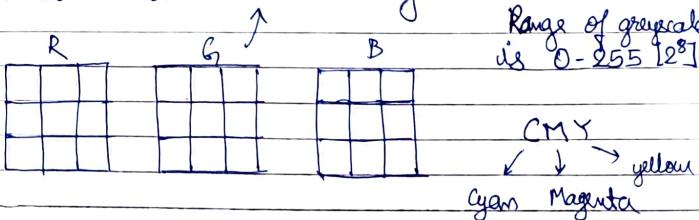


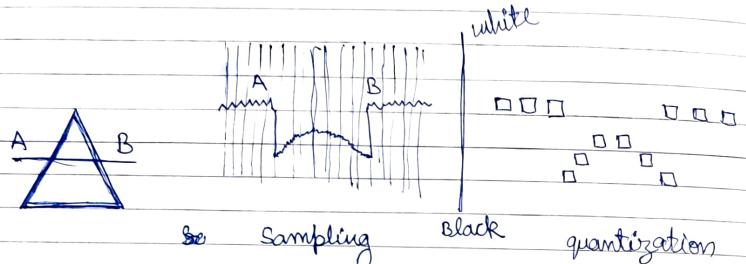
JPG → Joint Photography Group.

JPEG → Joint Photography Expert Group.

Digital images are represented in the form of their pixel intensity.

Green channel of any image has maximum information about the image.





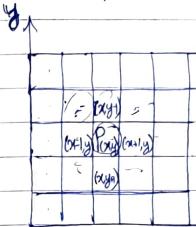
Digitization of coordinate value is called sampling.

Digitization of amplitude value is called quantization!

If we want to convert any image into digital form then we need to perform sampling and quantization.

After converting the image into digital form it only contains pixel and intensity values.

→ Relationship between pixels



left, right, top, bottom pixels

$$N_4(p) = \{(x+1, y), (x-1, y), (x, y+1), (x, y-1)\}$$

$$N_D(p) = \{(x+1, y+1), (x+1, y-1), (x-1, y+1), (x-1, y-1)\}$$

$$N_8(p) = N_4(p) \cup N_D(p)$$

diagonal neighbouring pixels

In case a pixel belongs to border of a particular image then their neighbouring pixel is less than 8

filtering

$\frac{1}{9}$	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1

5 5 5
10 10 10
25 25 25

Kernel or filter

will always be in
3x3, 5x5 or in other
united odd number
as we need center pixel

Average the intensity of window elements.

$$= \frac{10}{3} = 3.333 \quad \text{select } 3$$

Set the new intensity as the value of center pixel of the window.

Here only center pixel is changing which is not what we want.

In order to overcome this problem we do padding of the image which ultimately helps us to cover every pixel of the actual (or original image). For example we can do zero padding or mirror padding and then apply the mask.

replicating

→ Adjacency, Connectivity, Region and Boundary.

Assume 'V' set of intensity value used to define adjacency. In a grayscale image we have,

$$V = \{0, 1, \dots, 255\}$$

Three types of adjacency :

- Four adjacency (adjacent)
- 8 adjacent
- m adjacent

• 4 adjacency :-

Two pixels p and q with values from V are 4-adjacent if q is in the set $N_4(p)$.

• 8-adjacent :-

Two pixels p and q with values from V are 8-adjacent if q is in the set of $N_8(p)$.

• m-adjacency :-

Two pixels p and q with values from V are m-adjacent if,

- i) q is in $N_4(p)$, or,
- ii) q is in $N_8(p)$ and set $N_4(p) \cap N_4(q)$ has no pixels whose value are from V.

Eg,

	0	1	2	3	4
0	0	1	1	2	3
1	1	1	2	0	1
2	2	2	q ₄	q ₁	q ₂
3	1	3	q ₅	P	q ₃
4	0	0	q ₆	q ₇	q ₈

$$V = \{0, 1, 2, 3\}$$

$$N_4(p) = \{q_1, q_3, q_7, q_5\}$$

$$N_8(p) = \{q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8\}$$

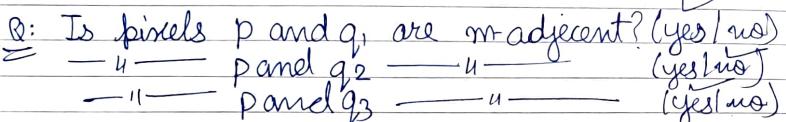
$$N_D(p) = \{q_4, q_2, q_8, q_6\}$$

$$N_4(p) = \{(2,3), (3,4), (4,3), (3,2)\}$$

$$N_D(p) = \{(2,2), (4,4), (2,4), (4,2)\}$$

$$N_8(p) = \{(2,2), (2,3), (2,4), (3,4), (4,4), (4,3), (4,2), (3,2)\}$$

	4-adjacent	8-adjacent
p & q ₁	✓	✓
p & q ₂	✗	✓
p & q ₃	✗	✗
p & q ₄	✗	✓
p & q ₅	✓	✓
p & q ₆	✗	✓
p & q ₇	✓	✓
p & q ₈	✗	✗



