Digital Image Processing

Lecture # 9
Color Processing & Textures

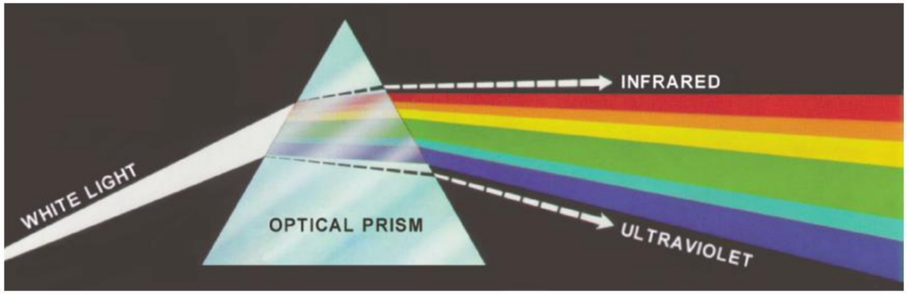
COLOR IMAGE PROCESSING

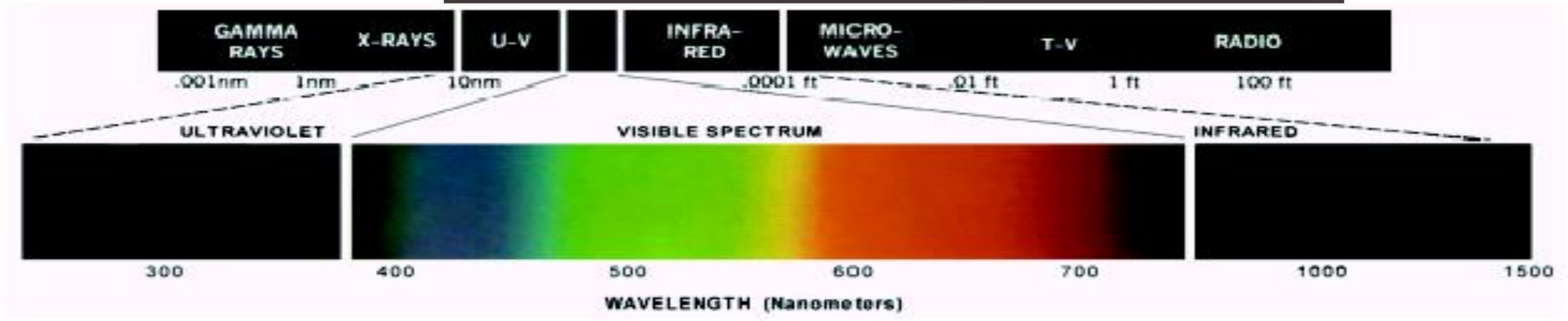
COLOR IMAGE PROCESSING

- Color Importance
  - Color is an excellent descriptor
    - Suitable for object Identification and Extraction
  - Discrimination
    - Humans can distinguish thousands of color shades and intensities but few shades of gray levels
- Color Image Processing
  - Full-Color Processing
    - Color is acquired with a full-color sensor
  - Pseudo-Color Processing
    - Assigning colors to monochrome images

COLOR FUNDAMENTALS

- Colors that humans perceive in an object are determined by the nature of the light reflected from the object
- Visible light is composed of a relatively narrow band of frequencies in the electromagnetic spectrum
- A body that reflects light that is balanced in all visible wavelengths appears white to the observer
- A body that favours reflectance in a limited range of the visible spectrum exhibits some shades of color
- Green objects reflect light with wavelengths primarily in the 500 to 570 nm range while absorbing most of the energy at other wavelengths





HUMAN PERSCEPTION OF COLOR

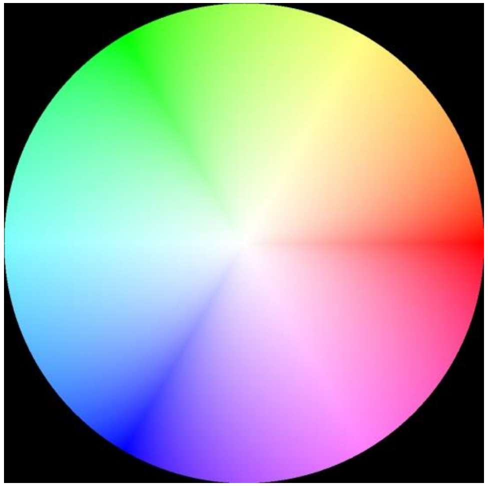
- Retina contains receptors
  - Cones
    - Day vision, can perceive color tone
    - Red, green, and blue cones
  - Rods
    - Night vision, perceive brightness only
- Color sensation
  - Luminance (brightness)
  - Chrominance
    - Hue (color tone)
    - Saturation (color purity)

Monochromatic images

- Image processing - static images -
- Monochromatic static image - continuous image function f(x,y)
  - arguments - two co-ordinates (x,y)
- Digital image functions - represented by matrices
  - co-ordinates = integer numbers
  - Cartesian (horizontal x axis, vertical y axis)
  - OR (row, column) matrices
- Monochromatic image function range
  - lowest value - black
  - highest value - white
- Limited brightness values = gray levels

Chromatic images

- Colour
  - Represented by vector not scalar
    - Red, Green, Blue (RGB)
    - Hue, Saturation, Value (HSV)
    - luminance, chrominance (Yuv , Luv)



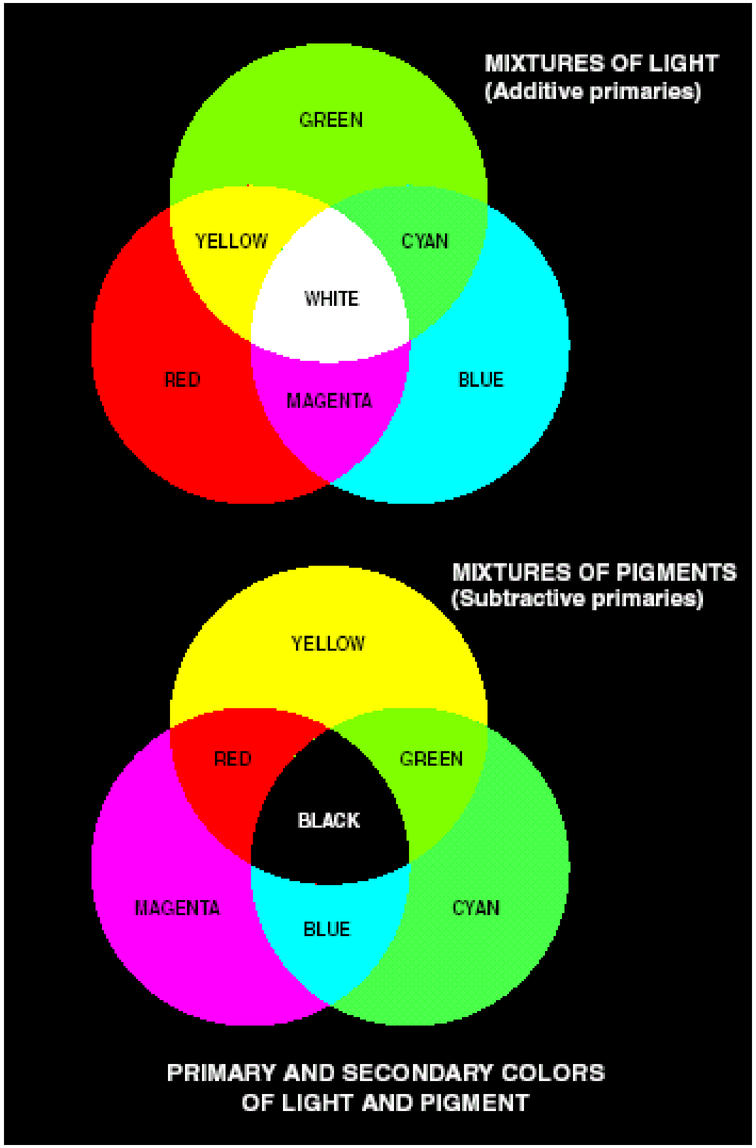
PRIMARY AND SECONDARY COLORS OF LIGHT AND PIGMENTS

- The primary colors can be added to produce the secondary colors of light
- The primary colors of light and primary colors of pigments are different

Magenta = Red + Blue
Cyan = Blue + Green
Yellow = Green + Red

- For pigments, a primary color is defined as one that absorbs a <u>primary color of light</u> and reflects the other two
- Therefore, the <u>primary colors of pigments</u> are magenta, cyan, and yellow

Magenta = White - Green
Cyan = White - Red
Yellow = White - Blue

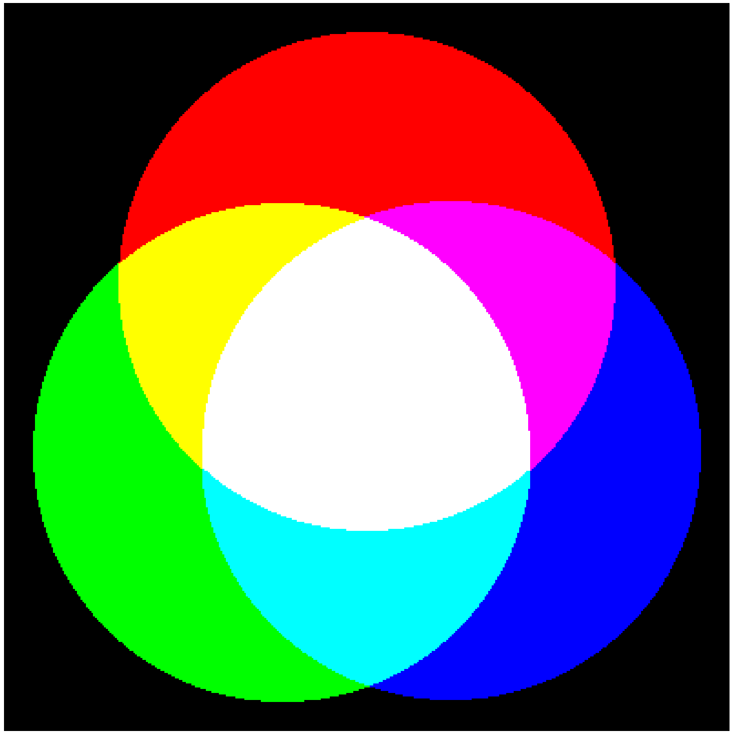


COLOR MODELS

- Color Model
  - Specify colors in a standard way
  - A coordinate system that each color is represented by a single point.
- Most used models:
  - RGB model (Monitor/TV)
  - CMY model (3-color Printers)
  - HSI model (Color Image Processing and Description)

RGB Color model

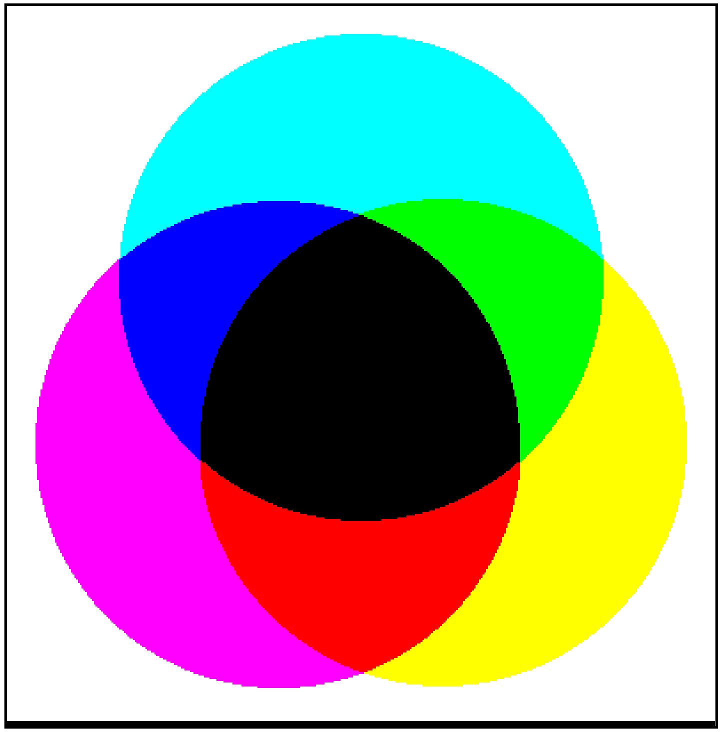
Source: www.mitsubishi.com



Active displays, such as computer monitors and television sets, emit combinations of red, green and blue light. This is an **additive** color model

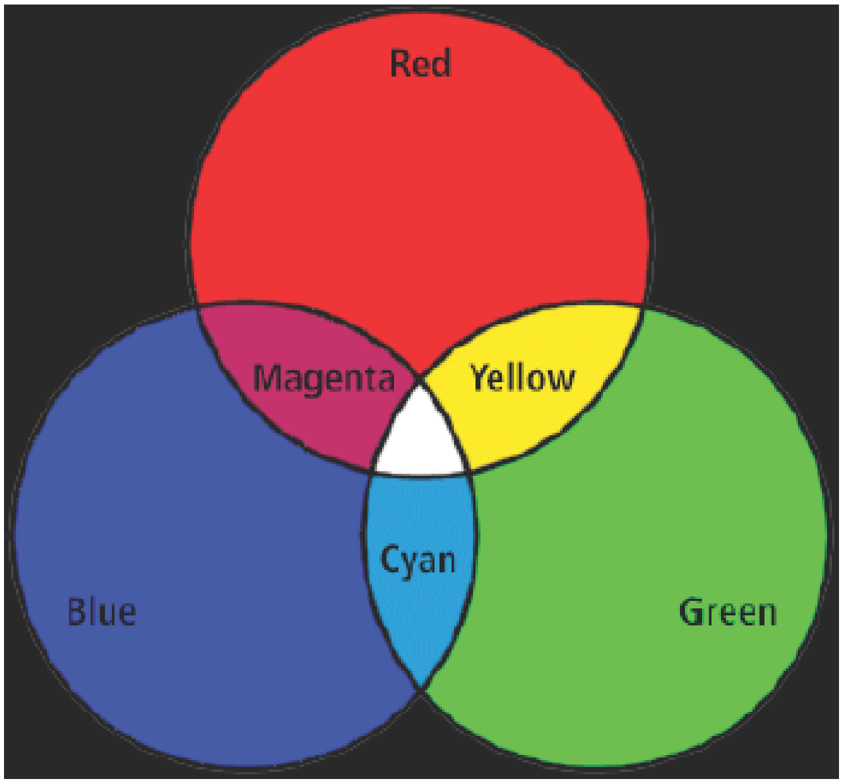
CMY Color model

Source: www.hp.com

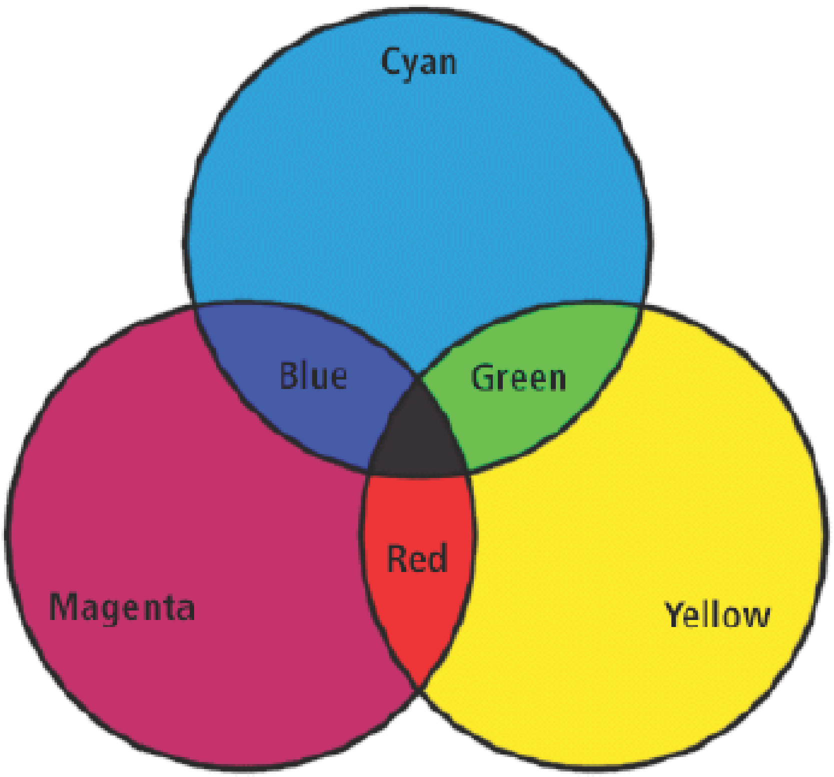


Passive displays, such as color inkjet printers, **absorb** light instead of emitting it. Combinations of **cyan**, **magenta** and **yellow** inks are used. This is a **subtractive** color model.

