Color Image Processing
with Biomedical Applications

Rangaraj M. Rangayyan,
Begoña Acha, and Carmen Serrano

University of Calgary, Calgary, Alberta, Canada
University of Seville, Spain

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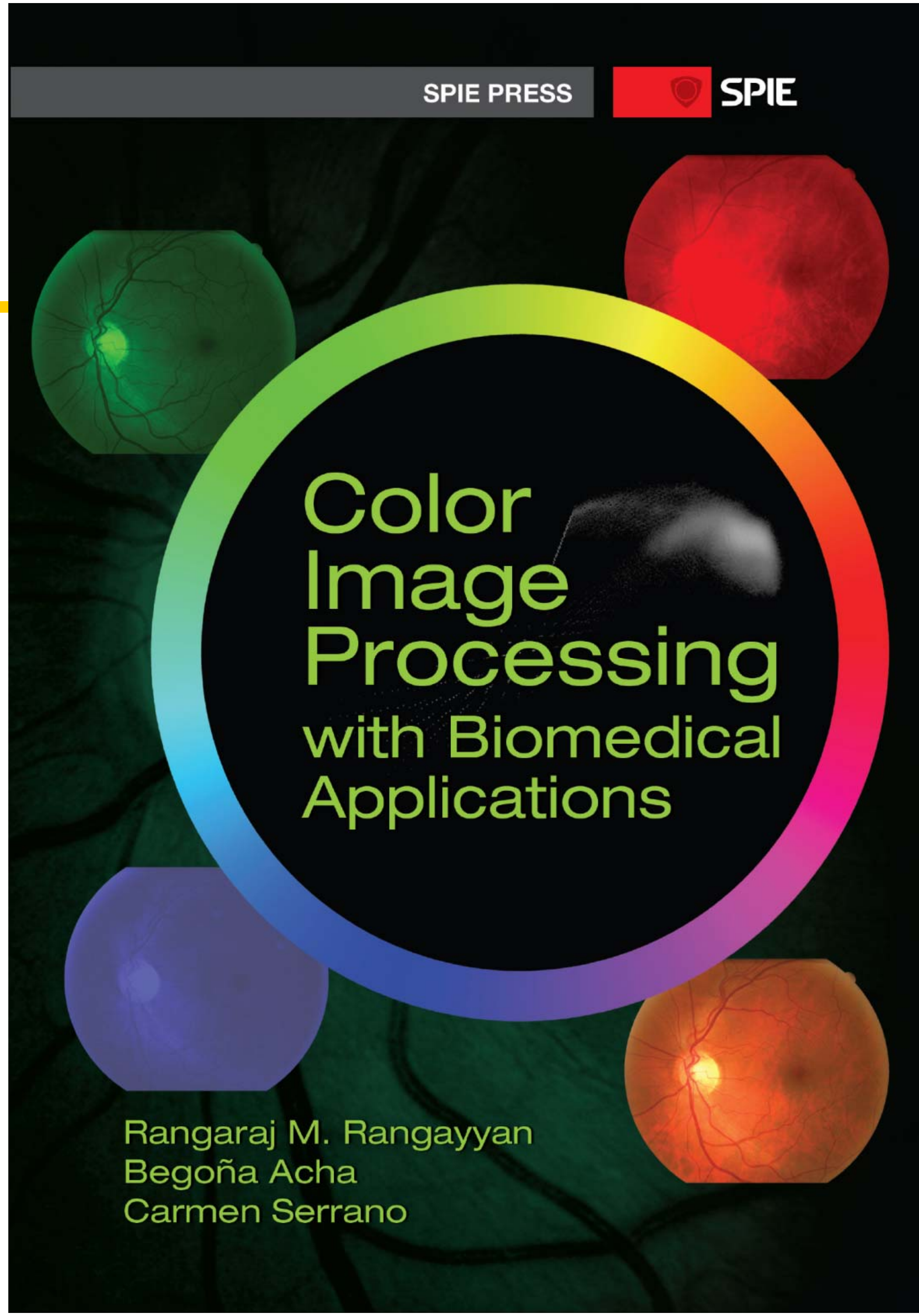

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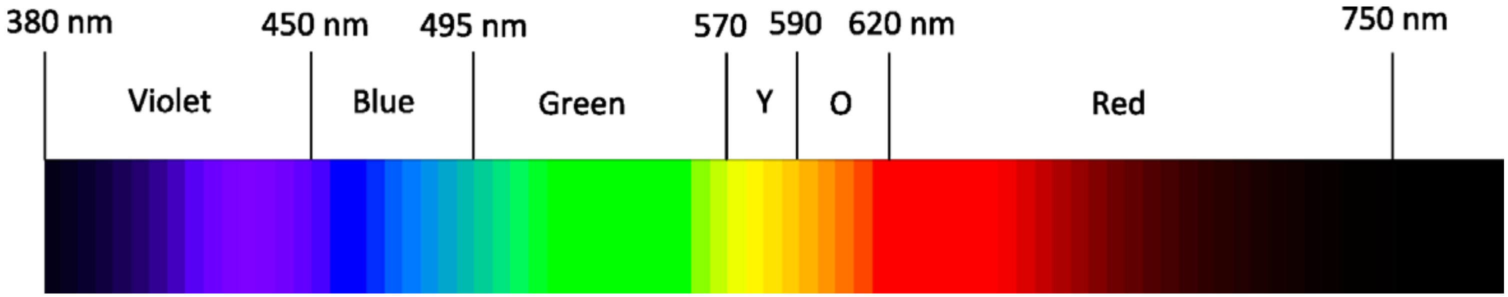
The Nature of Color Images

Photo courtesy of Chris Pawluk



Color Attributes

Hue: dominant wavelength or band

Saturation: quality or colorfulness, not diluted with white

Intensity or Brightness: primary visual sensation related to physical luminance

Also used: Chroma, Lightness

Color Perception and Trichromacy

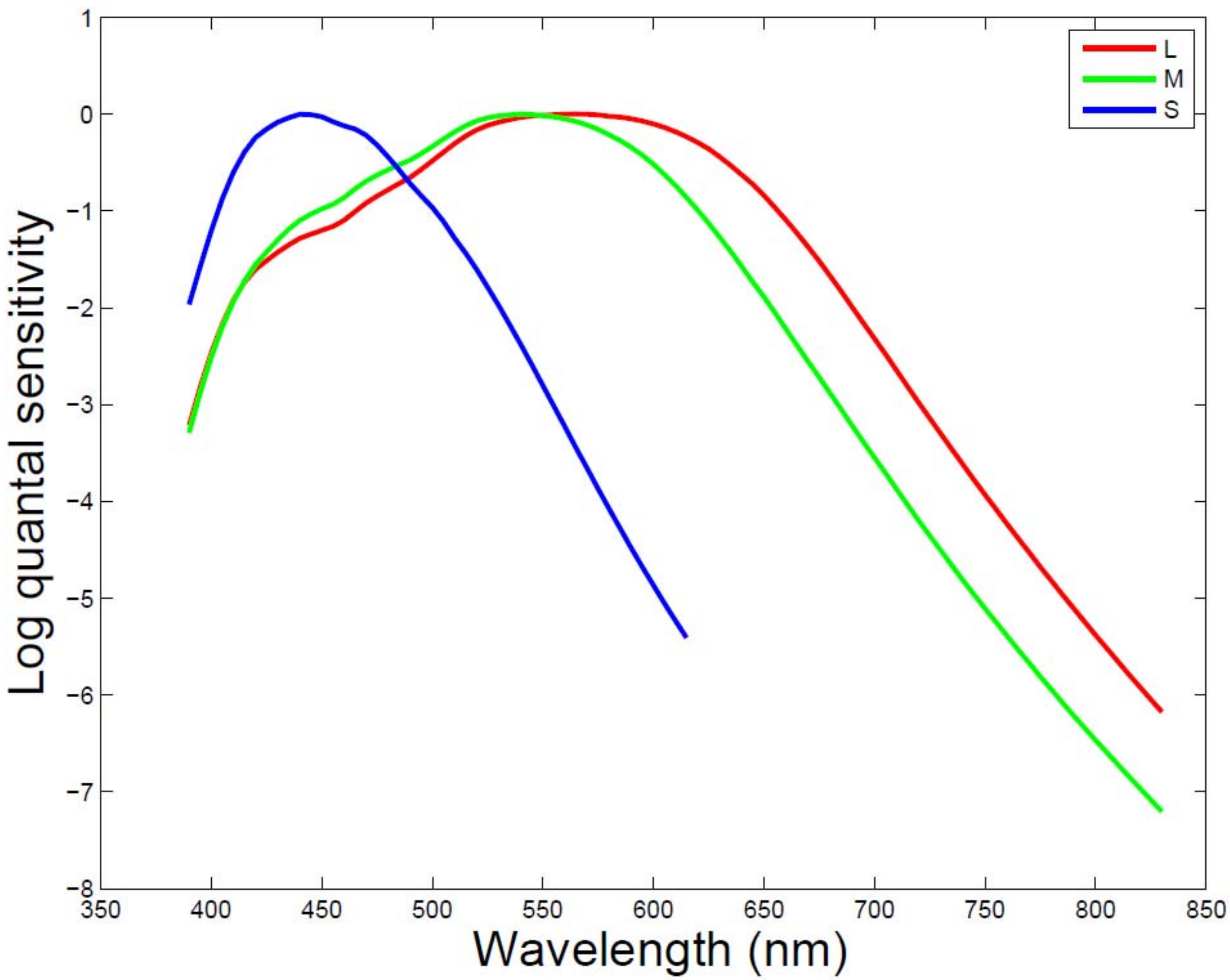


Figure 1.7 Spectral sensitivities of the L (red), M (green), and S (blue) cones.

Rods: sensitive to light intensity

Cones: sensitive to red, green, and blue wavelength bands

Representation of Color Images: Color Spaces

A color image may be represented using the following standard representations:

- [red, green, blue] or RGB
- [cyan, magenta, yellow, black] or CMYK
- [hue, saturation, intensity] or HSI
- L*u*v*, L*a*b*
- YIQ, YUV, CIE RGB, CIE XYZ
- others…

Color-matching Functions

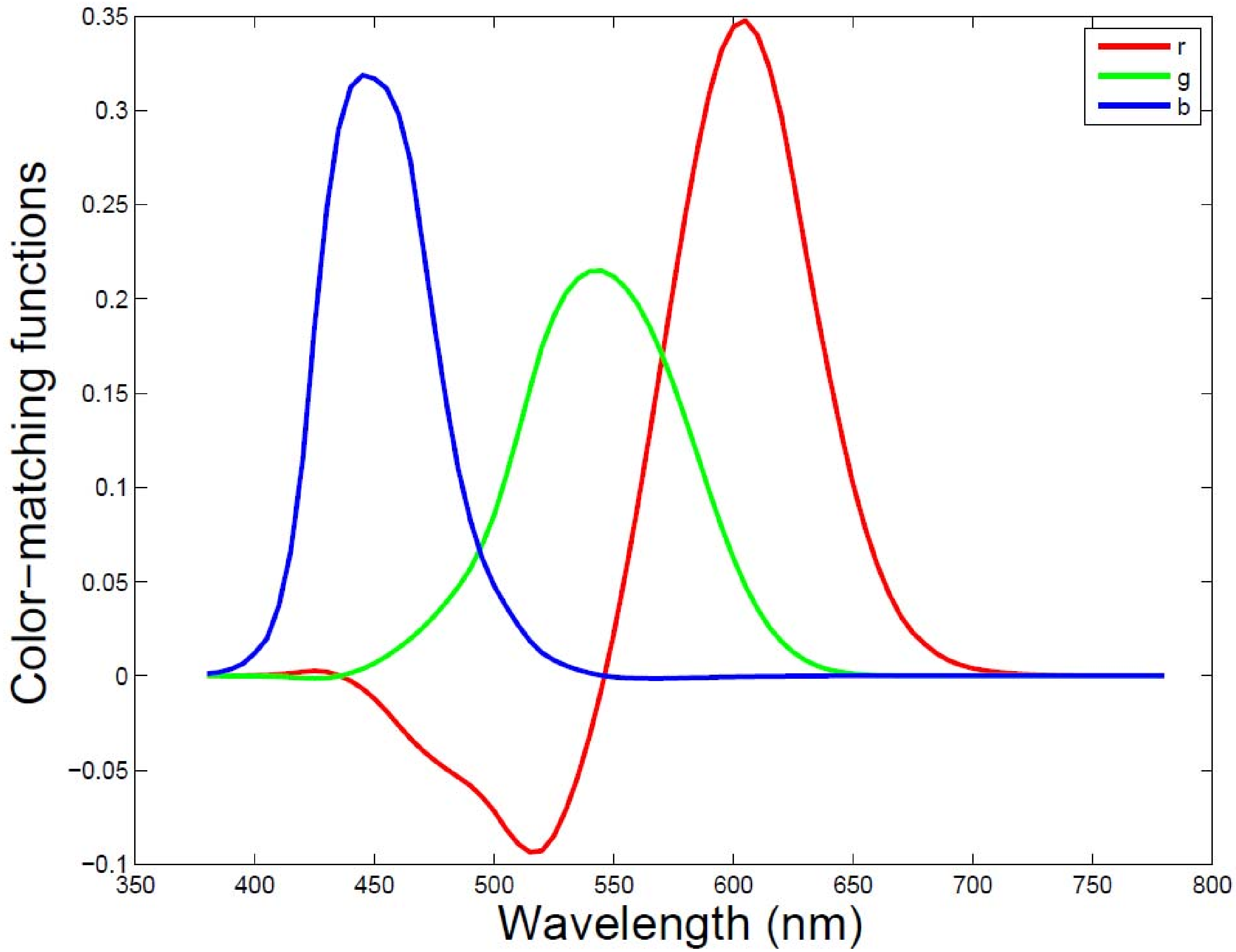


Figure 1.8 The $\overline{r}$, $\overline{g}$, and $\overline{b}$ color-matching functions.

r function has negative values!

