Digital Image Processing and Pattern Recognition

E1528

Lecture 3

Intensity Transformations and Spatial Filtering

INSTRUCTOR

DR / AYMAN SOLIMAN

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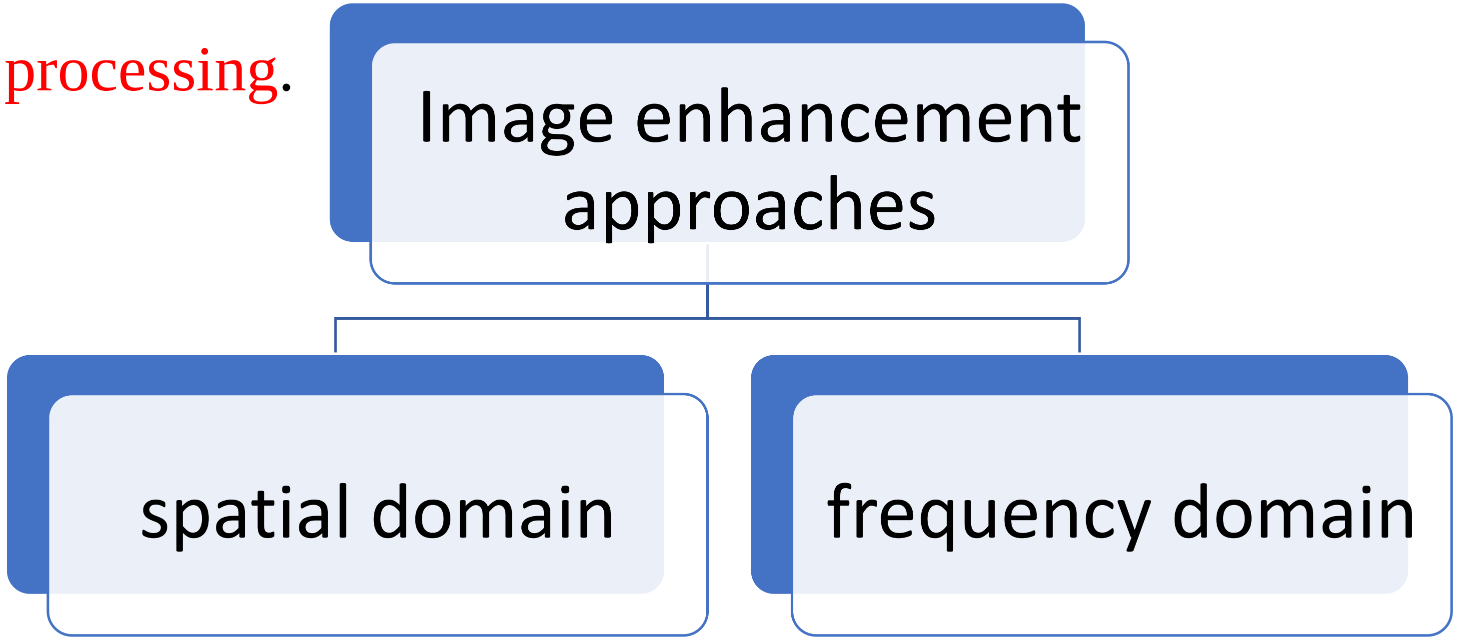
➢ Some Basic Gray Level Transformations

- The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application.

- Image enhancement is one of the most interesting and visually appealing areas of image processing.



spatial domain Vs. Frequency domain

- 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.
- Frequency domain processing techniques are based on modifying the fourier transform of an image.
- There is no general theory of image enhancement.

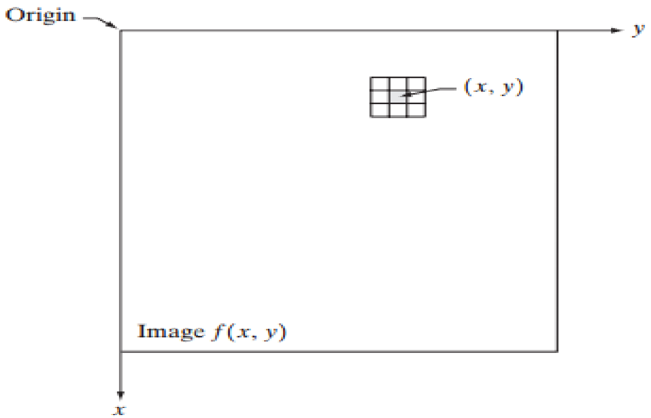
➢ Background

➢ Spatial domain processes will 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 processed image, and T is an operator on f, defined over some neighborhood of (x, y).

