### EEE-6512: Image Processing and Computer Vision

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Lecture #4: Intensity Transformations and Spatial Filtering

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### **Outline**

- Section 3.1: Background
- **Section 3.2:** Some Basic Intensity Transformation Functions
- Section 3.3: Histogram Processing
- Section 3.4: Fundamentals of Spatial Filtering
- Section 3.5: Smoothing (Lowpass) Spatial Filters
- Section 3.6: Sharpening (Highpass) Spatial Filters
- Section 3.7: Highpass, Bandreject, and Bandpass Filters from Lowpass Filters

### Background

### Background

The spatial domain processes that we discuss in this chapter are based on the expression:

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

where f(x,y) is an input image, g(x,y) is the output image, and T is operator defined of a point (x,y).

Smallest neighborhood is 1x1, in this special case equation becomes:

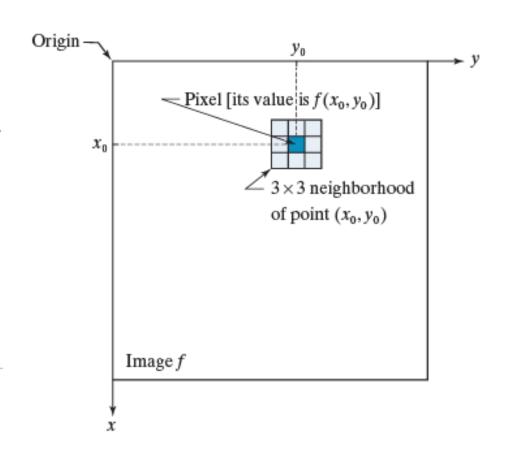
$$s = T(r)$$

This is referred to as a point processing technique as opposed to neighborhood processing techniques.

# Background: Neighborhood Processing

#### FIGURE 3.1

 $A.3 \times 3$ neighborhood about a point  $(x_0, y_0)$  in an image. The neighborhood is moved from pixel to pixel in the image to generate an output image. Recall from Chapter 2 that the value of a pixel at location  $(x_0, y_0)$  is  $f(x_0, y_0)$ , the value of the image at that location.



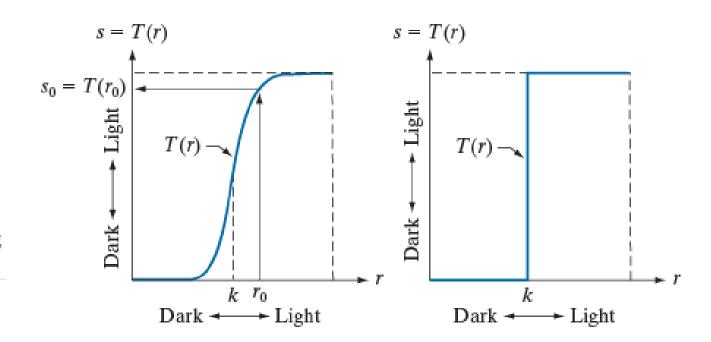
### **Background: Point Processing**

a b

#### FIGURE 3.2

Intensity transformation functions.

- (a) Contraststretching function.
- (b) Thresholding function.



### Background

- Many applications of spatial filtering methods, we will focus on image enhancement.
- Enhancement is the process of manipulating an image so that the result is more suitable that the original for a specific application.
- Enhancement techniques are problem-oriented.
- There is no general "theory" of image enhancement.

#### FIGURE 3.3

Some basic intensity transformation functions. Each curve was scaled independently so that all curves would fit in the same graph. Our interest here is on the shapes of the curves, not on their relative values.

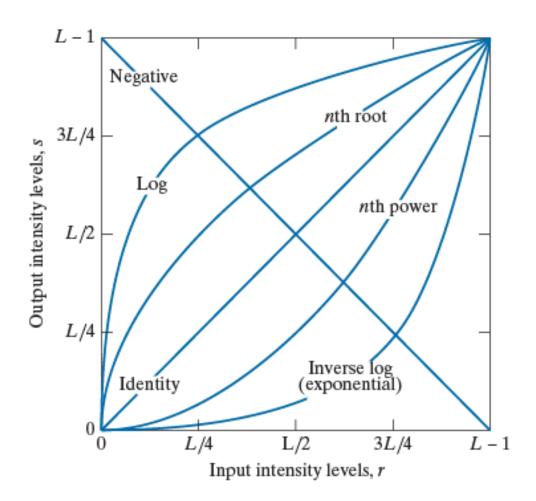


Image Negative: s = L-1-r

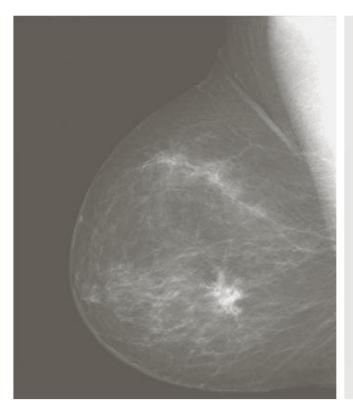
a b

FIGURE 3.4

(a) A

digital
mammogram.

