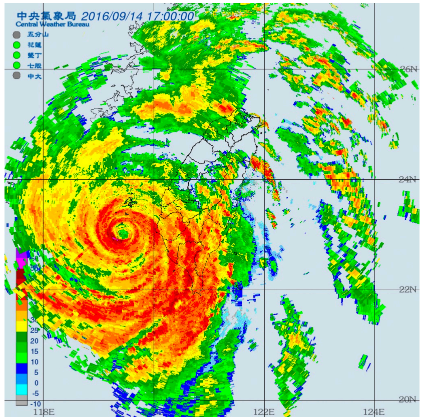
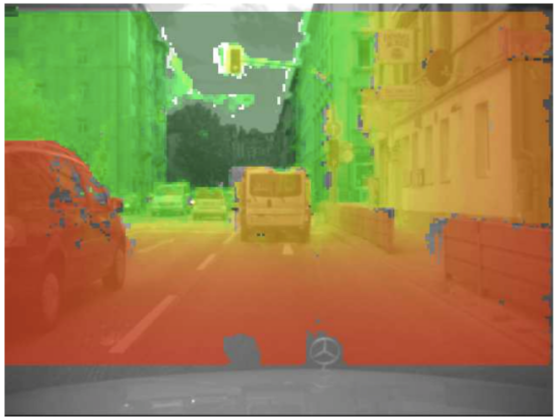
6.3 Pseudocolor Image Processing

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

- The principle use of pseudocolor image processing is for human visualisation .
    - Humans can discern between thousands of color shades and intensities, compared to only about two dozen or so shades of gray.

