CPE409 Image Processing

Part 4
Intensity Transformations and Histogram Processing

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It makes all the difference whether one sees darkness through the light or brightness through the shadows. ~David Lindsay

Outline

3. Intensity Transformations and Spatial Filtering
   - Some Basic Intensity Transformation Functions
   - Histogram Processing
   - Fundamentals of Spatial Filtering
   - Smoothing Spatial Filters
   - Sharpening Spatial Filters
   - Combining Spatial Enhancement Methods
   - *Using Fuzzy Techniques for Intensity Transformations and Spatial Filtering*

Spatial Domain Process

- The two basic categories of spatial processing are intensity transformations and spatial filtering.

- Intensity transformations are applied to a single pixel of the image for contrast enhancement and image thresholding.

- Spatial filtering handles processes such as sharpening by processing in the neighborhood of each pixel in the image.

Spatial Domain Process

Image plane itself, directly process the intensity values of the image plane

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

$$f(x,y): \text{input image}$$

$$g(x,y): \text{output image}$$

$$T: \text{an operator on } f \text{ defined over}$$

$$\text{a neighborhood of point } (x,y)$$

Spatial Domain Process

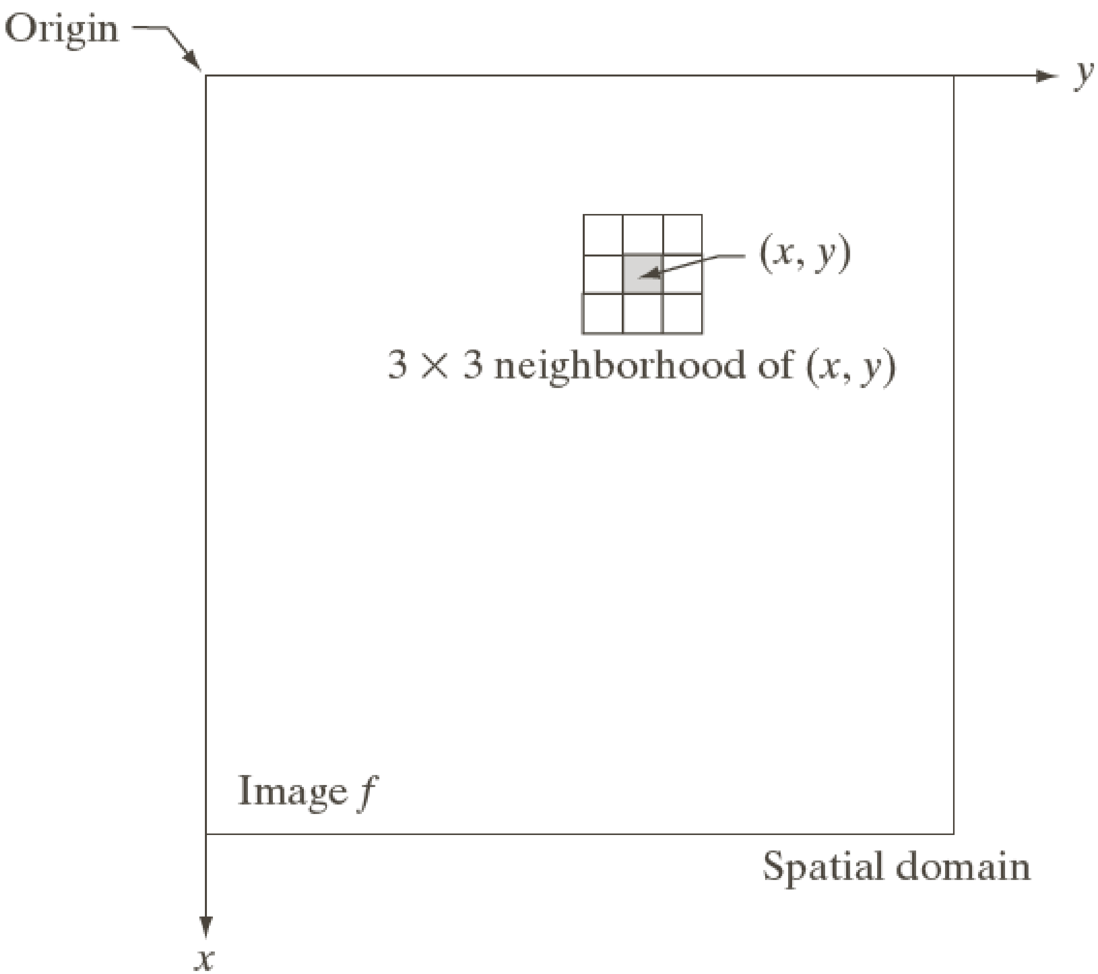
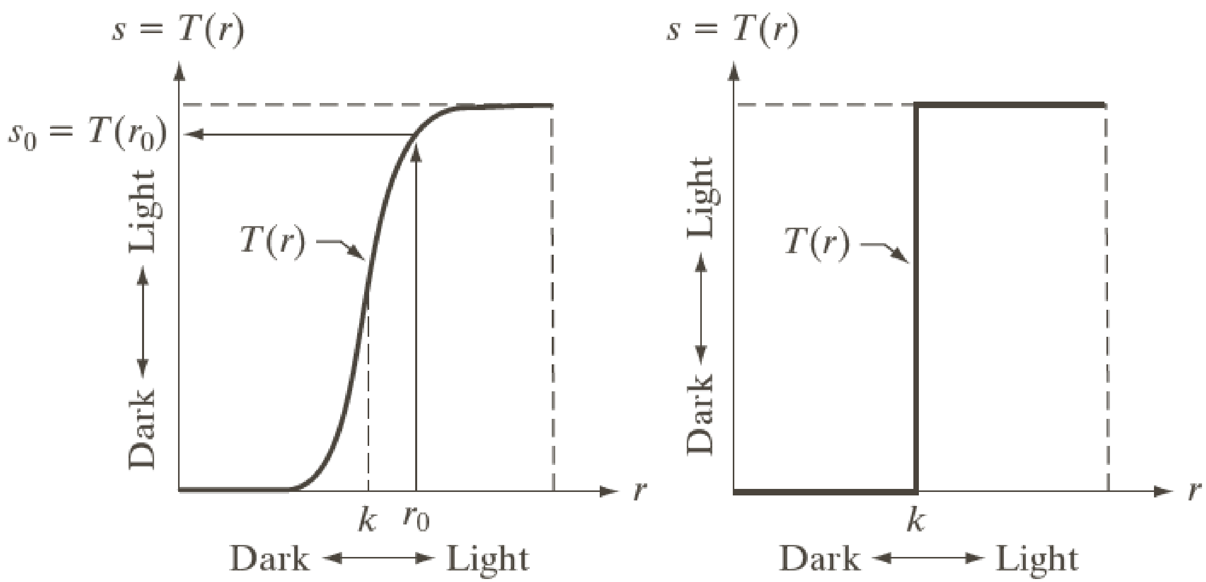


FIGURE 3.1 A 3 × 3 neighborhood about a point (x, y) in an image in the spatial domain. The neighborhood is moved from pixel to pixel in the image to generate an output image.

Spatial Domain Process

Intensity transformation function

$$s = T(r)$$



a b

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

Some Basic Intensity Transformation Functions

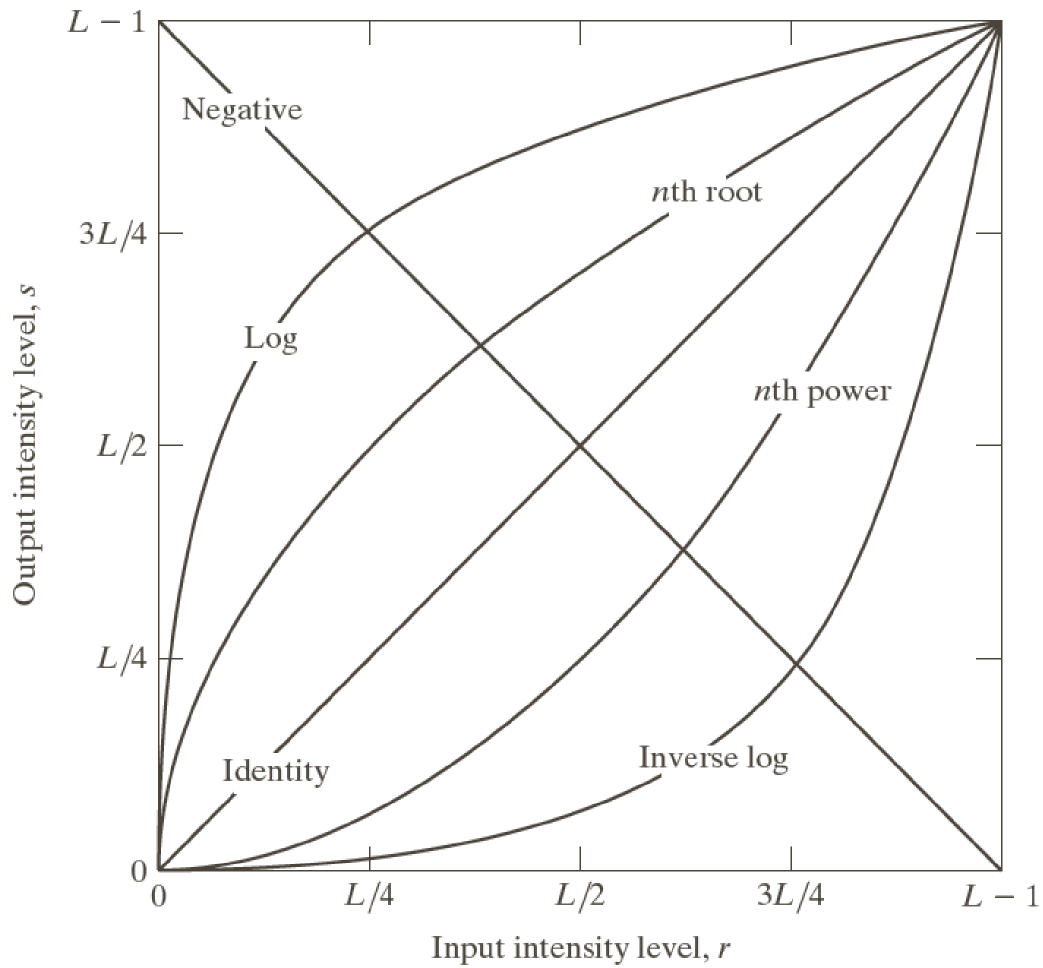


FIGURE 3.3 Some basic intensity transformation functions. All curves were scaled to fit in the range shown.

