

R5: Read chapter 3 from the text book

Section 3.1

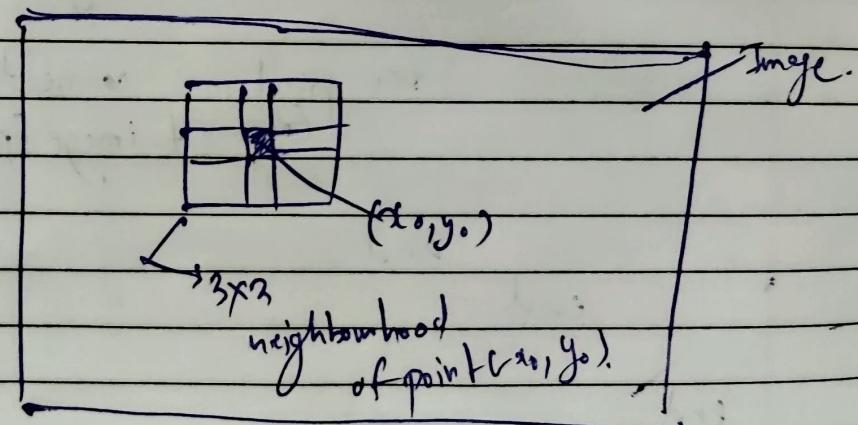
- * spatial domain \rightarrow image plane
- * spatial domain techniques operate directly on the pixels of an image.

The basis of intensity transformation and spatial filtering

$$g(x, y) = T[f(x, y)] \rightarrow ①$$

$f(x, y) \rightarrow$ input image
 $g(x, y) \rightarrow$ output image

T is an operator on f defined over a neighbourhood of point (x, y)



& ~~eg~~(2) elaborate it

- * we move the center of the neighbourhood pixel from pixel to pixel and apply the operator to the pixels in the neighbourhood

to yield an output value at that location (x_0, y_0)

Example

$$(x_0, y_0) = (100, 150)$$

$T \rightarrow$ (average intensity of the pixels in the neighbourhood)

$$g(100, 150) = T [f(100, 150)]$$

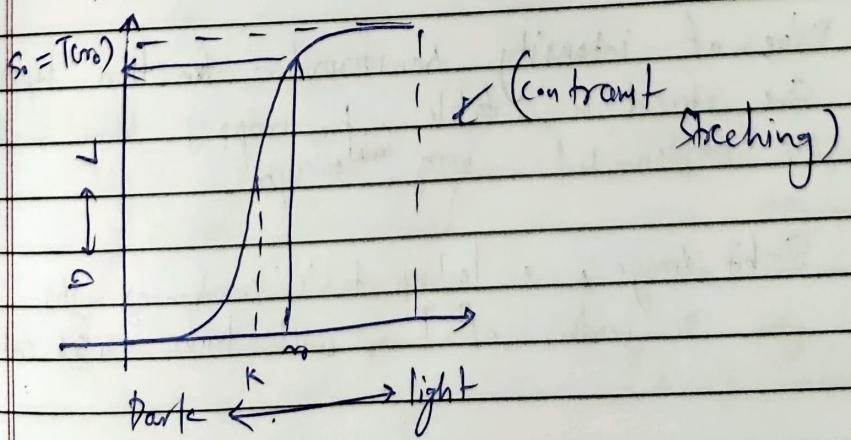
sum of $f(100, 150)$ and its 8 neighbour
hood divided by 9.

& Smallest possible neighbourhood is of size 1×1

& In this case g depends on value of single point (x, y)

$$s = T(r) \rightarrow \begin{array}{l} (\text{becomes}) \\ \text{intensity transformation function} \end{array}$$