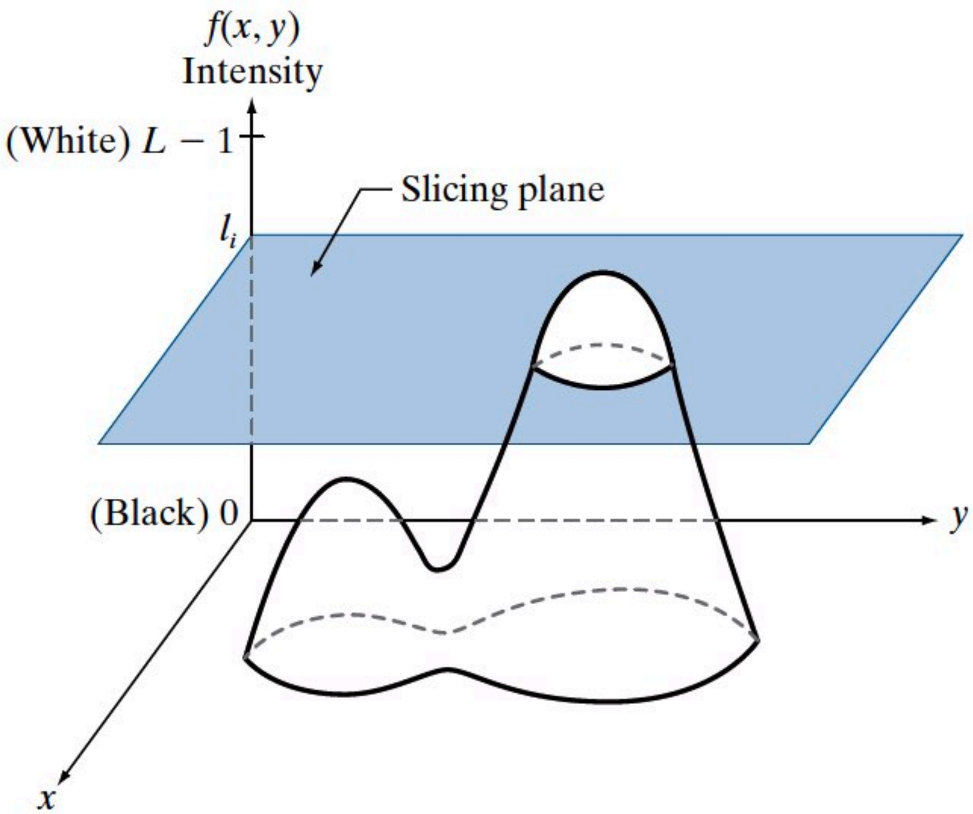




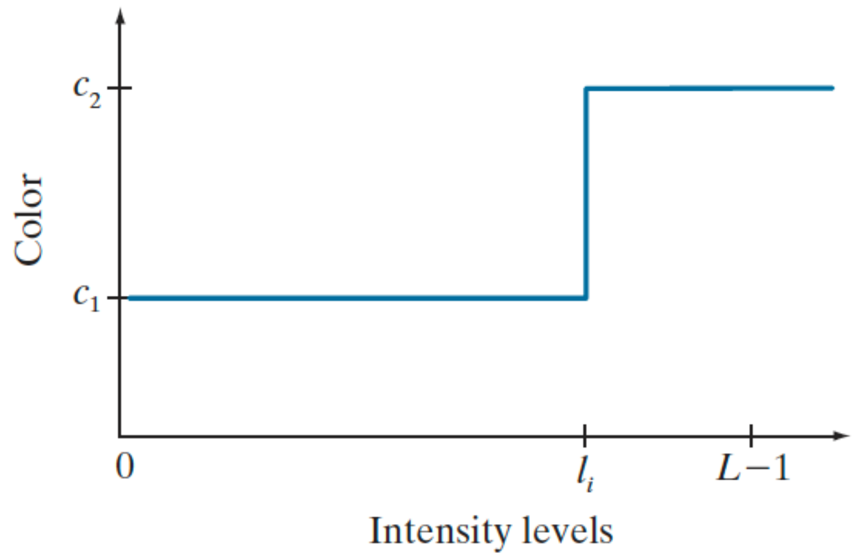
credit of this slide: C. Nikou

6.3 Pseudocolor Image Processing - Intensity Slicing and Color Coding

Intensity Slicing

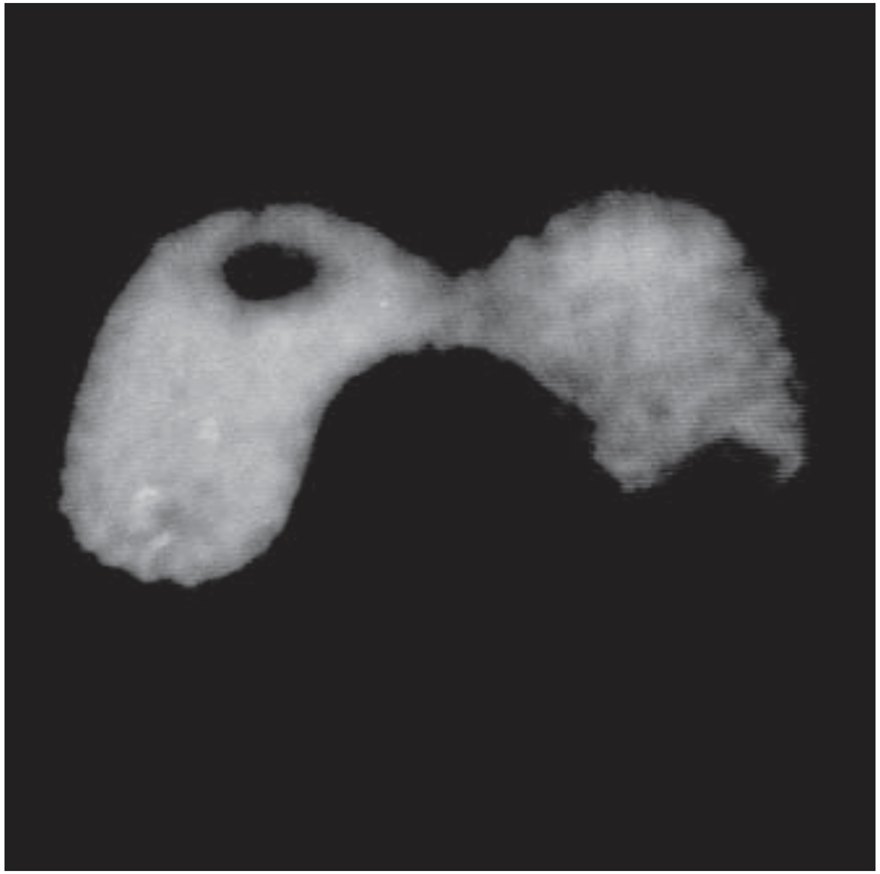


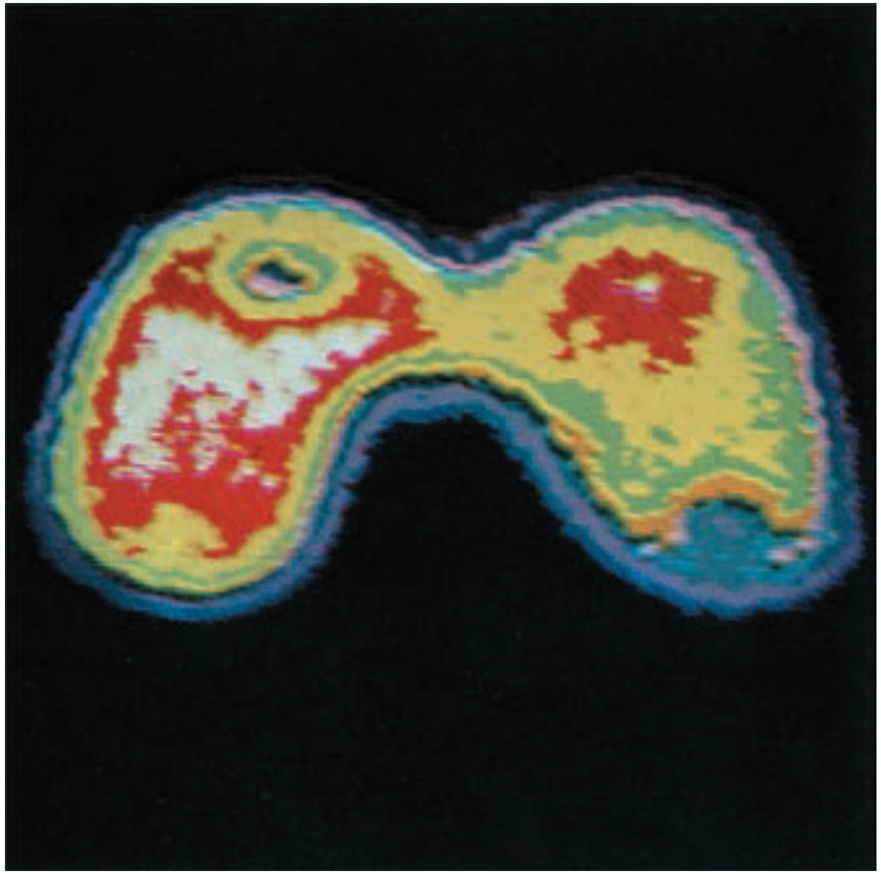
Color Coding



6.3 Pseudocolor Image Processing
- Intensity Slicing and Color Coding

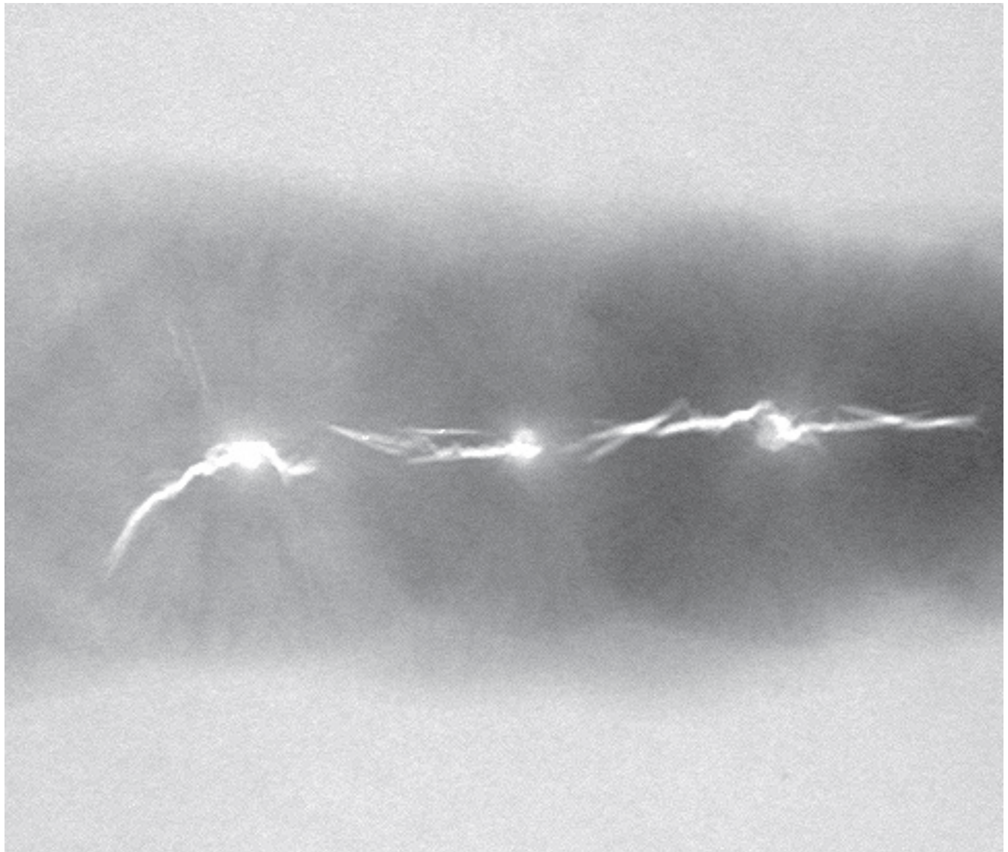
Example of Intensity Slicing

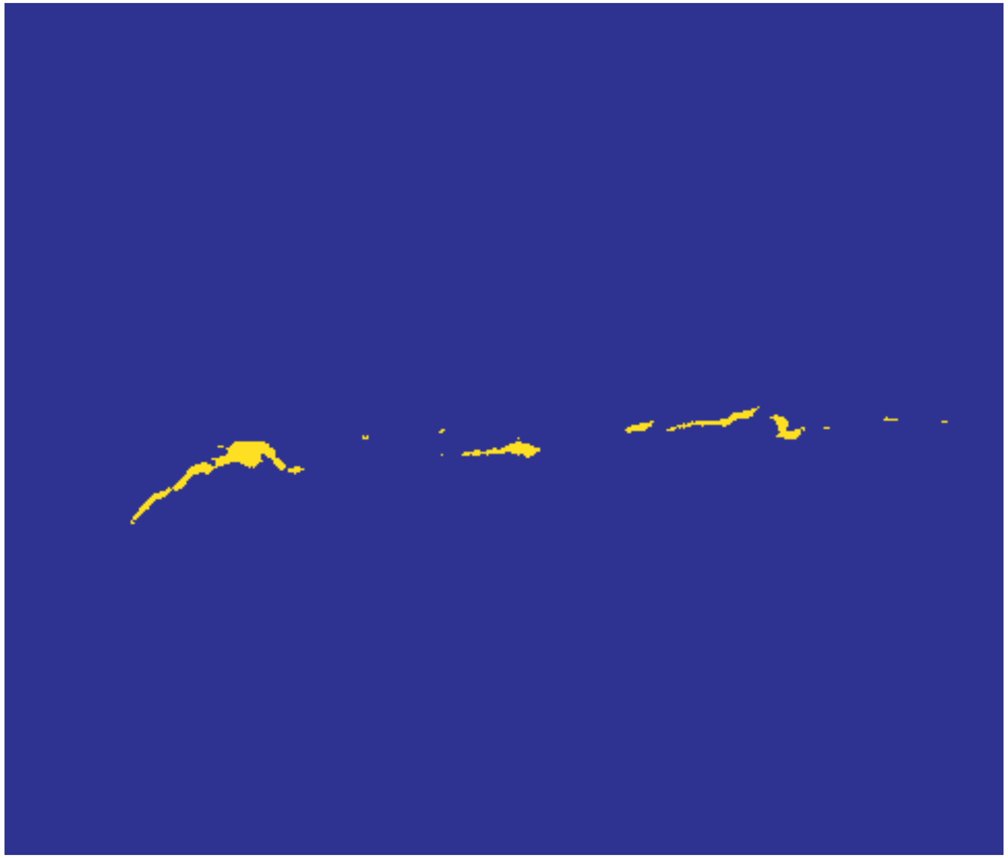




6.3 Pseudocolor Image Processing - Intensity Slicing and Color Coding

Example of Color Coding



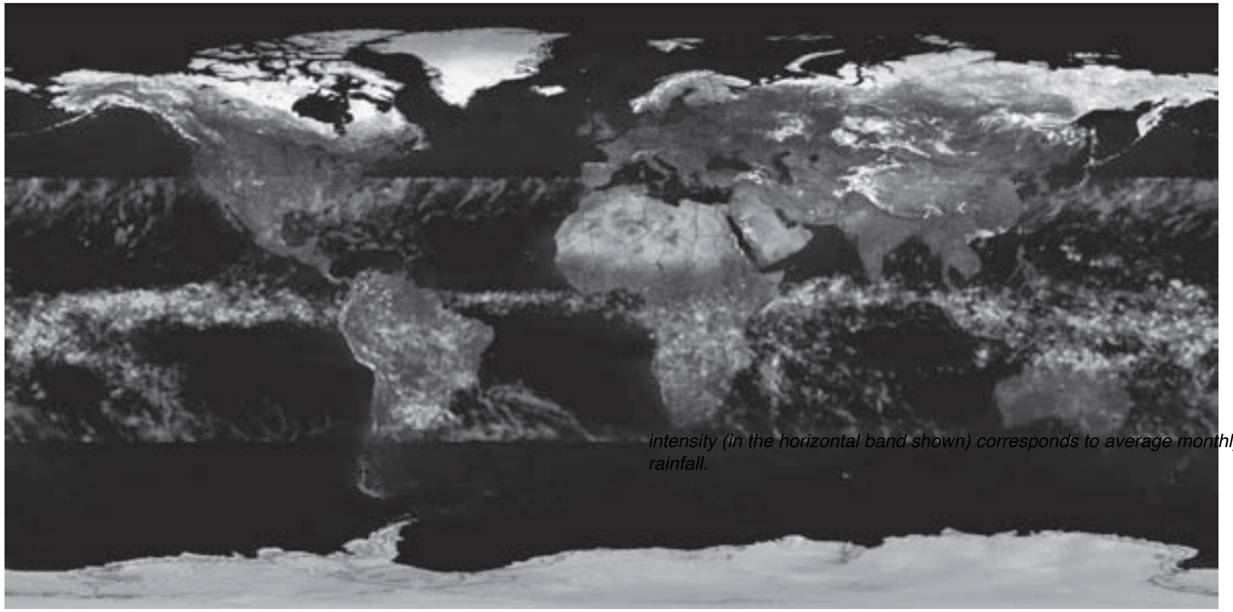


- Assigning the yellow color to intensity 255 and the blue color to the rest of the intensities may help a human inspector to rapidly evaluate a crack in an image of a weld.

credit of this slide: C. Nikou

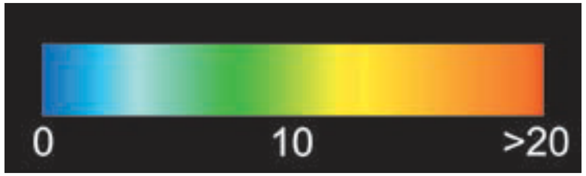
6.3 Pseudocolor Image Processing
- Intensity Slicing and Color Coding

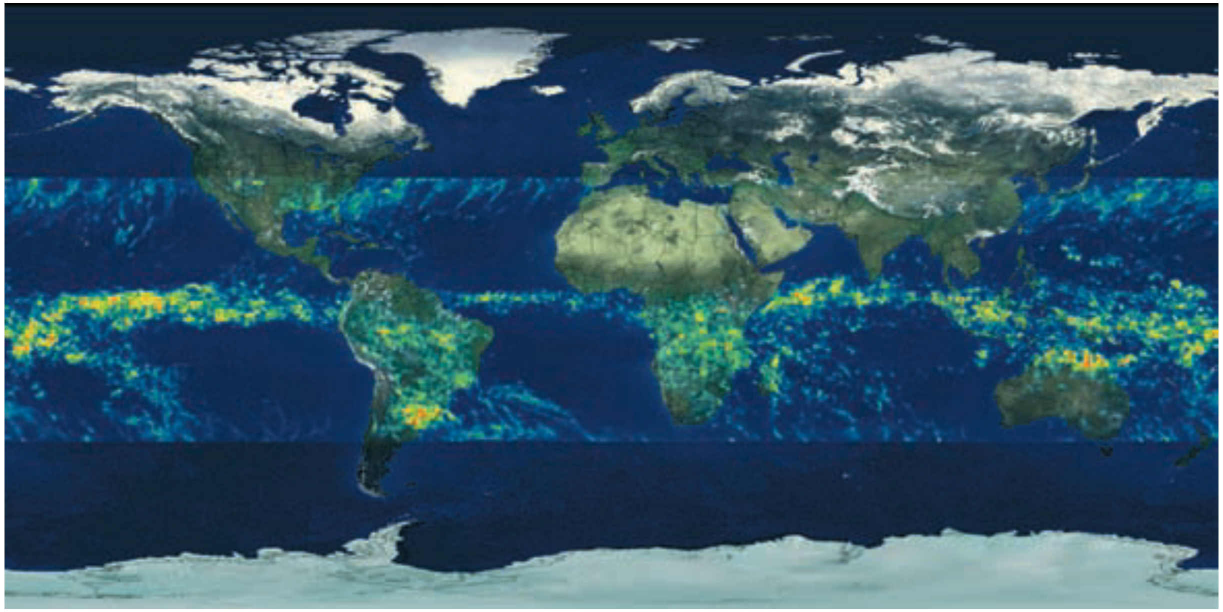
Example of Intensity Slicing

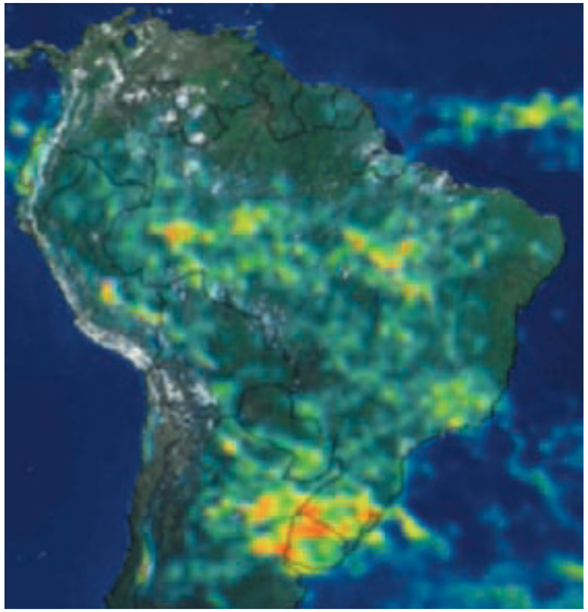


intensity (in the horizontal band shown) corresponds to average monthly rainfall.

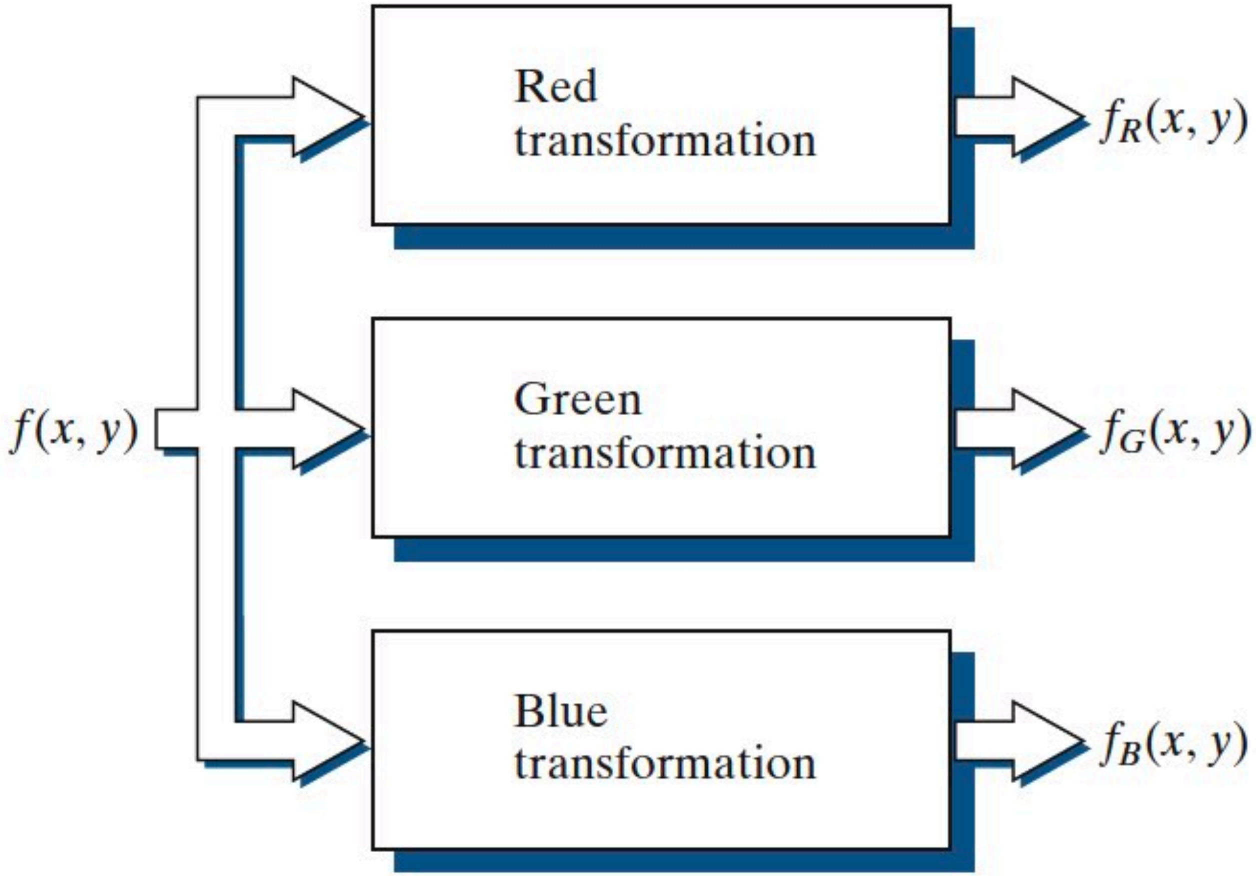
Intensity corresponds to average monthly rainfall







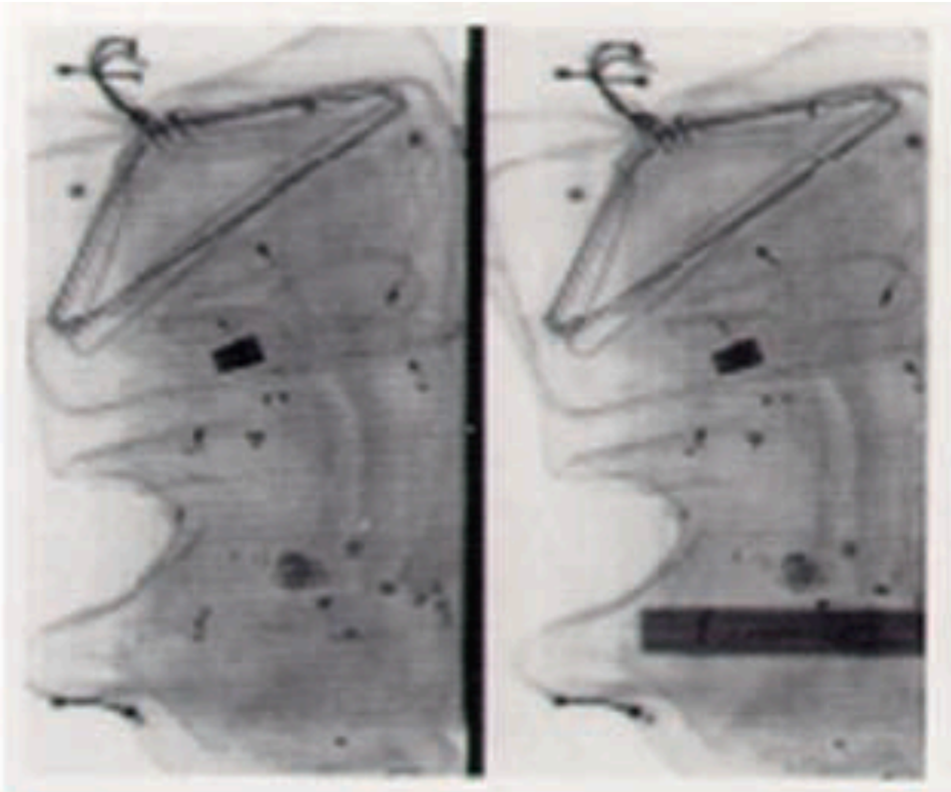
6.3 Pseudocolor Image Processing - Intensity to Color Transformation



- Three independent transformations of the intensity.
- The results are fed into the R, G, B channels.
- The resulting composite image highlights certain image parts.