Color-matching Functions

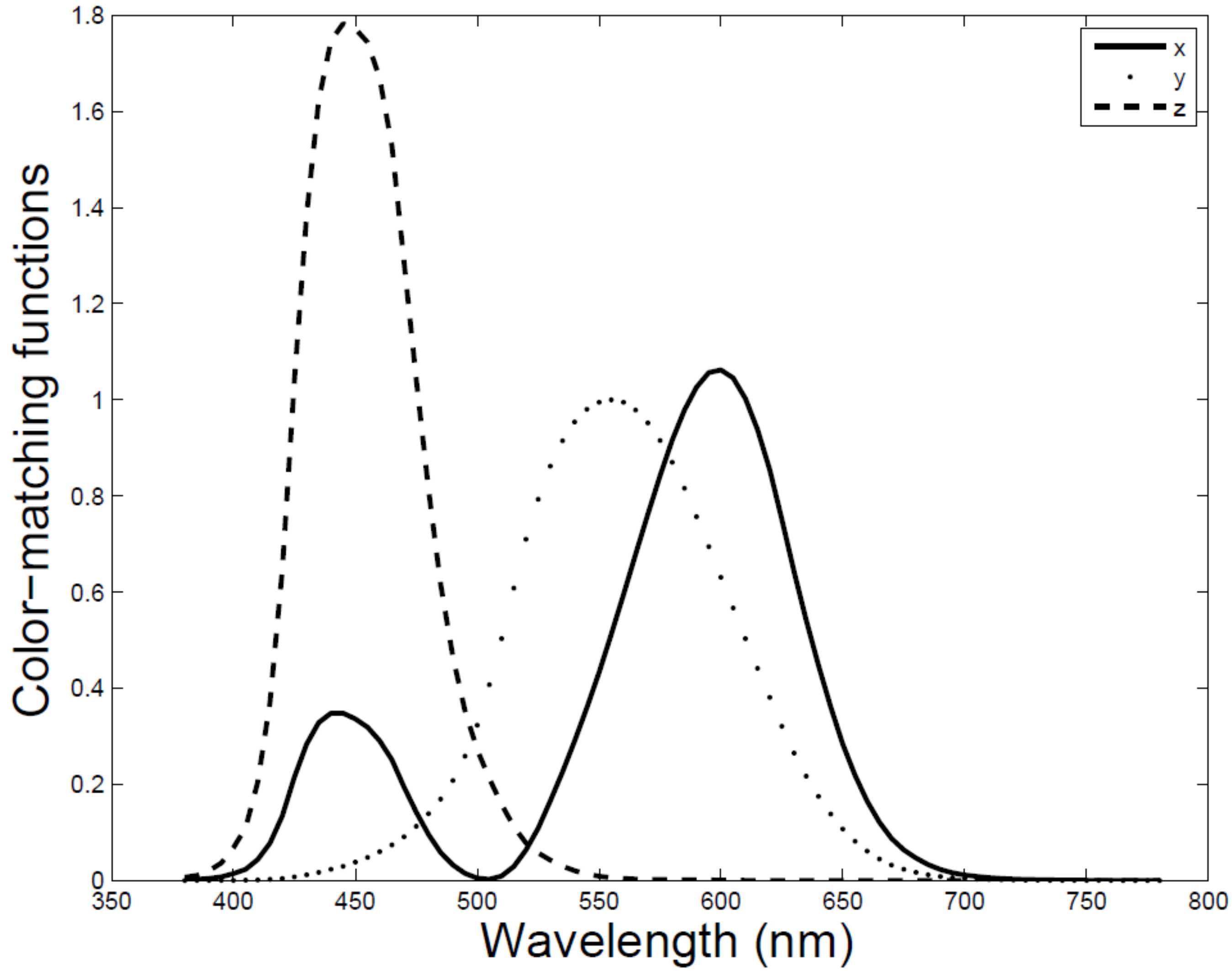
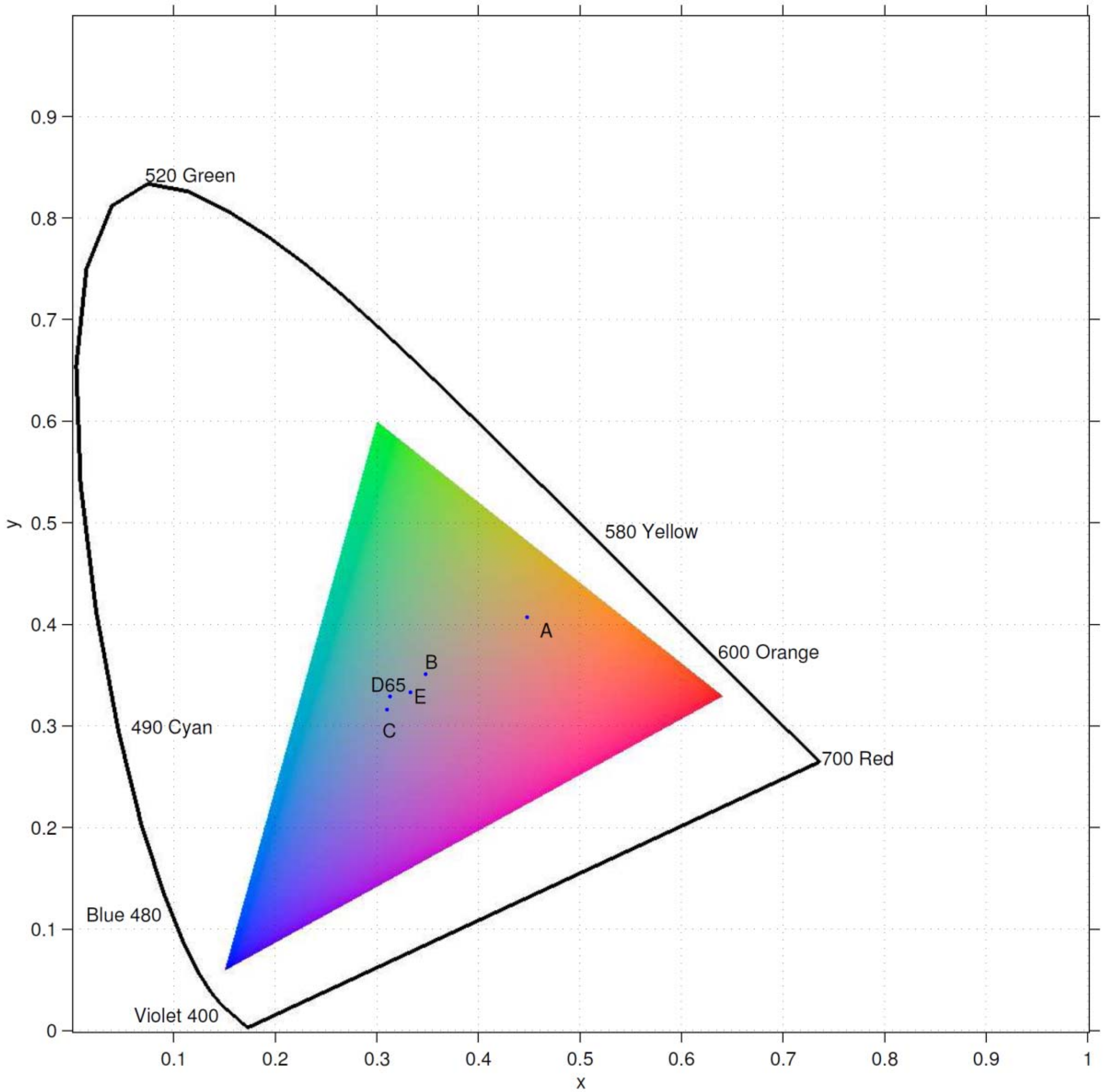


Figure 1.9 The $\overline{x}$, $\overline{y}$, and $\overline{z}$ color-matching functions.

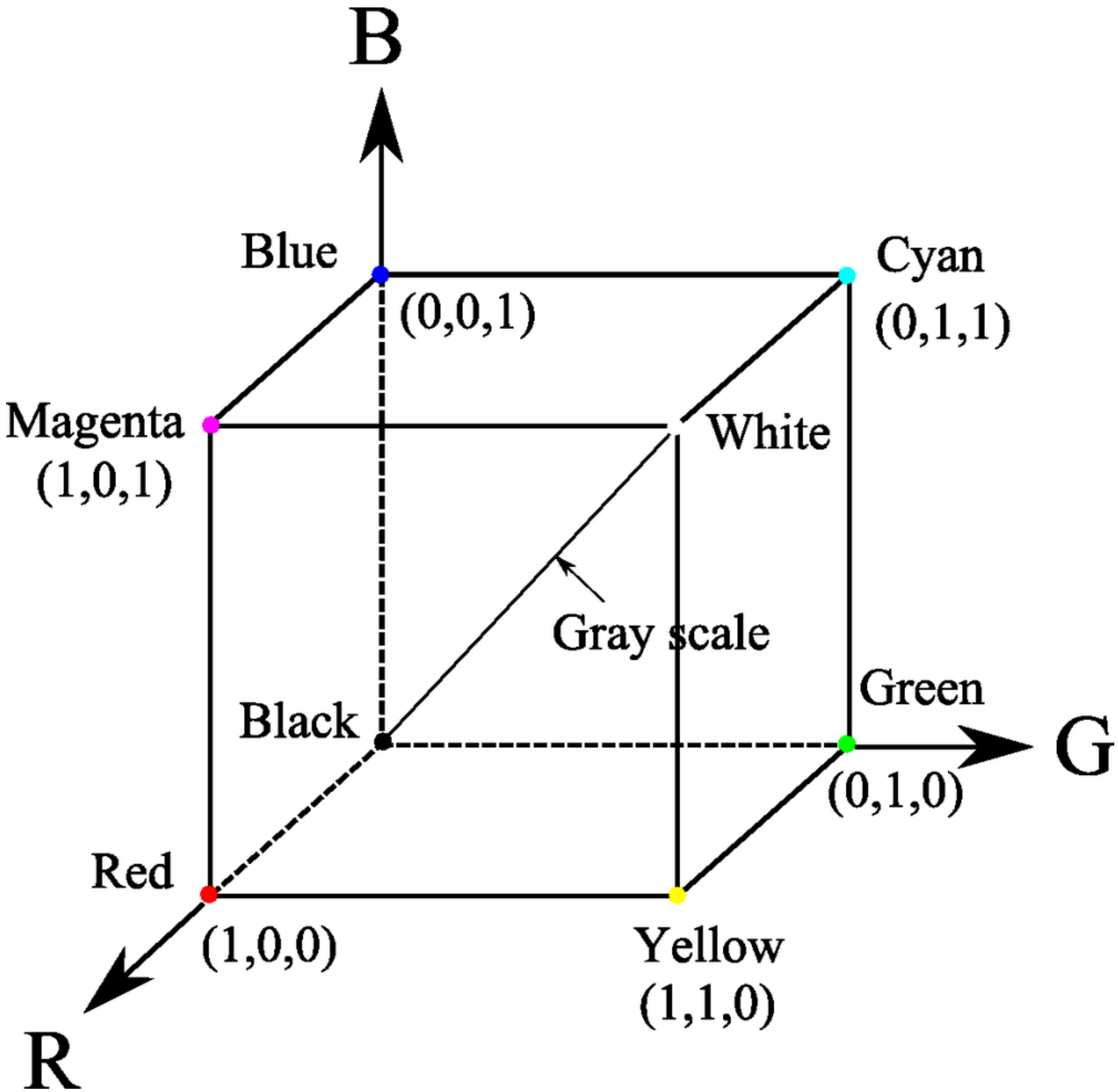
CIE Chromaticity Diagram: Triangular Gamut of sRGB

