less the average gray value of the dark region. This value is then compared to a threshold value to determine whether the feature occurs in the image.

Proposition 6.1 - Haar-Like Feature Types

There are a finite set of *Haar-Like Features Types*



Definition 6.4 - Image Integral

The *Integral* of an image I is the image J where $J(x, y) = \sum_{i=0}^x \sum_{j=0}^y I(i, j)$. *i.e.* Each pixel value is the sum of all pixels between it and the origin, inclusive.

Proposition 6.2 - Calculating Image Integral

Let I be an image then we can calculate the *Integral* of J in *Linear Time* using the following formulae

$$\begin{aligned}
 A(x, -1) &= 0 \\
 A(x, y) &= A(x, y - 1) + I(x, y) \\
 J(-1, y) &= 0 \\
 J(x, y) &= J(x - 1, y) + A(x, y)
 \end{aligned}$$

Theorem 6.1 - Integration Rule of Convolution

Proposition 6.3 - Calculating the Average Pixel Value of a Large Block

Calculating the average pixel value of a large block can be very slow if the region is very large. Here is a technique that can do it by only querying 4 values.

- i) Create a matrix which is the same size as the image.

- ii) Encode the matrix st its values are 1 in the region we want to check & 0 everywhere else.
- iii) Double Differentiate this matrix to produce I''

(a) First, horizontally by applying $\begin{pmatrix} 0 & -1 & 1 \end{pmatrix}$ to every pixel.

(b) Then, vertically by applying $\begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix}$ to every pixel.

This leaves us with four non-zeros values (two 1s and two -1 s).⁷

- iv) Calculate the image integral J .

v) Return $\sum_i \sum_j I''(i, j) \times J(i, j)$

N.B. This can be simplified to just be the four non-zero terms in I'' .

Proposition 6.4 - Training Data

Two categories of *Training Data* should be provided: *Positive Samples*, images of the object you wish to classify' and, *Negative Samples*, images which do not contain the object. These should be labeled (x_i, y_i) with $y_i = 0, 1$ for *Negative* and *Positive Samples* respectively.

Definition 6.5 - Adaboost

Adaboost (Short for *Adaptive Boosting*) is a machine learning algorithm.

Let $(x_1, y_1), \dots, (x_n, y_n)$ with $y_i = 0, 1$ for negative & positive samples respectively

- i) Initialise weights $w_{1,i} = \begin{cases} \frac{1}{2^m}, & \text{if } y_i = 0 \\ \frac{1}{2^l}, & \text{if } y_i = 1 \end{cases}$ where m is the number of negative samples & l is the number of positive samples.

- ii) For $t = 1, \dots, T$ where T is the number of features you wish to find

- (a) Normalise the weights st w_t is a probability distribution

$$w_{t,i} := \frac{w_{t,i}}{\sum_{j=1}^n w_{t,j}}$$

- (b) For each feature, j , train a classifier h_j which is restricted to using a single feature (Haar-Like Feature). Calculate the error wrt w_t

$$e_j = \sum_i w_i |h_j(x_i) - y_i|$$

- (c) Choose the classifier, h_t , with the lowest error e_t .

- (d) Update the weights

$$w_{t+1,i} = w_{t,i} \left(\frac{e_t}{1 - e_t} \right)^{1 - e_i}$$

where $e_i = 0$ if sample x_i is classified correctly and $e_i = 1$ otherwise

- iii) The final strong classifier is

$$h(x) = \begin{cases} 1 & \sum_{i=1}^T \log \left(\frac{e_t}{1 - e_t} \right) h_t(x) \geq \frac{1}{2} \sum_{t=1}^T \log \left(\frac{1 - e_t}{e_t} \right) \\ 0 & \text{otherwise} \end{cases}$$

0 Reference

0.1 Definitions

Definition 0.1 - *Connectivity*

When analysing a pixel there are several ways to consider its adjacent neighbourhood.

- 4-Connectivity. The pixels above, below, left & right.
- 8-Connectivity. Above, below, left, right & single step diagonals.

Definition 0.2 - *Kernel*

A *Kernel* is a small matrix used in convolution. Typically 3×3 or 5×5 . *Kernels* can be defined for blurring, sharpening, embossing, edge detection & more *N.B.* This definition only applies to image processing & is different from the definition in linear algebra.