credit of this slide: C. Nikou

6.3 Pseudocolor Image Processing - Intensity to Color Transformation

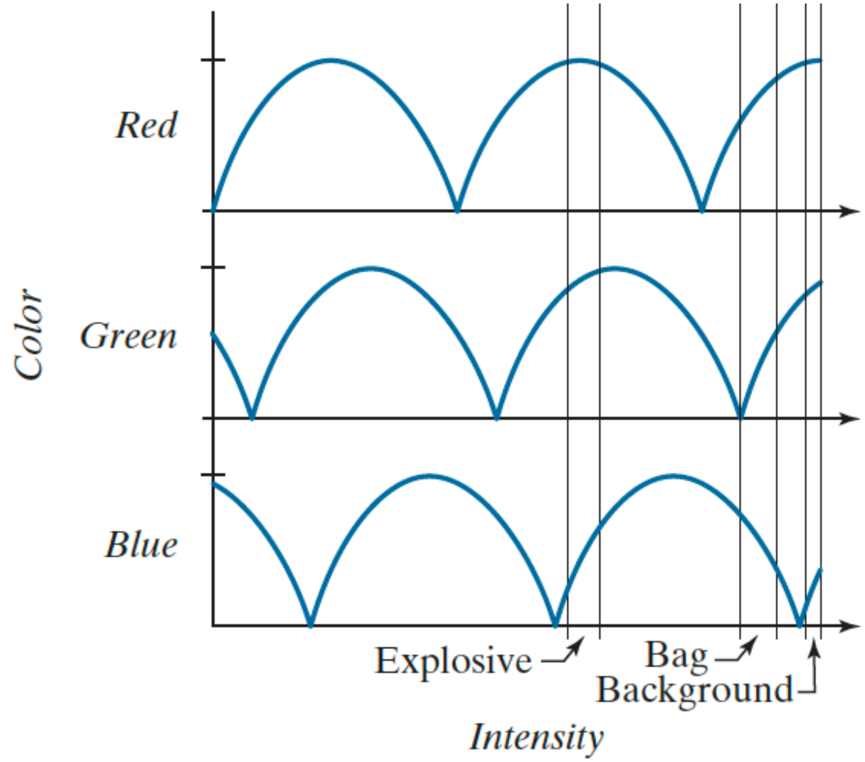


- X-ray images from airport scanning system.
- The image on the right contains plastic explosives.

credit of this slide: C. Nikou

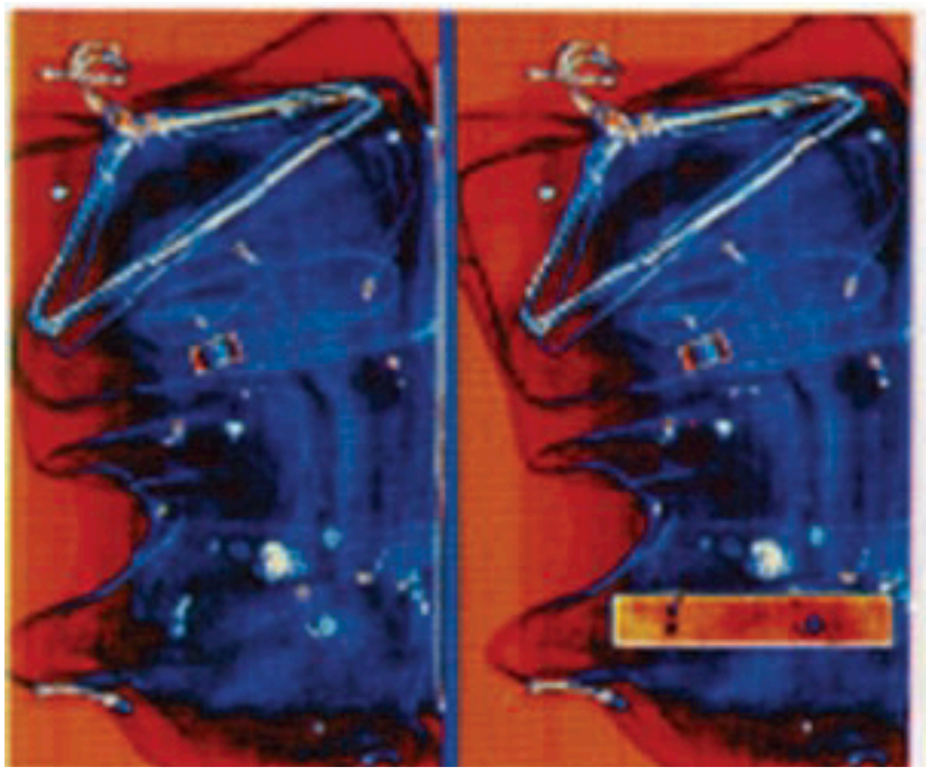
6.3 Pseudocolor Image Processing - Intensity to Color Transformation

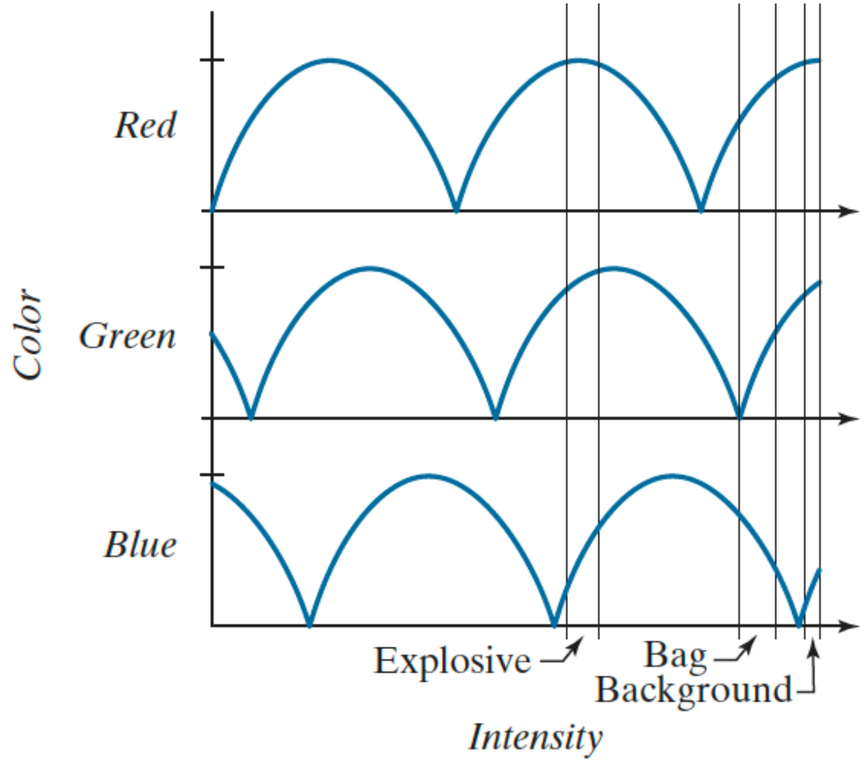
- Sinusoidal transformation functions.
- Changing the phase or the frequency of the transformation functions can emphasize ranges in the gray scale.
    - A small change in the phase between the transformations assigns a strong color to the pixels with intensities in the valleys.



credit of this slide: C. Nikou

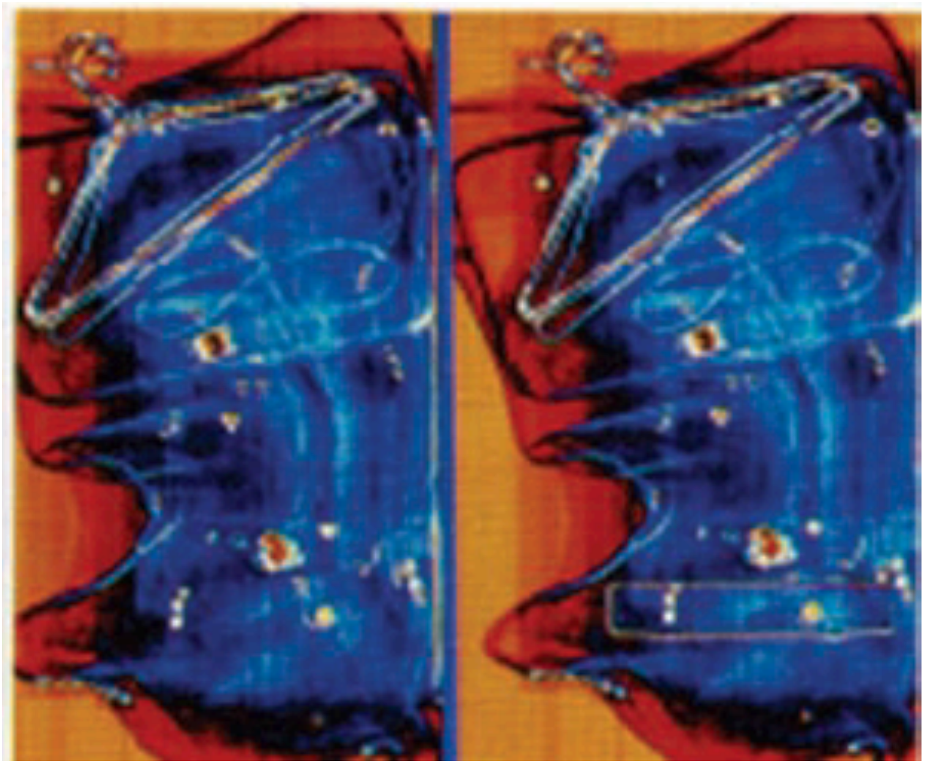
6.3 Pseudocolor Image Processing - Intensity to Color Transformation

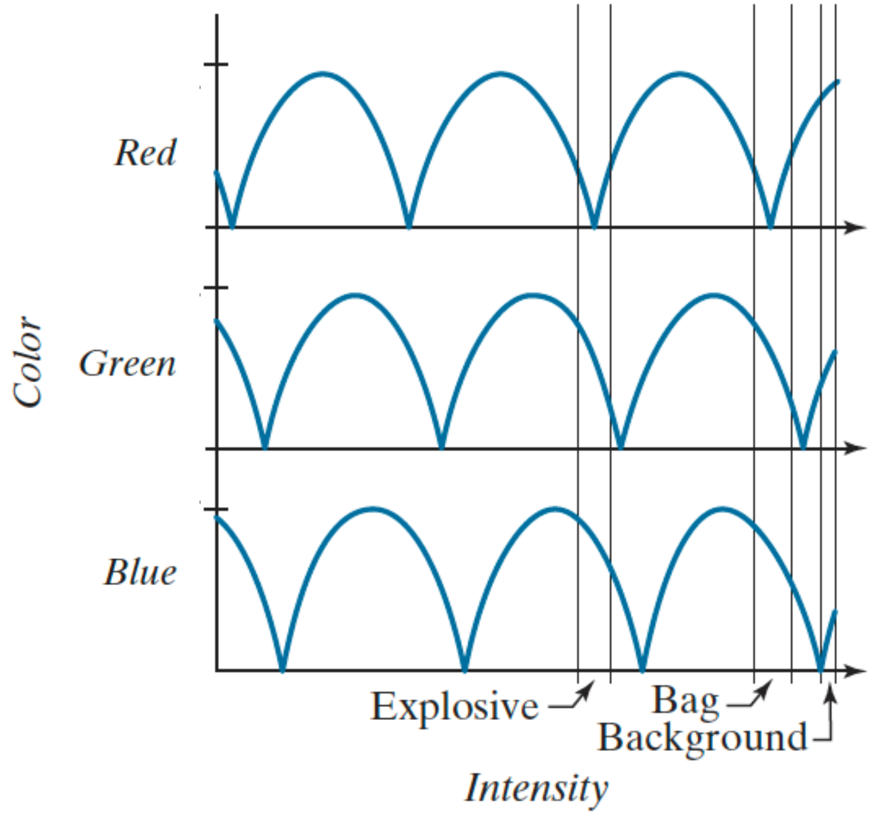




- Background and explosives are coded with approximately the same color although they differ.
- This is due to the periodicity of the sine waves.

6.3 Pseudocolor Image Processing - Intensity to Color Transformation





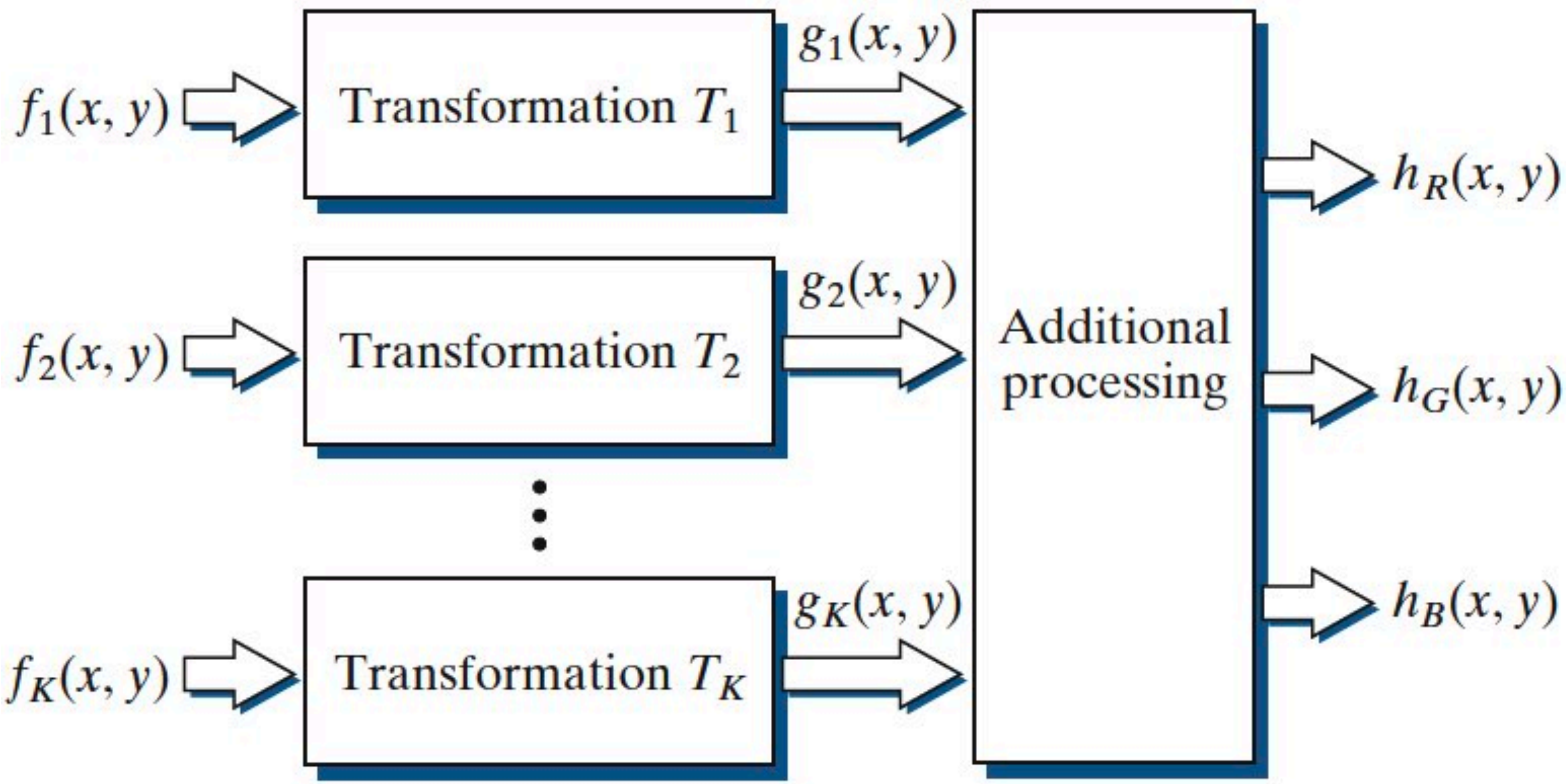
- Explosives and bag content are mapped by similar transformations and were assigned to the same color.
- The observer may "see" through the explosives and not mistake them for the background.