A:

$$N_4(p) = \{(2,3), (3,4), (4,3), (3,2)\}$$

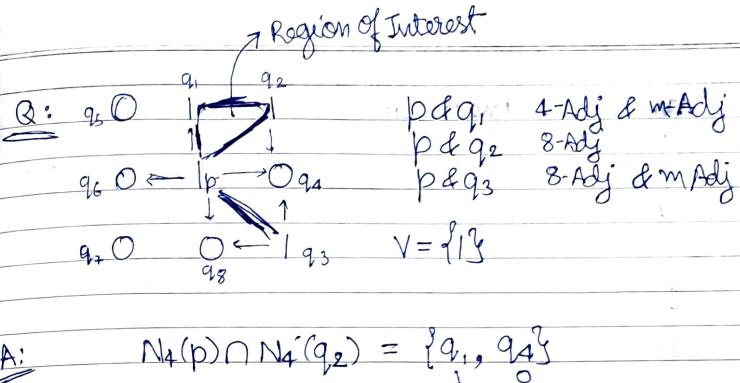
$$N_4(q_1) = \{(1,4), (2,3), (3,4)\}$$

$$N_4(p) \cap N_4(q_1) = \{(3,3), (2,4), (4,4)\}$$

$$(3, 1)$$

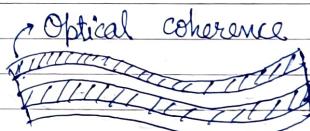
$$N_4(q_3) = \{(3,3), (2,4), (4,4)\}$$

$$N_4(p) \cap N_4(q_3) = \emptyset$$



$$N_4(p) \cap N_4(q_3) = \{q_3\}$$

Since no element in the intersection set thus m-adj.



Using adjacency we can find the connectivity and hence the boundary or region of interest.

→ Distance, Euclidean distance, city block distance and chess-board distance

$$\text{Euclidean } [D_E] = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

$$\text{City-block } [D_4] = D(p, q) = |x_1 - x_2| + |y_1 - y_2|$$

$$\text{Chess-board } [D_8] = D_8(p, q) = \max(|x_1 - x_2|, |y_1 - y_2|)$$

If we get decimal values then consider upside (not if not mentioned)

Distance theorem: Distance between two points p and q must be ≥ 0 .

Q: Write a short note on type of facial features used for face detection (or identification).

→ Point processing

↳ Spatial domain
spatial

↳ Point processing
↳ Neighbourhood processing
↳ define 4, 8, m neighbours
↳ define adjacency matrix
↳ define connectivity
↳ if complete path the region
↳ defined region
↳ extract features
↳ classify the image

In point processing we work with single pixel. It means if value of $g(x, y)$ depends on transformation function means.

$g(x, y) = T f(x, y)$, where $f(x, y) \rightarrow$ intensity of pixel at (x, y) location.

Transformation function.

Point processing techniques :

- ① Image negation
- ② Image thresholding
- ③ Image clipping
- ④ Image contrast stretching
- ⑤ Bit plane slicing
- ⑥ Gray level slicing

→ Image Negation → brighter to darker [kind off darker to brighter] image enhancement
Transformation function $S = T(x)$ given image

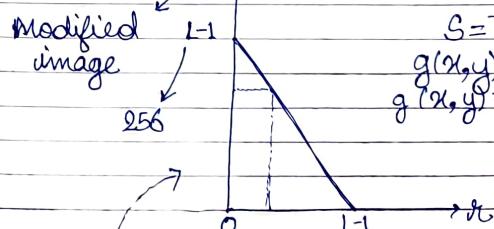
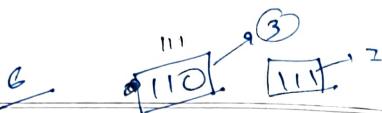


Image negation for grey scale image

$$S = T(x) = L - 1 - x$$

$$g(x, y) = T_f(x, y)$$

$$g(x, y) = (L-1) - f(x, y)$$

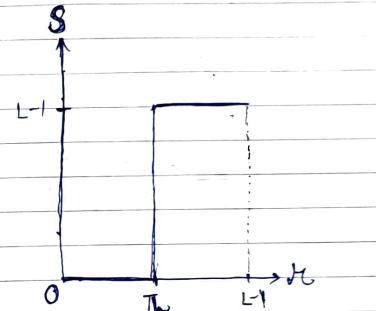


Q: Consider a given image of size 4 by 4,

1	7	3	3
3	6	4	6
2	4	2	2
3	2	5	3

Step 2

Thresholding function, $S = \begin{cases} L-1; & r \geq Th \\ 0; & r < Th \end{cases}$



What is the corresponding output negative image?

A: $L = 8 \rightarrow 3\text{-bit image}$
as $L-1 = 7 \Rightarrow L=8$

6	0	4	4
4	1	3	1
5	3	5	5
4	5	2	4

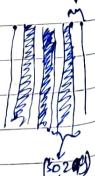
$$g(x,y) = T_f(x,y)$$

$$g(x,y) = (L-1) - f(x,y)$$

→ Image thresholding

Image thresholding is basically used for ^{process} image segmentation.

Cropping / defining / highlighting
Region of Interest.



Q: What is the output of previous question if we apply thresholding with threshold value as 3?

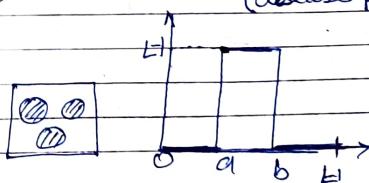
A:

0	7	7	7
7	7	7	7
0	7	0	0
7	0	7	7

→ Image clipping

Intensity level slicing without background

→ Application
image segmentation
(disease prediction)



$$S = \begin{cases} L-1, & a \leq I_p \leq b \\ 0, & \text{otherwise} \end{cases}$$

intensity of
the image

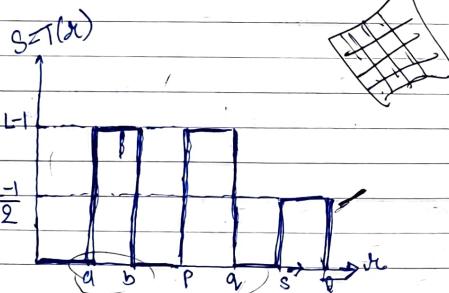
B: Apply image clipping to previous example
with $a=2$ and $b=4$.