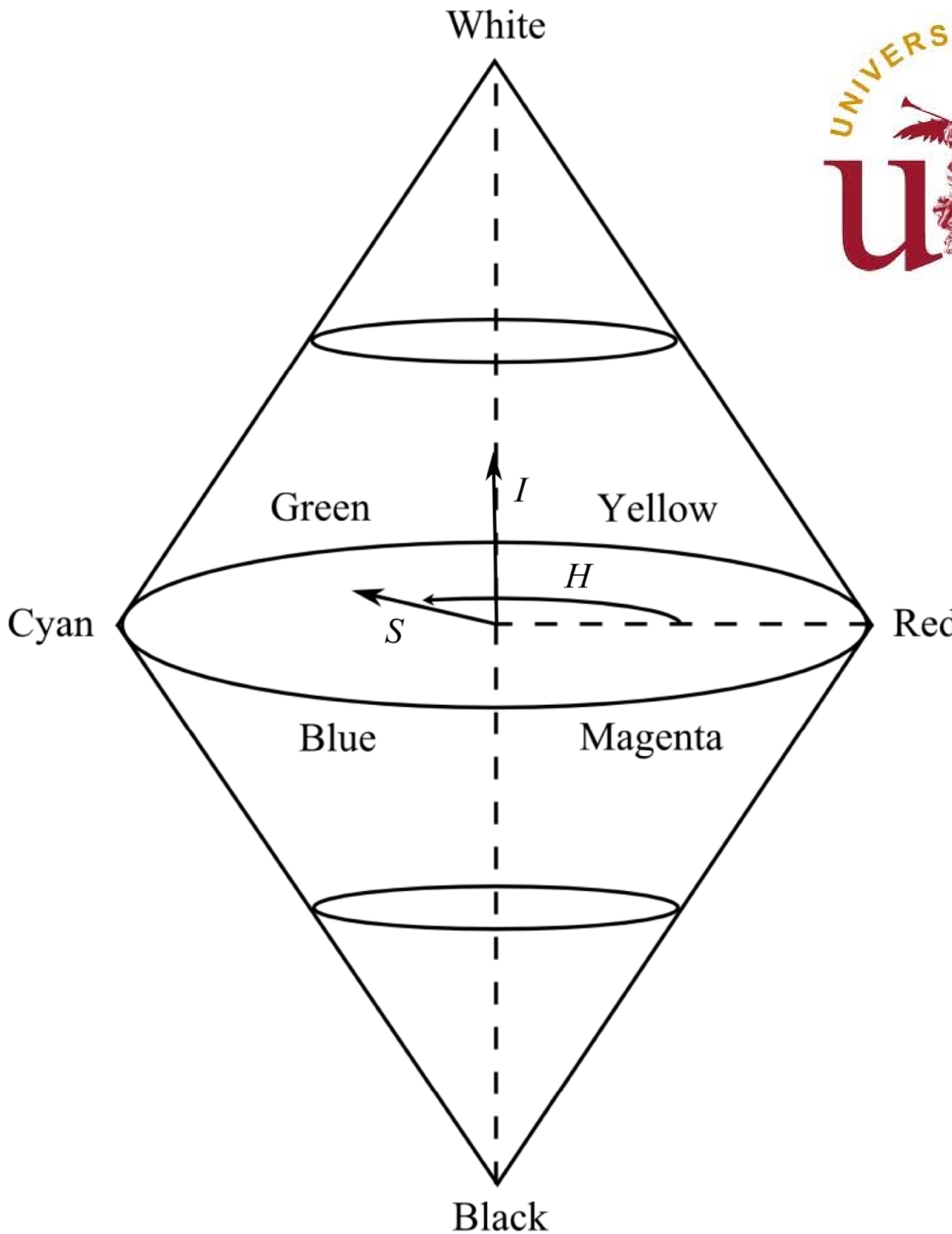


x–y plane

$z = 1 - x - y$

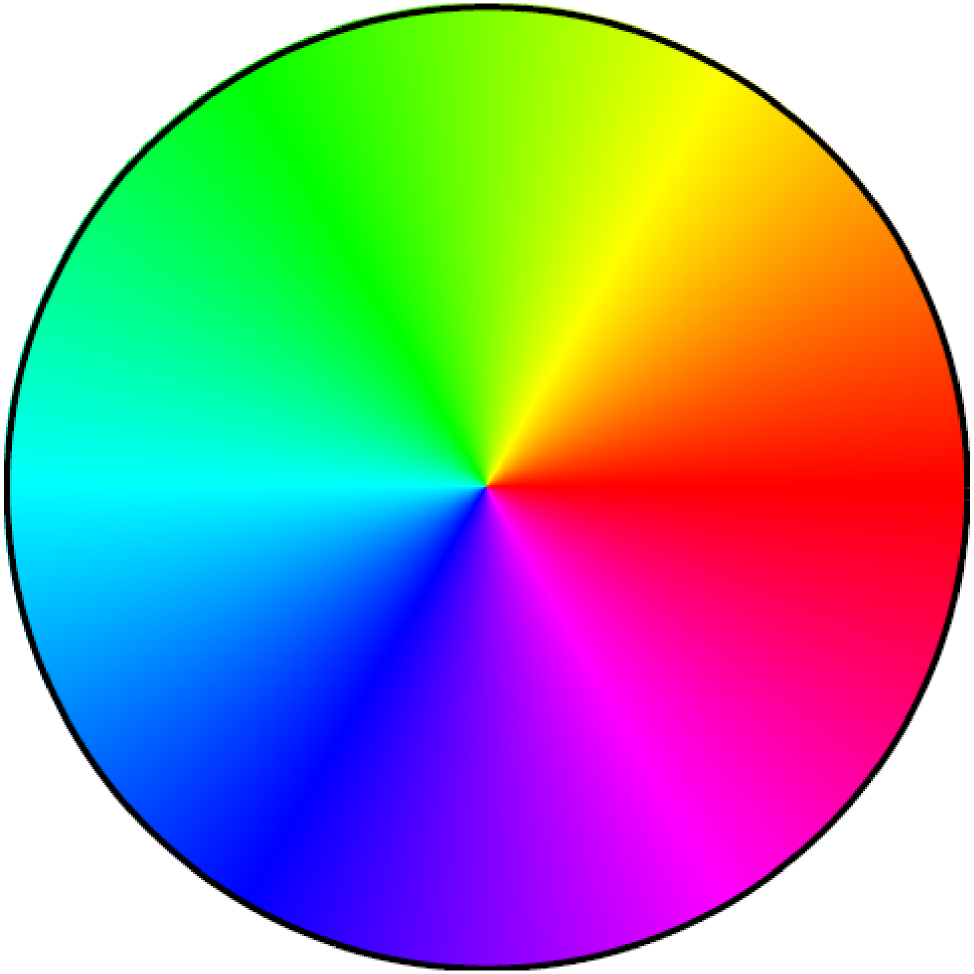
The RGBW-CMYK Cube



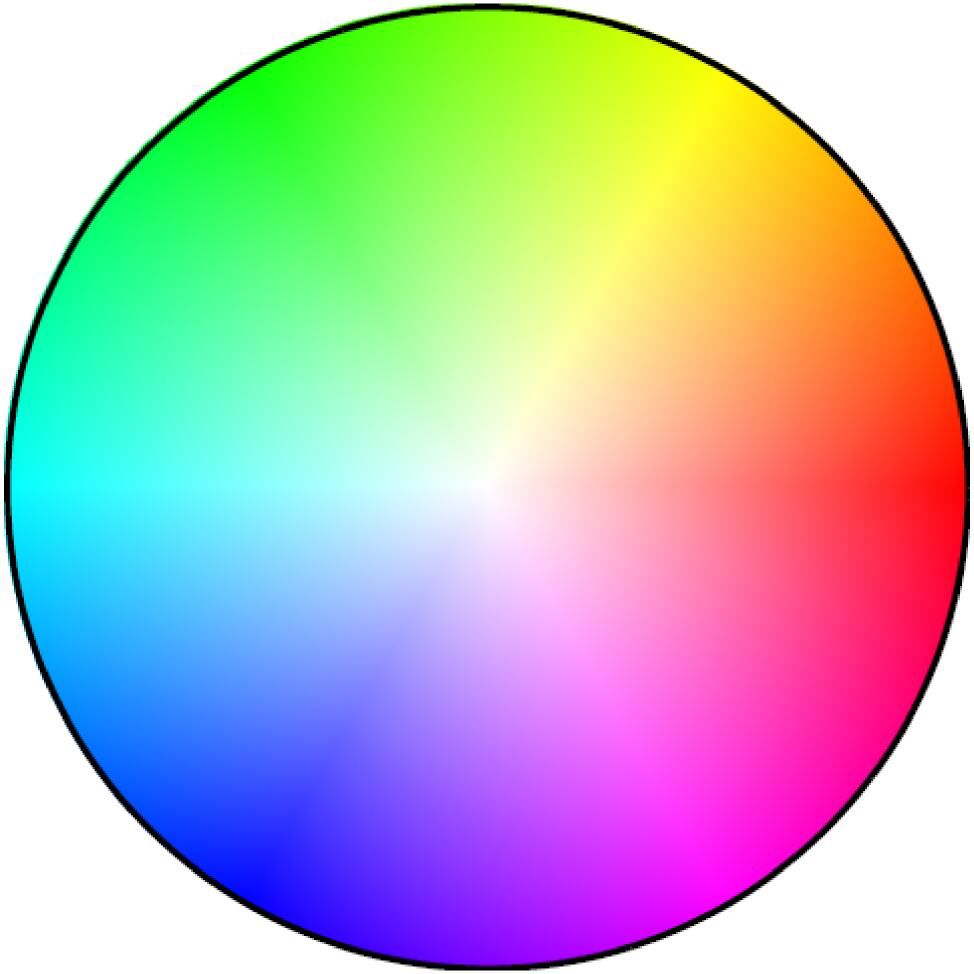


Relationships between RGBW, HSI, and CMYK representations of color images

Hue, Saturation, and Intensity



Varying hue with constant saturation and intensity



Varying hue and saturation with constant intensity

Representation of Color Images: RGB

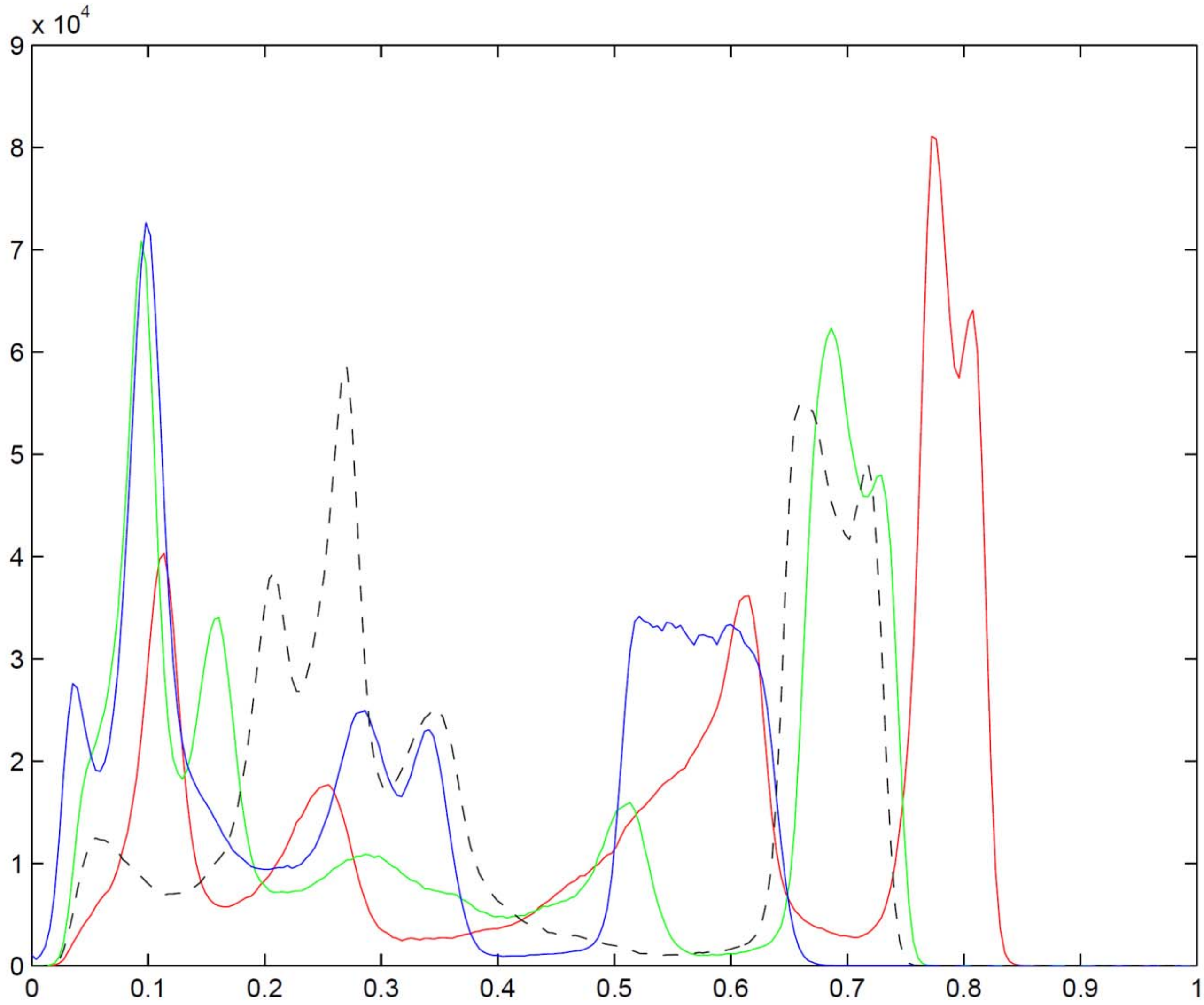
Original image

Red component

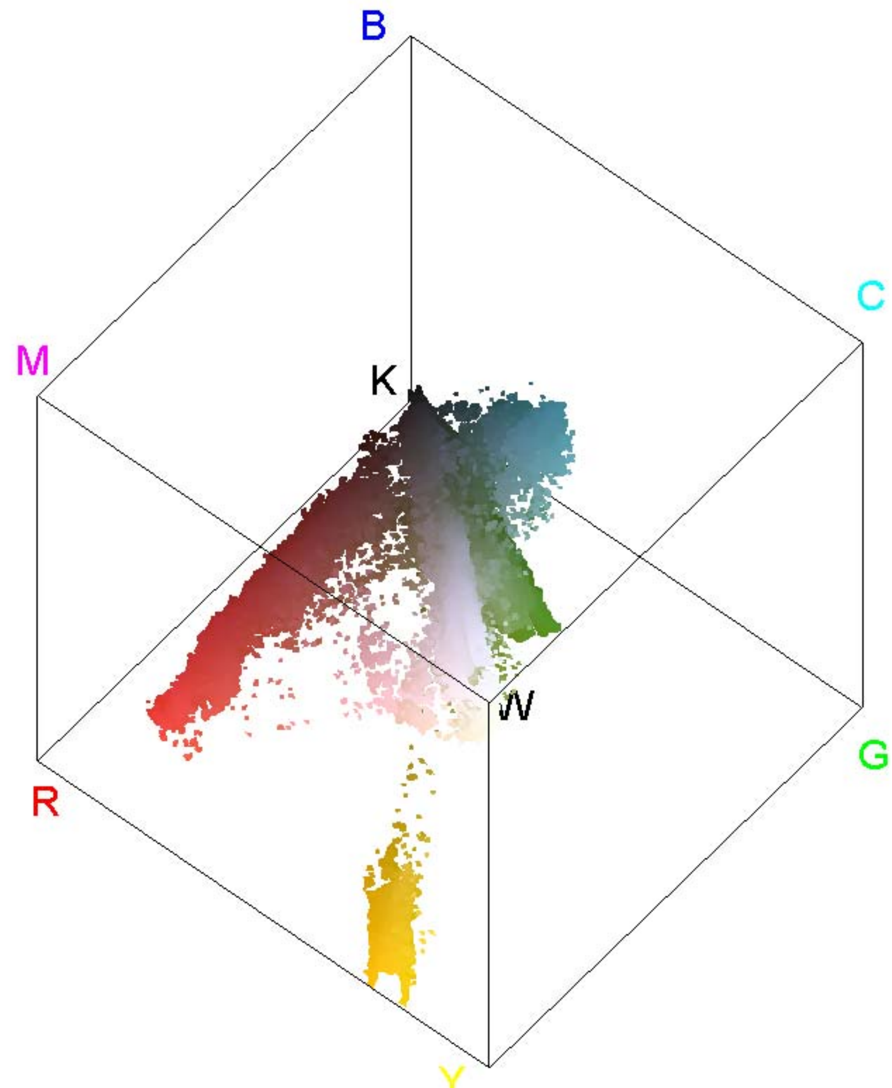
Green component

Blue component

Representation of Color Images: RGBV Histograms



Representation of Color Images: RGB Histogram



Representation of Color Images: HSI

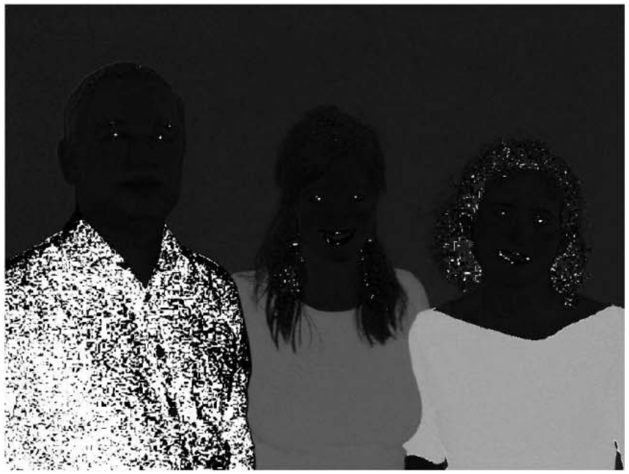
Original image

Hue

Saturation

Intensity

Representation of Color Images: HSI

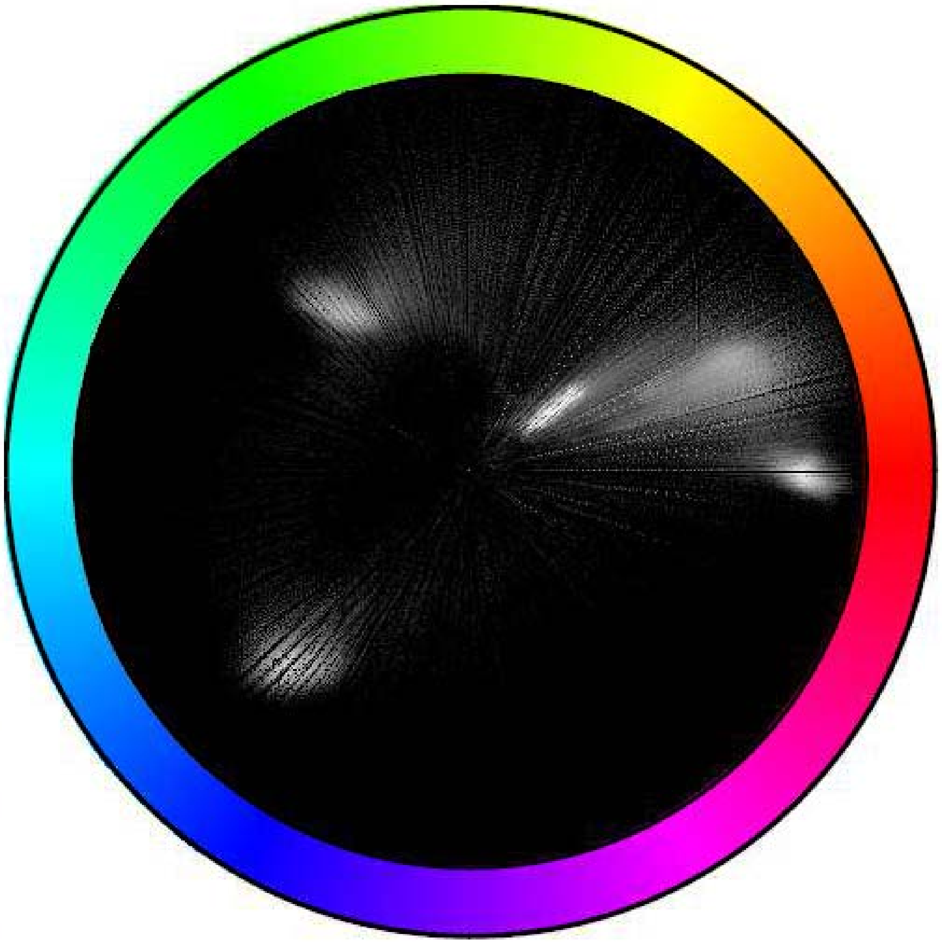


Original image *Hue*

Sin (hue/2) = distance from red *Sin[(hue-120)/2] = distance from green*

Representation of Color Images: HSI

Original image



Hue-saturation histogram

HSI: Roles of Hue, Saturation, and Intensity

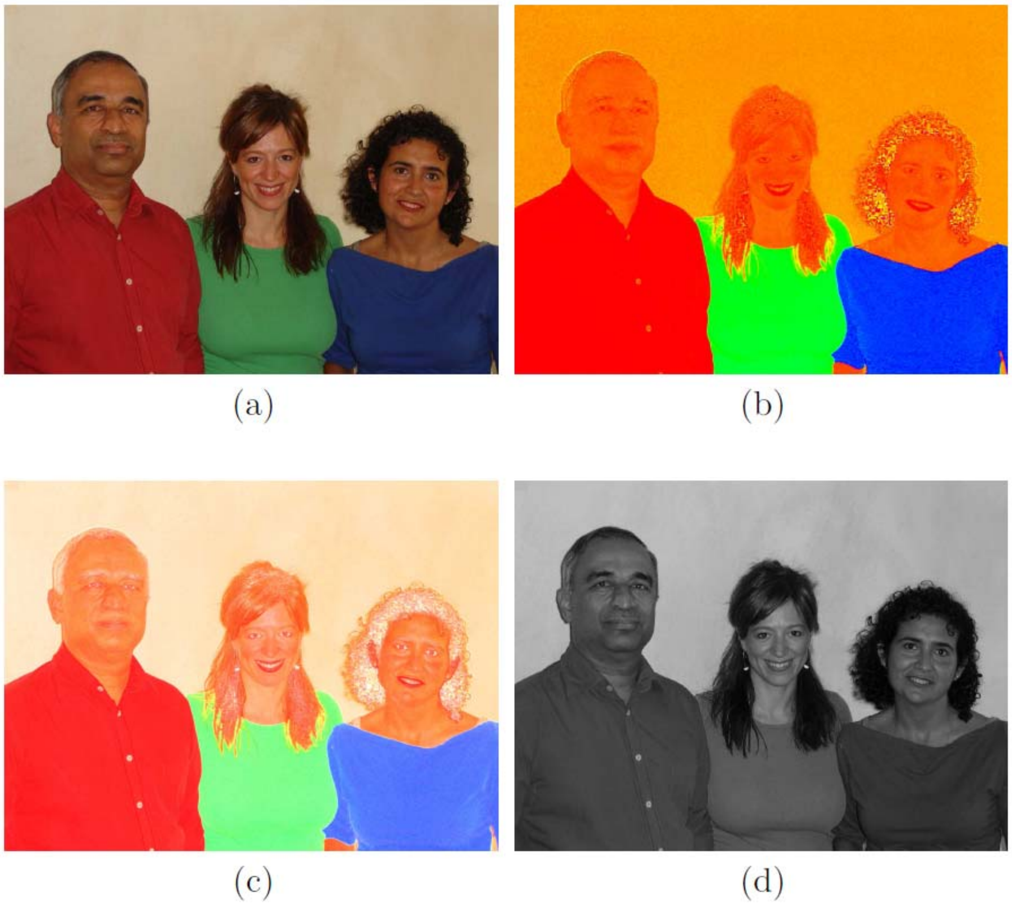
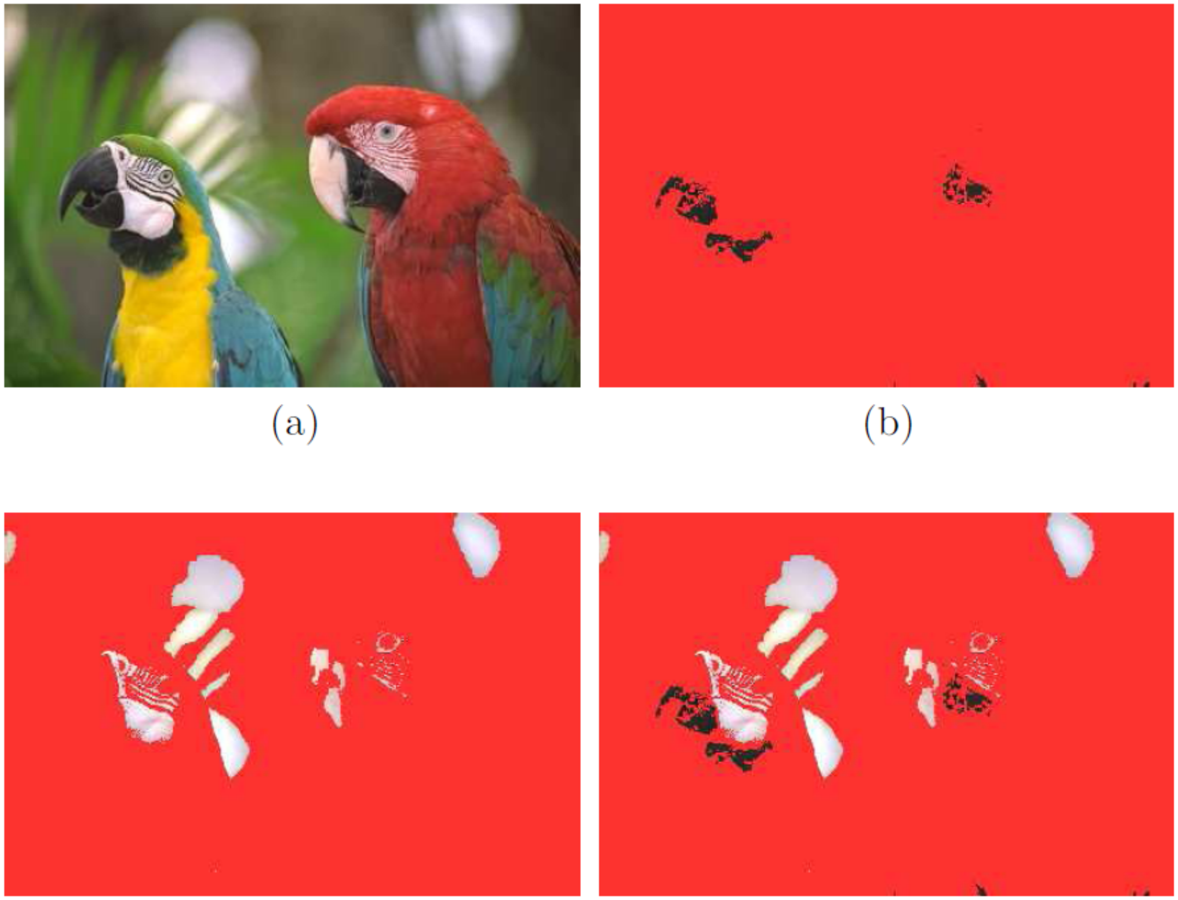


