

## Image sampling & Quantization:

An image function  $f(x,y)$  must be digitalized with spatially and in amplitude in order to become suitable for digital processing.

Hence in order to create an image which is digital, we need to convert continuous data into digital form.

There are two steps in which digitization is done:

- Sampling (digitizing the sampling co-ordinate values)
  - Quantization (digitizing the amplitude values)
- The sampling value determines the spatial resolution of the digitized image while the quantization level determines the number of gray level in the digitized image.

A magnitude of sampled image is expressed as a digital value in image processing. The transition between continuous values of the image function and its digital equivalent is called quantization.

The number of quantization levels should be high enough for human perception of fine shading details in the image. The occurrence of false contours is the main problem in image

which has been quantized with sufficient brightness level.

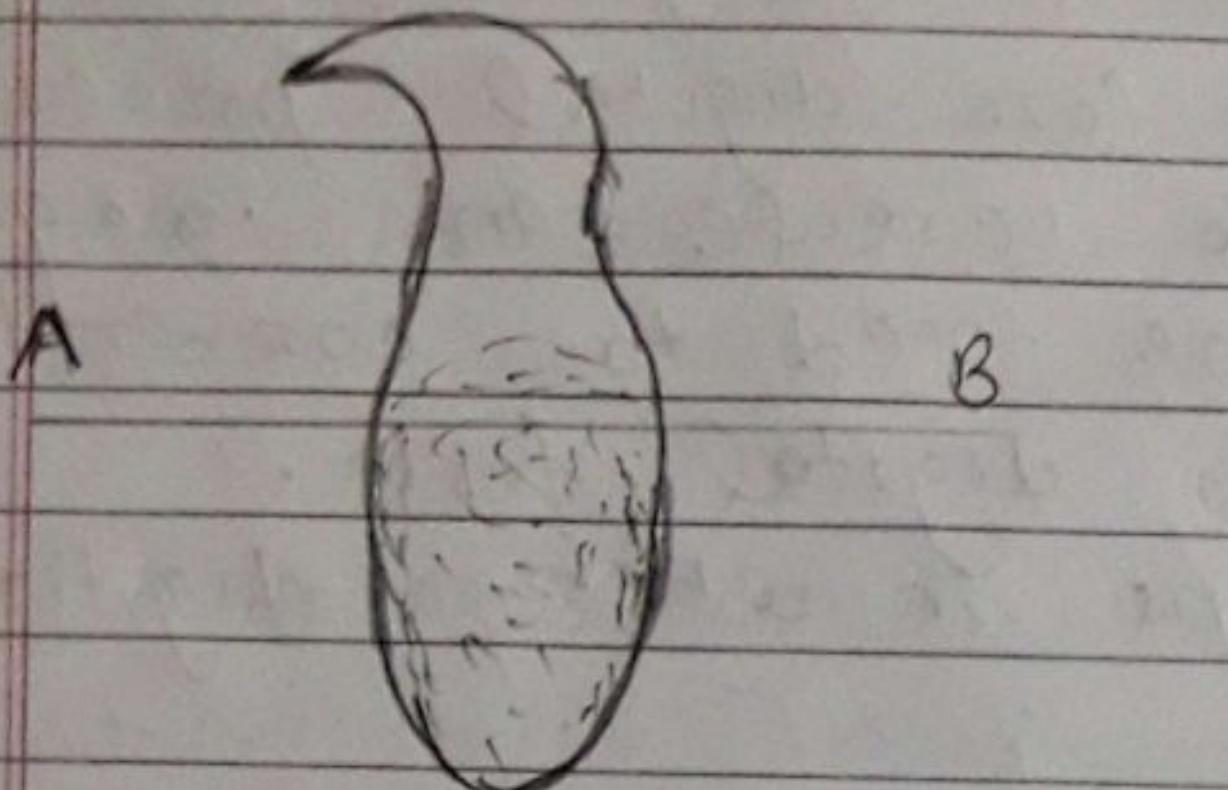


fig (a) continuous image

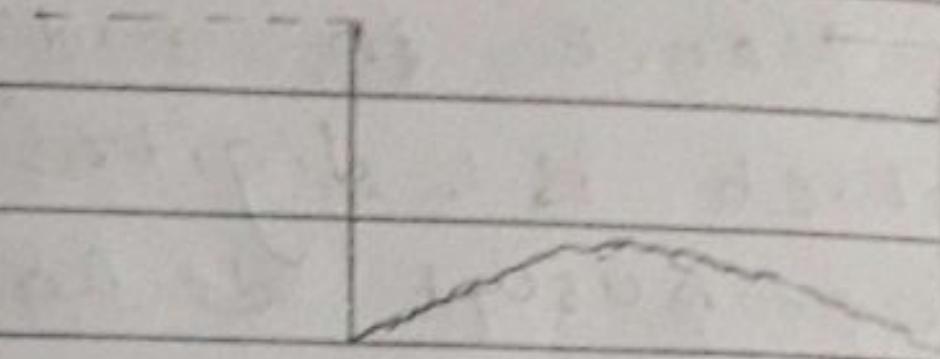
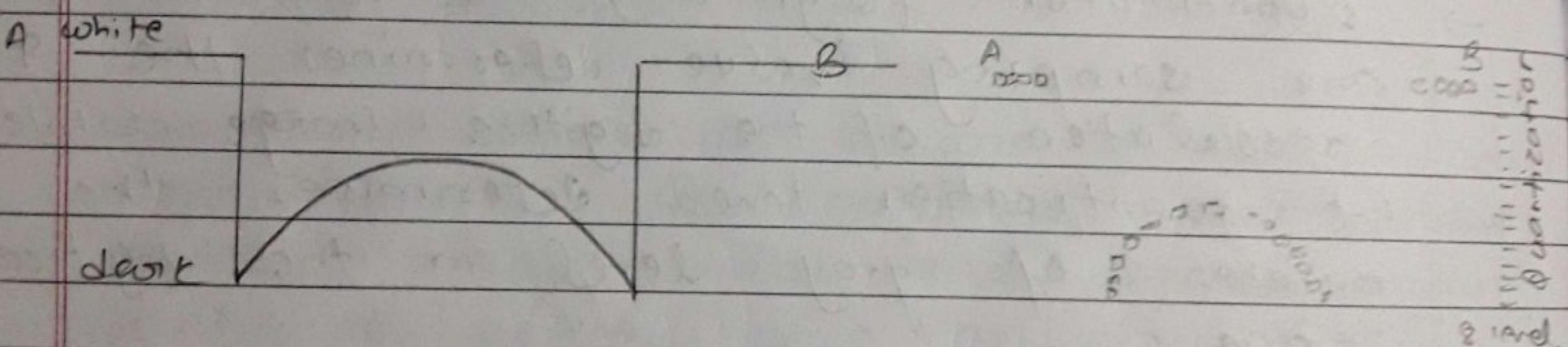


fig (b) scan line from  
A to B in the continuous  
image



The fig (a) shows a continuous image i.e. to be converted to digital form. An image may be continuous with respect to  $x$  and  $y$  co-ordinates and also in amplitude.

To convert it to digital form, we have to sample the function in both co-ordinates and in amplitude.

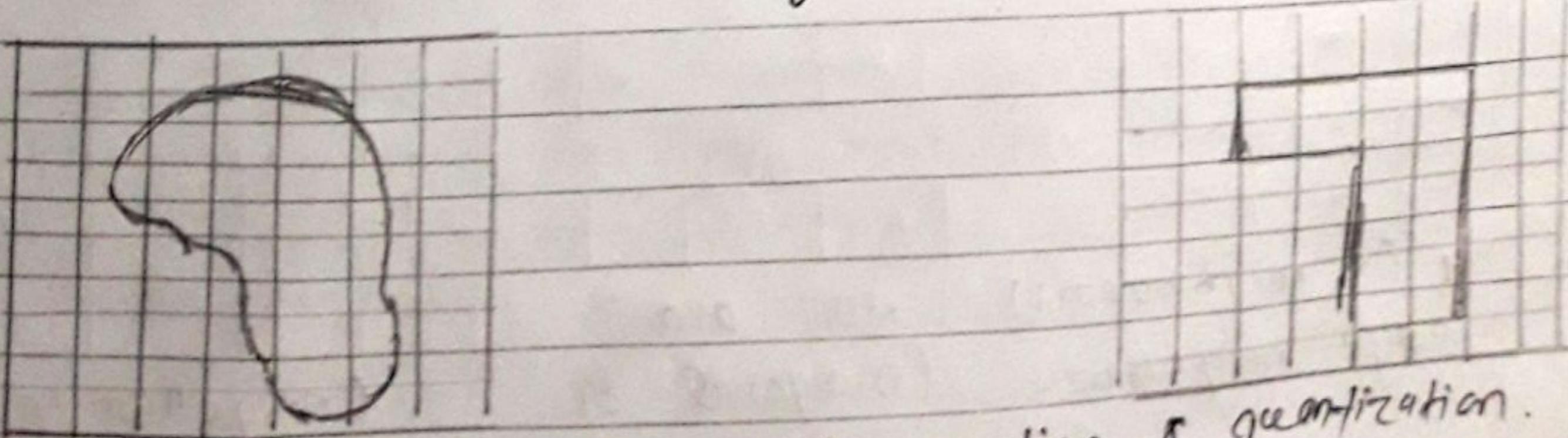
The one dimensional function in figure 1(b) is a plot of amplitude (intensity level) values of the continuous image along the line segment AB in fig(a).

The random variations are due to the image noise.

To sample this function we take equally spaced samples along line AB as shown in figure (c). For the formation of digital function, the intensity value also must be converted quantized into discrete quantities.

The intensity scale is divided into eight discrete intervals running from black to white. The continuous intensity level are quantized by assigning one of the eight values to each sample.

Starting at the top of the image and carry out this procedure line by line produces a two dimensional digital image.



result of image sampling & quantization.

- \* Some basic relationship like neighbour, Connectivity, Distance measure between pixels.

## Neighbors of a pixel:

A pixel at co-ordinate  $(x, y)$  has four horizontal and vertical neighbours whose co-ordinates are given by:

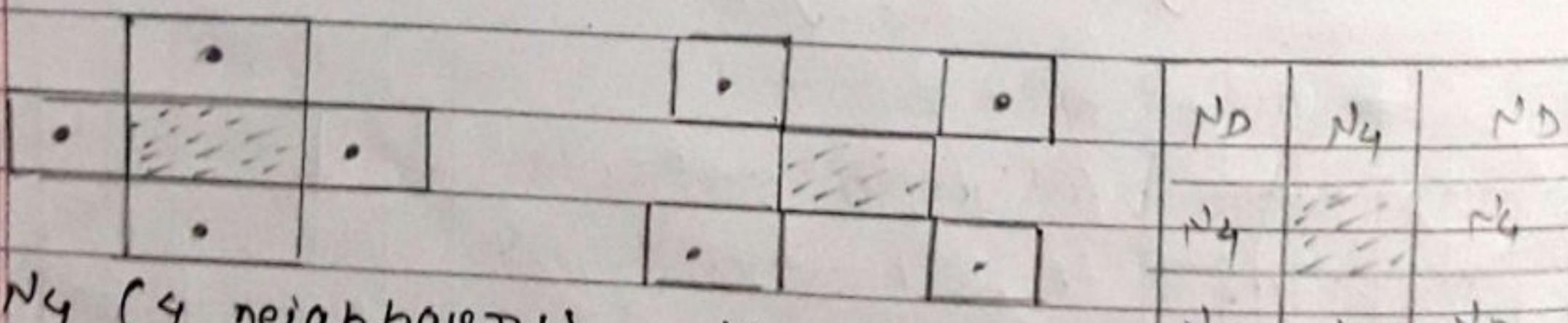
$(x+1, y)$   $(x-1, y)$   $(x, y+1)$   $(x, y-1)$

This set of pixel is called the 4 neighbours of  $p$  denoted by  $N_4(p)$ .

The four diagonal neighbours of  $p$  have co-ordinates:

$(x+1, y+1)$   $(x+1, y-1)$   $(x-1, y+1)$   $(x-1, y-1)$   
and are denoted by  $N_D(p)$

These points together with the 4 neighbours are called the neighbours of  $p$ , denoted by  $N_8(p)$ .



