INTENSITY TRANFORMATION AND SPATIAL FILTERS

- BASIC INTENSITY TRANSFORMATION FUNCTIONS

  Image Negative

  log transformations

  power law (Gamma) transformations

- HISTOGRAMS
  - Histogram Equalization
  - Histogram Matching (Specification)
  - Local Enhancement
  - Use of Histogram Statistics for Image Enhancement

BASICS OF SPATIAL FILTERS

Smoothing Spatial Filters

Smoothing Linear Filters

Non-Liniear filters: Order-Statistics Filters

Sharpening Spatial Filters

Foundation

Use of Second Derivatives for Enhancement– The Laplacian

INTENSITY TRANFORMATION AND SPATIAL FILTERS

- Different method Image enhancement

Image enhancement is the process of manipulating an image so that results is more suitable than the original for a specific problem. The enhancement techniques are Problem specific. A method suitable for X-Ray image enhancement may not be best suitable for enhancing Satellite images taken in Infrared Band.

Methods of Image enhancement:

- Spatial domain : Peform operations directly on the Image iteself.
- Frequency domain: Perform operations on the Fourier transform of an image, rather than on the original image itself.
- Combined methods:

INTENSITY TRANFORMATION AND SPATIAL FILTERS

Spatial domain : spatial domain techniques are more efficient computationally and require less processing resources to implement.

It will change Pixel by Pixel on Input image directly
We can implement Intensity Transformation
We can do Spatial Filters

Spatial domain processes we discuss in this chapter can be denoted by the expression
g(x, y) = T[f(x, y)]
where f(x, y) is the input image, g(x, y) is the output image, and T is an operator on f defined over a neighborhood of point (x, y).

Suitable for: Point processing, Neighbor hood proessing, Image enhancement, Adding Noise, Filtering Image, Contrast streching

Frequency domain :
Transforms the image in to Fourier Image and process further
Inverse Transformatin is applied to bring bcack to Spatial domain

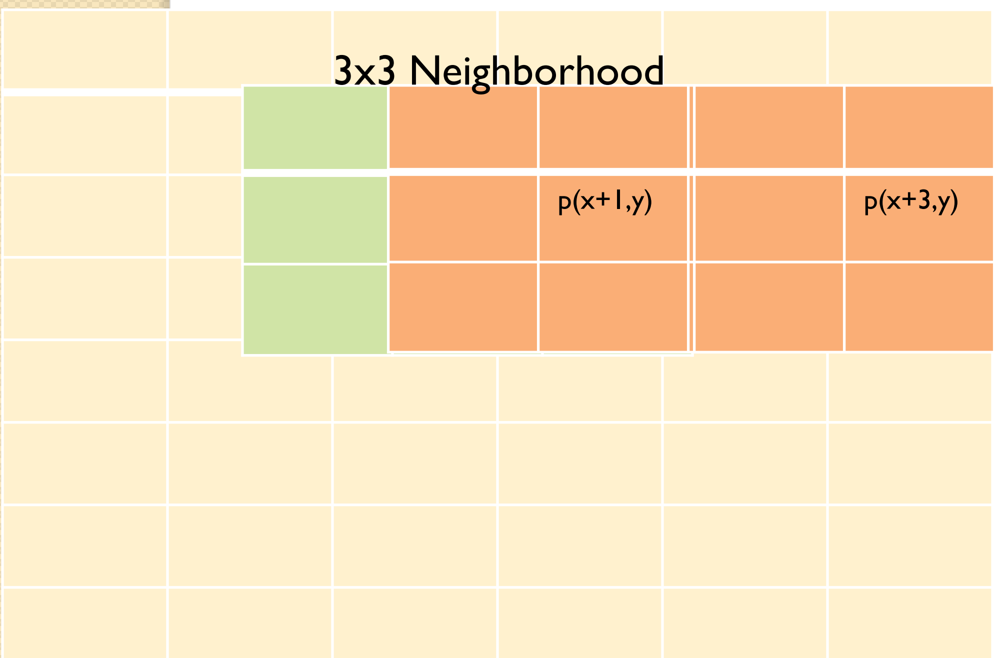
Filters are used for Smoothening & Sharpening

It will change the Whole Image

Suitable for: Images having Higher noice like sinusoidal noice, Periodic Noises

INTENSITY TRANFORMATION AND SPATIAL FILTERS (Play Animation)

Spatial domain :



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

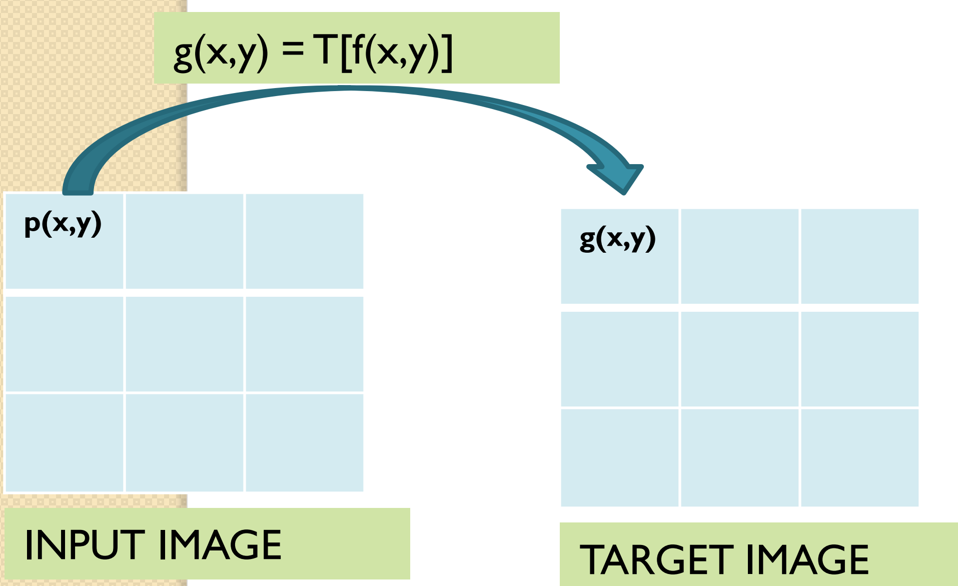
$g(x,y)$: Target Image
$f(x,y)$ = Input / Original Image
T = Transformation Function

What kind of Transformation Functions we can have? (T)

Average of 3x3 kernel? (a.k.a Spatial Filtering)
Min Intensity of 3x3 kernel?

INTENSITY TRANFORMATION AND SPATIAL FILTERS

Spatial domain :



g(x, y) = T[f(x, y)]

g(x,y) : Target Image
f(x,y) = Input / Original Image
T = Transformation Function

What kind of Transformation Functions we can have? if 1x1 Neighborhood (T)

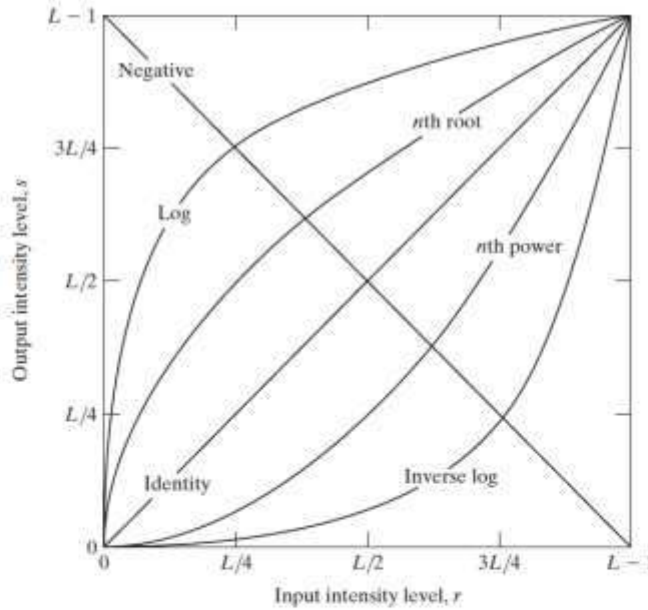
Input intensity map to required output intensity (a.k.a Intensity Transformation)

- Make Negatives Out of Original Image
- Log Transformations
- Power Law Transformation (Gamma)

INTENSITY TRANFORMATION

Image Negatives: s = |L-r-1| where *L is Max Intensity, and* r is input intensity.

FIGURE 3.3 Some basic intensity transformation functions. All curves were scaled to fit in the range shown.



Output image pixel intensity (s) = L-r-1
(r) = input image pixel intensity.

Plot is mapped
X-Axis: Input Intenstiy divided into 4 portions of L/4
Y-Axis: Input Intenstiy divided into 4 portions of L/4

Input Image has max Intensity L = 240

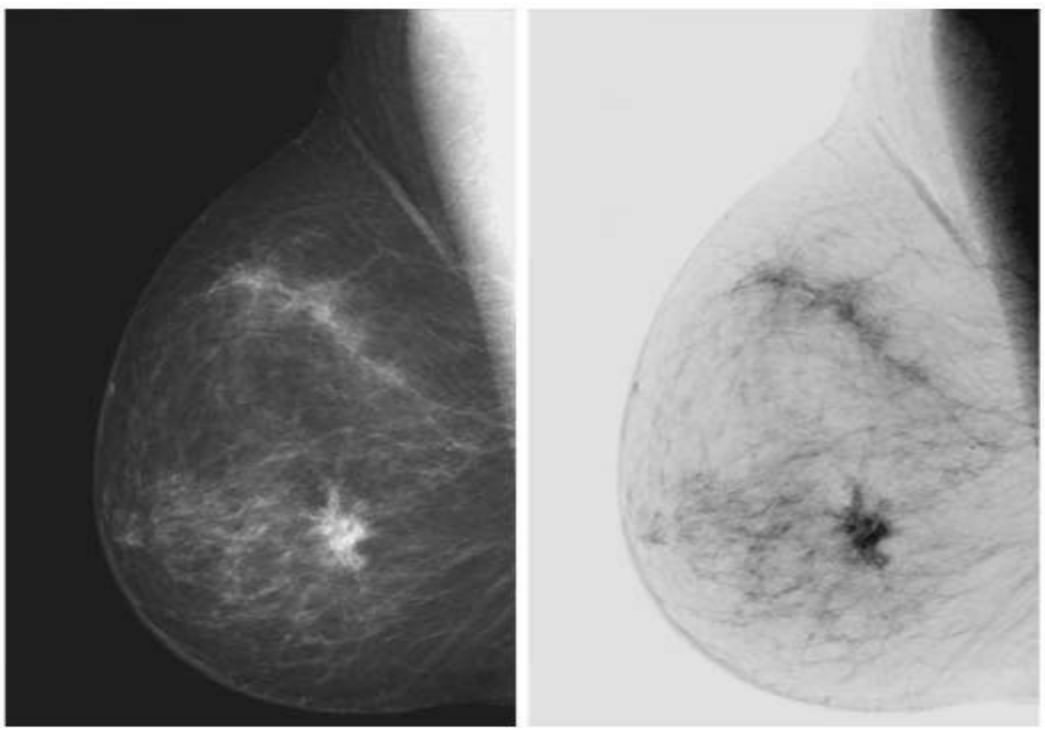
1	10	20	30
40	50	60	70
80	90	100	120
140	180	200	240

Output Image: Negative

239	229	219	
			1

INTENSITY TRANFORMATION

- Which Image is better for analysing a Cancer or Tumor presence in the Region Left or Right?



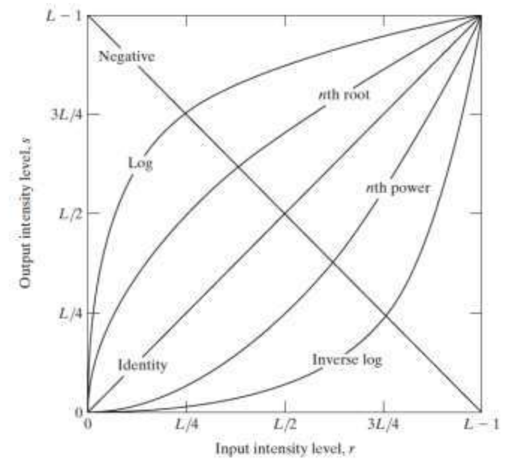
a b

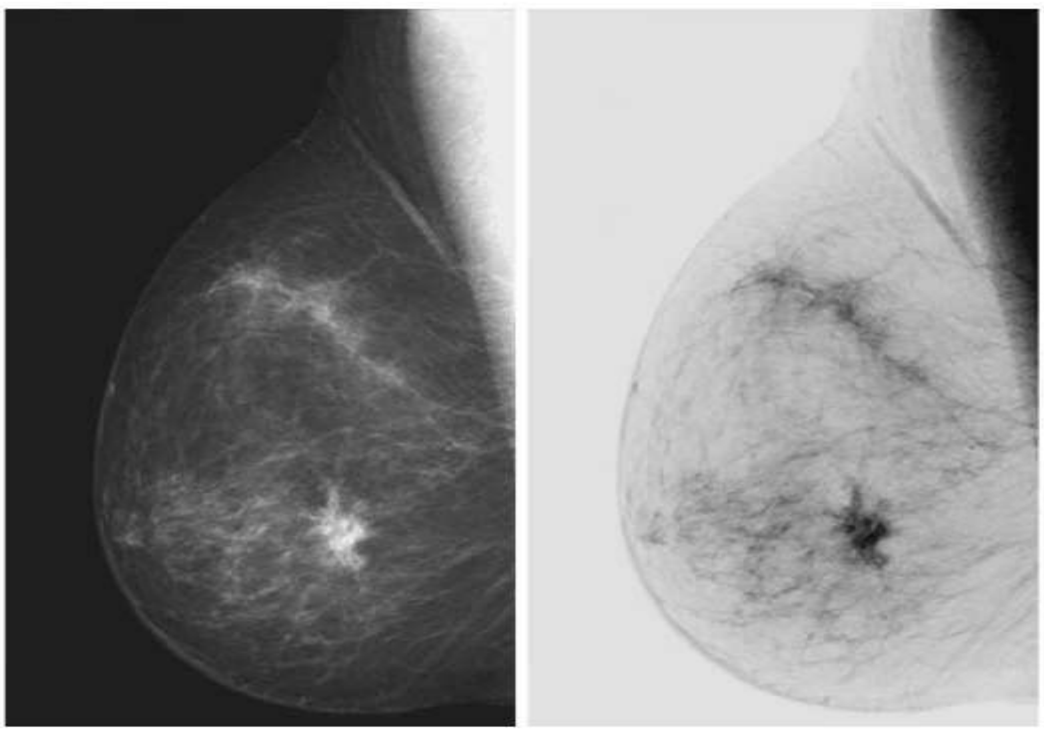
FIGURE 3.4 (a) Original digital mammogram. (b) Negative image obtained using the negative transformation in Eq. (3.2-1). (Courtesy of G.E. Medical Systems.)

INTENSITY TRANFORMATION

Cancer Mammographic Negatives used to enhance the Image for easy study.

FIGURE 3.3 Some basic intensity transformation functions. All curves were scaled to fit in the range shown.



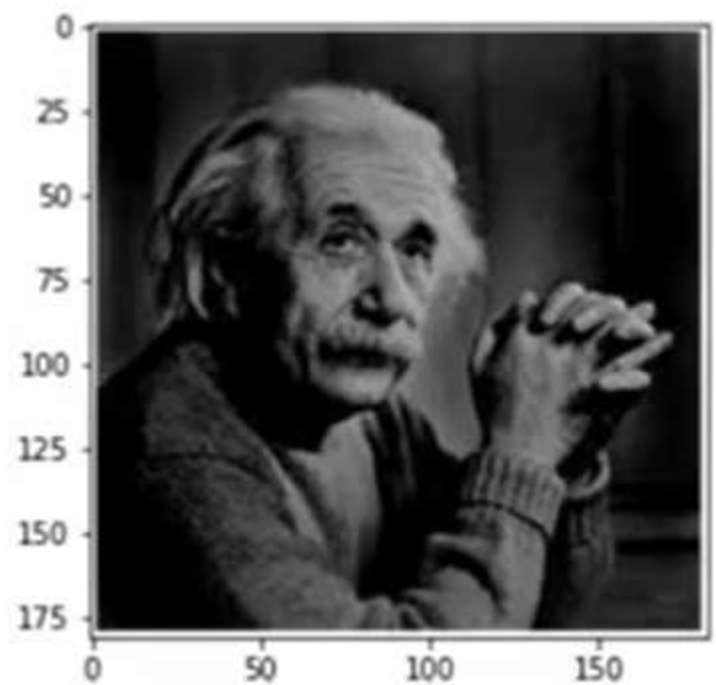


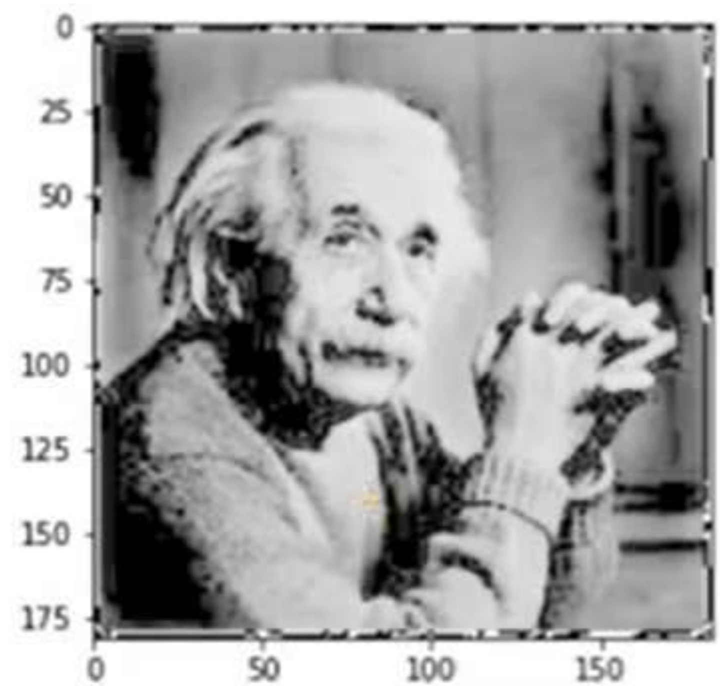
a b

FIGURE 3.4 (a) Original digital mammogram. (b) Negative image obtained using the negative transformation in Eq. (3.2-1). (Courtesy of G.E. Medical Systems.)