Image Negatives

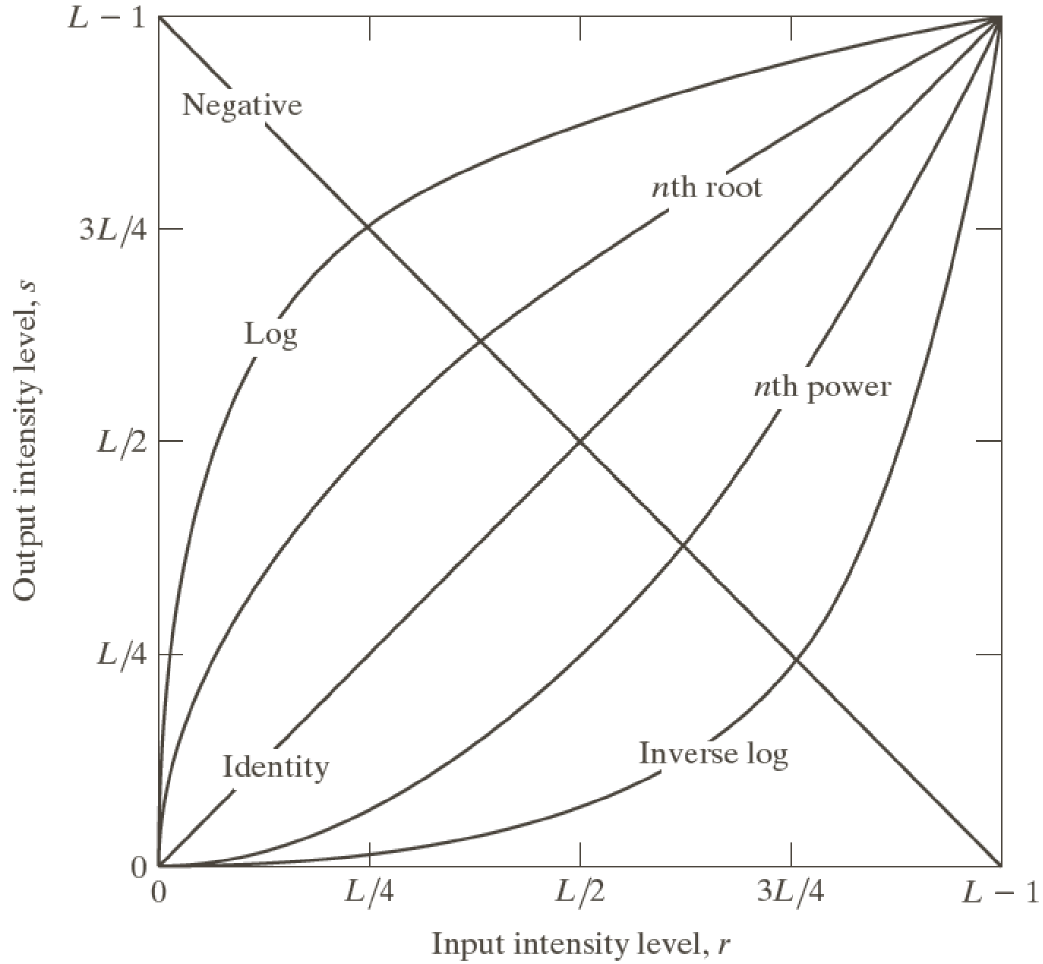
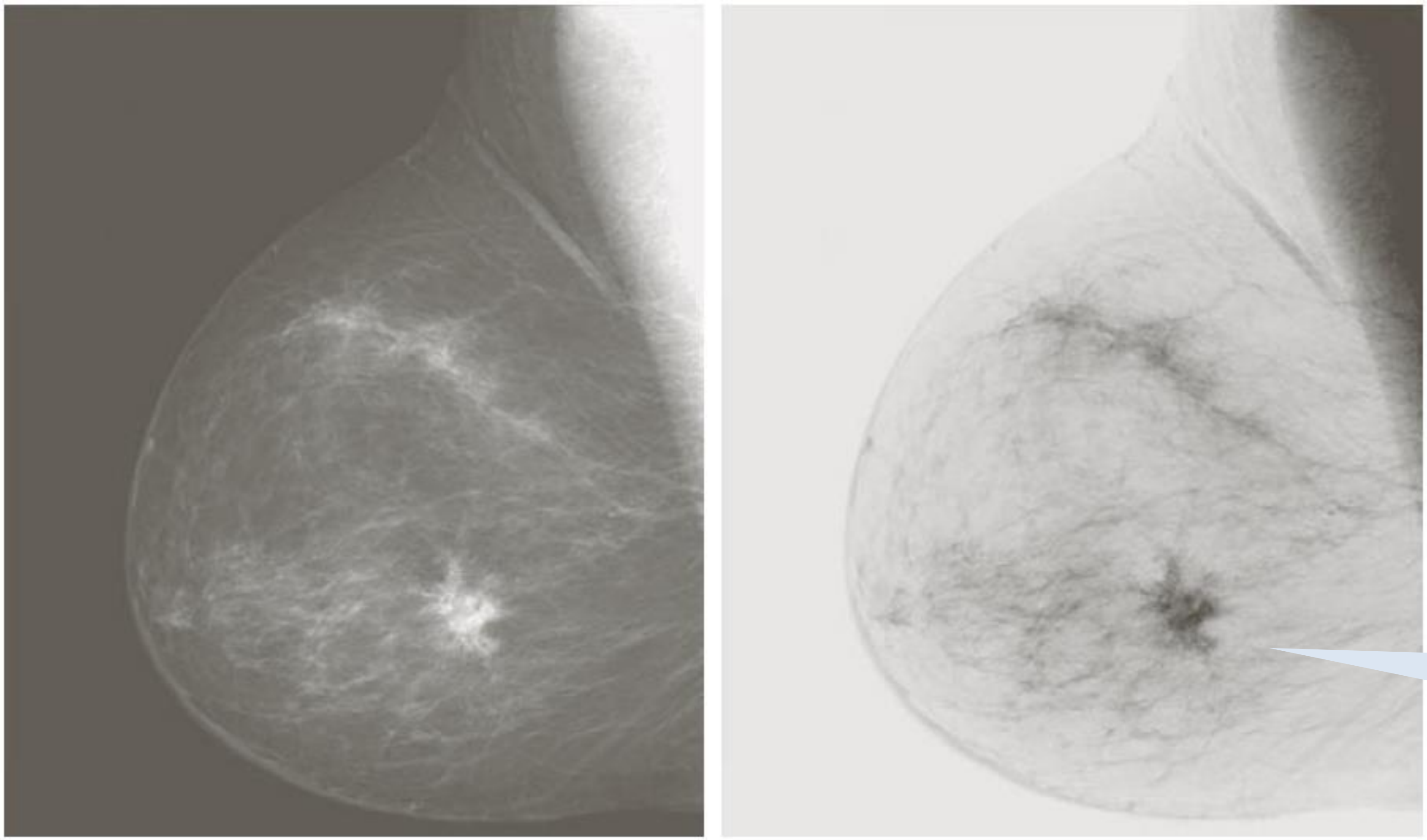


Image negatives

$$s = L - 1 - r$$

Intensity values are between [0 L-1].

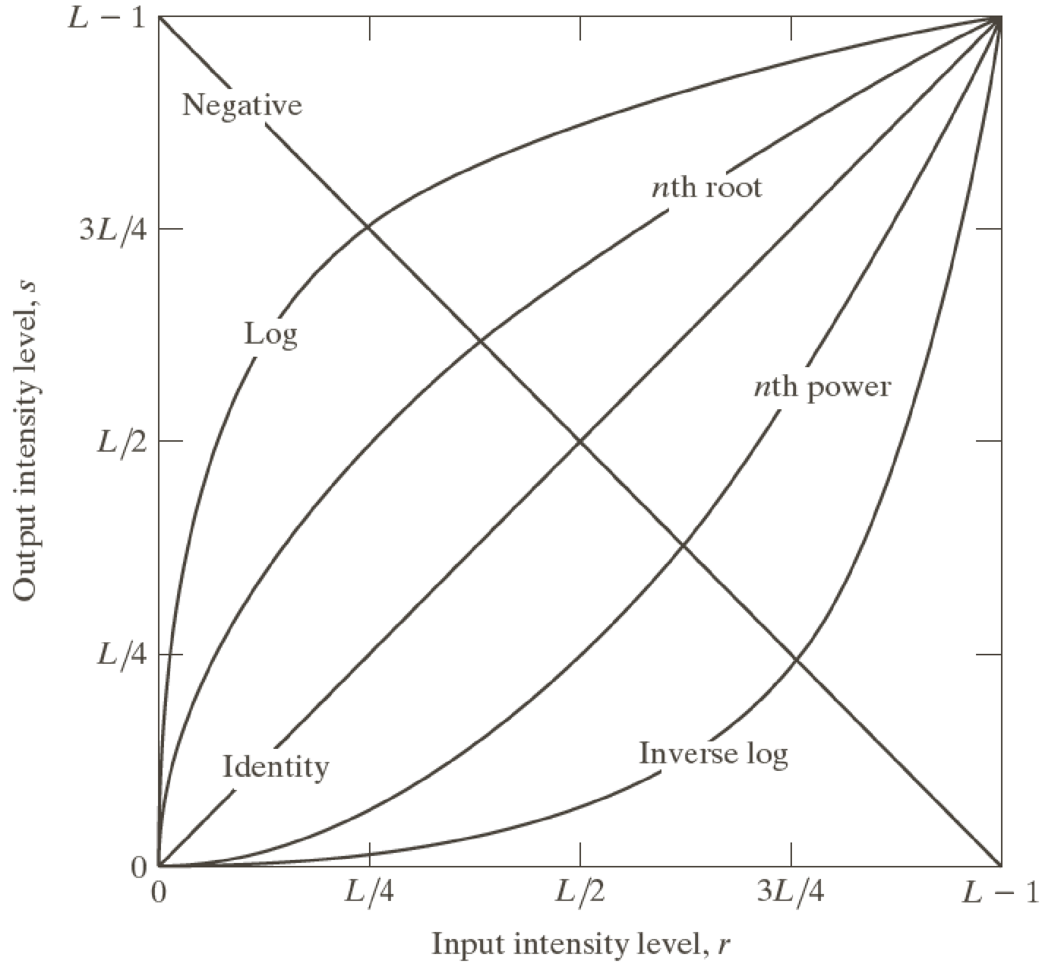
Example: Image Negatives



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.)