A:

0	0	7	7
7	0	7	0
7	7	7	7
7	7	0	7

$$L-1=8 \Rightarrow L=7$$

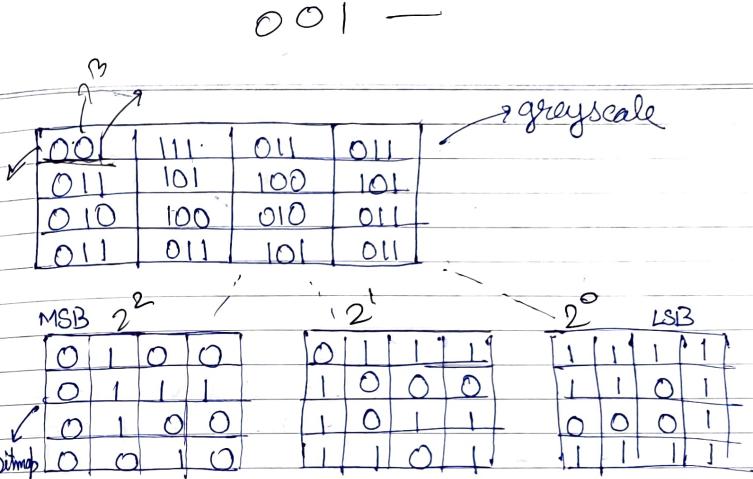
$a=2$ and $b=4$



→ Bit-plane slicing

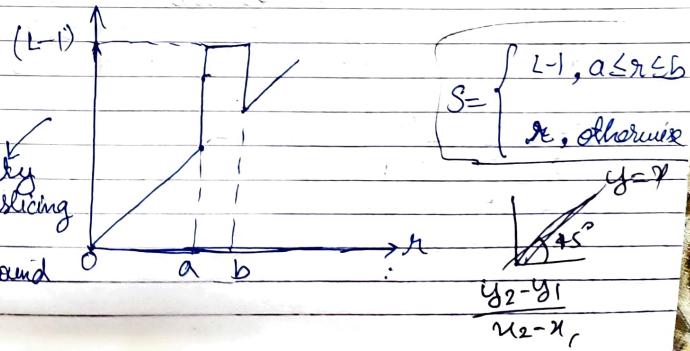
No. of planes \times No. of intensity levels will decide no. of planes as,

No. of planes = No. of bits required to represent the maximum intensity levels.



Three bit planes

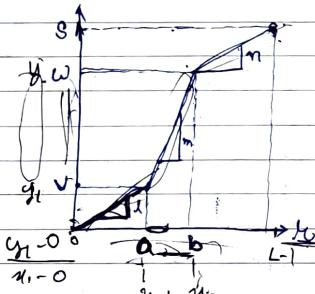
To combine these images (bit planes) to get back the original grayscale image we have to perform the conversion of binary to decimal number based on MSB and LSB.



3 contrast stretching

→ contrast stretching

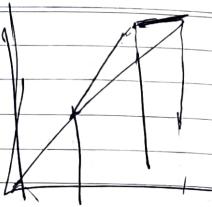
→ Contrast Stretching



$$s = l \cdot r \quad \text{if } 0 \leq r \leq a$$

$$s = m(r-a)+v \quad \text{if } a < r \leq b$$

$$s = n(r-b)+w \quad \text{if } b < r \leq c$$



where l, m, n and are the slope

$$l \neq n < 1$$

$$\cdot m > 1$$

Many times when low contrast images due to poor illuminance or due to wrong setting of lens aperture. It is required to enhance the image by using contrast stretch.

Q:	7	12	2	3	$v=4$
	10	(15)	10	1	$w=8$
	12	4	6	(5)	then find the output image
	8	2	7	15	$a=8$

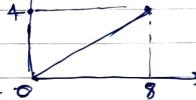
$$b=12$$

$$A: \quad S_{\text{prf}} \quad l = \frac{4}{8} = \frac{1}{2}$$

$$m = \frac{12-8}{8-4} = 1$$

$$\frac{255-8}{255-12} =$$

$$\frac{255-8}{255-12} = m = \frac{15-8}{15-12} = \frac{7}{3}$$



3.5	8	1	1.5
6	15	0.5	0.5
8	2	3	15
4	1	3.5	15

3.4	8	1	2
6	15	0.1	0.1
8	2	3	15
4	1	4.5	15

Take the significant digit and round off.

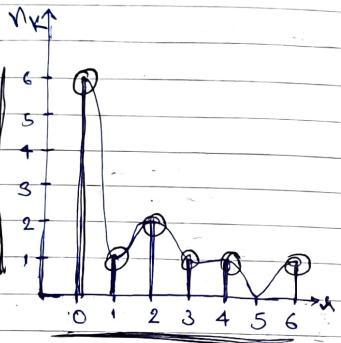
Explain multilevel contrast stretching using graph.

$$\frac{2}{3} \times \frac{15-12}{15-8} \\ 7-8$$

→ Histogram

0	0	0	0	0
0	1	2	3	
0	9	4	6	

D / 10



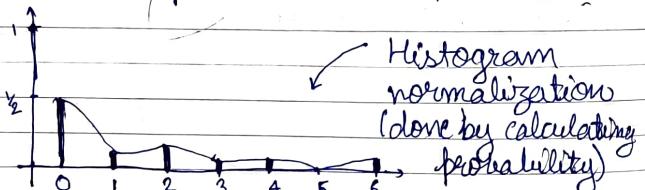
$$P(x_k) = \frac{n_k}{N}$$

Total number
of pixel in the
image

probability
of occurrence of
gray level x_k

x_k	0	1	2	3	4	5	6
f	6	1	9	1	1	0	1

$$p(x_k) = \frac{f}{N}$$



Histogram
normalization
(done by calculating
probability)

If we normalize the histogram then
quality of image may improve.