(b) Negative
image obtained
using Eq. (3-3).
(Image (a)
Courtesy of
General Electric
Medical Systems.)

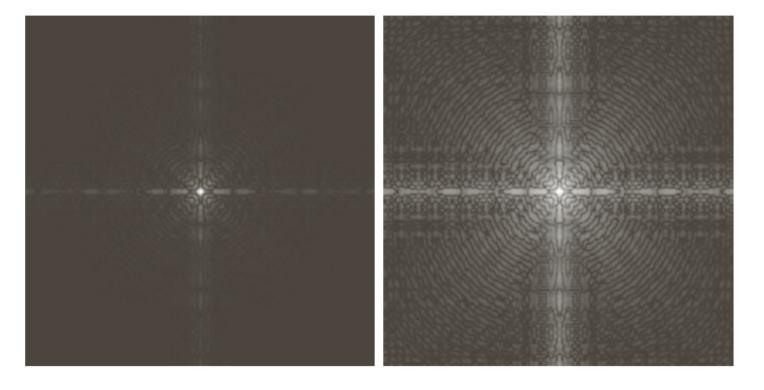




**Log Transformation:**  $S = c \log (1+r) c$  is constant and  $r \ge 0$ 

- Maps a narrow range of low intensity values in the input to a wider range of output values.
- Conversely, higher input levels are mapped to a narrower range in the output.
- Opposite is true of the inverse log (exponential) transformation.

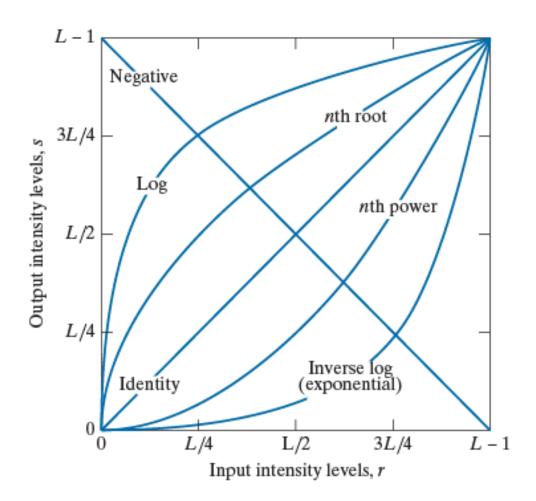
# a b FIGURE 3.5 (a) Fourier spectrum displayed as a grayscale image. (b) Result of applying the log transformation in Eq. (3-4) with c = 1. Both images are scaled to the range [0, 255].



- Fourier spectrum with values in the range of 0 to 1.5 x 10<sup>6</sup> scaled linearly for display in an 8-bit system (left)
- Log transformation applied with c=1, range of values becomes 0 to 6.2.

#### FIGURE 3.3

Some basic intensity transformation functions. Each curve was scaled independently so that all curves would fit in the same graph. Our interest here is on the shapes of the curves, not on their relative values.



**Power Law (Gamma):**  $S = Cr^{\gamma}$  c and  $\gamma$  are positive constants

- As with log transformations, power-law curves with fractional values of γ map a narrow range of dark input values into a wider range of output values.
- Conversely, higher input levels are mapped to a narrower range in the output.
- Curves generated with  $\gamma > 1$  have exactly the opposite effect as those generated with values of  $\gamma < 1$ .

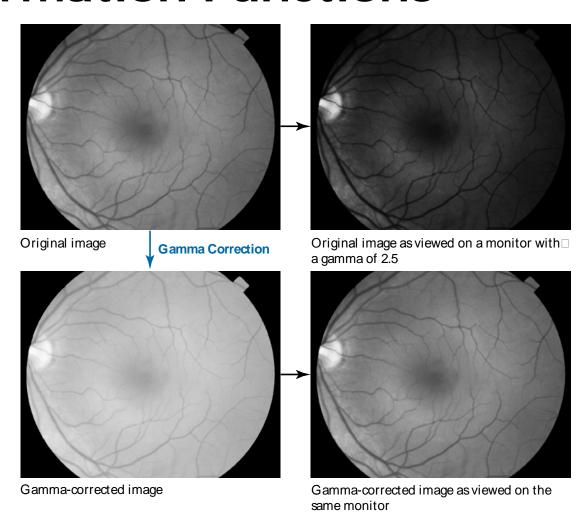
When  $c = \gamma = 1$  then equation reduces to the identity function.