INTENSITY TRANFORMATION

- Which Image is more appealing LEFT or RIGHT Image?



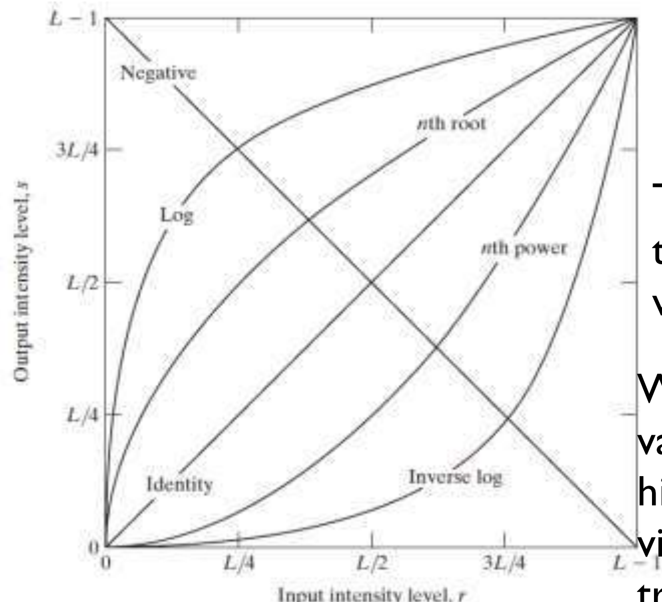


of L/4

INTENSITY TRANFORMATION

Logarthamic (Log and Inverse Log) Transformations: s = c log (1 + r) where where *c is a constant, and it is assumed that* r >= 0.

FIGURE 3.3 Some basic intensity transformation functions. All curves were scaled to fit in the range shown.



ference from Side Map?

The shape of the log curve in Fig. 3.3 shows that this transformation maps a narrow range of low intensity values in the input into a wider range of output levels.

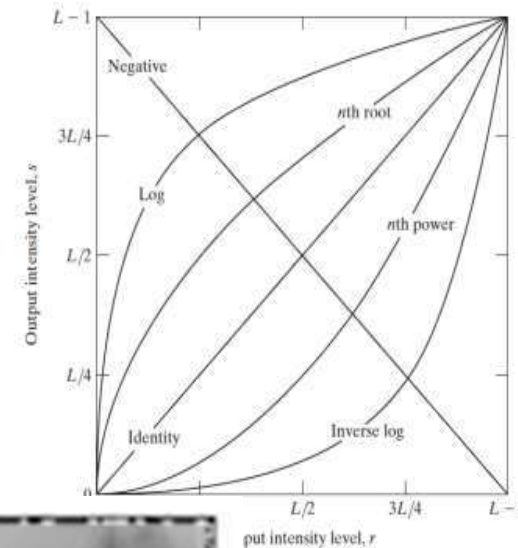
We use a transformation of this type to expand the values of dark pixels in an image while compressing the higher-level values. Some things which are clearly not visible in the image we can apply the LOG transformations to Highlight them.

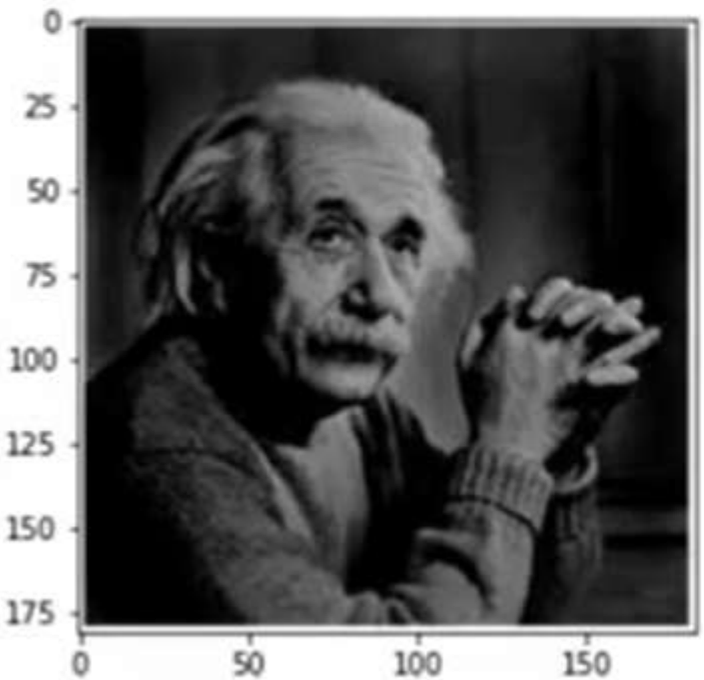
Plot is mapped
X-Axis: Input Intenstiy divided into 4 portions of L/4
Y-Axis: Input Intenstiy divided into 4 portions of L/4

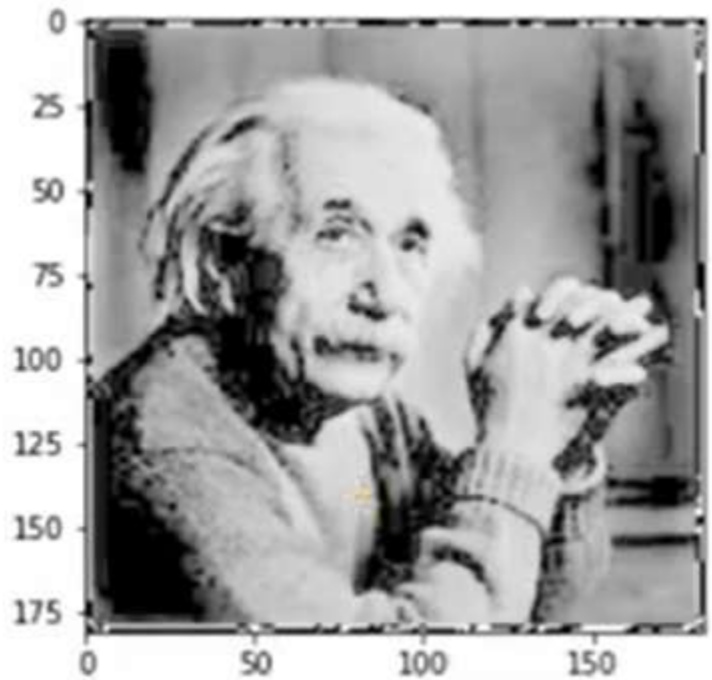
INTENSITY TRANFORMATION

- Logarthamic (Log and Inverse Log) Transformations: s = c log (1 + r) where where *c is a constant, and it is assumed that* r >= 0.

FIGURE 3.3 Some basic intensity transformation functions. All curves were scaled to fit in the range shown.







INTENSITY TRANFORMATION

Power Law [nth Power and nth root Transformations](GAMMA) $s = c(r + \varepsilon)^{\Upsilon}$ where where *c and* $^{\Upsilon}$ *are +ve constants, and* ε Offset. *it is assumed that* r >= 0.

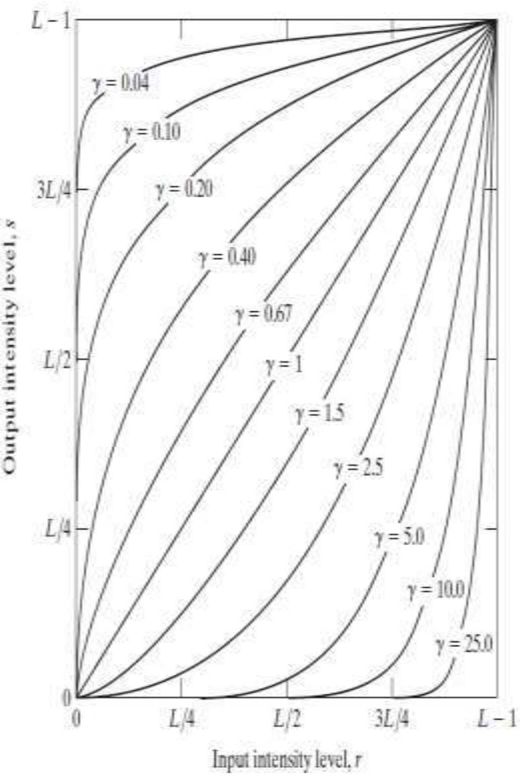


FIGURE 3.6 Plots of the equation $s = cr^{\gamma}$ for various values of γ ($c = 1$ in all cases). All curves were scaled to fit in the range shown.

Inference from Side Map?

Plots of *s versus r for* various values of are shown in Fig. 3.6. As in the case of the log transformation, power-law curves with fractional values of map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input levels.

Unlike the log function, however, we notice here a family of possible transformation curves obtained simply by varying ϒ. ϒ>1 have exactly the opposite effect as those generated with values of ϒ<1

Variety of devices used for image capture, Printing, and Display respond according to a POWER LAW The process used to correct these power-law response phenomena is called *gamma correction.*

INTENSITY TRANFORMATION :

1. Contrast Streching
2. Thresholding Function
3. Bit Plane Intensity Slicing

Contrast Streching *is a process that expands the* range of intensity levels in an input image so that it spans the full intensity range of the recording medium or display device. This is used in enhancement of Low contrast images.

Look at Figure 3.2 a and GUESS the output Image for a given INPUT Image?

Thresholding: Converting an Image into a Binary Image.

Convert all i/p intensity < k = o/p 0 (ZERO)
i/p intensity > k => o/p is set to 1 (ONE)

Thresholding Function

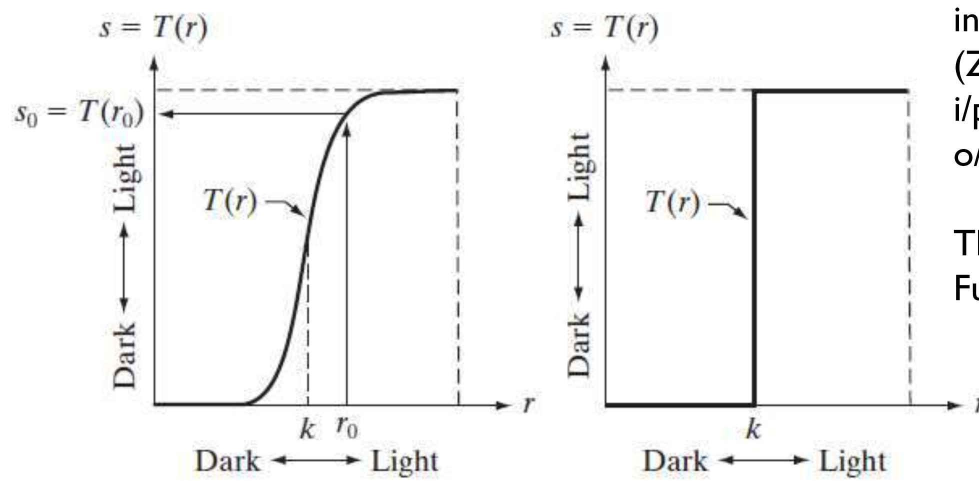
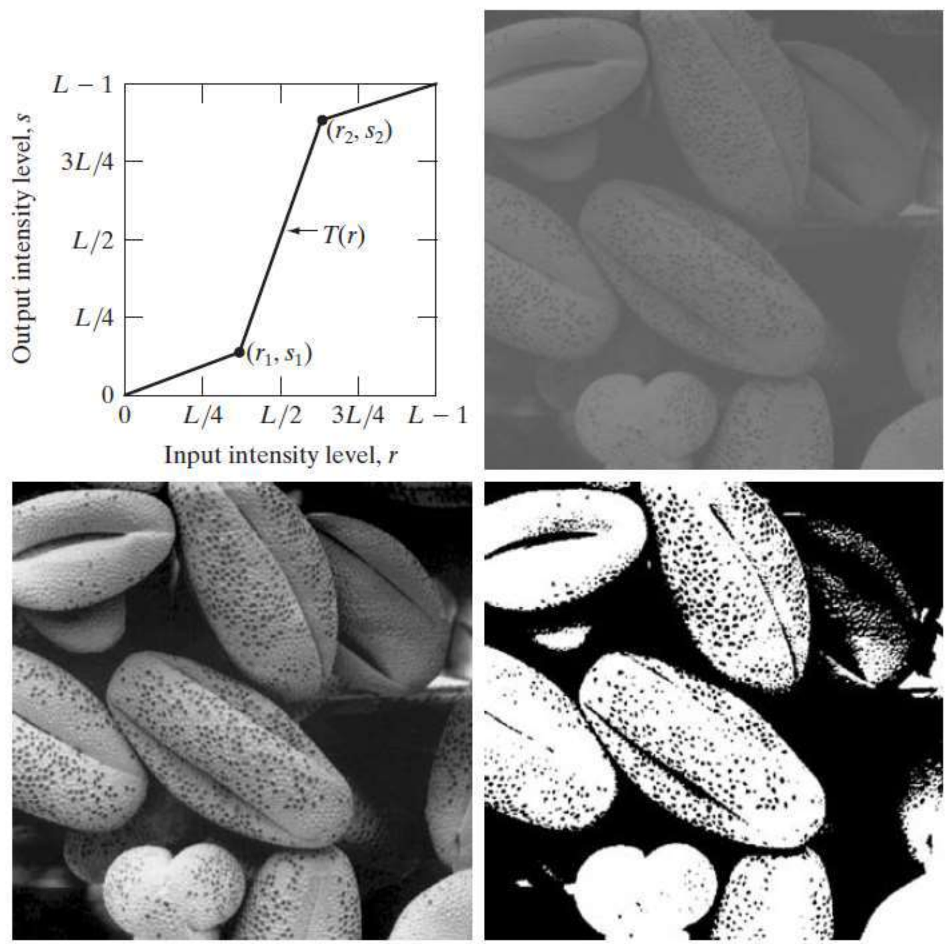


FIGURE 3.2 Intensity transformation functions. (a) Contrast-stretching function. (b) Thresholding function.

INTENSITY TRANFORMATION

Examples of Contrast Streching and Thresholding.



a b
c d

FIGURE 3.10 Contrast stretching. (a) Form of transformation function. (b) A low-contrast image. (c) Result of contrast stretching. (d) Result of thresholding. (Original image courtesy of Dr. Roger Heady, Research School of Biological Sciences, Australian National University, Canberra, Australia.)

INTENSITY TRANFORMATION

INTENSITY LEVEL SLICING: Highlighting a specific range of intensities in an image often is of interest to know its contribution to the Image display.

USE:

- Enhancing features such as masses of water in satellite imagery
- Enhancing flaws in X-ray images.

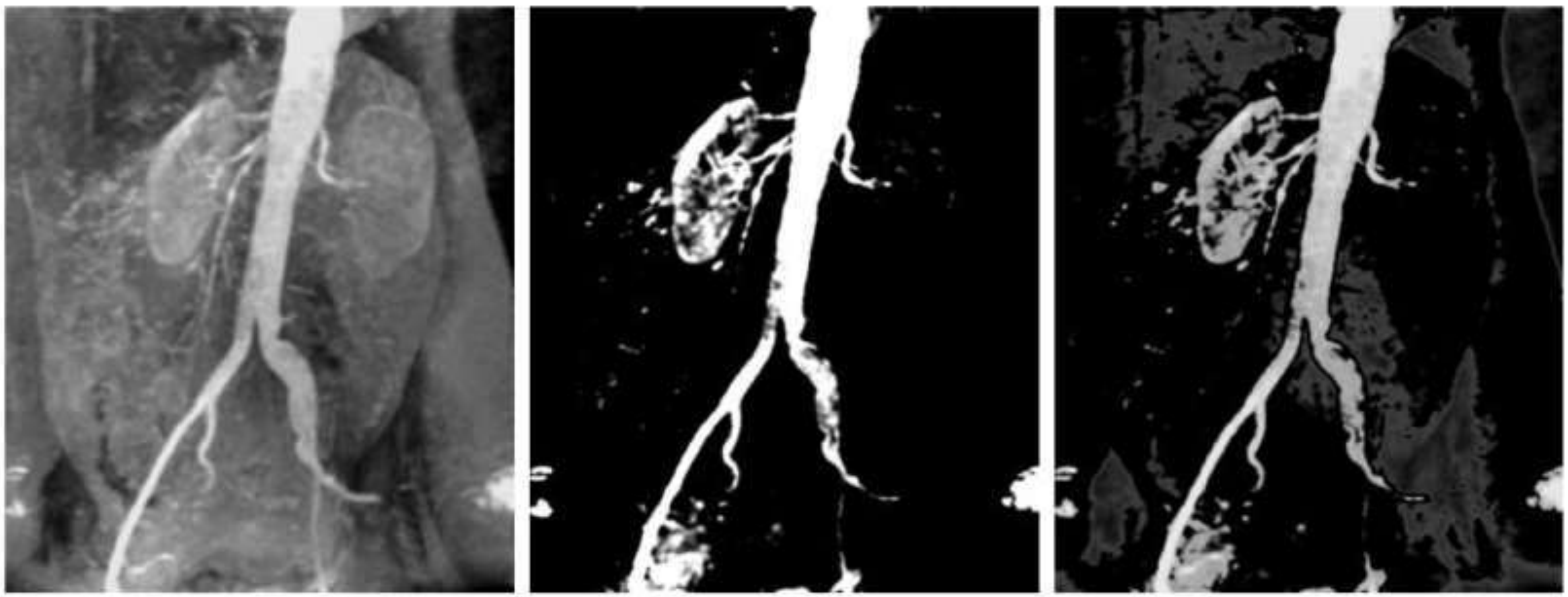
METHODS OF INTESITY LEVEL SLICING:

1.) One approach is to display in one value (say, white) all the values in the range of interest and in another (say, black) all other intensities. This transformation, shown in Fig. 3.11(a), produces a binary image.