①

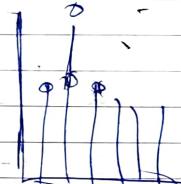
→ Histogram equalization / Histogram stretching /
Linear stretching

$$S = T(x) = \frac{S_{\max} - S_{\min}}{x_{\max} - x_{\min}} (x - x_{\min}) + S_{\min}$$

This will give us histogram equalized image.

②

GL	0	1	2	3	4	5	6	7
old :	f	6	1	9	13	19	20	13



→ Methods.:

- 1) Histogram stretching
- 2) Histogram equalization
- 3) Histogram generalization specification
- 4) Histogram generalization

GL	0	1	2	3	4	5	6	7
fold	0	3	8	13	19	20	13	5
freq	6	1	9	13	19	20	13	5
St. freq	3	8	13	10	19	20	13	5

Total pixels = 81
(3x9)²

$$S = \frac{S_{\max} - S_{\min}}{x_{\max} - x_{\min}} (x - x_{\min}) + S_{\min}$$

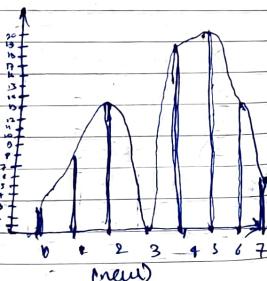
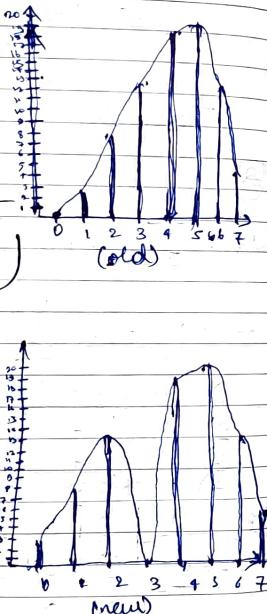
$$S = \frac{7-0}{7-0} (x-0) + 0 \Rightarrow S = \frac{7(x-0)}{7} = 7x$$

for sake
of understanding
the table simple
probability

$$S = \frac{7}{6}(x-1)$$

$$\begin{aligned} S(0) &= -\frac{7}{6} = -1.17 \approx 0 \\ S(1) &= 0 \\ S(2) &= \frac{7}{6} = 1.17 \approx 1 \\ S(3) &= \frac{14}{6} \approx 2.33 \approx 2 \\ S(4) &= \frac{21}{6} = 3.5 \approx 4 \\ S(5) &= \frac{28}{6} = 4.67 \approx 5 \\ S(6) &= \frac{35}{6} = 5.84 \approx 6 \\ S(7) &= \frac{42}{6} = 7 \end{aligned}$$

x	s	round-off (\bar{s})
0	-1.17	0
1	0	0
2	1.17	1
3	2.33	2
4	3.5	4
5	4.67	5
6	5.84	6
7	7	7



Histogram equalisation

This can be done by
using cumulative distribution
and joint distribution

GL	N_k	$p(k) = \frac{N_k}{N}$	CDF	$S_k * (k-1)$	Round-off
0	0	0.0	0.0	0.0	0
1	3	$3/81 = 0.037$	0.037	0.259	1
2	8	$8/81 = 0.098$	0.135	0.945	1
3	13	$13/81 = 0.160$	0.295	2.065	2
4	19	$19/81 = 0.235$	0.530	3.710	4
5	20	$20/81 = 0.248$	0.778	5.446	5
6	13	$13/81 = 0.160$	0.938	6.559	7
7	5	$5/81 = 0.062$	1	7.000	7

$$\sum N_k = 81$$

$$\sum p(k) = 1$$

GL	0	1	2	3	4	5	6	7
fold	0	3	8	13	19	20	13	5
new	3	8	13	0	19	20	0	18

Histogram specifications

equal
imp

First equalize the given two images
after that we perform the mapping
of the equalized images.

β	GL	GLA	GLB	GLF
0	1	0		
1	2	0		
2	3	0		?
3	3	0		
4	5	2		
5	6	4		
6	7	6		
7	7	7		

I _A	GL	0	1	2	3	4	5	6	7
freq	8	10	10	2	12	16	4	12	

I _B	GL	0	1	2	3	4	5	6	7
freq	0	0	0	0	20	20	16	8	

<u>Image A</u>	GL	freq	p(k)	CDF ΣP	Σk	Round off
0	8	8/64				0
1	10	10/64				2
2	10	10/64				3
3	2	2/64				3
4	12	12/64				5
5	16	16/64				6
6	4	4/64				7
7	2	2/64				7

GL	freq	p(k)	CDF	$(L-1)\Sigma P$	Round off
0	0	0/64			0
1	0	0/64			0
2	0	0/64			0
3	0	0/64			0
4	20	20/64			2
5	20	20/64			4
6	16	16/64			6
7	8	8/64			7