$N_4$  (4 neighbours)  
edge neighbour

ND, aka

Diagonal or  
point neighbour

Together 4 and P  
neighbours  $N_8 - P$   
(neighbour)

$N_4$  (4 neighbors)

edge neighbors)

Two pixels are connected if they are neighbors and their gray level satisfy some specified criteria of similarity.

To determine whether the pixels are adjacent in some sense, let  $V$  be the set of gray level values used to define connectivity then two pixels  $p, q$  that have values from the set of  $V$  are:

(a) 4 connected if  $q$  is in the set  $N_4(p)$

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

(b) 8 connected if  $q$  is in the set  $N_8(p)$

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

(c)  $m$  is connected if

(i)  $q$  is in  $N_4(p)$  or

(ii)  $q$  is in  $N_8(p)$  and the set

$N_4(p) \cap N_4(q)$  is empty

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

## Distance Measure:

Given pixels  $p$ ,  $q$  and  $z$  with co-ordinates,  $(x, y)$ ,  $(s, t)$ ,  $(u, v)$  respectively, the distance function  $D$  has the following properties.

- (a)  $D(p, q) \geq 0$  [ $D(p, q) = 0$ , if  $p = q$ ]
- (b)  $D(p, q) = D(q, p)$
- (c)  $D(p, z) \leq D(p, q) + D(q, z)$

## Different Distance measure

### (a) Euclidean distance

$$D_e(p, q) = [(x-s)^2 + (y-t)^2]^{1/2}$$

### (b) city Block distance (D<sub>1</sub> distance)

$$D_1(p, q) = |x-s| + |y-t|$$

2	1	2
2	1	0
2	1	2
2		

### (c) chess board distance (D<sub>8</sub> distance)

$$D_8(p, q) = \max(|x-s|, |y-t|)$$

2	0	2	2	2
2	1	1	0	2
2	1	0	1	2
2	1	1	1	2

## Element of visual perception:

Although the digital image processing field is built on a foundation of mathematical and probabilistic formulation, human intuition and analysis play a central role in the choice of one technique versus another and this choice often is more based on subjective, visual judgments.

### 1. Image formation in the eye.

The principle difference between the lens of the eye and an ordinary lens is that the lens of eye is flexible. Muscle within the eye can be used to changes the shape of lens allowing us focus on objects that are near or far away.

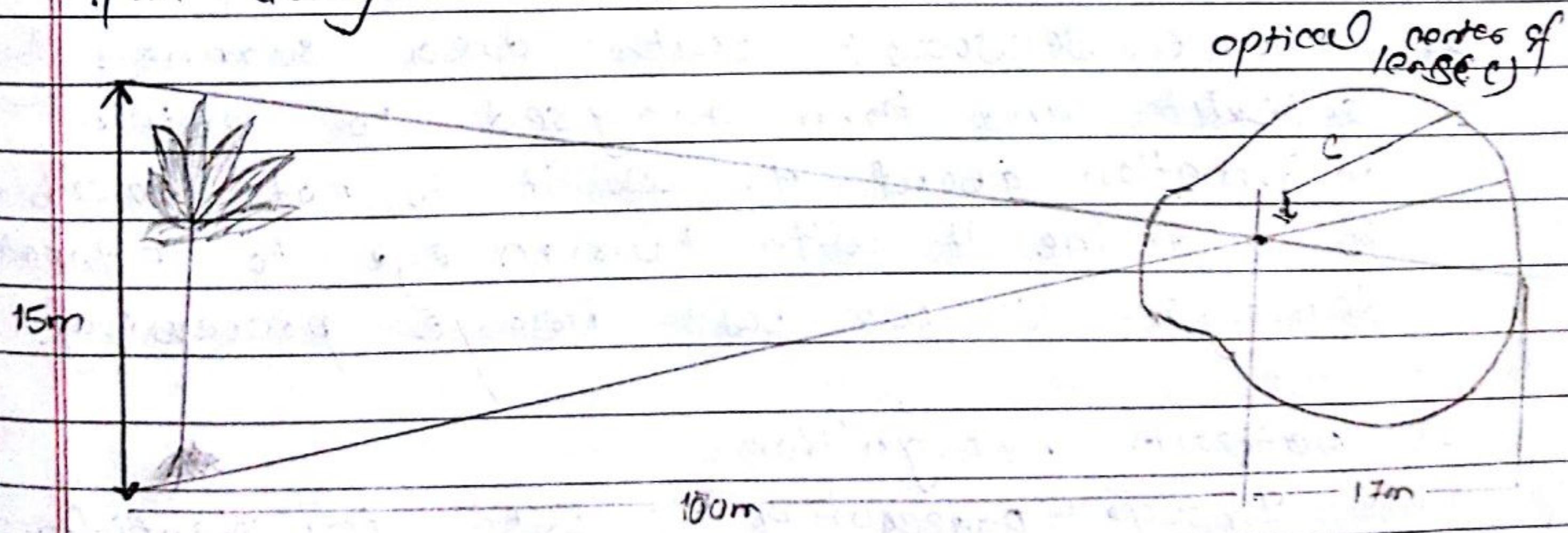


fig: graphical representation of the eye looking at a plan tree.

2. Brightness adaptation and discrimination  
Because digital image are displayed as a discrete set of intensities, the ability to discriminate between different intensity level is an important consideration in presenting image processing results. The retina is covered with light. The human visual system focus light from objects on to retina. The retina is covered with light receptors called cone and rods.

## Application of digital image processing

- (1) Medical science:- X-ray, mammography, MRI, CTSCAN
- (2) Remote sensors:- Earth area scanned by satellite and then analysed to obtain information about it. As it is not possible to examine it with human eye to estimate damages, so we use image processing.
- (3) pattern recognition  
Image processing is used for identifying the objects in an image and then machine learning is used to learn the system for change in pattern.

## (4) video processing.

Fundamental steps in image processing:

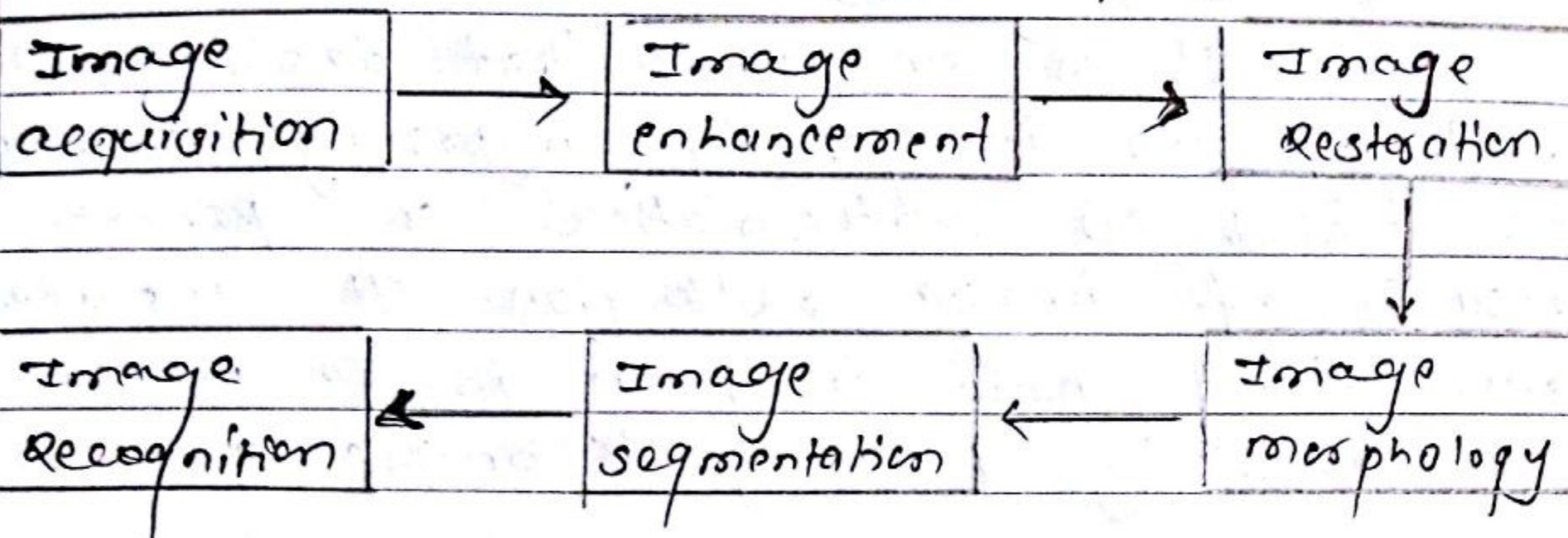


fig: steps in image processing.

### Image acquisition:

It involves acquiring a digital image using a image sensor/ camera and do necessary preprocessing. If the image is not digital, an analog to digital conversion process is required.

### Image enhancement:

It improves the quality of an image by highlighting certain feature of interest in an image like increasing/ decreasing the contrast of an image quality gets improved with two methods.

Spatial domain: Deal with time constraint  
frequency domain: Deal with frequency constraint

### Image Restoration:

It is an area that deals with restoring an image by improving its appearance based on mathematical or probabilistic models of image restoration. It includes eliminating noise from an image which can be done by filtering technique and so on.

### Image morphology:

It deals with tools for extracting image component that are useful in the representation and description of shape

e.g.: The width of the alphabets get combined with each other for removing the expanded edges of these characters, we do image morphology.

Image morphology deals with edges and boundaries.

### Image segmentation:

It includes breaking an image into constituent parts. It is the most difficult task in digital image processing.

Good segmentation simplifies the problem poor segmentation make the task

impossible.

## Image recognition!

It is the process which assigns a label to an image based on the information provided by its descriptions.

## Types of images:

- (i) Binary  $\rightarrow$  two pixel values (0 & 1)  
(black & white)
- (ii) Gray scale  $\rightarrow$  256 levels (0 to 255)  
(1 element - 8 bits)
- (iii) Coloured  $\rightarrow$  (R, G, B) (1 element -  $8 \times 3 = 24$  bits)

## COURSE CONTENTS:

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## Image Enhancement :

The principle objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. Thus for eg. a method that is quite useful for enhancing x-ray images may not necessarily be the best approach for enhancing pictures of M

There are two broad categories of image enhancement:

- ① spatial domain
- ② frequency domain method.

The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image.

The value of a pixel with co-ordinate  $(x,y)$  in the enhanced image is the result of performing some operation on the pixels in the neighbourhood of  $(x,y)$  in the input image.  
F. Neighbourhood can be any shape, but usually they are rectangular.

Frequency domain processing techniques are based on modifying the Fourier transform of an image.

### Technique of image enhancement in spatial domain

- Image Negatives
- Gray level transformations:
  - ↳ linear (Negative (Intensity))
  - ↳ logarithmic (Log / Inverse Log)
  - ↳ power law ( $n^{th}$  power /  $n^{th}$  root)
- piecewise linear transformations:
  - ↳ Gray level slicing
  - ↳ Bit plane slicing
- Histogram processing
- Enhancement using arithmetic / logic operation (Image street subtraction, Image Averaging)
- spatial filtering
- Spatial domain process will be denoted by the expression.

$$g(m, y) = T[f(m, y)]$$

*f(m, y)* is the input image

*g(m, y)* is the processed image.