$$s = T(r_0)$$

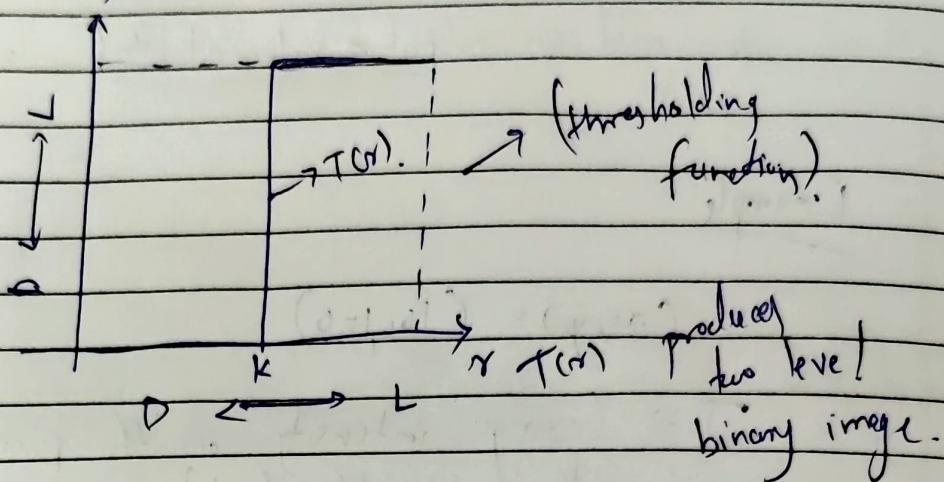


& Darkening the intensity

values below k

& Brightening the intensity
values above k

$$g = T(u)$$



Enhancement → It is the process of manipulating an image so that the result is more suitable than the original for a specific application.

& It is most visually appealing area of image processing.

3.2 Some basic intensity transformation functions

→ Values of intensity transformation function typically are stored in a table, the mappings from a to s are implemented via table lookups.

8-bit image, a lookup table containing the values of T will have 256 entries.

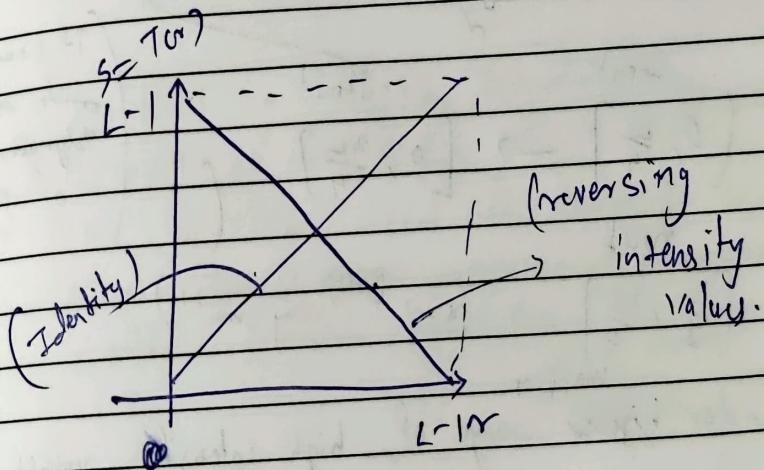
functions :-

- linear (negative and identity transformation)
- logarithmic (log and inverse-log transformation)
- power-law (n^{th} power and n^{th} root transformation)

image negative

negative of an image with intensity levels in the range $[0, L-1]$ is obtained using negative transformation:

$$S = L - I - \alpha$$

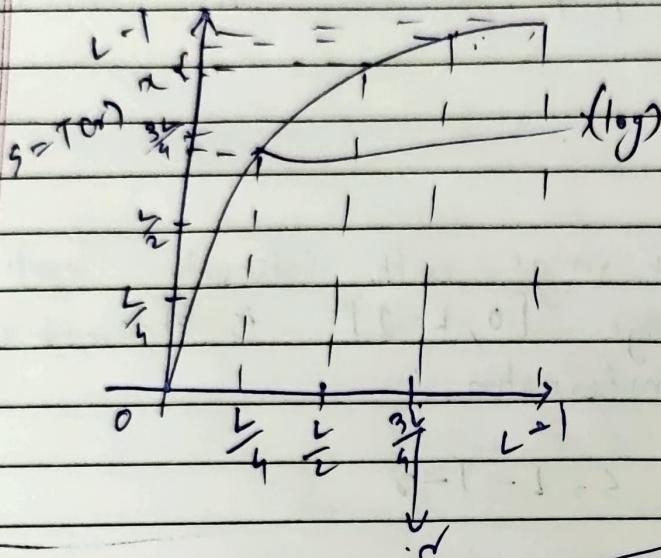


Uses

- It is used in enhancing white or gray detailed embedded in dark regions of an image. (when black area is dominant),
- Breast cancer can be detected as any like tissue will be more finely detailed.