credit of this slide: C. Nikou

6.3 Pseudocolor Image Processing - Intensity to Color Transformation

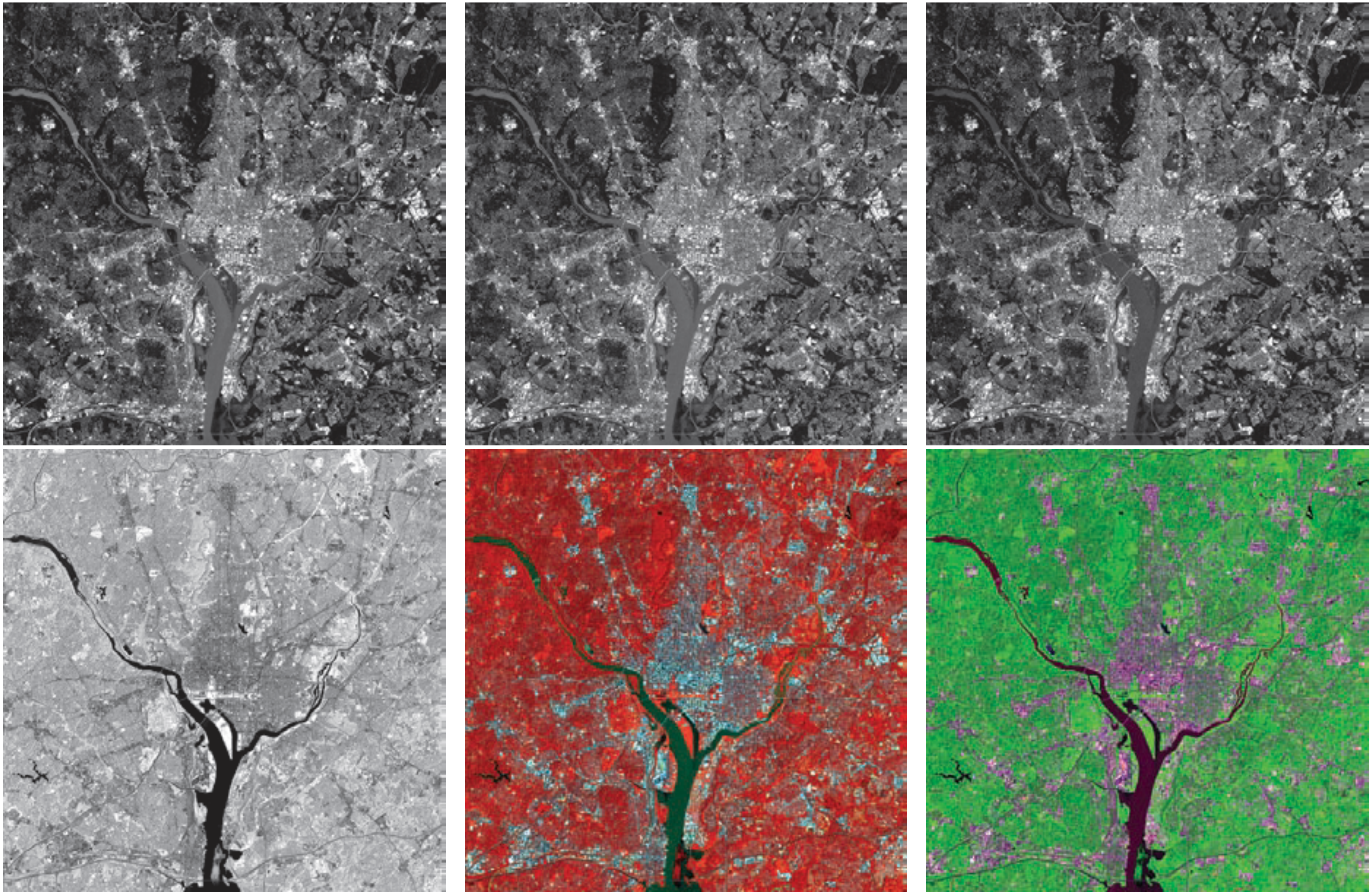
Color coding of multispectral images

- A pseudocolor coding approach using multiple grayscale images



Color coding of multispectral images

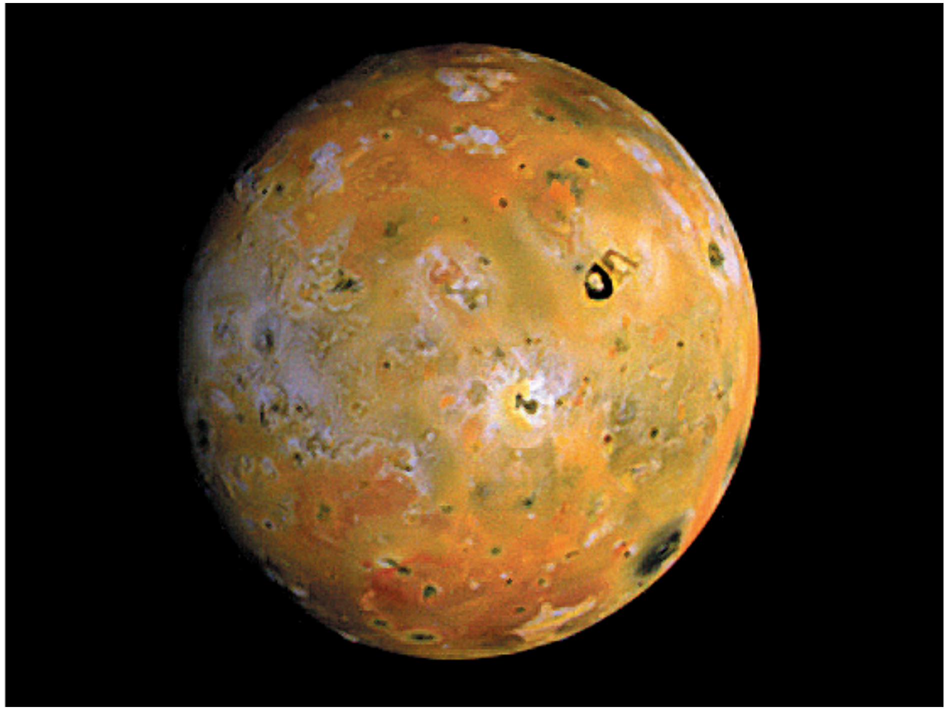
R G B



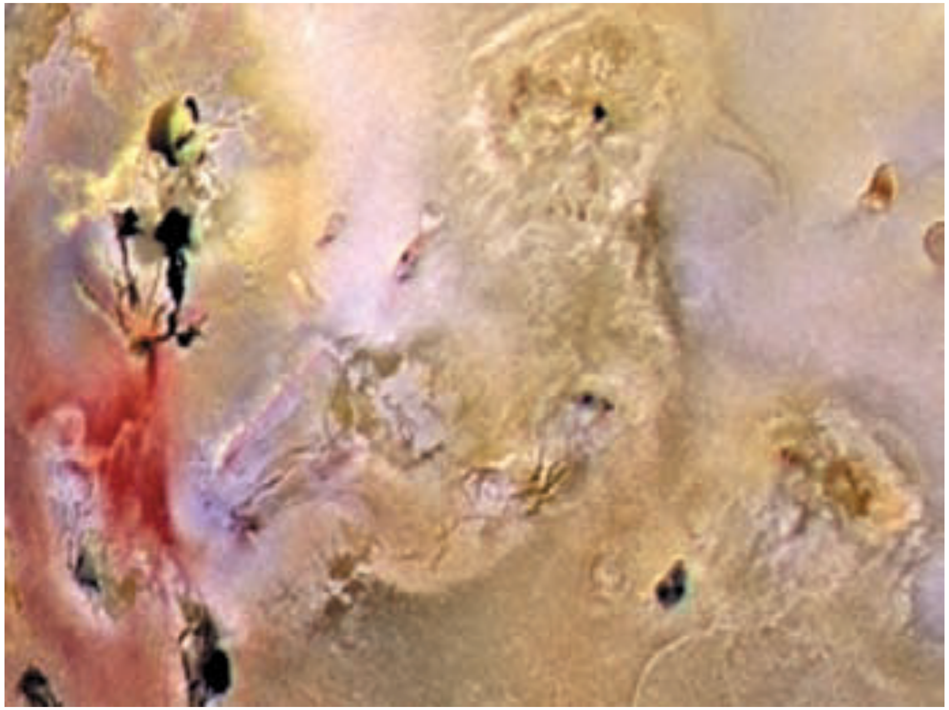
Near-infrared (IR) IR, G, B R, IR, B

6.3 Pseudocolor Image Processing - Intensity to Color Transformation

Color coding of multispectral images



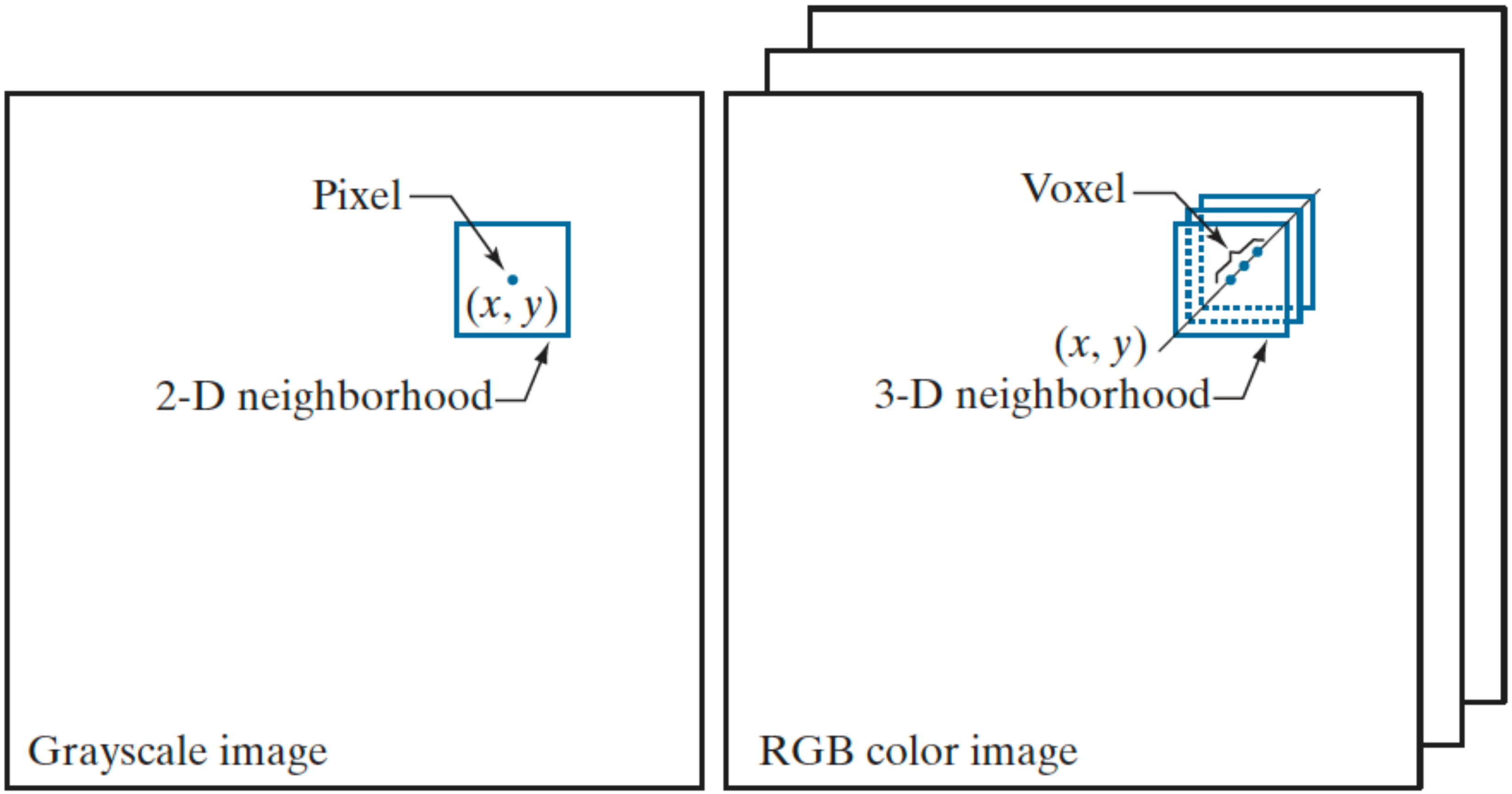
Pseudocolor rendition of Jupiter Moon Io (木衛一)



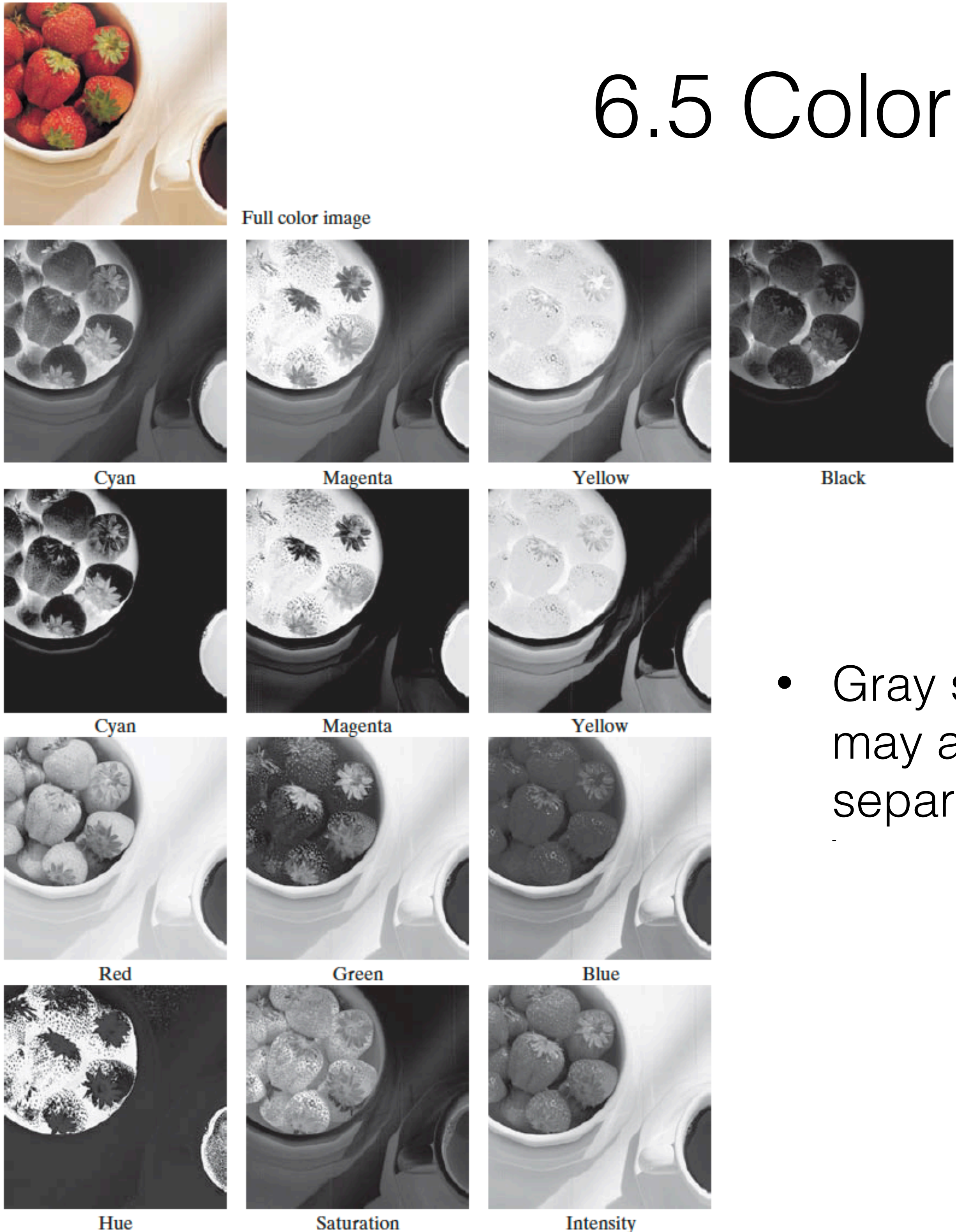
- bright red: depicts material newly ejected from an active volcano
- the surrounding yellow materials are older sulfur deposits