Figure 1.37 (a) An original color image. (b) Hue component with maximum saturation and intensity. (c) Isointensity rendition with the original hue and saturation, but intensity equal to unity for the entire image. This image gives the chrominance information. (d) Intensity component; this gives the luminance information. See also Figures 1.18 and 1.34.

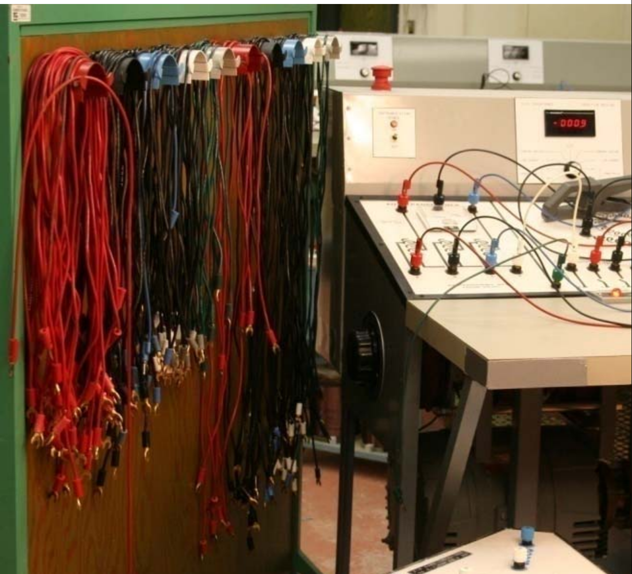
Chromatic vs Achromatic Pixels

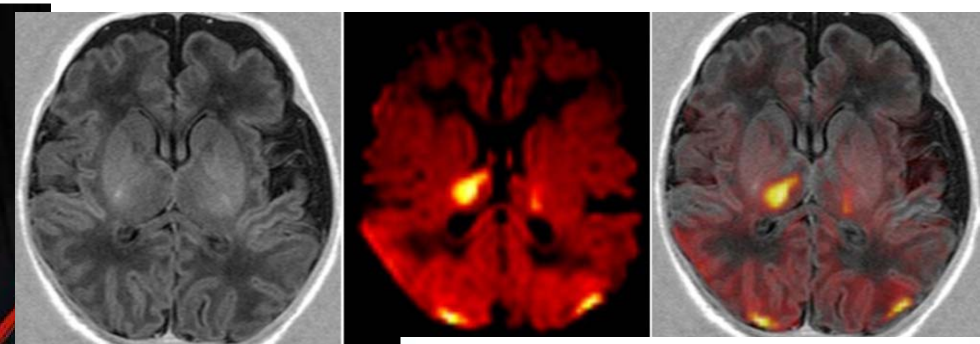


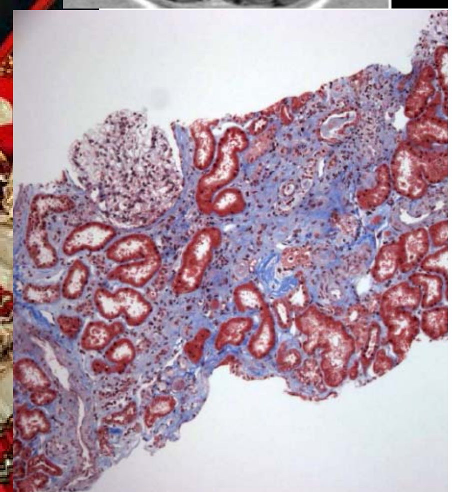
(a) (b) (c) (d)

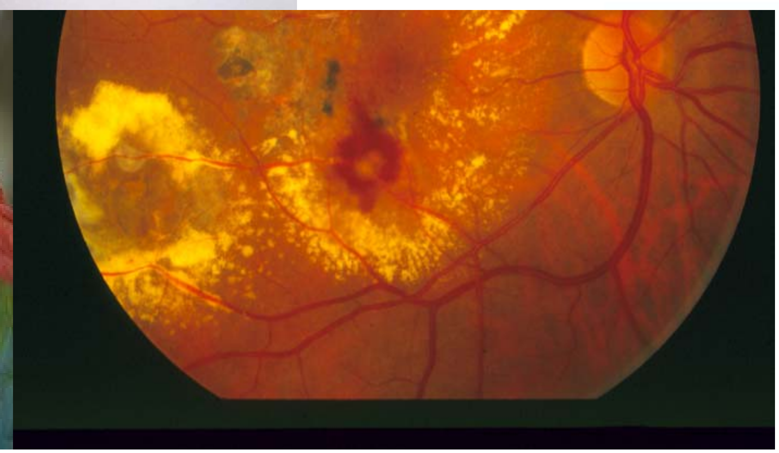
Figure 1.39 (a) An original color image. (b) Dark or black achromatic pixels. (c) Bright or white achromatic pixels. (d) All achromatic pixels. In each case, pixels not selected have been assigned an arbitrary background color. See also Figure 1.36.

Natural versus Pseudo Color









Acquisition of Color Images

1. Sensor color filter array data
2. Dark current correction
3. White balance
4. Demosaicking
5. Color transformation to unrendered color space
6. Color transformation to rendered color space

Demosaicking by Interpolation

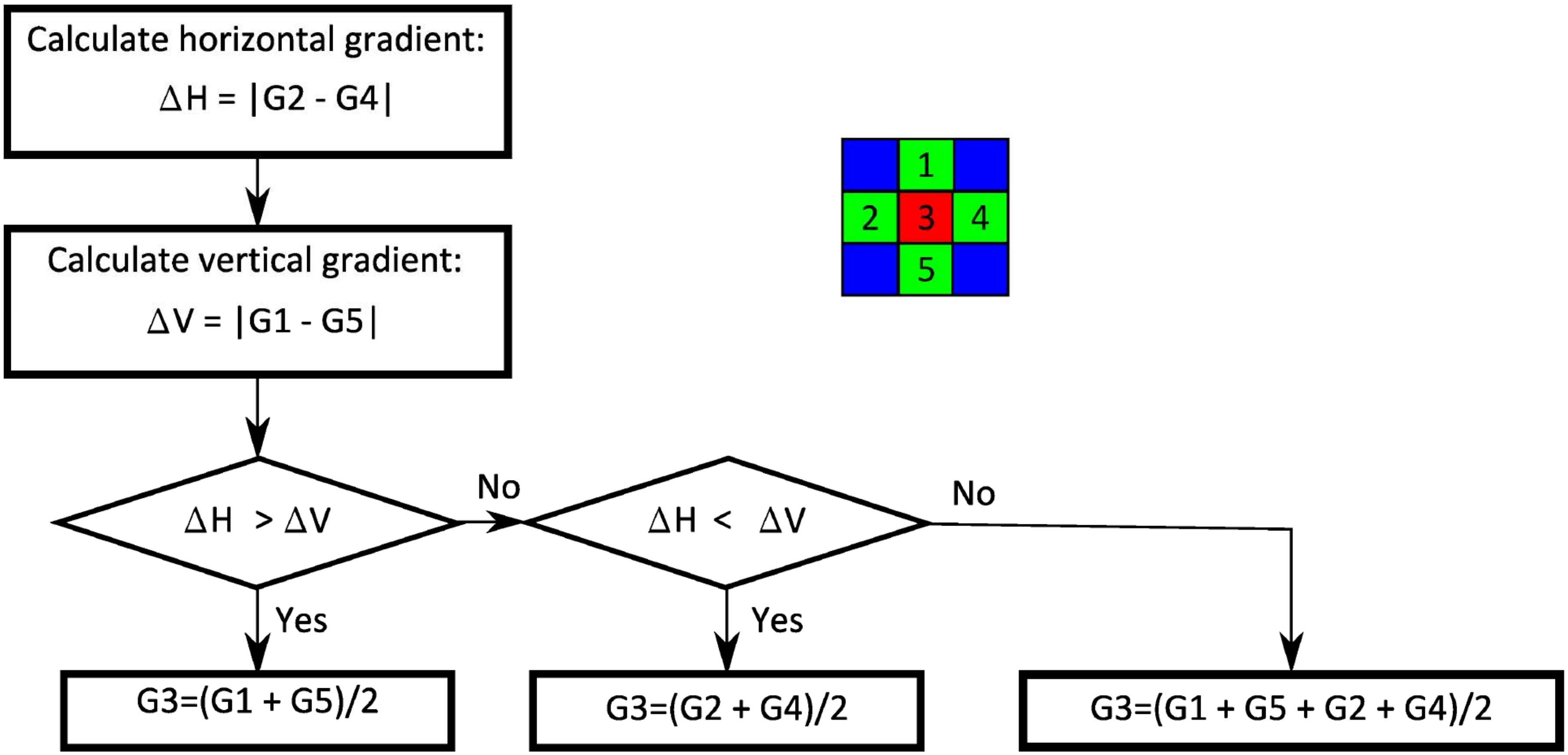
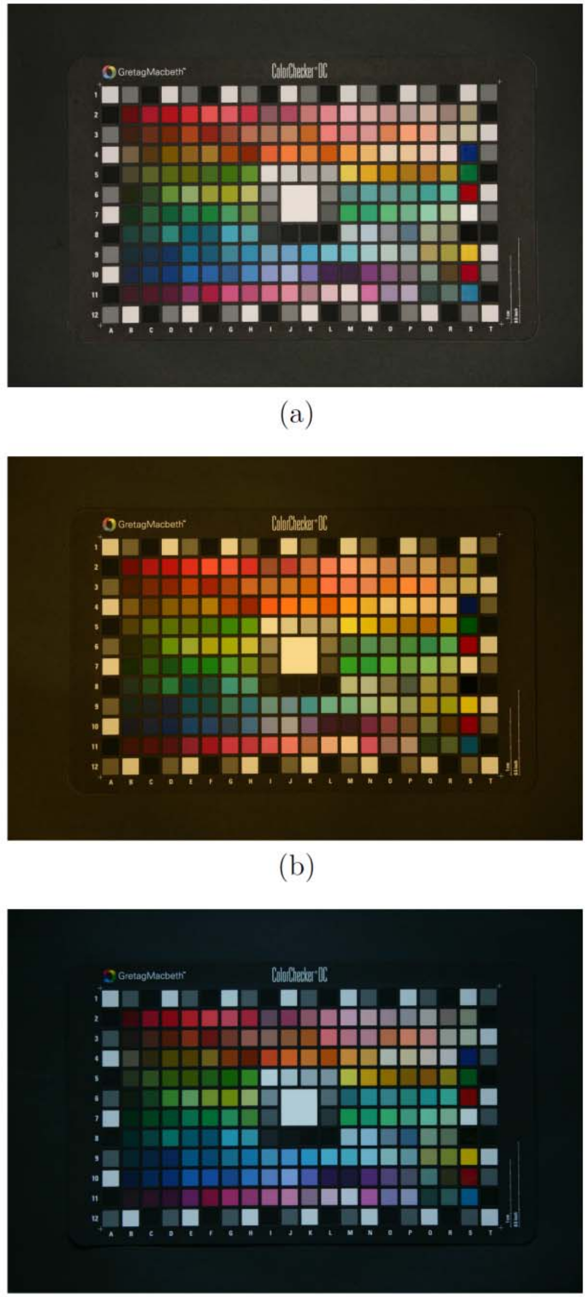