log transformation

$$s = c \log(1 + r) \quad r \geq 0$$



(mapping
(narrow range of
low intensity values
in the input
into wider range
of output levels))

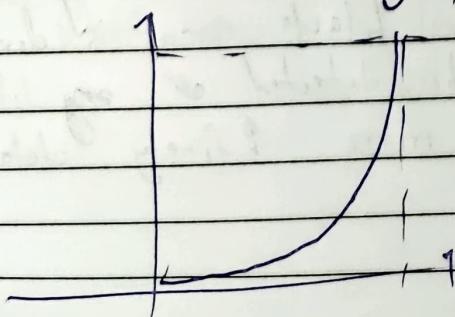
Input $[0, \frac{L}{4}] \rightarrow [0, \frac{3L}{4}]$ (if compresses wide range dynamic range of pixel values)

input $[\frac{L}{2}, \frac{3L}{4}] \rightarrow [x \rightarrow \dots]$ (range is very small).
mapping

wider ~~better~~ range of high intensity values in input into narrow

(inverse log opposite of log)

range of output levels



power-law (gamma) transformations

$$S = C V^{\gamma}$$

$$S = C(V + \epsilon)^{\gamma}$$

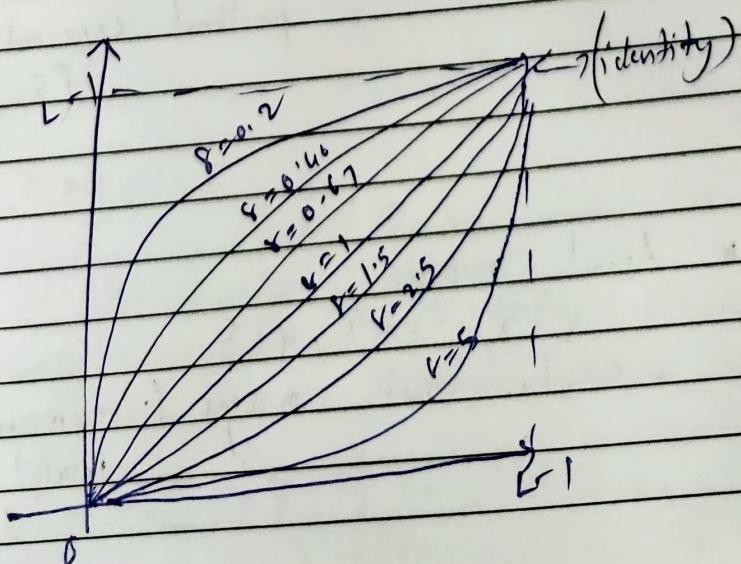
(offset)

* offsets ~~are~~ typically are an issue of display calibration, and are ignored.

* family of transformation can be obtained by varying γ .

* $\gamma > 1$ curves have opposite effect as those are generated with $\gamma < 1$.

* $C = \gamma = 1 \rightarrow$ identity transformation
* The response of many devices used for image capturing obey a power law
* The process used to correct these power law ~~non~~ response phenomena is called gamma correction or gamma encoding



Example

Cathode ray tube (CRT) devices have an intensity-to-voltage response that is a power function, with exponents varying from approximately 1.8 to 2.5

- Image is viewed on monitor with $\beta = 2.5$

& So before showing the image on monitor

we apply gamma transformation, with $\gamma = 0.4$ on original image.

& Then when it is displayed a proper image is shown:

Ques :

- MRI (magnetic resonance image) of a human upper spine with a fracture dislocation.

The fracture is visible. Here we use - power law transformation with a fractional exponent ($\beta = 0.5, 0.9, 0.3$)

Aerial images

$$\gamma = 3, \alpha = 4, \beta = 5$$

→ weighed-out images (compression of intensity levels).

