2. Basic Image Features

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Color

- Used heavily in human vision
- Color is a pixel property, making some recognition problems easy
- Visible spectrum for humans is 400 nm (blue) to 700 nm (red)
- Machines can “see” much more;
  ex. X-rays, infrared, radio waves

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Coding methods for humans

- RGB is an additive system (add colors to black) used for displays.
- CMY is a subtractive system for printing.
- HSI is a good perceptual space for art, psychology, and recognition.
- YIQ used for TV is good for compression.

RGB color cube

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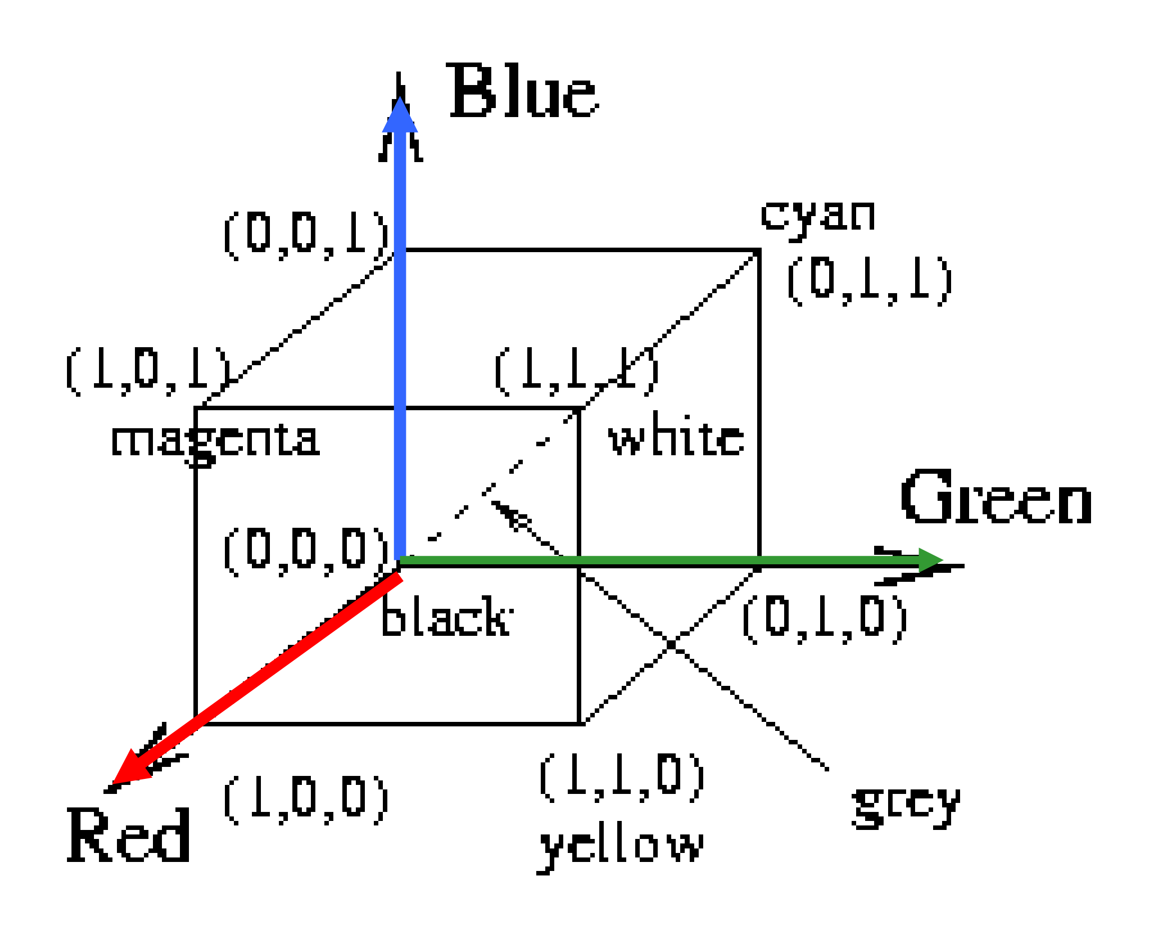
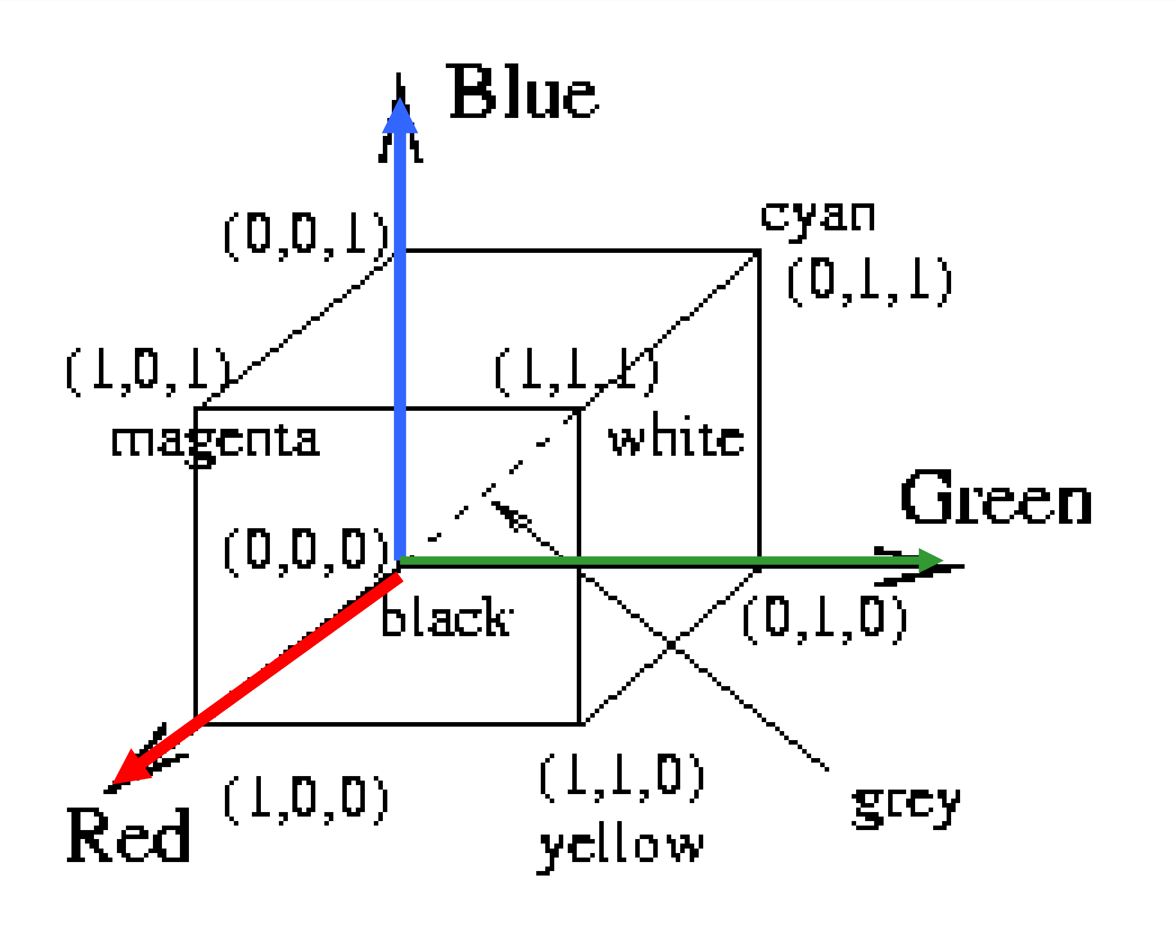