RGB vs CMY



Magenta = Red + Blue
Cyan = Blue + Green
Yellow = Green + Red

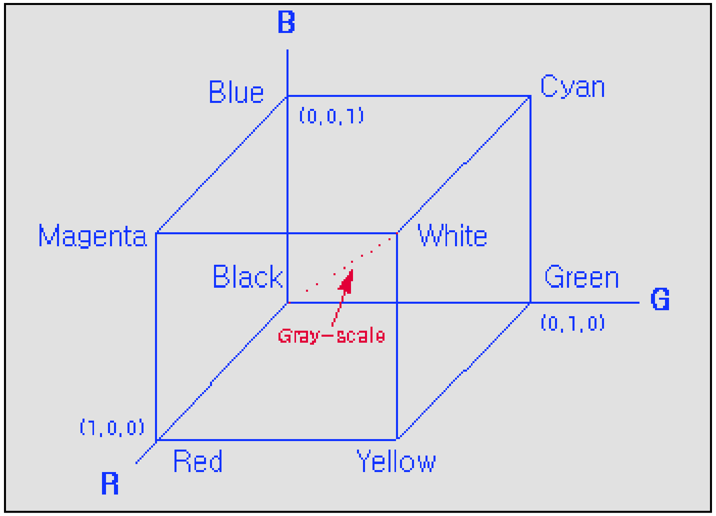


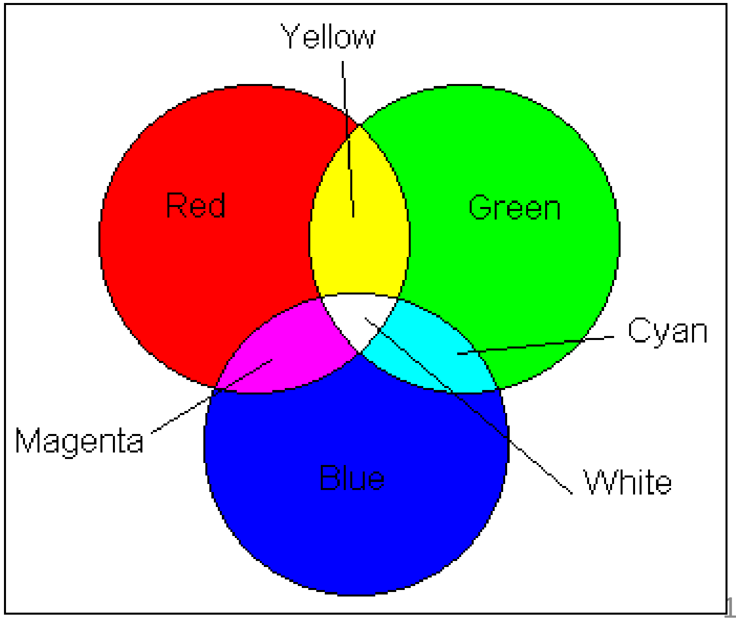
Magenta = White - Green
Cyan = White - Red
Yellow = White - Blue

RGB COLOR MODEL

- Pixel Depth: The number of bits used to represent each pixel in RGB space.
- Full-color image: 24-bit RGB color image.
  - (R, G, B) = (8 bits, 8 bits, 8 bits)
  - Number of colors:

$$\left(2^8\right)^3 = 16{,}777{,}216$$





a
b

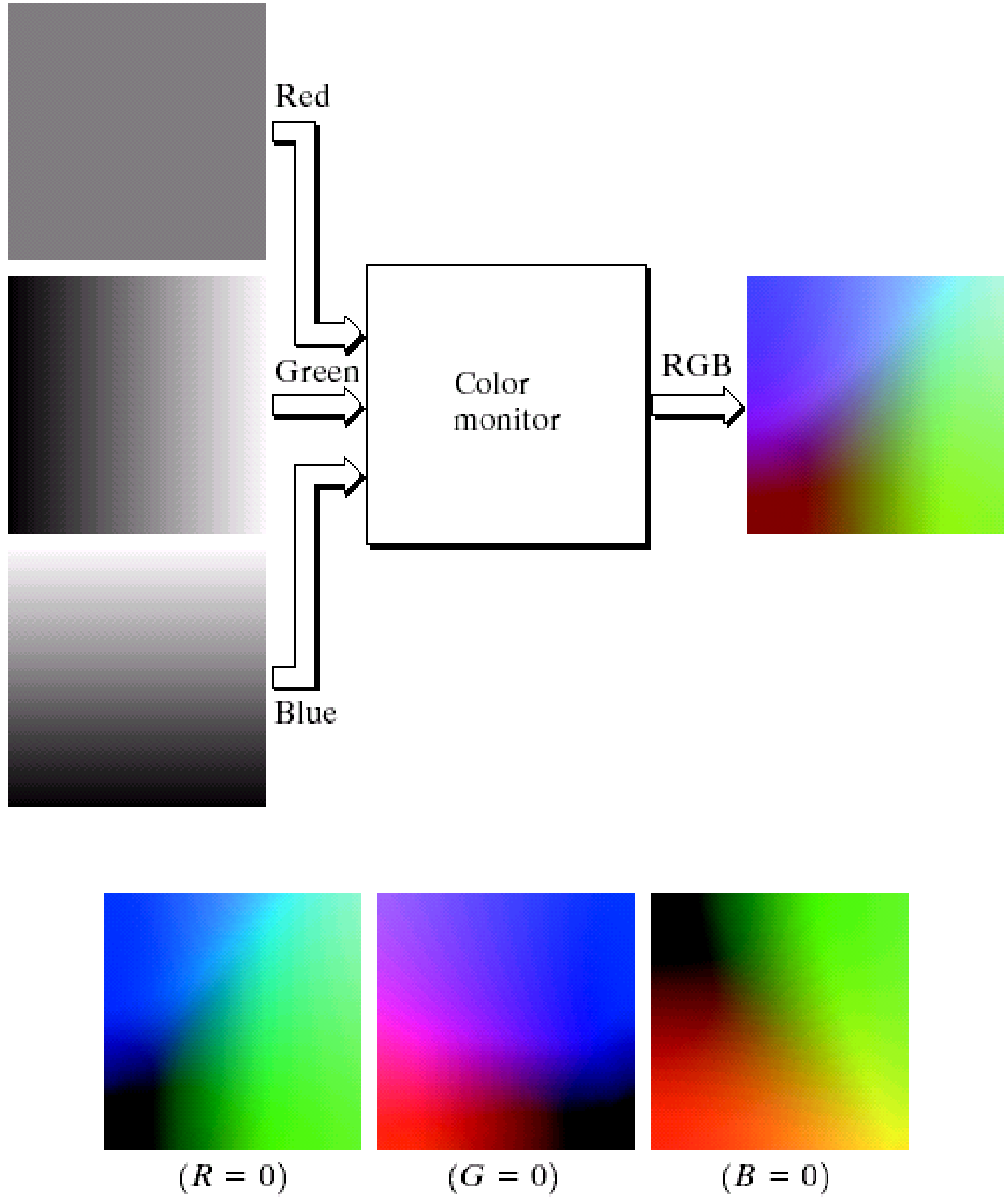


FIGURE 6.9 (a) Generating the RGB image of the cross-sectional color plane $(127, G, B)$. (b) The three hidden surface planes in the color cube of Fig. 6.8.

COLOR IMAGE - RGB

Color Image

FIGURE 6.38
(a) RGB image.
(b) Red component image.
(c) Green component.
(d) Blue component.

R-Channel

G-Channel

B-Channel

CMY Model

– Color Printer, Color Copier

– RGB data to CMY

$$\begin{bmatrix} C \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

HSI COLOR MODEL

- Human description of color is Hue, Saturation and Brightness:
- Hue
  - represents dominant color as perceived by an observer. It is an attribute associated with the dominant wavelength.
- Saturation
  - refers to the relative purity or the amount of white light mixed with a hue. The pure spectrum colors are fully saturated.
    - Pure colors are fully saturated.
    - Pink is less saturated.
- Intensity
  - reflects the brightness.

HSI Color Model

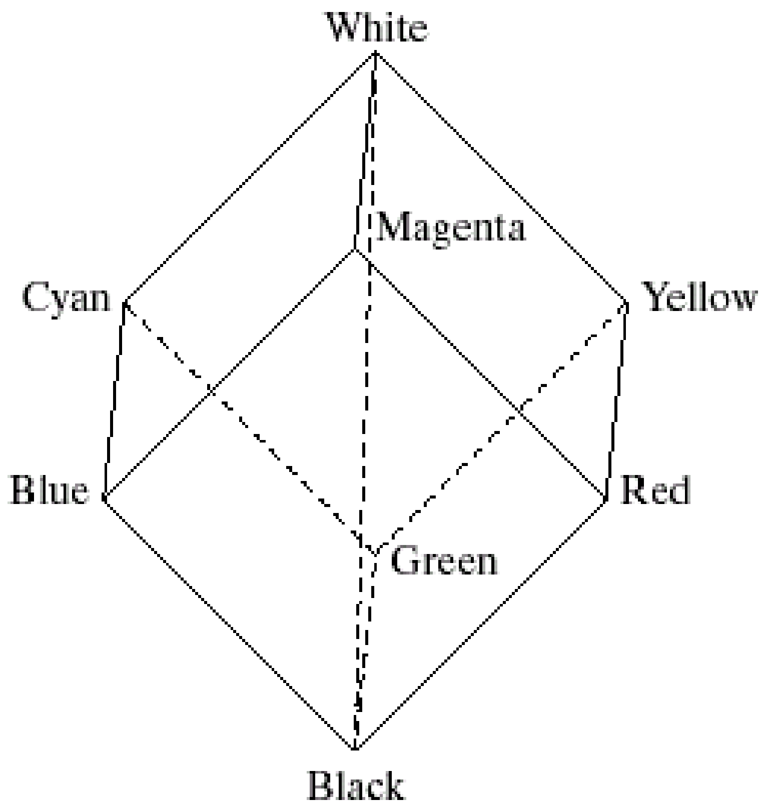
- The HSI model uses three measures to describe colors:
  - Hue: A color attribute that describes a pure color (pure yellow, orange or red)
  - Saturation: Gives a measure of how much a pure color is diluted with white light
  - Intensity: Intensity is the same achromatic notion that we have seen in grey level images

HSI Color Model

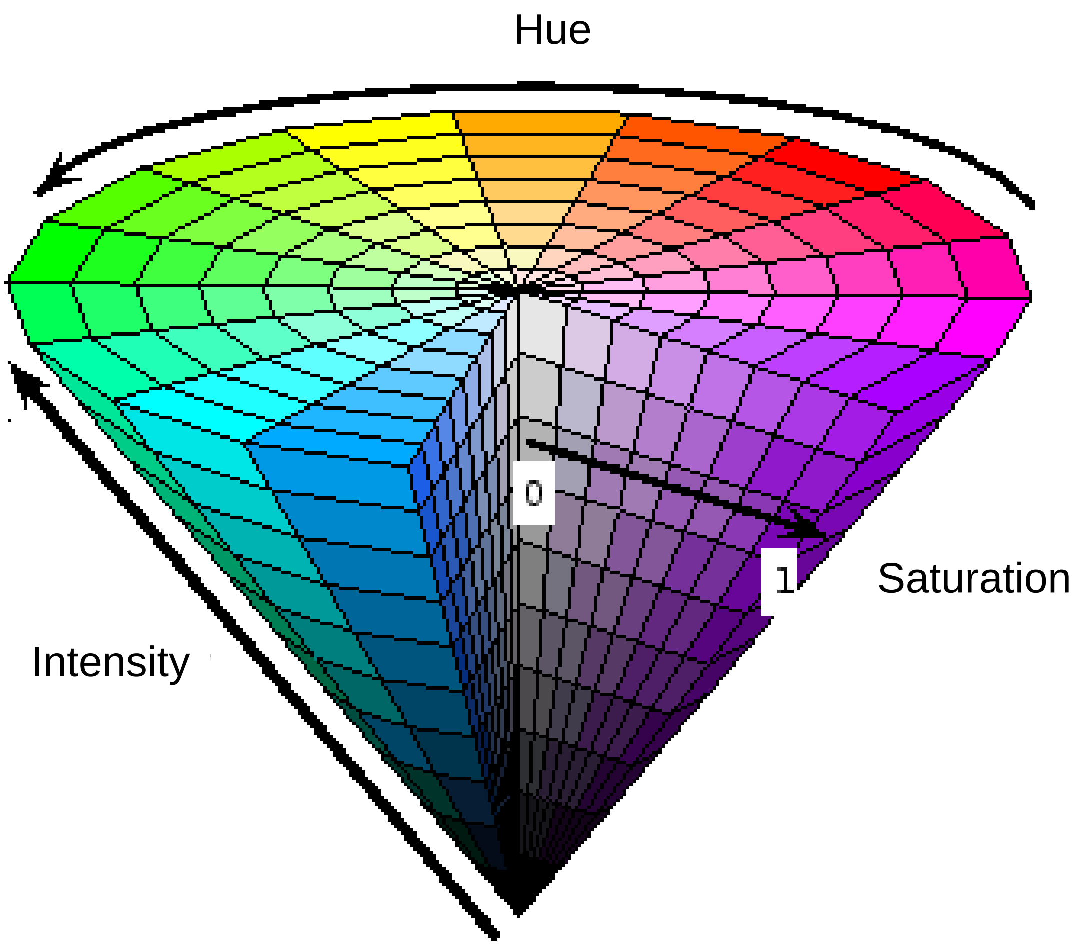
- Intensity can be extracted from RGB images
- Remember the diagonal on the RGB color cube that we saw previously ran from black to white
- Now consider if we stand this cube on the black vertex and position the white vertex directly above it

HSI Color Model

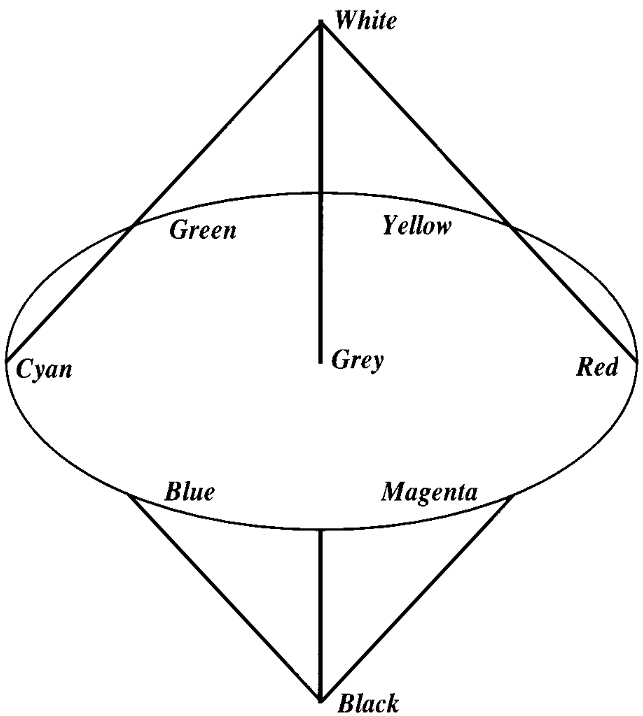
- The intensity component of any color can be determined by passing a plane *perpendicular* to the intensity axis and containing the color point
- The intersection of the plane with the intensity axis gives us the intensity component of the color