Log Transformations



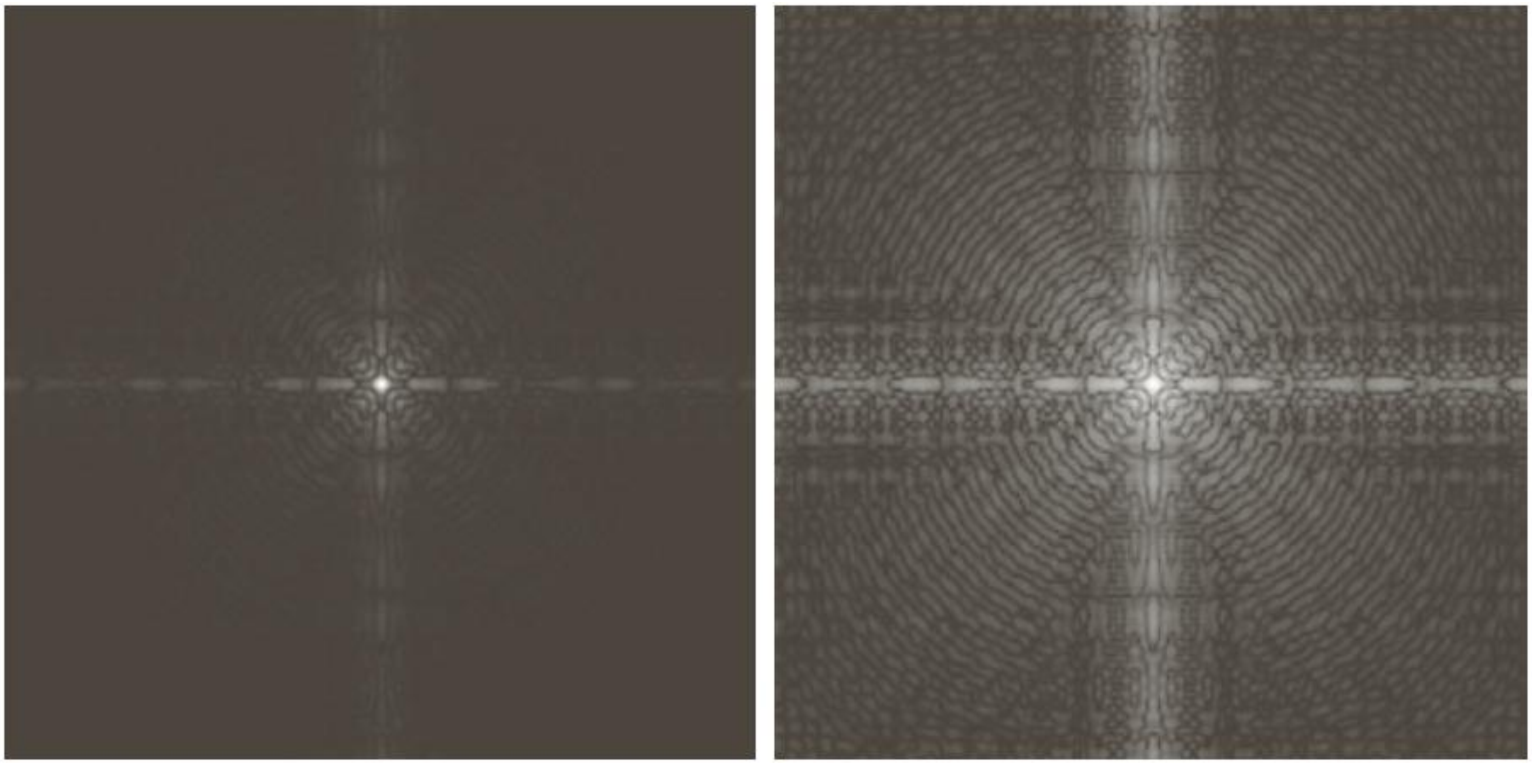
Log Transformations

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

c is constant and r>=0.

It transmits a narrow range of low intensity values at the input to a wider output level range.

Example: Log Transformations



a b

FIGURE 3.5 (a) Fourier spectrum. (b) Result of applying the log transformation in Eq. (3.2-2) with $c = 1$.

Power-Law (Gamma) Transformations

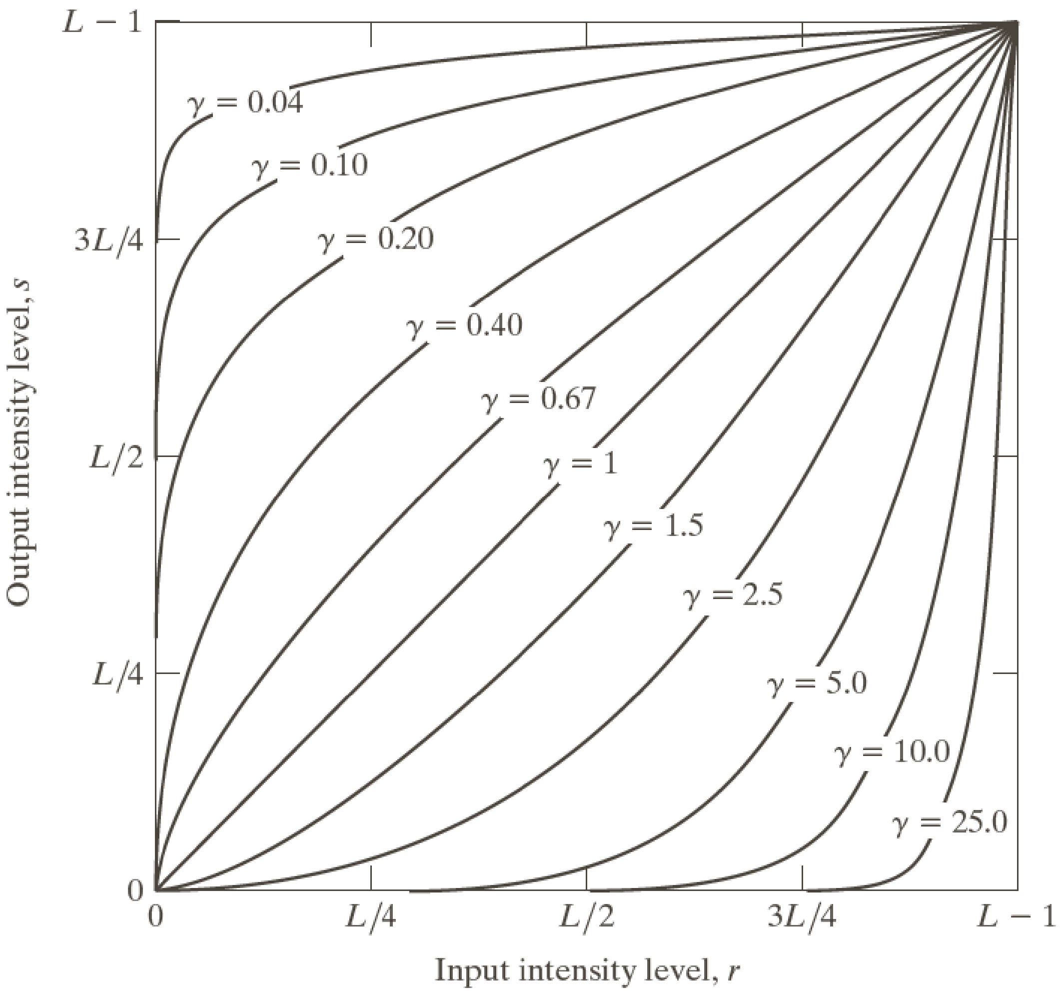


FIGURE 3.6 Plots of the equation $s = cr^{\gamma}$ for various values of γ ($c = 1$ in all cases). All curves were scaled to fit in the range shown.