- R, G, B values normalized to (0, 1) int erval
- human perceives gray for triples on t he diagonal
- "Pure colors" on corners

RGB color cube



- R, G, B values normalized to (0, 1) int erval
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Color palette and normalized RGB

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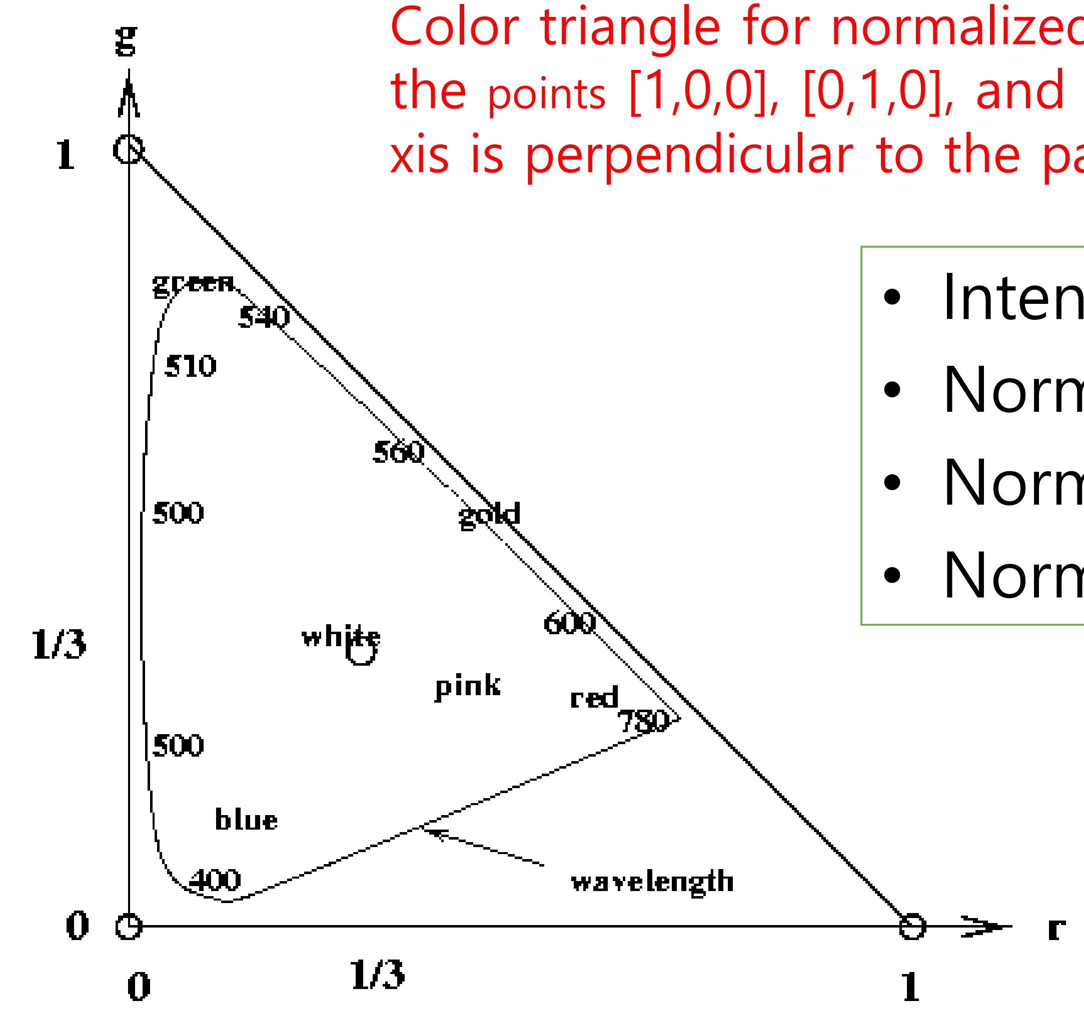


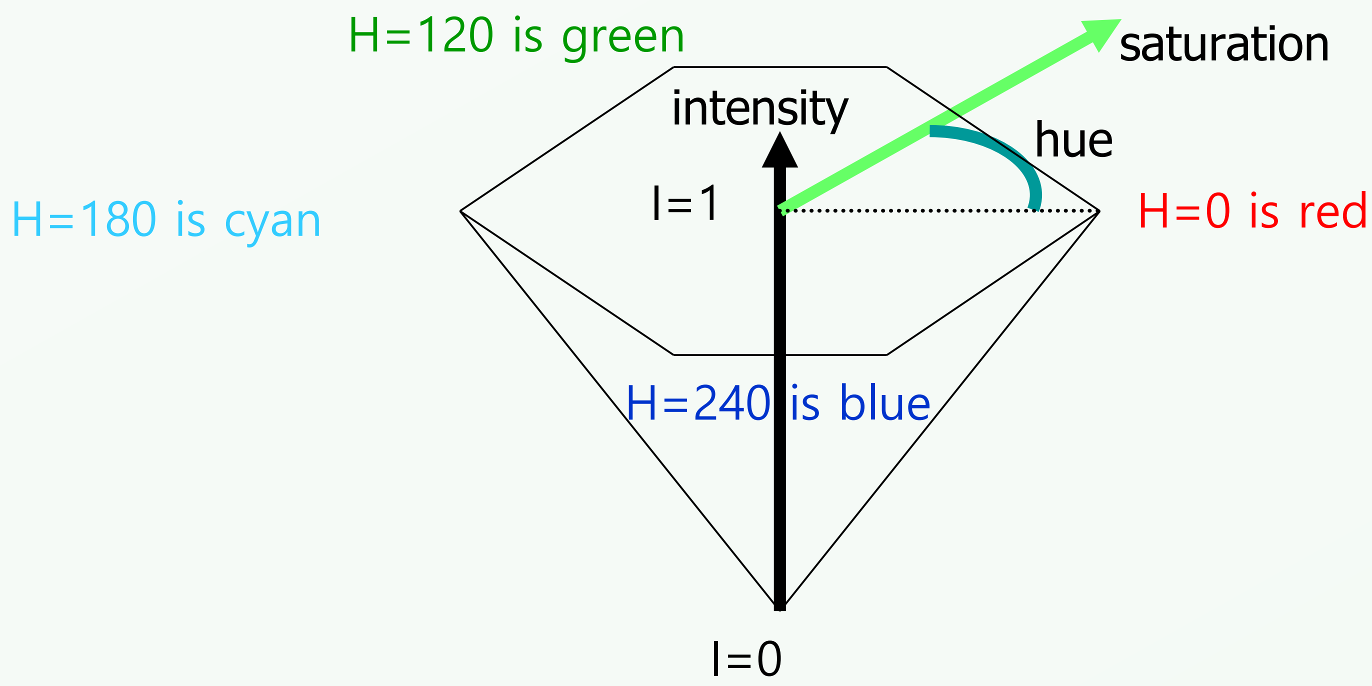
Color triangle for normalized RGB coordinates is a slice through the points [1,0,0], [0,1,0], and [0,0,1] of the RGB cube. The blue a xis is perpendicular to the page.