Figure 2.4 Edge-directed interpolation: the green value of the central pixel labeled with the number 3 is interpolated from the green components of its four neighbors. Gn represents the green component of pixel n [169].

The Need for Calibration of Color Images



(a)

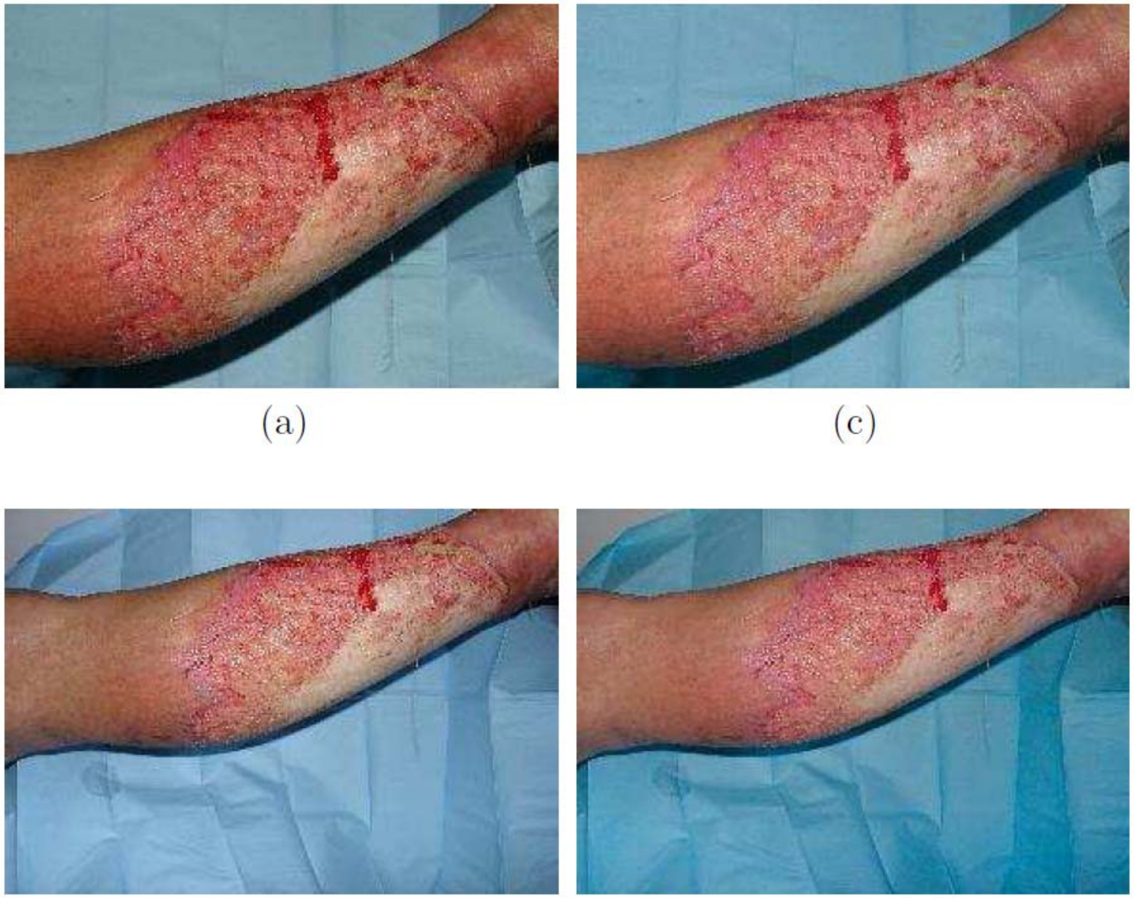
(b)

(c)

Figure 2.34 Three images of the Macbeth Color Checker® chart DC (Gretag-Macbeth GmbH, Martinsried, Germany) obtained under different lighting conditions: (a) xenon flash, (b) fluorescent light, and (c) diffuse sunlight.

Image Alert!

Color Characterization



(a) (c)

(b) (d)

Figure 2.36 Original digital photographic images of a burn wound taken using a xenon flash with (a) a Canon camera and (b) a Sony camera. (c)-(d) Characterized versions of the images in (a) and (b), respectively.

Filtering to Remove Noise

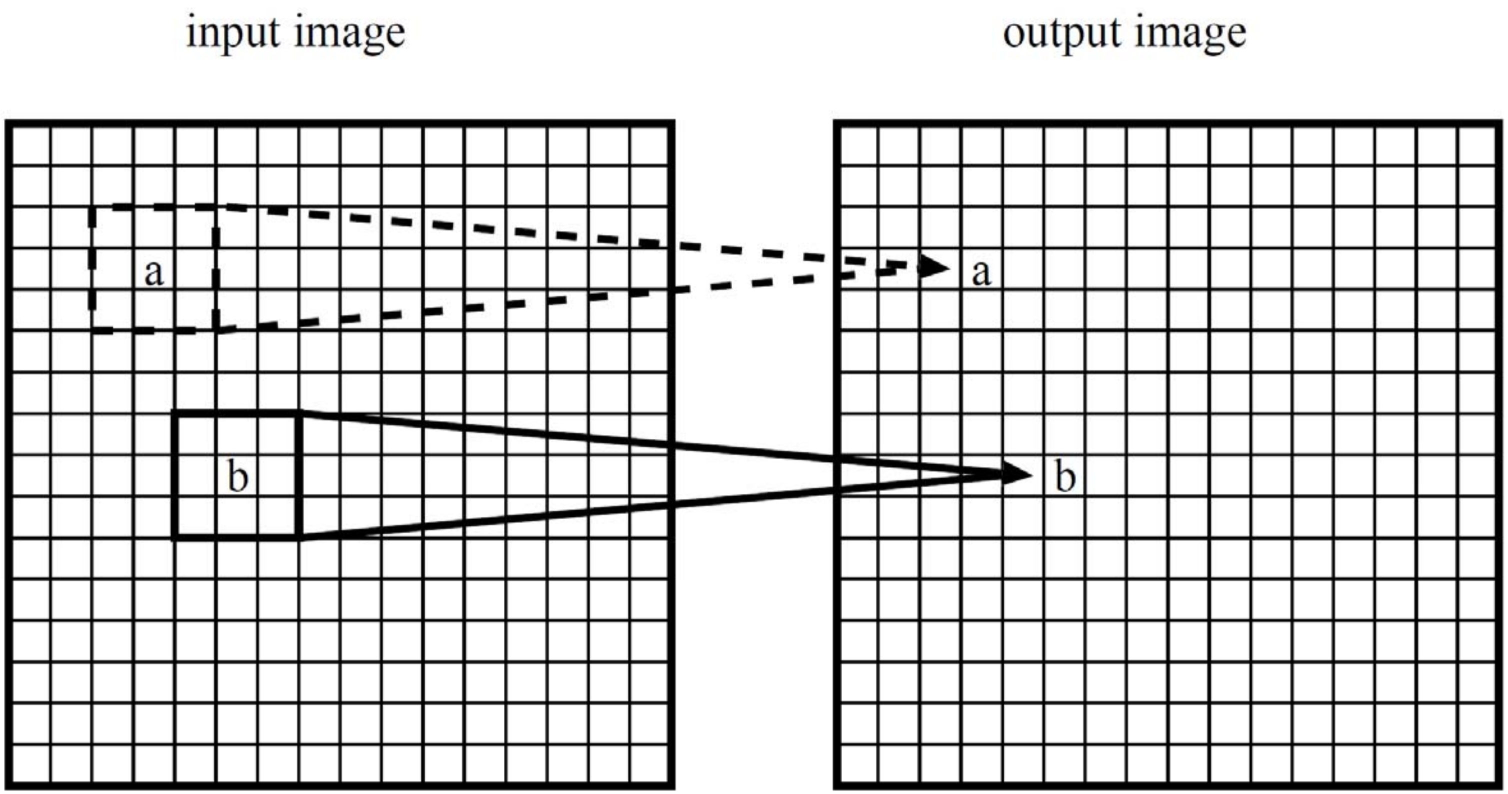
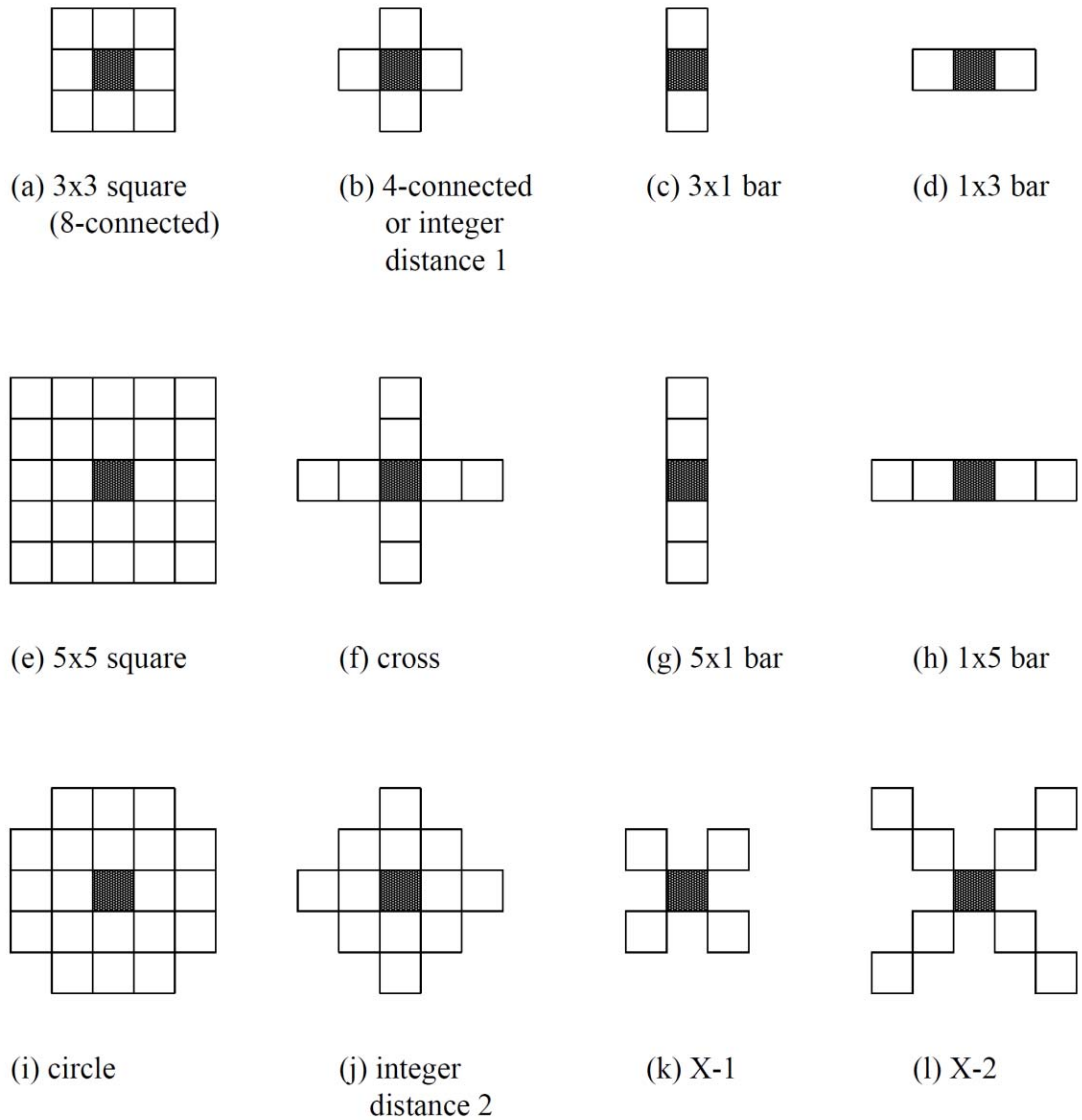


Figure 3.1 Moving-window or moving-average filtering of an image. The size of the moving window in the illustration is 3×3 pixels. Statistical measures or other values computed by using the pixels within the window in the input image are used to derive the output value. The moving window is shown for two pixel locations marked "a" and "b."