2.) The second approach, based on the transformation in Fig. 3.11(b), brightens (or darkens) the desired range of intensities but leaves all other intensity levels in the image unchanged.

INTENSITY TRANFORMATION

INTENSITY LEVEL SLICING: The objective of this example is to use intensity-level slicing to highlight the major blood vessels that appear brighter as a result of an injected contrast medium. This type of enhancement produces a binary image and is useful for studying the *shape of the flow of the contrast medium (to detect blockages, for* example).



a b c

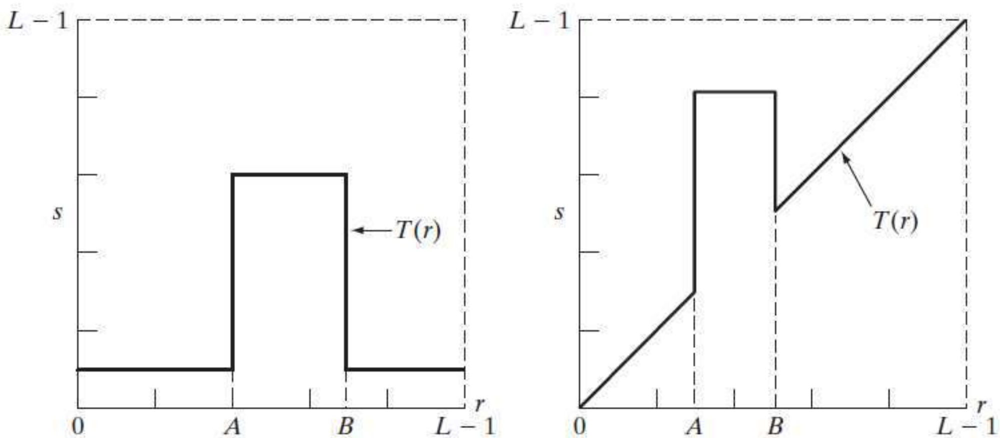
FIGURE 3.12 (a) Aortic angiogram. (b) Result of using a slicing transformation of the type illustrated in Fig. 3.11(a), with the range of intensities of interest selected in the upper end of the gray scale. (c) Result of using the transformation in Fig. 3.11(b), with the selected area set to black, so that grays in the area of the blood vessels and kidneys were preserved. (Original image courtesy of Dr. Thomas R. Gest, University of Michigan Medical School.)

INTENSITY TRANFORMATION

INTENSITY LEVEL SLICING has 2 METHODS:

a b

FIGURE 3.11 (a) This transformation highlights intensity range $[A, B]$ and reduces all other intensities to a lower level. (b) This transformation highlights range $[A, B]$ and preserves all other intensity levels.



INTENSITY TRANFORMATION

BIT PLANE SLICING: Pixels are digital numbers composed of bits. For example, the intensity of each pixel in a 256-level gray-scale image is composed of 8 bits (i.e., one byte). Instead of highlighting intensity-level ranges, we could highlight the contribution made to total image appearance by specific bits.

a b c
d e f
g h i

FIGURE 3.14 (a) An 8-bit gray-scale image of size 500 × 1192 pixels. (b) through (i) Bit planes 1 through 8, with bit plane 1 corresponding to the least significant bit. Each bit plane is a binary image.

INTENSITY TRANFORMATION

BIT PLANE SLICING: Can you try with muliple Bits contribution to the Image?

which 2 bits are enough to resemble original image?

which 3 bits are enough to resemble original image?

and more…

INTENSITY TRANFORMATION

BIT PLANE SLICING: Below image shows Bit plane 8, 7 and 6 contribution is enough to reconstruct the original image in the previous slide.

Use:

> Decomposing an image into its bit planes is useful for analyzing the relative importance of each bit in the image, a process that aids in determining the adequacy of the number of bits used to quantize the image.

> Decomposition is useful for image compression.

a b c

FIGURE 3.15 Images reconstructed using (a) bit planes 8 and 7; (b) bit planes 8, 7, and 6; and (c) bit planes 8, 7, 6, and 5. Compare (c) with Fig. 3.14(a).

IMAGE HISTOGRAM

Histogram means GRAPH of DISTRIBUTION OF DATA

IMAGE HISTOGRAM: GRAPHICAL representation of TONAL DISTRIBUTION in a DIGITAL IMAGE, HISTOGRAM plots nubmer of Pixels in each Tonal value.

Uses:

Spatial Domain Processing

Image Enhancement

Image compression

Image Segmentation

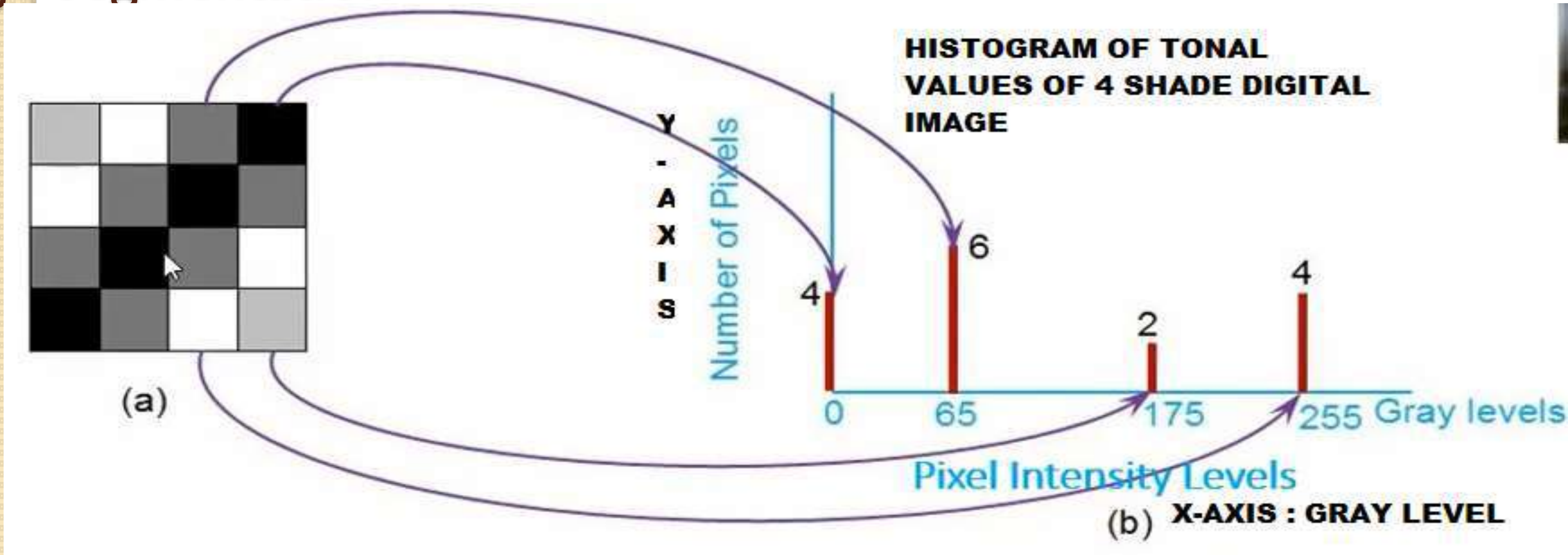


IMAGE HISTOGRAM

Histogram means GRAPH of DISTRIBUTION OF DATA

Look at these below Digital Images whose position Pixels of each intensity are different but their HISTOGRAM is same.

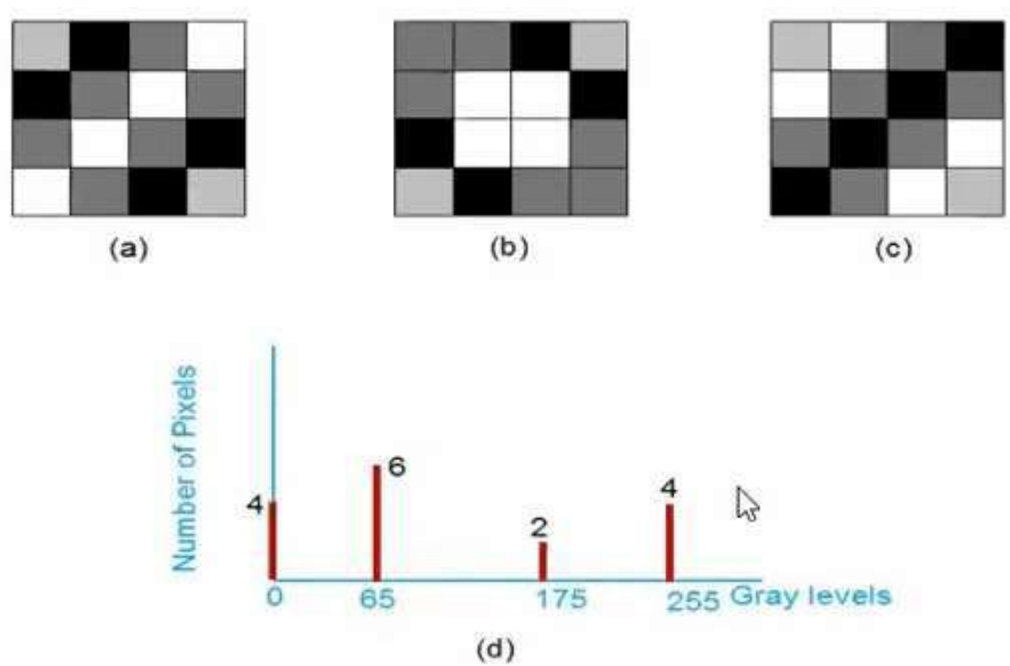
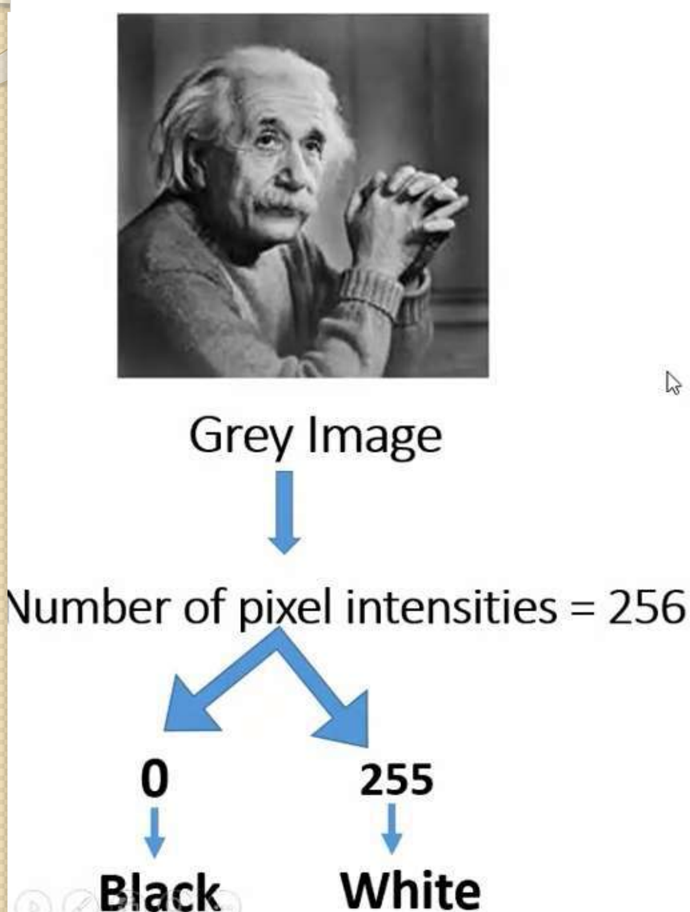


IMAGE HISTOGRAM

Let us draw an Image Histogram of Einstein Digital Image given below which as Grey scale [0..255]



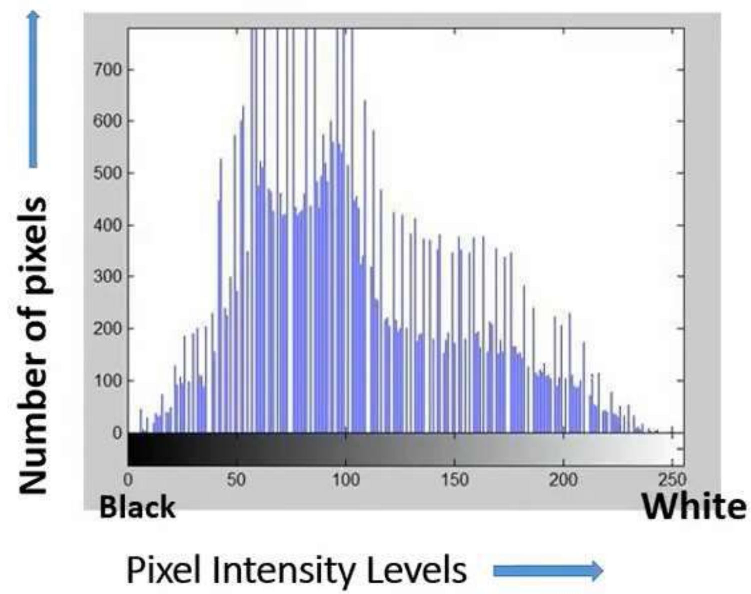
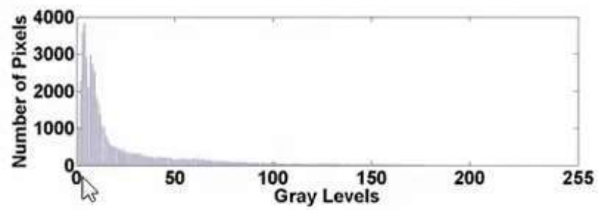
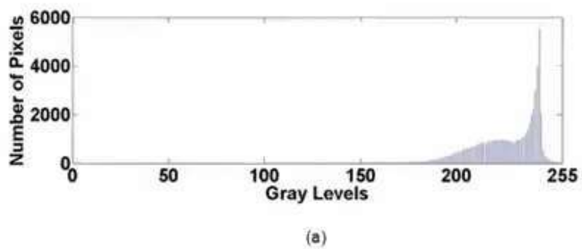


IMAGE HISTOGRAM

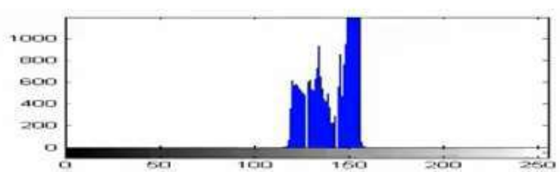
Let us draw an Image Histogram of different Images and understand the Tonal distribution (Intensity Distriution) of Digita Images