- Intensity $I = (R+G+B) / 3$
- Normalized red $r = R/(R+G+B)$
- Normalized green $g = G/(R+G+B)$
- Normalized blue $b = B/(R+G+B)$

In this normalized representation, $b = 1 - r - g$, so we only need to look at r and g to characterize the color.

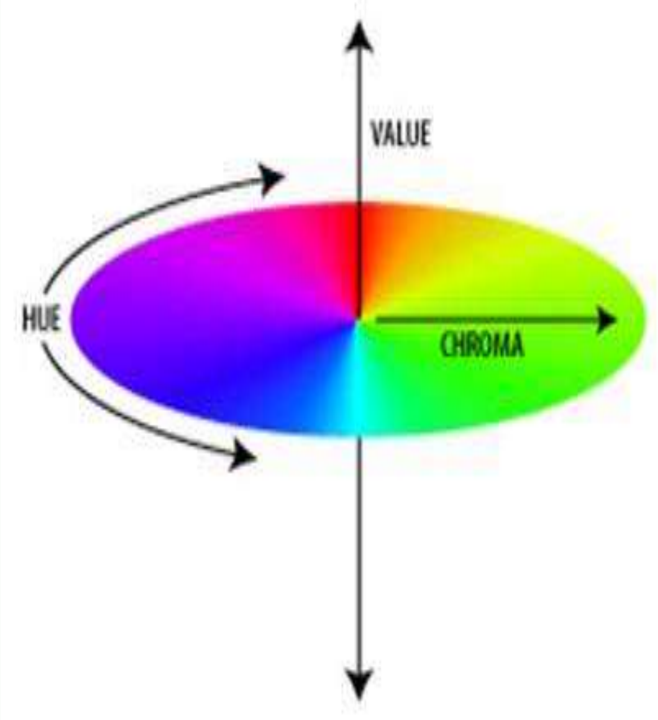
Color hexagon for HSI (HSV)

- Hue is encoded as an angle (0 to 2π).
- Saturation is the distance to the vertical axis (0 to 1).
- Intensity is the height along the vertical axis (0 to 1).



RGB to HSI Transform

- RGB → HSI



$$r = \frac{R}{R+G+B},\ g = \frac{G}{R+G+B},\ b = \frac{B}{R+G+B}$$

$$s = 1 - 3 \cdot \min(r, g, b)\ ; \qquad s \in [0,1]$$

$$i = (R+G+B)/(3 \cdot 255)\ ; \qquad i \in [0,1]$$

$$h = \cos^{-1}\left\{ \frac{0.5 \cdot [(r-g)+(r-b)]}{\left[(r-g)^2 + (r-b)(g-b)\right]^{1/2}} \right\} \qquad h \in [0, \pi] \text{ for } b \le g$$

$$h = 2\pi - \cos^{-1}\left\{ \frac{0.5 \cdot [(r-g)+(r-b)]}{\left[(r-g)^2 + (r-b)(g-b)\right]^{1/2}} \right\} \qquad h \in [\pi, 2\pi] \text{ for } b > g$$