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

positive constants

Example: Gamma Transformations

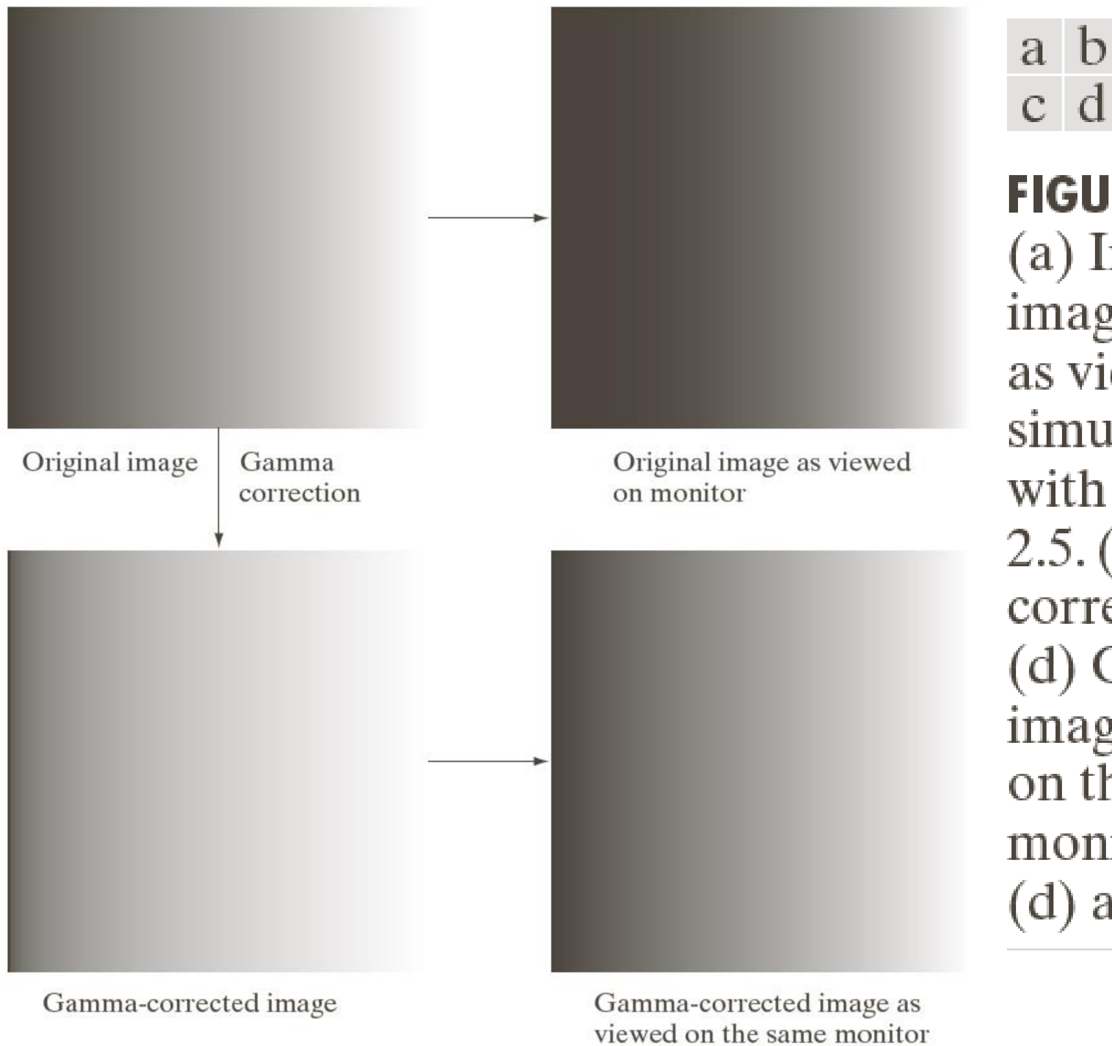
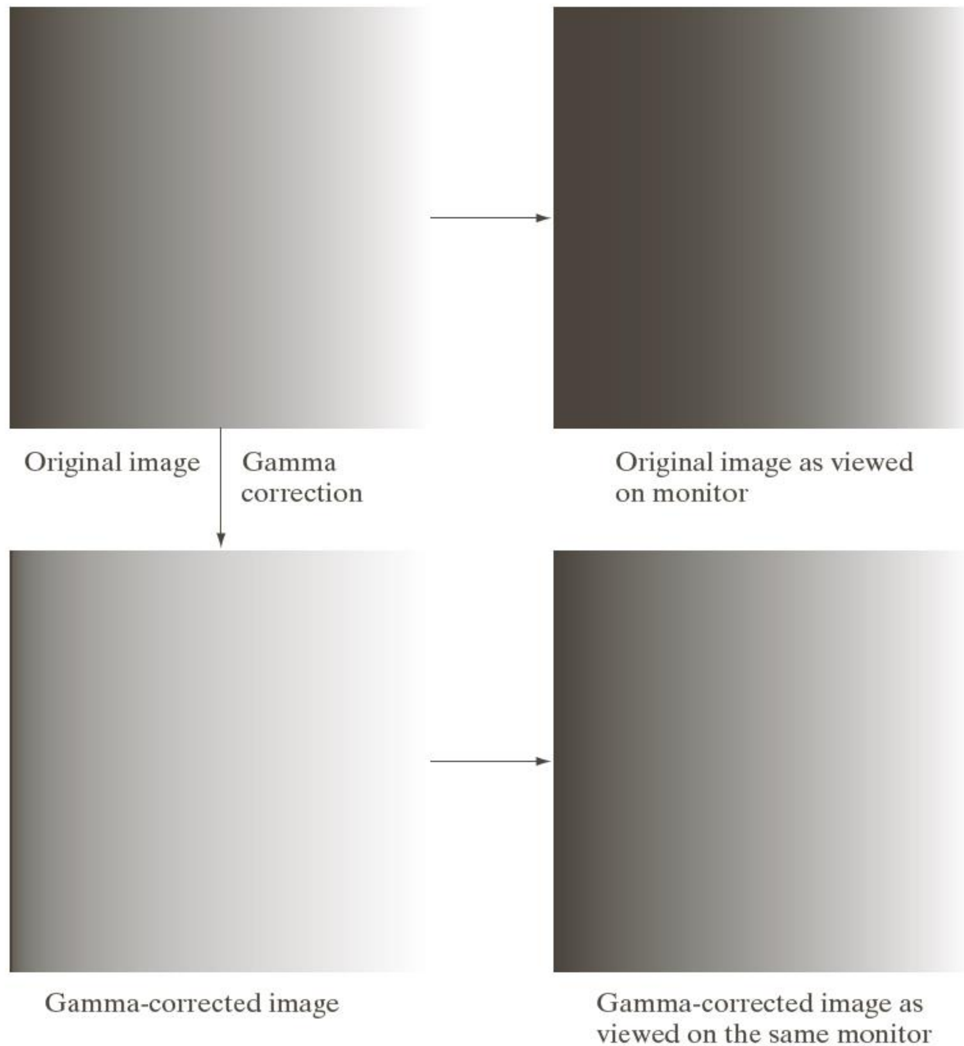


FIGURE 3.7
(a) Intensity ramp image. (b) Image as viewed on a simulated monitor with a gamma of 2.5. (c) Gamma-corrected image. (d) Corrected image as viewed on the same monitor. Compare (d) and (a).

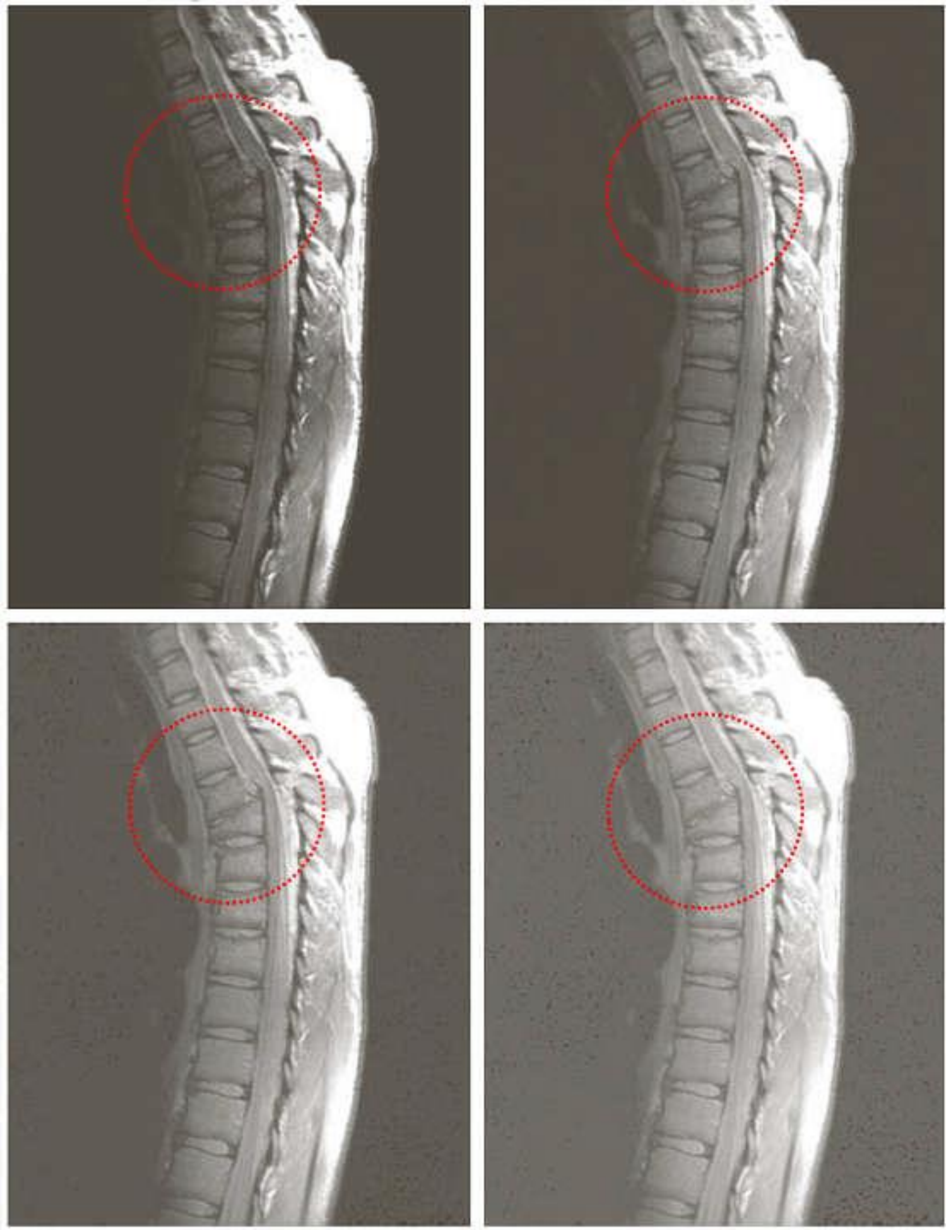
Example: Gamma Transformations

$$s = r^{1/2.5}$$



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

Example: Gamma Transformations



a b
c d

FIGURE 3.8 (a) Magnetic resonance image (MRI) 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 courtesy of Dr. David R. Pickens, Department of Radiology and Radiological Sciences, Vanderbilt University Medical Center.)