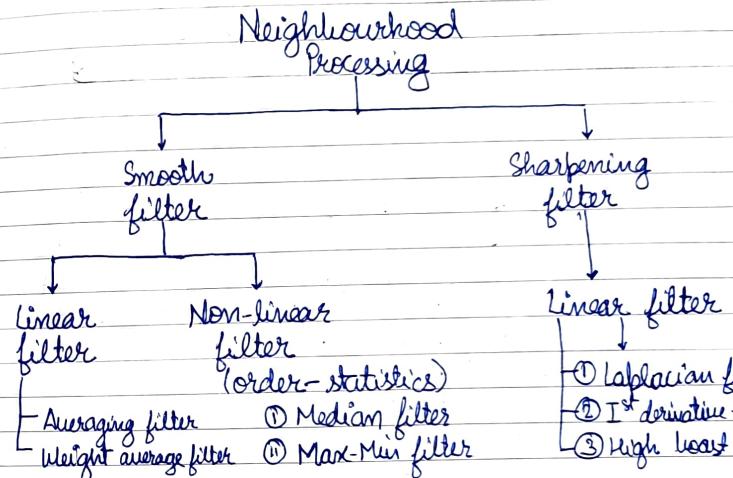
GL	Round off A	Round off B	GLF
0	0	0	0
1	1	1	1
2	2	3	5
3	3	3	5
4	4	4	4
5	5	6	6
6	6	6	6
7	7	7	7

final image
 $GL_B \geq GL_A$

GL	0	1	2	3	4	5	6	7
freq	0	0	0	0	18	12	28	6

Q: Maylee 3 reference image are given
in the question (EXAM)

- Neighbourhood Processing (Spatial Filter)



Smoothing filter are used for reducing the blurring and noise.

Sharpening spatial filter highlights the fine detail that has been blurred and in both cases we use either mask or kernel or window or template.

1. How to design a kernel?
2. How to generate a kernel?
3. What is the characteristic of kernel?



• 4×4 we need to do the average but if this might cause the problem and borders might ~~not~~ be blurred. That's why we take 3×3 or 5×5 or \dots so that we get a center pixel.

4)	1	1	13	1	3	8	2	10	12
	0	0	0	1	7	9	8	6	13
	-1	-1	-1	1	8	3	6	8	9
Kernel	1	3	5	7	8	15			
3×3	4	4	4	5	3	12			



I/P image

a)	1	1	1	1	1	1	1
	1	3	6	6	1	1	1
	1	3	7	8	8	8	1
	1	3	7	6	8	6	1
	1	3	5	5	7	3	1
	1	1	4	3	3	1	1
	1	1	1	1	1	0	1

1	3	6	6	1
3	7	8	8	8
3	7	6	8	6
3	5	5	7	3
1	4	3	3	1



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b)	1	1	1	1	1	1	1	1	1	1	13	13
	1	9	9	10	12	13	1	1	1	1	9	9
	1	9	9	10	13	13	1	1	1	1	10	13
	1	9	9	9	15	15	1	1	1	1	9	9
	1	8	8	8	15	15	1	1	1	1	8	8
	1	5	7	7	15	15	1	1	1	1	7	15
	1	1	1	1	1	1	1	1	1	1	1	15

c)	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	2	2
	1	1	2	2	2	1	1	1	1	1	2	2
	1	1	3	2	2	1	1	1	1	1	3	2
	1	1	3	2	2	1	1	1	1	1	3	2
	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1

(highlighting)

Although we are getting the boundary but image is completely changed using ~~min~~ 1 or 0 padding and apply min filter.

→ Larger mask size results in greater smoothing effect which results in more blurring because of information loss.

Averaging filter

$$g(x, y) = \frac{1}{\sum_{s=a}^a \sum_{t=b}^b w(s, t)} \sum_{s=a}^a \sum_{t=b}^b w(s, t) f(x+s, y+t)$$

averaging filter we assume origin at center pixel.

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

$$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

→ weighted averaging filter

The values in mask (also called sub-image) are called coefficients rather than pixels.

Order-statistics filter. (Non-linear)

Order-statistics filters are nonlinear spatial filters whose response is based on ordering or ranking of pixels which are in the given domain of pixels.

Derivative filters

Ist order derivatives

one dimensional $f(x)$ \rightarrow x-direction

2-D second order derivatives

$$\frac{\partial f}{\partial x} = f(x+1) - f(x) \Rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x) \Rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 1 & -2 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

→ Laplacian derivative

$$\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} = \nabla^2 f \quad \rightarrow \text{For 2D image.}$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y) \rightarrow x \text{ direction}$$

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y) \quad \downarrow \text{y direction}$$

$$\nabla^2 f = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y)$$

$$\begin{bmatrix} 1 & & \\ & -4 & \\ & & 1 \end{bmatrix}$$

→ Laplacian mask

so Smoothing \rightarrow integration \rightarrow low pass filter

Sharpening \rightarrow differentiation
Highpass filter - change in intensity

Highlight a transition in intensity is performed in sharpening.

Applications.

