

I(a) Signal to Noise Ratio (SNR) - is defined as
energy of signal divided by energy of noise.

$$SNR = \frac{E_s}{E_N} = \frac{\sigma_s^2}{\sigma_N^2}$$

For an image,

$$SNR = \frac{\text{variance of pixels in a sequence of images}}{\text{variance of in a uniform area of the image.}}$$

measured
in dB

1(b)

Gaussian noise

→ noise take on gaussian distribution giving peaks on cross-profile of an image

Impulsive noise.

→ The impulsive noise also called pepper & salt noise gives small white & black spots on image & some pixels are flipped in cross-profile

Q

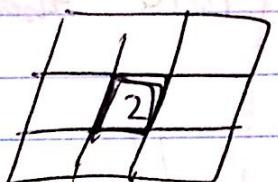
Impulsive noise uses median filtering for reducing it.

1c)

$$I = \begin{array}{|c|c|c|} \hline 2 & 2 & 2 \\ \hline 2 & 3 & 2 \\ \hline 2 & 2 & 2 \\ \hline \end{array}$$

Filter used will be = $\frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$

so middle entry will be 2.



i) d) For taking derivative.

$$\frac{d}{dx} (f * g) = \frac{d}{dx}(f) * g = f * \frac{d}{dx}(g)$$

so what we can do is take derivative of filter & apply this resultant filter to the image to get the convoluted image (new).

Both this will have same effect as the

taking derivative of $(f * g)$.

Also, we can do is take filter & apply to derivative of image \rightarrow to get convoluted image.

- 1(e) To handle boundaries during convolution.
we use:
- Zero padding - when the boundary value is assigned '0'.
 - Replication - when the boundary value is replicated
of the centre value of the convoluted.
 - Here we do not care about the boundary value
this is used when filter is very small in comparison
to image size

1f) Basic 3x3 smoothing filter.

$$\begin{array}{|c|c|c|} \hline Y_9 & Y_9 & Y_9 \\ \hline Y_9 & Y_9 & Y_9 \\ \hline Y_9 & Y_9 & Y_9 \\ \hline \end{array}$$

$$\rightarrow \text{sum} = 3.$$

The sum of entries of this filter is 3 because if the values increases the intensity will increase or if sum is lesser the intensity will decrease.

$I(g)$ | 2D convolution can be implemented by Gaussian using two 1D convolution filters :-

$$G(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$
$$= e^{-\frac{x^2}{2\sigma^2}} \cdot e^{-\frac{y^2}{2\sigma^2}}$$
$$= G(x) \cdot G(y)$$

So now if we do convolution of Image I :-

$$I * g(x, y) = G(y) * (I * G(x))$$

This is more efficient way as this will more computationally efficient taking only $\mathcal{O} M \times N \times m$ rather than normal convolution will take $M \times N \times m^2$

I(h)

$$\sigma = 2.$$

accordingly)

$$\sigma \leq \frac{m}{5}$$

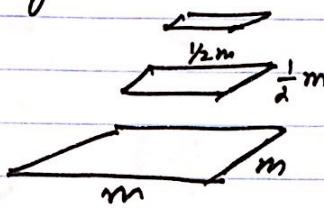
$$so \ m \geq 10$$

so size of filter should be 10 or more.

1(i) Gaussian Image pyramids

- Gaussian Image pyramids are produced by taking the image at level ' j ', then performing gaussian smoothing on it, & then down sampling it. This is repeated to get a pyramid of images., where no. of levels = $\log_{\frac{1}{2}} \text{[size of original image } m]$

$$(j) = \log_{\frac{1}{2}} (m)$$



- While doing multiple scale analysis , we get a problem of choosing the size of window , so what we do is . we try to choose same size of the windows but down scale & smooth the image iteratively.

- total computations we go through = $m^2 + \frac{1}{4}m^2 + \dots + \frac{1}{3}m^2$
(per pixel)

so to the total we just adding $\frac{1}{3}$ times.
approx.

1(j) For Laplacian pyramid, is produced in following step by step:-

a) Take the image at level "j" where $j = \log(m)$

m :- size of the image matrix

b) Then Gaussian smooth it.

c) Then down sample it.

d) Again up-sample it (doubling the size of pixel)

e) smooth it using gaussian

f) to produce image at level $(j-1)$

Repeat ^{above} step (a - f) to produce each level of Laplacian pyramid.

This is mostly use for compression of images, as the images produced at each further levels have many errors, which can be compressed easily & also we can reproduce the image again by Iterating back.

Q.