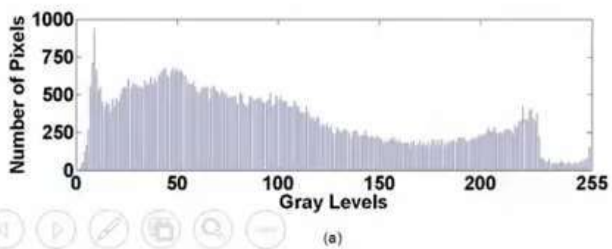
More Black Pixels



More White Pixels



Dull Image

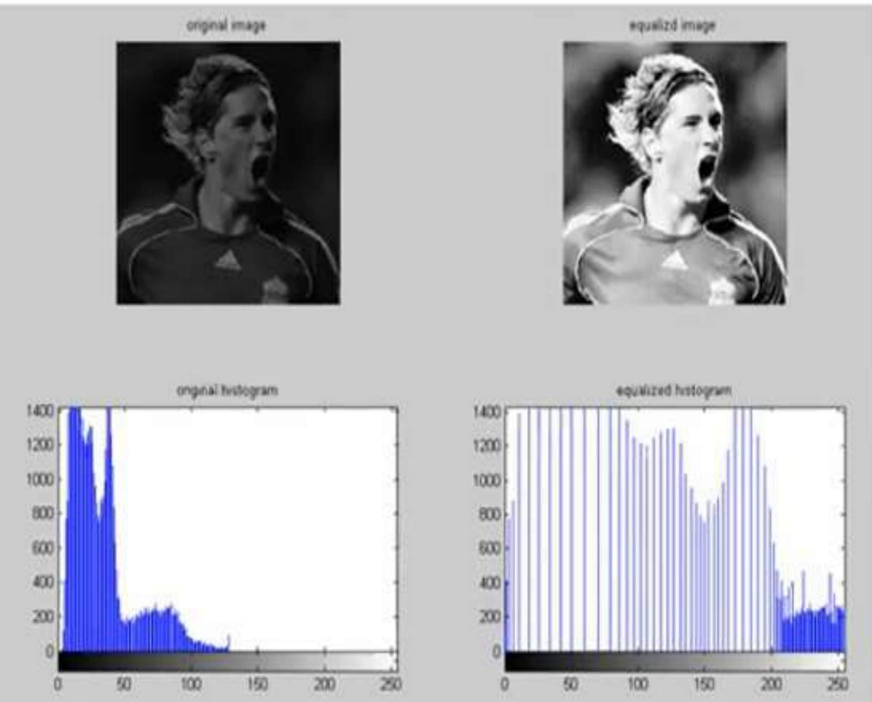


Pixels of all intensity levels

IMAGE HISTOGRAM

USES of HISTOGRAM

Histogram Applications



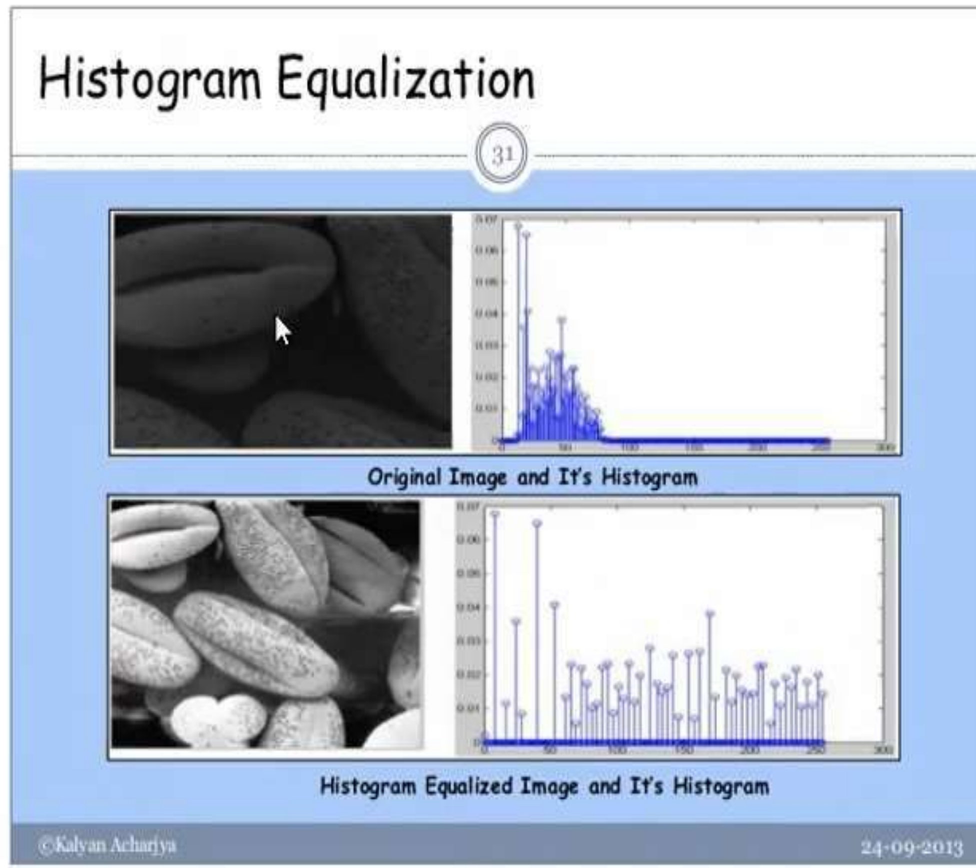


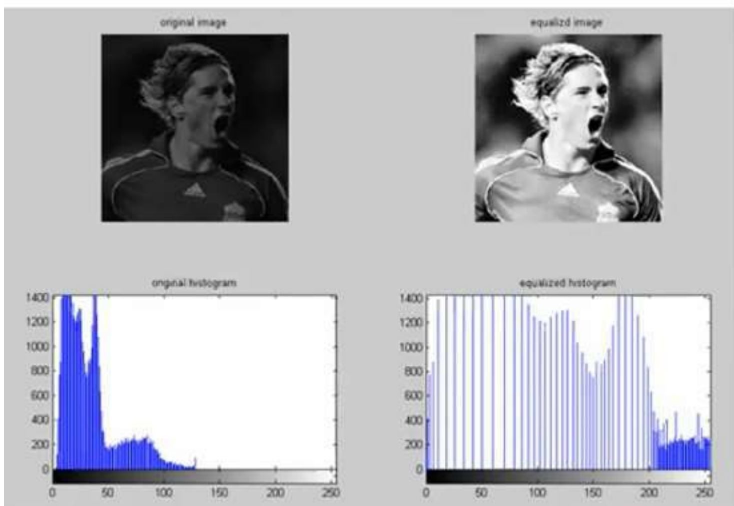
IMAGE HISTOGRAM EQUALIZATION

> This is a process that **spreads out the Gray level** in an Image so that their level is **evenly distributed** over the Range.

> This is **Technique** in which RESULT image has as flat as possible

> Visually pleasing results across wider range of Image

Histogram Applications



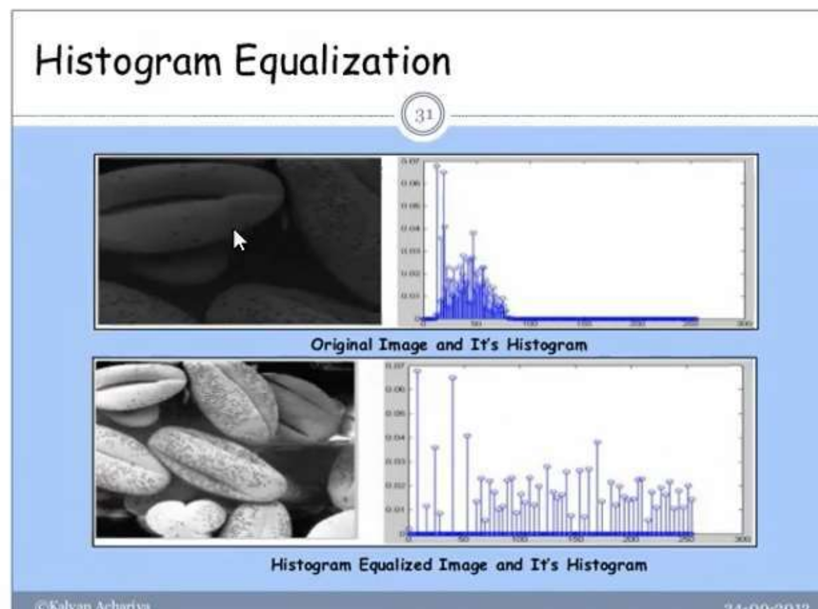


IMAGE HISTOGRAM EQUALIZATION

PROBLEM:To Find the image Histogram of INPUT image Size 5x5 given below f(x,y)

Maximum gray value = 5

No of bits required to represent each intensity = 3 bits

Number of possible gray levels = 8 that varies from 0 to 7.

4	4	4	4	4
3	4	5	4	3
3	5	5	5	3
3	4	5	4	3
4	4	4	4	4

Gray level	0	1	2	3	4	5	6	7
No. of pixel nk	0	0	0	6	14	5	0	0

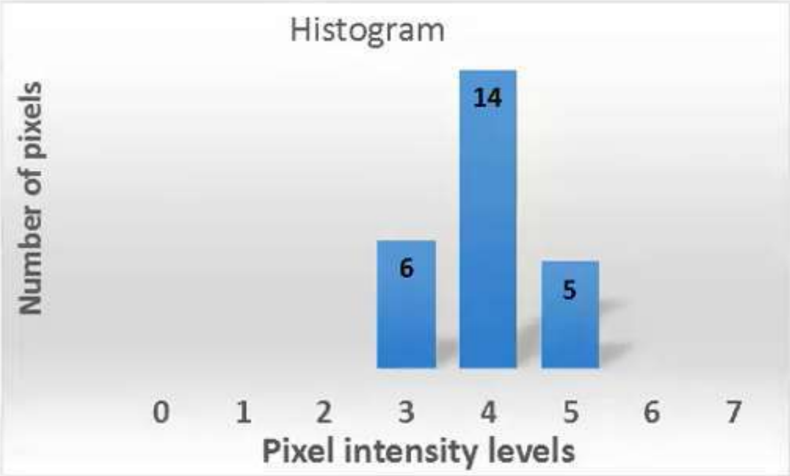


IMAGE HISTOGRAM EQUALIZATION

PROBLEM:* *Find the image* *Histogram Equilization* *of 5x5 given below image f(x,y) having 8 intensity levels [0..7]

PDF: PROBABILIT Y DENSITY FUNCTION

CDF: CUMULATIVE DENSITY FUNCTION

ROUND OFF TO NEEAR INTEGER in RUNNING SUM (nk)

INPUT IMAGE INTENSITY VALUES ARE GIVEN BELOW	No. of pixel = nk	PDF = $\frac{\text{No.of pixel}}{sum}$ $P_k = \frac{nk}{N}$	(Running sum) CDF S_k	Running sum * maximum gray level 7 x sk	HISTOGRAM EQUALIZTION VALUES => OUTPUT IMAGE INTENSITY VALUES
0	0	0/25 = 0	0	7 X 0 = 0	0
1	0	0/25 = 0	0	7 X 0 = 0	0
2	0	0/25 = 0	0	7 X 0 = 0	0
3	6	6/25 = 0.24	0.24	7 X 0.24 = 1.68	2
4	14	14/25 = 0.56	0.8	7 X 0.8 = 5.6	6
5	5	5/25 = 0.2	1	7 X 1 = 7	7
6	0	0/25 = 0	1	7 X 1 = 7	7
7	0	0/25 = 0	1	7 X 1 = 7	7
	N= 25				

4	4	4	4	4
3	4	5	4	3
3	5	5	5	3
3	4	5	4	3
4	4	4	4	4

AFTER EQUALIZATI ON

6	6	6	6	6
2	6	7	6	2
2	7	7	7	2
2	6	7	6	2
6	6	6	6	6

IMAGE HISTOGRAM EQUALIZATION

CONTINUED PREVIOUS PROBLEM

Input Image

4	4	4	4	4
3	4	5	4	3
3	5	5	5	3
3	4	5	4	3
4	4	4	4	4

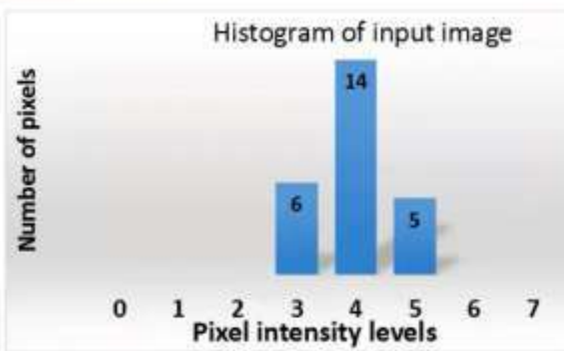
After equalization

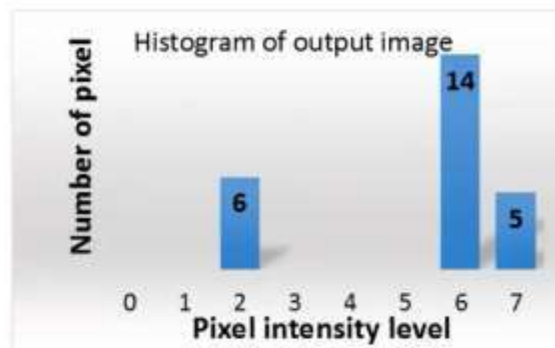
Output Image

6	6	6	6	6
2	6	7	6	2
2	7	7	7	2
2	6	7	6	2
6	6	6	6	6

Gray level	0	1	2	3	4	5	6	7
No. of pixel nk	0	0	0	6	14	5	0	0

Gray level	0	1	2	3	4	5	6	7
No. of pixel nk	0	0	6	0	0	0	14	5



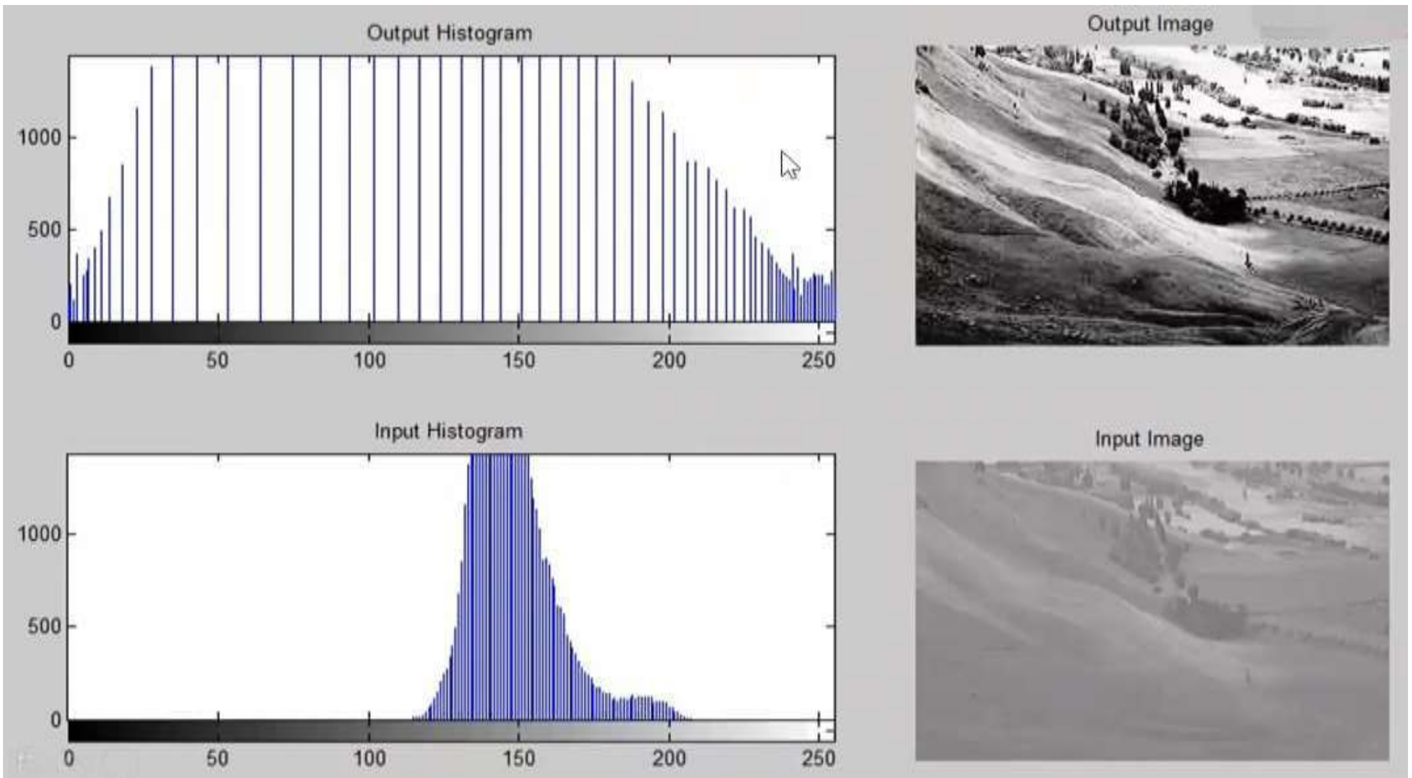


ON

OUTPUT IMAGE don't see much flat of image pixels due to small input image is considered, if you take WHOLE IMAGE to see enhancement of image quality.

IMAGE HISTOGRAM EQUALIZATION

EXAMPLES OF IMAGE ENHANCEMENT USING IMAGE HISTOGRAM EQUALIZATION



EQUALIZATI
ON

IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

Histogram Specification or Histogram Matching is a Transformation of an Image so its HISTOGRAM matches a SPECIFICED/REFERENCE HISTOGRAM

GOAL of HISTOGRAM EQUALIZATION is to produce an OUTPUT image that has FLATTENED HISTOGRAM

The GOAL of HISTOGRAM MATCHING is to take an INPUT IMAGE and generate OUTPUT IMAGE that is based upon the shape of SPEICIFIC (or REFERENCE) HISTOGRAM.
➔ Change the input image histogram based on Given/Reference Histogram

IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

For EXAMPLE:

CONVERT a given Image Histogram to a REFERENCE Histogram.

WHAT IS YOUR ANALYSIS OF THIS IMAGE (a) AND (b)?

Example : Given histogram (a) & (b), modify histogram (a) as given by histogram (b)

(a)

Gray level.	0	1	2	3	4	5	6	7
No. of pixels	790	1023	850	656	329	245	122	81

(b)

Gray level.	0	1	2	3	4	5	6	7
No. of pixels	0	0	0	614	819	1230	819	614

IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

For EXAMPLE:

CONVERT a given Image Histogram to a REFERENCE Histogram.

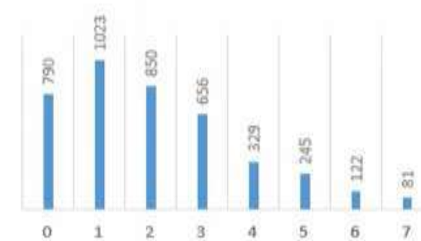
IMAGE A: Most of pixels are scattered on the Left (lower Intensity side)

IMAGE B: Most of pixels are scattered on the Right (Higher Intensity side

Example : Given histogram (a) & (b), modify histogram (a) as given by histogram (b)

(a)

Gray level.	0	1	2	3	4	5	6	7
No. of pixels	790	1023	850	656	329	245	122	81



(b)

Gray level.	0	1	2	3	4	5	6	7
No. of pixels	0	0	0	614	819	1230	819	614

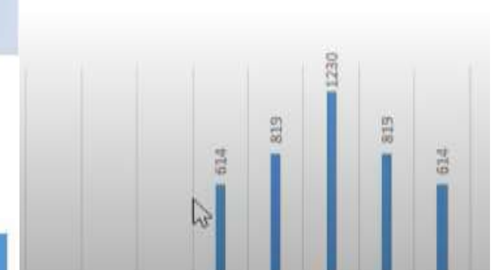


IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

For EXAMPLE:

STEP1: CALCULATE the HISTOGRAM of IMAGE (a) and also find **new nk**

STEP2: CALCULATE the HISTOGRAM of IMAGE (b)

STEP3: MAP the HISTOGRAM of IMAGE (b) to IMAGE (a)

STEP4: CREATE A new HISTOGRAM of Image (a) to the shape of REFERENCE HISTOGRAM of IMAGE (b)

Equalize histogram (a)

Gray level	nk	PDF	CDF	Sk x 7	Round off	New nk.
0	790	0.19	0.19	1.33	1	790
1	1023	0.25	0.44	3.08	3	1023
2	850	0.21	0.65	4.55	5	850
3	656	0.16	0.81	5.67	6 656+329	985
4	329	0.08	0.89	6.23	6	
5	245	0.06	0.95	6.65	7	
6	122	0.03	0.98	6.86	7 245 +122+81	448
7	81	0.02	1	7	7	
	N=4096					

IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

For EXAMPLE:

STEP2: CALCULATE the HISTOGRAM of IMAGE (b) ***(upto Round OFF)***

Now equalize histogram (b).