1. Electronic ~~point~~ printing
2. Medical imaging
3. Autonomous guidance in military systems

Laplacean and sharp masking

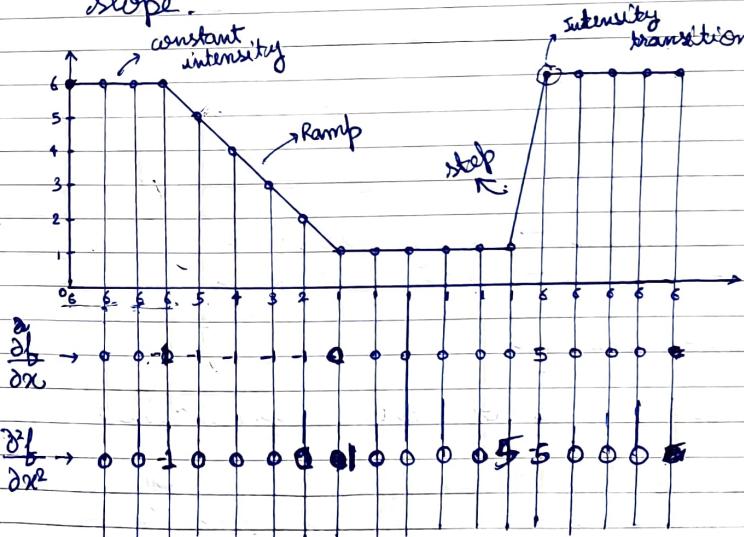
Property of 1st derivative :

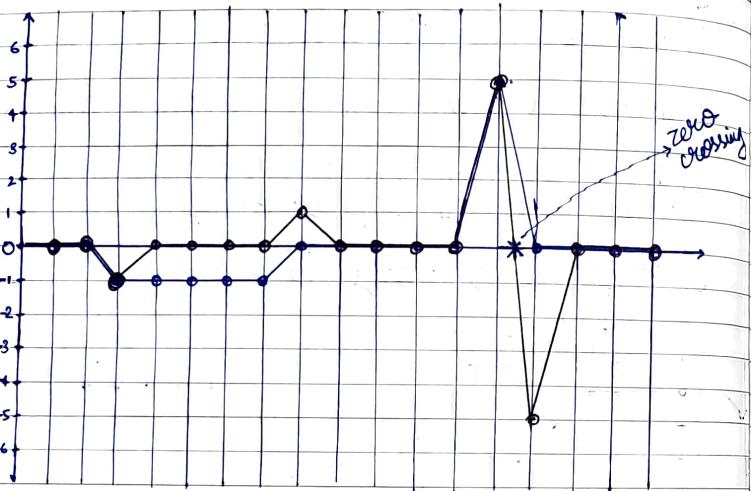
1. Must be 0 in area of constant intensity.
2. Must be non-zero at the onset of an intensity ~~step~~ step or ramp.

continuous sudden change
constant increase in intensity
3. Must be non-zero along the ramp.

Property of 2nd derivative :

1. Must be 0 in area of constant intensity.
2. Must be non-zero at the onset and end of an intensity step or ramp.
3. Must be 0 along the ramp of constant slope.





Black line \rightarrow second derivative
 Blue line \rightarrow first derivative

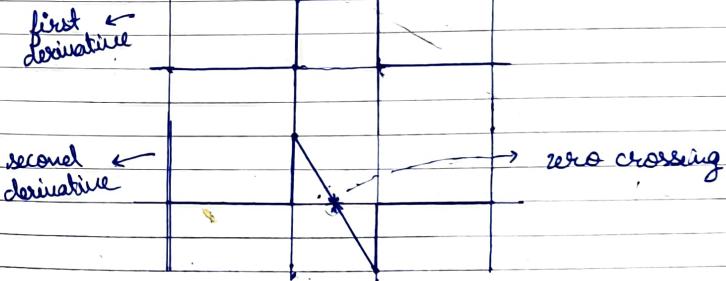
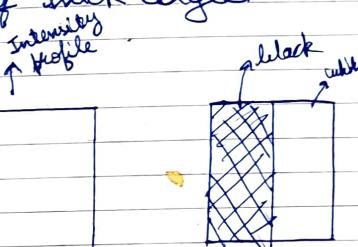
~~zero crossings~~

Observations of the above graphs:

- 1) The magnitude of first derivative can be used to detect the presence of an edge at a point in the image.
- 2) Sign of second derivative can be used to determine whether an edge pixel lie

on the light or darker side of the edge.

- 3) In second derivative it produce two values for every edge in an image.
- 4) Its zero crossing can be used for locating the center of thick edges



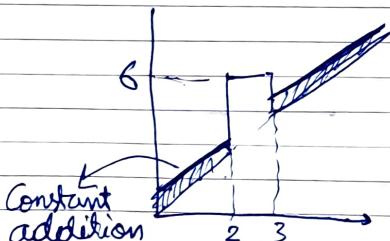
Quiz next Thursday

Image operations are array operations, are done on a pixel-by-pixel basis. Array operations are different from matrix operations. For example, consider two images

$$F_1 = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \text{ and } F_2 = \begin{bmatrix} E & F \\ G & H \end{bmatrix}$$

Two images can be added in a direct manner.

$$g(x,y) = f_1(x,y) + f_2(x,y)$$



After adding constant contrast stretching may change or may not change the overall image.

The image subtraction of two images can be done as follows:

$$g(x,y) = |f_1(x,y) - f_2(x,y)|$$

↓
to avoid -ve values

Image division

$$g(x,y) = \frac{f_1(x,y)}{f_2(x,y)}$$

→ Logical Operations

1. AND/NAND
2. OR/NOR

3. XOR/ENOR
4. Invert/Logical NOT

→ Geometric Operation.

$$x' = x + Sx$$

$$y' = y + Sy$$

⇒ Scaling operation

$$x' = x \times Sx$$

$$y' = y \times Sy$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} Sx & 0 \\ 0 & Sy \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$



probability

$$\text{Entropy } H = -\sum_{i=1}^n P_i \log_2 P_i$$

0	1	2	3	4	5	6	7
5	6	2	3	9	10	10	2

Find probability.