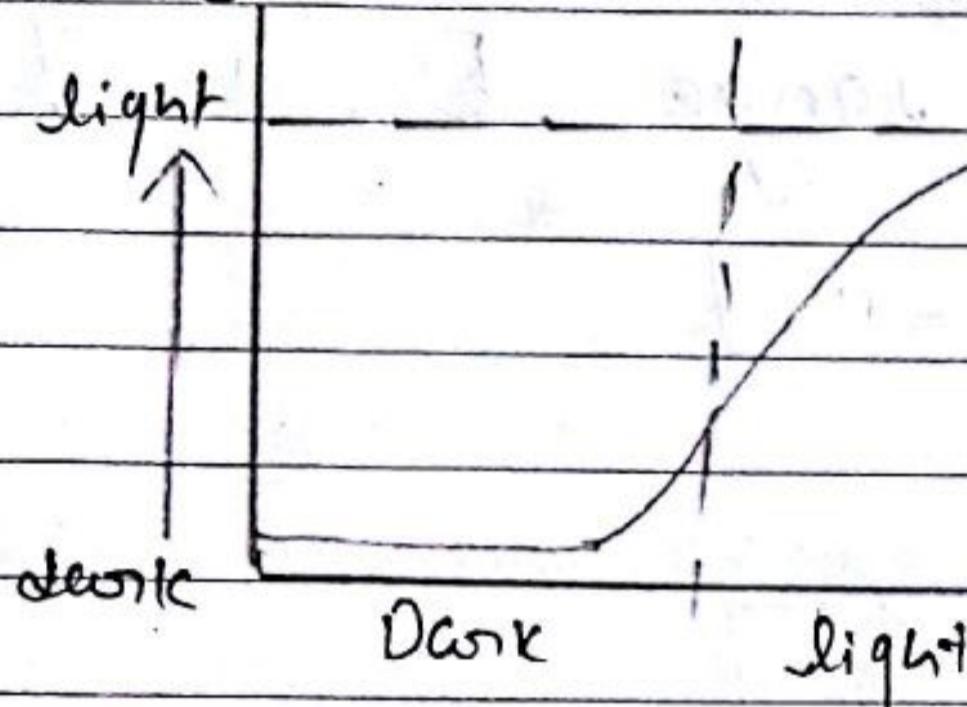
*T* is an operation on *f* defined over some neighbourhood of *f(m, y)*

point processing operation takes the form

$$S = T(r)$$

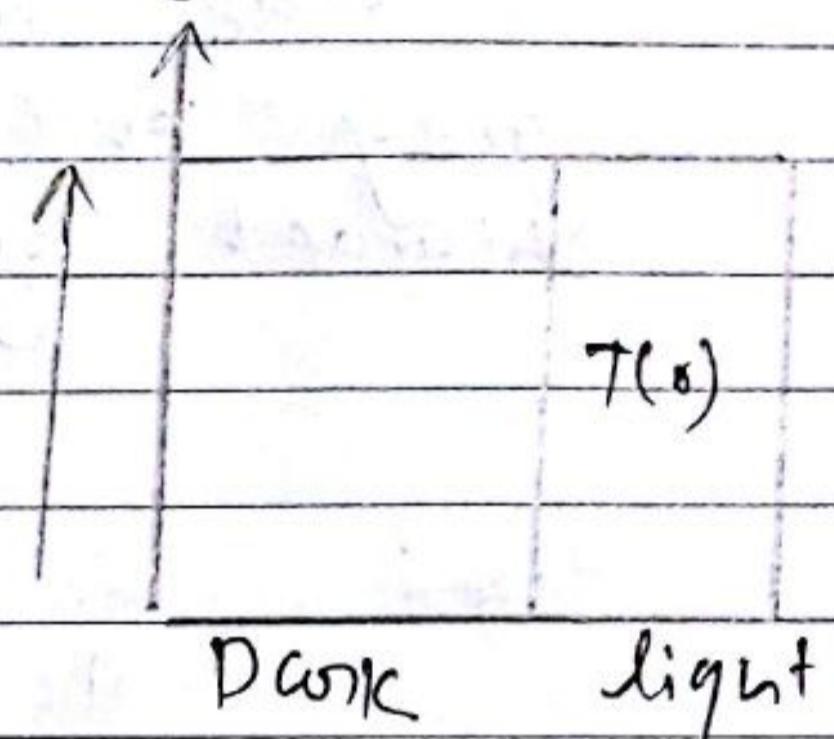
Thresholding function:

$$S = (r)$$



fig(a)

$$S = T(r)$$



fig(b)

→ The function increase the contrast in an image by lowering levels below  $m$  and brightening the levels above  $m$  in the original image. The figure (b) shows the two level (binary) image. A mapping of this form is called as a thresholding function which is given by

$$S = \begin{cases} 1 & r \geq \text{threshold} \\ 0 & r < \text{threshold.} \end{cases}$$

Image Negatives:

This type of processing is particularly suitable for enhancing white or gray detail embedded in dark regions of

an image specially when the dark areas were dominant in size.

e.g.: it is useful in analyzing the breast tissue from a digital mammogram.

The negative of an image with gray levels in the range  $[0, L-1]$  is obtained by

$$S = [L-1 - r]$$

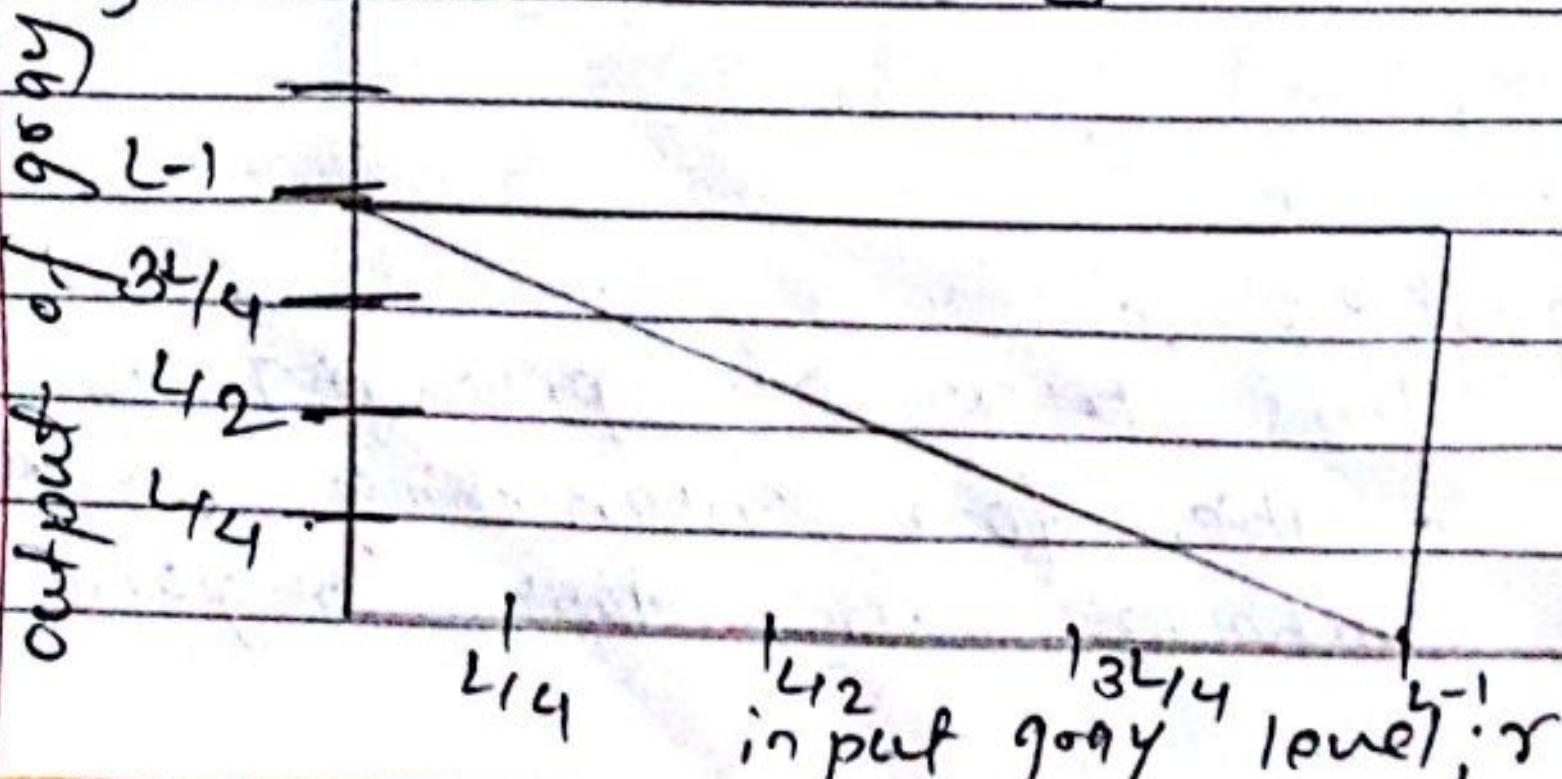
e.g.:

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

Now, negative of image A,

$$A' = \begin{bmatrix} 9-1 & 9-2 & 9-3 \\ 9-4 & 9-5 & 9-6 \\ 9-7 & 9-8 & 9-9 \end{bmatrix}$$

$$= \begin{bmatrix} 8 & 7 & 6 \\ 5 & 4 & 3 \\ 2 & 1 & 0 \end{bmatrix}$$



## Log transformations:

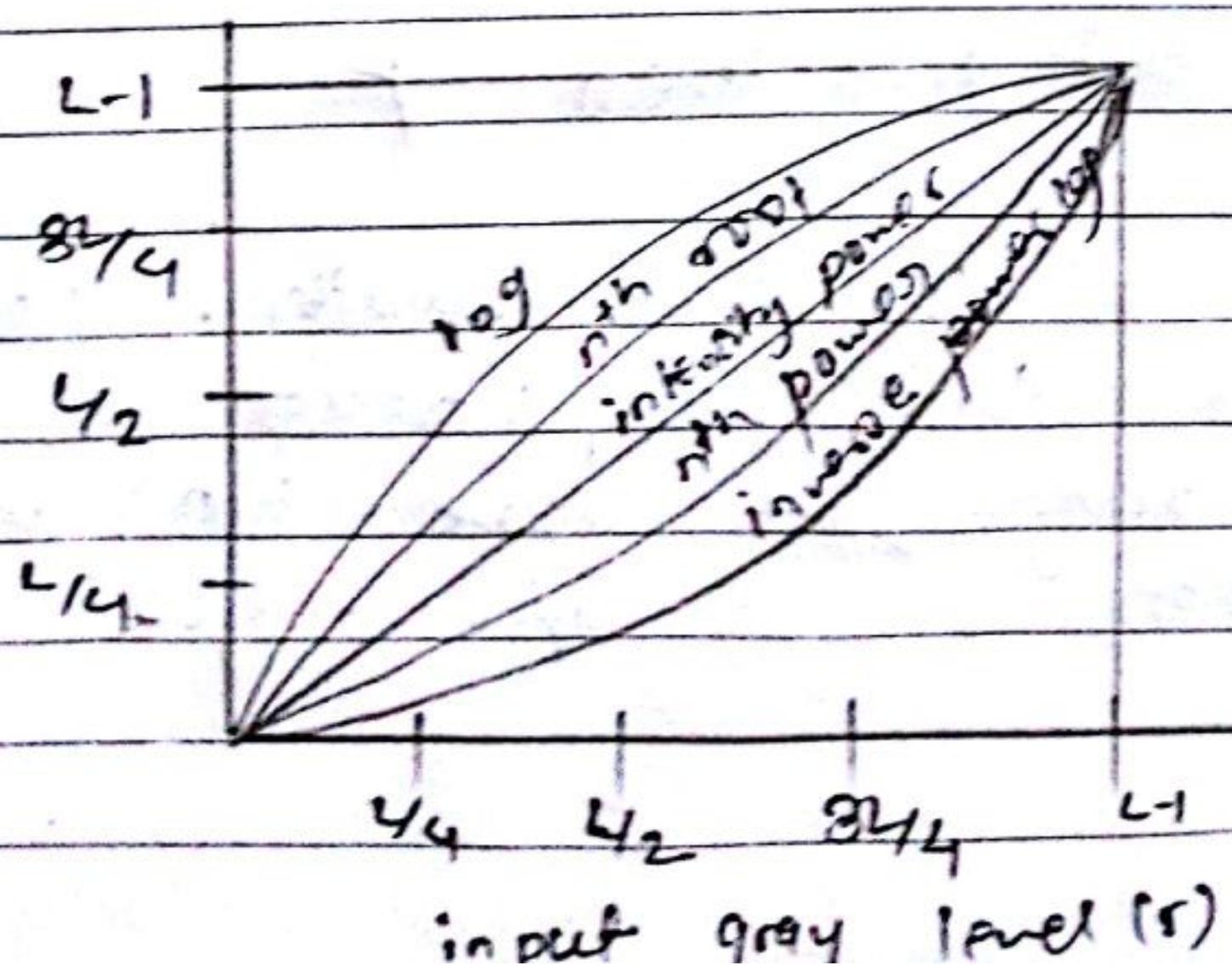
The general form of log transformation is

$$S = C \log(1+r)$$

where,  $C$  is a constant which is usually set to 1 and it is assumed that  $r \geq 0$ .

→ This transformation maps a narrow range of low gray levels values in the input image into a wider range of output levels. The opposite is true for higher values of input levels.