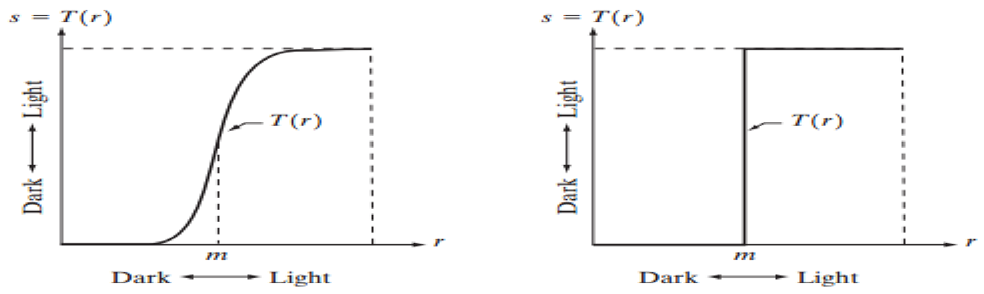
In addition, T can operate on a set of input images, such as performing the pixel-by-pixel sum of K images for noise reduction



➢ Background

- The simplest form of T is when the neighborhood is of size 1*1 (that is, a single pixel). In this case, g depends only on the value of f at (x, y), and T becomes a gray-level (also called an intensity or mapping) transformation function of the form $s = T(r)$

- where, for simplicity in notation, r and s are variables denoting, respectively, the gray level of f(x, y) and g(x, y) at any point (x, y).

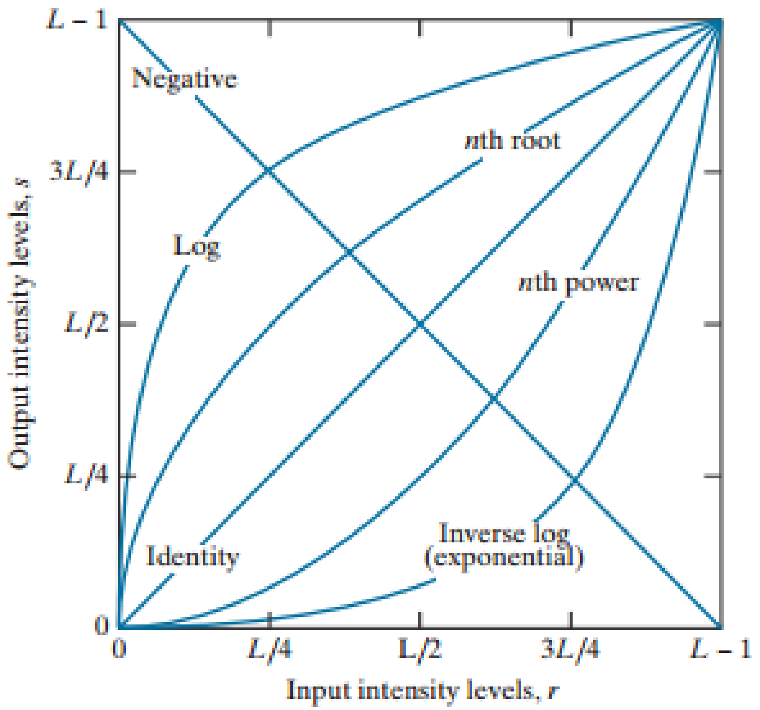


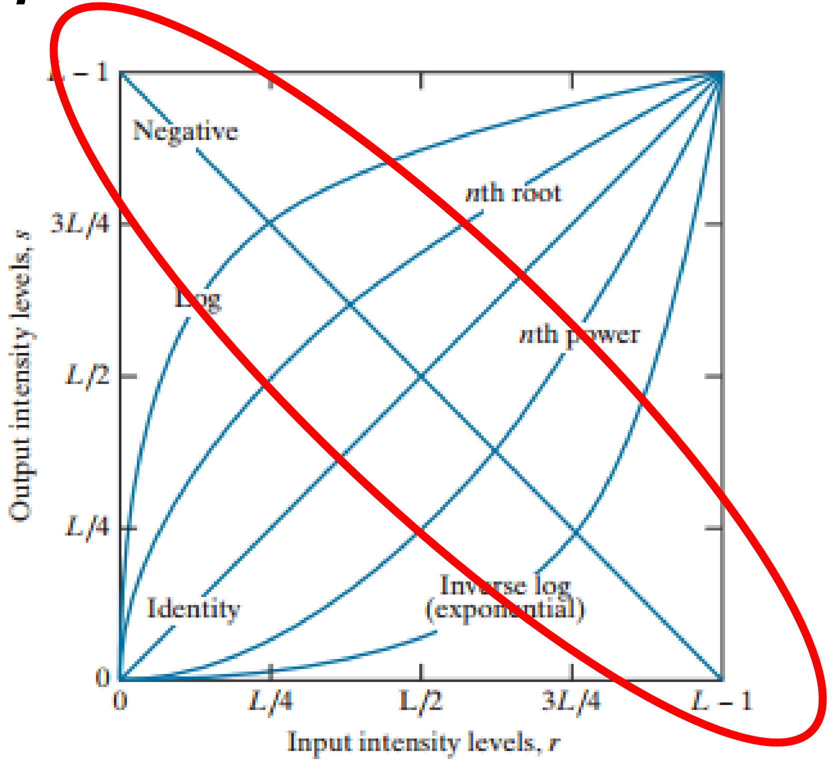
➢ Some Basic Gray Level Transformations

- Image Enhancement Transformations
  - linear
    - negative
    - identity
  - logarithmic
    - log
    - inverse-log
  - power-law
    - *n*th power
    - *n*th root