Suppose total no. of pixels in image = N

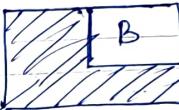
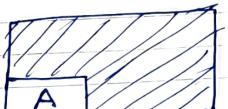
$$P_0 = \frac{5}{N}, P_1 = \frac{6}{N}, \dots$$

$$H = -\sum_{i=0}^7 P_i \log_2 P_i$$

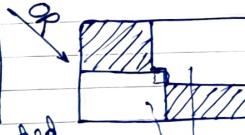
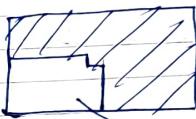
$$= -(P_0 \log_2 P_0 + P_1 \log_2 P_1 + \dots + P_7 \log_2 P_7)$$

0	1	1
1	0	0
1	1	0

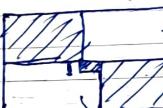
XOR
selected region is here



$$A \text{ AND } [\text{NOT}(B)] =$$

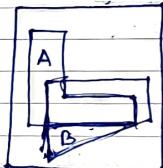


$$A \text{ XOR } B =$$

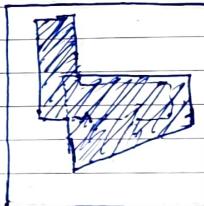


selected region is here
selected region is here
selected region is here

AUB

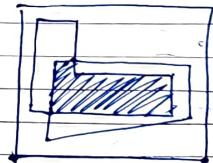


$$A \cup B =$$

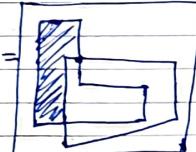


$$A \cap B =$$

AND



$$A - B =$$



Convolution

Correlation

difference of 180°

We will find sum of product of intensity

Padding \rightarrow 0 or 1

Wrapping

Put the first and last row and column at the last row and first row and columns

4	8	9	4	8
3	1	2	3	1
7	5	6	7	5
4	8	9	4	8
3	1	2	3	1

Convolution means how image is closely related.

$$\text{Convolution} = M \cdot I$$

$$\text{Correlation} = M * I$$

mask

given image

If the mask we have in correlation and rotate it by 180° then we will get convolution.

5	4	9
5	4	9
5	4	9

horizontally
 90°

9	4	5
9	4	5
9	4	5

vertically
 90°

9	4	5
9	4	5
9	4	5

$$M_{\text{Conv}} = 1 \ 2 \ 3 \ 2 \ 8$$

$$M_{\text{Corr}} = 8 \ 2 \ 3 \ 2 \ 1$$

1	2	3
4	5	6
7	8	9

9	8	7
6	5	4
3	2	1

out

1	2	2	3
3	2	4	1
1	3	3	2
4	1	1	3

Image

0	1	0
1	1	1
0	1	0

Mask.

Apply wrapping then find the resultant image after convolution.

1	3	4	1	1	3	4
3	1	2	2	3	1	
1	3	2	4	1	3	
2	1	3	3	2	1	
3	4	1	1	1	3	4
3	1	2	2	3	1	

Edge detection

- Three types of basic edges →

- Horizontal
- Vertical
- Diagonal

- Masks:

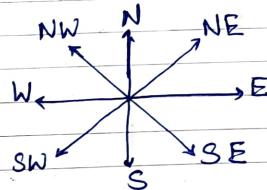
Prewitt

Sobel

Robinson Compass Mask

Kirsch Compass Mask

Laplacian Mask



- Prewitt (Horizontal and vertical mask)

gradient
G_y

-1	0	1
-1	0	1
-1	0	1

G_x
gradient

-1	-1	-1
0	0	0
1	1	1

$$\theta = \tan^{-1} \left(\frac{G_x}{G_y} \right)$$

$$|G| = \sqrt{G_x^2 + G_y^2}$$

2. Sobel Mask

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

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

3. Robinson Mask. (8 directional edges can be identified)

$$G_{xy} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix} \xrightarrow{45^\circ}$$

N-direction mask

NE-direction mask

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \xrightarrow{45^\circ}$$

E-direction mask

SE-direction mask

S-direction mask

$$\begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix}$$

SW direction mask

W direction mask

NW direction mask

4. Kirsch mask (Weights are adjusted)

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \xrightarrow{45^\circ}$$

N-direction

NE-direction

E-direction

$$\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \xrightarrow{45^\circ}$$

SE-direction

S-direction

SW-direction

$$\begin{bmatrix} 5 & 5 & 5 \\ 3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \xrightarrow{45^\circ} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

W-direction

NW-direction

Step edges
Ramp edges
Line edges
Roof edges

Segmentation

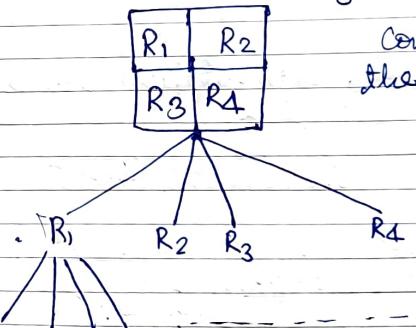
different from each other
based on certain feature

Discontinuity based segmentation

Similarity based segmentation

based on certain feature / characteristics

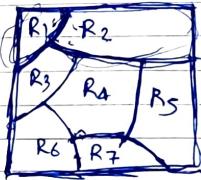
Region Growing → Based on thresholding
split and Merge → Divide the image into regions.



Continuously divide
the regions.