HSI to RGB Transform

- HSI → RGB
  - **RG area (0 ≤ H ≤ 120)**

$$b = \frac{1}{3}(1 - S)$$

$$r = \frac{1}{3}[1 + \frac{S\cos(H)}{\cos(60 - H)}]$$

$$g = 1 - (r + b)$$

  - **GB area (120 ≤ H ≤ 240)**

$$H = H - 120$$

$$g = \frac{1}{3}[1 + \frac{S\cos(H)}{\cos(60 - H)}]$$

$$r = \frac{1}{3}(1 - S)$$

$$b = 1 - (r + g)$$

- Notes
  - Saturation is not defined when intensity I = 0.
  - Hue is not defined when S = 0.

Editing saturation of colors

- (Left) Image of food originating from a digital camera;
- (center) saturation value of each pixel decreased 20%;
- (right) saturation value of each pixel increased 40%.

YIQ and YUV for TV signals

- Have better compression properties
- Luminance Y encoded using more bits than chrominance values I and Q; humans more sensitive to Y than I,Q
- Luminance used by black/white TVs
- All 3 values used by color TVs
- YUV encoding used in some digital video and JPEG and MPEG compression

Conversion from RGB to YIQ

An approximate linear transformation from RGB to YIQ:

$$
\begin{array}{rrcrcrcr}
luminance & Y & = & 0.30R & + & 0.59G & + & 0.11B \\
R - cyan & I & = & 0.60R & - & 0.28G & - & 0.32B \\
magenta - green & Q & = & 0.21R & - & 0.52G & + & 0.31B
\end{array}
$$

We often use this for color to gray-tone conversion.

Histogram

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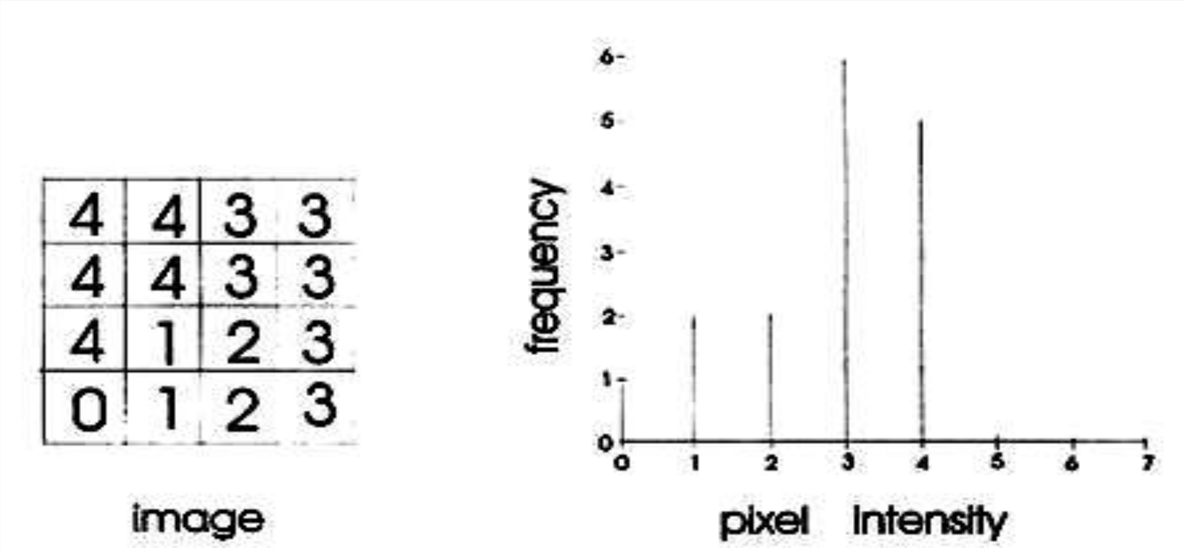
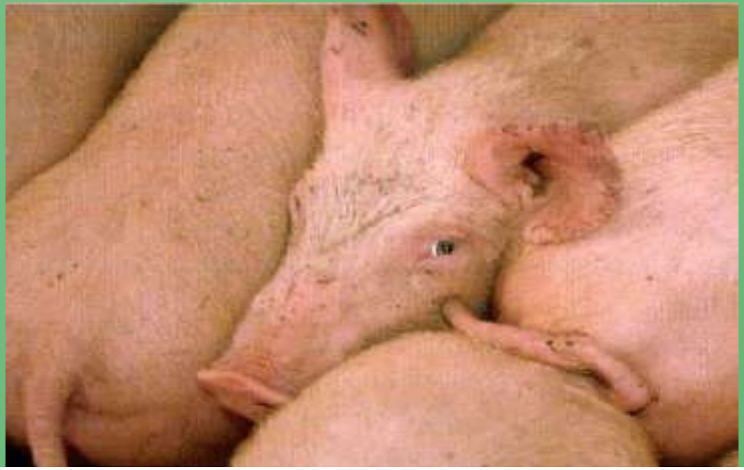
- Color histogram can represent an image
- Histogram is fast and easy to compute.
- Size can easily be normalized so that different image histo grams can be compared.
- Can match color histograms for database query or classifi cation.