6.4 Basics of Full-Color Image Processing

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



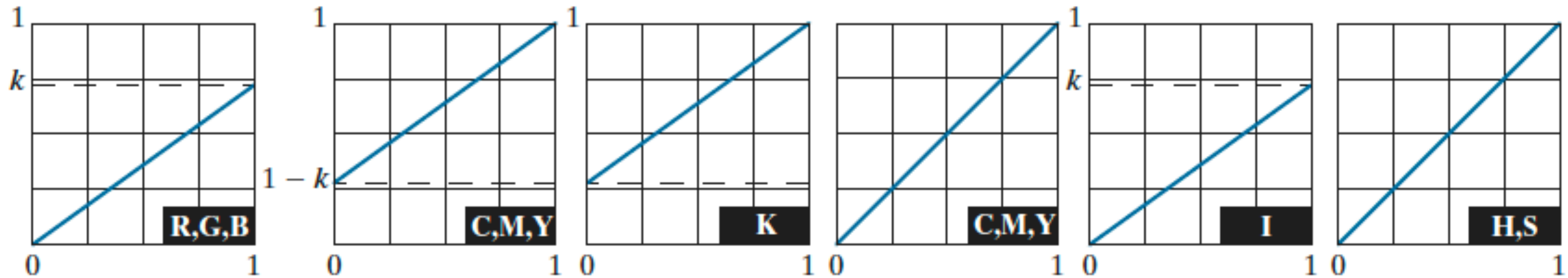
6.5 Color Transformations



- Gray scale image transformations may also be applied to each color separately.

credit of this slide: C. Nikou

6.5 Color Transformations

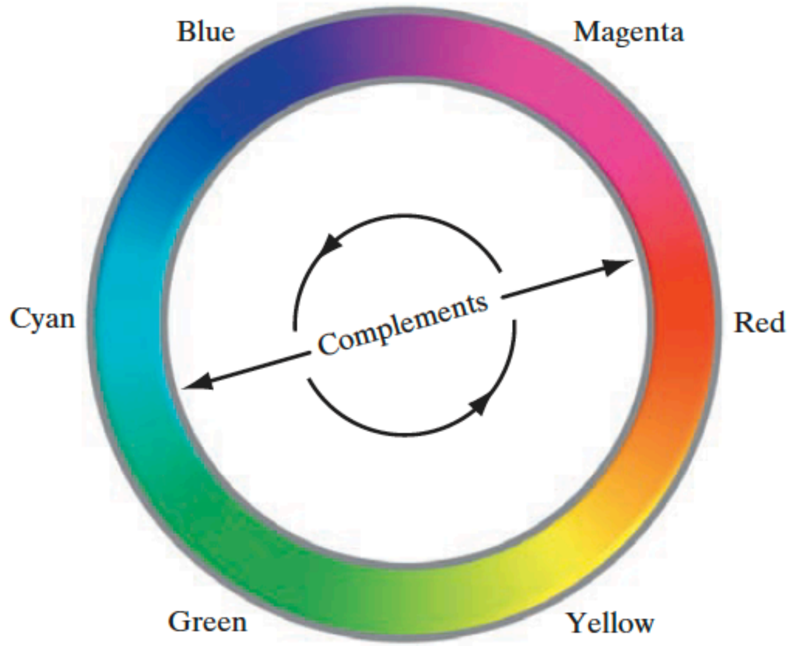


- **Intensity adjustment** in RGB, CMYK, CMY and HSI spaces.
- The output is the same regardless of the color space.

credit of this slide: C. Nikou

6.5 Color Transformations - Color Complements

- For enhancement of dark regions.
- Opposite hues in the color circle.
- Straightforward in RGB space.
- No equivalent transformation in HSI space.
  - The saturation (S) component cannot be computed from the S component of the original image.



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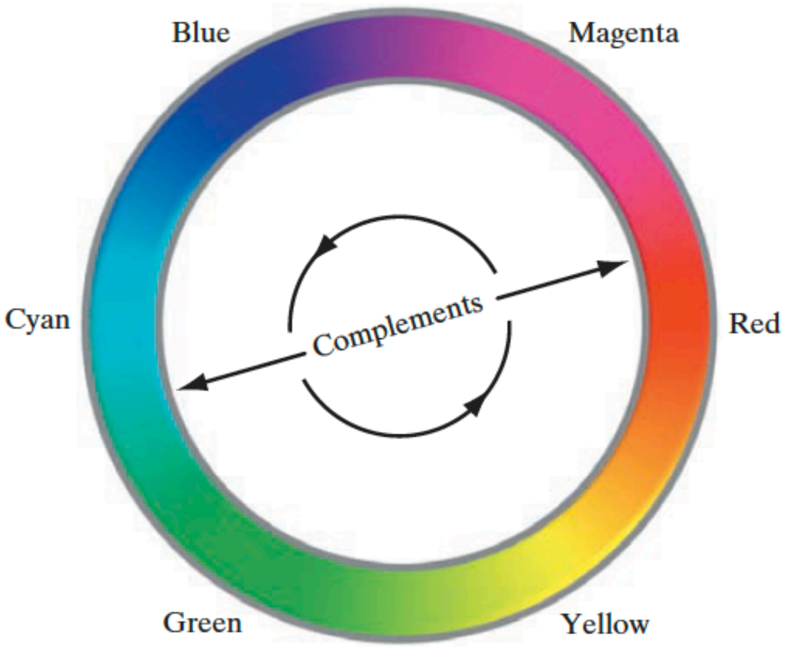
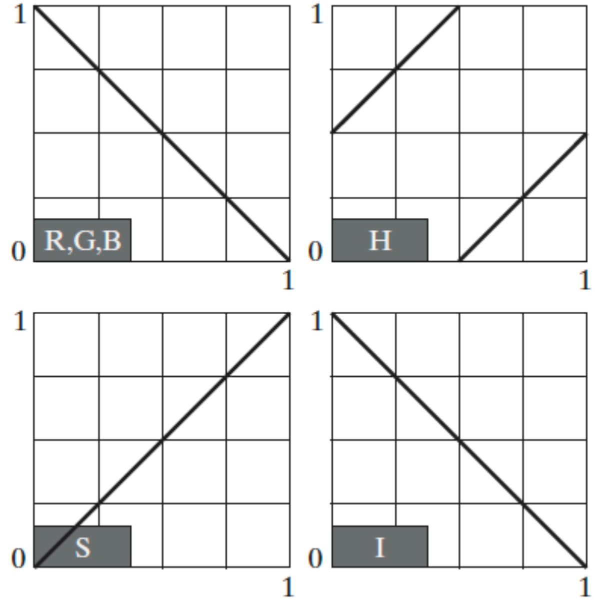
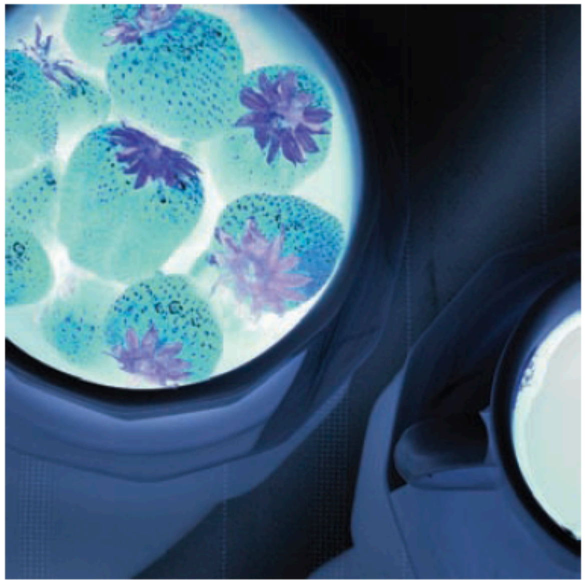
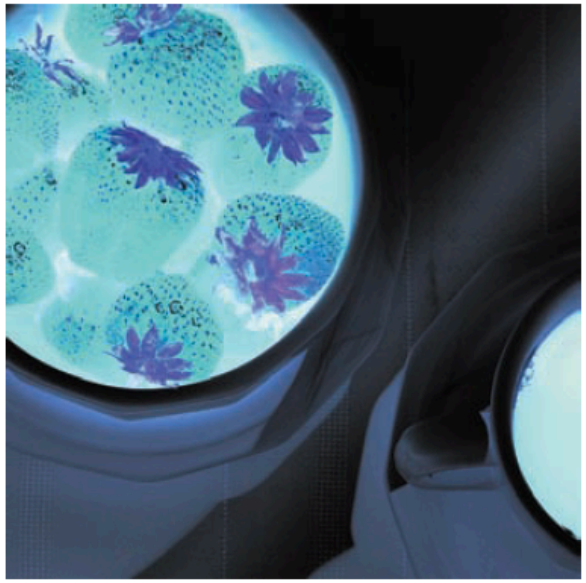
6.5 Color Transformations - Color Complements







with RGB



approximation with HSI

6.5 Color Transformations - Color Slicing

- Highlighting a specific range of colors is useful for separating objects from their surroundings.

- One of the simplest ways to "slice" a color image is to map the colors outside some range of interest into a nonprominent neutral color.

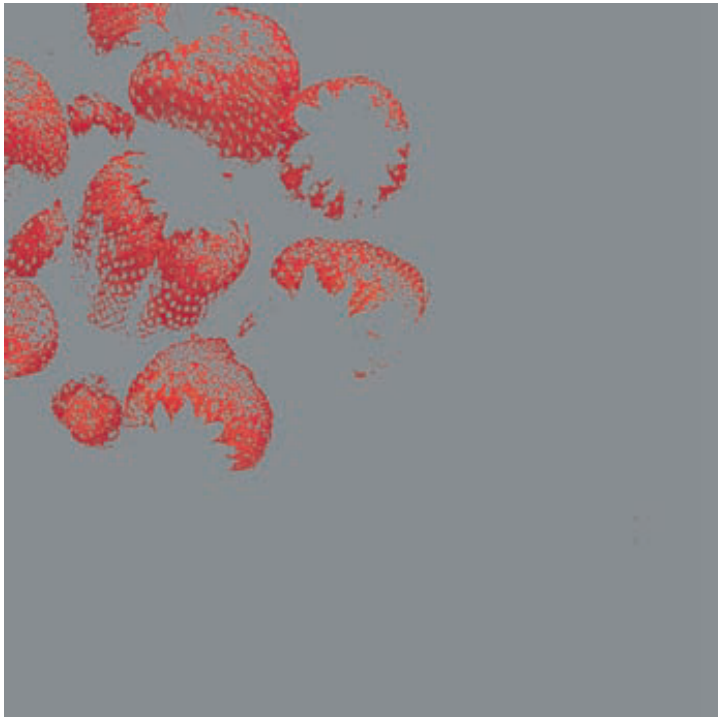
Cube

$$s_i = \begin{cases} 0.5 & \text{if} \left[\left| r_j - a_j \right| > \dfrac{W}{2} \right]_{\text{any } 1 \le j \le n} \\ r_i & \text{otherwise} \end{cases} \qquad i = 1, 2, \ldots, n$$

Sphere

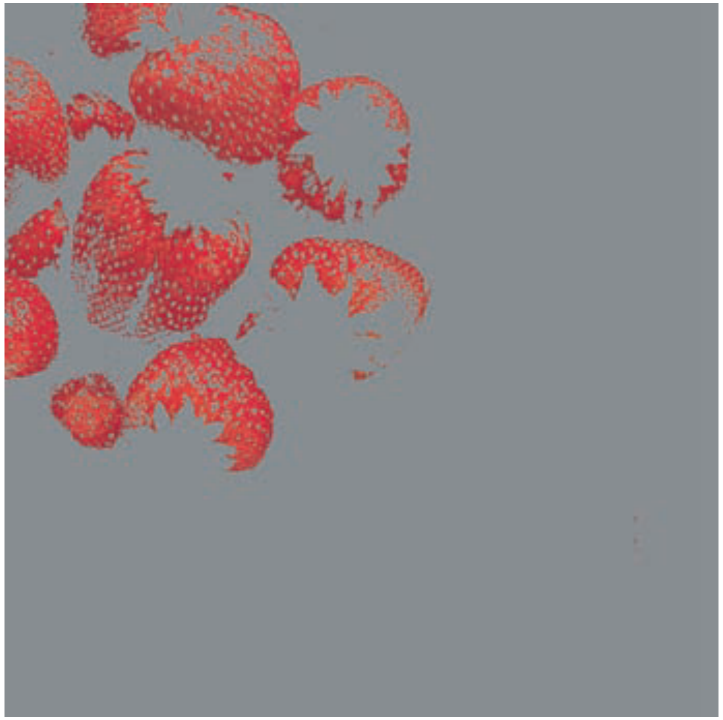
$$s_i = \begin{cases} 0.5 & \text{if} \quad \sum_{j=1}^{n} \left(r_j - a_j \right)^2 > R_0^2 \\ r_i & \text{otherwise} \end{cases} \qquad i = 1, 2, \ldots, n$$

6.5 Color Transformations - Color Slicing



Cube

W = 0.2549 centered at (0.6863, 0.1608, 0.1922)