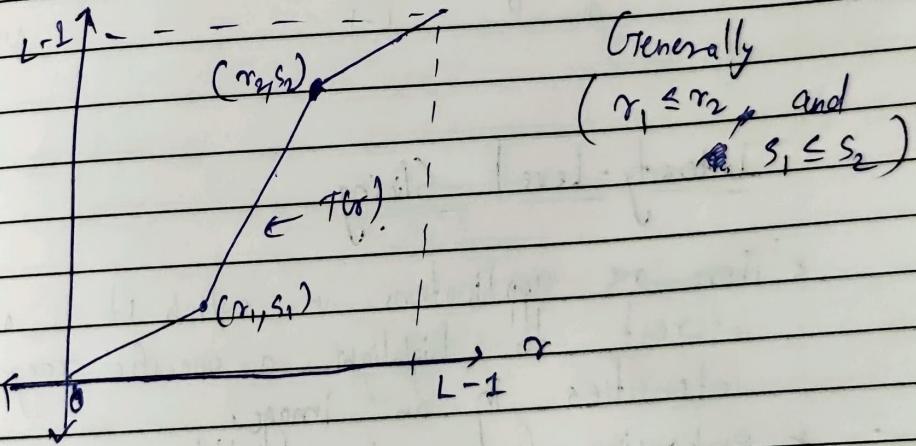
Piecewise linear transformation functions

Constr

Contrast stretching

Low-contrast images can result from poor illumination, lack of dynamic range in the imaging sensor

Contrast stretching expands the range of intensity levels in an image so that it spans the ideal full intensity range of the recording medium or display device.



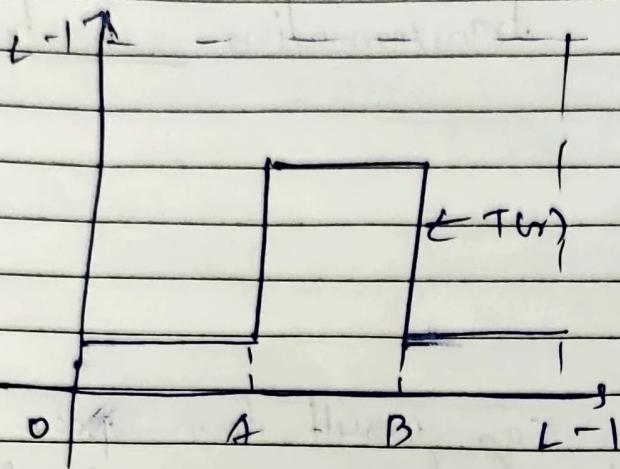
location of (r_1, s_1) and (r_2, s_2) control the shape of transformation function.

$r_1 = s_1$ and $r_2 = s_2 \rightarrow$ (No change in intensity).

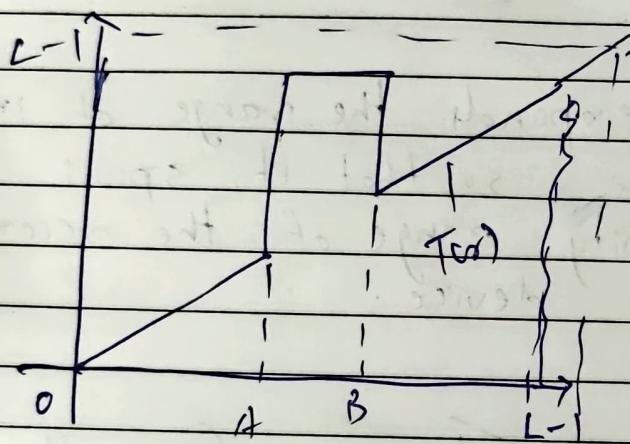
$s_1 = r_2$, $s_2 = 0$, $s_1 = L-1$ (thresholding function?)

$$r (r_1, s_1) \rightarrow (r_{min}, 0) \\ (r_2, s_2) \rightarrow (r_{max}, L-1)$$

$$(m, s_1) \rightarrow (m, 0) \\ (r_2, s_2) \rightarrow (m, L-1) \quad (m = \text{mean of intensity levels})$$



(This highlights range [A,B] and reduces all other intensity.)



(This highlights range [A,B] and leaves other intensity unchanged.)