Gray level	nk	PDF	CDF	Sk x 7	Round off
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	614	0.149	0.149	1.05	1
4	819	0.20	0.35	2.50	3
5	1230	0.30	0.65	4.55	5
6	819	0.20	0.85	5.97	6
7	614	0.15	1	7	7
	N=4096				

IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

For EXAMPLE:

STEP3: MAP the HISTOGRAM of IMAGE (b) to IMAGE (a)

Mapping

First and last columns of histogram (b)

Gray level	Round off
0	0
1	0
2	0
3	1
4	3
5	5
6	6
7	7

Last two columns of histogram (a)

Round off	New nk.
1	790
3	1023
5	850
6	
6	985
7	
7	448
7	

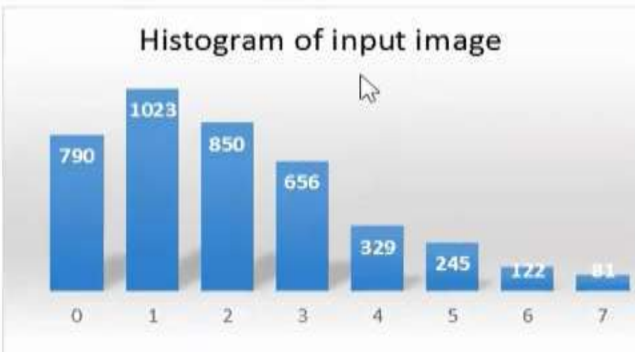
Gray level.	0	1	2	3	4	5	6	7
No. of pixels	0	0	0	790	1023	850	985	448

modified HISTOGRAM

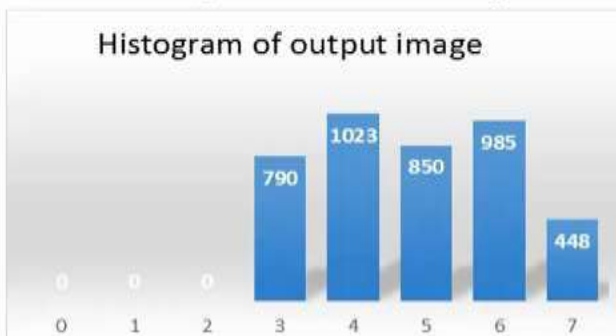
IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING

For EXAMPLE:

STEP4: CREATE A new HISTOGRAM of Image (a) to the shape of REFERENCE HISTOGRAM of IMAGE (b)

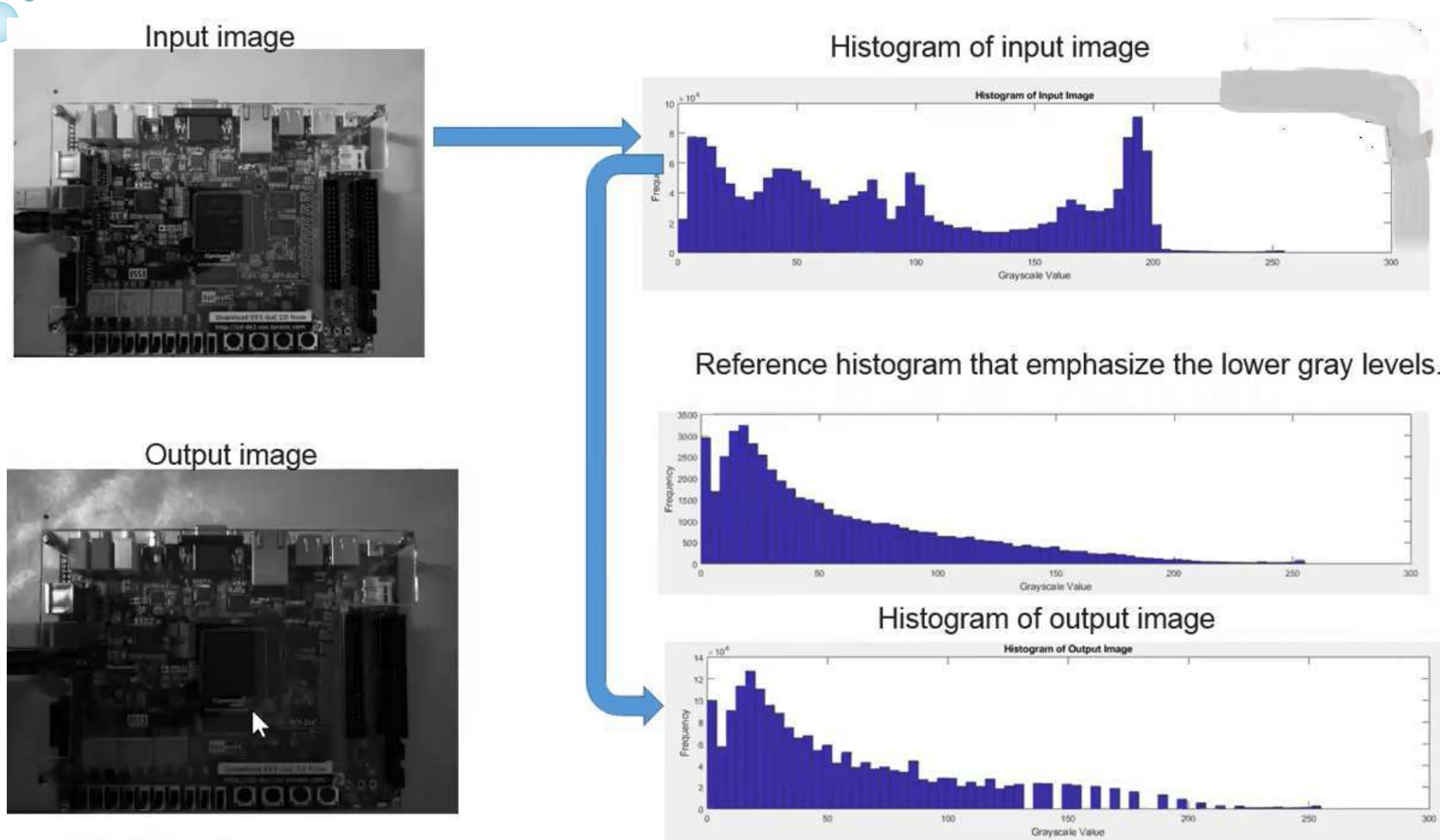


Plot histogram for modified image.



Gray level.	0	1	2	3	4	5	6	7
No. of pixels	0	0	0	790	1023	850	985	448

IMAGE HISTOGRAM SPECIFICATION OR HISTOGRAM MATCHING



WHEN TO APPLY HISTOGRAM ON IMAGES

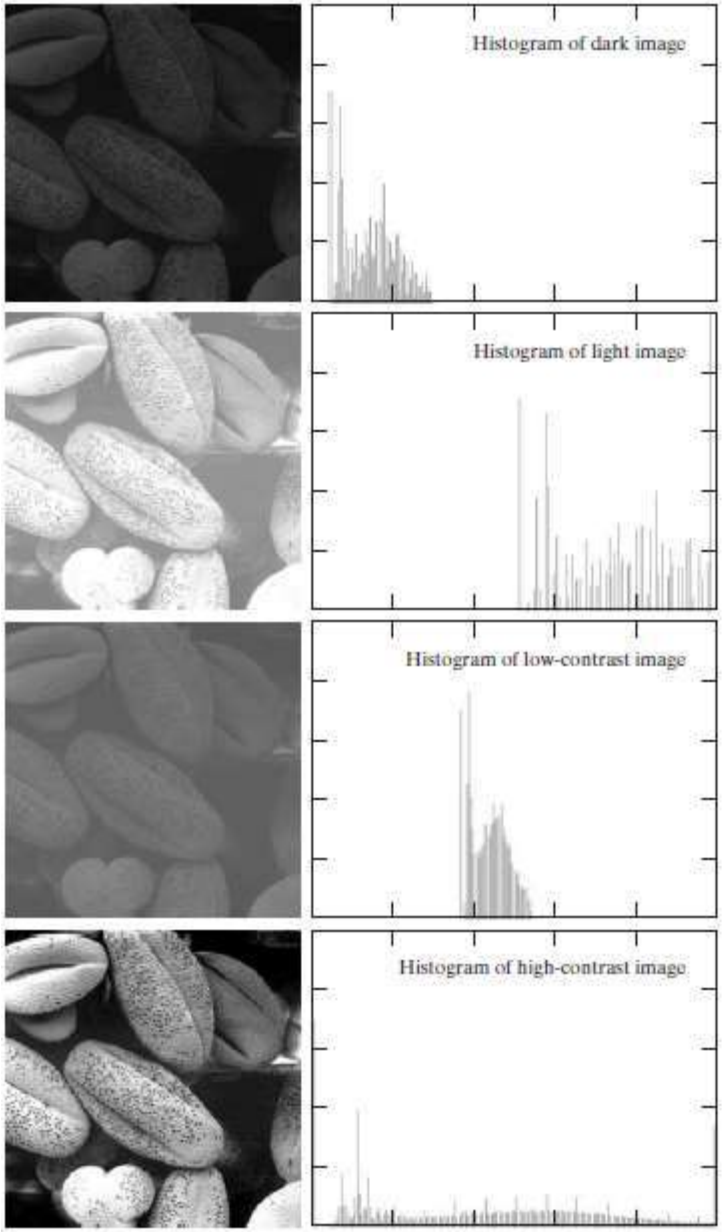


FIGURE 3.16 Four basic image types: dark, light, low contrast, high contrast, and their corresponding histograms.

ARE THERE ANY SIMPLE TOOLS AVAILABLE WHICH STUDENTS FREELY CAN USE?

ANSWER IS: YES
MATLAB,
OPENCV

TYPES OF HISTOGRAM PROCESSING ON IMAGES

GLOBAL HISTOGRAM EQUALIZATION PROCESSING
LOCAL HISTOGRAM EQUALIZATION PROCESSING

DRAW BACK OF GLOBAL HISTOGRAM EQUALIZATION

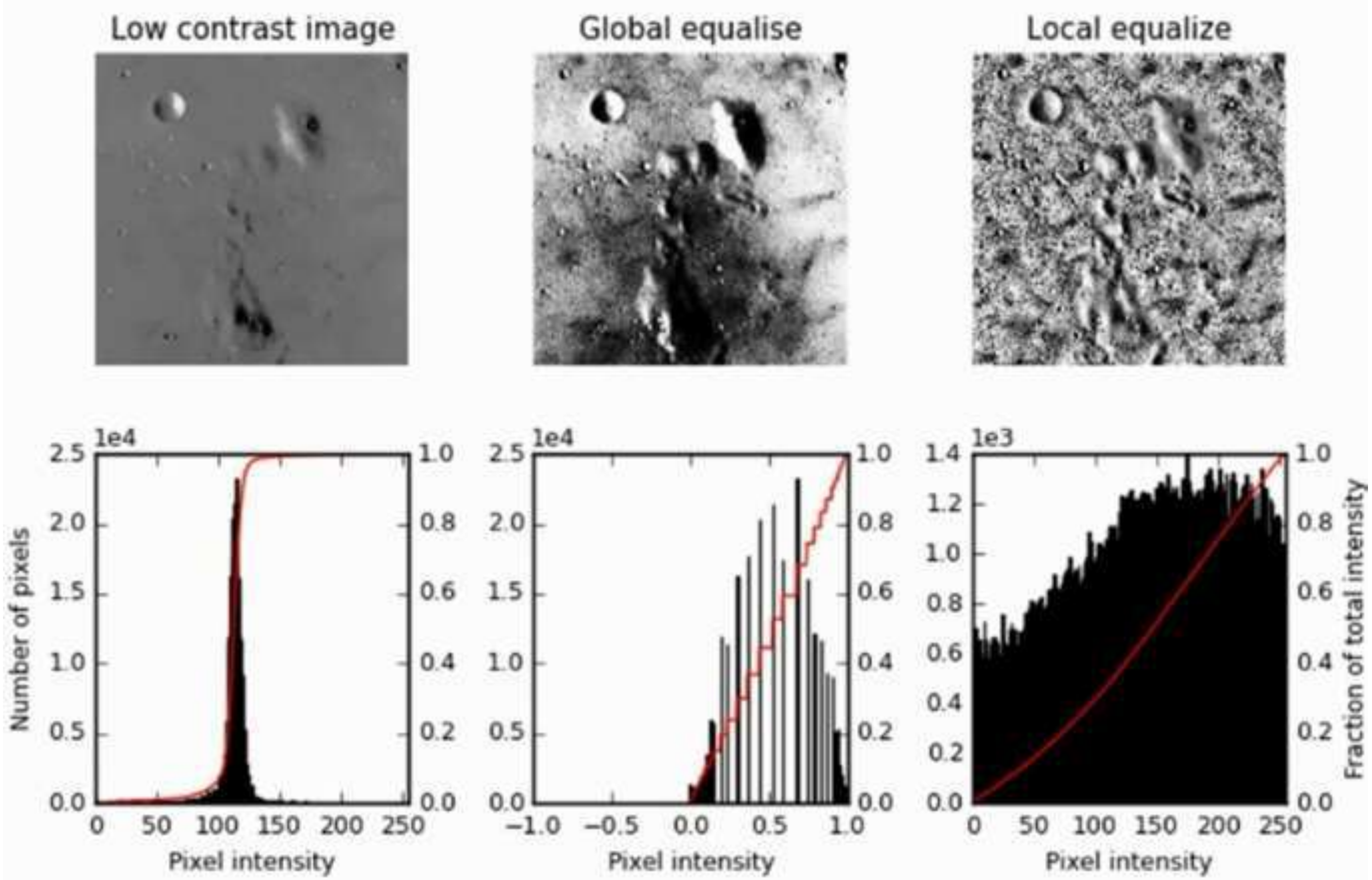
1.) Most contrast range to High narrow peaks
2.) Some images it is necessary to enhace smaller areas of the Image

To solve this LOCAL HISTOGRAM EQUALIZATION is devised.
In this technique consider individula Pixels and compute a Transformation Function from the histogram of a Pixel Neighborhood.

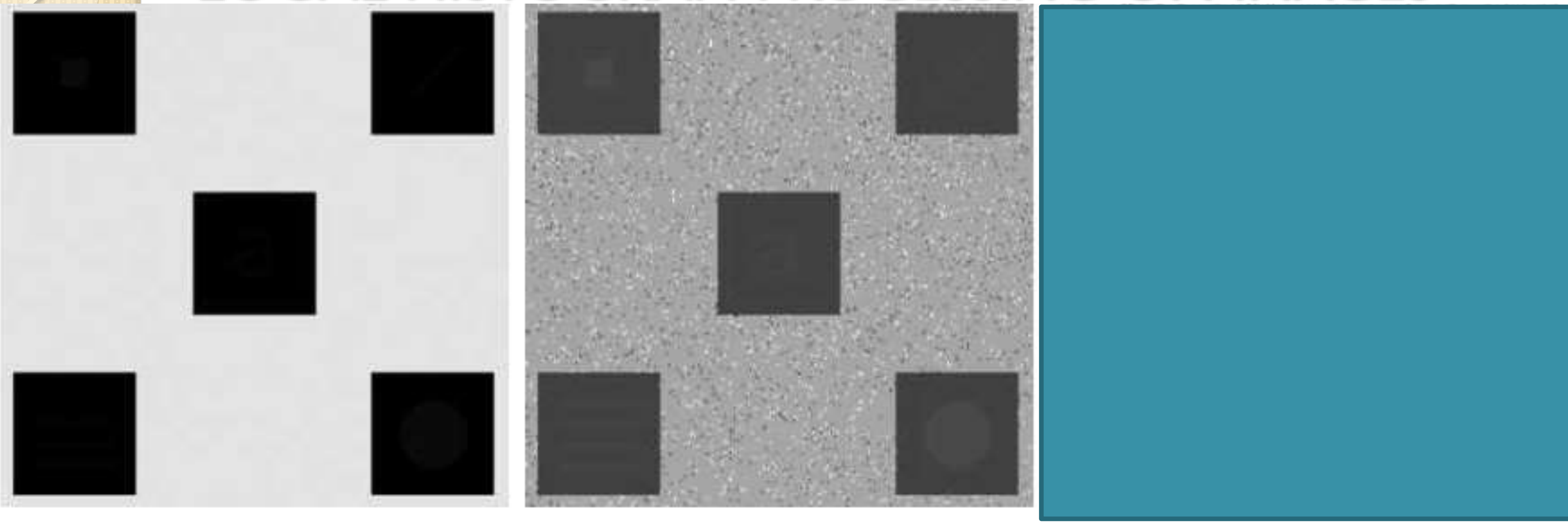
The center of the Neighborhood region is then moved to an adjacent Pixel location and the procedure is repeated again.

LOCAL HISTOGRAM PROCESSING ON IMAGES

IMAGE OF LOCAL HISTOGRAM EQUALIZATION



LOCAL HISTOGRAM PROCESSING ON IMAGES



a b c

FIGURE 3.26 (a) Original image. (b) Result of global histogram equalization. (c) Result of local histogram equalization applied to (a), using a neighborhood of size 3×3.

Figure 3.26(a) shows an 8-bit, image that at first glance appears to contain five black squares on a gray background. The image is slightly noisy, but the noise is imperceptible. Figure 3.26(b) shows the result of global histogram equalization. As often is the case with histogram equalization of smooth, noisy regions, this image shows significant enhancement of the noise. Aside from the noise, however, Fig. 3.26(b) does not reveal any new significant details from the original, other than a very faint hint that the top left and bottom right squares contain an object. Figure 3.26(c) was obtained using local histogram equalization with a neighborhood of size Here, we see significant detail contained within the dark squares. The intensity values of these objects were too close to the intensity of the large squares, and their sizes were too small, to influence global histogram equalization significantly enough to show this detail.

STEPS FOR LOCAL HISTOGRAM PROCESSING ON IMAGES

LOCAL ENHANCEMENT

- The histogram processing techniques are easily adaptable to local enhancement.
- The procedure is to define a square or rectangular neighborhood and move the center of this area from pixel to pixel.
- At each location, the histogram of the points in the neighborhood is computed and either a histogram equalization or histogram specification transformation function is obtained.
- This function is finally used to map the gray level of the pixel centered in the neighborhood.
- The center of the neighborhood region is then moved to an adjacent pixel location and the procedure is repeated.
- Since only one new row or column of the neighborhood changes during a pixel-to-pixel translation of the region, updating the histogram obtained in the previous location with the new data introduced at each motion step is possible.
- This approach has obvious advantages over repeatedly computing the histogram over all pixels in the neighborhood region each time the region is moved one pixel location

SPATIAL FILTERING IN IMAGE PROCESSING

SPATIAL Filtering is one of the principal tools used in this field for a broad spectrum of applications, so it is highly advisable that you develop a solid understanding of these concepts.