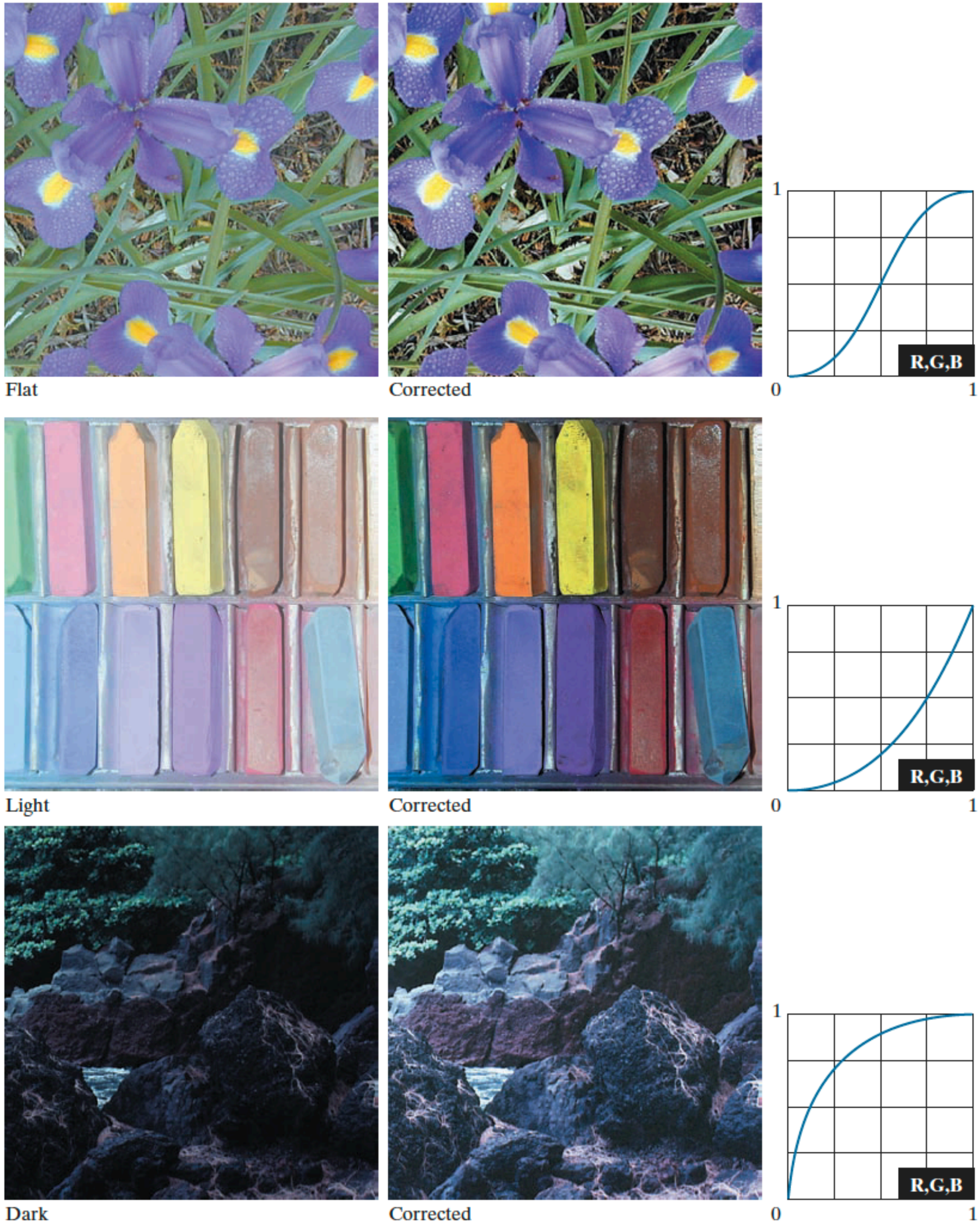


Sphere

radius = 0.1765 centered at the same point

6.5 Color Transformations - Tone and Color Corrections

Example:
Tonal transformations

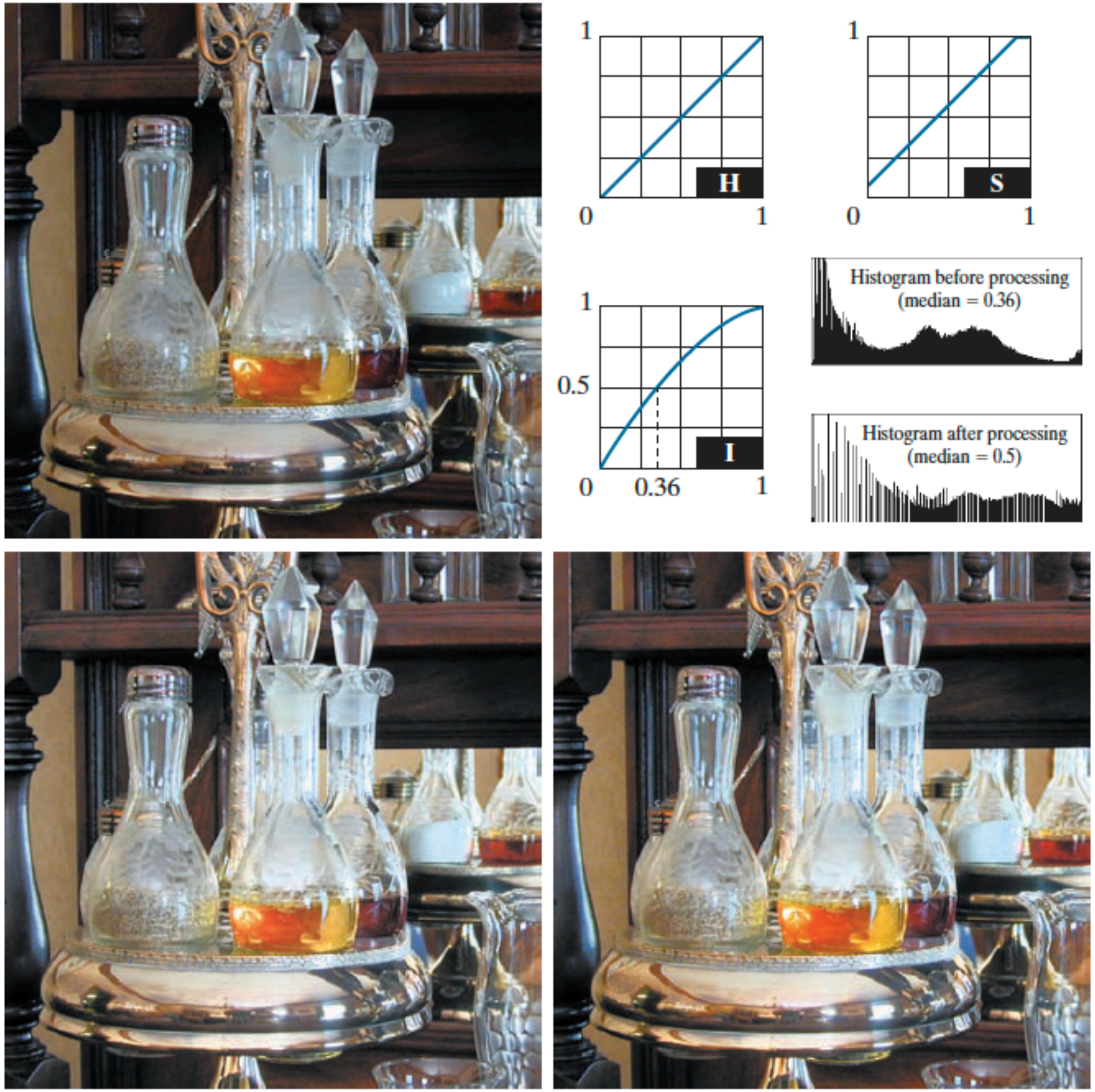


6.5 Color Transformations - Tone and Color Corrections

Example:
Color balancing

6.5 Color Transformations
- Histogram Processing of Color Images

- Unwise to histogram equalize the component images of a color image independently. This results in erroneous color.



Histogram equalizing intensity (left) followed by saturation adjustment (right)

6.6 Color Image Smoothing and Sharpening - Color Image Smoothing

RGB Image Smoothing:

$$\bar{\mathbf{c}}(x,y) = \begin{bmatrix} \dfrac{1}{K} \displaystyle\sum_{(s,t)\in S_{xy}} R(s,t) \\ \dfrac{1}{K} \displaystyle\sum_{(s,t)\in S_{xy}} G(s,t) \\ \dfrac{1}{K} \displaystyle\sum_{(s,t)\in S_{xy}} B(s,t) \end{bmatrix}$$

R

G B

6.6 Color Image Smoothing and Sharpening - Color Image Smoothing

HSI Image Smoothing:

processing the intensity component of the HSI image and converting to RGB.

H

S I

6.6 Color Image Smoothing and Sharpening
- Color Image Smoothing

Image Smoothing with a 5x5 averaging kernel:

with RGB components

with HSI components

Difference between
the two results

6.6 Color Image Smoothing and Sharpening - Color Image Sharpening

Color Image Sharpening (using Laplacian):

RGB:

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

HSI:

Similar to image smoothing, also processing the intensity component of the HSI image and converting to RGB.

6.6 Color Image Smoothing and Sharpening - Color Image Sharpening

Color Image Sharpening (using Laplacian):

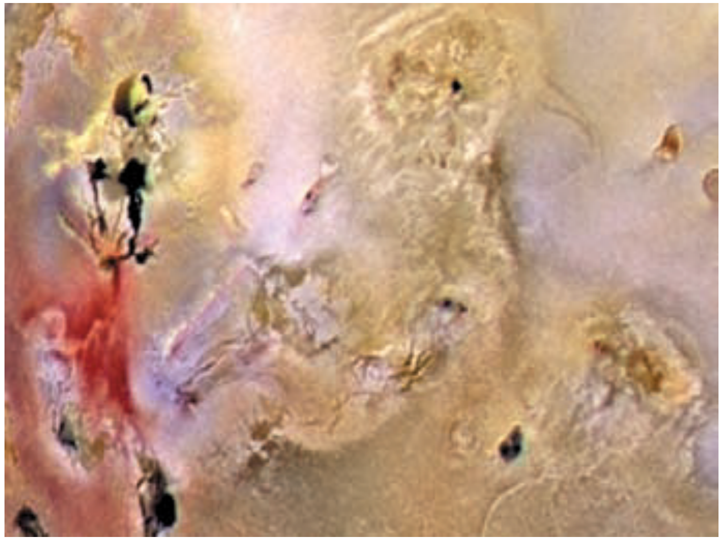
with RGB components

with HSI components

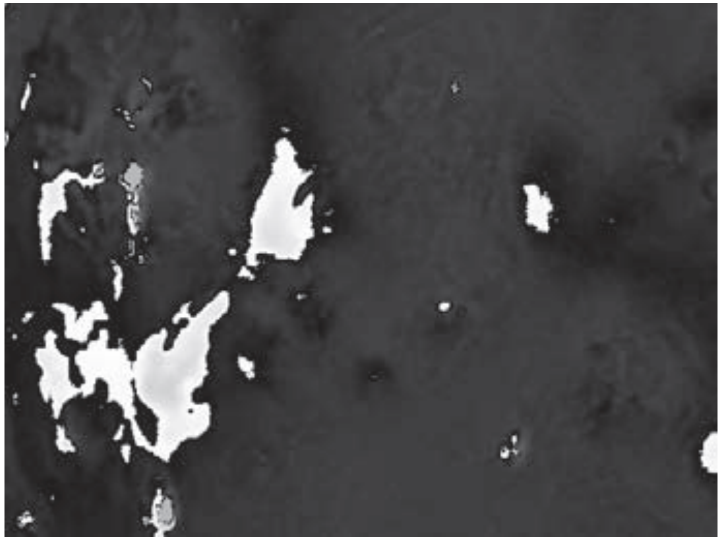
Difference between the two results

6.7 Using Colour in Image Segmentation - Segmentation in HSI Color Space

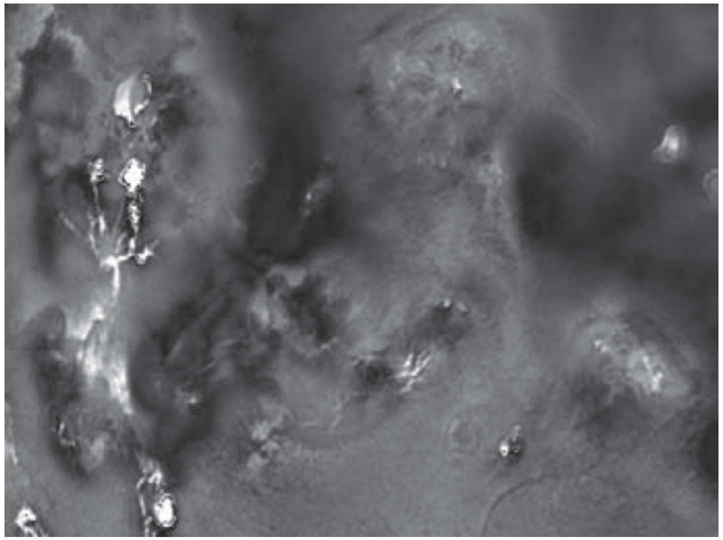
- **Hue**: for interesting color selection
- **Saturation**: masking image in order to isolate further regions of interest