→ We use this type of transformation to expand the values of dark pixels in an image while compressing the higher level values. The opposite is true for inverse log transformation.



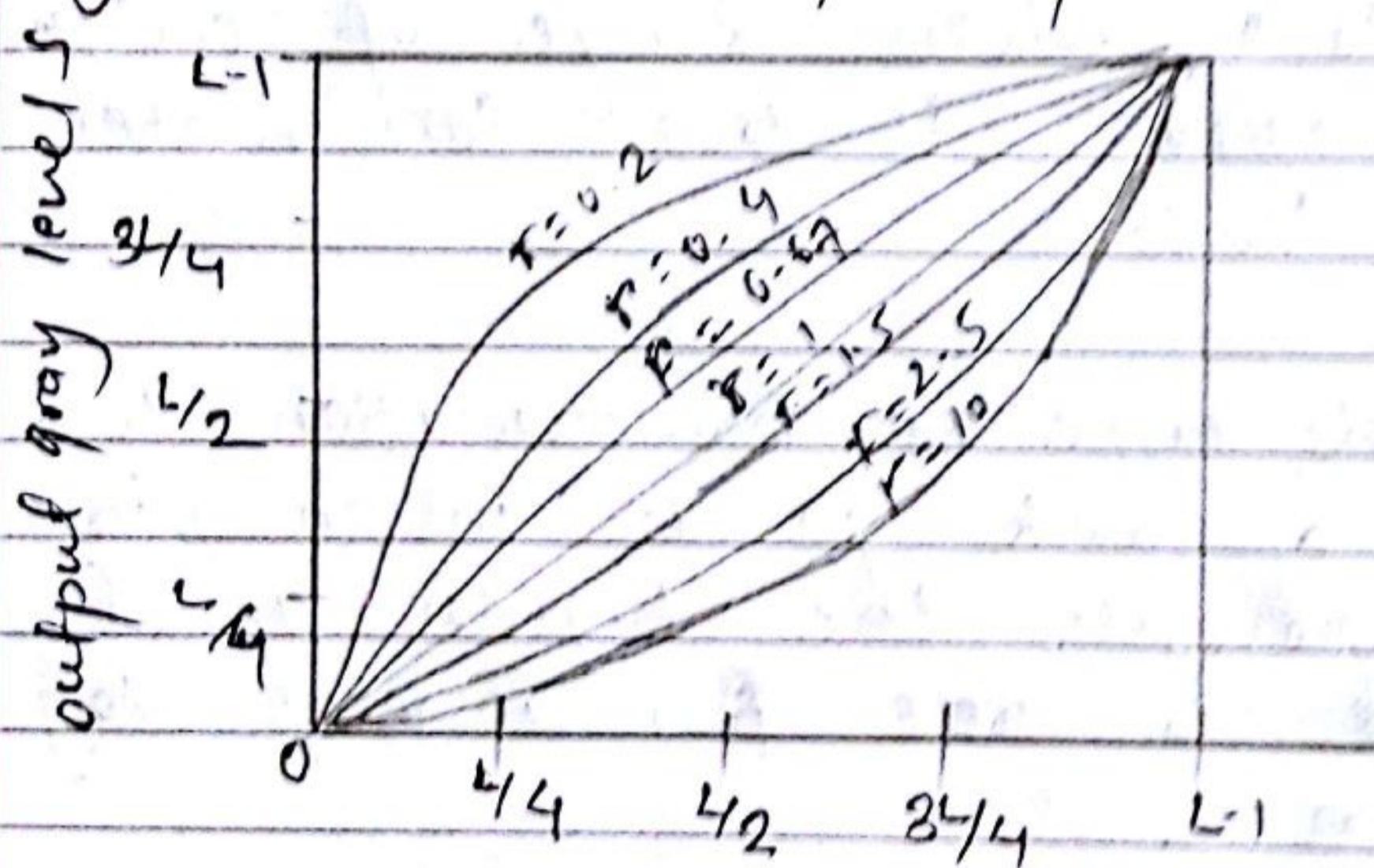
## Power law transformation

power law transformation have the basic form,

$$S = C \cdot I^{\gamma} \quad [\gamma = \text{gamma}]$$

where  $C$  and  $\gamma$  are positive constants.

as in case of log transformation, power law curves with functional values of  $\gamma$  map a narrow range of dark i/p values into a wider range of output values with the opposite being done for higher values of input levels.



input gray levels,  $I$

As in case of log transformation, power law curves with functional values of  $\gamma$  map a narrow range of dark i/p values into a wider range of output values.

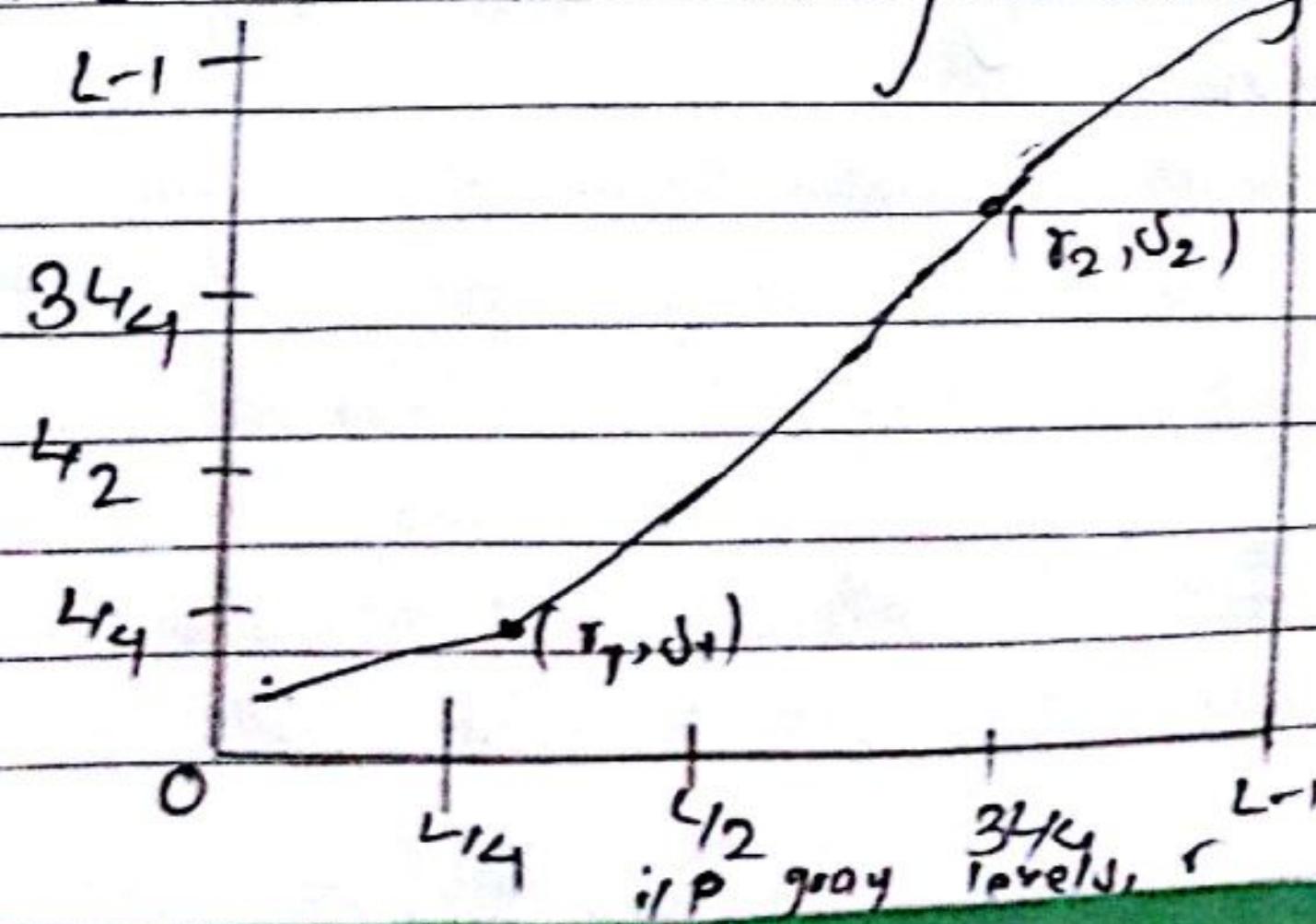
- unlike the log function we can obtain a family of possible transformation curves by simply varying  $\gamma$
- The curves generated with values,  $\gamma > 1$  have exactly the opposite effect as those generated with value of  $\gamma < 1$
- The variation reduces to identify transformation when,

$$c = \gamma = 1$$

The process of connecting for the power law response is referred to as gamma correction.

### Piecewise Linear Transformation Function:

Contrast stretching: The idea behind contrast-stretching is to increase the dynamic range of gray level in the image being processed.



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Page \_\_\_\_\_

The figure shows the typical transformation used for contrast stretching. The location of points  $(x_1, y_1)$  and  $(x_2, y_2)$  control the shape of transformation.

- If  $y_1 = s_1$  and  $y_2 = s_2$ , the transformation is a linear function that produces no change in gray levels.
- The contrast stretched image from previous graph is obtained from the equation of the line having following points  $(x_1, y_1) = (r_{\min}, 0)$  and  $(x_2, y_2) = (r_{\max}, 1)$ .

### Gray level slicing:

It is used to highlight a specific range of intensities in an image that might be of interest.

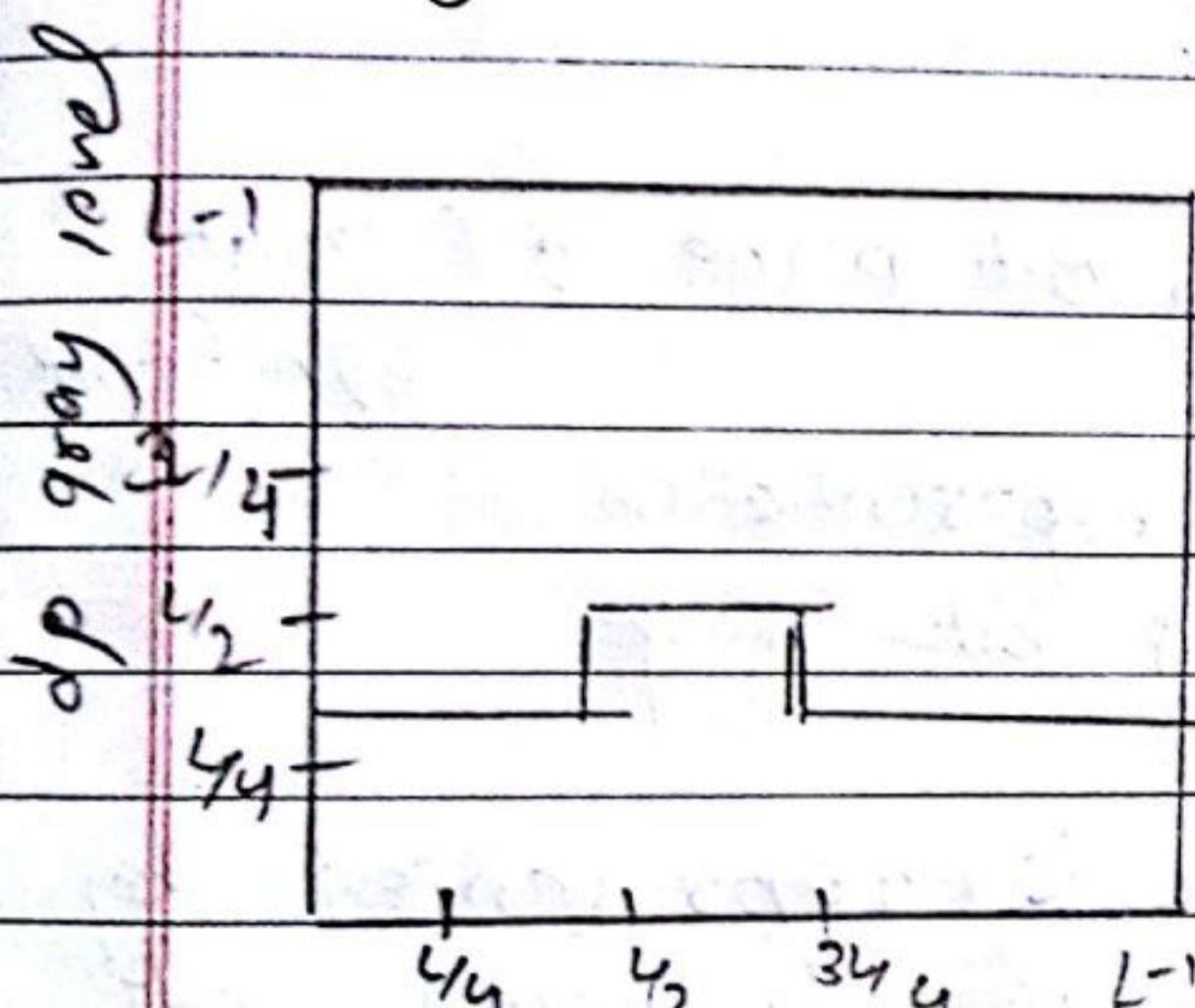
e.g.: Enhancing features such as a mall of water

→ There are two approach for gray level slicing.