➢ Linear - Image Negatives

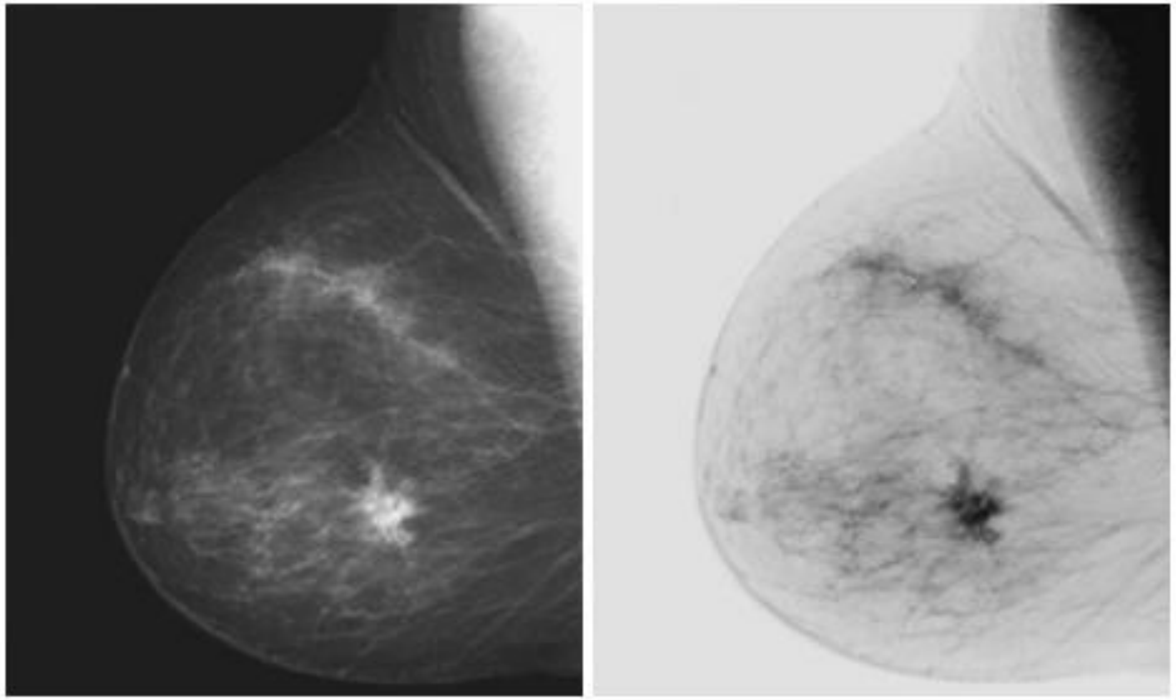
- ➢ The negative of an image with gray levels in the range [0, L-1] is obtained by using the negative transformation shown below, which is given by the expression $$s = L - 1 - r$$





➢ Linear - Image Negatives

- ➢ The original image is a digital mammogram showing a small lesion. Although the visual content is the same in both images,
- ➢ Note how much easier it is to analyze the breast tissue in the negative image in this case.

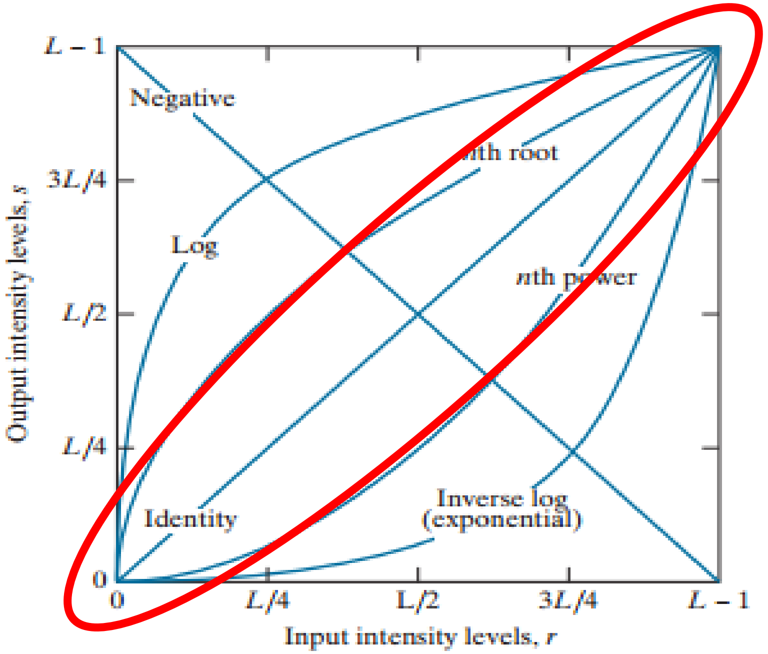


a b

(a) Original digital mammogram. (b) Negative image obtained using the negative transformation in

➢ Linear - Image identity

- The identity function is the trivial case in which output intensities are identical to input intensities.
- It is included in the graph only for completeness.



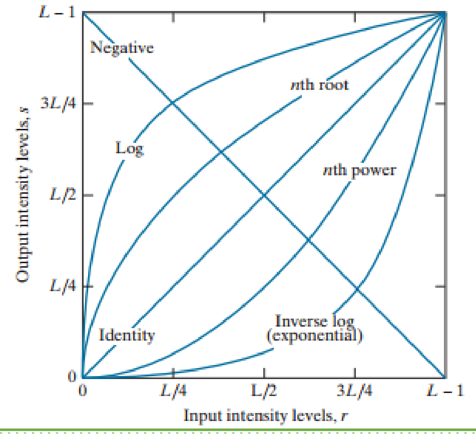
➢ Log Transformations

- ➢ The general form of the log transformation is

$$s = c\log(1 + r)$$

where c is a constant, and it is assumed that r >= 0.