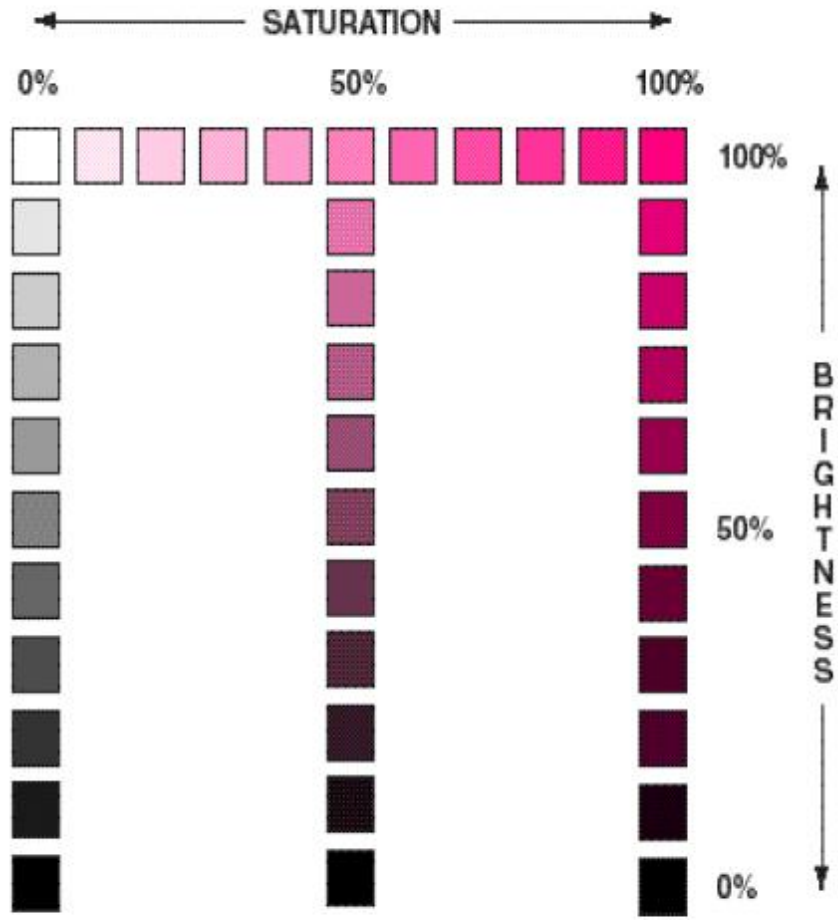


HSI Color Model



HSI COLOR MODEL- SINGLE HUE





HSI Color Model

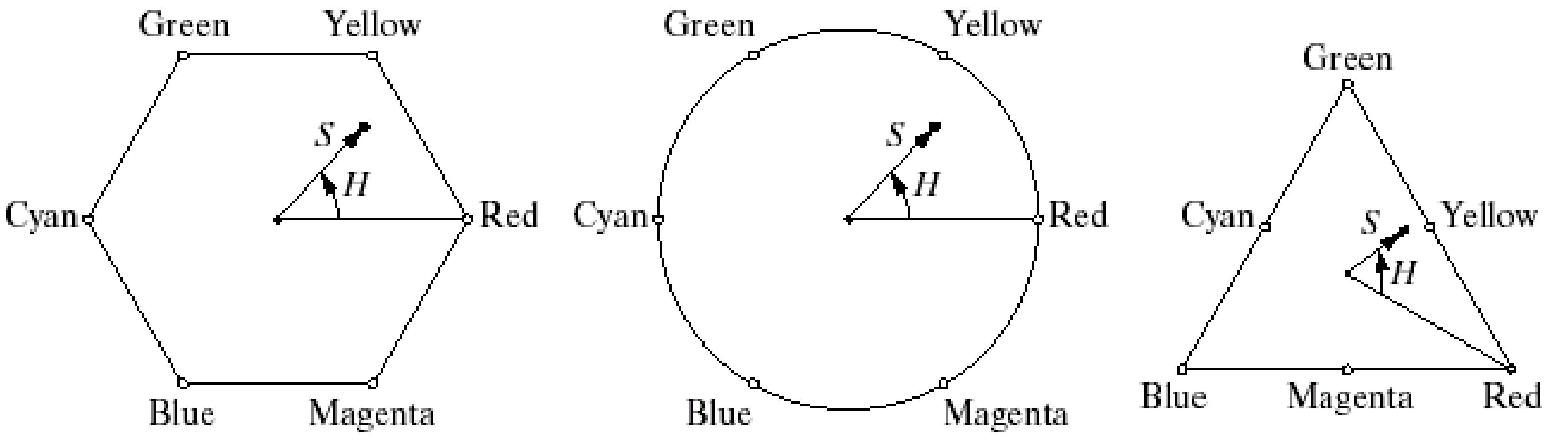
- **Hue** is defined as an angle
  - 0 degrees is **RED**
  - 120 degrees is **GREEN**
  - 240 degrees is **BLUE**

- **Saturation** is defined as the percentage of distance from the center of the HSI triangle to the pyramid surface.
  - Values range from 0 to 1.

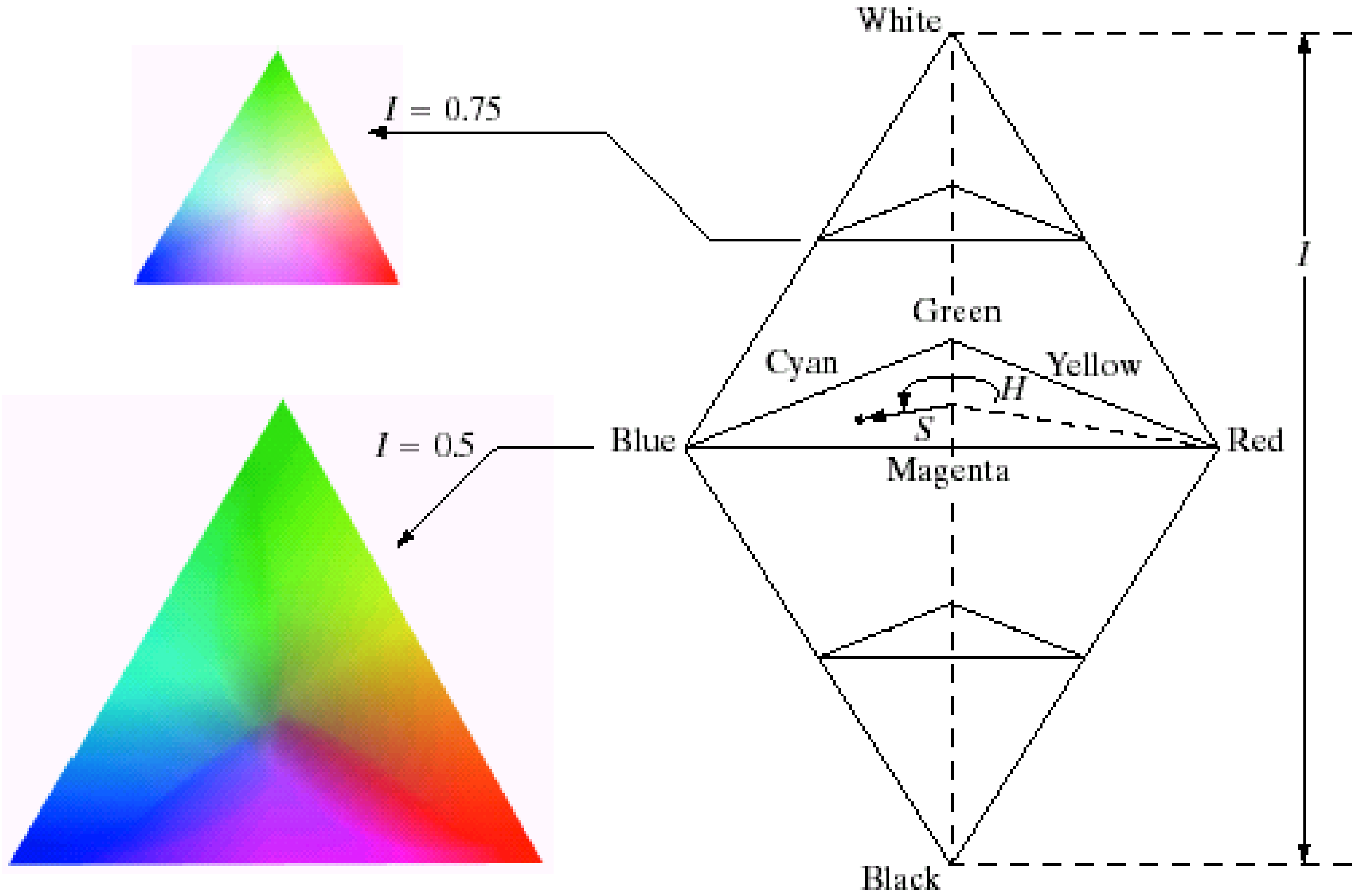
- **Intensity** is denoted as the distance “up” the axis from black.
  - Values range from 0 to 1

HSI Color Model

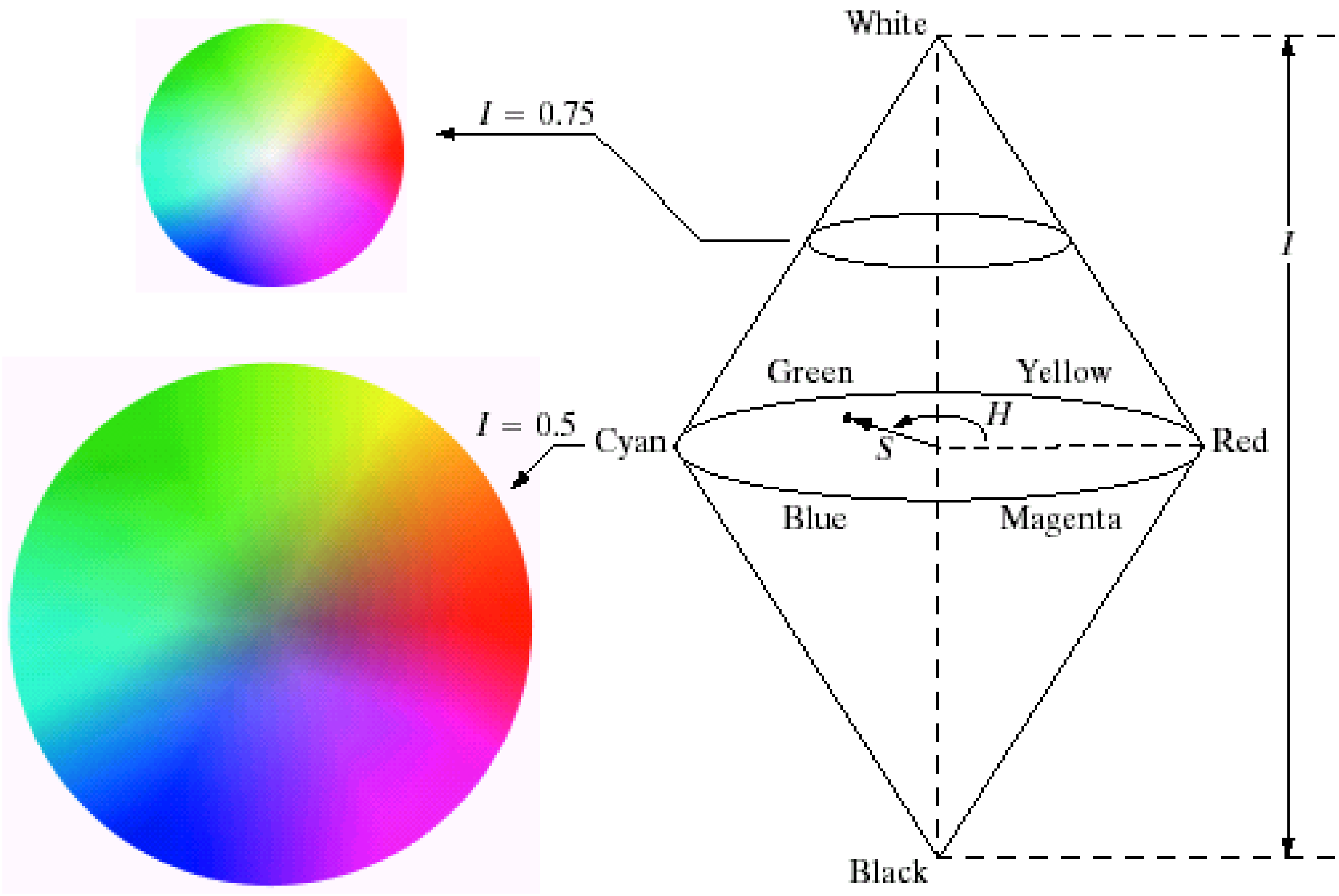
Because the only important things are the angle and the length of the saturation vector this plane is also often represented as a circle or a triangle



HSI Color Model



HSI Color Model



Converting from RGB to HSI

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{\frac{1}{2}}} \right\}$$

$$H = \begin{cases} \theta & if\, B \leq G \\ 360-\theta & if\, B > G \end{cases}$$

$$S = 1 - \frac{3}{(R+G+B)}\left[\min(R,G,B)\right]$$

$$I = \tfrac{1}{3}(R+G+B)$$

Conversion Between RGB and HSI

- Converting color from RGB to HSI

$$H = \begin{cases} \theta & if\ B \le G \\ 360 - \theta & if\ B > G \end{cases} \quad with\ \theta = \cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)\right]^{\frac{1}{2}}} \right\}$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)]$$

$$I = \frac{1}{3}[R+G+B]$$

- Converting color from HSI to RGB

RG sector (0⩽H<120)

$$B = I(1-S)$$

$$R = I\left[1 + \frac{S\cos H}{\cos(60-H)}\right]$$

$$G = 1-(R+B)$$

GB sector (120⩽H<240)

$$R = I(1-S)$$

$$G = I\left[1 + \frac{S\cos(H-120)}{\cos(60-(H-120))}\right]$$

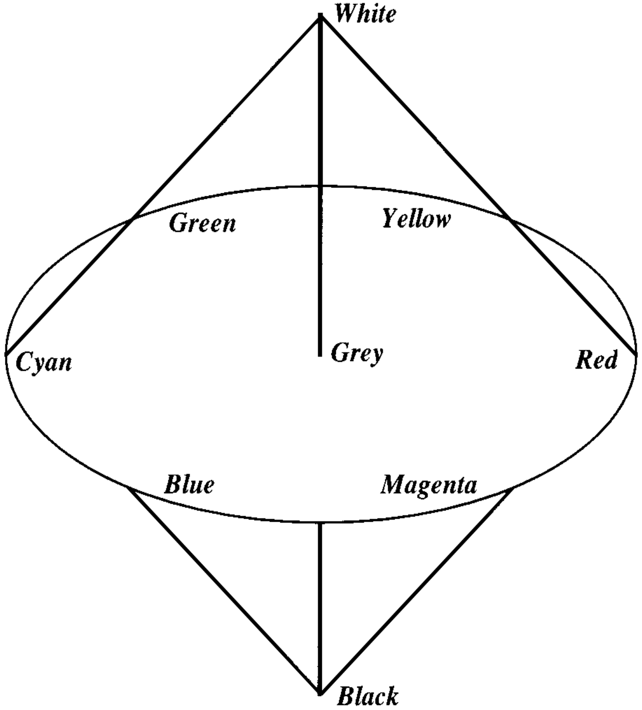
$$B = 1-(R+G)$$

BR sector (240⩽H<360)

$$G = I(1-S)$$

$$B = I\left[1 + \frac{S\cos(H-240)}{\cos(60-(H-240))}\right]$$

$$R = 1-(G+B)$$



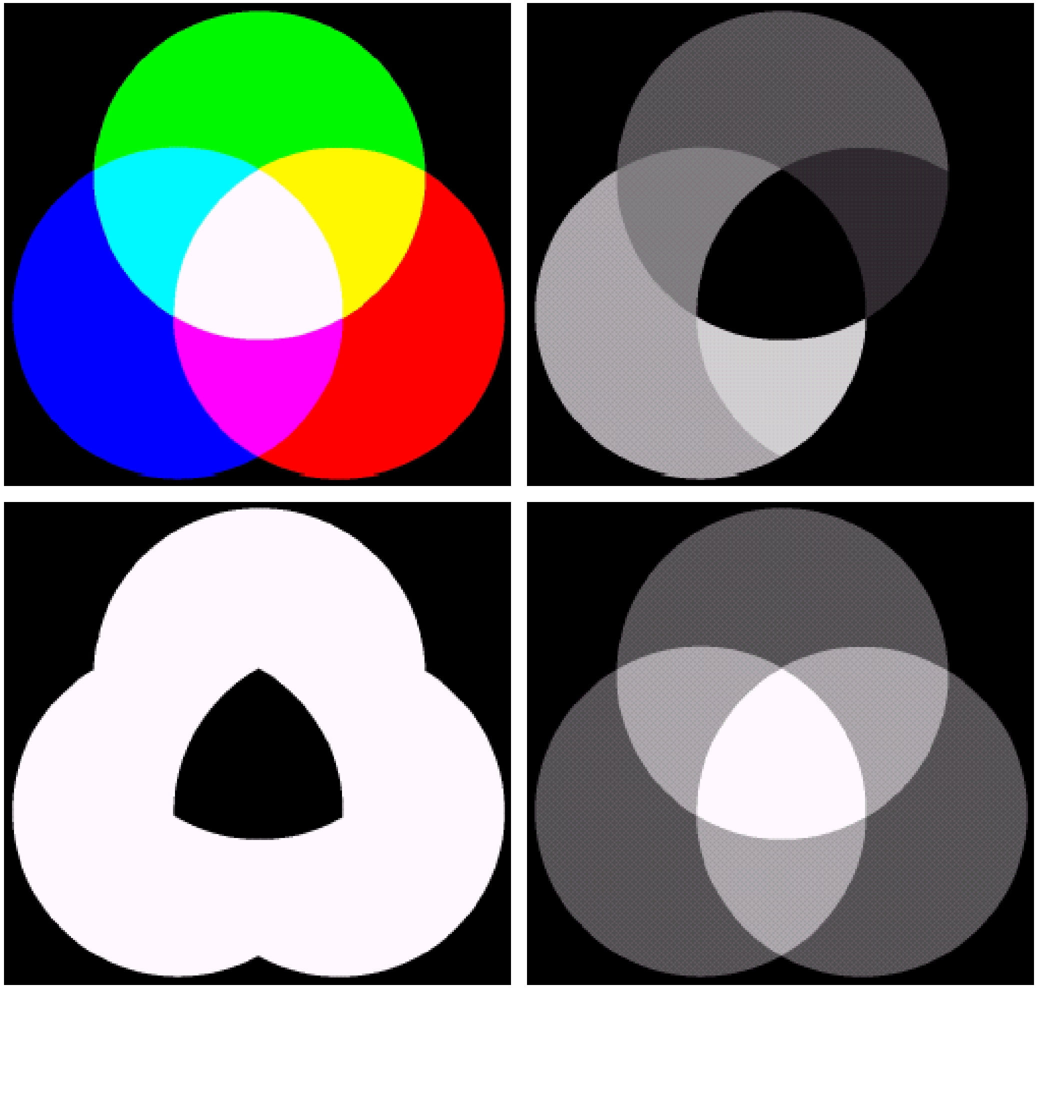
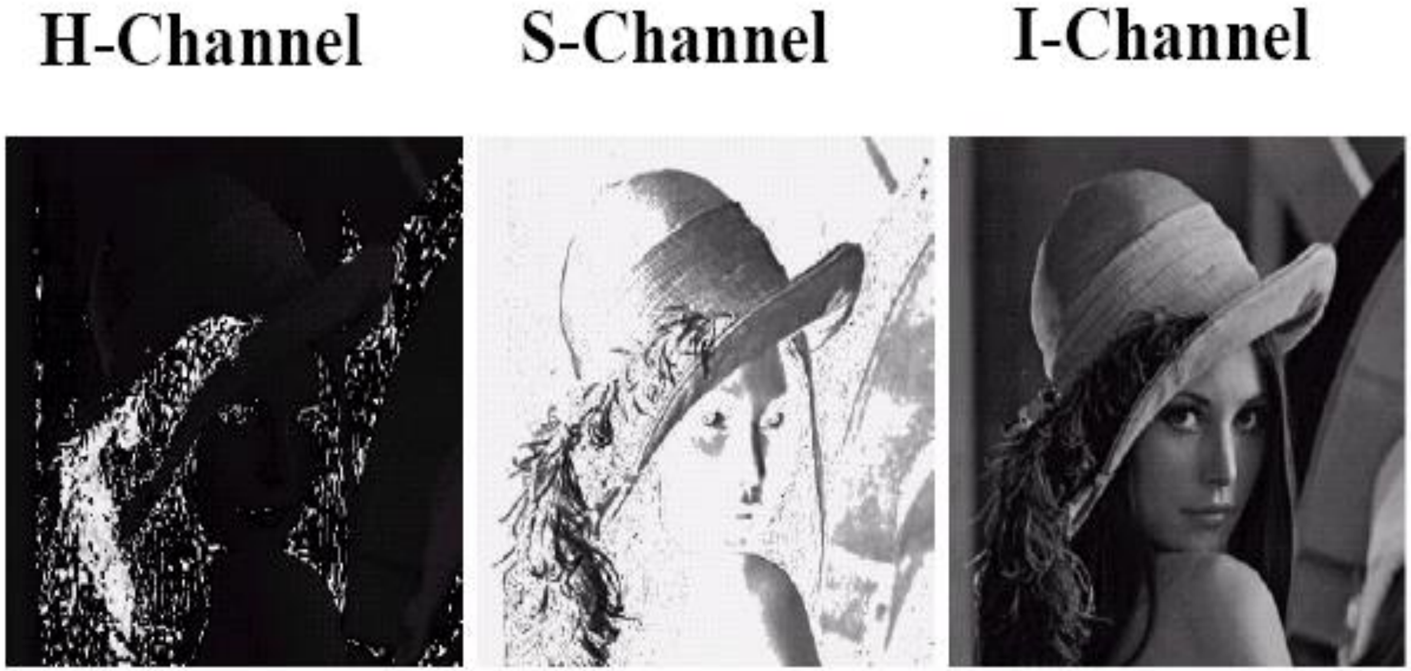