(i) Set all pixel values within a range of interest to one value (white) and all others to another value (black).

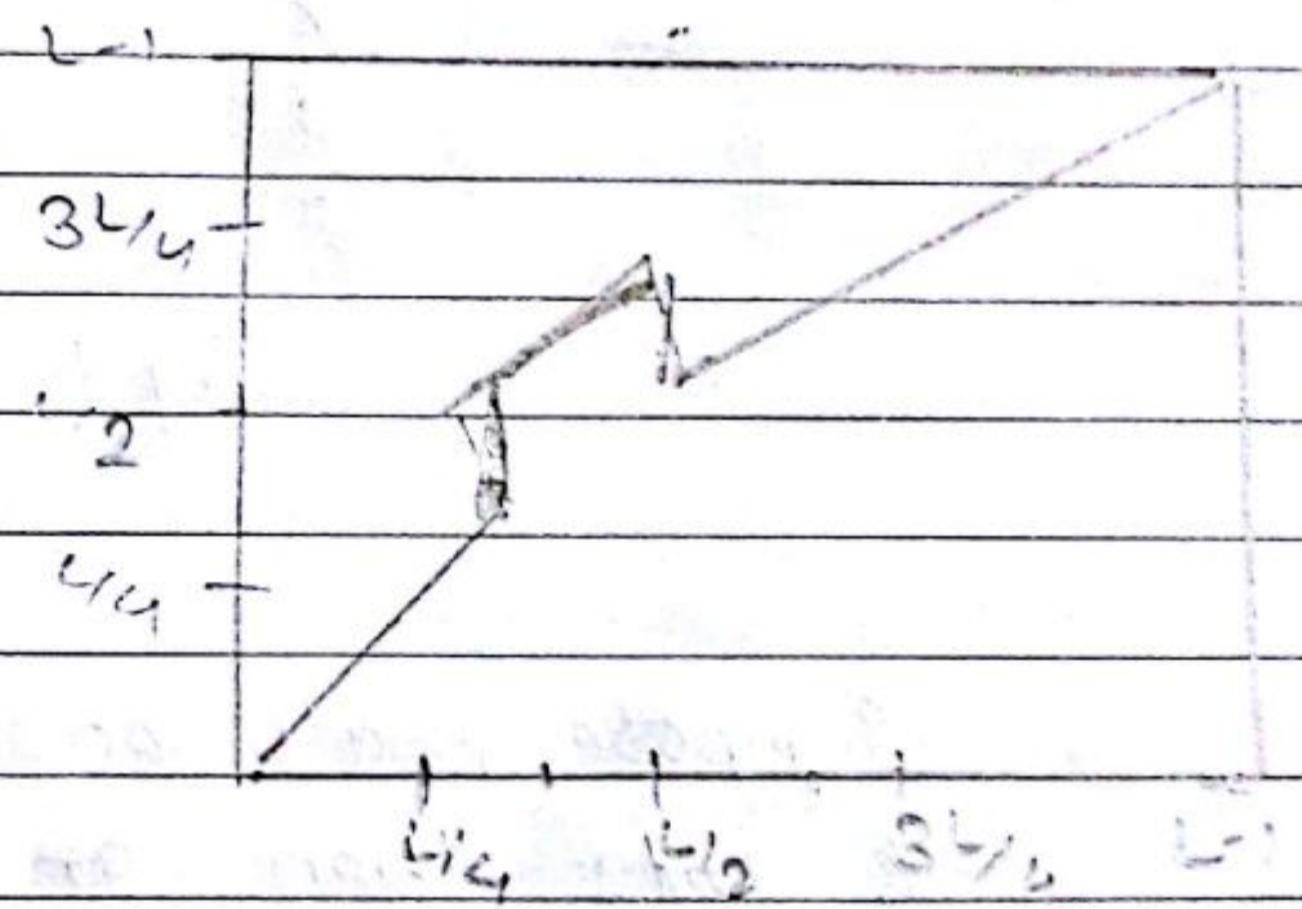
It produces a binary image.

(ii) Brighten (or darken) pixel values in a range of interest and leave all others unchanged.



i/p gray level  
value

fig(a)



i/p gray level

fig(b)

→ The transformation in fig(a) highlight the range  $[A, B]$  of gray level and reduces all others to a constant level.

→ The transformation in fig(b) highlight the range  $[A, B]$  but preserve all others levels.

### A Bit plane slicing:

It highlight the contribution made by specific bits.

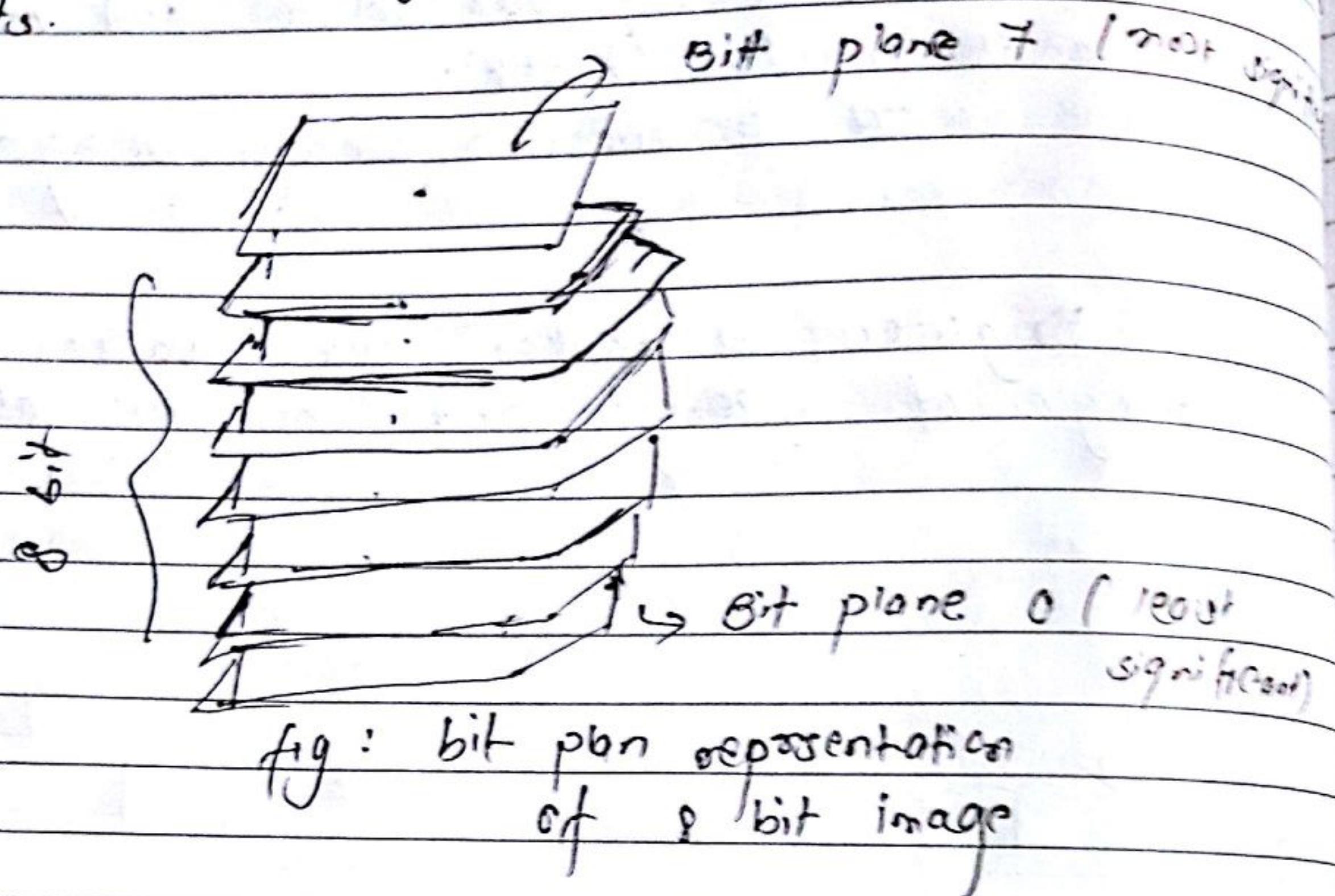


fig : bit pbn representation  
of 8 bit image

Suppose that each pixel is represented by 8 bits then an image is composed of eight 1 bit plane ranging from bit plane 0 for the least significant bit to the bit plane 7 for the most significant bit.

- The higher order bits (especially the top four) contain majority of the visually significant data.
- The other bit planes contribute to more subtle details in the image.

Also, this type of decomposition is a useful for image compression.

## Histogram Processing :-

- The histogram of an image shows us the distribution of gray levels in an image
- The histogram of a digital image with gray levels in the range  $[0, L-1]$  is a discrete function ;  $h(r_k) = n_k$   
where,  $r_k$  is the  $k^{\text{th}}$  gray level and  $n_k$  is the no. of pixels ~~are~~ in the image having gray level  $r_k$ .
- It is a common practice to normalize a histogram by dividing each of its values by the total no. of pixels in the image denoted by  $n$ .

thus. a normalized histogram is given by

$$p(r_k) = \frac{n_k}{n} \text{ for } k = 0, 1, 2, \dots (.)$$

where  $p(r_k)$  gives an estimate of the probability of occurrence of gray level  $r_k$ .

- Histogram is the basis for numerous spatial domain processing techniques.
- It provides useful image statistics and the information inherent in histogram is useful. In other image processing application such as image compression and segmentation.
- Histograms are simple to calculate in software and also lend themselves to economic hardware implementation thus making them a popular tool for real time image processing.

## Histogram Equalization:

- It is the process for increasing the contrast in an image by spreading the histogram out to the approximately uniformly distributed
- The increase in dynamic range produce an increase in contrast.
- The gray level of an image that has been subjected to histogram equalization are spread out and always reach white.

→ For image with low contrast, histogram equalization has the adverse effect of increasing visual.