- ➢ The shape of the log curve in Fig. below shows that this transformation maps a narrow range of low gray-level values in the input image into a wider range of output levels.

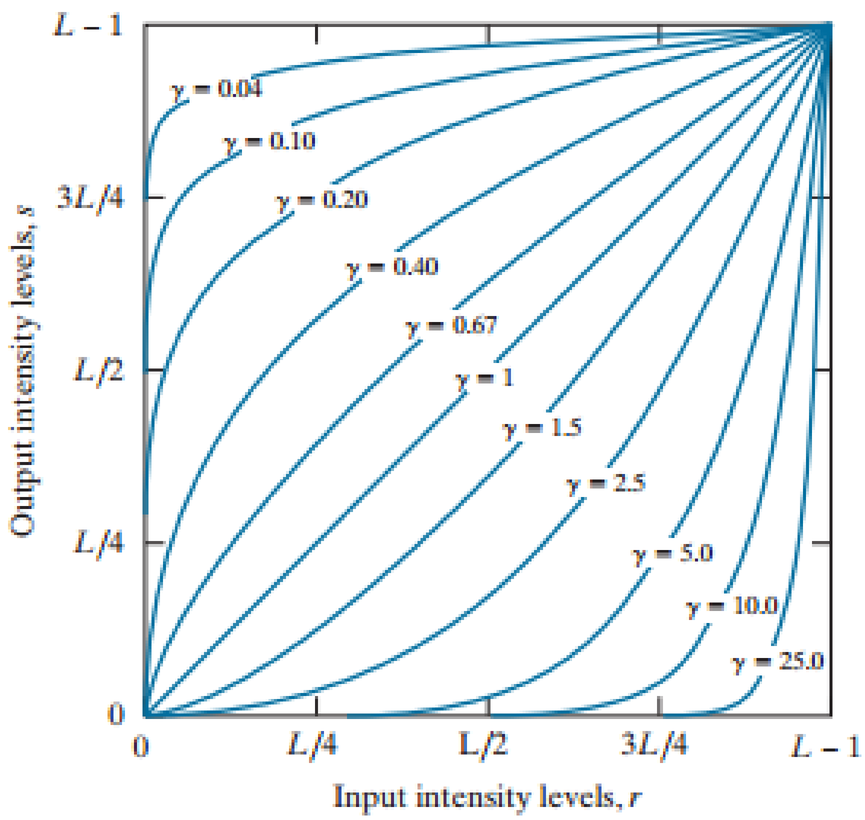


Power-Law Transformations

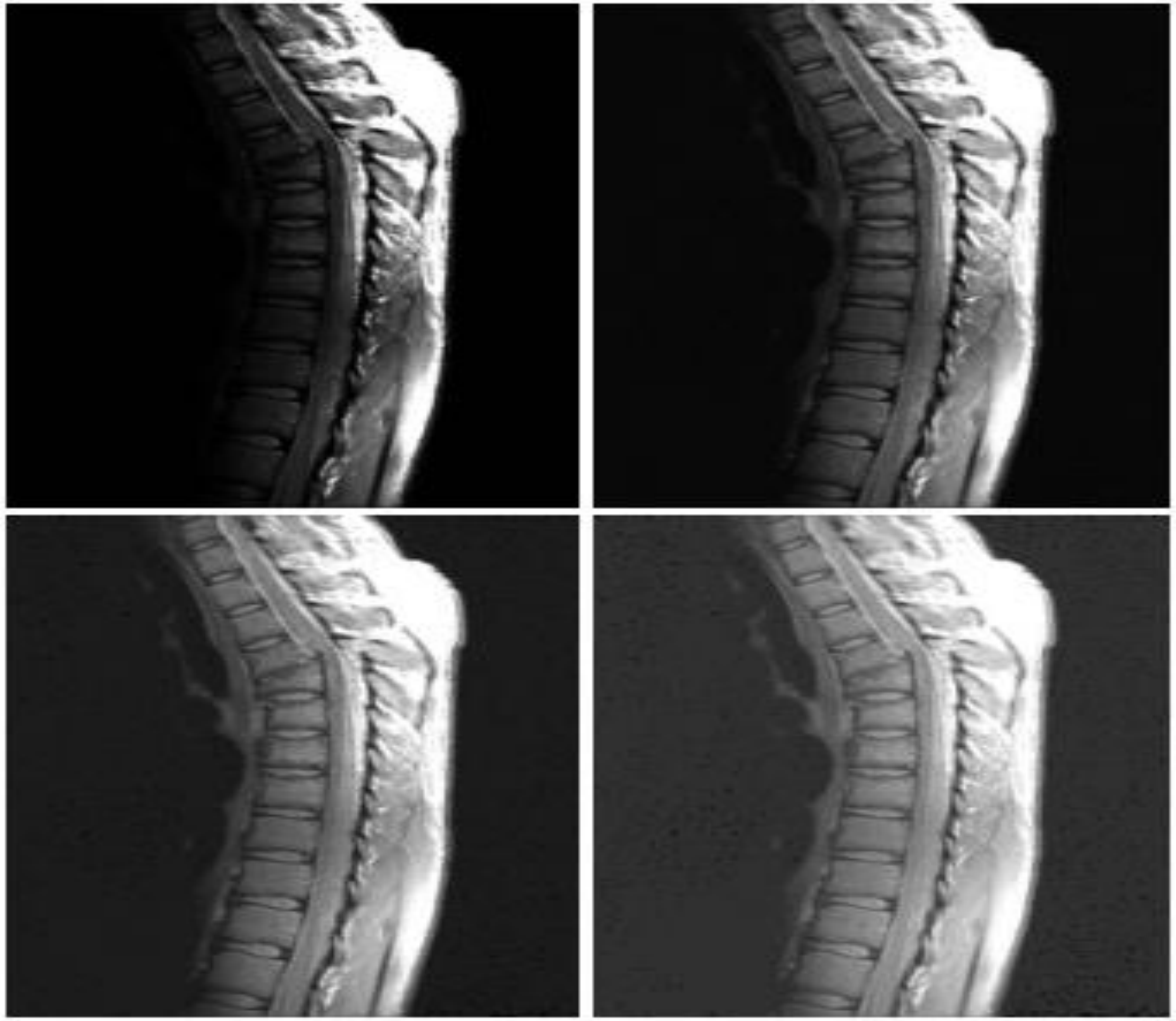
- Power-law transformations have the basic form