•Used in image enhancement

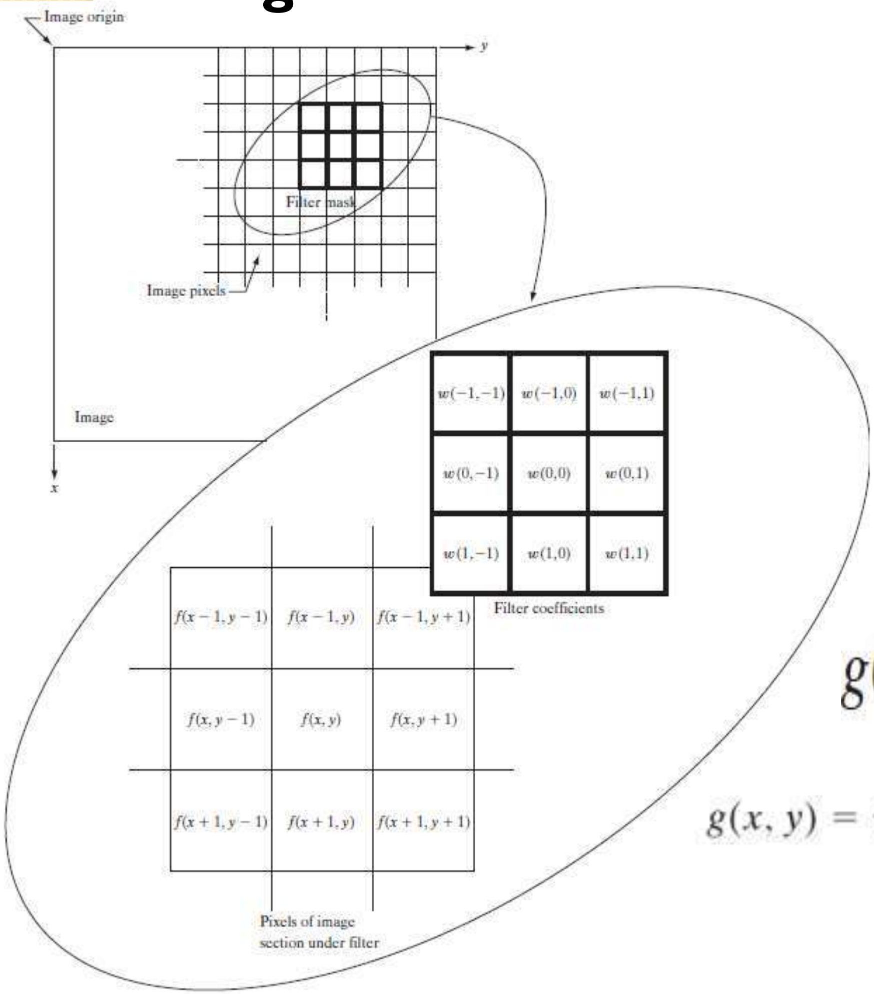


FIGURE 3.28 The mechanics of linear spatial filtering using a 3 × 3 filter mask. The form chosen to denote the coordinates of the filter mask coefficients simplifies writing expressions for linear filtering.

COMPUTATIONAL PROCEDURE:

SUM OF THE PRODUCT OF THE FILTER ELEMENTS BY IMAGE PIXES TO COMPUTE A TARGET IMAGE

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

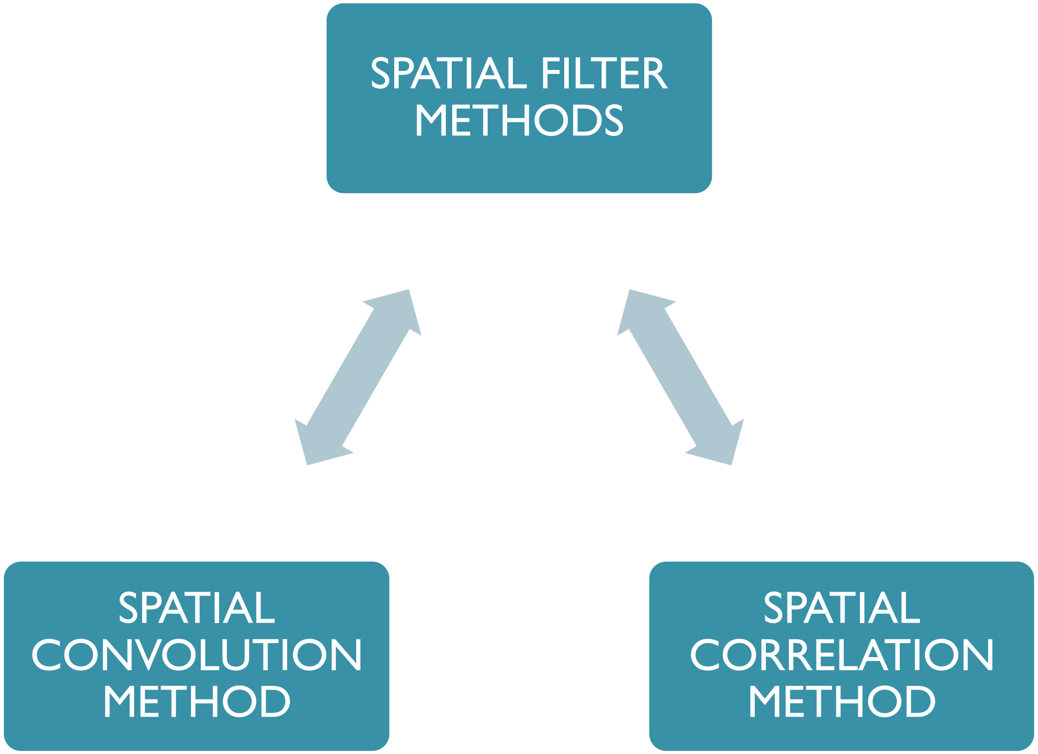
$$g(x, y) = w(-1, -1)f(x - 1, y - 1) + w(-1, 0)f(x - 1, y) + \dots + w(0, 0)f(x, y) + \dots + w(1, 1)f(x + 1, y + 1)$$

SPATIAL FILTERING IN IMAGE PROCESSING

METHODS TO FIND THE FILTERS

CORRELATION METHOD

CONVOLUTION METHOD



SPATIAL FILTERING IN IMAGE PROCESSING

WORKING OF THE CORRELATION METHOD

Origin $f(x, y)$

$$\begin{matrix} 0&0&0&0&0\\ 0&0&0&0&0\\ 0&0&1&0&0\\ 0&0&0&0&0\\ 0&0&0&0&0 \end{matrix} \qquad w(x,y)\quad \begin{matrix} 1&2&3\\ 4&5&6\\ 7&8&9 \end{matrix}$$

(a)

Padded f

$$\begin{matrix} 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&1&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0 \end{matrix}$$

(b)

1.) Padding origin image 5x4 with 3-1=2 pixels to the Left & Right of each Row and each Top&Bottom of each column with zeroes(0) value to the Origin image. 5x5 ➔ 9x9

2.) Start from Initial Position do Computation as shown in Formula (Initial position for w)

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

Initial position for w

$$\begin{matrix} 1&2&3&0&0&0&0&0&0\\ 4&5&6&0&0&0&0&0&0\\ 7&8&9&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&1&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0 \end{matrix}$$

(c)

Full correlation result

$$\begin{matrix} 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&9&8&7&0&0&0\\ 0&0&0&6&5&4&0&0&0\\ 0&0&0&3&2&1&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0 \end{matrix}$$

(d)

Cropped correlation result

$$\begin{matrix} 0&0&0&0&0\\ 0&9&8&7&0\\ 0&6&5&4&0\\ 0&3&2&1&0\\ 0&0&0&0&0 \end{matrix}$$

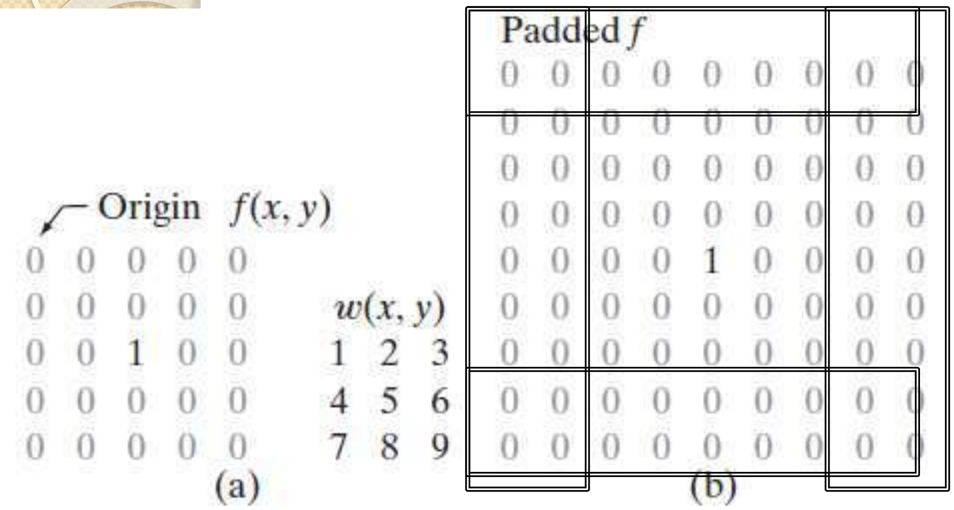
(e)

3.) Travel through the entire Origin image to calculate the corresponding Target Image Pixels (Full Correlation Result)

4.) Crop the correlation image to get original Size of Image

SPATIAL FILTERING IN IMAGE PROCESSING

WORKING OF THE SPATIAL FILTER : CONVULTION METHOD

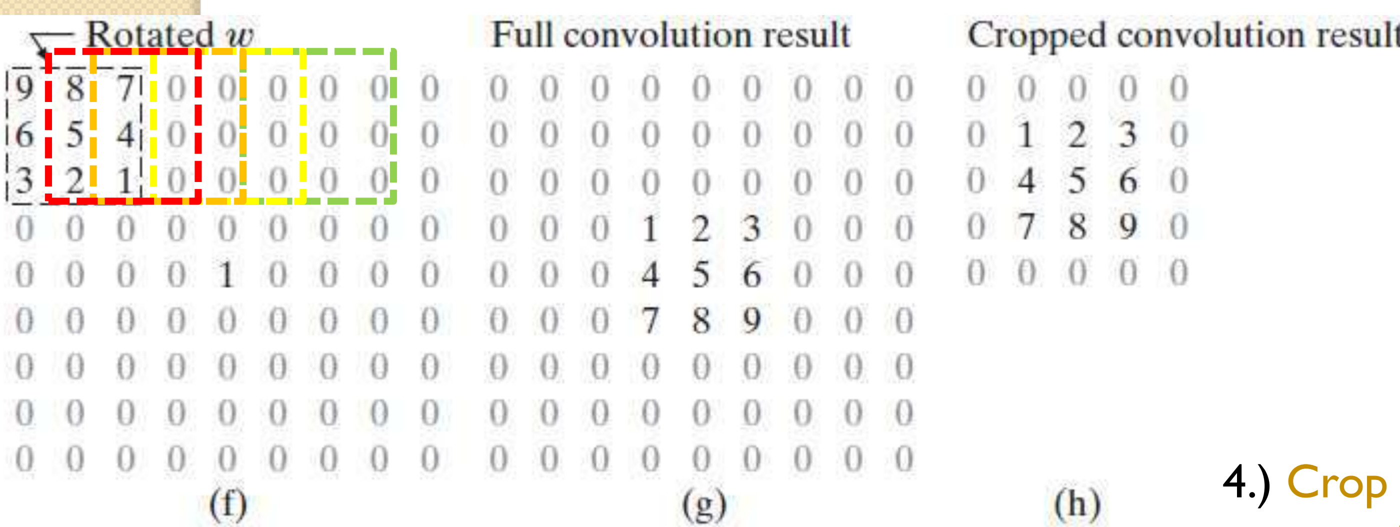


1.) Padding origin image 5x4 with 3-1=2 pixels to the Left & Right of each Row and each Top&Bottom of each column with zeroes(0) value to the Origin image. 5x5 ➔ 9x9

1b) ROTATE FILTER BY 180 ^{0}

2.) start from Initial Position do Computation as shown in Formula (Initial position for w)

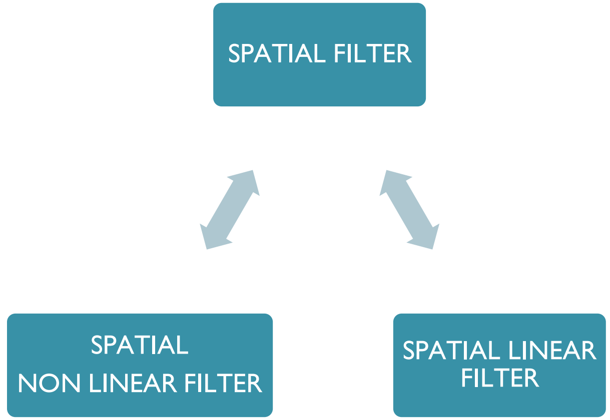
$$g(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s, t) f(x + s, y + t)$$



3.) Travel through the entire Origin image to calculate the corresponding Target Image Pixels (Full Correlation Result)

4.) Crop the correlation image to get original Size of Image

SPATIAL FILTERING IN IMAGE PROCESSING



	LINEAR FILTER	NON LINEAR FILTER
1.	The average of the pixels contained in the neighborhood of the filter mask	The Median Filters. replaces the value of a pixel by the median of the intensity values in the neighborhood of that pixel (the original value of the pixel isincluded in the computation of the median).
2.	Low Pass Filter	Low Pass Filter
3.	Replacing the value of every pixel in an image by the average of the intensity levels in the neighborhood defined by the filter mask	Response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter, and then replacing the value of the center pixel with the value determined by the ranking result.
4	Reduced "sharp" transitions in intensities	considerably less blurring than linear smoothing filters of similar size
5.	Reduce Noises in image	*Suitable for impulse noise*, a.k.a *salt-and-pepper noise*

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING

Smoothing filters are used for blurring and for noise reduction.

Blurring : used in preprocessing tasks, such as removal of small details from an image prior to (large) object extraction, and bridging of small gaps in lines or curves.

Noise reduction : This can be accomplished by blurring with a linear filter and also by nonlinear filtering.

Bridge the gaps in Lines and Curves.

Smoothing Linear Filters

Non-Linear Filters

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING (Smoothing Linear Filters)

- The output (response) of a smoothing, linear spatial filter is simply the average of the pixels contained in the neighborhood of the filter mask. These filters sometimes are called *averaging filters. As mentioned in the previous section,* they also are referred to a *lowpass filters*.

  Why it works?
  The idea behind smoothing filters is straightforward. By replacing the value of every pixel in an image by the average of the intensity levels in the neighborhood defined by the filter mask, this process results in an image with reduced "sharp" transitions in intensities. Because random noise typically consists of sharp transitions in intensity levels, the most obvious application of smoothing is noise reduction. However, edges (which almost always are desirable features of an image) also are characterized by sharp intensity transitions, so averaging filters have the undesirable side effect that they blur edges. Another application of this type of process includes the smoothing of false contours that result from using an insufficient number of intensity levels.

  Uses: the reduction of "irrelevant" detail in an image. By "irrelevant" we mean pixel regions that are small with respect to the size of the filter mask.

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING (Smoothing Linear Filters)

$$\frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad \frac{1}{16} \times \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

These two are 3x3 Smoothing filters.

First Filter is having all 1's

Second Filter is having a Euclidean Distance 1 and Diagnoal as less weight

What is the Effect of the above Two Filters applying on the Original Image i.e. Input Image?

First is Averages the Pixels on Box

Second: Calculates the Weighted average of the Pixes. (Gaussian Filter)

WHAT ABOUT EFFECTS OF FILTER SIZES ?

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING

(EFFECT OF SMOOTHING ON FILTER SIZES?)

shows an original image and the corresponding smoothed results obtained using square averaging filters of sizes 5, 9, 15, and 35 pixels.

First is Averages the Pixels on Box
Second: Calculates the Weighted average of the Pixes.

WHAT ABOUT EFFECTS OF FILTER SIZES ?

a b
c d
e f

FIGURE 3.33 (a) Original image, of size 500 × 500 pixels. (b)–(f) Results of smoothing with square averaging filter masks of sizes m = 3, 5, 9, 15, and 35, respectively. The black squares at the top are of sizes 3, 5, 9, 15, 25, 35, 45, and 55 pixels, respectively; their borders are 25 pixels apart. The letters at the bottom range in size from 10 to 24 points, in increments of 2 points; the large letter at the top is 60 points. The vertical bars are 5 pixels wide and 100 pixels high; their separation is 20 pixels. The diameter of the circles is 25 pixels, and their borders are 15 pixels apart; their intensity levels range from 0% to 100% black in increments of 20%. The background of the image is 10% black. The noisy rectangles are of size 50 × 120 pixels.