→ The intensity transformation function we are constructing is of the form,

$$s = T(r) \quad 0 \leq r \leq L-1$$

An output intensity level  $s$  is produced for every pixels in the input image having intensity  $r$  we assume  $T(s)$  is monotonically increasing in the interval  $0 \leq r \leq L-1$

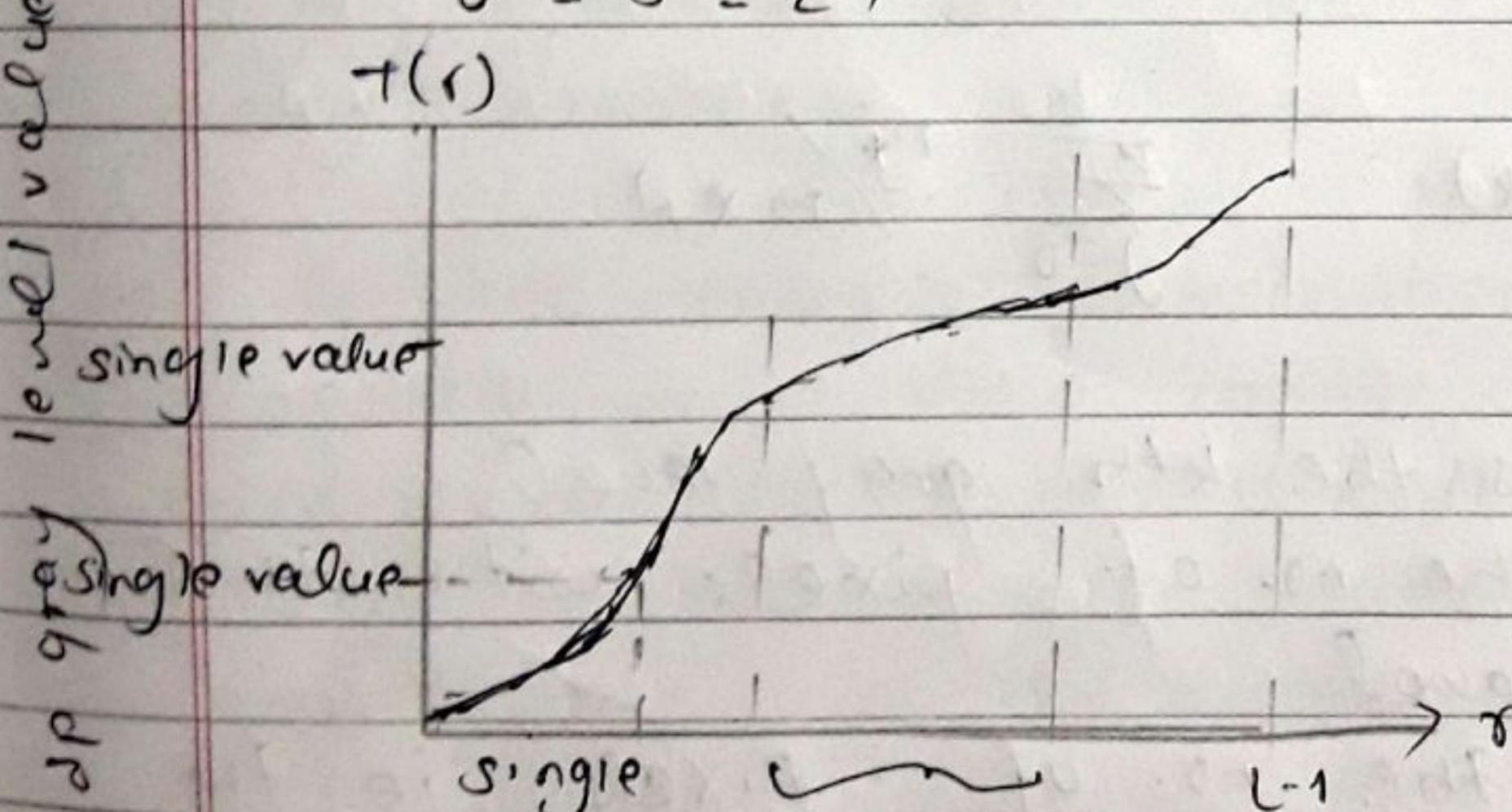
$$\text{i.e., } 0 \leq T(r) \leq L-1 \text{ for } 0 \leq r \leq L-1$$

If we define increase,

$$r = T^{-1}(s)$$

$$0 \leq s \leq L-1$$

$$T(r)$$



multiple values  $\mapsto$  single value

fig(a): monotonically increasing function showing how multiple values map to single value.

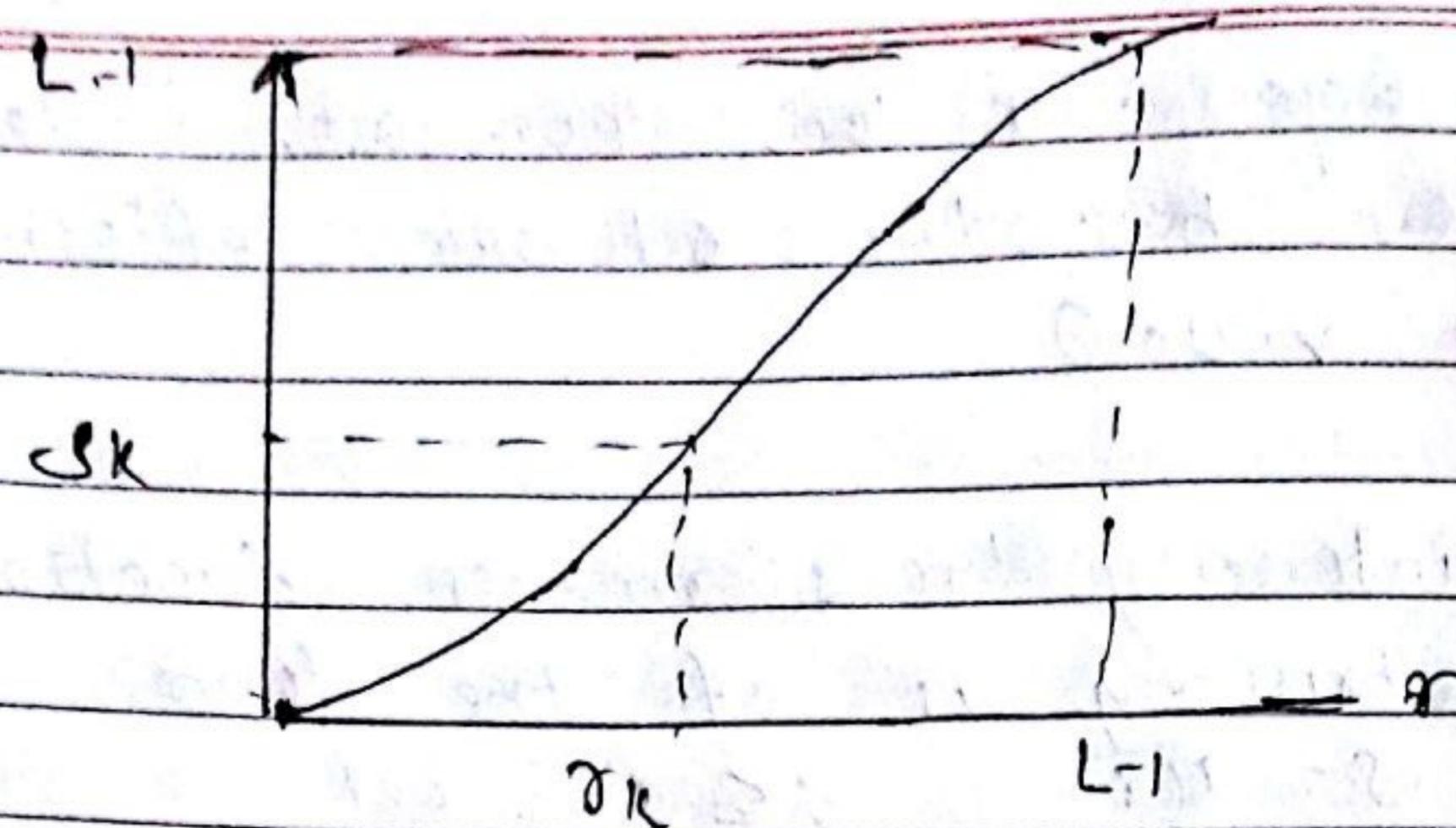


fig: - strictly monotonically increasing  
(one to one mapping)

→ Spreading out the frequencies in an image (or equalizing the image) is a simple way to improve contrast on washed out images.

Now, the transformation function  $s_k$  is given as,

$$s_k = T(r_k) = \sum_{j=0}^k n_j / m \times N$$

where,  $r_k$  is the  $k$ th gray level  
 $n_j$ , is the no. of pixels with that gray level

$m \times N$ , is the no. of pixels in the image and

$$k = 0, 1, \dots, L-1$$

This yields an 's' with as many elements

as the original image's histogram (normally 256 for our test images).

The values of  $s$  will be in the range  $(0, 1)$  for constructing a new image,  $s$  would be scaled to the range  $[1, 256]$

$$s_{ik} = T(\tau_{ik}) = \frac{L-1}{M \times N} \sum_{j=0}^k n_j$$

## Enhancement using arithmetic and logic operations

→ Arithmetic / logic operations involving images are performed on a pixel by pixel basis between two or more images. (Excluves logic operation NOT, which is performed on a single image).

→ As an example, subtraction of two images results in a new image whose pixel at co-ordinate  $(x, y)$  is the difference b/w the pixel in the same location in the two images being subtracted.

The difference b/w two images  $f(x, y)$  and  $h(x, y)$  is expressed as,

$$g(x, y) = f(x, y) - h(x, y)$$

→ The AND and OR operations are used for marking i.e. for selection sub image in an image.

## Spatial filtering!

- Use of spatial mask for filtering is called spatial filtering
- It may be linear or non linear.
- The process consists simply of moving the filter mask from point to point in an image.
- At each point  $(x, y)$  the response of the filter at that point is calculated using a predetermined relationship.

## Linear filters!

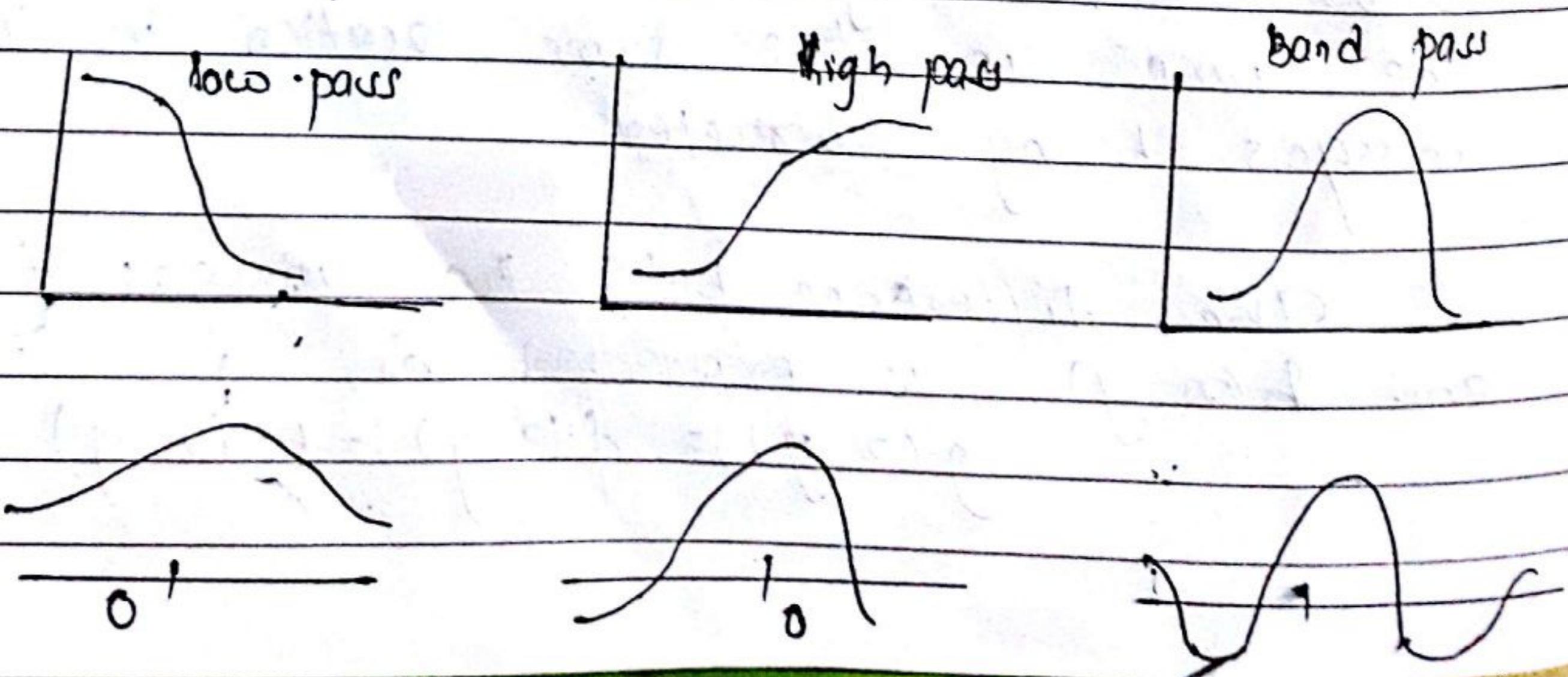


fig: filters in frequency domain and their corresponding spatial filters.

low pass :- attenuate (or eliminate) high frequency components such as characterized by edge and sharp details in an image. The net effect is image blurring.

high pass :- attenuate (or eliminate) low frequency components such as slowly varying characteristics. The net effect is sharpening of edges and other details.

Band pass: attenuate (or eliminate) a given frequency range which is used primarily for image restoration.