$$s = cr^{\gamma}$$

where c and γ are positive constants. Sometimes this Eq. is written as $s = c(r + \varepsilon)^{\gamma}$ to account for an offset (that is, a measurable output when the input is zero).



➢ Power-Law Transformations Example



a b
c d

(a) Magnetic resonance (MR) image of a fractured human spine. (b)–(d) Results of applying the transformation in Eq. (3.2-3) with $c = 1$ and $\gamma = 0.6, 0.4$, and 0.3, respectively. (Original image for this example courtesy of Dr. David R. Pickens, Department of Radiology and Radiological Sciences, Vanderbilt University Medical Center.)

➤ Power-Law Transformations Example

a b
c d

(a) Aerial image. (b)–(d) Results of applying the transformation in Eq. (3.2-3) with $c = 1$ and $\gamma = 3.0, 4.0,$ and 5.0, respectively. (Original image for this example courtesy of NASA.)

Histogram Processing

- 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_{th} gray level and n_k is the number of pixels in the image having gray level r_k.
- It is common practice to normalize a histogram by dividing each of its values by the total number of pixels in the image, denoted by n.
- Thus, a normalized histogram is given by $p(r_k)=n_k/n$, for k=0, 1, … , L-1.
- Loosely speaking, $p(r_k)$ gives an estimate of the probability of occurrence of gray level r_k. Note that the sum of all components of a normalized histogram is equal to 1.

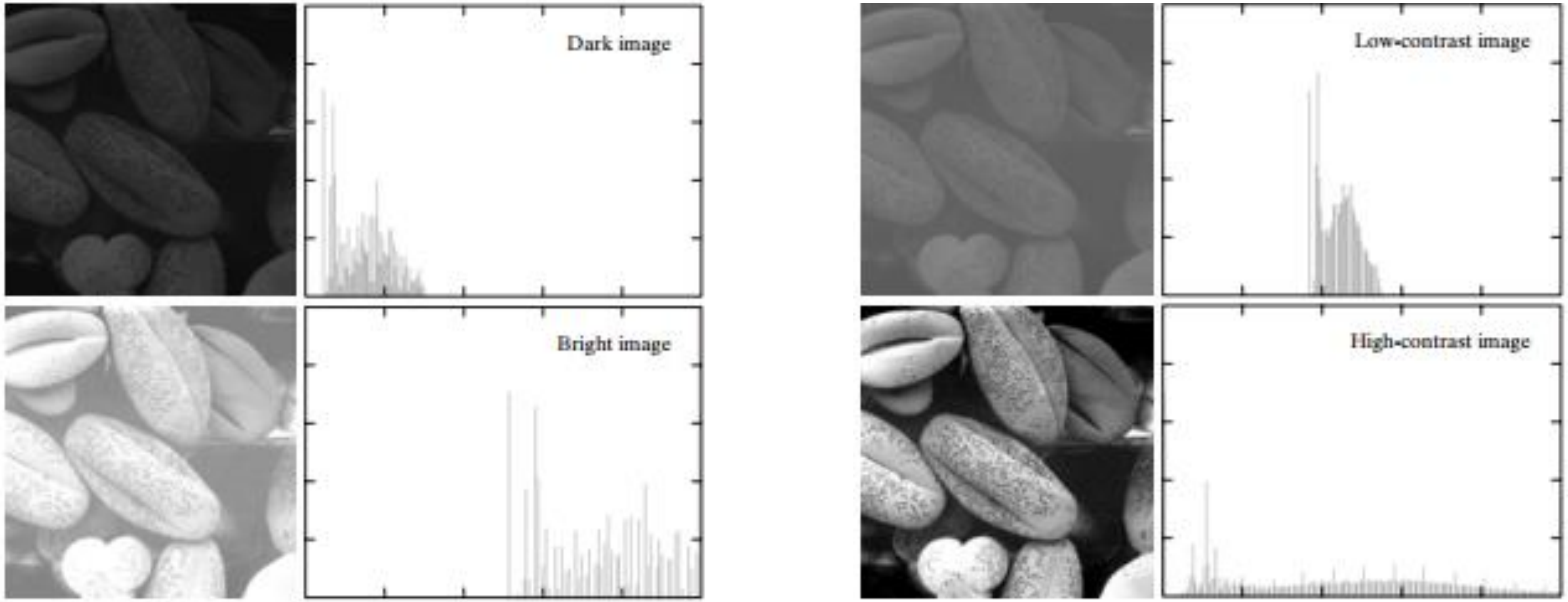
➢ Histogram Processing

- Histograms are the basis for numerous spatial domain processing techniques.