EDGE DETECTION

(M) प्र० ४)

- 2(a) Edge Detection - It is used to detect the boundaries of different objects in the image. Different types of discontinuities that we can detect using edge detection are as follows:
- discontinuity of Normal vector & slanted edges
 - illumination discontinuity
 - texture discontinuity (unlike previous two)
 - depth discontinuity

Ques Properties of edge detection are:-

- Correspond to scene element where the feature of the scene is highlighted.
- Reliable and consistent detection detection
- Invariant → example, the result should be same if a person's photo is taken from side and front.

Q b) STEPS for edge detection include:-

→ Smoothing → It is used because derivatives are ~~sensitive~~ sensitive to noise, so we smooth before taking derivative.

$$I \xrightarrow{G * \frac{\partial}{\partial x}}$$

→ Enhancement - It is used for enhancing the edges, we calculate gradient magnitude.

→ Localization - The location of the edges are estimated. Here when we enhance we get a band of edges (expected area to get a edge) so we do localization to detect exact location.

2c) Two ways to compute the gradient matrix are:-

→ Forward Difference [consider forward neighbours]

→ Central difference [take diff b/w current & previous neighbours]

(i) Forward difference :-

$$f_x = \frac{f(x+h) - f(x)}{h} = \lim_{x \rightarrow 0} \frac{I(x+h, y) - I(x, y)}{h}$$

$$(\text{put } h=1) = I(x+1, y) - I(x, y) \rightarrow \text{in } x$$

$$I(x, y+1) - I(x, y) \rightarrow \text{in } y$$

$$I_x = \begin{bmatrix} -1 & 1 \\ -1 & 1 \\ -1 & 1 \end{bmatrix}$$

$$I_y = \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix}$$

→ convoluting the image with these matrix will also give the gradient.

(ii) Central difference:-

$$I_x = I(x+1, y) - I(x-1, y) \rightarrow \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ 1 & 0 & 1 \end{bmatrix}$$

$$I_y = I(x, y+1) - I(x, y-1)$$

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

2(d) During edge detection,
we need to smooth first before doing / taking
derivative so,

$$= I \times \left[G_1 * \frac{\partial}{\partial x} \right]$$

so
as we
know,

Gaussian Filter = $\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$

Derivative filter = $\begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix}$

so $\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} * \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \rightarrow \text{for } x \text{ derivative}$

This filter is called Sobel
filter, which is applied
on image

similar for 'y' derivative;

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

So we also observe that, takes derivative in one direction & also
doing smoothing in other direction.

2(e) In, more accurate filter,
 we try approximate $h(n)$ with gaussian $\cdot G(x)$.
 & one derivative can be taken for $G(x)$ (\because it is continuous)
 $f(n) * G'[n] \rightarrow$ to get edges.

$$G_{xy} = G_x \cdot G_y \quad \rightarrow \text{more accurate derivative.}$$

$$I_x = I * G_y * G'_x \quad \rightarrow \text{along rows (derivative of } G)$$

$$I_y = I * G_x * G'_y$$

$$\text{where } \Rightarrow G_x = e^{-\frac{x^2}{2\sigma^2}}, \quad G_y = e^{-\frac{y^2}{2\sigma^2}}$$

$$G'_x = \frac{-x}{\sigma^2} e^{-\frac{x^2}{\sigma^2}}, \quad G'_y = \frac{-y}{\sigma^2} e^{-\frac{y^2}{\sigma^2}}$$

So for a filter -

$$\text{we know } \sigma \leq \frac{m}{5}$$

$$m \geq 10 \quad [\text{for } \sigma = 2].$$

so

filter size will be 10.