FIGURE 6.16 (a) RGB image and the components of its corresponding HSI image: (b) hue, (c) saturation, and (d) intensity.

COLOR IMAGE - HSI

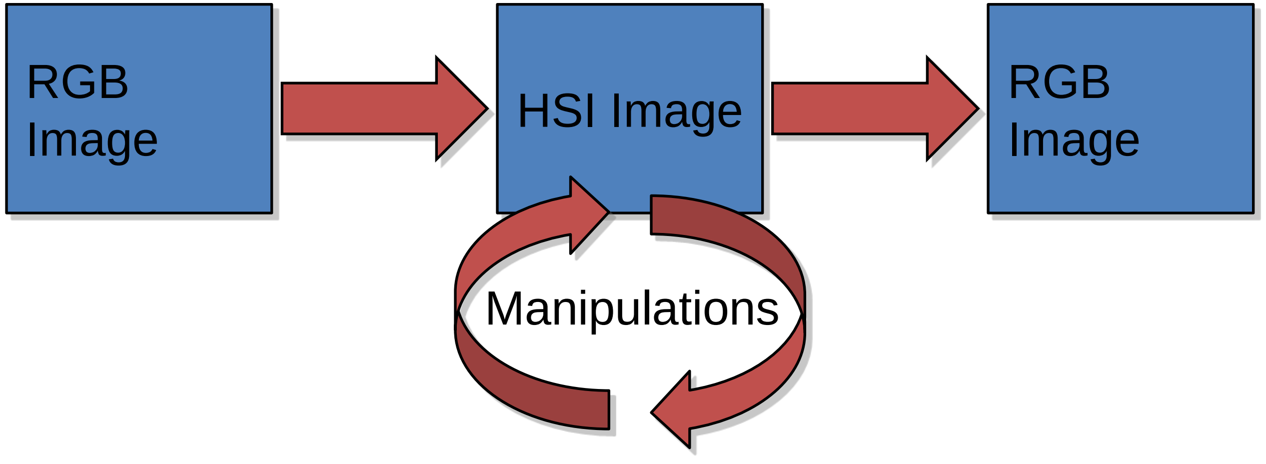


a b c

FIGURE 6.39 HSI components of the RGB color image in Fig. 6.38(a). (a) Hue. (b) Saturation. (c) Intensity.

Manipulating Images In The HSI Model

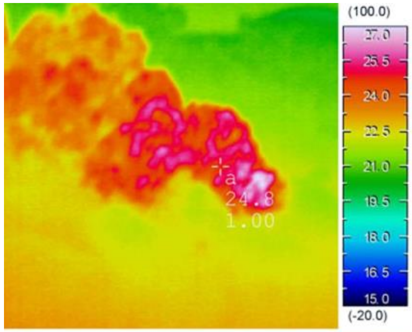
- In order to manipulate an image under the HSI model we:
  - First convert it from RGB to HSI
  - Perform our manipulations under HSI
  - Finally convert the image back from HSI to RGB

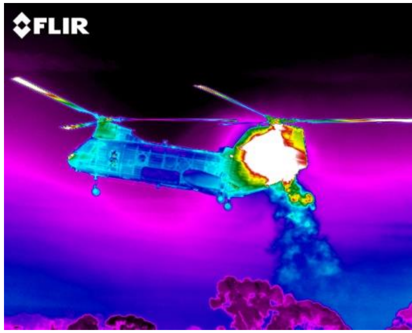


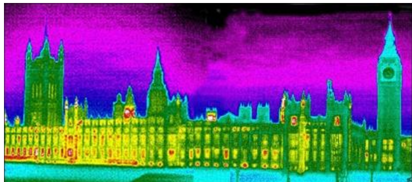
Pseudocolor Image Processing

- Pseudocolor (also called false color) image processing consists of assigning colors to grey values based on a specific criterion

- The principle use of pseudocolor image processing is for human visualization



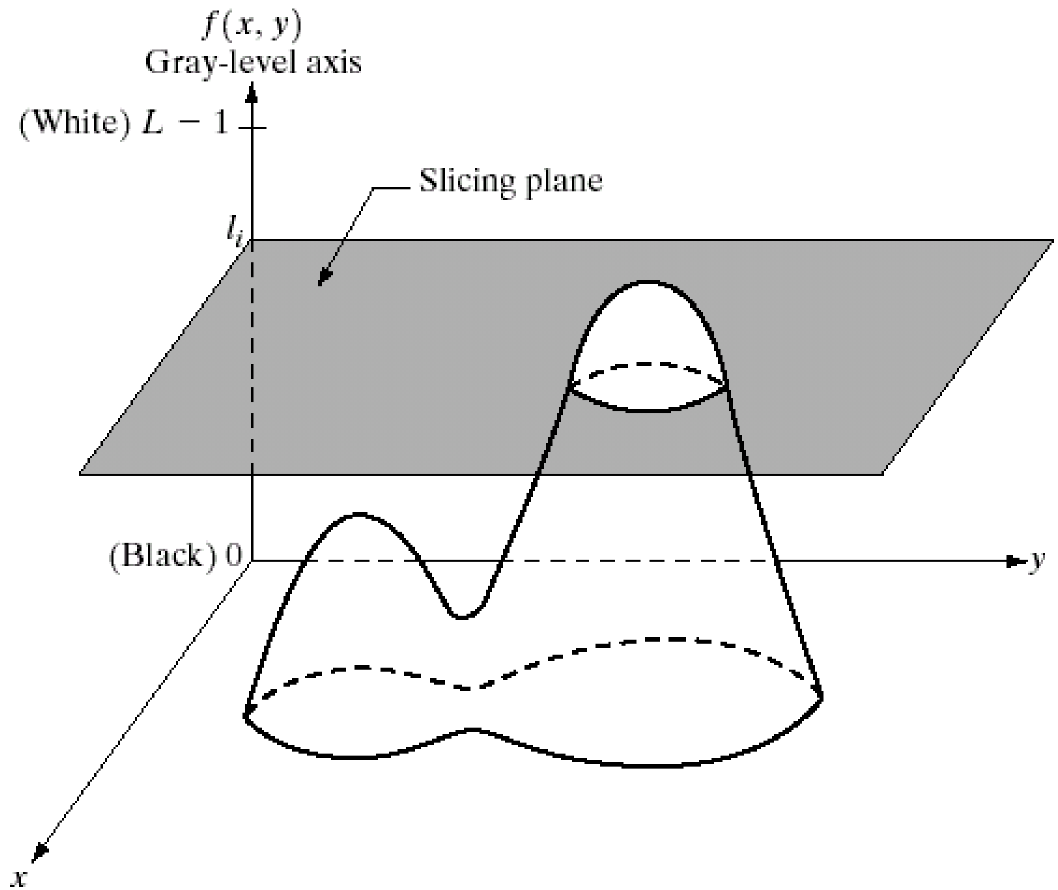




Pseudo Color Image Processing – Intensity Slicing

- Intensity slicing and color coding is one of the simplest kinds of pseudocolor image processing
- First we consider an image as a 3D function mapping spatial coordinates to intensities (that we can consider heights)
- Now consider placing planes at certain levels parallel to the coordinate plane
- If a value is one side of such a plane it is rendered in one color, and a different color if on the other side

Pseudo Color Image Processing – Intensity Slicing



Pseudo Color Image Processing – Intensity Slicing

- In general intensity slicing can be summarized as:
  - Let [$0, L-1$] represent the grey scale
  - Let l_0 represent black [$f(x, y) = 0$] and let l_{L-1} represent white [$f(x, y) = L-1$]
  - Suppose P planes perpendicular to the intensity axis are defined at levels $l_1, l_2, \ldots, l_p$
  - Assuming that $0 < P < L-1$ then the P planes partition the grey scale into $P + 1$ intervals $V_1, V_2, \ldots, V_{P+1}$

Pseudo Color Image Processing – Intensity Slicing

– Grey level color assignments can then be made according to the relation:

$$f(x,y) = c_k \qquad \text{if } f(x,y) \in V_k$$

– where c_k is the color associated with the k^{th} intensity level V_k defined by the partitioning planes at $l = k - 1$ and $l = k$

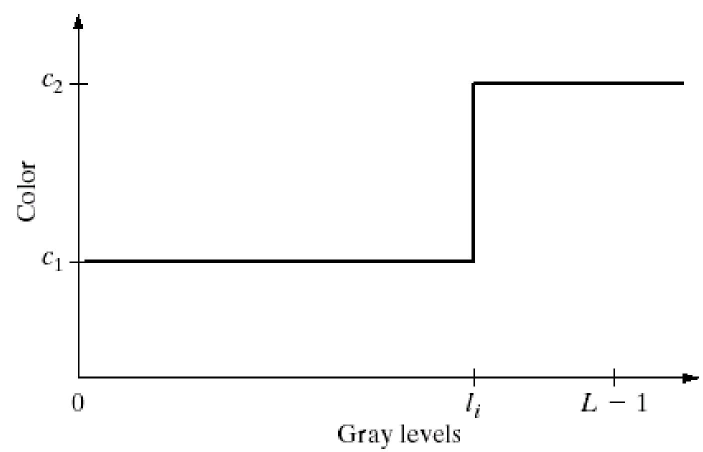
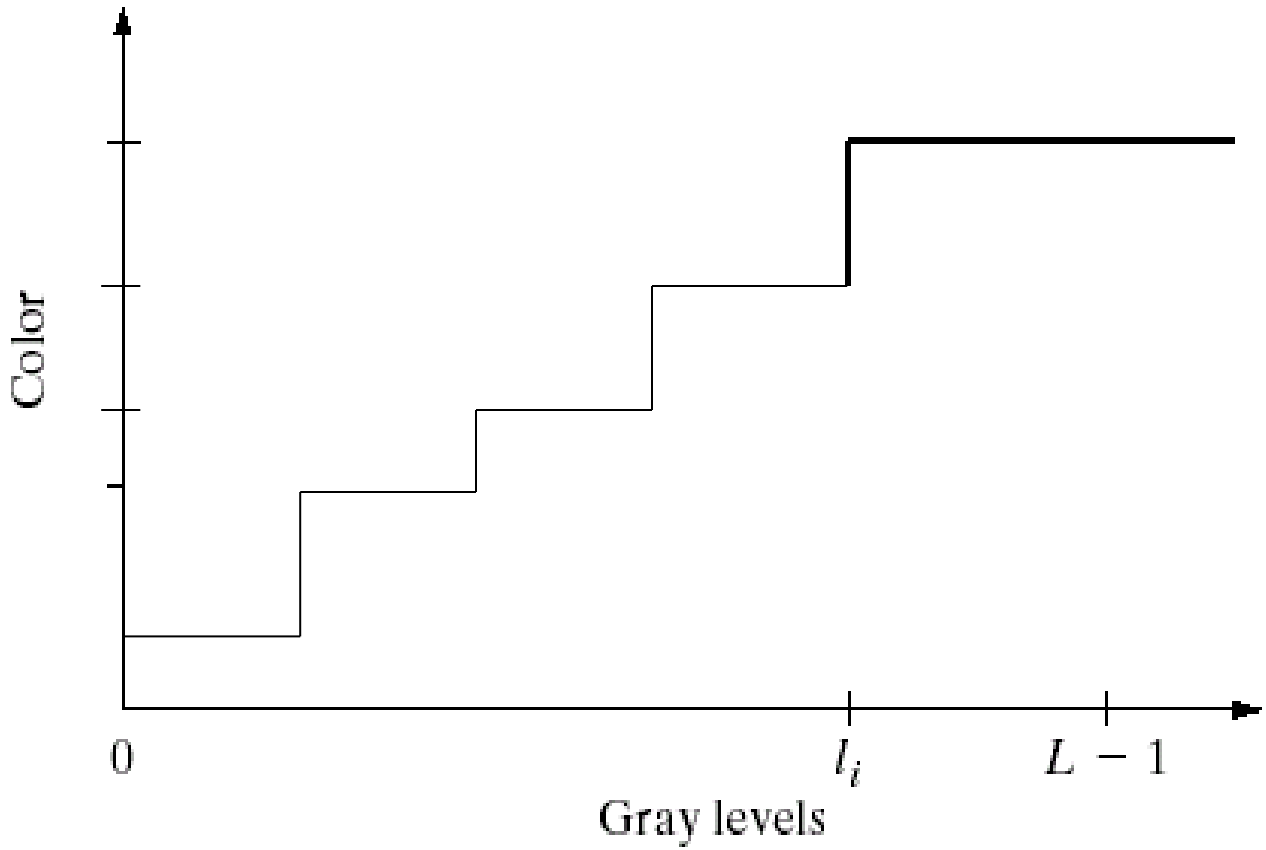


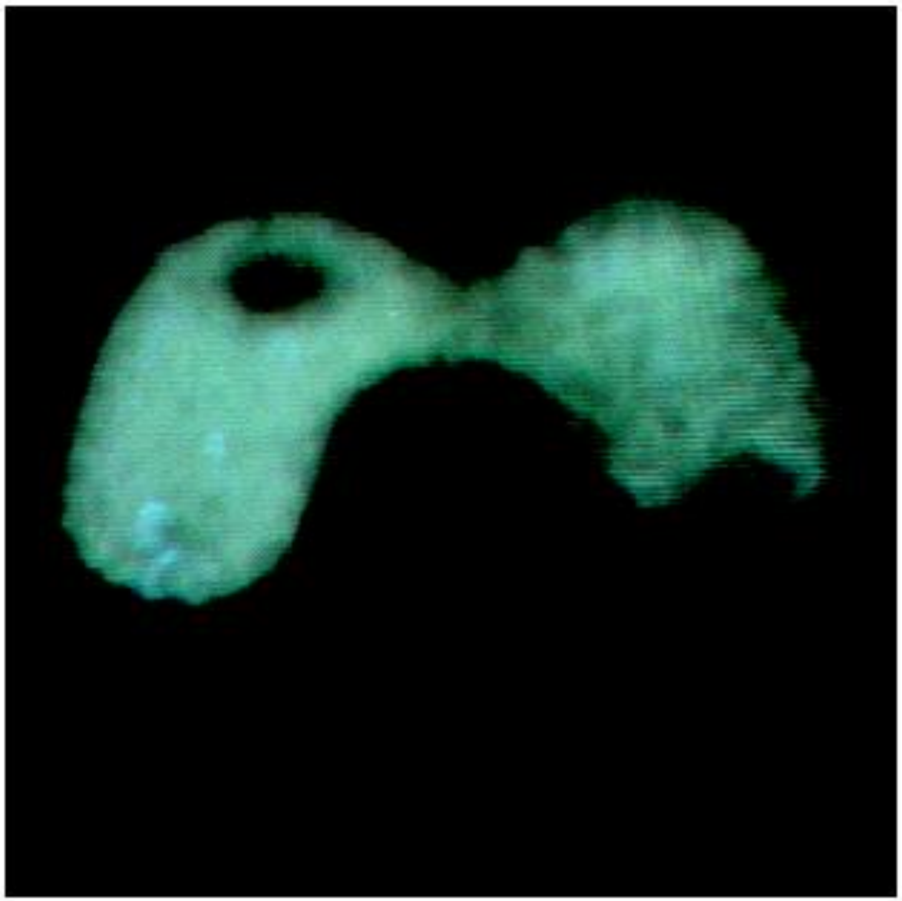
FIGURE 6.19 An alternative representation of the intensity-slicing technique.