- Histogram manipulation can be used effectively for image enhancement, In addition to providing useful image statistics.

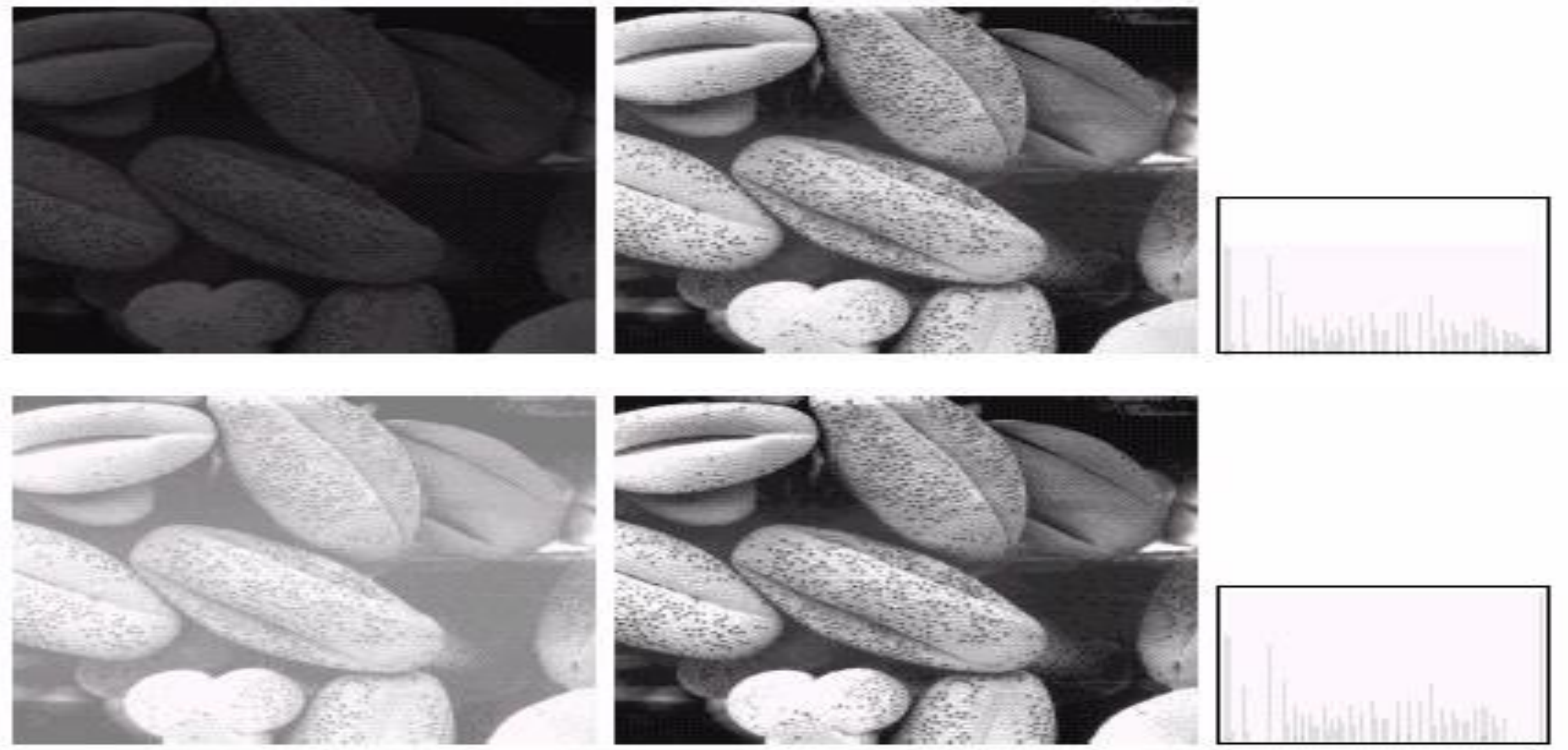
- Histograms are simple to calculate in software and lend themselves to economic hardware implementations, thus making them a popular tool for real-time image processing.