Example: Gamma Transformations

a	b
c	d

FIGURE 3.9 (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.)

Piecewise-Linear Transformations

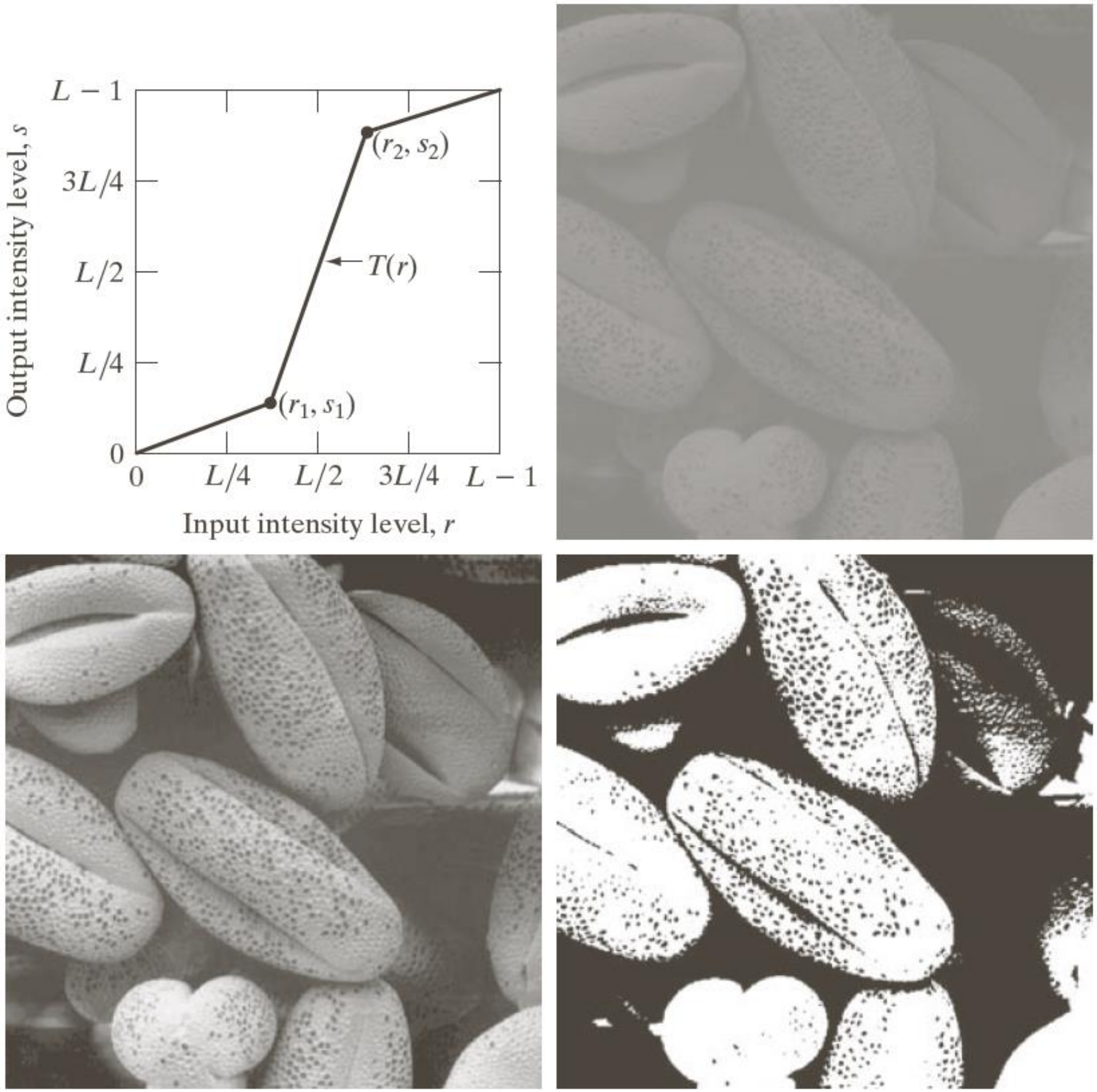
- **Contrast Stretching**

  Expands the range of intensity levels in an image so that it spans the full intensity range of the recording medium or display device.

- **Intensity-level Slicing**

  Highlighting a specific range of intensities in an image.

Contrast Stretching



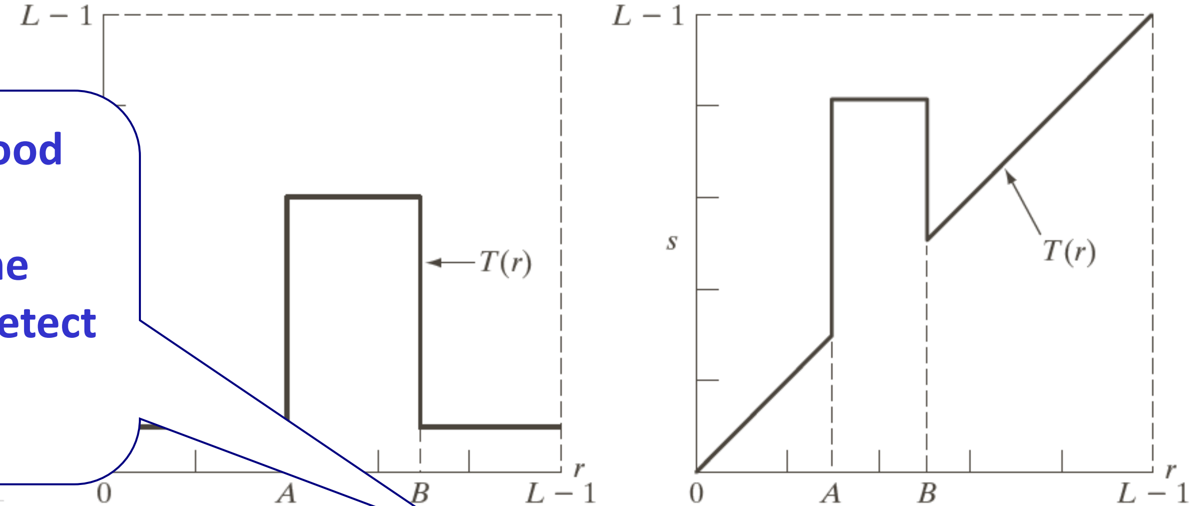
a b
c d

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.)

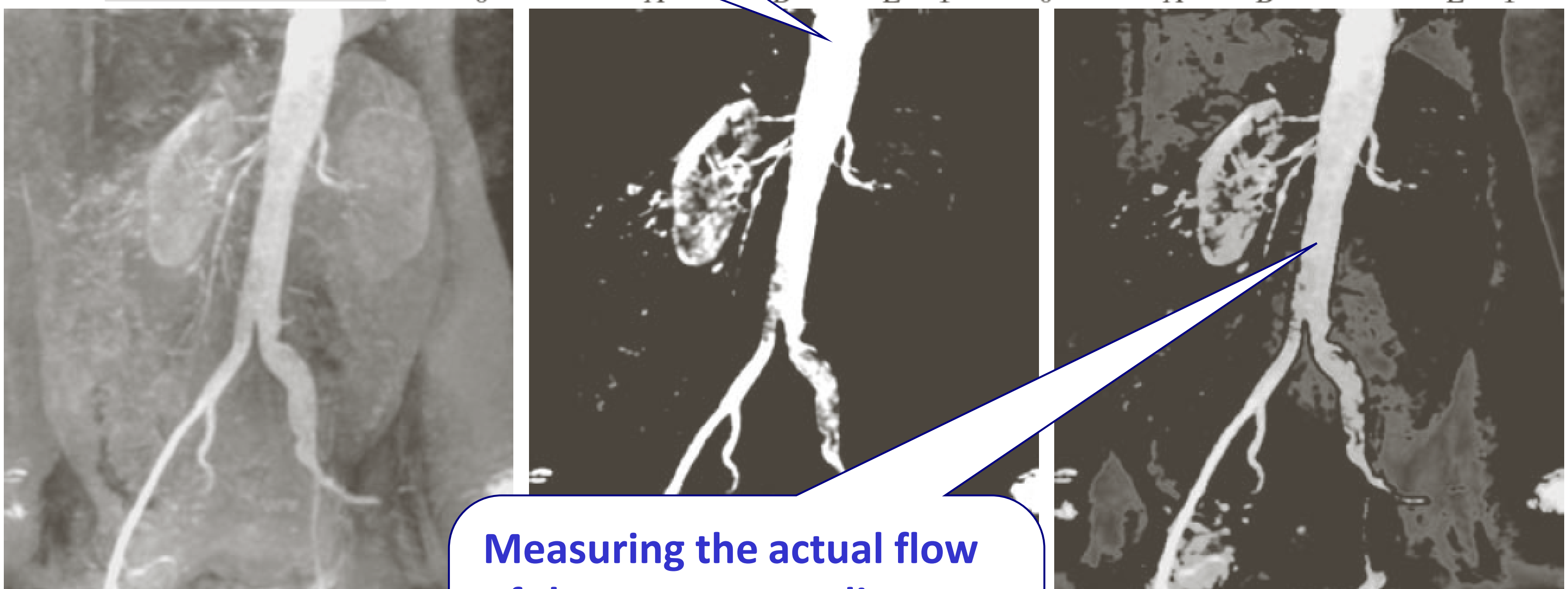
Intensity-level Slicing

a b

FIGURE 3.11 (a) This



Highlight the major blood vessels and study the shape of the flow of the contrast medium (to detect blockages, etc.)



Measuring the actual flow of the contrast medium as a function of time in a series of images

a b c

FIGURE 3.12 (a) Aortic angiog… mation of the type illustrated in Fig. 3.11(a), with the range of inte… end of the gray scale. (c) Result of using the transformation in Fig… ack, 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.)