Power Law transformation used for gamma correction to maximize the visual quality of the signal.

#### a b c d

#### FIGURE 3.7

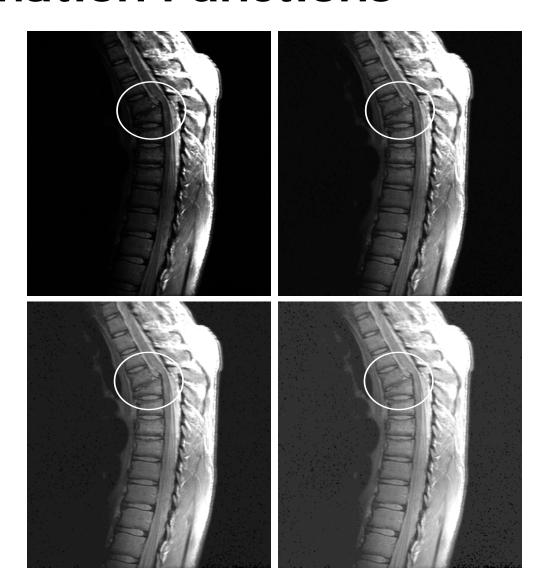
(a) Image of a human retina. (b) Image as as it appears on a monitor with a gamma setting of 2.5 (note the darkness). (c) Gamma-corrected image. (d) Corrected image, as it appears on the same monitor (compare with the original image). (Image (a) courtesy of the National Eye Institute, NIH)



a b

#### FIGURE 3.8

(a) Magnetic resonance image (MRI) of a fractured human spine (the region of the fracture is enclosed by the circle). (b)-(d) Results of applying the transformation in Eq. (3-5) 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.)



a b

#### FIGURE 3.9

(a) Aerial image.
(b)–(d) Results of applying the transformation in Eq. (3-5) with γ = 3.0, 4.0, and 5.0, respectively.
(c = 1 in all cases.)
(Original image courtesy of NASA.)



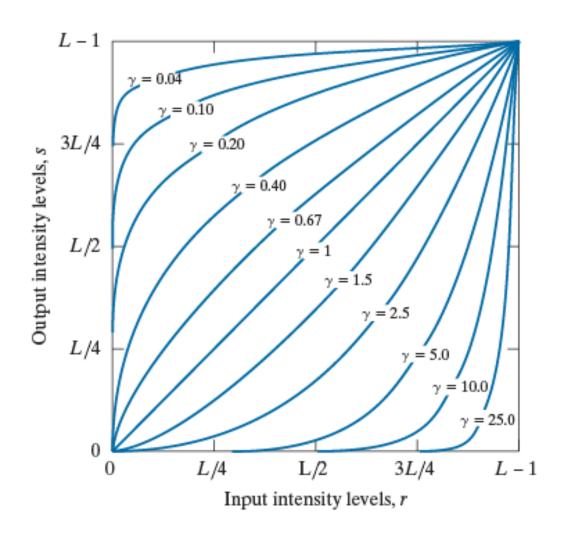






#### FIGURE 3.6

Plots of the gamma equation  $s = cr^{\gamma}$  for various values of  $\gamma$  (c = 1 in all cases). Each curve was scaled *independently* so that all curves would fit in the same graph. Our interest here is on the *shapes* of the curves, not on their relative values.