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING (EFFECT OF SMOOTHING ON FILTER SIZES? ANALYSIS OF PREVIOUS EXPERIMENT)

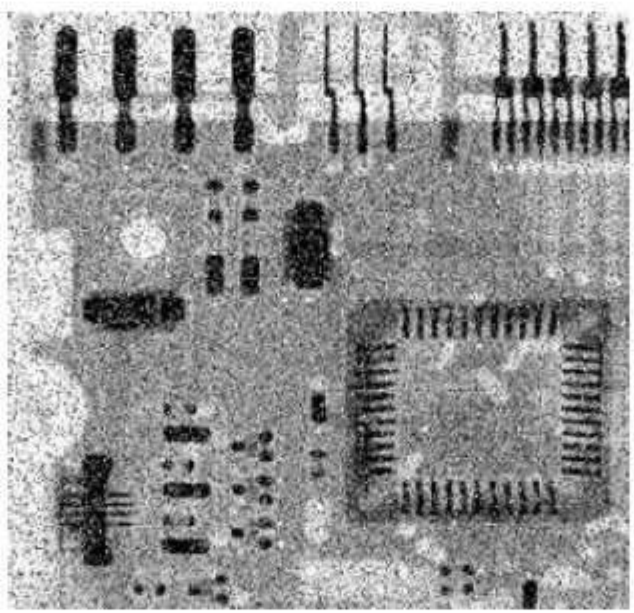
For we note a general slight blurring throughout the entire image but, as expected, details that are of approximately the same size as the filter mask are affected considerably more. For example, the and black squares in the image, the small letter "a," and the fine grain noise show significant blurring when compared to the rest of the image. Note that the noise is less pronounced, and the jagged borders of the characters were pleasingly smoothed. The result for is somewhat similar, with a slight further increase in blurring. For we see considerably more blurring, and the 20% black circle is not nearly as distinct from the background as in the previous three images, illustrating the blending effect that blurring has on objects whose intensities are close to that of its neighboring pixels. Note the significant further smoothing of the noisy rectangles. The results for and 35 are extreme with respect to the sizes of the objects in the image. This type of aggresive blurring generally is used to eliminate small objects from an image. For instance, the three small squares, two of the circles, and most of the noisy rectangle areas have been blended into the background of the image Note also in this figure the pronounced black border. This is a result of padding the border of the original image with 0s (black) and then trimming off the padded area after filtering. Some of the black was blended into all filtered images, but became truly objectionable for the images.

smoothed with the larger filters.

AVERAGING FILTER USE: the intensity of smaller objects blends with the background and larger objects become "bloblike" and easy to detect

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING (NON-LINER SMOOTHING FILTERS a.k.a ORDER STATISTICS (NON-LINEAR) FILTERS)

If you have an image shown below, how do you enhance the Image?



Analyse the Image:

1. This image has more dots
2. Dots of type Black and White
3. Patterns of dots: All over the Image

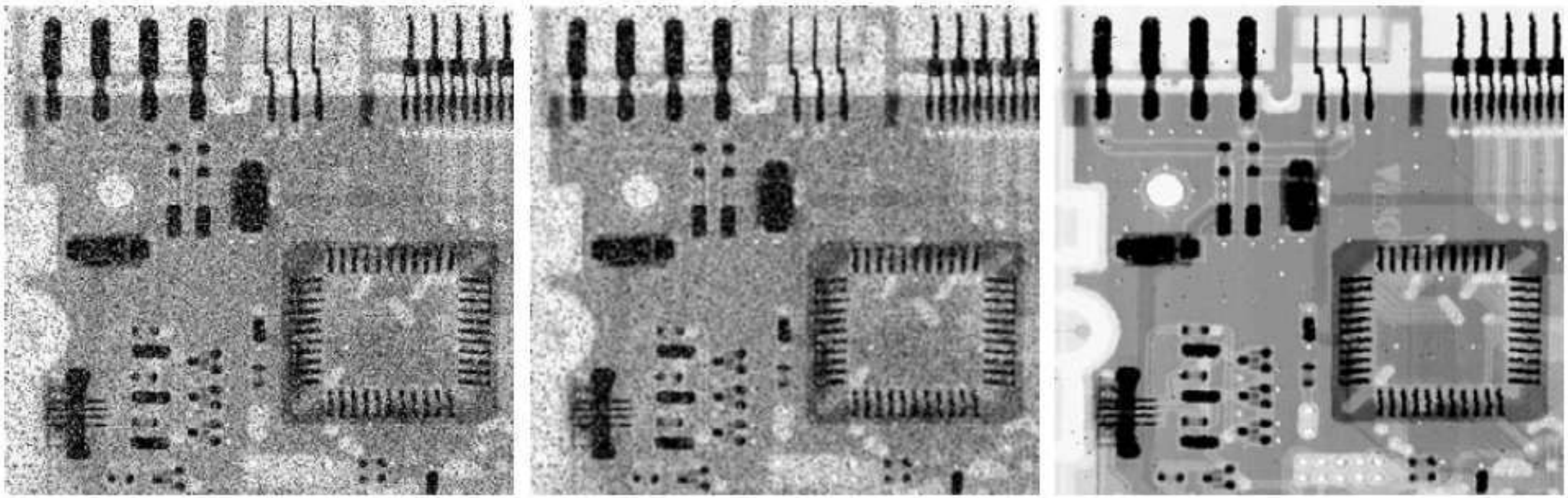
If we apply Averaging Filter What happens?

If we take Median of the Filter?

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING (NON-LINER SMOOTHING FILTERS a.k.a ORDER STATISTICS (NON-LINEAR) FILTERS)

If you have an image shown below, how do you enhance the Image?

Median Filters are used



a b c

FIGURE 3.35 (a) X-ray image of circuit board corrupted by salt-and-pepper noise. (b) Noise reduction with a 3 × 3 averaging mask. (c) Noise reduction with a 3 × 3 median filter. (Original image courtesy of Mr.

SMOOTHING SPATIAL FILTERING IN IMAGE PROCESSING (NON-LINER SMOOTHING FILTERS a.k.a ORDER STATISTICS (NON-LINEAR) FILTERS)

If you have an image shown below, how do you enhance the Image?

Median Filters are used

Order-statistic filters are nonlinear spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter, and then replacing the value of the center pixel with the value determined by the ranking result.The best-known filter in this category is the *median filter,* which, as its name implies, replaces the value of a pixel by the median of the intensity values in the neighborhood of that pixel (the original value of the pixel is included in the computation of the median). Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters of similar size.

USE OF Median filters They are particularly effective in the presence of *impulse noise,* also called *salt-and-pepper noise because of its appearance as white and black* dots superimposed on an image.

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

To highlight transitions in intensity levels in Input Image

- **Highlight the Fine details in Image**
- **Enhance the Blurred Images**
- **Enhance the Edges**

Useful in these Businesses Applications:

- **Electronic printing**
- **Medical imaging**
- **Industrial inspection and**
- **Autonomous guidance in Military systems**

The strength of the response of a derivative operator is proportional to the degree of intensity discontinuity of the image at the point at which the operator is applied.

Reason it Works: Image differentiation enhances edges and other discontinuities (such as noise) and deemphasizes areas with slowly varying intensities

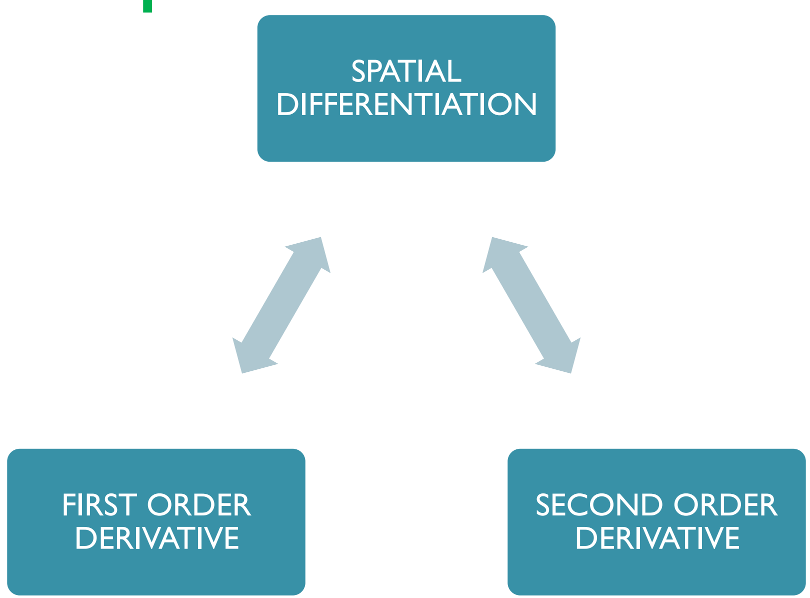
SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

We use Spatial Differentiation to perform the Image Sharpening $\partial f/\partial x$ (Read as Doh-f/Doh-x)

The strength of the response of a derivative operator is proportional to the degree of intensity discontinuity of the image at the point at which the operator is applied.

Reason it Works: Image differentiation enhances edges and other discontinuities (such as noise) and deemphasizes areas with slowly varying intensities

To Peform the Spatial Differentiation we use 2 Derivatives



SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

First Order Derivative:

Consider one-dimensional Image → → We consider One Line in the Input Image (X-Direction).

In the Input image we are interested in the Image portion where intensity is varying like **:-**

Areas of constant intensity,

At the **onset** (start) and **end of discontinuities in Intensity (step & ramp intensity** discontinuities), and

Along intensity **ramps**. (Downwards Slope Intensities)

We use Below image for our examining the First order derivatives Behavior. Below is an approximaged Image that has Constant Intensity, Ramp Intensity and Step Intensity.

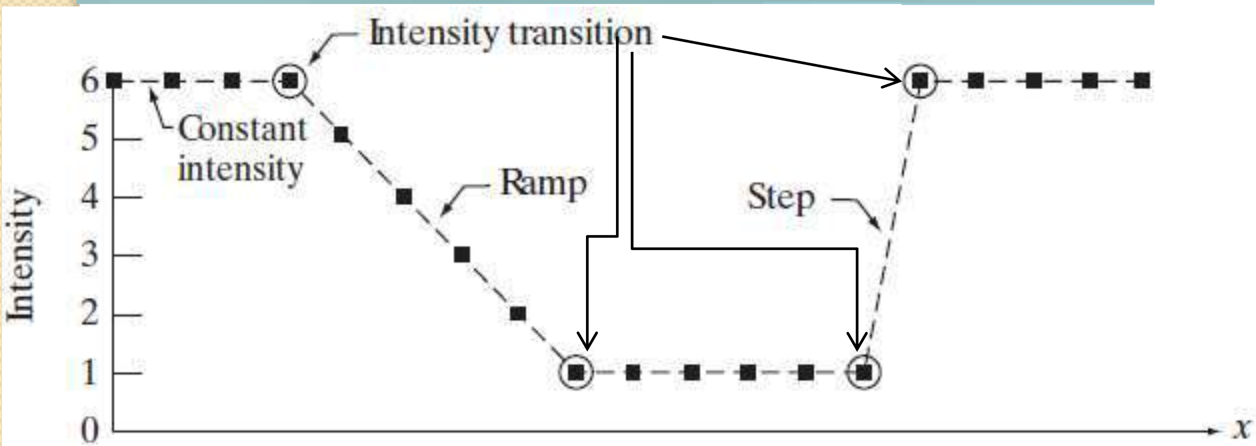
SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING :

FIRST ORDER DERIVATIVE OF 1-D FUNCTION

A basic definition of the first-order derivative of a one-dimensional function $f(x)$ is the difference

Read as doh-f/doh-x
f(x): current pixel Intensity

$$\frac{\partial f}{\partial x} = f(x+1) - f(x) \qquad (3.6\text{-}1)$$



Example SCAN LINE ZOOMED AND SHOWED ABOVE **INTENSITY PROFILE**
For a 1-D (Dimension) Function we can plot a SCAN LINE having Intensity Values.

Scan line	6	6	6	6	5	4	3	2	1	1	1	1	1	1	6	6	6	6	6

$\to x$

1st derivative 0 0 −1 −1 −1 −1 −1 0 0 0 0 0 5 0 0 0 0

2nd derivative 0 0 −1 0 0 0 0 1 0 0 0 0 5 −5 0 0 0

We define the second-order derivative of $f(x)$ as the difference

Read as doh²-f/doh-x²

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x) \qquad (3.6\text{-}2)$$

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

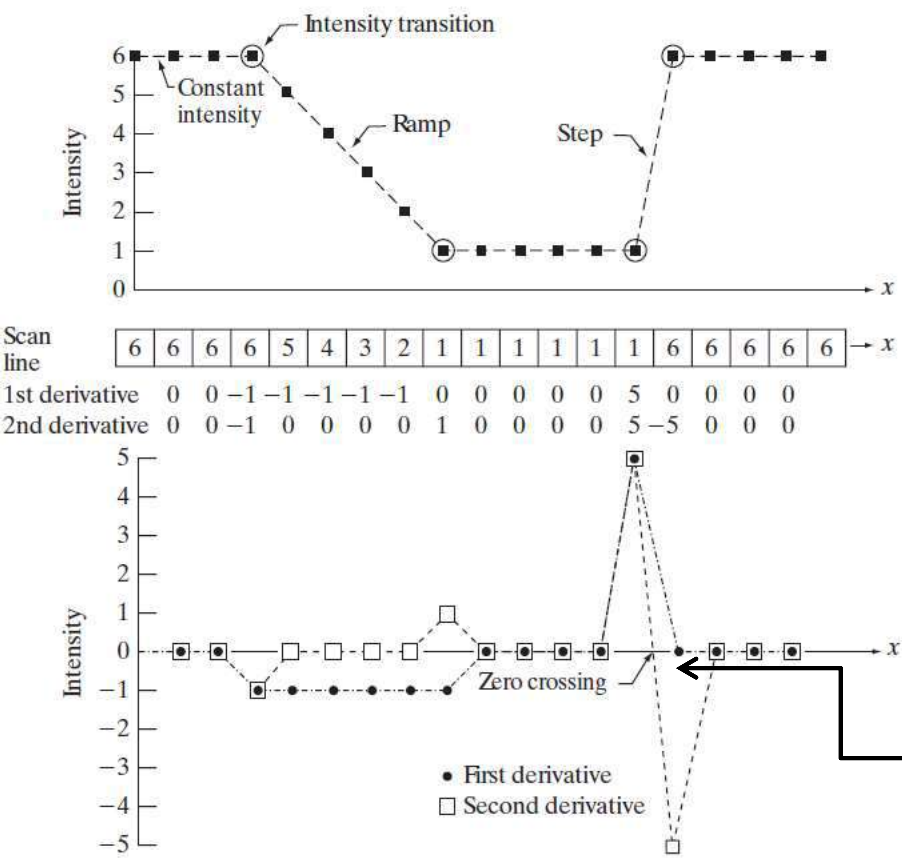
BEHAVIORS OF FIRST ORDER AND SECOND ORDER DERAVATIVES

FIRST ORDER derivative: (DEFINITION or BEHAVIOR)

(1) *Must be zero in areas of constant* intensity;

(2) Must be nonzero at the onset of an intensity step or ramp; and

(3) Must be nonzero along ramps



a
b
c

FIGURE 3.36 Illustration of the first and second derivatives of a 1-D digital function representing a section of a horizontal intensity profile from an image. In (a) and (c) data points are joined by dashed lines as a visualization aid.

ZERO CROSSING

SECOND ORDER derivative: (DEFINITION OR BEHAVIOR

(1) Must be zero in constant areas;

(2) Must be nonzero at the onset *and* end of an intensity step or ramp;

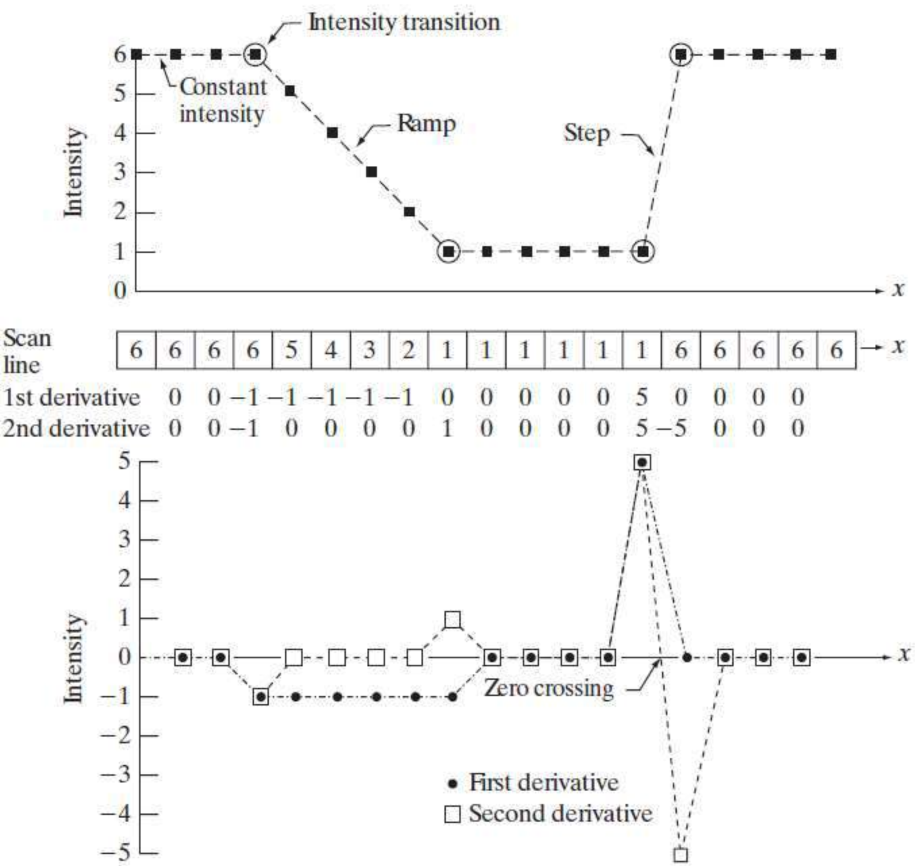
(3) Must be zero along ramps of constant slope.

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

What is your Observation?

FIRST Order Derivative: Creates Thicker Edges

SECOND Order Derivatives: Creates Sharp Edges (Double Edge)



a
b
c

FIGURE 3.36 Illustration of the first and second derivatives of a 1-D digital function representing a section of a horizontal intensity profile from an image. In (a) and (c) data points are joined by dashed lines as a visualization aid.

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

Using 2nd Order Derivative to Sharpen 2-D Image: The Laplacian:

Suitable for Images of type ISOTROPE (Apply Filter and rotate Image or Rotate Image and Apply Filter Both has same result)

Apply One-Dimension to 2nd Order Derivative to X-Direction and Y-Direction?