Bit-plane Slicing

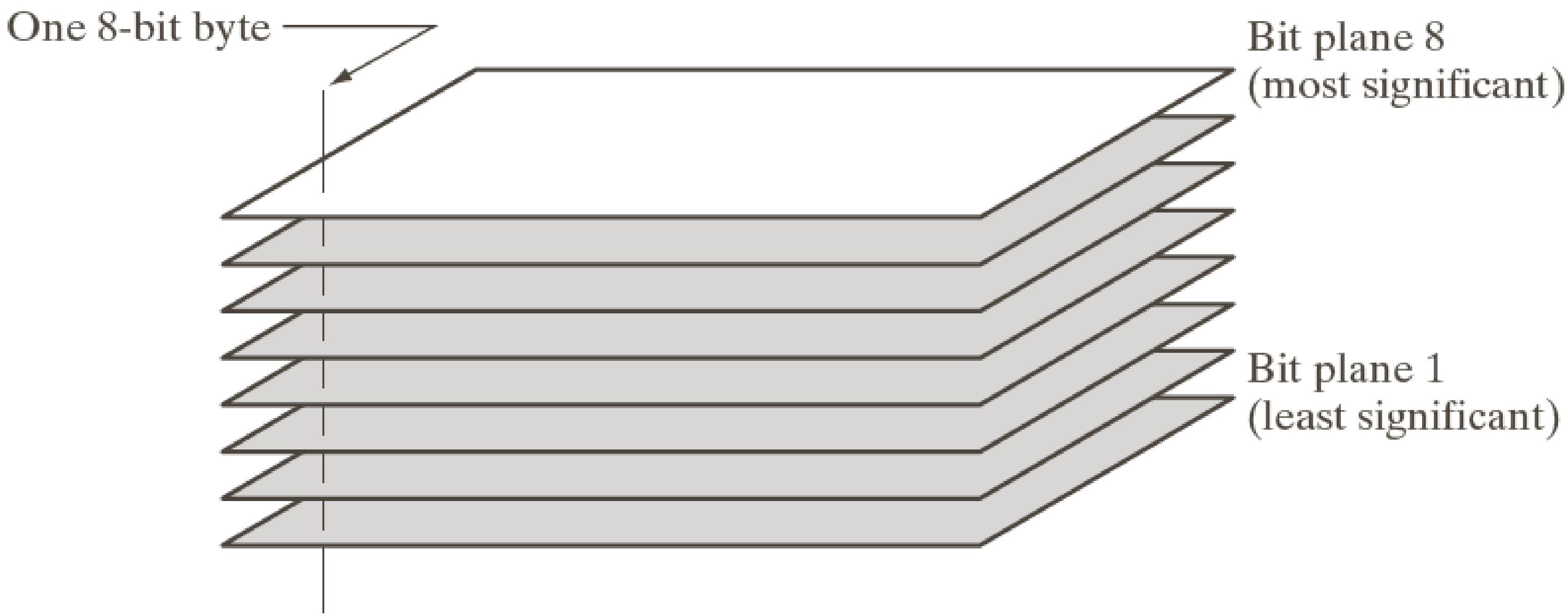


FIGURE 3.13
Bit-plane representation of an 8-bit image.

Bit-plane Slicing

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.

Bit-plane Slicing

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).

What is Histogram?

- It is a graphical representation of the distribution of the gray values in the image.
- The X axis shows the gray values (reflection values) in the image, while the Y axis shows the total number of pixels in that gray value.
- As you move to the left (closer to the origin) on the X-axis, the pixels of darker and black areas are represented.
- The middle parts of the histogram on the X-axis represent the gray areas of moderate darkness, and the left extreme sides represent the white area with plenty of light.

Histogram Processing

Histogram $\quad h(r_k) = n_k$

r_k is the k^{th} intensity value

n_k is the number of pixels in the image with intensity r_k

Normalized histogram $\quad p(r_k) = \frac{n_k}{MN}$

n_k: the number of pixels in the image of

size $\mathrm{M} \times \mathrm{N}$ with intensity r_k

Histogram Processing

Histogra

r_k is the

n_k is the n

Consult the book
Web site for a brief
review of probability
theory.

mage with intensity r_k

Normalized histogram $p(r_k) = \frac{n_k}{MN}$

n_k: the number of pixels in the image of size $M \times N$ with intensity r_k

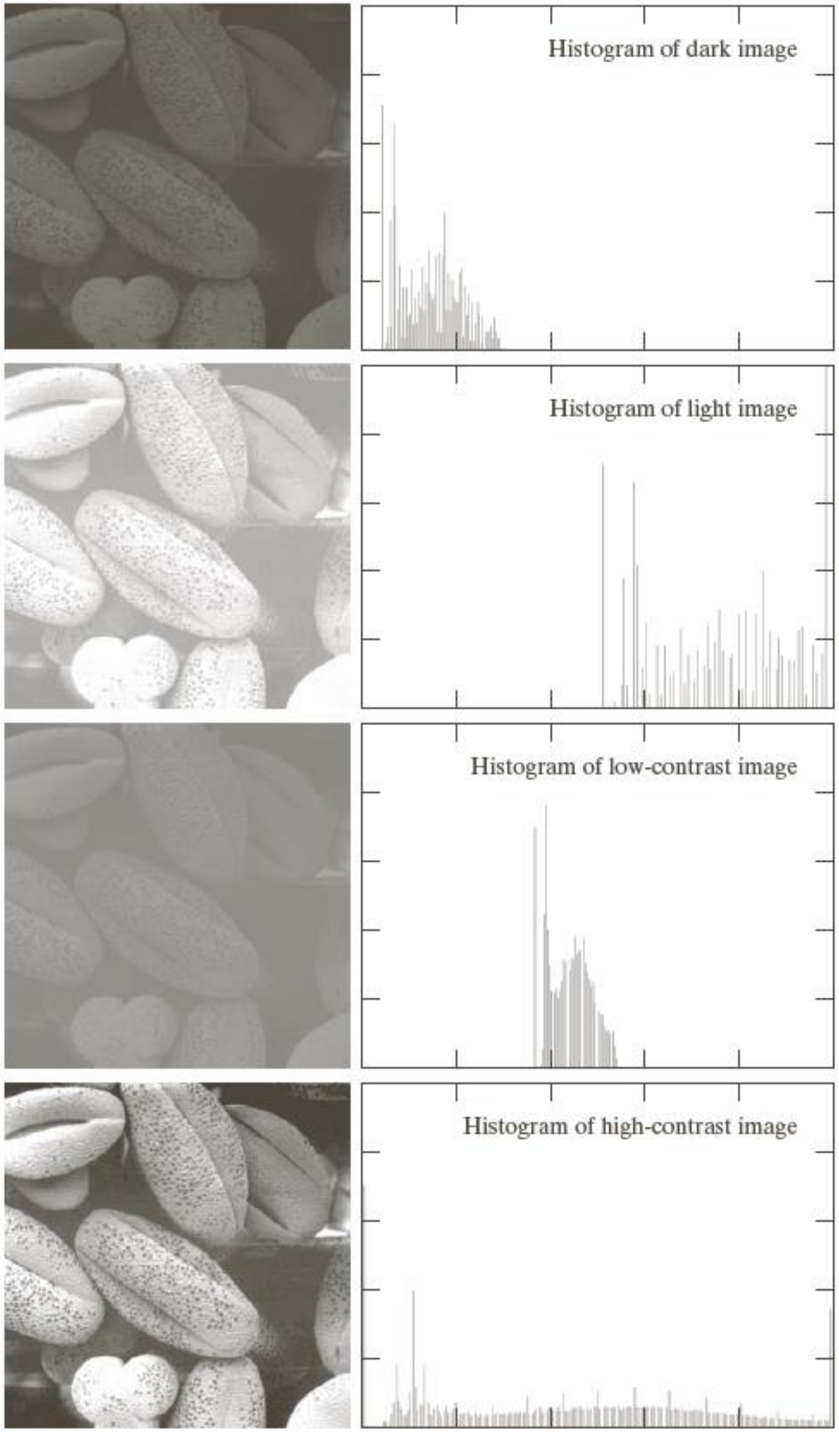
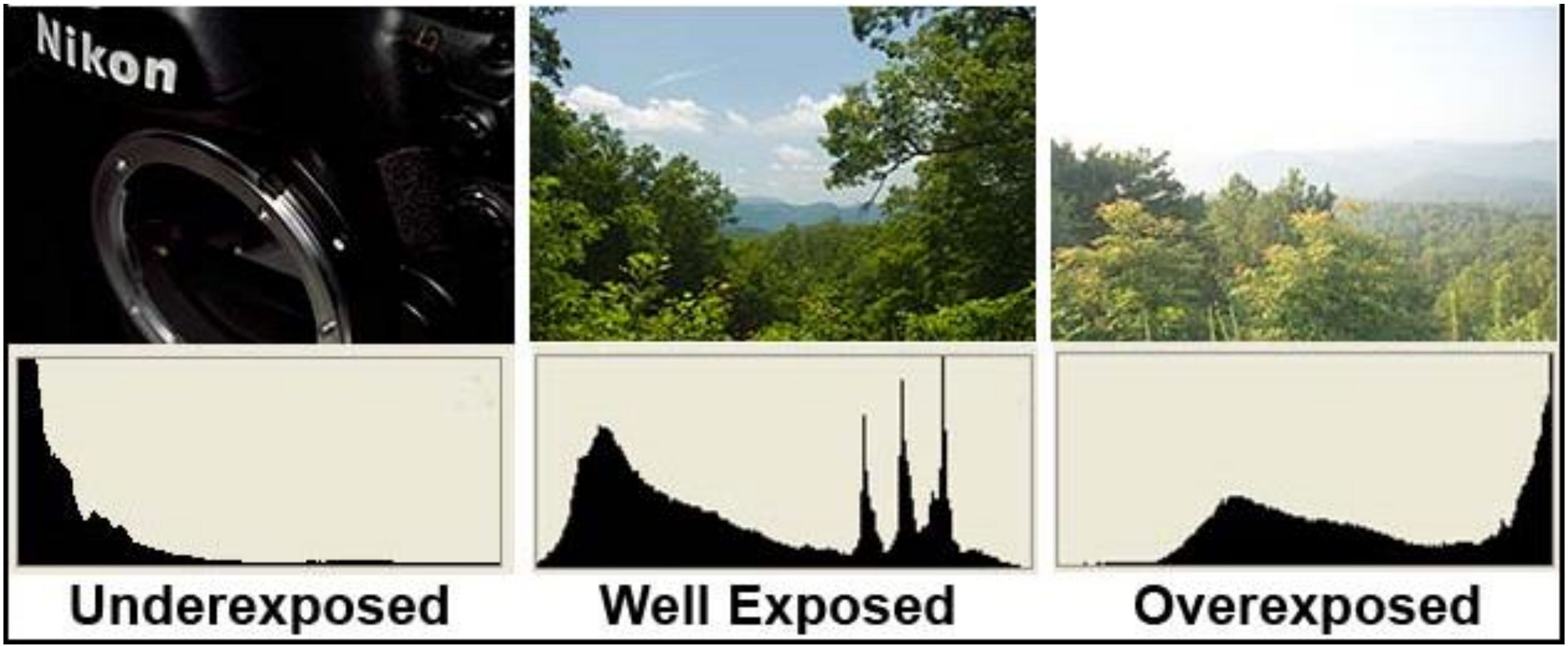