Intensity slicing (cont.)

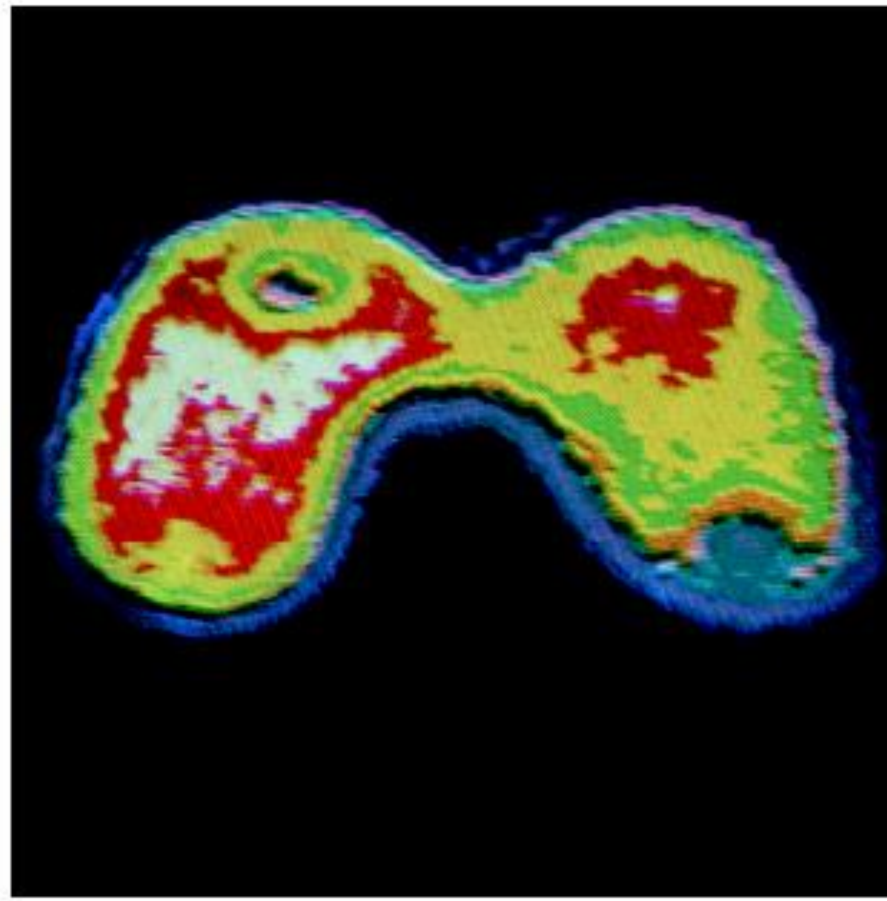
- More slicing plane, more colors



Pseudo Color Image Processing – Intensity Slicing

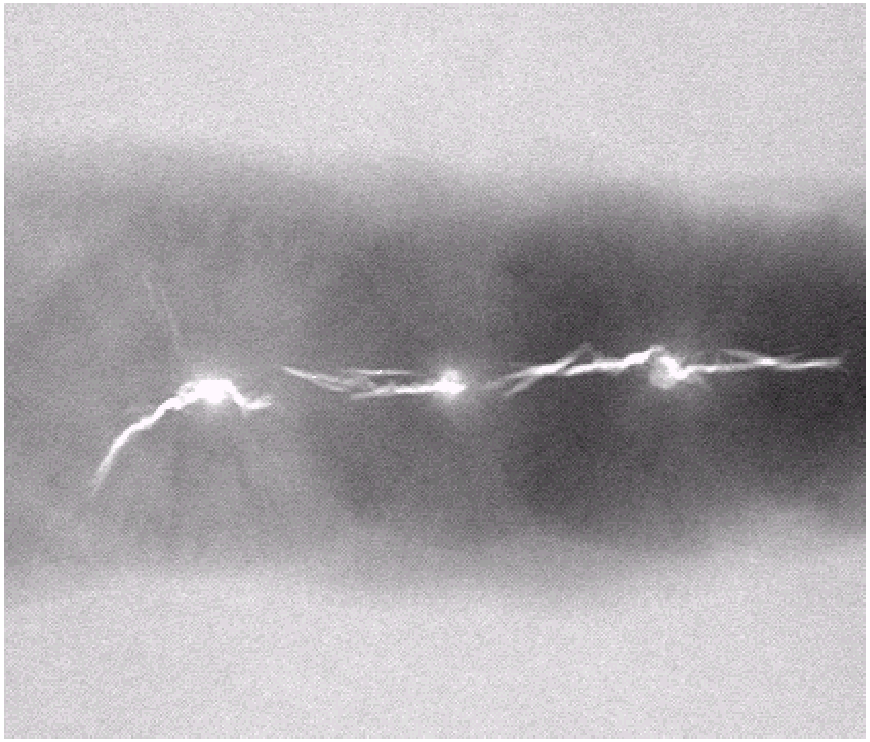


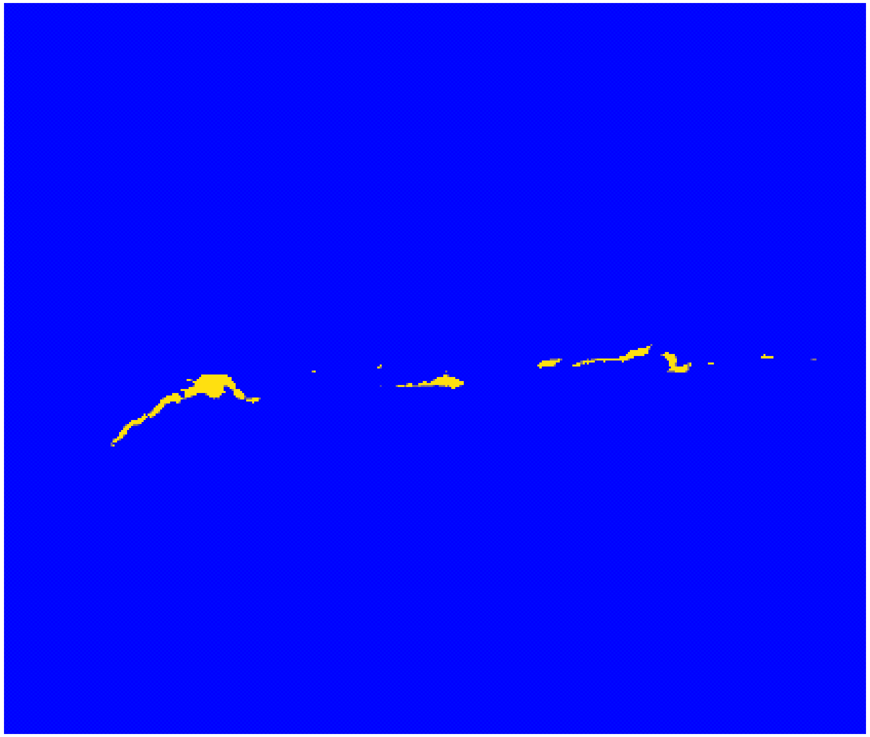
Radiation test pattern



8 color regions

Pseudo Color Image Processing – Intensity Slicing





Gray level to color transformation

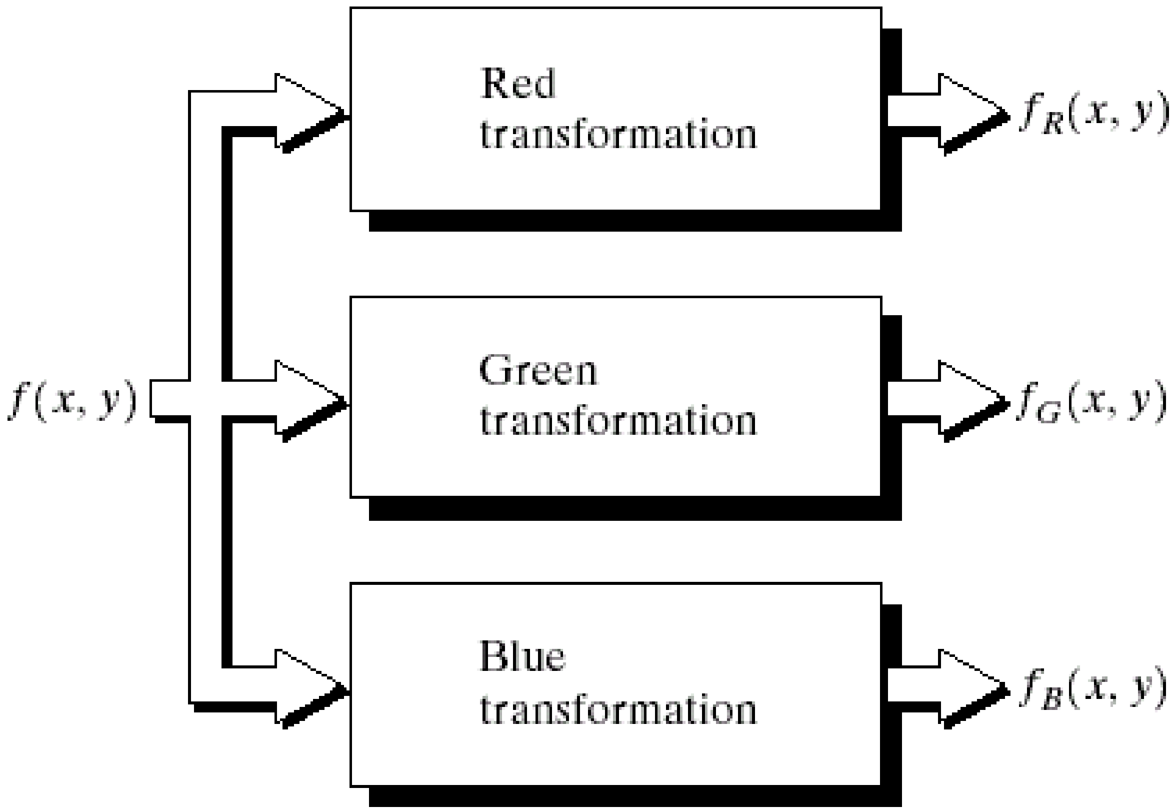


FIGURE 6.23 Functional block diagram for pseudocolor image processing. f_R, f_G, and f_B are fed into the corresponding red, green, and blue inputs of an RGB color monitor.

Color pixel

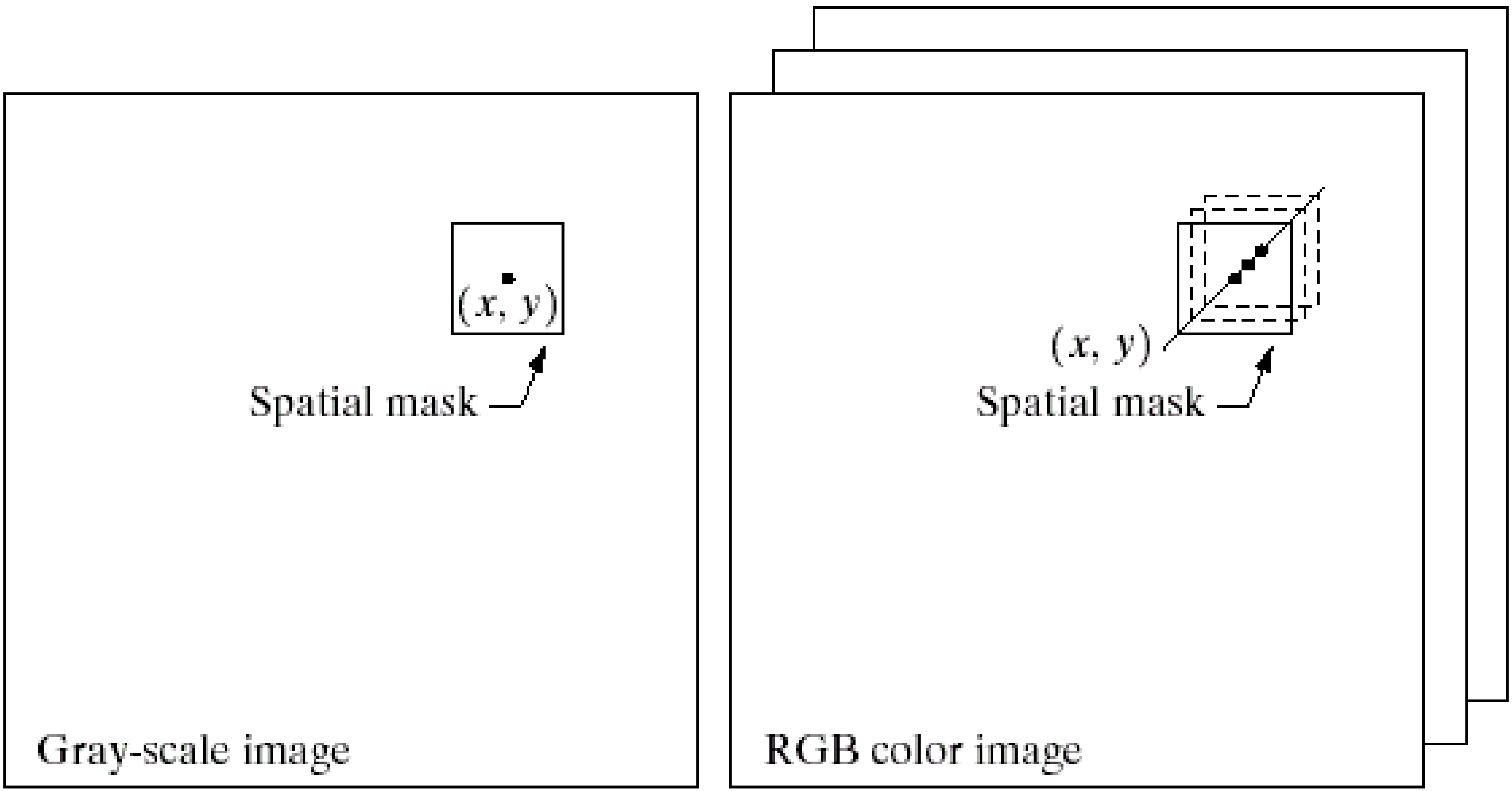
- A pixel at (x,y) is a vector in the color space
  - RGB color space

$$\mathbf{c}(x,y) = \begin{bmatrix} R(x,y) \\ G(x,y) \\ B(x,y) \end{bmatrix}$$

c.f. gray-scale image

f(x,y) = I(x,y)

Example: spatial mask



How to deal with color vector?