(READ as Del^{2}f) $$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad (3.6\text{-}3)$$

Because derivatives of any order are linear operations, the Laplacian is a linear operator. To express this equation in discrete form, we use the definition in Eq. (3.6-2), keeping in mind that we have to carry a second variable. In the x-direction, we have

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y) \qquad (3.6\text{-}4)$$

and, similarly, in the y-direction we have

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y) \qquad (3.6\text{-}5)$$

Therefore, it follows from the preceding three equations that the discrete Laplacian of two variables is

$$\nabla^2 f(x, y) = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y) \qquad (3.6\text{-}6)$$

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING (Build Laplacian Mask 3x3)

Therefore, it follows from the preceding three equations that the discrete Laplacian of two variables is

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

$$g(x, y) = f(x, y) + c\left[\nabla^2 f(x, y)\right] \qquad (3.6\text{-}7)$$

4 Neighbor

C = -1

f(x-1,y)

f(x,y11) f(x,y) f(x,y+1)

f(x+1,y)

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

8 Neighbor

C = 1

0	−1	0
−1	4	−1
0	−1	0

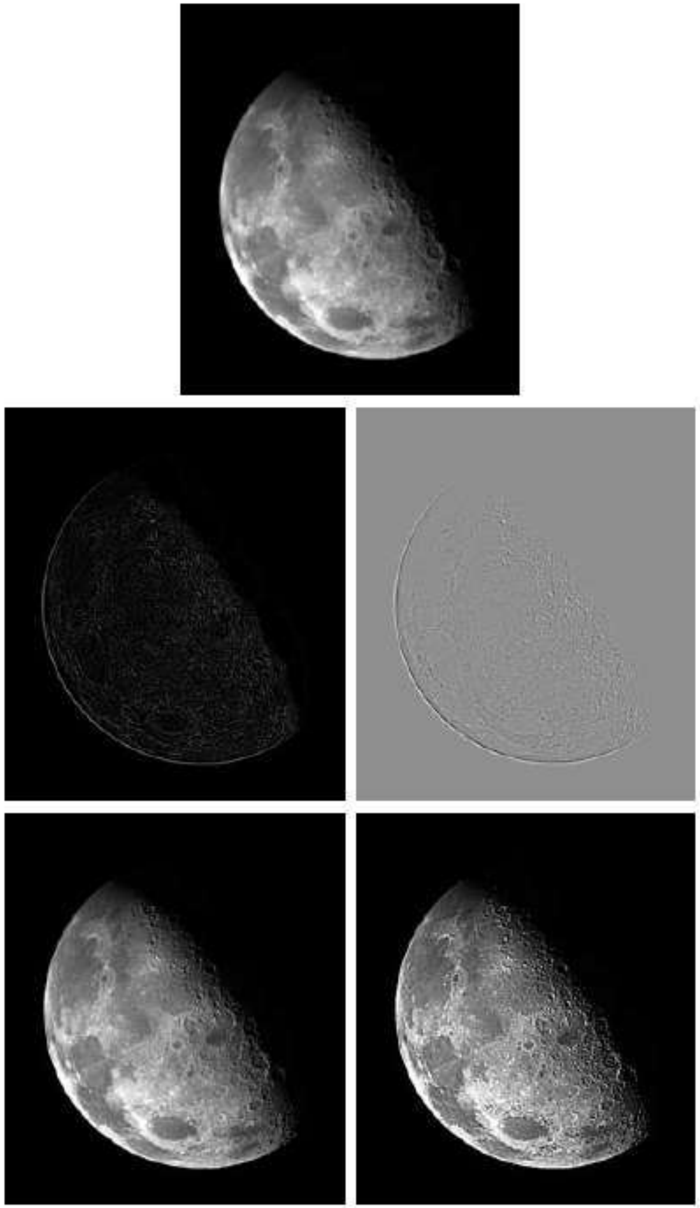
−1	−1	−1
−1	8	−1
−1	−1	−1

3x3 FILTER Mask is formed using the CO-Efficients of the above Equation.

Mask: Sum of all elements in Filter is ZERO

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

Examples of Using Laplacian Filter



a
b c
d e

FIGURE 3.38 (a) Blurred image of the North Pole of the moon. (b) Laplacian without scaling. (c) Laplacian with scaling. (d) Image sharpened using the mask in Fig. 3.37(a). (e) Result of using the mask in Fig. 3.37(b). (Original image courtesy of NASA.)

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING UNSHARP MASKING and HIGHBOOST FILTER

For What Intesity Profile this is suitable?

The intensity profile in Fig. 3.39(a) can be interpreted as a horizontal scan line through a vertical edge that transitions from a dark to a light region in an image

$$g(x, y) = f(x, y) + k * g_{mask}(x, y) \quad (3.6\text{-}9)$$

k=1 Unsharp Masking Filter

k>1 High Boost Filtering

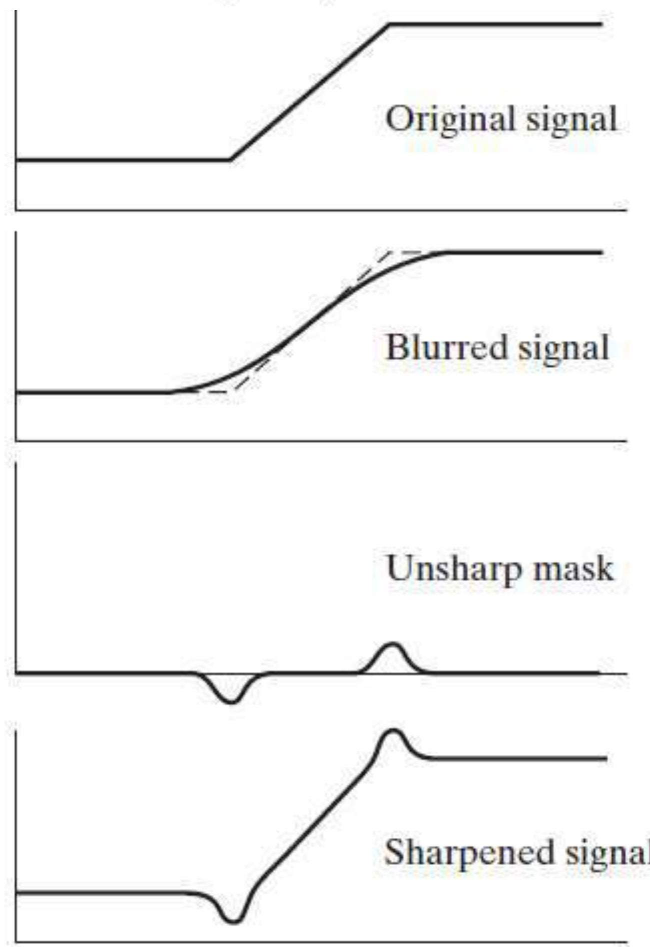


FIGURE 3.39 1-D illustration of the mechanics of unsharp masking. (a) Original signal. (b) Blurred signal with original shown dashed for reference. (c) Unsharp mask. (d) Sharpened signal, obtained by adding (c) to (a).

Smoothing and Over imposed original

Subtract Blurred image from Original Image

Add difference to Original Image

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING
UNSHARP MASKING and HIGHBOOST FILTER

A process that has been used for many years by the printing and publishing industry to sharpen images consists of subtracting an unsharp (smoothed) version of an image from the original image. This process, called *unsharp masking,* consists of the following steps:

STEPS TO DO THE UnSHARP Mask & Highboot SPATIAL FILTER

1. Blur the original image. (Use Gaussian Blur)

2. Subtract the blurred image from the original (the resulting difference is called the *mask.)*

3. Add the Filter Mask to the original (Upto Step3 called UNSHARP MASKING) (k=1)

(OR)

4. Use High Boost Filtering to get SHARPENED SPATIAL FILTERED IMAGE (k>1)

SHARPENING SPATIAL FILTERING IN IMAGE PROCESSING

a
b
c
d
e

FIGURE 3.40 (a) Original image. (b) Result of blurring with a Gaussian filter. (c) Unsharp mask. (d) Result of using unsharp masking. (e) Result of using highboost filtering.

Using First-Order Derivatives for (Nonlinear) Image Sharpening—The Gradient (x and y directions)

First Derivatives in images processing are implemented using the **Magnitude of Gradient**. For a function , **the gradient of** *f(x,y) at coordinates (x, y) is defined* as the two-dimensional column *vector*

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix} \qquad (3.6\text{-}10)$$

This vector has the important geometrical property that it points in the direction of the greatest rate of change of *f at location (x, y)*.

The *magnitude (length) of vector Δf denoted as M(x, y), where*

$M(x, y) = \text{mag}(\Delta f) = \text{SQRT}(g^2x + g^2y)$ --- (3.6-11)

is the *value at (x, y) of the rate of change in the direction of the gradient vector*.

Note that *M(x, y) is an image of the same size as the original, created when x and y are allowed to vary over all pixel locations in f. It is common practice* to refer to this image as the *gradient image (or simply as the gradient when the* meaning is clear).

$M(x, y) =\sim |g_x| + |g_y|$

Using First-Order Derivatives for (Nonlinear) Image Sharpening—The Gradient

Construct the Mask using the above Magnitude function M(x,y)

Let us mark the Image 3x3 and its corresponding z

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

Z1	Z2	Z3
Z4	Z5	Z6
Z7	Z8	Z9

W.R.T **Z5 corresponds to f(x,y) First 3x3**

g_x = ∂f/∂x = (Using First order Derivative) = f(x+1,y)-f(x,y) = Z8-Z5

g_y = ∂f/∂y = (Using First order Derivative) = f(x,y+1)-f(x,y) = Z6-Z5

$$\mathbf{M}_{(x,y)} = |g_x| + |g_y| = |\mathbf{Z8-Z5}| + |\mathbf{Z6-Z5}|$$

-1	0
1	0

-1	1
0	0

2x2 Mask is formed.

g_x - Vertical **g_y - Horizontal**

What is the Problem in this Mask?

No Center Symmetry

Using First-Order Derivatives for (Nonlinear) Image Sharpening—The Gradient Sobels operators

Examples of Center Symmetry: 3x3, 5x5, 7x7 etc

Sobel Proposed these equations to determine the Co-efficients.

Z1	Z2	Z3
Z4	Z5	Z6
Z7	Z8	Z9

$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \qquad (3.6\text{-}16)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7) \qquad (3.6\text{-}17)$$

$$M(x, y) \approx |(z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)| + |(z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)| \qquad (3.6\text{-}18)$$

Using First-Order Derivatives for (Nonlinear) Image Sharpening—The Gradient Sobel's Operators

Examples of Center Symmetry: 3x3, 5x5, 7x7 etc

Sobel Proposed these equations to determine the Co-efficients.

$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \qquad (3.6\text{-}16)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7) \qquad (3.6\text{-}17)$$

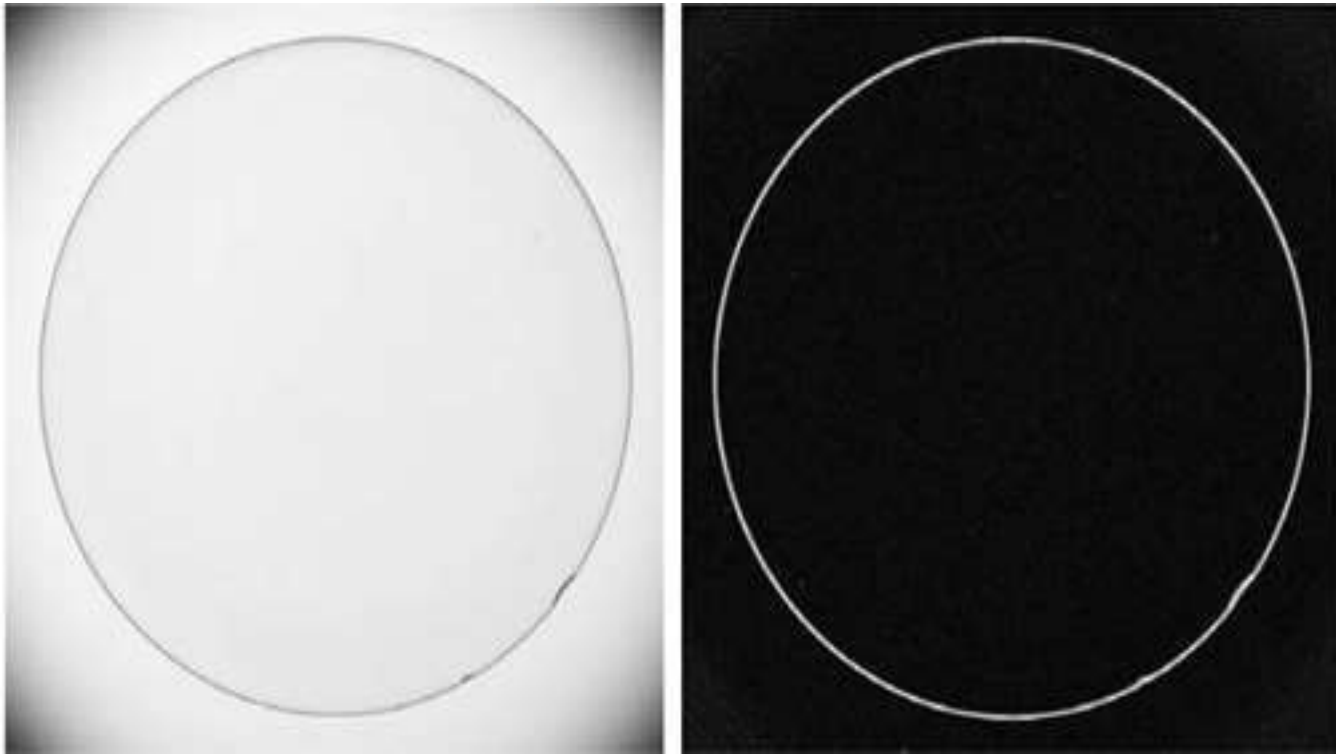
$$M(x, y) \approx |(z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)| + |(z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)| \qquad (3.6\text{-}18)$$

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

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

Using First-Order Derivatives for (Nonlinear) Image Sharpening—The Gradient Sobels Cross Gradients

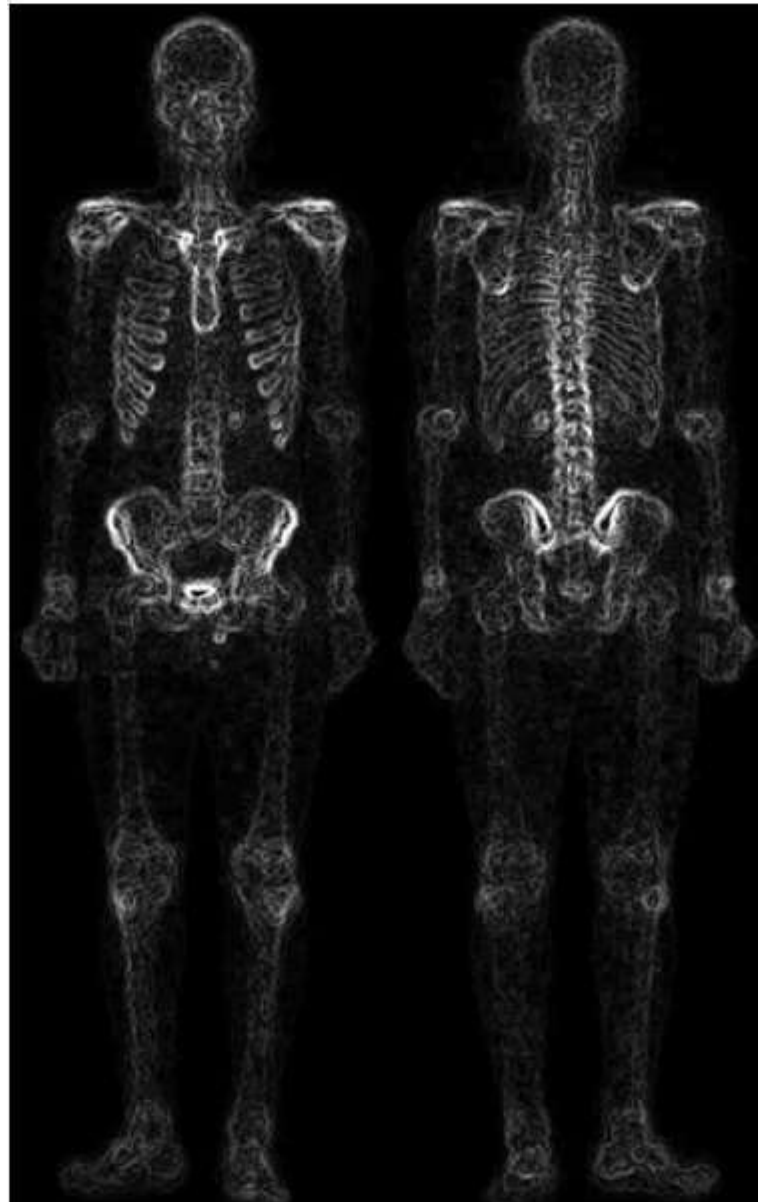
Figure 3.42(a) shows an optical image of a contact lens, illuminated by a lighting arrangement designed to highlight imperfections, such as the two edge defects in the lens boundary seen at 4 and 5 o'clock. Figure 3.42(b) shows the gradient obtained using Eq. (3.6-12) with the two Sobel masks in Figs. 3.41(d) and (e). The edge defects also are quite visible in this image, but with the added advantage that constant or slowly varying shades of gray have been eliminated, thus simplifying considerably the computational task required for automated inspection. The gradient can be used also to highlight small specs that may not be readily visible in a gray-scale image (specs like these can be foreign matter, air pockets in a supporting solution, or miniscule imperfections in the lens). The ability to enhance small discontinuities in an otherwise flat gray field is another important feature of the gradient. ■



a b

FIGURE 3.42 (a) Optical image of contact lens (note defects on the boundary at 4 and 5 o'clock). (b) Sobel gradient. (Original image courtesy of Pete Sites, Perceptics Corporation.)

Combining SPATIAL Enhancement Methods



Some times in Real Life a task will require application of several complementary techniques in order to achieve an acceptable result.

Given Two Images which is better to analyse the Medica Images?

What the Problems in Fig 1?

- Intensity Profile
- Intensity Range
- Sharp Edges missing
- High Noise