➢ Histogram Processing Example



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

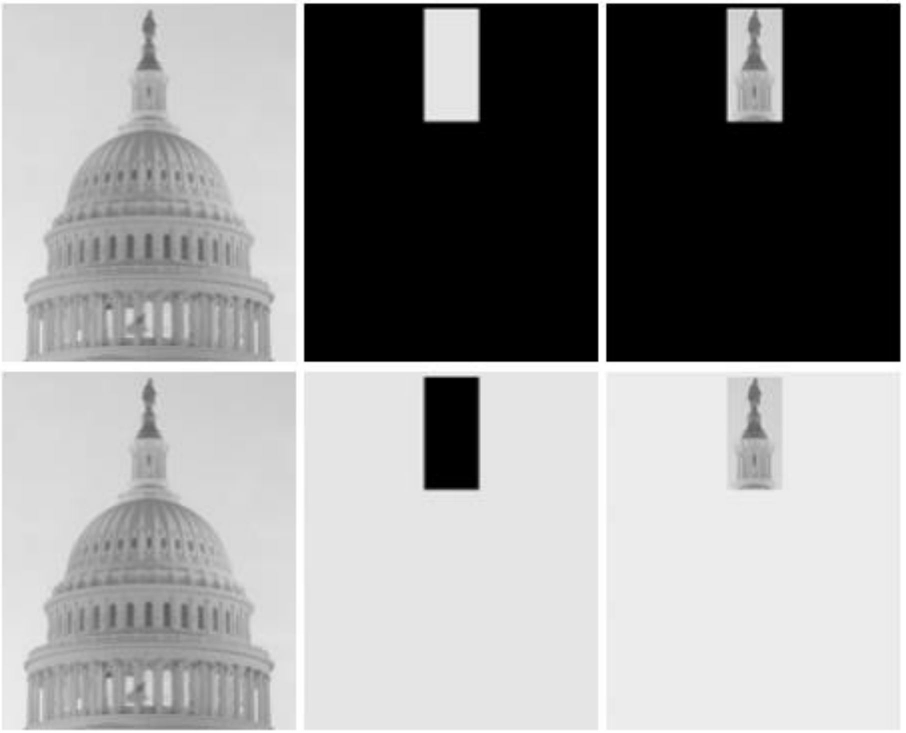
1. Histogram Equalization



(a) Images (b) Results of histogram equalization. (c) Corresponding histograms.

➢ Enhancement Using Arithmetic/Logic Operations

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



a b c
d e f

(a) Original image. (b) AND image mask. (c) Result of the AND operation on images (a) and (b). (d) Original image. (e) OR image mask. (f) Result of operation OR on images (d) and (e).

➢ Basics of Spatial Filtering

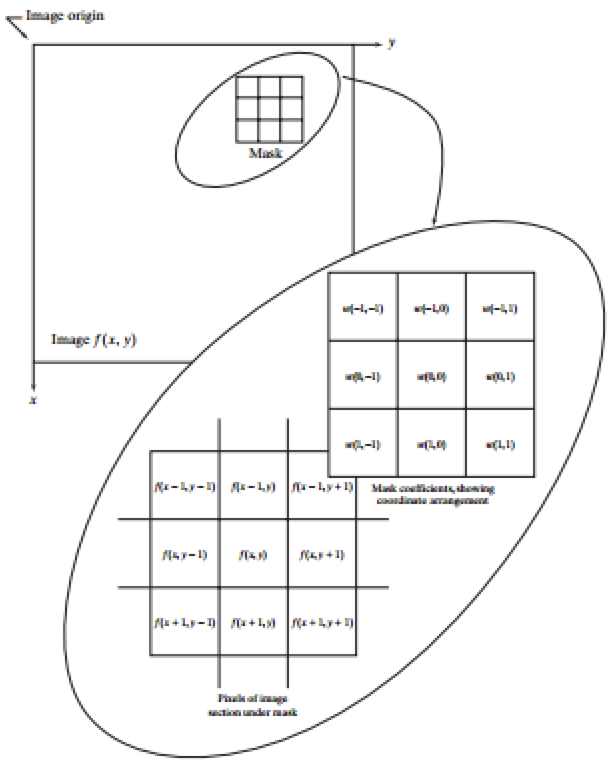
- As mentioned, some neighborhood operations work with the values of the image pixels in the neighborhood and the corresponding values of a sub-image that has the same dimensions as the neighborhood.

- The sub-image is called a filter, mask, kernel, template, or window, with the first three terms being the most prevalent terminology.

- The values in a filter sub-image are referred to as coefficients, rather than pixels.

➢ Mechanics of spatial filtering

- 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 predefined relationship.



- For linear spatial filtering, the response is given by a sum of products of the filter coefficients and the corresponding image pixels in the area spanned by the filter mask.

Smoothing Spatial Filters

- Smoothing filters are used for blurring and for noise reduction.

- Blurring is used in preprocessing steps, 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 can be accomplished by blurring with a linear filter and by nonlinear filtering.

➢ 1. 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.