Neighborhood Shapes



Mean and Median Filtering

$$\begin{array}{rrr} 102 & 72 & 48 \\ 83 & 115 & 76 \\ 90 & 143 & 87 \end{array}.$$

The rank-ordered pixels, arranged in increasing order, are as follows:

$$48 \quad 72 \quad 76 \quad 83 \quad \mathbf{87} \quad 90 \quad 102 \quad 115 \quad 143.$$

$$(102 + 72 + 48 + 83 + 115 + 76 + 90 + 143 + 87)/9 = 90.67.$$

Mean = 90.67

Median = 87

Ordering of Vectorial Data

RGB pixel values in a 3x3 neighborhood of a color image:

$$
\begin{matrix}
[252 & 170 & 146] & [200 & 80 & 57] & [247 & 158 & 119] \\
[226 & 138 & 86] & \boxed{[244 \quad 77 \quad 180]} & & & [235 & 155 & 78] \\
[224 & 116 & 82] & [203 & 96 & 75] & [236 & 114 & 100].
\end{matrix}
$$

Marginal Median: sort by R, G, B

$$
\begin{aligned}
&[200 \quad 77 \quad 57] \\
&[203 \quad 80 \quad 75] \\
&[224 \quad 96 \quad 78] \\
&[226 \quad 114 \quad 82] \\
&[235 \quad 116 \quad 86] : \text{Median} : \ \text{MMF} \\
&[236 \quad 138 \quad 100] \\
&[244 \quad 155 \quad 119] \\
&[247 \quad 158 \quad 146] \\
&[252 \quad 170 \quad 180].
\end{aligned}
$$

Reduced Ordering: Euclidean distance to mean

$$d_i^2 = (\mathbf{x}_i - \overline{\mathbf{x}})^T (\mathbf{x}_i - \overline{\mathbf{x}}) = \sum_{j=1}^{P} [\mathbf{x}_i(j) - \overline{\mathbf{x}}(j)]^2$$

$$\begin{array}{l}
[236 \;\; 114 \;\; 100] : 11 : \mathrm{Median} : \mathrm{RDM} \\
[224 \;\; 116 \;\; 82] : 22 \\
[226 \;\; 138 \;\; 86] : 23 \\
[235 \;\; 155 \;\; 78] : 41 \\
[247 \;\; 158 \;\; 119] : 43 \\
[203 \;\; 96 \;\; 75] : 47 \\
[252 \;\; 170 \;\; 146] : 68 \\
[200 \;\; 80 \;\; 57] : 69 \\
[244 \;\; 77 \;\; 180] : 91.
\end{array}$$

$$\overline{\mathbf{x}}(j) = \frac{1}{K} \sum_{i=1}^{K} \mathbf{x}_i(j)$$

$$= [229.7 \;\; 122.7 \;\; 102.6]$$

Vector Median and Vector Directional Filters

$$d_i = \sum_{k=1}^{K} d(\mathbf{x}_i, \mathbf{x}_k)$$

sum of distances from each vector to all other vectors

$$d(\mathbf{x}_i, \mathbf{x}_k) = \left[\sum_{j=1}^{P} [\mathbf{x}_i(j) - \mathbf{x}_k(j)]^2 \right]^{\frac{1}{2}}$$

$$d_\theta(\mathbf{x}_i, \mathbf{x}_k) = \cos^{-1} \left[\frac{\mathbf{x}_i^T \mathbf{x}_k}{||\mathbf{x}_i|| \, ||\mathbf{x}_k||} \right]$$

Filtering using statistics derived using adaptive neighborhoods

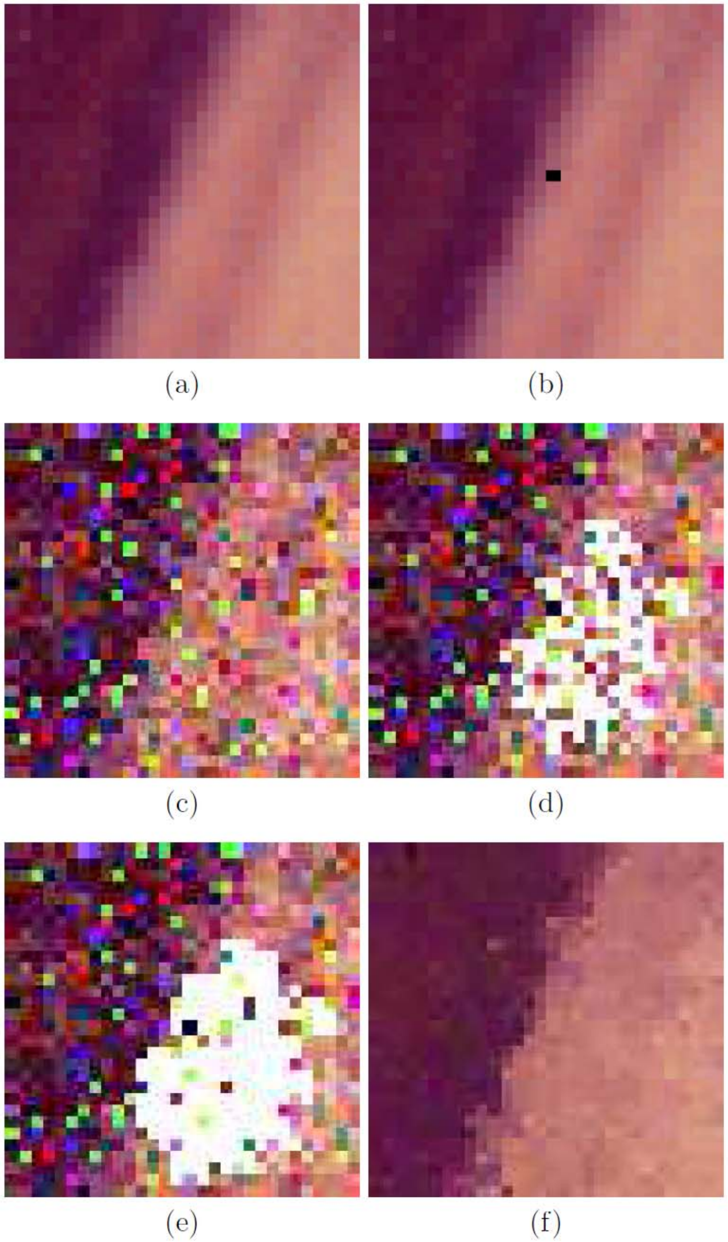


Figure 3.8 Illustration of the steps of adaptive-neighborhood region growing: (a) A 30 × 30-pixel wide portion of the "Lena" image. (b) Seed pixel shown in black. (c) The corresponding portion of a noisy image with additive Gaussian noise ($\sigma_\eta = 30$) and 5% impulsive noise. (d) Region grown after the first step: seed pixel in black, retained pixels in white, background pixels in their true (noisy) colors. (e) Region after step two. (f) The same portion of the image after filtering.

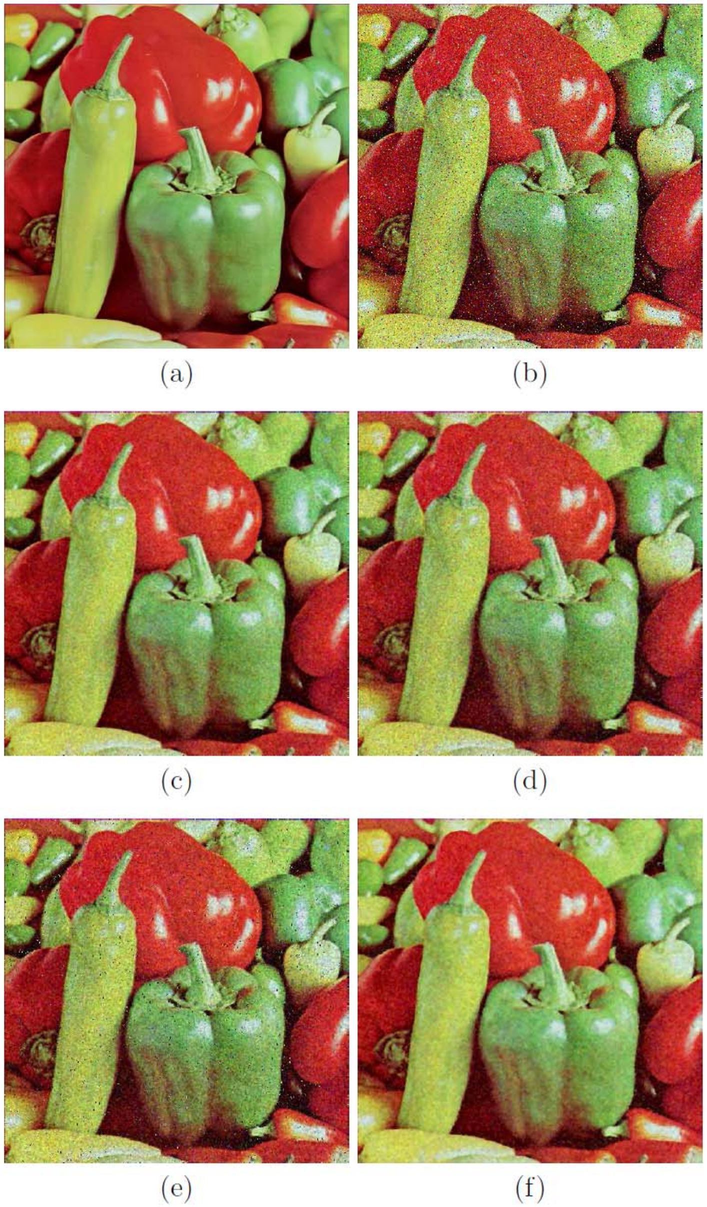


Figure 3.10 Original, noisy, and filtered versions of the 512×512-pixel, 24-bit "Peppers" image. (a) Original image. (b) Noisy image with Gaussian additive noise characterized by $\sigma_\eta = 30$, $\rho_{RG} = 0.5$, $\rho_{GB} = 0.4$, and $\rho_{BR} = 0.2$, and 5% impulsive noise. (c) Filtered with MMF. (d) Filtered with VMF. (e) Filtered with DDF. (f) Filtered with GVDF. Images courtesy of Dr. Mihai Ciuc, Laboratorul de Analiza şi Prelucrarea Imaginilor, Universitatea Politehnica Bucureşti, Bucharest, Romania [295].

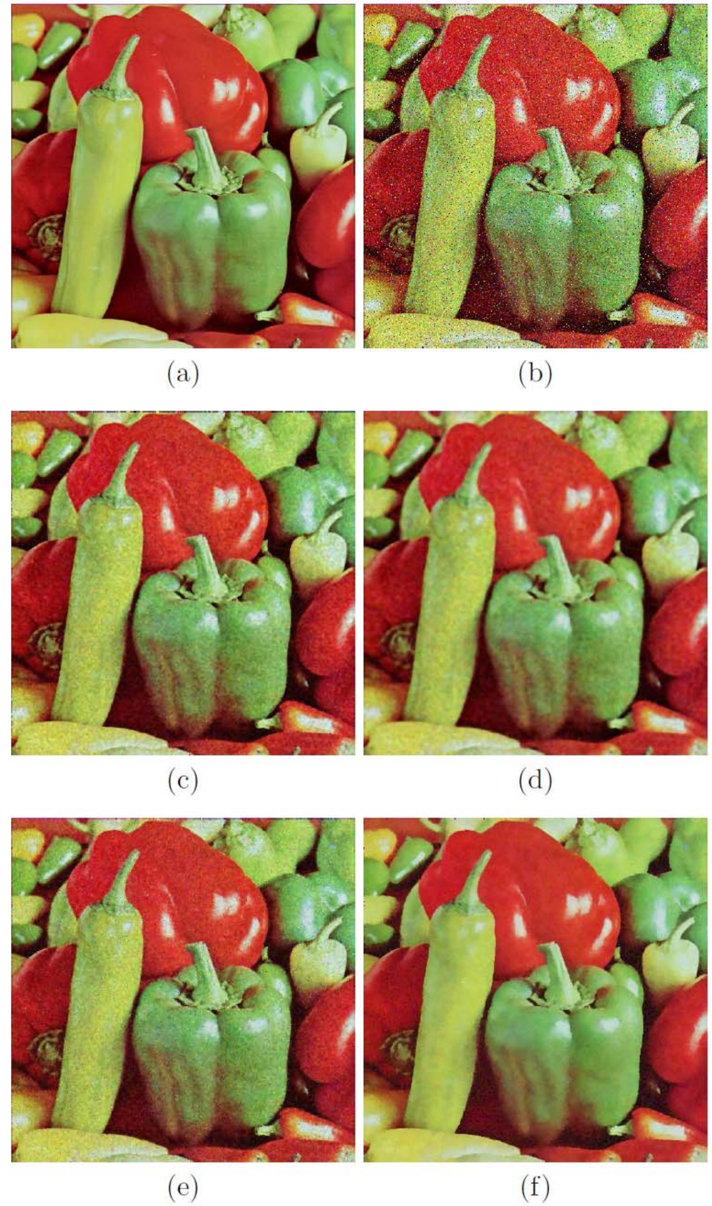


Figure 3.12 Original, noisy, and filtered versions of the 512×512-pixel, 24-bit "Peppers" image. (a) Original. (b) Noisy, with Gaussian additive noise characterized by $\sigma_\eta = 30$, $\rho_{RG} = 0.5$, $\rho_{GB} = 0.4$, and $\rho_{BR} = 0.2$, and 5% impulsive noise. (c) Filtered with DW-MTMF. (d) Filtered with AMNFG2. (e) Filtered with AHMF. (f) Filtered with ANF. Images courtesy of Dr. Mihai Ciuc, Laboratorul de Analiza şi Prelucrarea Imaginilor, Universitatea Politehnica Bucureşti, Bucharest, Romania [295].

Enhancement of Color Images

Quite often, the enhancement required would be only in the intensity component:

- Gamma correction,
- Histogram equalization.

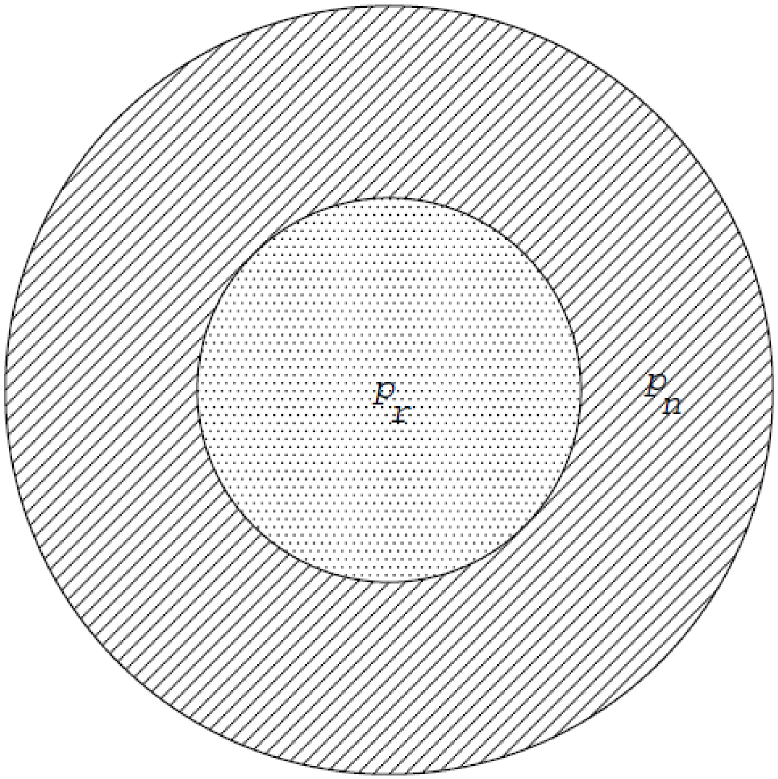
Sometimes, saturation may need to be increased.

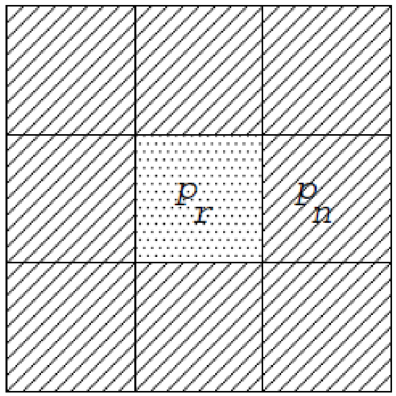
Rarely would we want to alter the hue component.

Processing the RGB components individually is not usually recommended.