FIGURE 3.16 Four basic image types: dark, light, low contrast, high contrast, and their corresponding histograms.

Histogram Processing



Histogram tells us about the contrast of the image.

Histogram Equalization

The intensity levels in an image may be viewed as random variables in the interval [0, L-1].

Let $p_r(r)$ and $p_s(s)$ denote the probability density function (PDF) of random variables r and s.

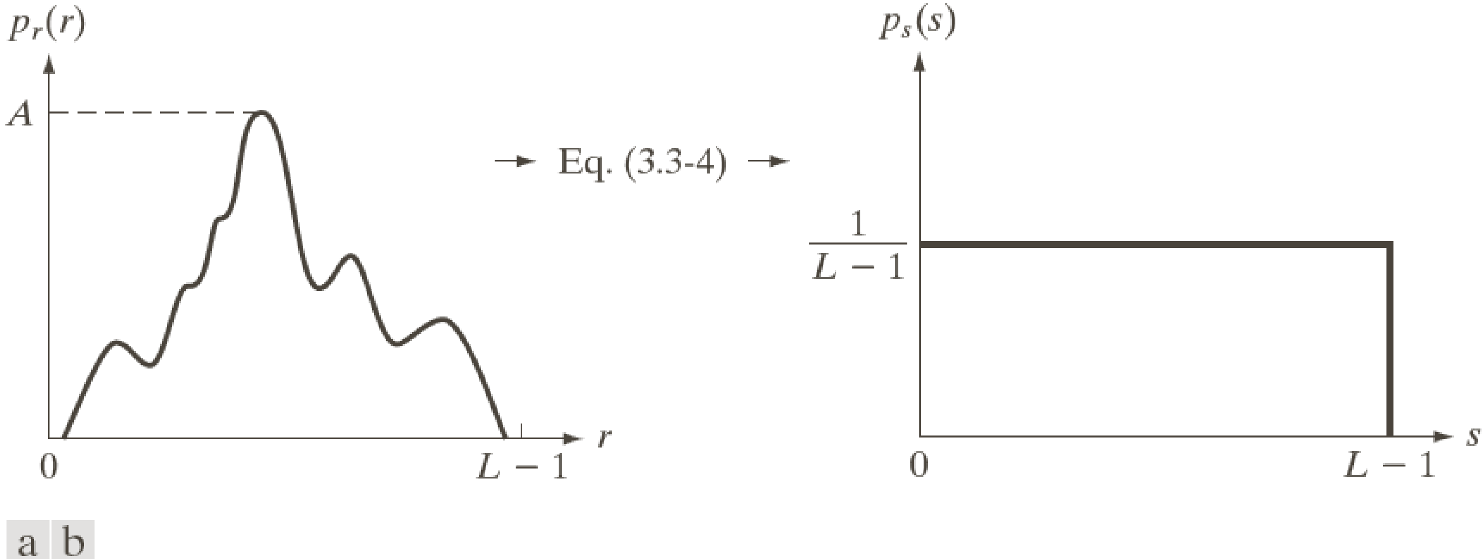


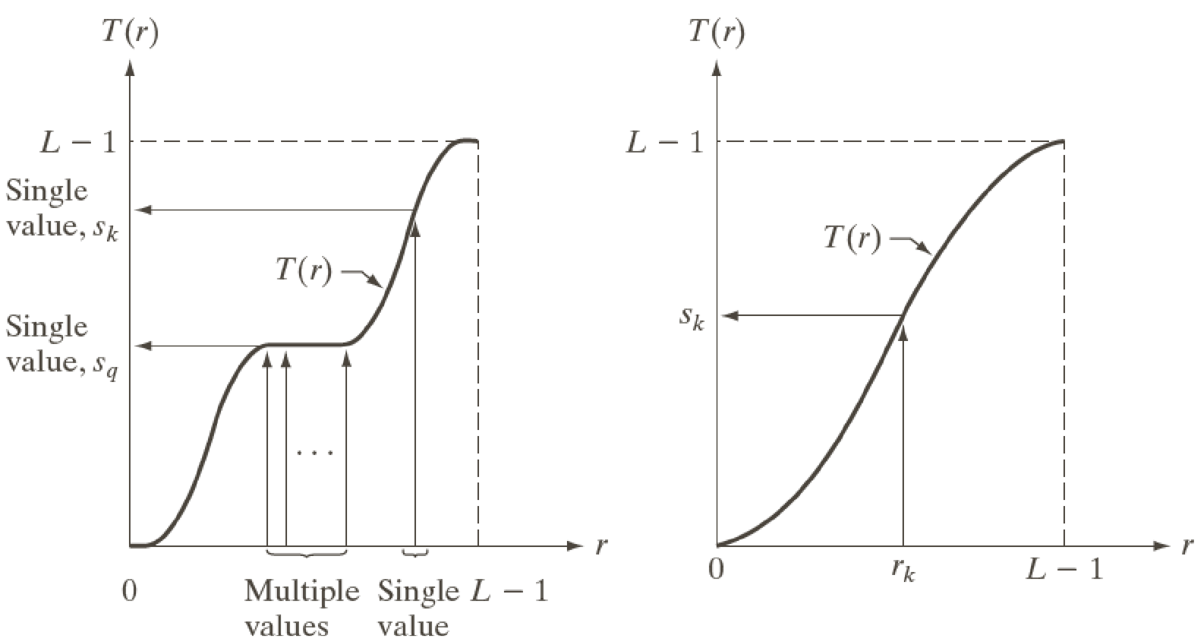
FIGURE 3.18 (a) An arbitrary PDF. (b) Result of applying the transformation in Eq. (3.3-4) to all intensity levels, r. The resulting intensities, s, have a uniform PDF, independently of the form of the PDF of the r's.

Histogram Equalization

$$s = T(r) \qquad 0 \le r \le L-1$$

a. T(r) is a strictly monotonically increasing function in the interval $0 \le r \le L\text{-}1$;

b. $0 \le T(r) \le L\text{-}1$ for $0 \le r \le L\text{-}1$.



a b

FIGURE 3.17 (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, both ways.

Histogram Equalization

$$s = T(r) \qquad 0 \le r \le L-1$$

$a.$ T(r) is a strictly monotonically increasing function in the interval $0 \le r \le L\text{-}1$;

$b.$ $0 \le T(r) \le L\text{-}1$ for $0 \le r \le L\text{-}1.$

$T(r)$ is continuous and differentiable.

$$p_s(s)ds = p_r(r)dr$$

Example: Histogram Equalization

Suppose that a 3-bit image (L=8) of size 64 × 64 pixels (MN = 4096) has the intensity distribution shown in following table.
Get the histogram equalization transformation function and give the $p_s(s_k)$ for each s_k.

r_k	n_k	$p_r(r_k) = n_k/MN$
$r_0 = 0$	790	0.19
$r_1 = 1$	1023	0.25
$r_2 = 2$	850	0.21
$r_3 = 3$	656	0.16
$r_4 = 4$	329	0.08
$r_5 = 5$	245	0.06
$r_6 = 6$	122	0.03
$r_7 = 7$	81	0.02

TABLE 3.1 Intensity distribution and histogram values for a 3-bit, 64 × 64 digital image.