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

1	1	1
1	1	1
1	1	1

$\frac{1}{16} \times$

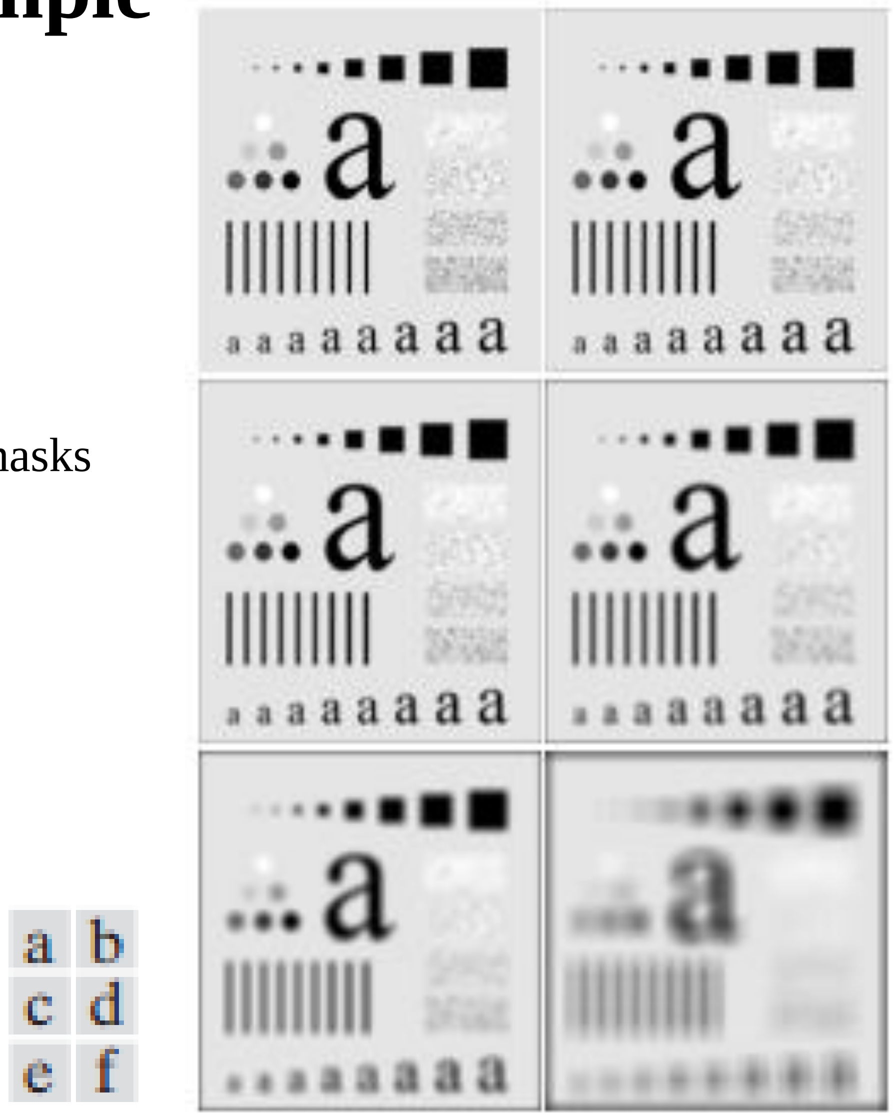
1	2	1
2	4	2
1	2	1

$$R = \frac{1}{\sum} \sum_{i=1}^{n} z_i$$

➢ 1. Smoothing Linear Filters Example

(a) Original image, of size 500*500 pixels.

(b) → (f) Results of smoothing with square averaging filter masks of sizes n=3, 5, 9, 15, and 35, respectively.



2. Order-Statistics Filters

- Order-statistics 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.

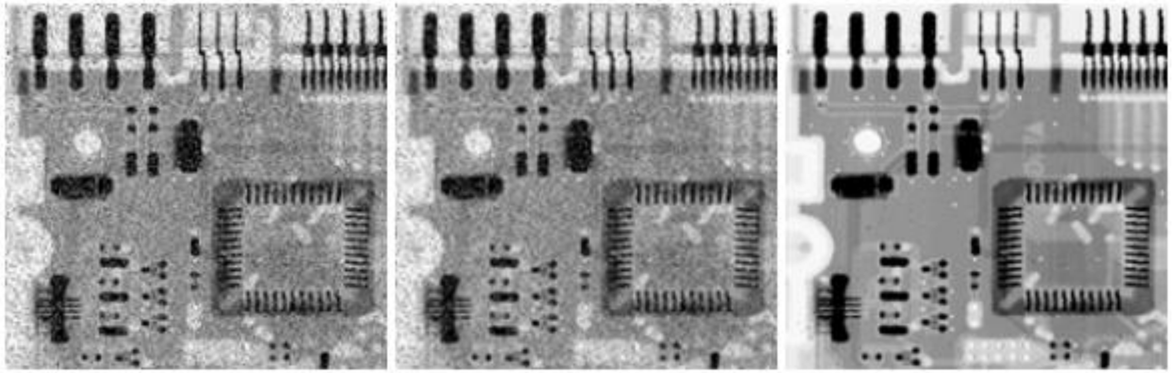
- The best-known example in this category is the median filter, which, as its name implies, replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel.

- 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.

2. Order-Statistics Filters - Median filter

- In order to perform median filtering at a point in an image, we first sort the values of the pixel in question and its neighbors, determine their median, and assign this value to that pixel.

- For example, suppose that a 3*3 neighborhood has values (10, 20, 20, 20, 15, 20, 20, 25, 100). These values are sorted as (10, 15, 20, 20, 20, 20, 20, 25, 100), which results in a median of 20.



- Example:-

- (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.

Sharpening Spatial Filters

- The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition.

- Uses of image sharpening vary and include applications ranging from electronic printing and medical imaging to industrial inspection and autonomous guidance in military systems.

1. Use of Second Derivatives for Enhancement–The Laplacian

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}.$$

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

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

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

(

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1


Thank you