- Per-color-component processing
  - Process each color component
- Vector-based processing
  - Process the color vector of each pixel
- When can the above methods be equivalent?
  - Process can be applied to both scalars and vectors
  - Operation on each component of a vector must be independent of the other component

Two spatial processing categories

- Similar to gray scale processing studied before, we have to major categories
- Pixel-wise processing
- Neighborhood processing

COLOR IMAGE - SMOOTHING

- Smoothing can be viewed as a spatial filtering operation in which the coefficients of the filtering mask are all 1's
- This concept can be easily extended to the processing of full-color images
- Simply smooth each of the RGB color planes and then combine the processed planes to form a smoothed full-color result

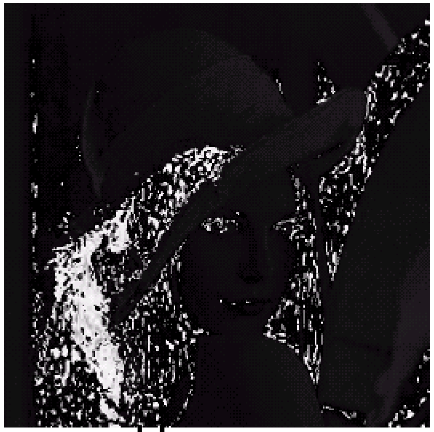
$$\hat{\mathbf{C}}(x,y) = \frac{1}{MN}\begin{bmatrix} \sum_{(x,y)\in S_{xy}} R(x,y) \\ \sum_{(x,y)\in S_{xy}} G(x,y) \\ \sum_{(x,y)\in S_{xy}} B(x,y) \end{bmatrix}$$

original

R

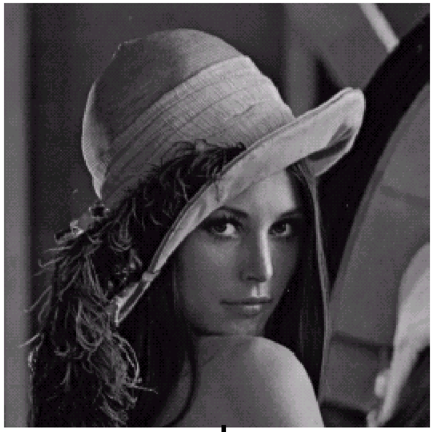
G

G



H

S



I

Example: 5x5 smoothing mask

RGB model

Smooth I
in HSI model

difference

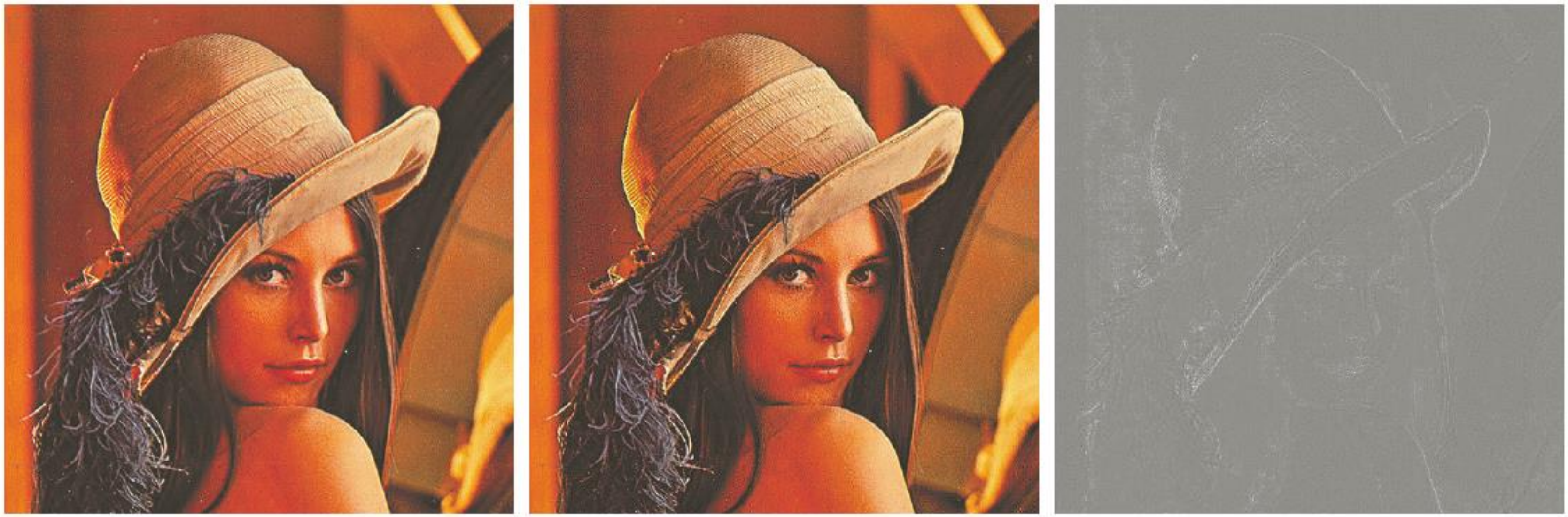
a b c

FIGURE 6.40 Image smoothing with a 5 × 5 averaging mask. (a) Result of processing each RGB component image. (b) Result of processing the intensity component of the HSI image and converting to RGB. (c) Difference between the two results.

Color Image Sharpening

The Laplacian of vector c is

$$\nabla^2 \left[c(x,y) \right] = \begin{bmatrix} \nabla^2 R(x,y) \\ \nabla^2 G(x,y) \\ \nabla^2 B(x,y) \end{bmatrix}$$



a b c

FIGURE 6.41 Image sharpening with the Laplacian. (a) Result of processing each RGB channel. (b) Result of processing the HSI intensity component and converting to RGB. (c) Difference between the two results.

Color Edge Detection (1)

Let r, g, and b be unit vectors along the R, G, and B axis of RGB color space, and define vectors

$$\mathrm{u} = \frac{\partial R}{\partial x}\mathrm{r} + \frac{\partial G}{\partial x}\mathrm{g} + \frac{\partial B}{\partial x}\mathrm{b}$$

and

$$\mathrm{v} = \frac{\partial R}{\partial y}\mathrm{r} + \frac{\partial G}{\partial y}\mathrm{g} + \frac{\partial B}{\partial y}\mathrm{b}$$

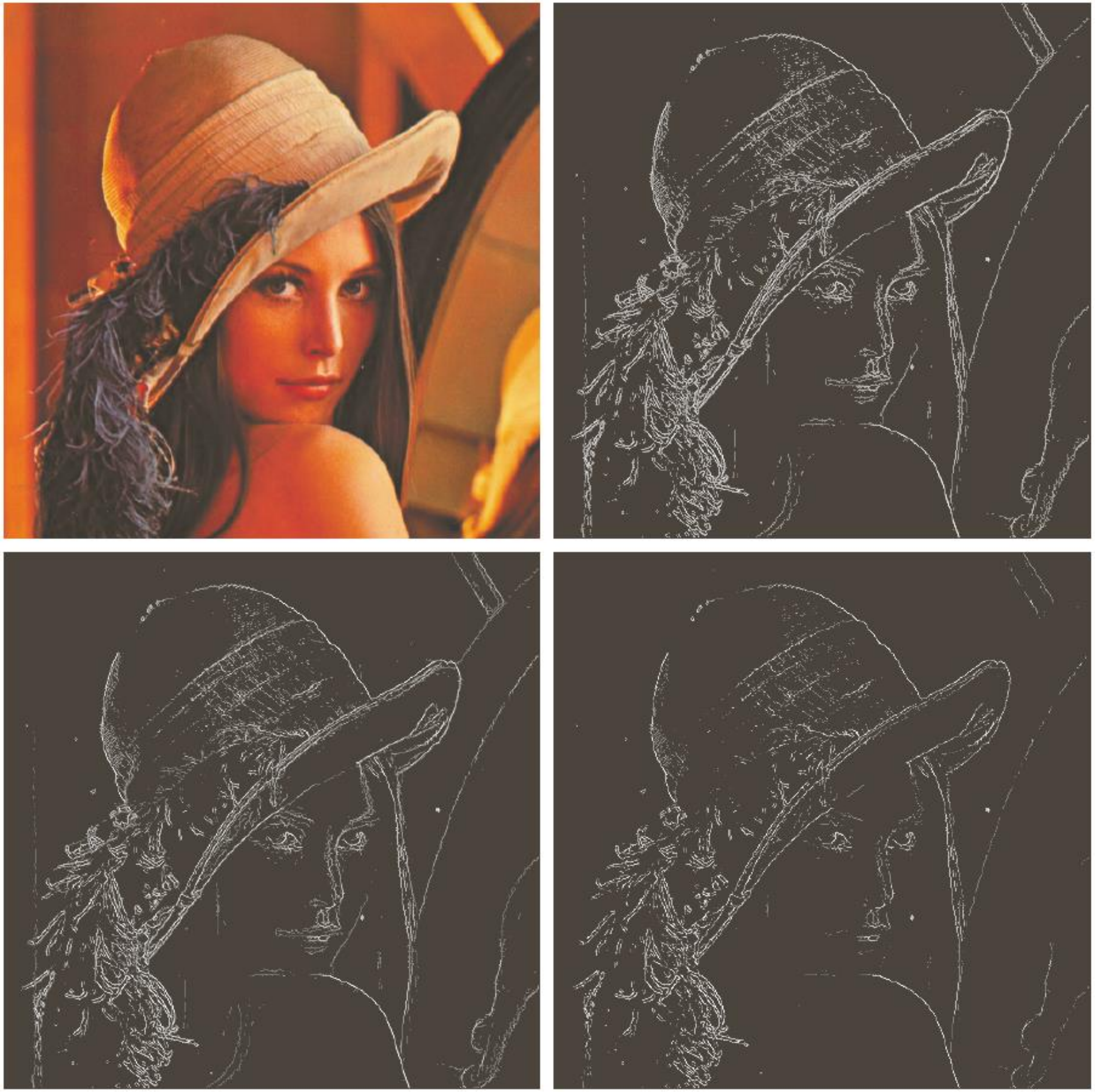
Color Edge Detection (2)

$$g_{xx} = \mathbf{u}\cdot\mathbf{u} = \left|\frac{\partial R}{\partial x}\right|^2 + \left|\frac{\partial G}{\partial x}\right|^2 + \left|\frac{\partial B}{\partial x}\right|^2$$

$$g_{yy} = \mathbf{v}\cdot\mathbf{v} = \left|\frac{\partial R}{\partial y}\right|^2 + \left|\frac{\partial G}{\partial y}\right|^2 + \left|\frac{\partial B}{\partial y}\right|^2$$

and

$$g_{xy} = \mathbf{u}\cdot\mathbf{v} = \frac{\partial R}{\partial x}\frac{\partial R}{\partial y} + \frac{\partial G}{\partial x}\frac{\partial G}{\partial y} + \frac{\partial B}{\partial x}\frac{\partial B}{\partial y}$$



a	b
c	d

FIGURE 6.46 (a) RGB image. (b) Gradient computed in RGB color vector space. (c) Gradients computed on a per-image basis and then added. (d) Difference between (b) and (c).

Texture Based Descriptors

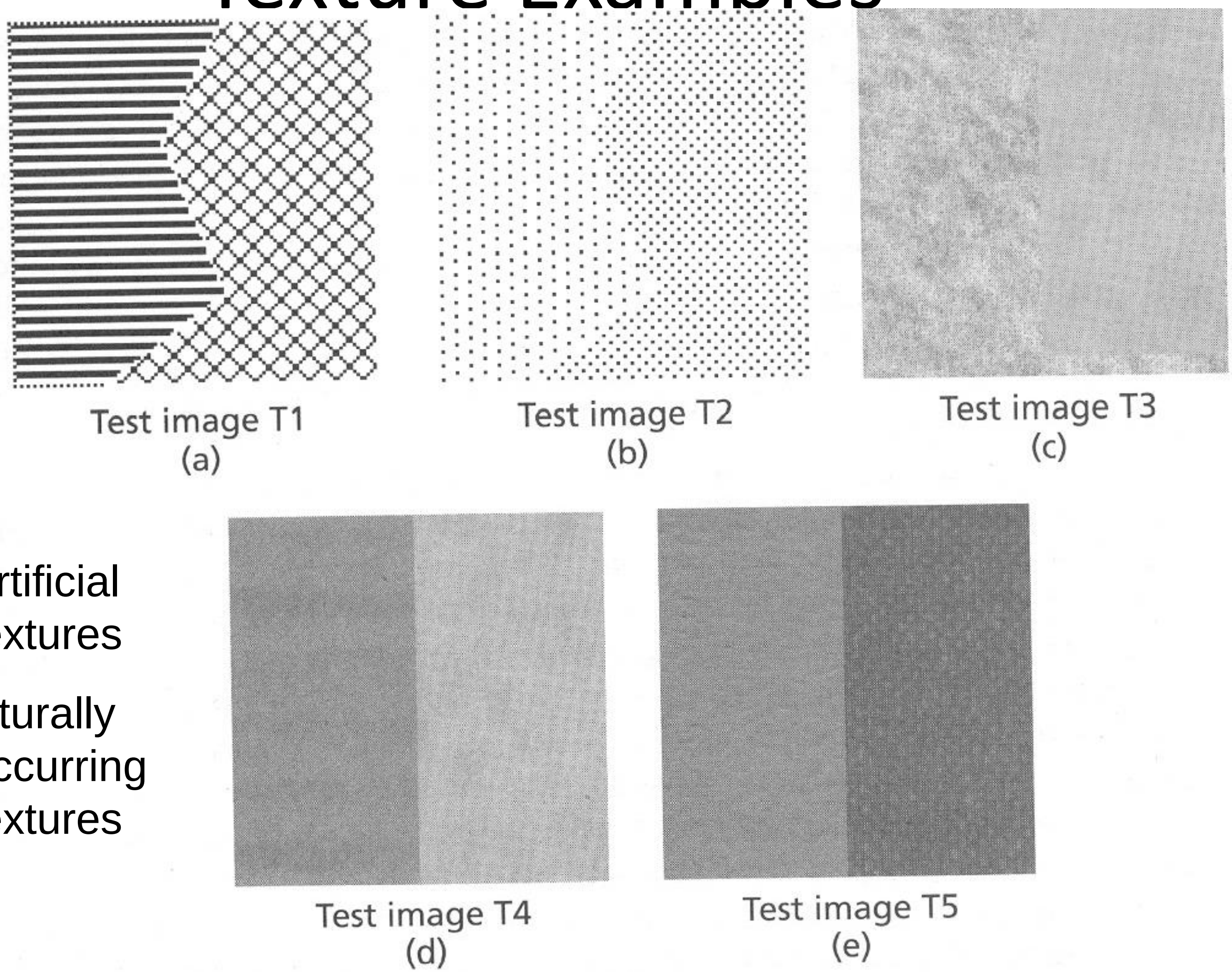
Texture

- Organized patterns of quite regular subelements called textons.
- Texture is a property of sufficiently large regions

Applications:

- Texture based segmentation
- Texture synthesis
- Texture analysis and texture based matching
- Shape (surface orientation) from texture

Texture Examples



Test image T1
(a)

Test image T2
(b)

Test image T3
(c)

Test image T4
(d)

Test image T5
(e)

(a,b): Artificial textures

(c,d,e): Naturally occurring textures

Representing textures

Statistical

yields characterization of textures as smooth, coarse grainy, etc.

Spectral

are based on Fourier spectrum and are primarily used to detect the global periodicity in an image by identifying high energy narrow peaks in the spectrum.

Statistical approaches

- Based on the histogram measures of image
- Based on the Grey Level Co-occurrence Matrix (GLCM) and related measurement

Histogram based texture description

Using statistical moments of grey level histogram of the image or region

Let $p(z_i)$ is the histogram of the grey levels z_i of an image

The nth moment about the mean is given by:

$$\mu_n(z) = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i)$$

Where mean is $$m = \sum_{i=0}^{L-1} z_i p(z_i)$$

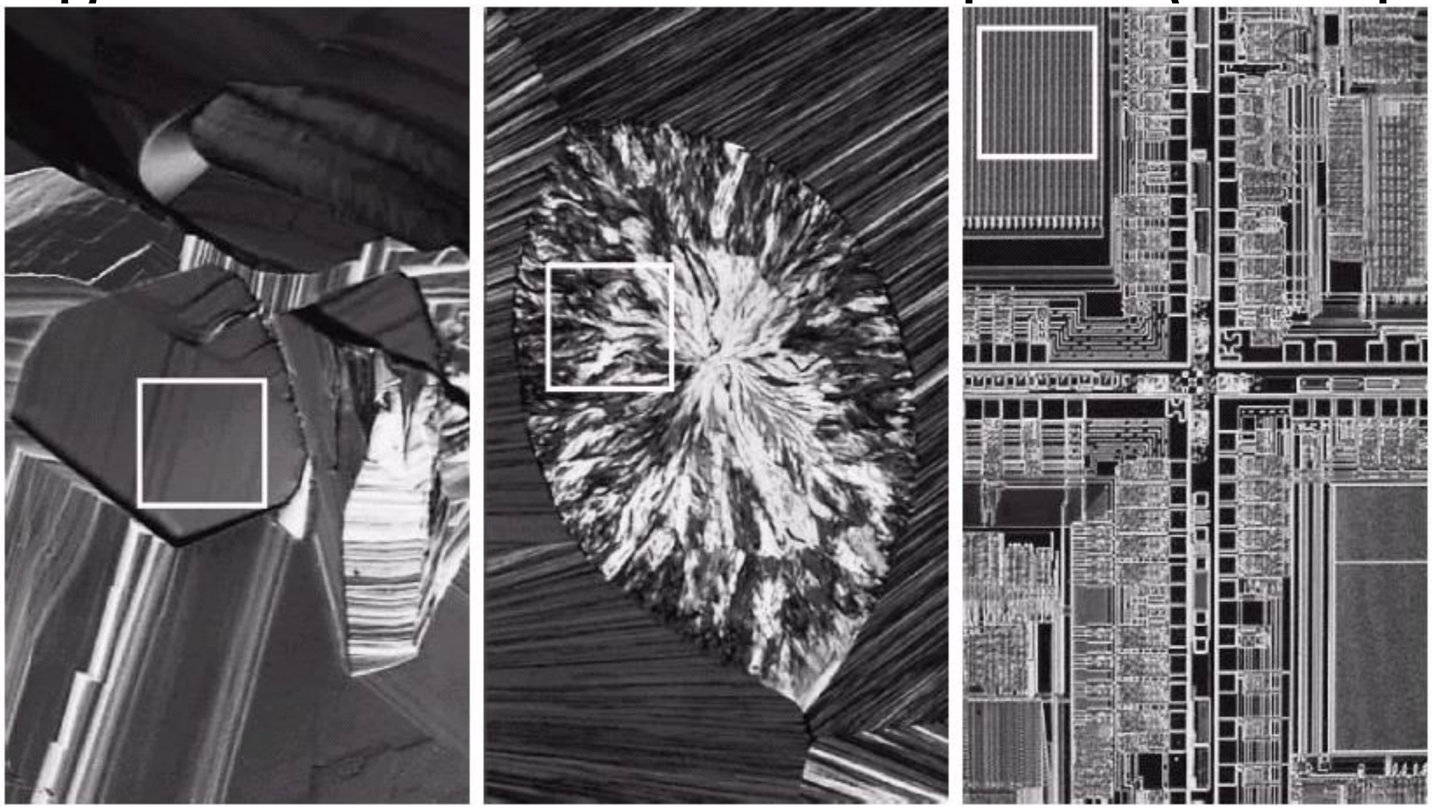
The variance is the second moment and is given by

$$\sigma^2(z) = \mu_2(z) = \sum_{i=0}^{L-1} (z_i - m)^2 p(z_i)$$

Histogram based texture description

- For texture description the following parameters are useful
  - Variance and related measures: descriptor of relative smoothness, use normalized variance $$R = 1 - \frac{1}{1+\sigma^2(z)}$$
  - Skewness of histogram $$\mu_3(z) = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$$
  - Relative flatness of histogram $$\mu_4(z) = \sum_{i=0}^{L-1} (z_i - m)^4 p(z_i)$$
  - Uniformity $$U = \sum_{i=0}^{L-1} p^2(z_i)$$
  - Average Entropy $$e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$$

Histogram based texture description (example)



Texture	Mean	Standard deviation	R (normalized)	Third moment	Uniformity	Entropy
Smooth	82.64	11.79	0.002	−0.105	0.026	5.434
Coarse	143.56	74.63	0.079	−0.151	0.005	7.783
Regular	99.72	33.73	0.017	0.750	0.013	6.674

GLCMs

- For texture description the following parameters of GLCM are measured and analyzed

Maximum probability

$$\max_{i,j}(c_{ij})$$

Contrast

$$\sum_i \sum_j (i-j)^2 c_{ij}$$

Uniformity

$$\sum_i \sum_j c_{ij}^2$$

Entropy

$$-\sum_i \sum_j c_{ij} \log_2 c_{ij}$$

FIGURE 11.29 How to generate a co-occurrence matrix.