→ The basic approach is to sum products between mask coefficients and pixels values.

$$\text{i.e. } Q = w_1 z_1 + w_2 z_2 + \dots + w_m z_m$$

$$= \sum_{i=1}^{mn} w_i z_i$$

$w$  = mask coefficient.

$z$  = values of image gray levels corresponding to those coefficient

$mn$  = total no. of coefficients in the mask : of size  $m \times n$ .

## Non-linear spatial filter:

→ Non-linear spatial filters also operate on neighbourhoods. Their operation is based directly on pixel values in the neighbourhood under construction.

(1) Median filter: It computes the median gray level values of the neighbourhood. The median value of a set of numbers is the midpoint value of that set e.g. from the set  $\{1, 7, 15, 18, 29\}$  15 is the median. It is used for noise reduction.

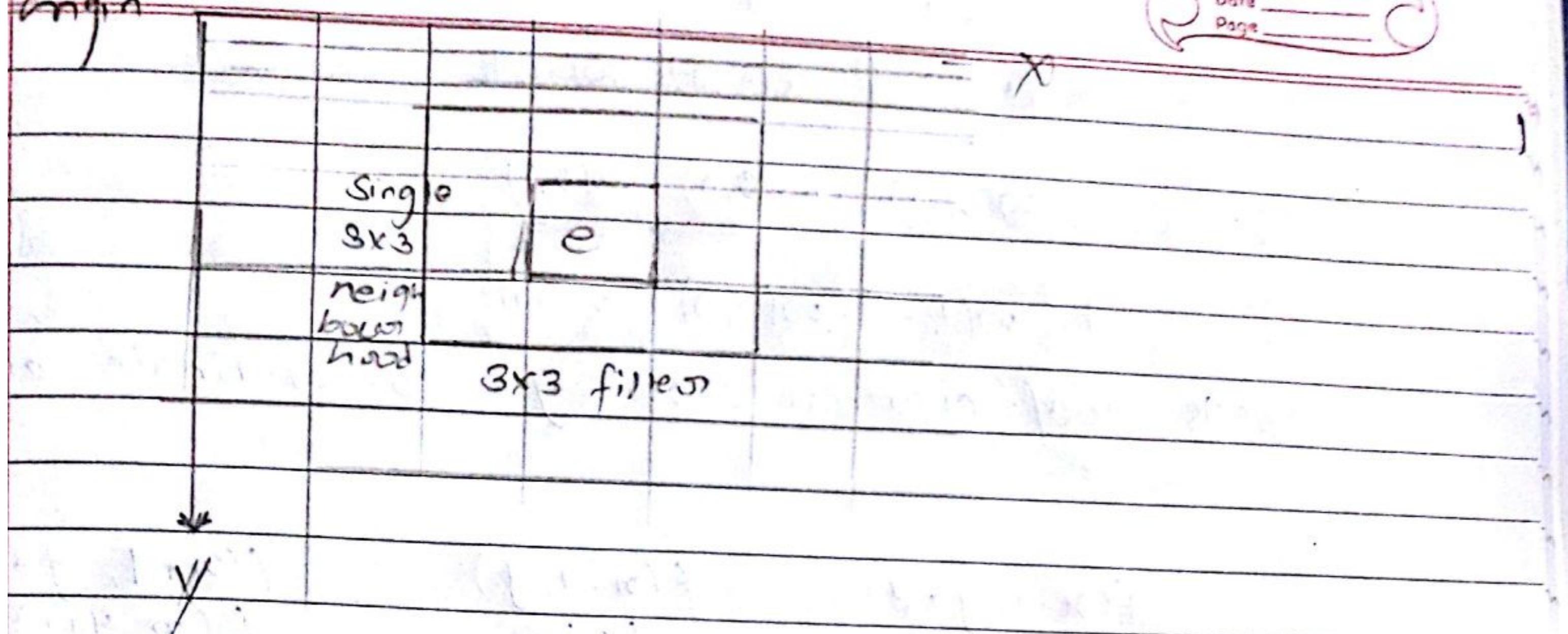
(2) Max filter: Used to find the brightest point in an image. The max operation set the pixel value to the maximum in the neighbourhood.

$$P = \max \{ z_k \mid k=1, 2, \dots, 93 \}$$

(3) Min filter: Used to find the dimmest point in an image. The min operation set the pixel value to the minimum in the neighbourhood.

$$P = \min \{ z_k \mid k=1, 2, \dots, 93 \}$$

origin



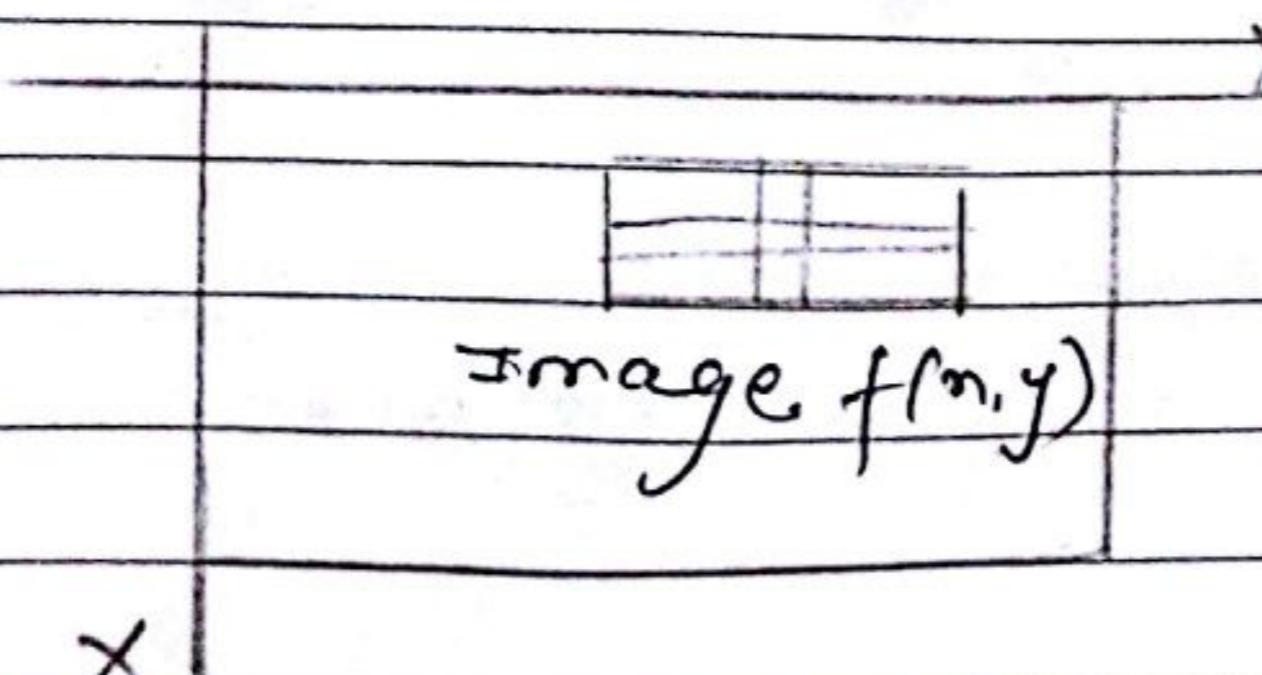
a	b	c	*	r	s	t
d	e	f	*	u	v	w
g	h	i	*	x	y	z

original image      after  
pixels

$$\begin{aligned} e_{\text{processed}} = & u * e + r * a + s * b + t * c + w * d \\ & + v * f + x * g + y * h + z * i \end{aligned}$$

The above process is repeated for every pixel in the above original image to generate the filtered image.

In general :



	-1	0	1
-1	$w(-1, -1)$	$w(-1, 0)$	$w(-1, 1)$
0	$w(0, -1)$	$w(0, 0)$	$w(0, 1)$
1	$w(1, -1)$	$w(1, 0)$	$w(1, 1)$

mask coefficient showing co-ordinate arrangement.

$f(n-1, y-1)$	$f(n-1, y)$	$f(n-1, y+1)$
$f(n, y-1)$	$f(n, y)$	$f(n, y+1)$
$f(n+1, y-1)$	$f(n+1, y)$	$f(n+1, y+1)$

pixels of image section under mask.

Spatial filtering in equation form can be expressed as

$$g(n, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(n+s, y+t)$$

## Smoothing Spatial filter:

- The shape of a image response needed to implement a lowpass (smoothing) filter indicates that filter should have all positive coefficient.
- for a  $3 \times 3$  mask, the simplest arrangement is to have all the coefficient values equal to one (neighbourhood averaging)
- The response would be the sum of all gray levels for the nine pixels in the mask which valid cause the value of out to be out of the valid gray level range

The solution is to scale the result by dividing by 9.

	1	1	1
1	1	1	1
1	1	1	1

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

Simple averaging filter especially useful in removing noise from image.

## weighted smoothing filter:

More effective smoothing thing filter can be generated by assigning different pixels in the neighbourhood different weights in the averaging function.

$\frac{1}{16}$	$\frac{2}{16}$	$\frac{1}{16}$
$\frac{2}{16}$	$\frac{4}{16}$	$\frac{2}{16}$
$\frac{1}{16}$	$\frac{2}{16}$	$\frac{1}{16}$

## weighted averaging filter

- pixels closer to the central pixel are more important thus are given more weights.
- One problem with the low pass filter it blurs edges and other sharp details. If the noise consists of strong spike like components and edge sharpness is to be preserved, then we can use median filtering.
- The value of each pixel is replaced the median pixel value in the neighbourhood.
- It forces pixels with distinct intensities to be more like their neighbours.

## Sharpening filter (high pass)

- The high pass filter indicates that the filter should have positive coefficients near its center and negative coefficient in the outer periphery.

For a  $3 \times 3$  mask, the simplest arrangement is to have the center coefficient positive and all others negative

	-1	-1	-1
$t_{1g}$	-1	8	-1
	-1	-1	-1

- Note that the sum of coefficient is zero
- when the mask is over a constant or slowly rising region, the o/p is zero or very small
- The result will be some what edge enhanced image over a dark back ground
- \* A high pass filter may be computed as,  
 High pass = original - lowpass  
 multiplying the original by an amplification factor yields a high boost on high frequency impulsive filter

$$\begin{aligned}
 \text{High boost} &= A(\text{original}) - \text{lowpass} \\
 &= (A-1) \text{ original} + \text{original} - \text{lowpass} \\
 &= (A-1) \text{ original} + \text{high pass}
 \end{aligned}$$

If  $A > 1$ , part of the original image is added to the high pass result (partially restoring low frequency component.)

Few approaches to deal with missing edge pixels.

- (1) Omit missing pixels.
- (2) pad the image
- (3) Replicate border pixels
- (4) Truncate the image
- (5) Allow pixels wrap around the image.

Comparison between the median filter and the average filter.

- The median filter is a non linear tool while the average filter is a linear tool one.
- In smooth uniform areas of the image, the median and the average filters will differ by very little.

- The median filter removes noise, while the average filter just spread it around evenly.
- The performance of median filter is particularly better for removing impact noise from average filter.

### Disadvantages of median filter:

Although median filter is a useful non linear image smoothing and enhancement technique, it also has some disadvantages.

The median filter removes both the noise and fine detail since it can't tell the difference between the two.

Anything relatively small in size compared to the size of the neighborhood will have minimal effect on the value of the median and will be filtered out.

In other words, the median filter can't distinguish fine detail from noise.

### Advantage median filter:

- The median filter performs relatively well on impulse noise as long as the spatial density of the impulse is not large.

- The adaptive median filter can handle much more spatially dense impulse noise and also performed some smoothing for non-impulse noise.
- The adaptive median filter performs spatial processing to determine which pixels in an image has been affected by impulse noise. It classifies pixels as noise by comparing each pixel in the image to its surrounding neighbour pixels. The size of neighbourhood is adjustable as well as the threshold for the comparison.
- A pixel that is different from a majority of its neighbour as well as being not structurally aligned with these pixels to which it is similar, is labeled as impulse noise. These noise are replaced by the median pixel value of the pixels in the neighbourhood that have passed the noise labeling test.
- The key feature of adaptive median filter is that the filter size changes depending on the characteristic of image.

Consider the following notation.