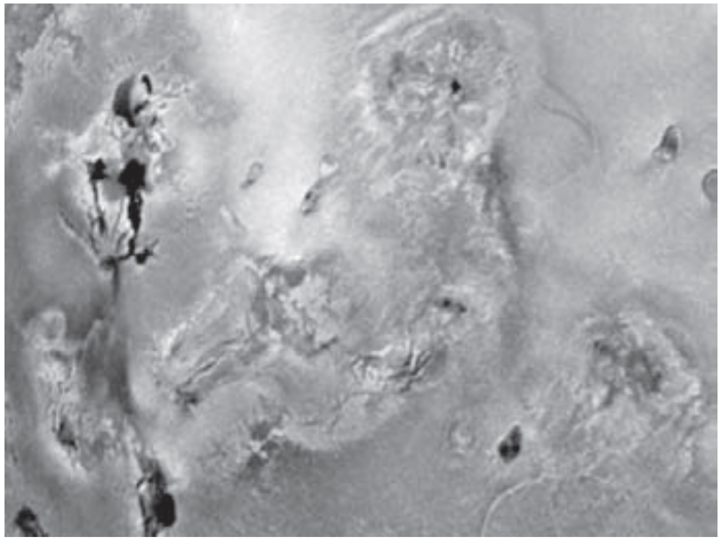
Original Image



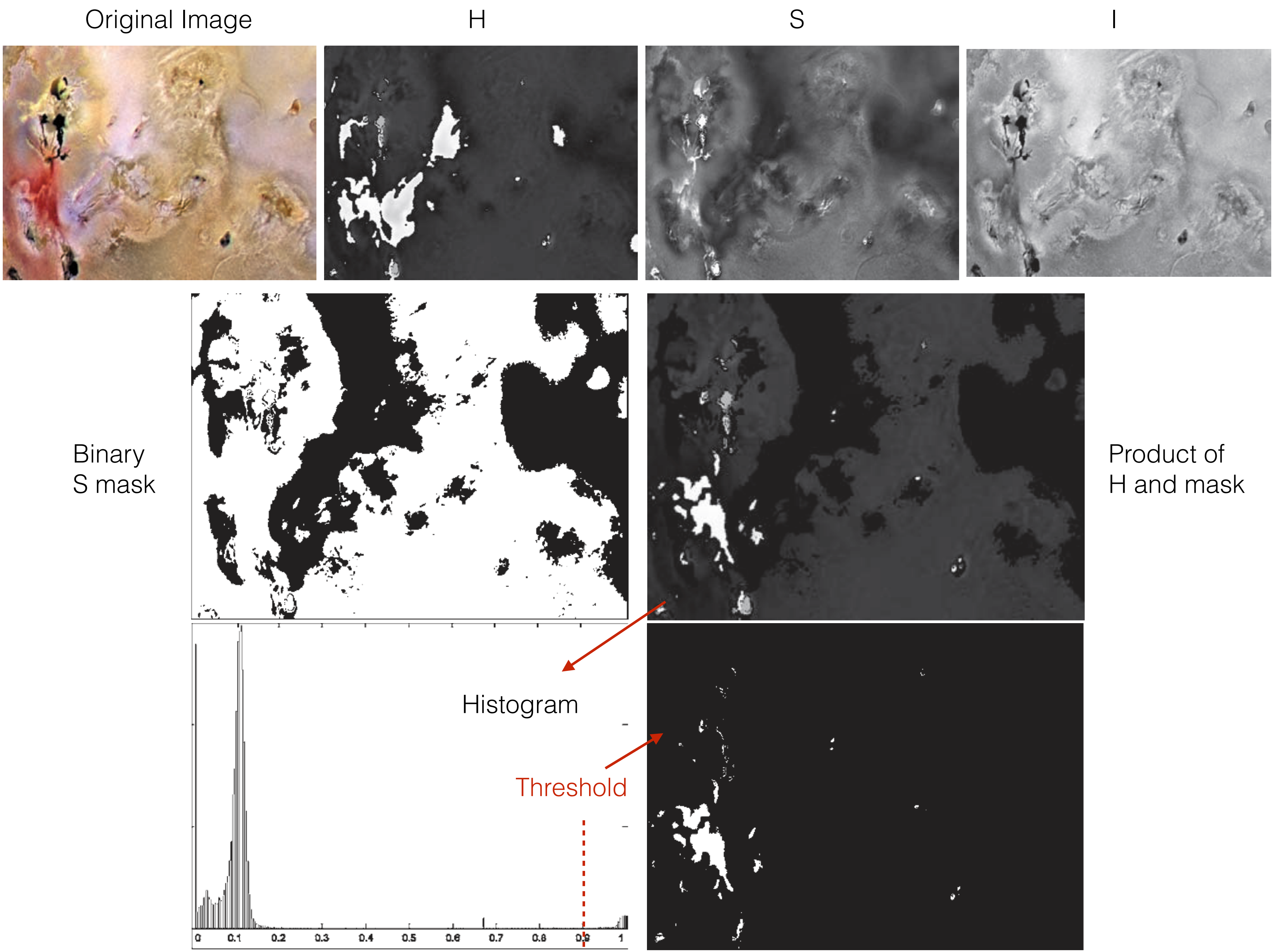
H



S



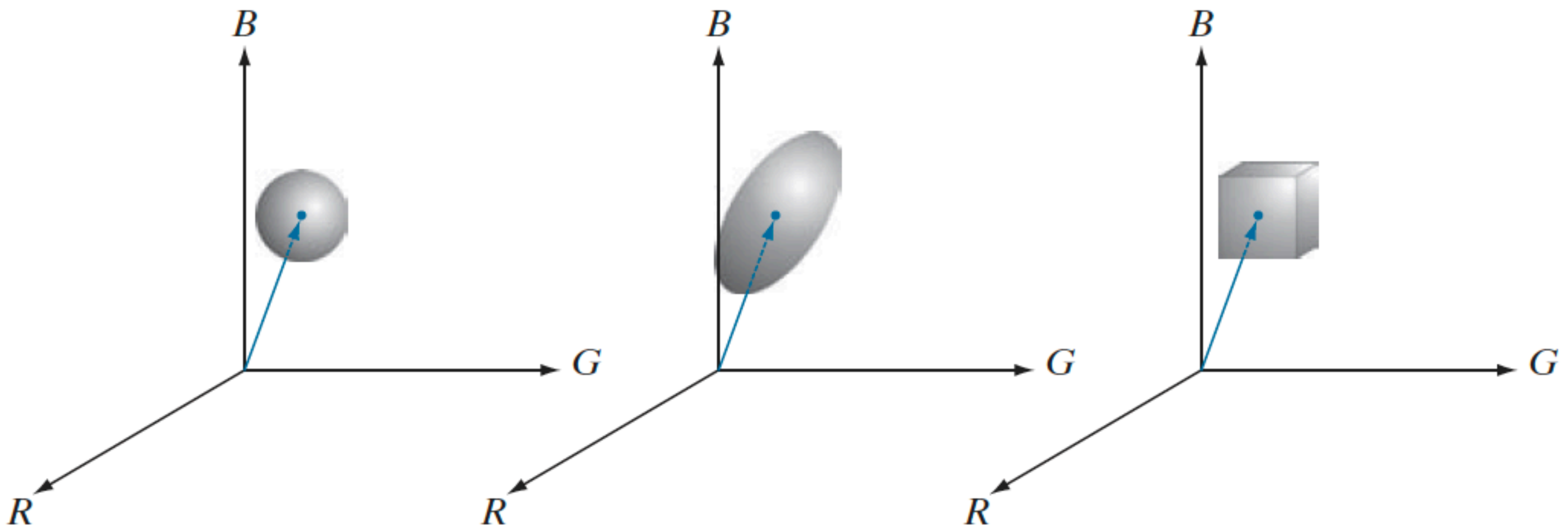
I



Original Image
H
S
I
Binary
S mask
Product of
H and mask
Histogram
Threshold
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

6.7 Using Colour in Image Segmentation - Segmentation in RGB Space

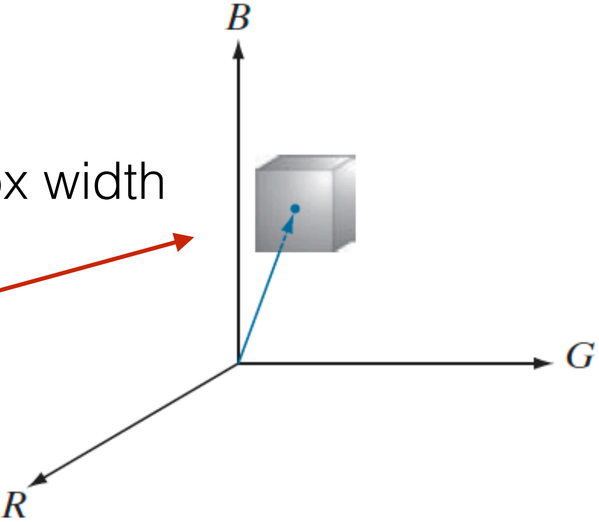
- Obtain an estimate of the “average” color that we wish to segment
- To determine the range for segmentation, one of the simplest measures is the Euclidean distance
- Three approaches for enclosing data regions for RGB vector segmentation:



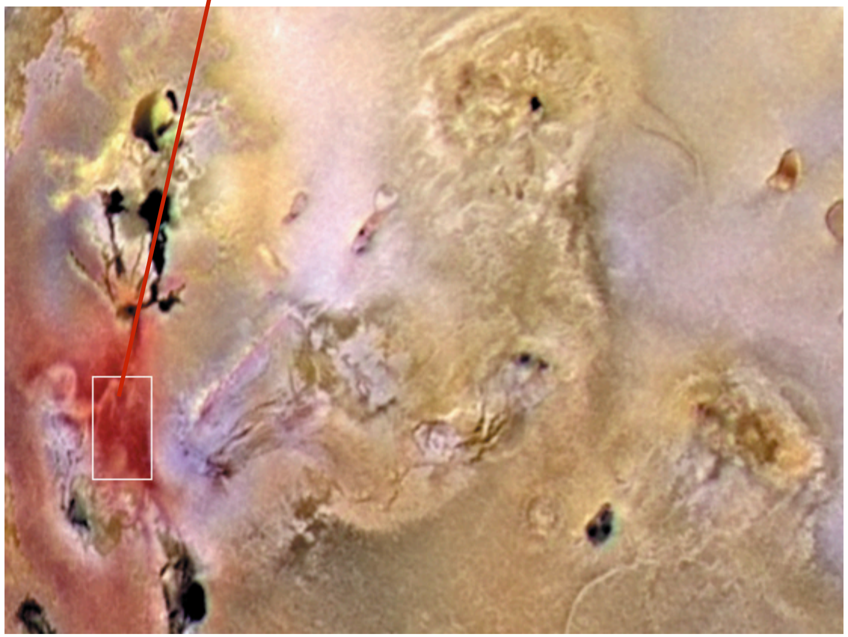
6.7 Using Colour in Image Segmentation - Segmentation in RGB Space

Example

- Cantered at mean
- Standard deviation for the box width



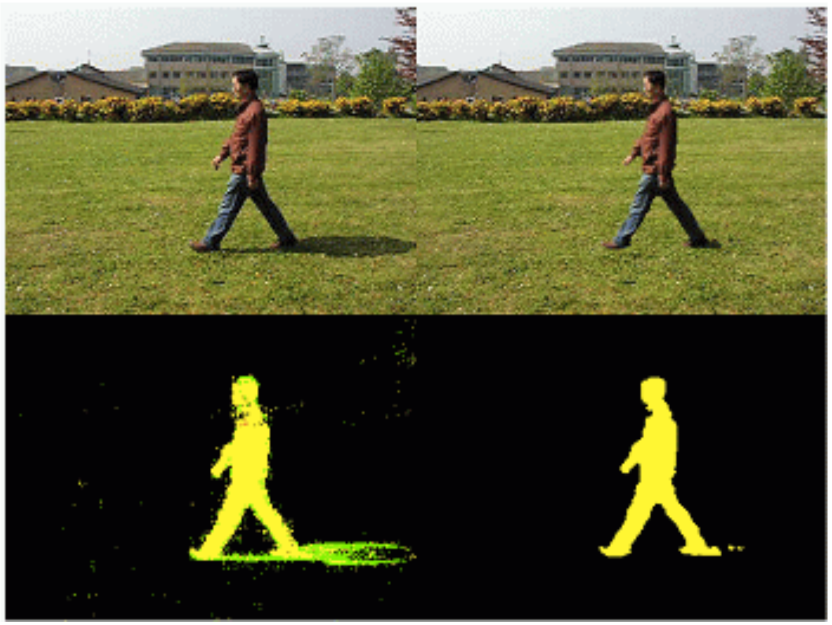
Compute mean and standard deviation

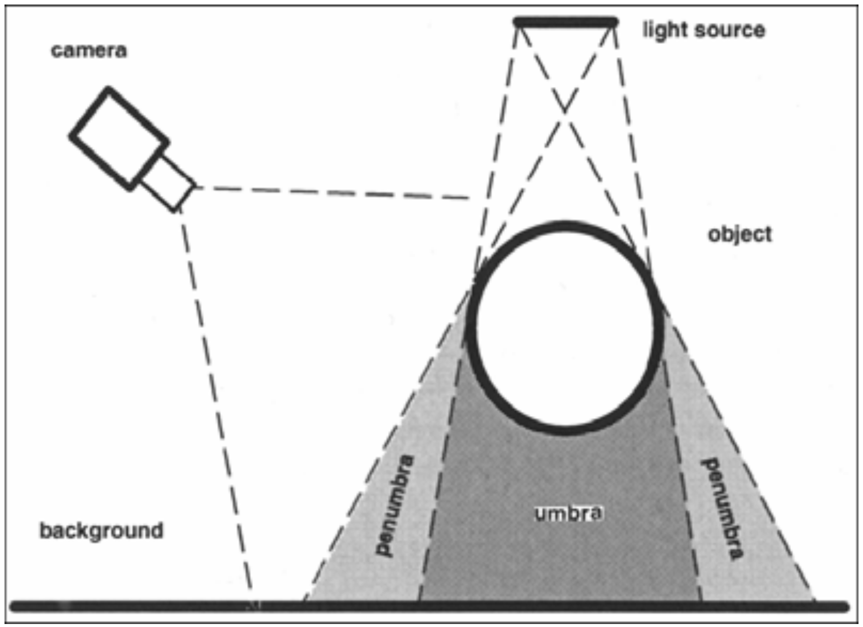


6.7 Using Colour in Image Segmentation - Segmentation in RGB Space

Example: Moving Cast Shadow Detection

- Shadow is formed by the change of illumination conditions and shadow detection comes down to a problem of finding the illumination invariant features.
- From the viewpoint of geometric relationship, shadow can be divided into umbra and penumbra
  - the umbra corresponds to the background area where the direct light is almost totally blocked by the foreground object,
  - in the penumbra area, the light is partially blocked

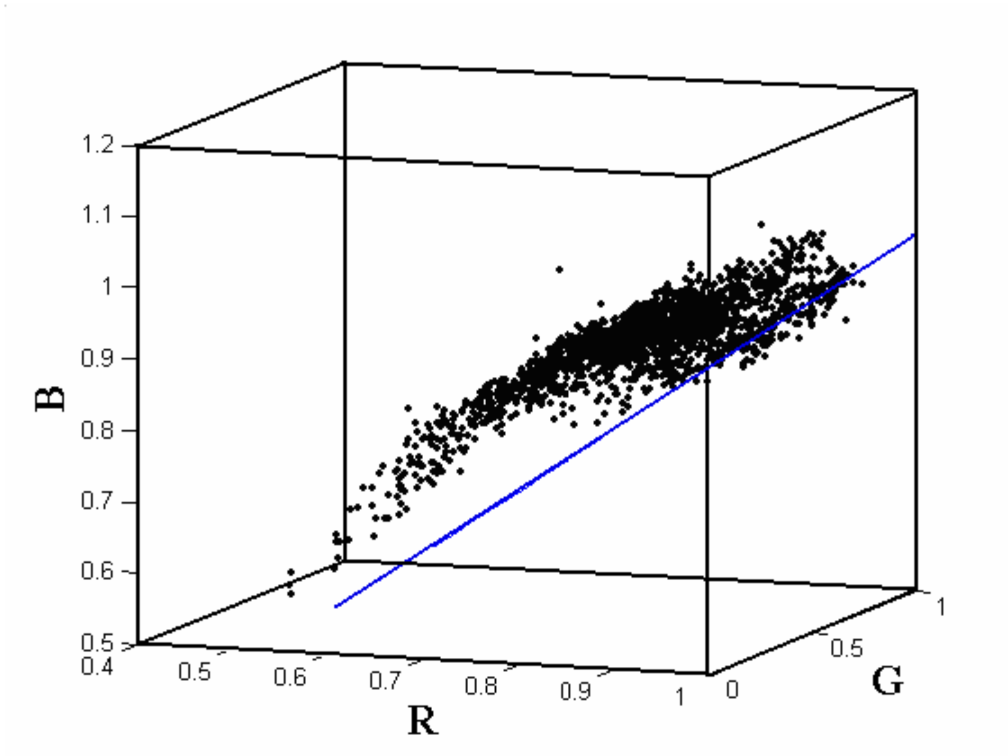




6.7 Using Colour in Image Segmentation - Segmentation in RGB Space

Example: Moving Cast Shadow Detection

- Color/Specturm-based shadow detection
  - shadows change the hue component slightly
  - decrease the saturation component significantly.