Figure 4.4 Results of gamma correction applied to the components of a color image: (a) Original image. (b) Intensity enhanced with $\gamma = 0.4$. (c) Intensity and saturation enhanced with $\gamma = 0.4$. (d) All three RGB components enhanced individually with $\gamma = 0.4$.

Enhancement of Contrast in Luminance and Color





$$c_{g1} = \frac{p_r - p_n}{p_n}$$

$$c_{g2} = \frac{p_r - p_n}{p_r + p_n}$$

Enhancement of Contrast in Luminance and Color

$$c_L(m,n) = \frac{|L(m,n) - L_m|}{\Delta L_{\max}}$$

$$CD = \left[(L_1^* - L_2^*)^2 + (a_1^* - a_2^*)^2 + (b_1^* - b_2^*)^2\right]^{\frac{1}{2}}$$

$$c_C(m,n) = \frac{CD_m}{CD_{\max}}$$

m: mean over 5x5 region
max: max over image

Enhancement of Contrast in Luminance and Color

$$c_E(m,n) = g_L(m,n)\, c_L(m,n) + g_C(m,n)\, c_C(m,n)$$

$$g_L(m,n) = \frac{\Delta c(m,n) - \Delta c_{\min}}{\Delta c_{\max} - \Delta c_{\min}}$$

$$g_C(m,n) = \frac{\Delta c_{\max} - \Delta c(m,n)}{\Delta c_{\max} - \Delta c_{\min}}$$

$$\Delta c(m,n) = c_L(m,n) - c_C(m,n)$$

Enhancement of Contrast in Luminance and Color

$$L_E(m,n) = \begin{cases} L_m + c_E(m,n)\,\Delta L_{\max}, & \text{if } L(m,n) > L_m \\ L_m - c_E(m,n)\,\Delta L_{\max}, & \text{otherwise.} \end{cases}$$

$$k(m,n) = \frac{L_E(m,n)}{L(m,n)}$$

$$R_E(m,n) = k(m,n)\,R(m,n)$$

Green and Blue channels also scaled as above [Liu & Yan]

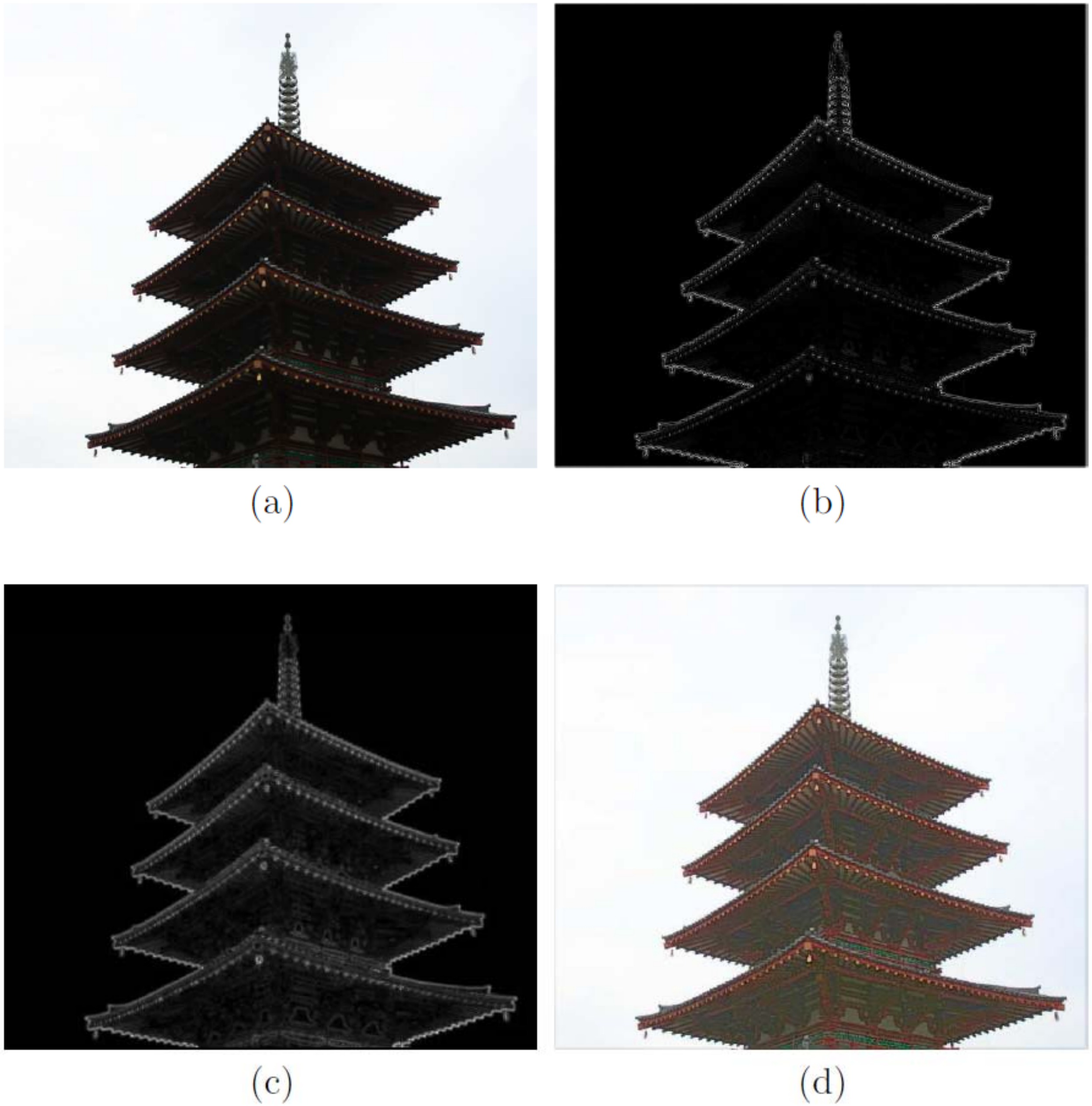


Figure 4.20 Combined enhancement of luminance contrast and color contrast: (a) Original image. (b) Pictorial rendition of luminance contrast values. (c) Pictorial rendition of color contrast values. (d) Enhanced image.

Color Histogram Equalization

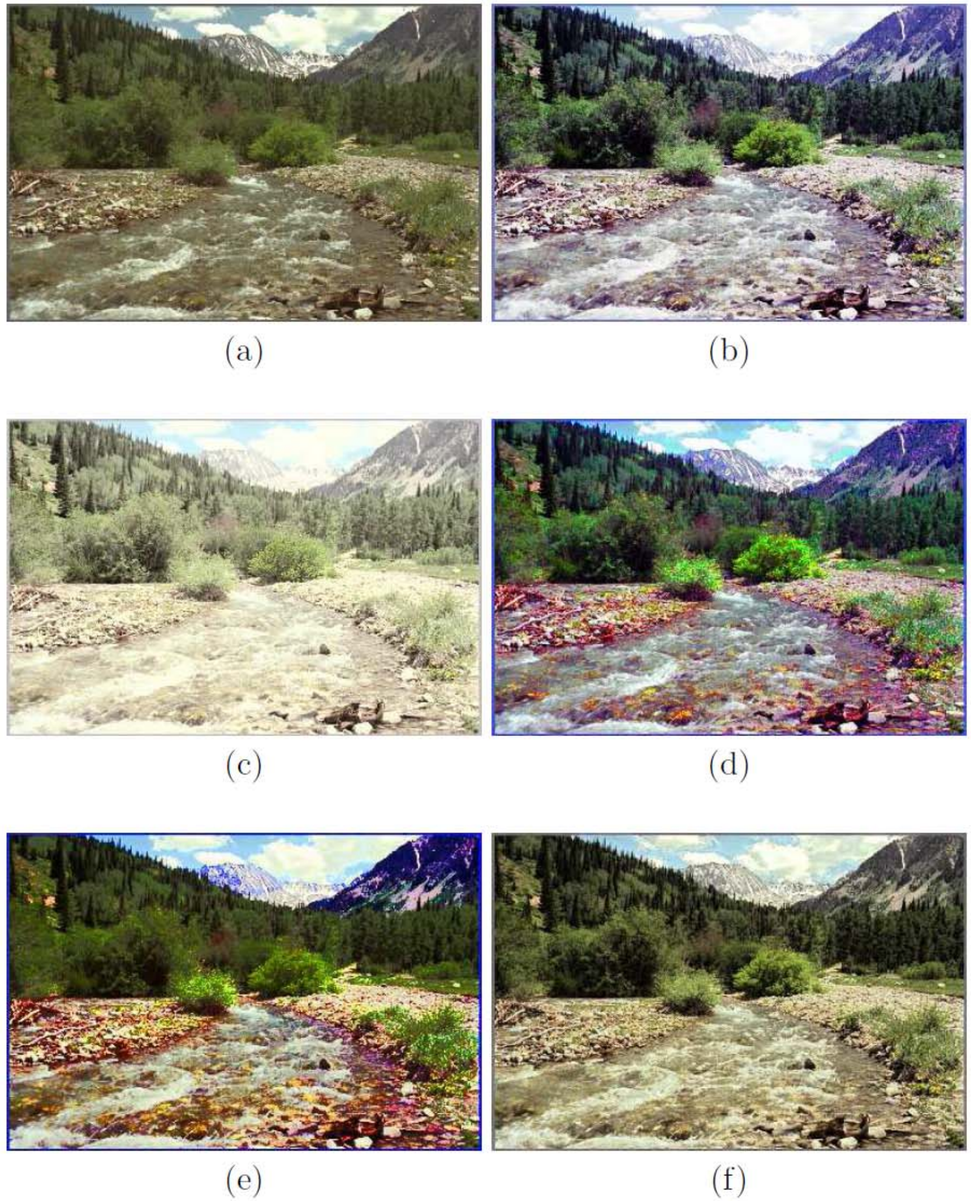
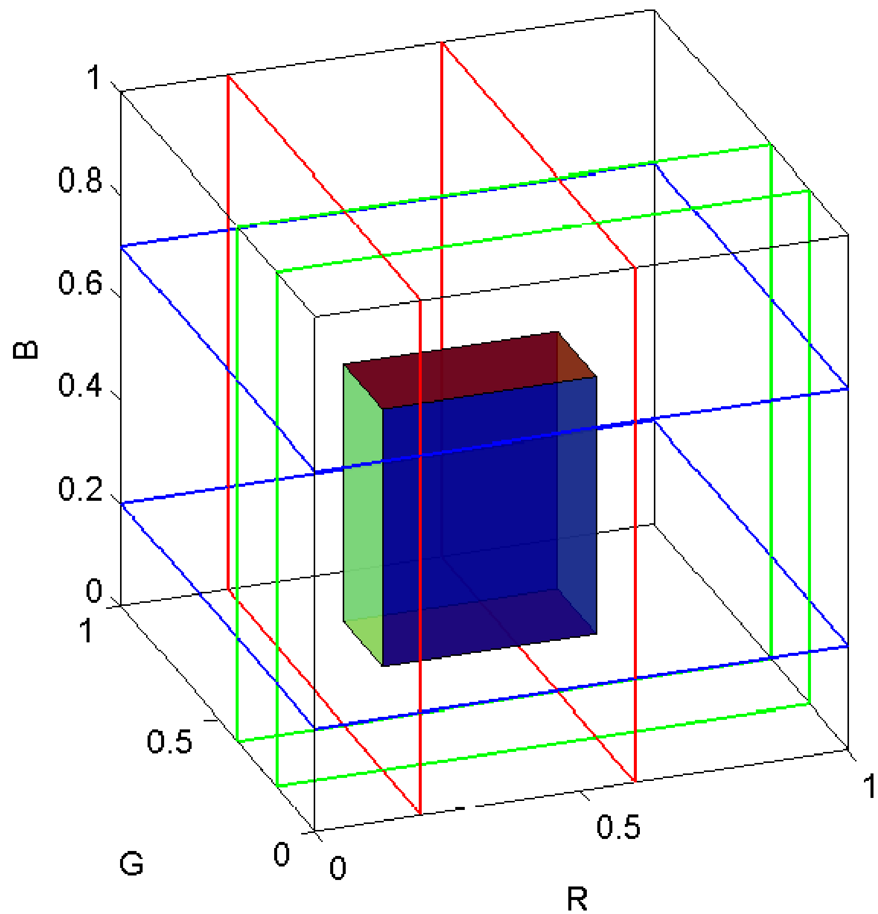
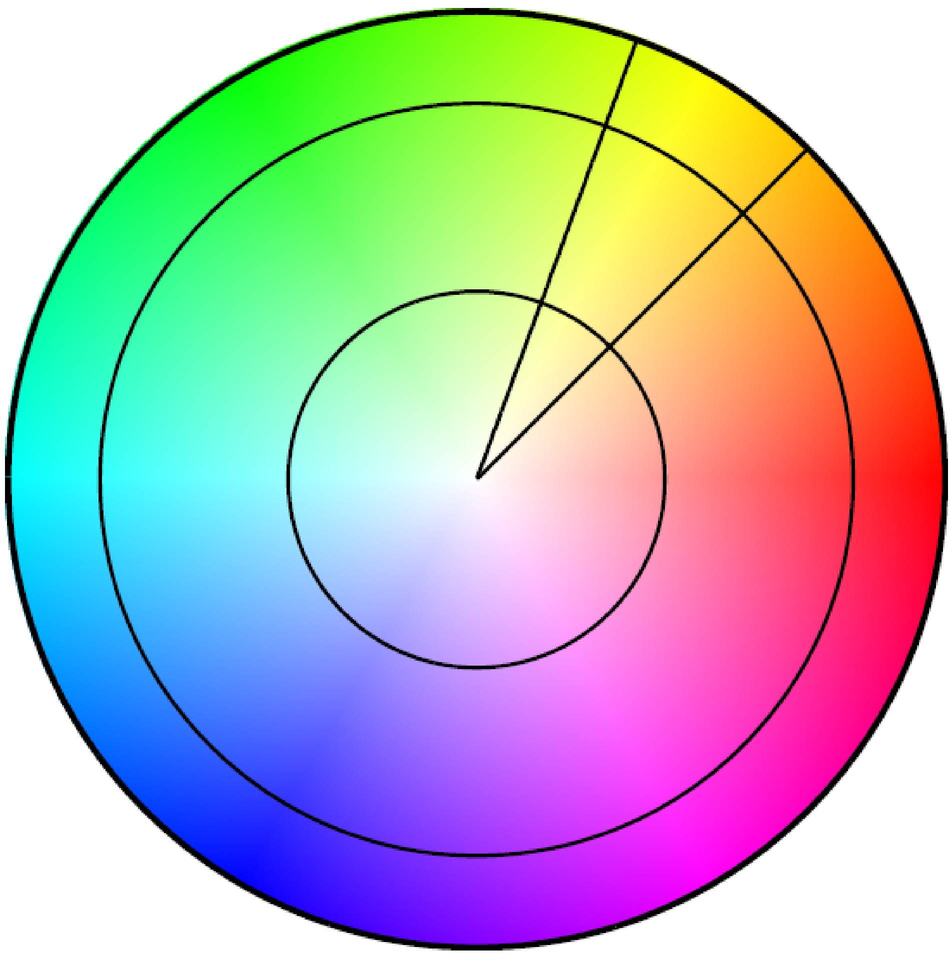


Figure 4.31 Results of histogram equalization: (a) The original 256×384-pixel "13" image from the ftp site ipl.rpi.edu. (b) The image after histogram equalization of each channel independently. (c) Result of 3D histogram equalization. (d) Result of histogram decimation. (e) Result of histogram explosion. (f) Result of ANHE with $N_{\mathrm{max}} = 100$, $N_{\mathrm{min}} = 20$, $T = 20$, and $\kappa = 3$. Reproduced with permission from Buzuloiu et al. [325].