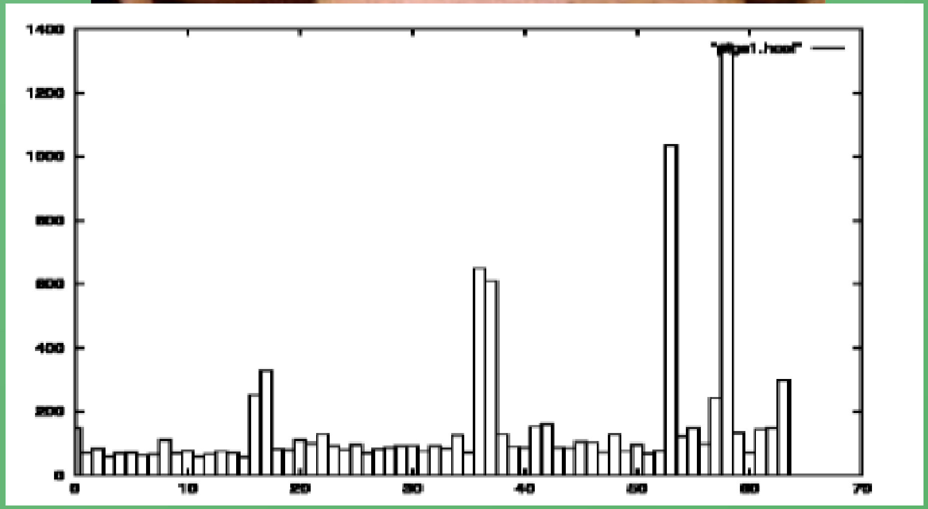
Histogram

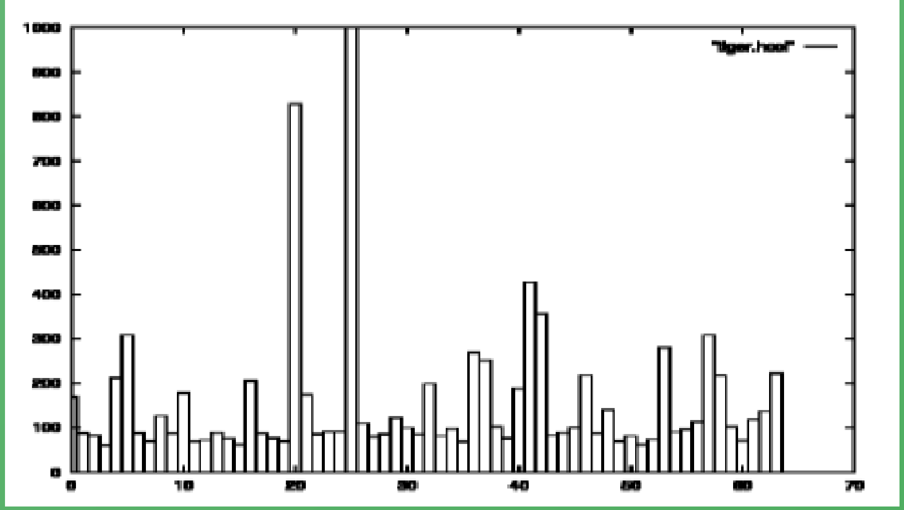


Sample image with histogram

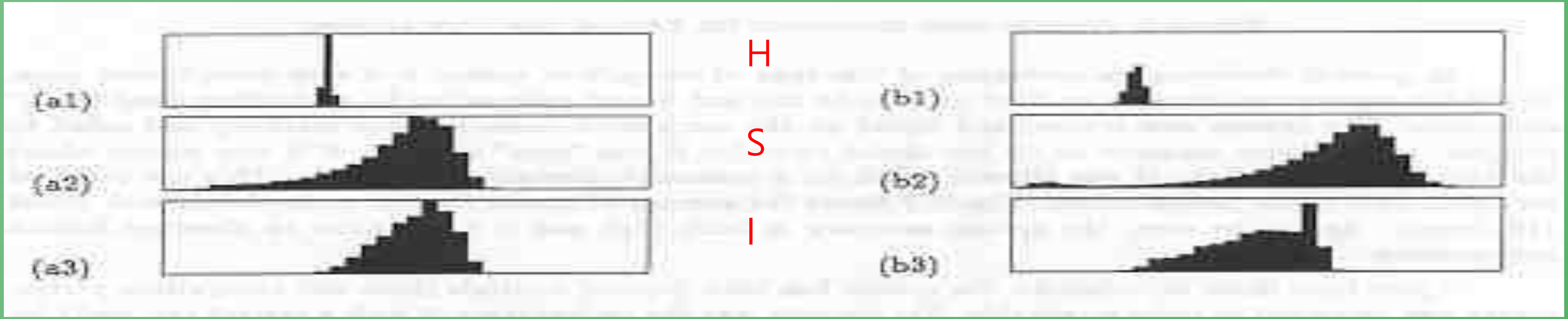
Histograms of two color images







Apples versus Oranges



Separate HSI histograms for apples (left) and oranges (right) used by IBM's VeggieVision for r