**Piecewise Linear Transformations** 

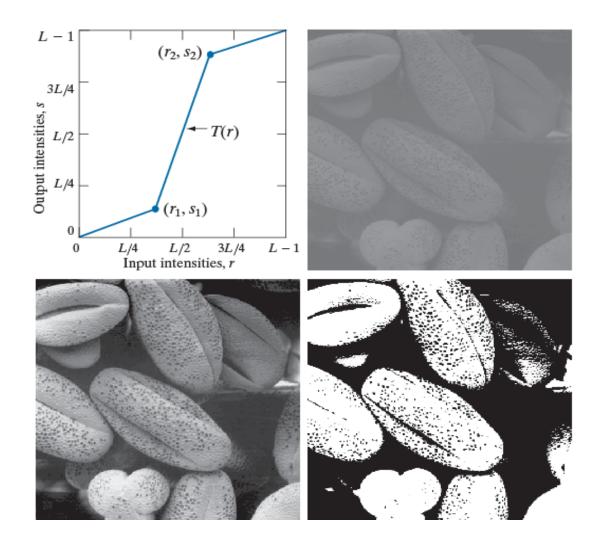
Advantage: Can be arbitrarily complex

**Disadvantage:** Their specification requires considerable user input.

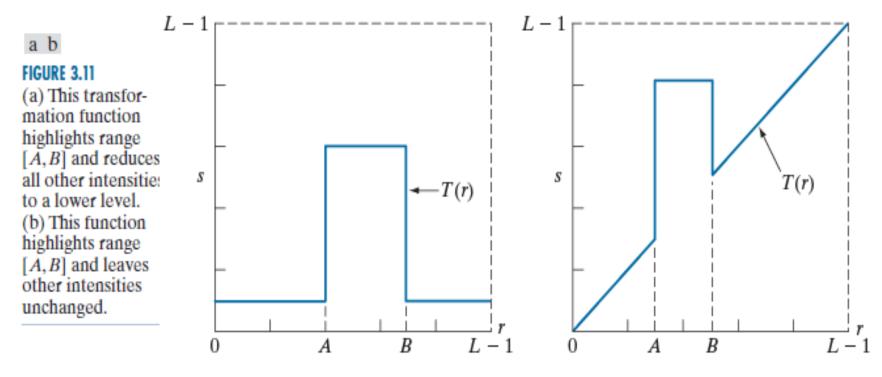
#### a b c d

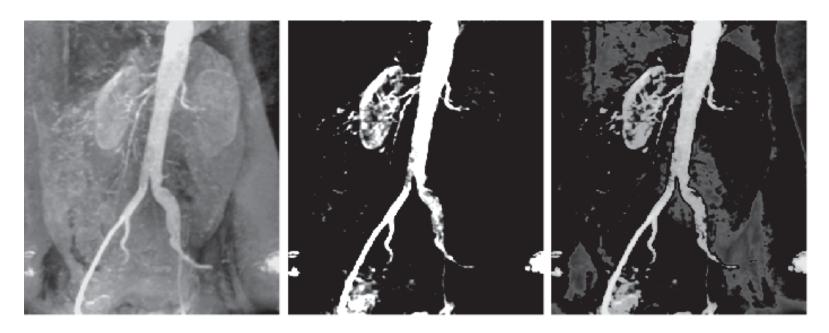
#### FIGURE 3.10

Contrast stretching. (a) Piecewise linear transformation function. (b) A lowcontrast electron microscope image of pollen, magnified 700 times. (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.)



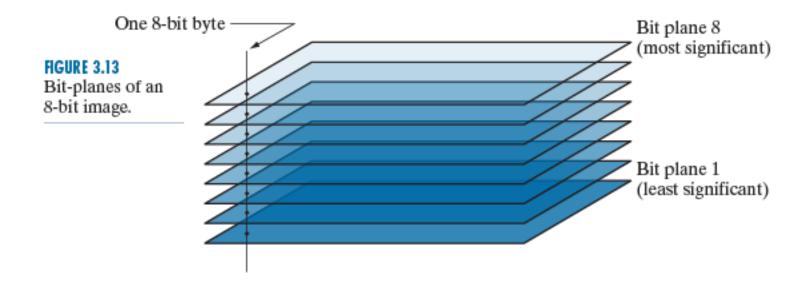
#### **Intensity Level Slicing**





a b 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 range set near black, so that the 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.)

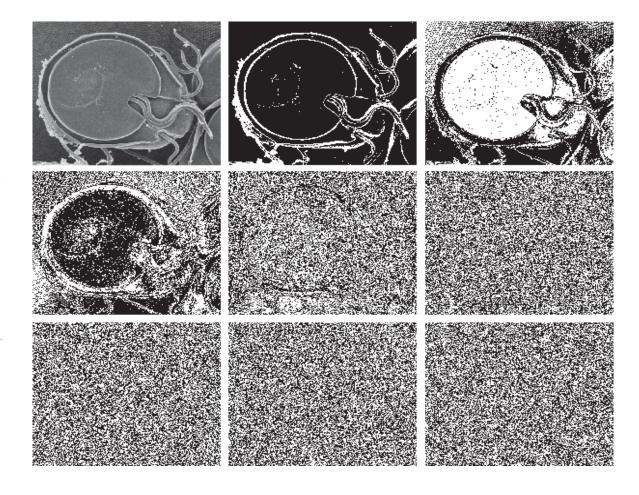


- Decomposing an image into its bit planes is useful for analyzing the relative importance of each bit in the image.
- Can be used to determine if adequacy of the number of bits used to quantize the image.
- This type of decomposition is useful for image compression.