Example: Histogram Equalization

r_k	n_k	$p_r(r_k) = n_k/MN$
$r_0 = 0$	790	0.19
$r_1 = 1$	1023	0.25
$r_2 = 2$	850	0.21
$r_3 = 3$	656	0.16
$r_4 = 4$	329	0.08
$r_5 = 5$	245	0.06
$r_6 = 6$	122	0.03
$r_7 = 7$	81	0.02

$$s_0 = T(r_0) = 7\sum_{j=0}^{0} p_r(r_j) = 7 \times 0.19 = 1.33 \quad \rightarrow 1$$

$$s_1 = T(r_1) = 7\sum_{j=0}^{1} p_r(r_j) = 7 \times (0.19 + 0.25) = 3.08 \quad \rightarrow 3$$

$$s_2 = 4.55 \quad \rightarrow 5 \qquad s_3 = 5.67 \quad \rightarrow 6$$

$$s_4 = 6.23 \quad \rightarrow 6 \qquad s_5 = 6.65 \quad \rightarrow 7$$

$$s_6 = 6.86 \quad \rightarrow 7 \qquad s_7 = 7.00 \quad \rightarrow 7$$

Example: Histogram Equalization

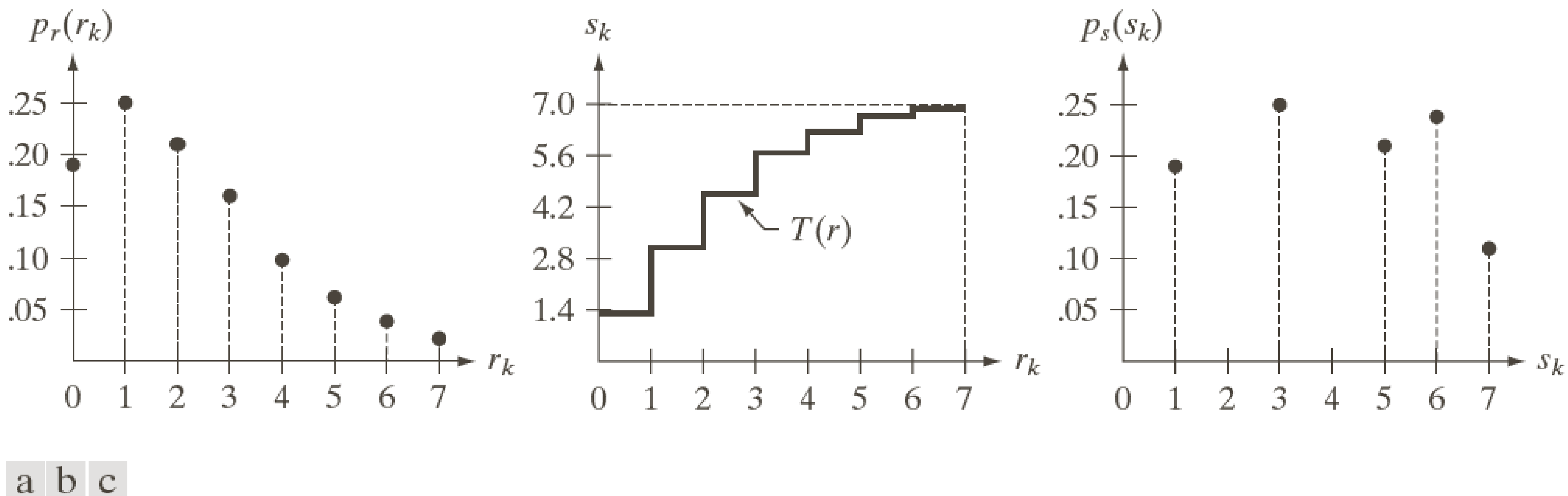


FIGURE 3.19 Illustration of histogram equalization of a 3-bit (8 intensity levels) image. (a) Original histogram. (b) Transformation function. (c) Equalized histogram.

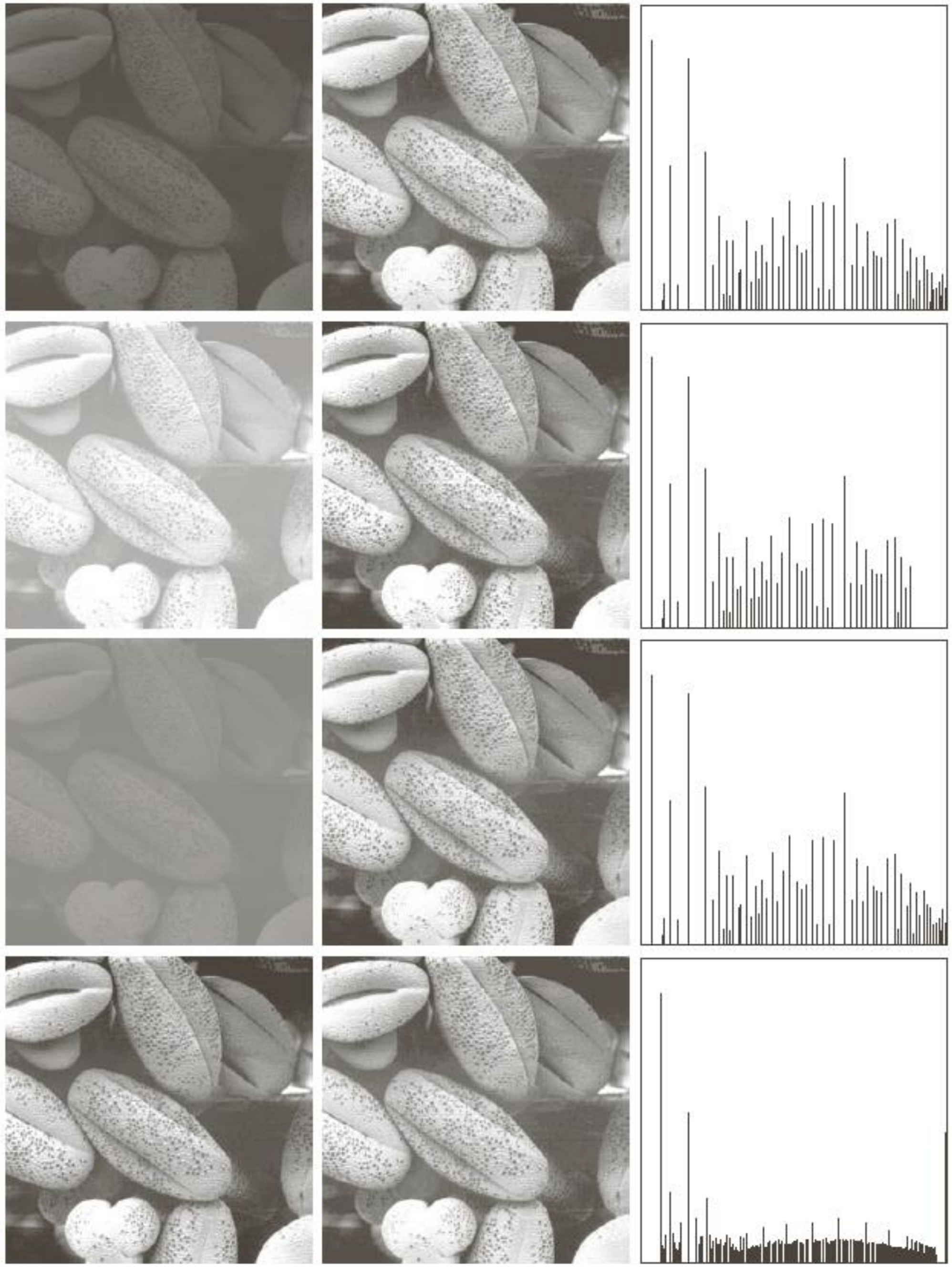
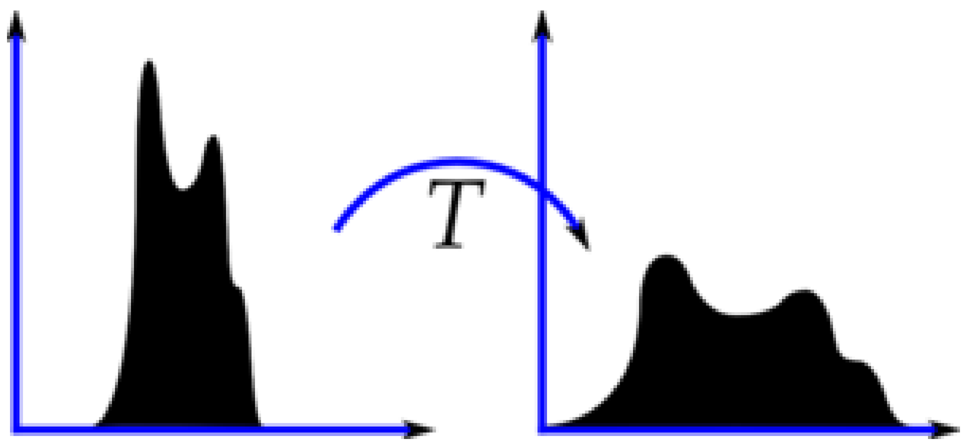


FIGURE 3.20 Left column: images from Fig. 3.16. Center column: corresponding histogram-equalized images. Right column: histograms of the images in the center column.

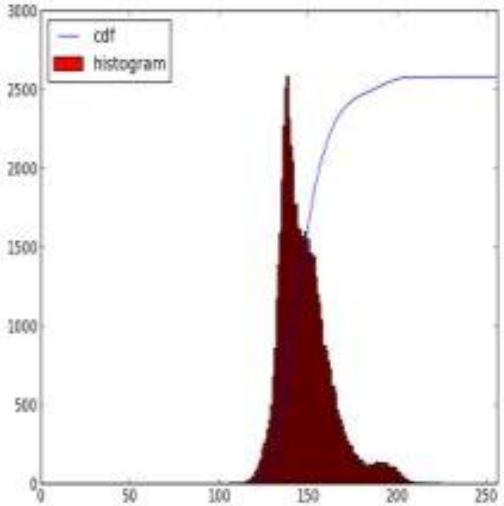
Histogram Equalization

- Consider an image whose pixel values are limited to only a certain range of values.
- For example, in a brighter image all pixels will be limited to higher values.
- But a good image should have pixels from all regions of the image.
- So, you need to stretch this histogram to both ends and that's what Histogram Equalization does.
- This normally improves the contrast of the image.



Histogram Equalization

```
import numpy as np
import cv2 as cv
from matplotlib import pyplot as plt
img = cv.imread('wiki.jpg',0)
hist,bins = np.histogram(img.flatten(),256,[0,256])
cdf = hist.cumsum()
cdf_normalized = cdf * float(hist.max()) / cdf.max()
plt.plot(cdf_normalized, color = 'b')
plt.hist(img.flatten(),256,[0,256], color = 'r')
plt.xlim([0,256])
plt.legend(('cdf','histogram'), loc = 'upper left')
plt.show()
```



Örnek: Histogram Equalization

```
img = cv.imread('wiki.jpg',0)
equ = cv.equalizeHist(img)
res = np.hstack((img,equ)) #stacking images side-by-side
cv.imwrite('res.png',res)
```

References

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