1	1	7	5	3	2
5	1	6	1	2	5
8	8	6	8	1	2
4	3	4	5	5	1
8	7	8	7	6	2
7	8	6	2	6	2

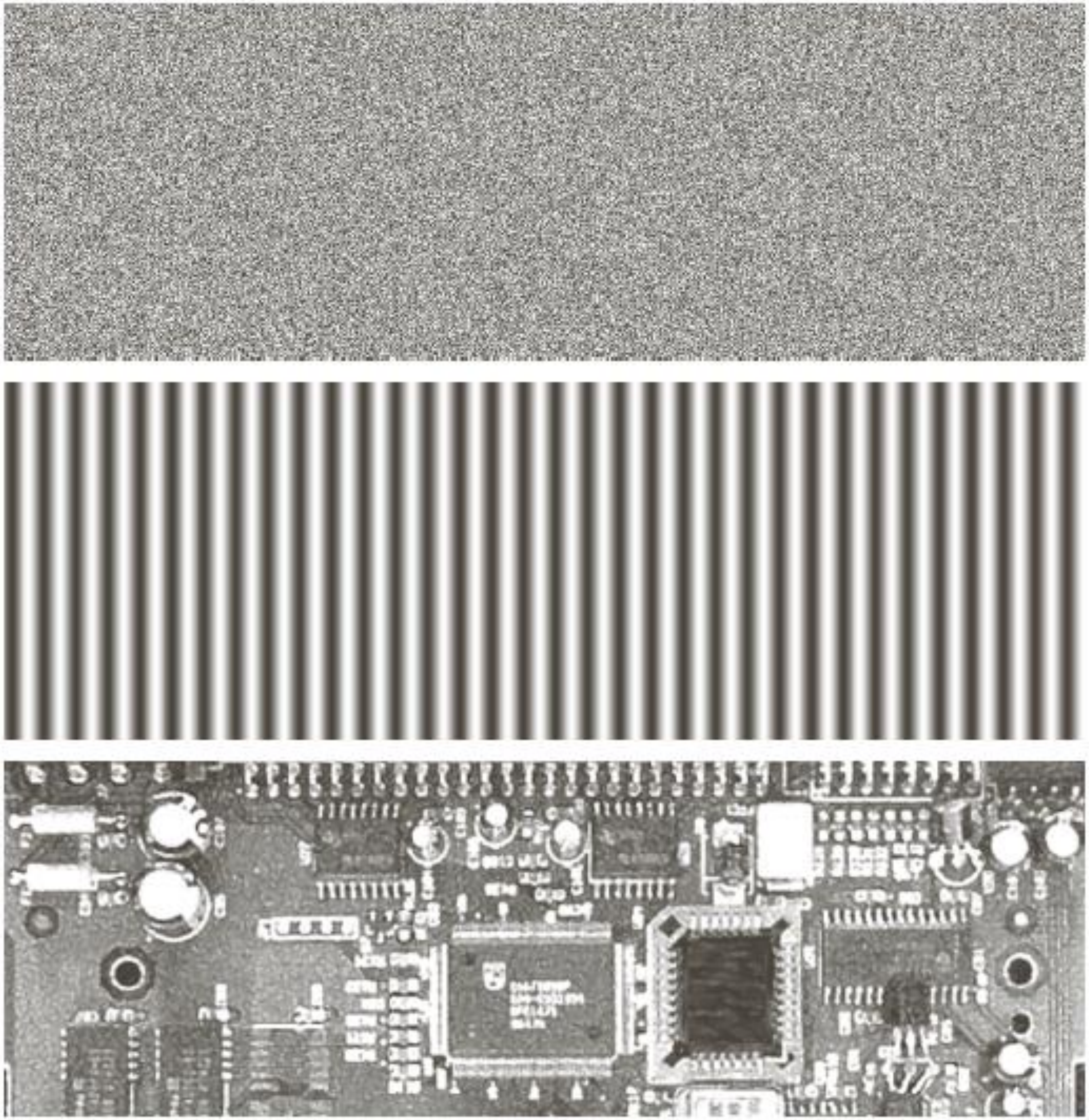
Image f

	1	2	3	4	5	6	7	8
1	1	2	0	0	0	1	1	0
2	0	0	0	0	1	1	0	0
3	0	1	0	1	0	0	0	0
4	0	0	1	0	1	0	0	0
5	2	0	1	0	1	0	0	0
6	1	3	0	0	0	0	0	1
7	0	0	0	0	1	1	0	2
8	1	0	0	0	0	2	2	1

Co-occurrence matrix **G**

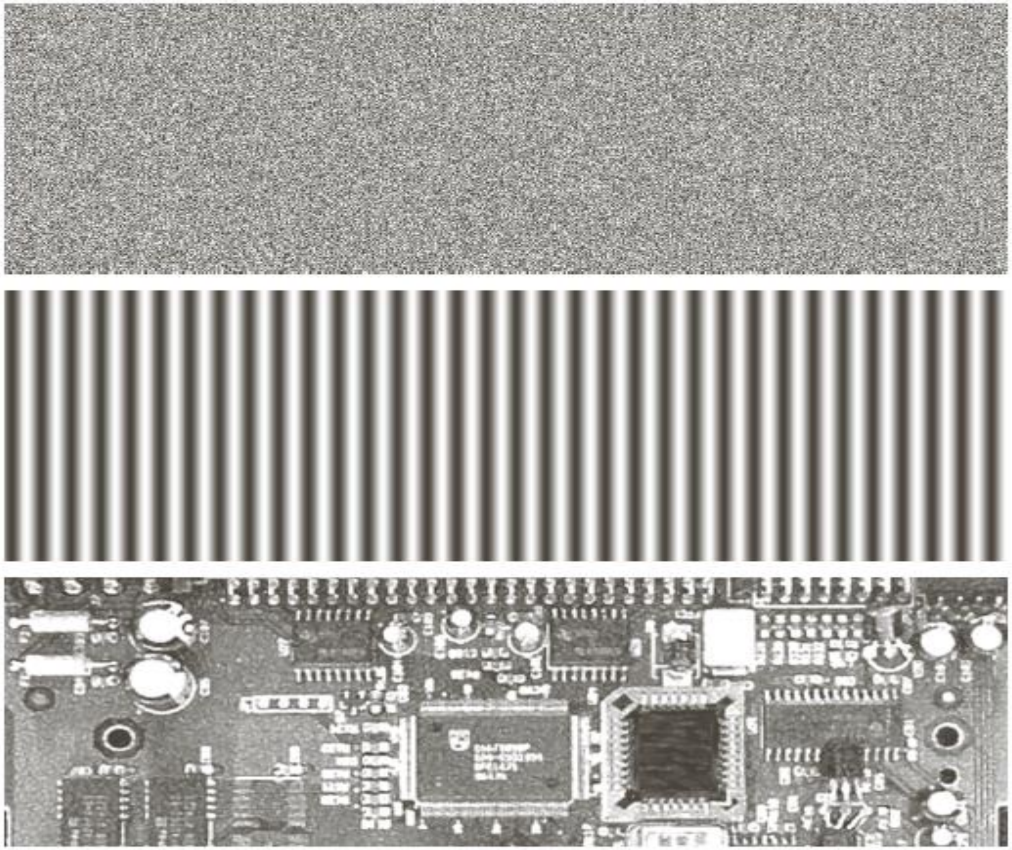
TABLE 11.3 Descriptors used for characterizing co-occurrence matrices of size $K \times K$. The term p_{ij} is the ijth term of **G** divided by the sum of the elements of **G**.

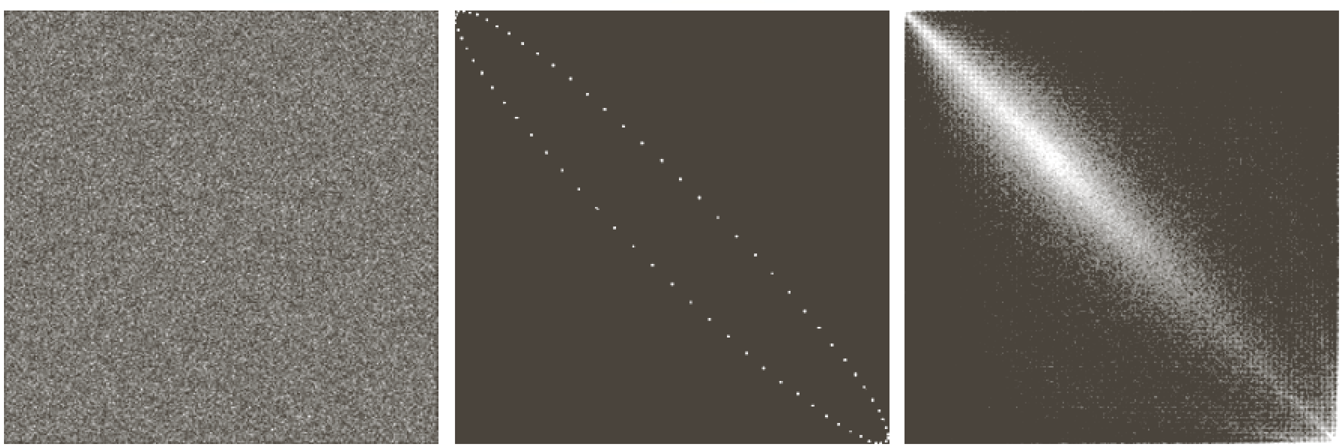
Descriptor	Explanation	Formula
Maximum probability	Measures the strongest response of **G**. The range of values is [0, 1].	$\max_{i,j}(p_{ij})$
Correlation	A measure of how correlated a pixel is to its neighbor over the entire image. Range of values is 1 to −1, corresponding to perfect positive and perfect negative correlations. This measure is not defined if either standard deviation is zero.	$\sum_{i=1}^{K}\sum_{j=1}^{K}\frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r\sigma_c}$ $\sigma_r \neq 0;\ \sigma_c \neq 0$
Contrast	A measure of intensity contrast between a pixel and its neighbor over the entire image. The range of values is 0 (when **G** is constant) to $(K-1)^2$.	$\sum_{i=1}^{K}\sum_{j=1}^{K}(i-j)^2 p_{ij}$
Uniformity (also called Energy)	A measure of uniformity in the range [0, 1]. Uniformity is 1 for a constant image.	$\sum_{i=1}^{K}\sum_{j=1}^{K}p_{ij}^2$
Homogeneity	Measures the spatial closeness of the distribution of elements in **G** to the diagonal. The range of values is [0, 1], with the maximum being achieved when **G** is a diagonal matrix.	$\sum_{i=1}^{K}\sum_{i=1}^{K}\frac{p_{ij}}{1+\lvert i-j\rvert}$
Entropy	Measures the randomness of the elements of **G**. The entropy is 0 when all p_{ij}'s are 0 and is maximum when all p_{ij}'s are equal. The maximum value is $2\log_2 K$. (See Eq. (11.3-9) regarding entropy).	$-\sum_{i=1}^{K}\sum_{i=1}^{K}p_{ij}\log_2 p_{ij}$



a
b
c

FIGURE 11.30 Images whose pixels have (a) random, (b) periodic, and (c) mixed texture patterns. Each image is of size 263×800 pixels.





a b c

FIGURE 11.31 256×256 co-occurrence matrices, $\mathbf{G}_1$, $\mathbf{G}_2$, and $\mathbf{G}_3$, corresponding from left to right to the images in Fig. 11.30.

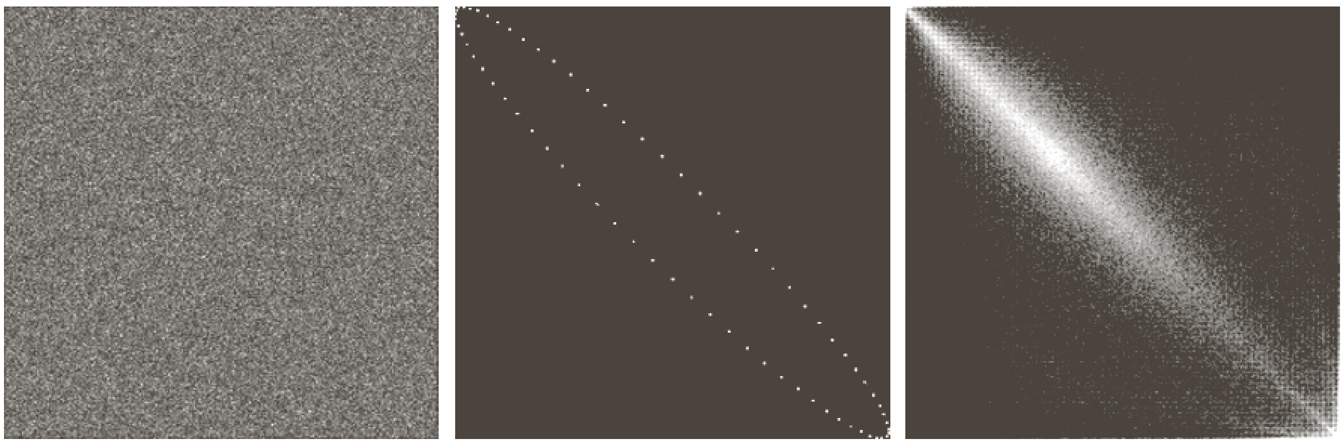


TABLE 11.4 Descriptors evaluated using the co-occurrence matrices displayed in Fig. 11.31.

Normalized Co-occurrence Matrix	Descriptor: Max Probability	Correlation	Contrast	Uniformity	Homogeneity	Entropy
$\mathbf{G}_1/n_1$	0.00006	−0.0005	10838	0.00002	0.0366	15.75
$\mathbf{G}_2/n_2$	0.01500	0.9650	570	0.01230	0.0824	6.43
$\mathbf{G}_3/n_3$	0.06860	0.8798	1356	0.00480	0.2048	13.58

Spectral Texture Analysis

Spectral techniques: Fourier transform

- Suitable to detect directionality of periodic and almost periodic 2-D patterns in an image
- Periodic texture patterns are easily detectable by concentration of high energy burst in the spectrum
- Features of Fourier spectrum for texture representation are:
  - Prominent peaks in the spectrum give the principal direction of texture patterns
  - The location of peaks give the frequency and thus the scale of repetition of a pattern
- Eliminating any periodic components via filtering leaves non-periodic image elements which can be described by statistical techniques

Spectral techniques: Fourier transform

- Simplified by expressing the spectrum in polar coordinates to yield a function $S(r, \theta)$ where S is the spectrum function and r and θ are the polar coordinates.