### a b c d e f g h i

#### FIGURE 3.14

(a) An 8-bit grayscale image of size 837 × 988 pixels. (b) through (i) Bit planes 8 through 1, respectively, where plane 1 contains the least significant bit. Each bit plane is a binary image. Figure (a) is an SEM image of a trophozoite that causes a disease called giardiasis. (Courtesy of Dr. Stan Erlandsen. U.S. Center for Disease Control and Prevention.)

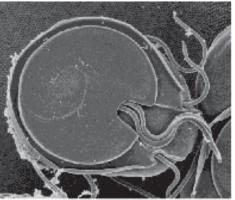


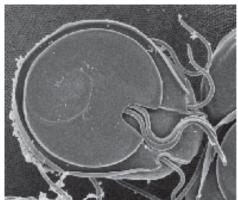
a b c

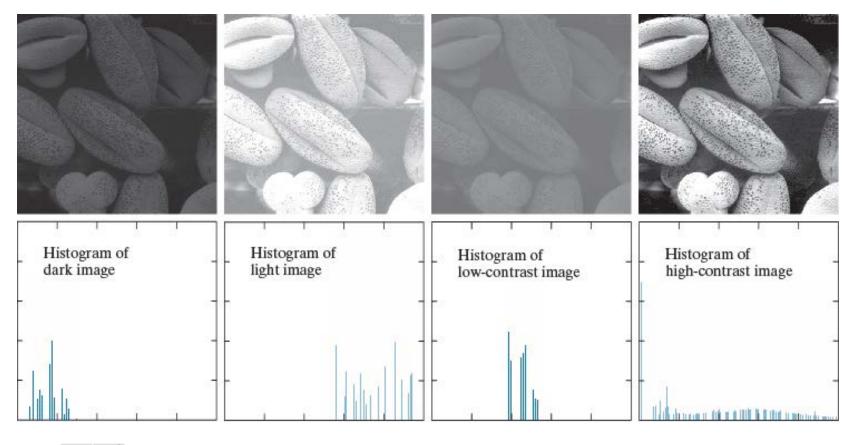
#### FIGURE 3.15 Image reconstructed from bit planes: (a) 8 and 7; (b) 8, 7, and 6;

(c) 8, 7, 6, and 5.







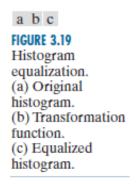


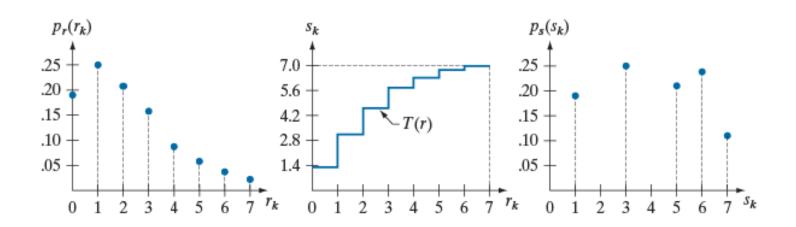
a b c d

**FIGURE 3.16** Four image types and their corresponding histograms. (a) dark; (b) light; (c) low contrast; (d) high contrast. The horizontal axis of the histograms are values of  $r_k$  and the vertical axis are values of  $p(r_k)$ .

**Histogram Equalization** is used to increase contrast in images.

We want intensity values that span a larger range of the intensity scale.





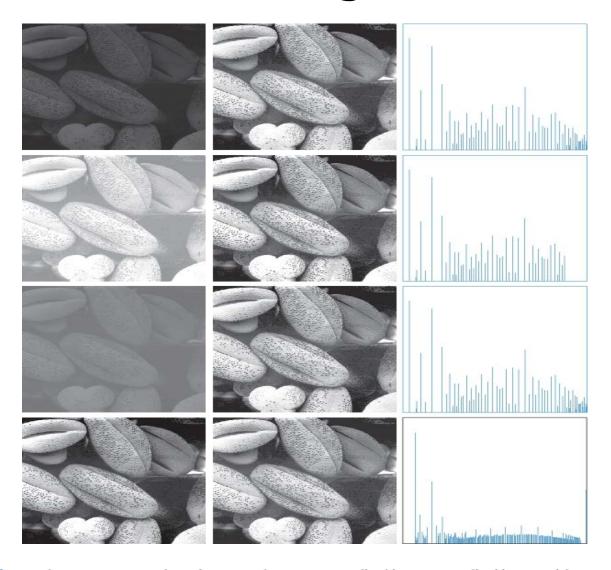


FIGURE 3.20 Left column: Images from Fig. 3.16. Center column: Corresponding histogram-equalized images. Right column: histograms of the images in the center column (compare with the histograms in Fig. 3.16).

### **Questions?**