(Confusion matrix question
in exam)



$$\textcircled{1} \quad R_1 \cup \dots \cup R_N = R$$

$$\textcircled{2} \quad R_i \cap R_j \text{ for } i \neq j = \emptyset$$

\textcircled{3}



Region oriented segmentation

Basic Formulation: R be a region describing the complete image and Let R_1, R_2, \dots, R_n regions

$$\textcircled{1} \quad \bigcup_{i=1}^n R_i = R \Rightarrow \text{Segmentation Process complete.}$$

\textcircled{2} R_i is connected regions. (4 or 8 connected)

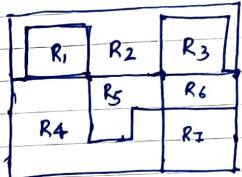
\textcircled{3} $R_i \cap R_j \neq \emptyset$ for all i, j where $i \neq j$ (disjoint property)

\textcircled{4} $P(R_i) = \text{True} \rightarrow$ means all ~~pixel~~ properties must be satisfied by all the pixels in the region R_i

Logical predicate over the points in set R_i

\textcircled{5} $P(R_i \cup R_j) = \text{False}$ for $i \neq j$

boundary representation



Seed point: Generally seed point is considered near to highest greylevel value. It gives less number of regions and number of isolated regions.

② Seed point may be considered any pixel having grey level (generally we consider middle grey level)

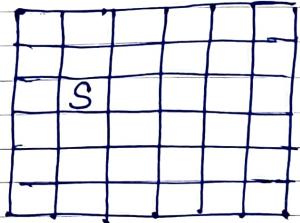
③ In case if we select seed point near to lowest greylevel value then it gives may be to give better result but depends on image quality.

8 Similarity function:

$$|f(x,y) - f(x',y')| < T \rightarrow \begin{array}{l} \text{Threshold value} \\ \downarrow \\ \text{Image point intensity} \end{array}$$

\downarrow
seed point intensity

\downarrow
multilevel local Adaptive global



→

1	0	3	8	7
0	1	8	9	8
0	0	7	9	8
0	1	8	8	9
1	2	8	8	9

seed point $S_1 = 9$ $S_2 = 1$
Thresholding condition $T \leq 4$

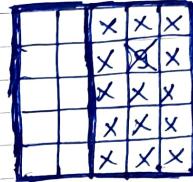
Apply region growing technique

If seed value = 9

$$|f(x,y) - f(x',y')| \leq T \leq 4$$

$$|f(x,y) - g| \leq 4$$

possible intensity values = {5, 6, 7, 8, 9}

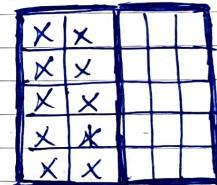


If seed value = 1

$$|f(x,y) - f(x',y')| \leq T \leq 4$$

$$|f(x,y) - 1| \leq 4$$

possible intensity values = {5, 4, 3, 2, 1, 0}

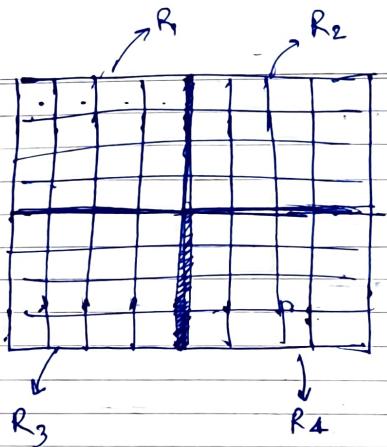


→

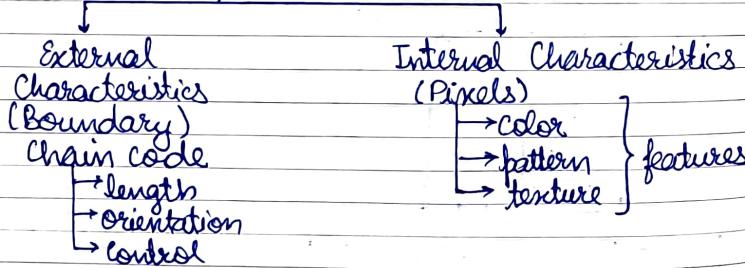
6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

Thresholding condition $T \leq 3$

$$I_{max} - I_{min} \leq T$$

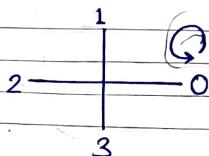


Region representation

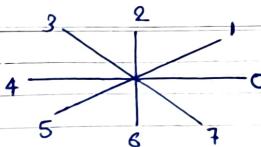


Boundary will be checked using 4 and 8 connectivity

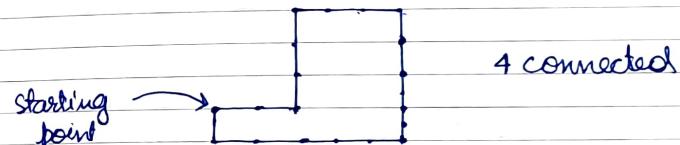
Criteria for 4-connected



Criteria for 8-connected



Translation and rotation invariant will have same chain code.



0 0 0 1 1 1 0 0 0 3 3 3 3 3 2 2 2 2 1

Now we have to take the smallest integer value for the chain code by performing shifting.

0 0 0 1 1 1 0 0 0 3 3 3 3 3 2 2 2 2 1
0 0 3 0 0 1 0 0 3 0 0 1 0 0 1

Now we take the minimum integer formed from shifting.

0 0 0 1 0 0 0 1 1 0 0 3 0 0 1 0 0 1

This is rotation invariant