$z_{\min} \rightarrow$  minimum gray level value in  $S_{xy}$

$z_{\max} \rightarrow$  maximum gray level value in  $S_{xy}$

$z_{\text{med}} \rightarrow$  median gray level value in  $S_{xy}$

$z_{xy} \rightarrow$  gray level at co-ordinate  $(x, y)$

$s_{\max} \rightarrow$  maximum allowed size of  $S_{xy}$ .

The adaptive median filtering algorithm works in two levels denoted by level A and level B as follows.

$$\text{Level A: } A_1 = z_{\text{med}} - z_{\min}$$

$$A_2 = z_{\text{med}} - z_{\max}$$

If  $A_1 > 0$  AND  $A_2 < 0$ , goto Level B  
else increase window size

If window size  $\leq s_{\max}$  repeat level A  
else output  $z_{xy}$ .

$$\text{Level B: } B_1 = z_{xy} - z_{\min}$$

$$B_2 = z_{xy} - z_{\max}$$

If  $B_1 > 0$  AND  $B_2 < 0$  output  $z_{xy}$   
else output  $z_{\text{med}}$ .

# Level 1: Compute  $\sigma_{xy}^2$  value noise  $\epsilon_{xy}^2$  of  $S_{xy}$   
measure  $\sigma_{xy}^2$

if noise  $\epsilon_{xy}^2$  (high) pixel value  $z_{xy}$  is  $\epsilon_{xy}^2$  assign  $z_{\text{med}}$ . But if noise is present then pixel value is median

The main purpose of this algorithm are:

- To remove salt and paper (impulse noise)
- To provide smoothing of other noise that may not be impulse
- To reduce digitization distortion such as excessive thinning, thinning or thickening of object boundaries.
- The value of  $Z_{min}$  and  $Z_{max}$  are considered to be "impulse like" noise component (statistically).
- Here, we see that the purpose of level A is to determine if the median filter output  $Z_{med}$  is an impulse (block or white) or not. If the condition  $Z_{min} < Z_{med}$  holds then  $Z_{med}$  can not be an impulse.
- In this case, we go to level B and test to see if the point  $Z_{ny}$  is itself an impulse ( $Z_{ny}$  is the point being processed).
- If the condition  $B_1 > 0$  and  $B_2 < 0$  is true then  $Z_{min} < Z_{ny} < Z_{max}$  can not be an impulse (so does  $Z_{med}$ ). In this cause algorithm outputs unchanged pixel values  $Z_{ny}$ .

If the condition  $B_1 > 0$  And  $B_2 < 0$  is false, then either  $z_{avg} = z_{min}$  or  $z_{avg} = z_{max}$ .

In either case, the value of pixel is an extreme value and algorithm outputs the median value  $z_{med}$ , which is not a noise impulse.

→ The problem is that the standard median filter replace every point in an image by the median of the corresponding neighbourhood. This causes unnecessary loss details.

→ suppose that level A does find an impulse (no branch to B)

The algorithm then increase the size of window and repeats level A.

→ This looping continues until the algorithm either finds a median value that is not an impulse (and branches to level B)

→ If the maximum window size is reached the algorithm returns the value of  $z_{avg}$ . But there is no guarantee that this value is not an impulse.

→ The smaller the noise probabilities the larger the  $I_{max}$  will be i.e. premature exit condition will occurs.

## Zooming:

- Zooming is the enlargement of an image in a sense that the details in the image become visible and clear.
- Zooming requires two steps
  - the creation of new pixel locations and the assignment of gray levels to those new location.
- It can be done in two ways
  - zooming by interpolation.
  - zooming by replication

zooming by replication.

e.g.:

1	2
3	4

Step 1: zero instance

1	0	2	0
0	0	0	0
8	0	4	0
0	0	0	0

Step 2: interpolate rows & columns.

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

zooming by interpolation

e.g.:  $\begin{bmatrix} 1 & 1 \\ 3 & 1 \end{bmatrix}$

Step 1: zero interchange  $\begin{bmatrix} 1 & 0 & 7 & 0 \\ 0 & 0 & 0 & 0 \\ 3 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$

Step 2: Interpolate rows

$$\begin{bmatrix} 1 & 4 & 7 & 3.5 \\ 0 & 0 & 0 & 0 \\ 8 & 2 & 1 & 0.5 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Step 3: Interpolate - columns

$$\begin{bmatrix} 1 & 2 & 7 & 3.5 \\ 2 & 3 & 4 & 0.5 \\ 3 & 2 & 1 & 0.5 \\ 1.5 & 1 & 0.5 & 0.25 \end{bmatrix}$$

zoom by interpolation

1	5	3
6	4	2
1	7	6

Step 1: zero interface

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

Step 2: Interpolate rows

1	3	5	1.5
0	0	0	0
6	5	4	1
4	4	7	3

Step 1:

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

Step 2:

1	3	5	4	3	1.5
0	0	0	0	0	0
6	5	4	3	2	1
0	0	0	0	0	0
1	4	7	6.5	6	3

Step 3:

1	3	5	4	3	1.5
8.5	4	4.5	4	2.5	1.25
6	5	4	3	2	1
3.5	4.5	2.2	4.75	4	2
1	4	7	6.5	6	3

- Q Given the following gray level histogram of an image. compute the following histogram equalization.

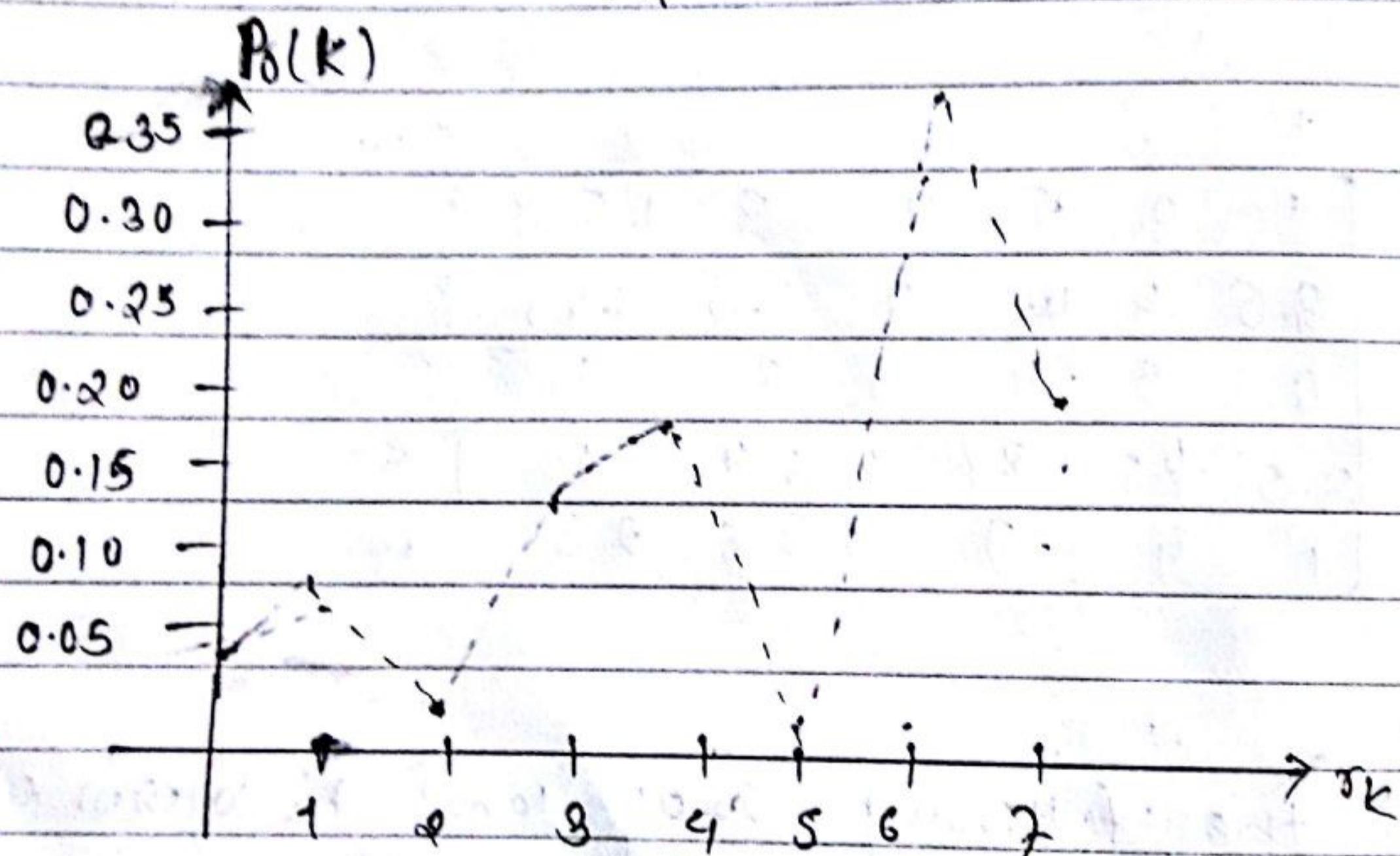
Gray level	0	1	2	3	4	5	6	7
frequency	200	500	40	600	800	60	1800	1000

Sol.

Given level ( $\sigma_k$ )	frequency, $n_k$	$P_{\sigma}(\sigma_k) = \frac{n_k}{M_N}$
$\sigma_0 = 0$	200	0.04
$\sigma_1 = 1$	500	0.1
$\sigma_2 = 2$	40	0.008
$\sigma_3 = 3$	600	0.12
$\sigma_4 = 4$	800	0.16
$\sigma_5 = 5$	60	0.012
$\sigma_6 = 6$	1800	0.36
$\sigma_7 = 7$	1000	0.2

$$\sum n_k = 5000$$

$$M_N = 5000$$



we have

$$\begin{aligned} \sigma_k &= T(\sigma_k) \\ &= (L-1) \sum_{j=0}^k p_{\sigma}(\sigma_j) \end{aligned}$$

$\sigma_k$  = probability of occurrence.

$$S_0 = T(r_0) \\ = (L-1) \sum_{j=0}^{k-1} p\sigma(r_j)$$

$$= T(r_0) = 7 \times p\sigma(r_0) = 7 \times 0.04 \\ = 0.28$$

$$S_1 = T(r_1) = 7 \{ p\sigma(r_0) + p\sigma(r_1) \} \\ = 7 \{ 0.04 + 0.1 \} \\ = 0.98$$

$$S_2 = 7 \{ p\sigma(r_0) + p(r_1) + p(r_2) \} \\ = 7 \{ 0.04 + 0.1 + 0.008 \} \\ = 1.036$$

$$S_3 = 7 \{ p\sigma(r_0) + p\sigma(r_1) + p\sigma(r_2) + p\sigma(r_3) \} \\ = 7 \{ 0.04 + 0.1 + 0.0008 + 0.12 \} \\ = 1.876$$

$$S_4 = 7 \{ 0.04 + 0.1 + 0.0008 + 0.12 + 0.16 \} \\ = 2.996$$

$$S_5 = 7 \{ 0.04 + 0.1 + 0.0008 + 0.12 + 0.16 + 0.12 \} \\ = 3.00$$

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$$S_6 = 7 \left[ \frac{0.04 + 0.1 + 0.088 + 0.12 + 0.16 + 0.015}{0.36} \right] \\ = 5.6$$

$$S_7 = 7 \left[ \frac{0.04 + 0.1 + 0.088 + 0.12 + 0.16 + 0.015 + 0.01}{0.2} \right] \\ = 7$$

Now,

$$S_0 = 0.28 \rightarrow 0$$

$$S_1 = 0.98 \rightarrow 1$$

$$S_2 = 1.036 \rightarrow 1$$

$$S_3 = 1.876 \rightarrow 2$$

$$S_4 = 2.996 \rightarrow 3$$

$$S_5 = 3.08 \rightarrow 3$$

$$S_6 = 5.6 \rightarrow 5$$

$$S_7 = 7 \rightarrow 7$$

$S_k$	$n_k$	$P_S(S_k) = \frac{n_k}{5000}$
0	200	0.04
1	$500 + 10 = 510$	0.108
2	1800	0.12
3	$800 + 60 = 860$	0.172
6	1800	0.36
7	1000	0.2
$\Sigma f = 5000$		

$S_1 + S_2 = S_{IK} = S(I) = \text{Sum of no. of pixel in } \tau_1 \text{ & } \tau_2$

$P_S(S_{IK})$

0.85

0.80

0.25

0.20

0.15

0.10

0.05

0

1

2

3

8

7

$S_K$