ecognizing produce at the grocery store checkout station.

Skin color in RGB space

(shown as normalized red vs normalized green)

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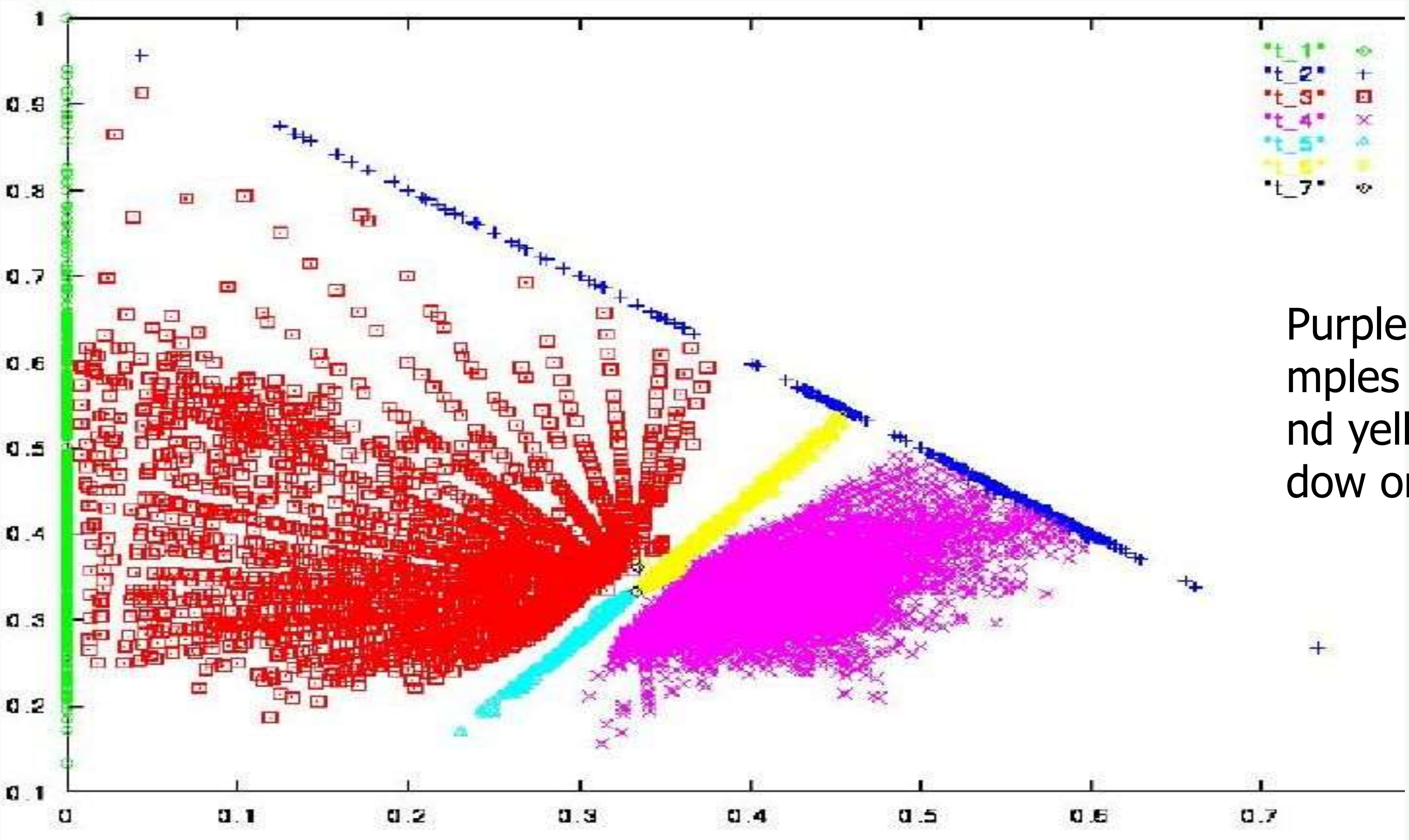
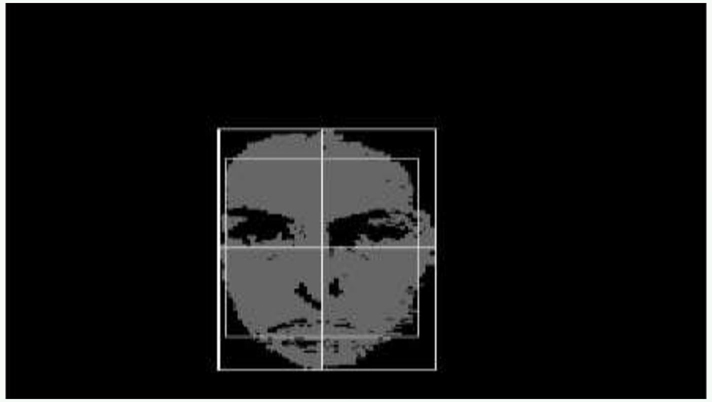