Intensity - Level Slicing

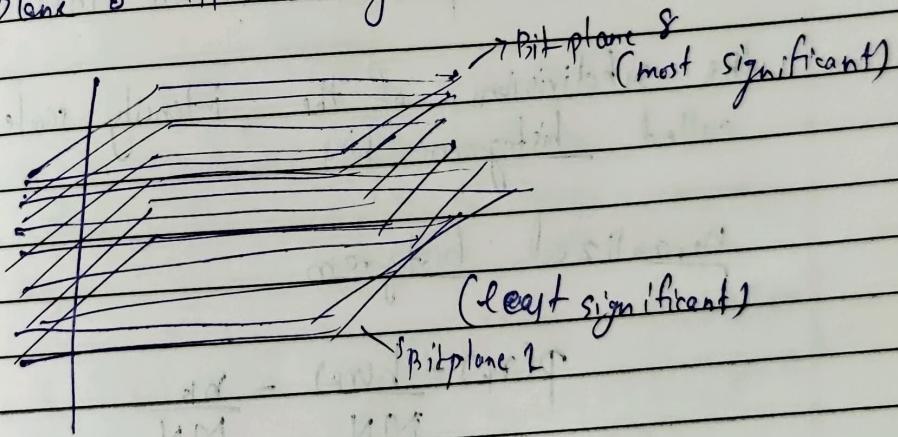
- * There are applications in which it is of interest to highlight a specific range of intensities in an image.
- * enhancing features in satellite imagery, such as mists of water
- * enhancing flows in X-ray images.

Bit plane Slicing

Pixel values are integers composed of bits.
Values in a 256-level gray-scale image are composed of 8 bits.

Instead of highlighting intensity-level ranges, we could highlight the contribution made to total image appearance by specific bits.

8 bit image may be considered as being composed of eight one-bit planes with plane 1 containing the lowest-order bit of all pixels in the image, and plane 8 all the highest-order bits.



Decomposing an image into its bit planes is useful for analyzing the relative importance of each bit in the image.

This type of decomposing is useful for image compression.

In some images four high-order bit planes would allow you to construct the original image in acceptable detail. Storing these four planes requires

For 50% less storage.

3.3 Histogram processing

Let r_k , for $k = 0, 1, 2, \dots, L-1$, denote the intensity of an L -level digital image, $f(x, y)$

Unnormalized histogram

$$h(r_k) = h_k \quad \text{for } k=0, 1, 2, \dots, L-1$$

where h_k is the number of pixels in f with intensity r_k

the subdivisions of the intensity scale are called histogram bins

Normalized histogram

$$p(r_k) = \frac{h(r_k)}{MN} = \frac{h_k}{MN}$$

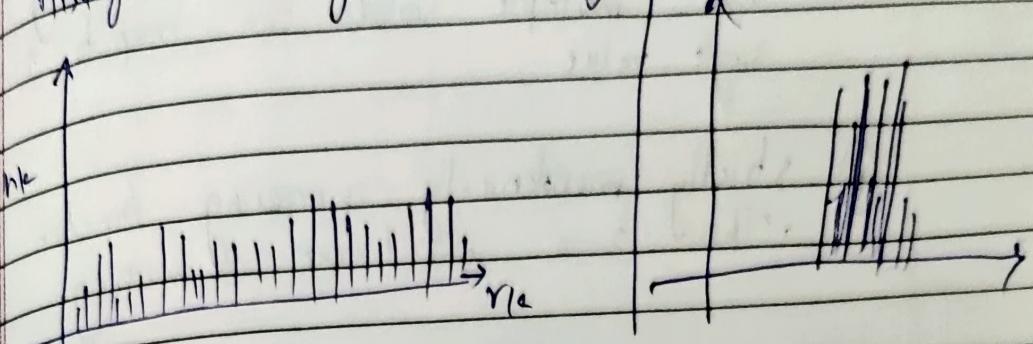
no. of rows no. of columns

1. Sum of $p(r_k)$ for all values of k is always 1.

2. The components of $p(r_k)$ are estimates of the probabilities of intensity levels occurring in an image.

Histograms of high contrast image

low contrast



* the distribution of pixel is uniform ; with few being higher.