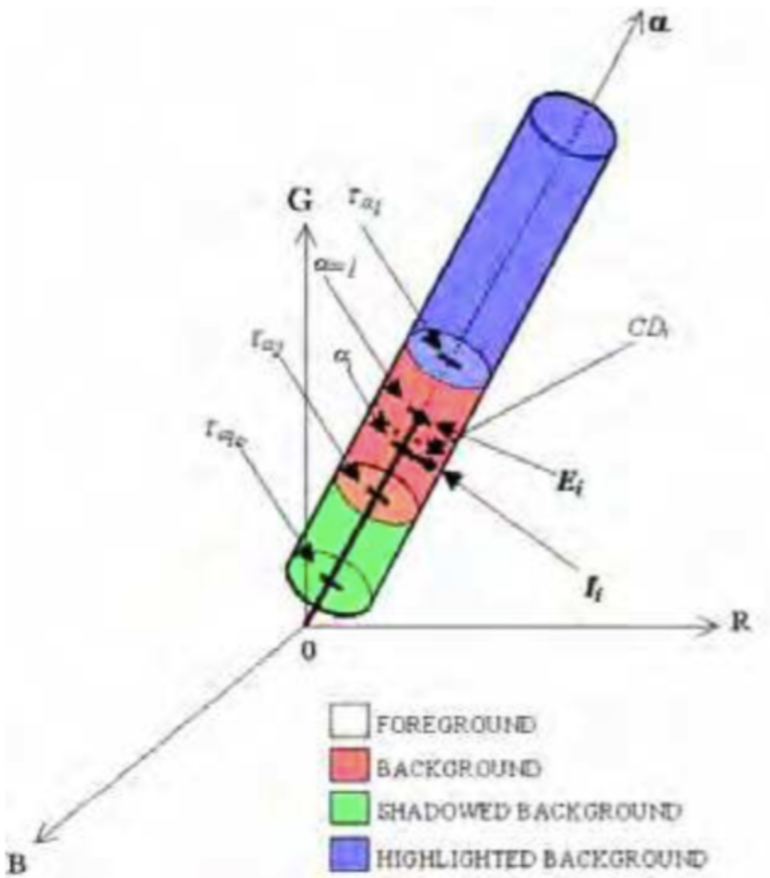


A scatter plot in the color ratios space of a shaded pixels set. The line corresponds to the equal ratio in RGB components.

6.7 Using Colour in Image Segmentation - Segmentation in RGB Space

Example: Moving Cast Shadow Detection

- Color/Specturm-based shadow detection
  - shadows change the hue component slightly
  - decrease the saturation component significantly.



Pixels classification using the normalized color distortion and normalized brightness distortion: original background, shaded background, highlight background, and moving foreground objects.

6.7 Using Colour in Image Segmentation - Color Edge Detection

- Review - Gradient magnitude for edge detection (Sec. 3.6)

$$M(x,y) = \|\nabla f\| = \mathrm{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$$

−1	0
0	1

0	−1
1	0

Sobel Operators

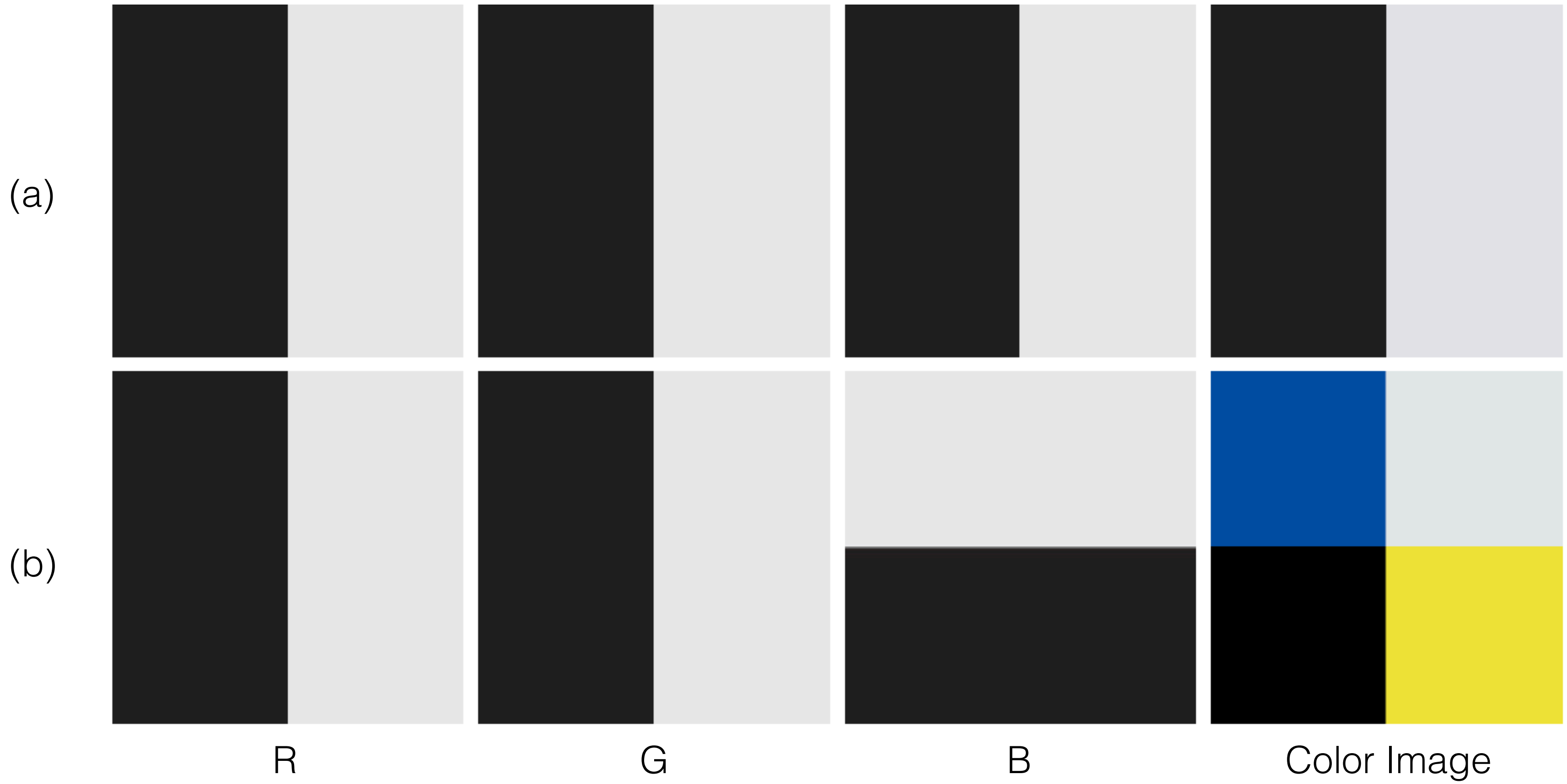
−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

6.7 Using Colour in Image Segmentation - Color Edge Detection

credit of this slide: C. Nikou

- To compute the gradient on individual components (ex. R, G, B) and then adding the results to form the corresponding gradient image will lead to erroneous results.
- In both cases (a) and (b), the above approach would give the same gradient magnitude at the center of the image. However, in (b) we would expect a lower magnitude as only two edges are in the same direction.



6.7 Using Colour in Image Segmentation - Color Edge Detection

The goal is to find a vector pointing in the direction of maximum rate of change of

$$\mathbf{c}(\mathrm{x,y})=[R(x,y)\ G(x,y),B(x,y)]^{\mathrm{T}}$$

(this is the definition of the gradient).

Let **r**, **g** and **b** be unit vectors along the R, G and B axes and define:

$$\mathbf{u} = \frac{\partial R}{\partial x}\mathbf{r} + \frac{\partial G}{\partial x}\mathbf{g} + \frac{\partial B}{\partial x}\mathbf{b} \qquad \mathbf{v} = \frac{\partial R}{\partial y}\mathbf{r} + \frac{\partial G}{\partial y}\mathbf{g} + \frac{\partial B}{\partial y}\mathbf{b}$$

credit of this slide: C. Nikou

6.7 Using Colour in Image Segmentation - Color Edge Detection

Let also:

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

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

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

credit of this slide: C. Nikou

6.7 Using Colour in Image Segmentation - Color Edge Detection

The direction of maximum rate of change of $\mathbf{c}(x,y)=[R(x,y)\ G(x,y),B(x,y)]^T$ is [Di Zenzo 86]:

$$\theta(x,y)=\frac{1}{2}\tan^{-1}\left(\frac{2g_{xy}}{g_{xx}-g_{yy}}\right)$$

and the value of that rate of change is:

$$F_\theta(x,y)=\left\{\frac{1}{2}\left[(g_{xx}+g_{yy})+(g_{xx}-g_{yy})\cos\left(2\theta(x,y)\right)+2g_{xy}\sin\left(2\theta(x,y)\right)\right]\right\}^{\frac{1}{2}}$$

(If you are interested, consult the paper by Di Zenzo [1986] for details.)

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6.7 Using Colour in Image Segmentation - Color Edge Detection

Example of Color Edge Detection

Original Image

Gradient computed in RGB color vector space

edge detail is more complete, but both approaches yielded reasonable results

Elementwise sum of three individual gradient images with Sobel operators.

Difference between the two results

6.8 Noise in Color Images

- The noise models discussed for grayscale images are also applicable to color images.

- However, in many applications, a color channel may be more or less affected than the other channels.

- For instance, using a red color filter in a CCD camera may affect the red component of the image (CCD sensors are noisier at low levels of illumination).

- We will take a brief look of how noise carries over when converting from one color model to another.

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An RGB image corrupted by additive Gaussian noise

R

G

B

Composite RGB image

Less visually noticeable in a color image than it is in a grayscale image.

Converting noisy RGB images to HSI.

Composite RGB image

H

S

I

- The hue and saturation components are Significantly degraded, because of the nonlinearity of the cos and min operations.
- The intensity component is smoother because it is the average of RGB

6.8 Noise in Color Images

- When only one channel is affected by noise, conversion to HSI spreads the noise to all HSI components images.

- This is due to the transformation that makes use of all RGB components to compute each HSI component.

RGB image with green plane corrupted by saltand-pepper noise.

H

S

I

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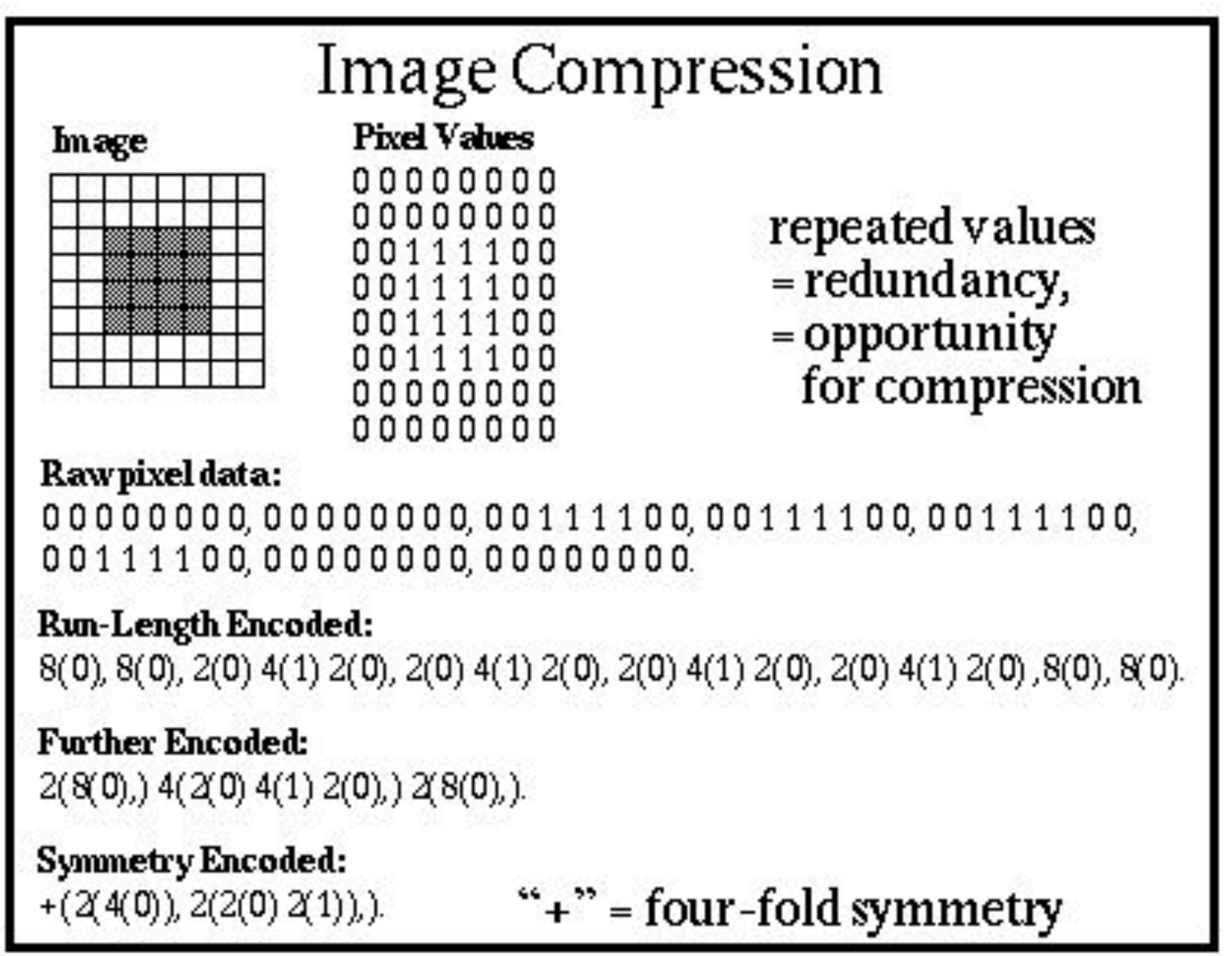
6.9 Color Image Compression

Original Image

JPEG 2000 compression
(compression ratio 230:1)

Digital Image Format: Image compression



Introduction to Image Processing

Ch 6. Color Image Processing

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