  For each direction θ, $S(r, \theta)$ = a 1-D function $S_\theta(r)$

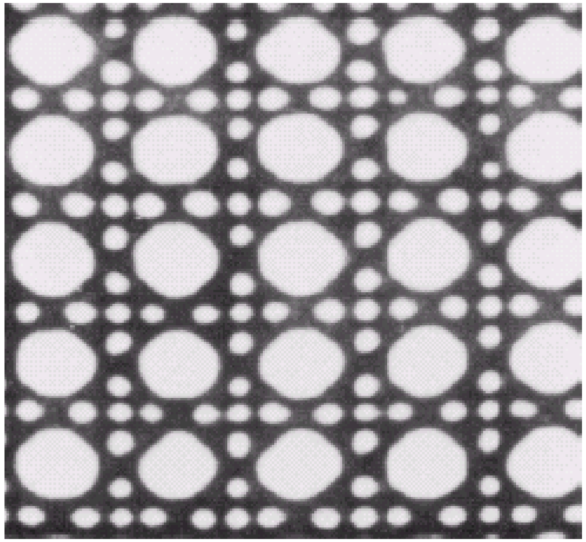
  For each frequency r, $S(r, \theta)$ = a 1-D function $S_r(\theta)$
- Analyzing $S_\theta(r)$ for a fixed θ, gives the distance from the origin and thus the scale of repetition of a texture pattern.
- Analyzing $S_r(\theta)$ for a fixed r, gives the direction and thus the orientation of the periodic texture pattern.
- To measure this analysis, we define two quantities

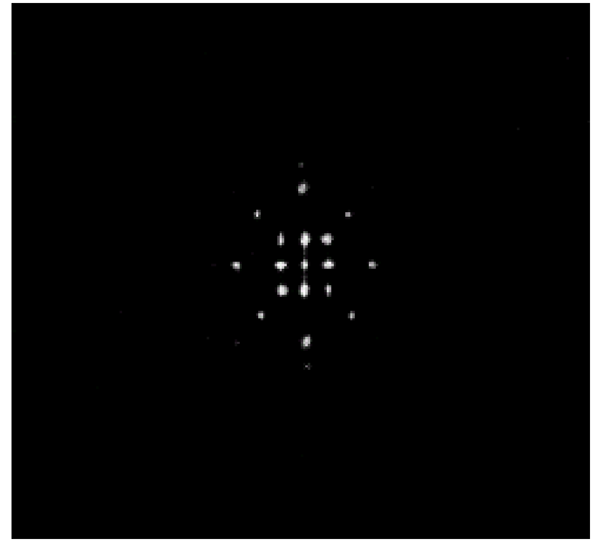
$$S(r) = \sum_{\theta=0}^{\pi} S_\theta(r), \qquad S(\theta) = \sum_{r=1}^{R_0} S_r(\theta).$$

These quantities measure the spectral response and give the dominant directions and scales of periodic texture patterns.

Spectral techniques: Fourier transform

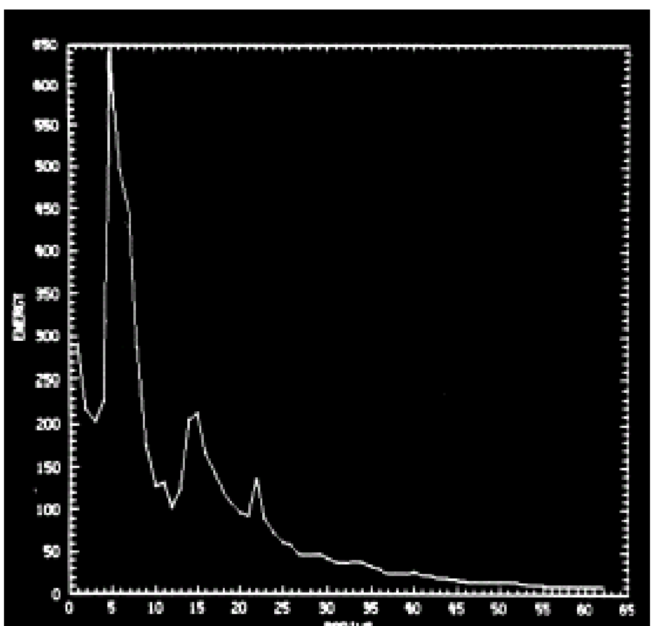
Image showing periodic texture

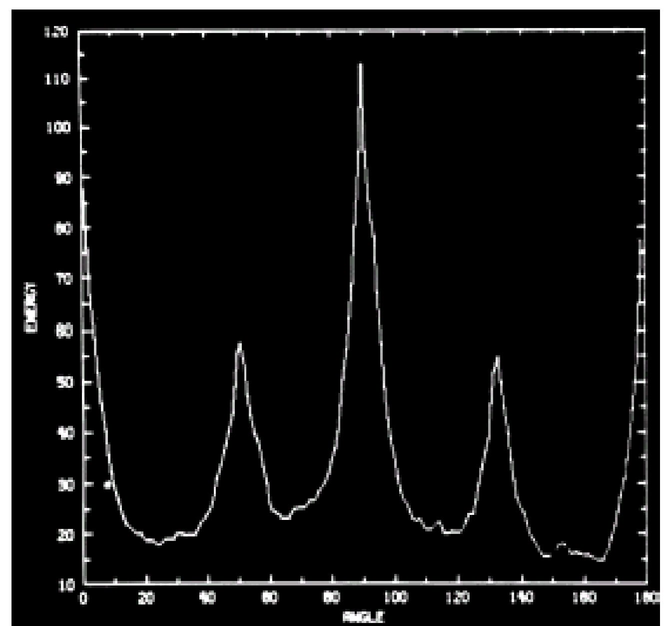




Spectrum

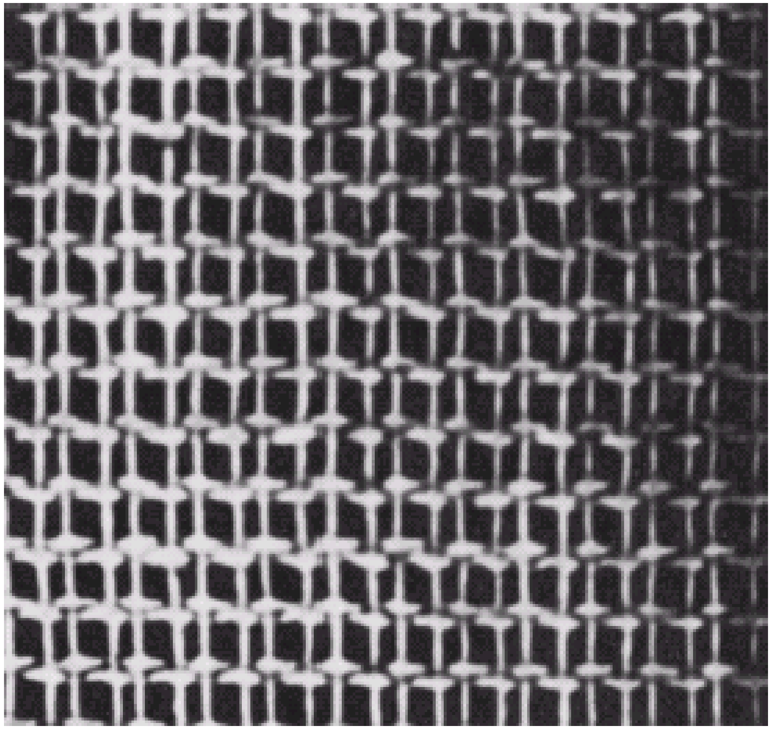
Plot of $S(r)$



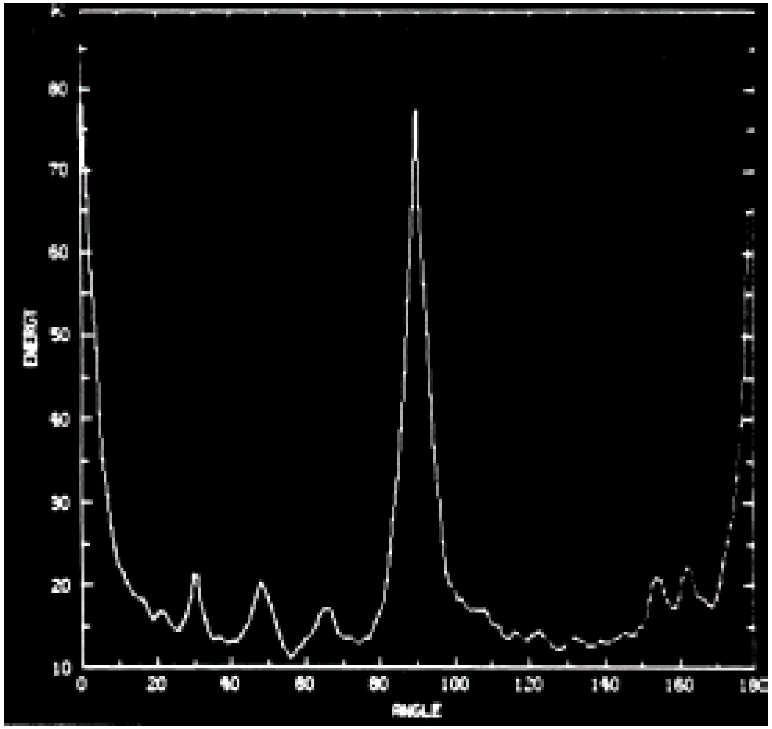


Plot of $S(\theta)$

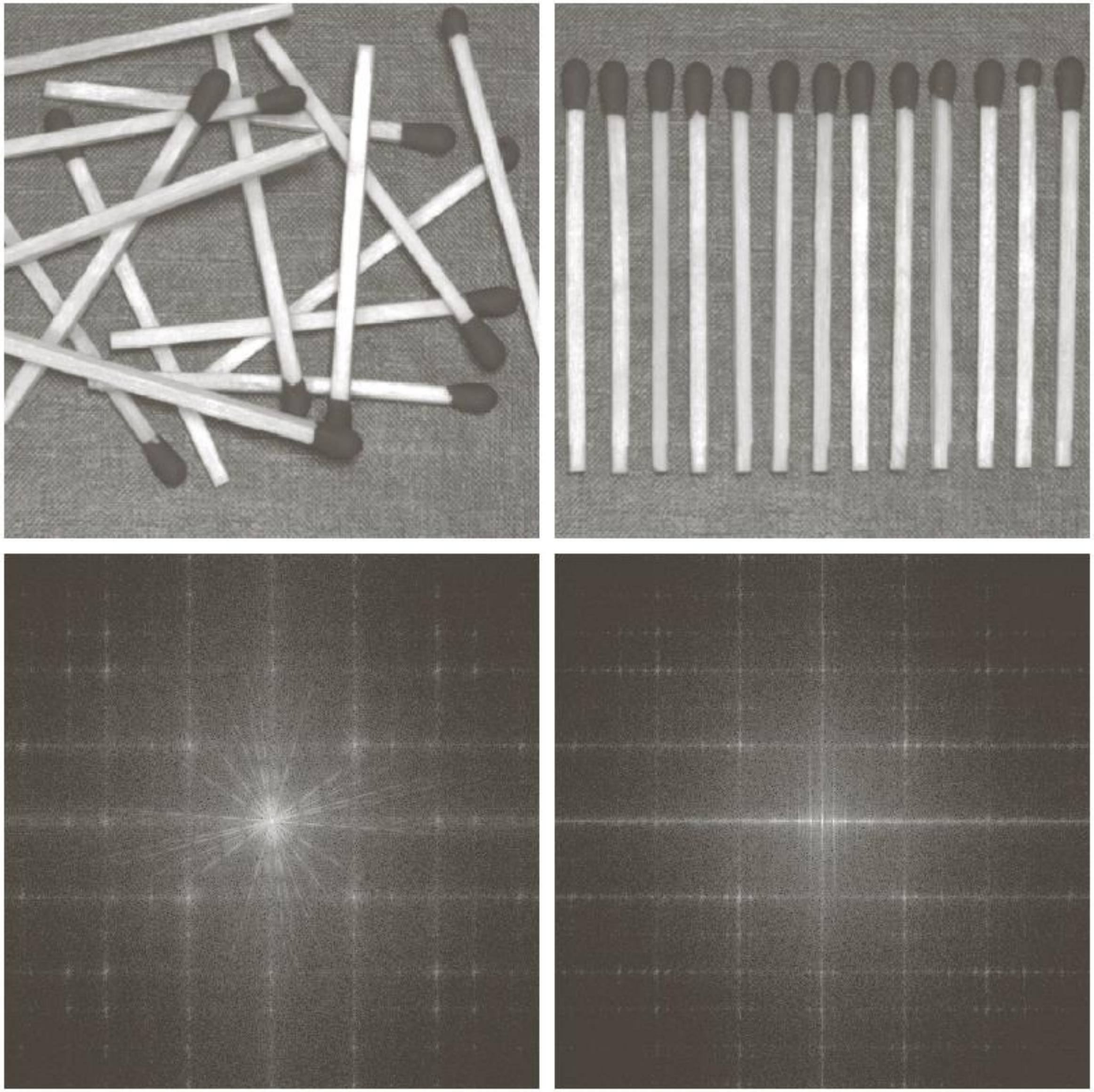
Spectral techniques: Fourier transform (example)



Another image showing periodic texture

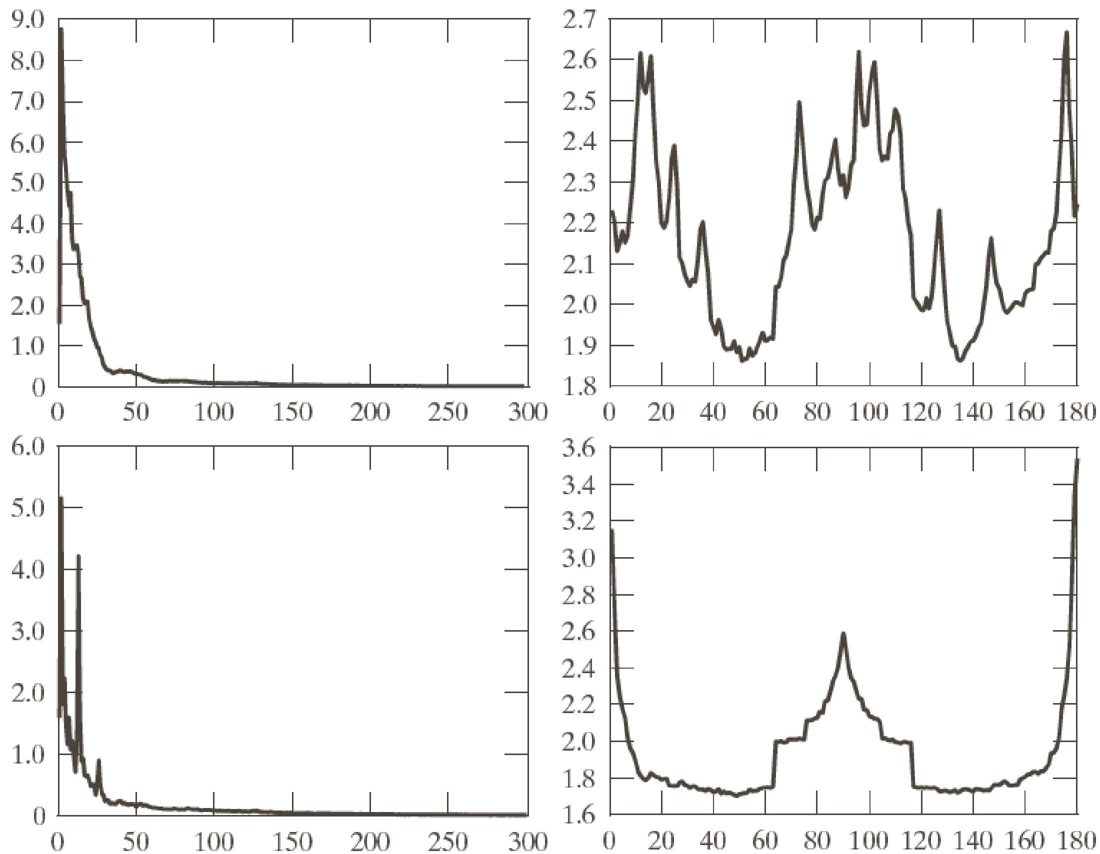


Plot of $S(\theta)$



a b
c d

FIGURE 11.35 (a) and (b) Images of random and ordered objects. (c) and (d) Corresponding Fourier spectra. All images are of size 600×600 pixels.



a	b
c	d

FIGURE 11.36 Plots of (a) $S(r)$ and (b) $S(\theta)$ for Fig. 11.35(a). (c) and (d) are plots of $S(r)$ and $S(\theta)$ for Fig. 11.35(b). All vertical axes are $\times 10^5$.

Readings from Book (3rd Edn.)

- Texture (Chapter-11)

Reading Assignment:

- Table-11.3, 11.4

Readings from Book (3rd Edn.)

- Color Processing Chapter-6

Acknowledgements

- Digital Image Processing", Rafael C. Gonzalez & Richard E. Woods, Addison-Wesley, 2002
- Computer Vision: Algorithms and Applications Richard Szeliski

Material in these slides has been taken from, the following resources