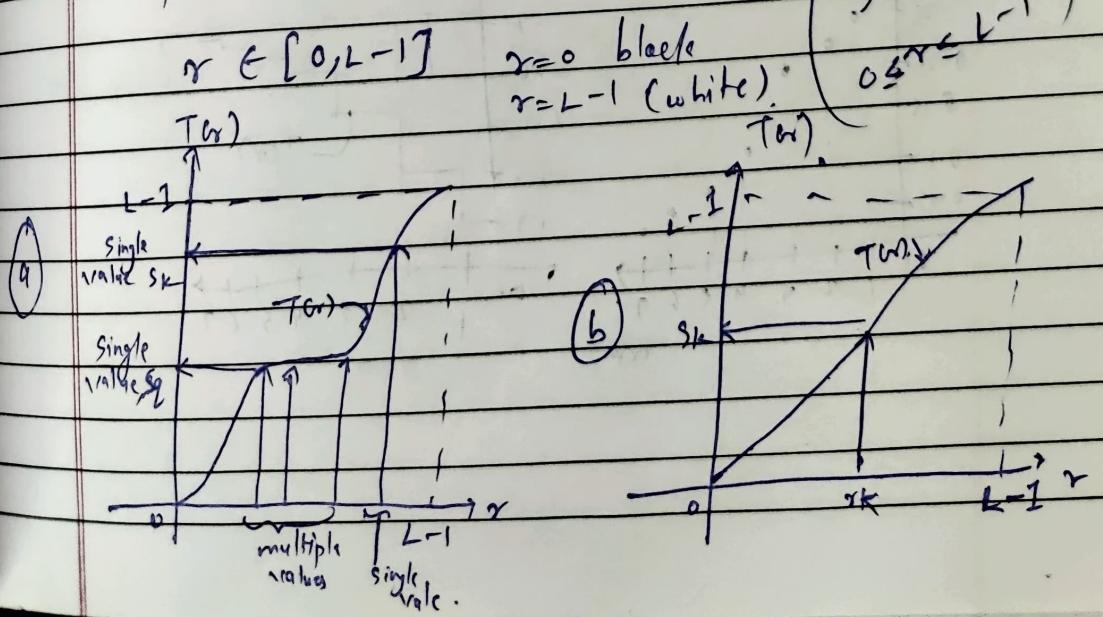
* Conclusion = Image whose pixels tend to be distributed uniformly will have appearance of high contrast and will exhibit a large variety of gray tones.

Histogram equalization

* Assume continuous intensity values

* r denote the intensities of image to be processed.

$$r \in [0, L-1] \quad r=0 \text{ black} \quad r=L-1 \text{ (white)} \quad g=T(r) \quad 0 \leq r \leq L-1$$



(a) Monotonically increasing function showing how multiple values can map to a single value.

(b) strictly monotonically increasing function. This is a one-to-one mapping.

$MN \rightarrow$ total number of pixels in the image

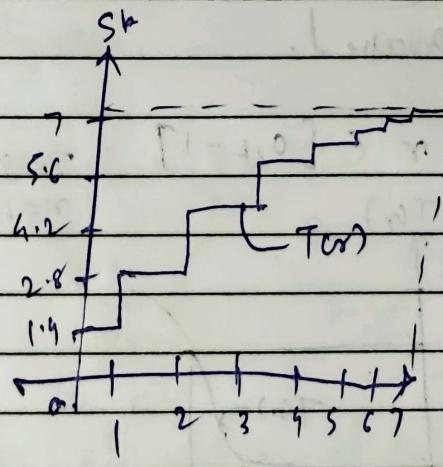
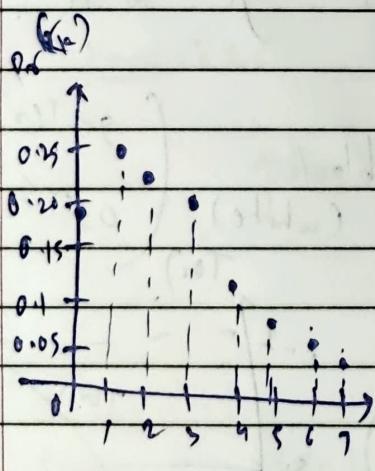
$h_k \rightarrow$ number of pixels that have intensity