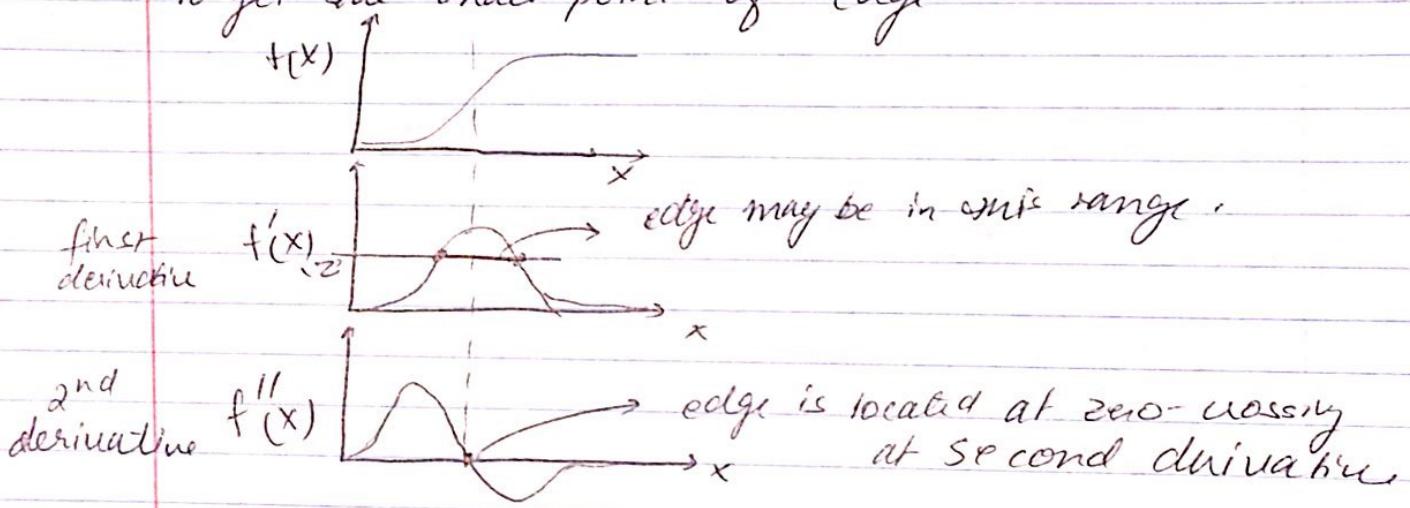
$$I_x = I * e^{-\frac{y^2}{8}} * \frac{-x}{4} e^{-\frac{x^2}{4}}$$

$$I_y = I * e^{-\frac{x^2}{8}} * \frac{-y}{4} e^{-\frac{y^2}{4}}$$

(f) Localization is used to detect edge's most accurate position,

so we take a derivative and see if the magnitude is above some threshold, ' Z ', we have a edge in that range. (so ^{we} get a stuck case)

So, now, we look at 2nd derivative to get the exact point of edge.



2g)

LOG filter $\rightarrow \Delta G$

ΔG , Laplacian Gaussian filters = $\Delta(I * G)$

$$= I * \Delta(G)$$

where

$$G = e^{-\frac{r^2}{2\sigma^2}} \quad \text{where } r = \sqrt{x^2 + y^2}$$

$$= \Delta G \frac{\sigma^2 - 2\sigma^2}{\sigma^4} e^{-\frac{r^2}{2\sigma^2}}$$

For $\sigma = 1$

$$\Delta G = (\sigma^2 - 2) e^{-\frac{r^2}{2}}$$

Edge detection with LOG:-

- Compute LOG convolution with LOG.
- Set a threshold as $= \begin{cases} 1 & \text{when } I * \text{LOG} > 0 \\ 0 & \text{where } I * \text{LOG} \leq 0 \end{cases}$
- On the resultant image, mark edges at transition ($0 \rightarrow 1$ or $1 \rightarrow 0$).

Q(h) The main difference between canny edge detection and other is that in canny we ~~do~~ take derivative in the direction of the normal of edges. Whereas, in other we take ~~in~~ in the direction $\partial x \& y$.

if $n = \nabla I = \nabla(I * a)$ where $n \rightarrow$ normal.

if $|n| > z'$
detect edges as max of $\frac{\partial I}{\partial n}$ or $\frac{\partial}{\partial n} [I * a]$

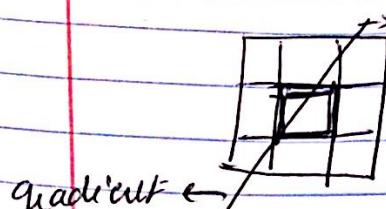
OR zero crossing of $\frac{\partial^2}{\partial n^2} (I * a)$

$$\frac{\partial}{\partial n} (I * a) = n \cdot \nabla (I * a)$$

\hookrightarrow produce gradient vector out to the direction n you

~~2(b)~~

2(i) Non-Maximum Supression



Let ∇I be the gradient computed.
So in non-maximum suppression we have to find any box in ∇I , where the gradient is maximum, so that we can take that box over boxes & suppress it.

Hysteresis threshold

One of the condition for edge-detection in canny is:-

$$|\nabla I| > \tau'$$

when if

$\rightarrow \tau'$ is high value - we will miss some of important edges.

$\rightarrow \tau'$ is low value \rightarrow we will wrongly detect edges.

so we select 2 values of τ' , (τ_H & τ_L)
But when

$$\tau_H > \tau_L$$

If we get $|\nabla I| > \tau_H$, we will be treaty τ_L .