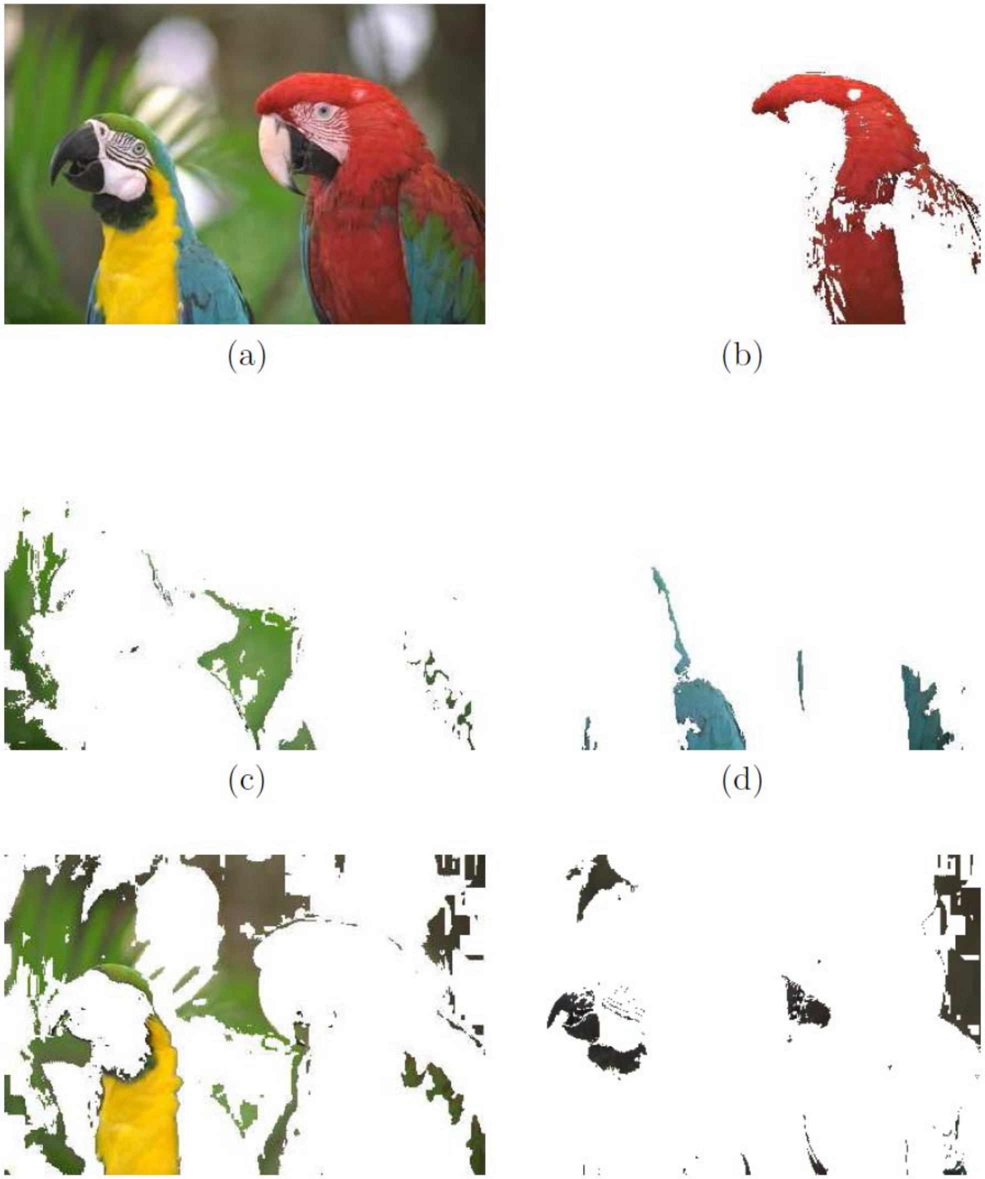
Segmentation of Color Images



Selecting ranges in RGB



Selecting ranges in HSI



(a) (b) (c) (d) (e) (f)

Figure 5.6 (a) Original color image. Segmentation based upon hue angle and saturation: (b) segmented red component; (c) segmented green component; (d) segmented cyan component; (e) segmented yellow component; (f) segmented black component. The segmented blue and magenta components were nearly empty. See also Figures 1.36 and 1.43.

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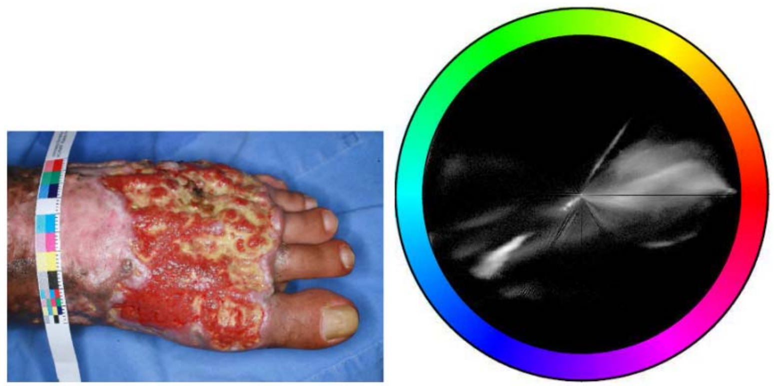
Image Alert!

Segmentation of Images of Skin Ulcers

Original image



(a) (b)

Hue-saturation histogram

Red (granulation)

S>0.4 and
H 300º to 0 to 30º

c) d)

Yellow (fibrin)

S>0.2 and
H 30º to 90º

Black (necrotic scar)

S<0.2 and
*I<0.25*max*

e) f)

Ulcer regions

Segmentation: *k*-means Algorithm

$$X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$$ *color pixel dataset*

$$\mathbf{x}_h \in \mathcal{R}^3$$

$$V = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$$ *code book of centroids*

$$\pi_i = \left\{ \mathbf{x} \in X \middle| i = \arg\left[\min_j \|\mathbf{x} - \mathbf{v}_j\|^2\right] \right\}$$

set of pixels corresponding to $\mathbf{v}_i$*: for which* $\mathbf{v}_i$ *is nearest*

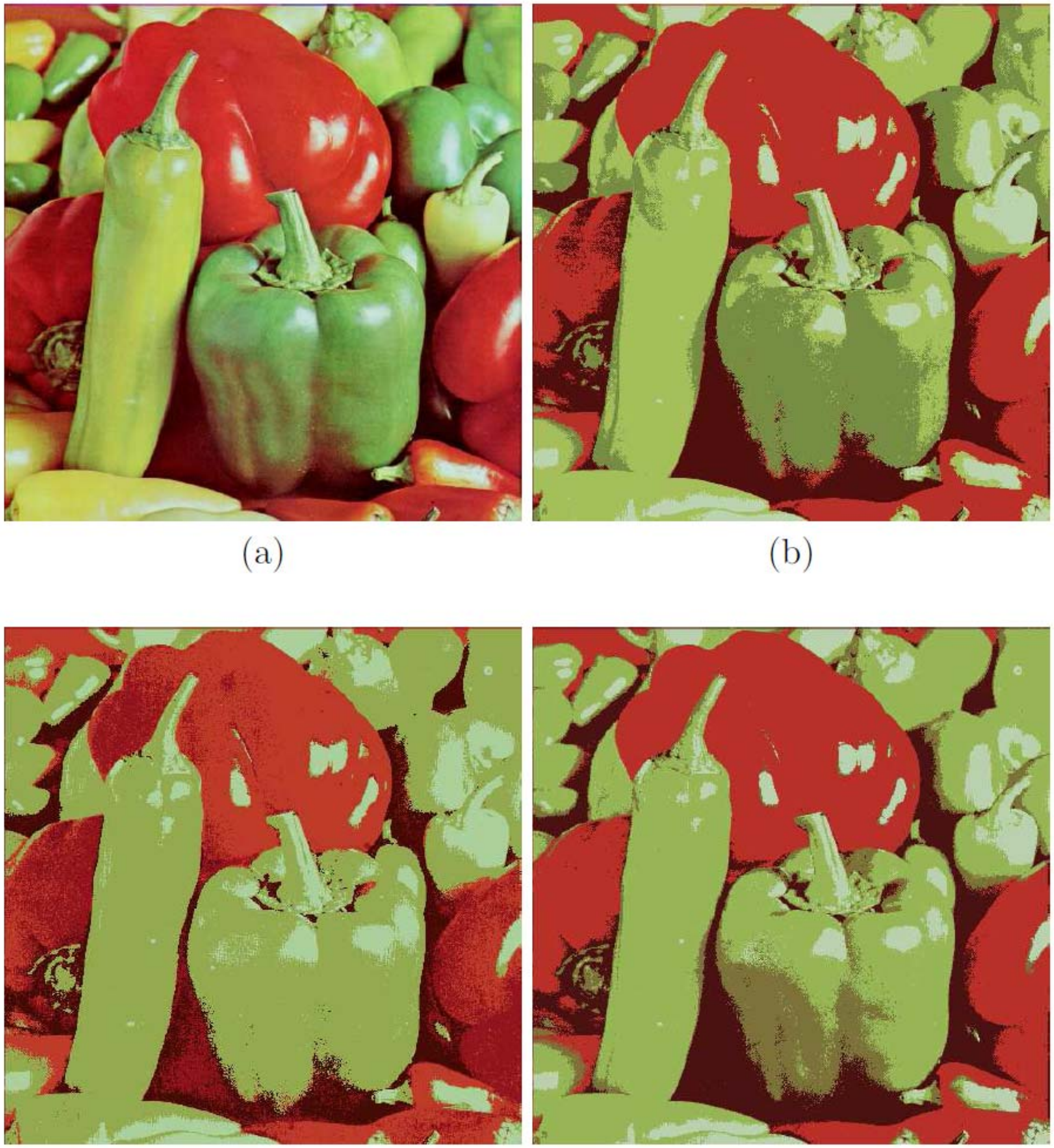
Segmentation: *k*-means Algorithm

Starting from the finite dataset ***X***, iteratively move the *k* code vectors so as to minimize an error measure and recalculate the sets.

Error: $$E(X) = \frac{1}{2n} \sum_{i=1}^{k} \sum_{\mathbf{x} \in \pi_i} \|\mathbf{x} - \mathbf{v}_i\|$$

New centroid: $$\mathbf{v}_i = \frac{1}{|\pi_i|} \sum_{\mathbf{x} \in \pi_i} \mathbf{x}$$

Figure 5.7 (a) Original color image. Results of segmentation using the k-means clustering algorithm in three different color spaces: (b) $sRGB$, (c) HSV, and (d) $L^*a^*b^*$. In each case, the image has been segmented into six regions. The color assigned to each region is the final centroid of the color values in the corresponding region in the original image after application of the k-means algorithm.



(a) (b) (c) (d)

Figure 5.8 (a) Original color image. Results of segmentation by application of the k-means algorithm in three different color spaces: (b) $sRGB$, (c) HSV, and (d) $L^*a^*b^*$.

Color Deconvolution in Histopathology Images

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$$\mathbf{P} = \begin{array}{c} \\ \\ \\ \end{array}\begin{array}{ccc} R & G & B \\ \end{array}$$

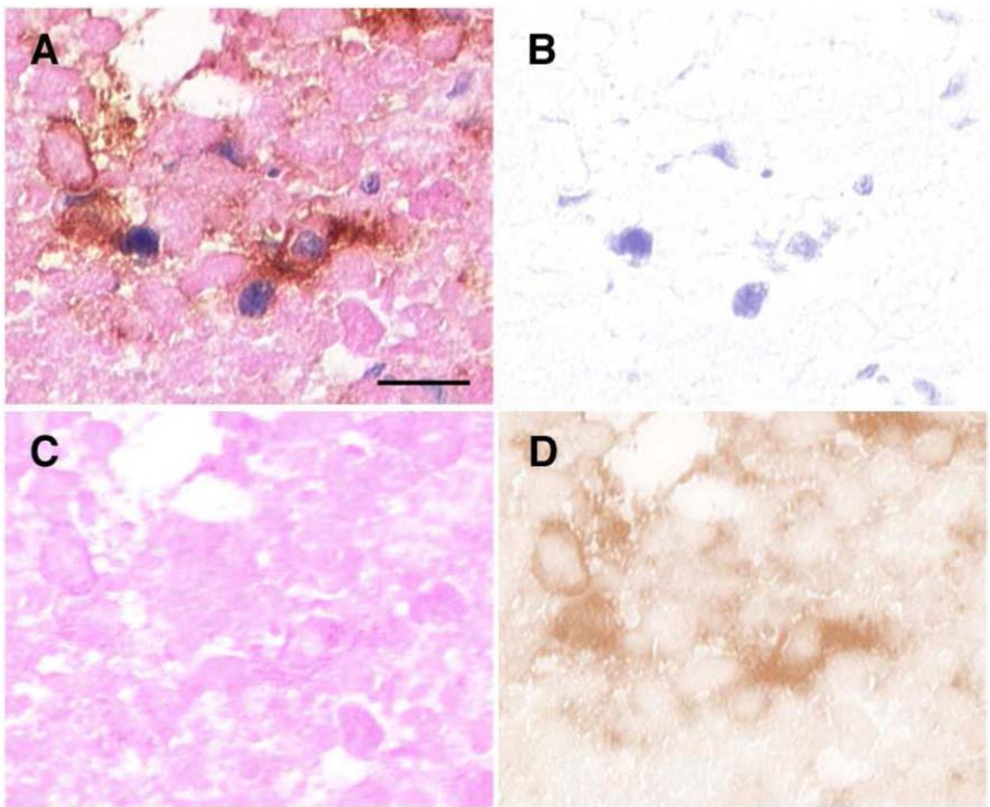
$$\mathbf{P} = \begin{bmatrix} 0.18 & 0.20 & 0.08 \\ 0.01 & 0.13 & 0.01 \\ 0.10 & 0.21 & 0.29 \end{bmatrix} \begin{array}{l} \leftarrow \text{hematoxylin} \\ \leftarrow \text{eosin} \\ \leftarrow \text{DAB.} \end{array}$$

$$m_{ij} = \frac{p_{ij}}{\left[\sum_{j=1}^{3} p_{ij}^2\right]^{\frac{1}{2}}}$$

Color pixel RGB vector: $\mathbf{y} = \mathbf{C}\,\mathbf{M}$

M: *Normalized matrix of RGB values for the dyes*

Color Separation in Histopathology Images



Stain mix vector for each pixel:

$$\mathbf{C} = \mathbf{y}\,\mathbf{M}^{-1}$$

Figure 5.44 A. Breast biopsy specimen stained with a combination of hematoxylin (blue), eosin (magenta), and DAB (brown). The length of the bar in the image represents 20 μm. The results of color separation or deconvolution: B. hematoxylin, C. eosin, and D. DAB. Reproduced with permission from Ruifrok AC and Johnston DA. Quantification of histochemical staining by color deconvolution. *Analytical and Quantitative Cytology and Histology*, 23:291–299, 2001. ©AQCH.

Additional Topics

Edge detection in color
Region growing in color
Morphological image processing in color
Hyperspectral image processing
Analysis of texture in color
Coding and data compression of multispectral data
Analysis of burn wounds
Analysis of skin ulcers
Teledermatology
Telepathology
Hyperspectral aerial photogrammetry with LiDAR...

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