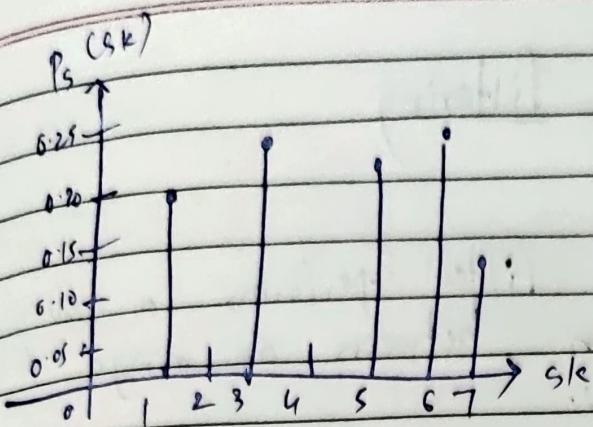
~~recc~~ r_k

$$r_k \in [0, L-1]$$

$$S_k = T(r_k) = (L-1) \sum_{j=0}^{r_k} p_r(r_j) \quad (k=0, 1, 2, \dots, L-1)$$

(Histogram equalization or histogram linearization transformation)





3.4 Fundamentals of spatial filtering

Filtering refers to passing, modifying, or rejecting specified frequency components of an image.

Example : - a filter that passes low frequencies is called a lowpass filter.

The net effect produced by a lowpass filter is to smooth an image by blurring it.

Spatial filtering modifies an image by replacing the value of each pixel by a function of the values of the pixel and its neighbors.

- linear spatial filter
- nonlinear spatial filter

Linear spatial filtering

A linear spatial filter performs a sum-of-products operation between an image f and a filter kernel, w .

Kernel \rightarrow It is an array whose size defines the neighbourhood of operation.
 \rightarrow whose coefficients determine the nature of the filter.

(matrix
template
and window)

3×3 kernel :
 at a point (x, y) in the image

$$g(x, y) = w(-1, -1)f(x-1, y-1) + w(-1, 0)f(x-1, y) + \dots + w(0, 0)f(x, y) + \dots + w(1, 1)f(x+1, y+1)$$

Center coefficient of the kernel $= w(0, 0)$

kernel size $m \times n$

$$m = 2a + 1$$

$$n = 2b + 1$$

(where a, b are non-negative integers)

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

Correlation and Convolution

- Correlation consists of moving the center of a kernel over an image and computing the sum of products at each location.
- Spatial Convolution are the same, except that the correlation kernel is rotated by 180° .
- when the values of a kernel are symmetric about its center, correlation and convolution yield the same result.

If $a=0$ $m=1$ former b
 $b=2$ $n=5$ $g(x) = \sum w(i)$
 $m \times n = 1 \times 5$ $s=-b$ $f(x+1)$

kernel $\begin{bmatrix} 1 & 2 & 4 & 2 & 8 \end{bmatrix}$
 zero padding

Image $\begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$
 $\begin{bmatrix} 1 & 2 & 4 & 2 & 8 \end{bmatrix}$

(Correlation)
 (Sum of product)

Apply on every
 pixel.

Final
 we get $(0 8 2 4 2 100)$

Convolution

we get final image $[0 8 2 4 2 8 00]$

3.5 Smoothing (Low pass) spatial filter

- Smoothing (also called averaging) spatial filters are used to reduce ~~the~~ sharp transitions in intensity.
- Random noise consists of sharp transitions in intensity, an obvious application of smoothing is noise reduction.
- It is used to reduce "irrelevant" refers to pixel regions that are small with respect to the size of the filter kernel.
- Convoluting a smoothing kernel with an image blurs the image, with the degree of blurring being determined by the size of the kernel and value of its coefficients.

Box Filter Kernels

- Simplest separable lowpass filter kernel is the ~~box~~ box kernel whose coefficient have same value (typically 1).
 - An $m \times n$ box filter is an $m \times n$ array of 1's with a normalizing constant in front of it.
- Constant = $\frac{1}{(\text{sum of values of the coefficients})}$.

- 8 The normalization has two purposes :-
- * The avg value of an area of constant intensity could equal that intensity in the filtered image
- * It introduces bias during filtering, that is the sum of the pixels of the original and filtered images will be same.

Low pass gaussian filter kernels

$$w(s,t) = G(s,t) = K e^{-\frac{s^2+t^2}{2\sigma^2}}$$

+ circularly symmetric kernels
 + $r = \sqrt{s^2+t^2}$

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