Purple region shows skin color samples from several people. Blue and yellow regions show skin in shadow or behind a beard.

Finding a face in video frame

- (left) input video frame
- (center) pixels classified according to RGB space
- (right) largest connected component with aspect similar to a face (all work contrib uted by Vera Bakic)



Edges

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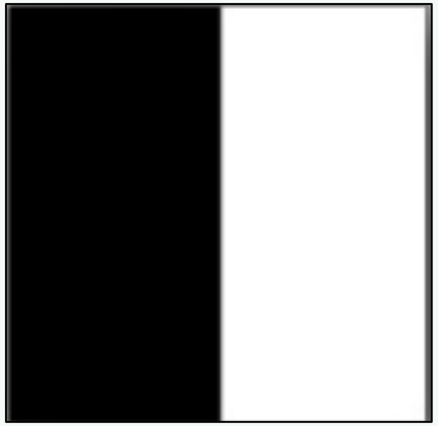
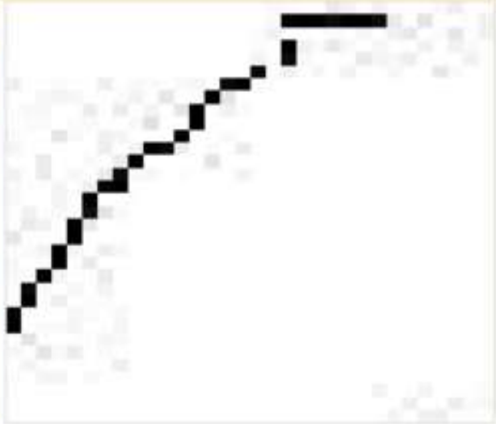
- Abrupt changes in the intensity of pixels
- Discontinuity in image brightness or contrast
- Usually edges occur on the boundary of two regions



Edges

Tulips Image

Part of the image



Edge of the part of the image

255	255	255	255	255	255	255	255	255	255	250	198	126
255	255	255	255	255	255	255	255	220	152	92	26	0
255	255	255	254	255	255	251	152	49	16	9	9	8
255	254	255	255	255	215	117	38	19	28	33	31	37
254	254	255	255	217	74	19	25	34	33	30	35	46
254	255	255	206	94	25	33	33	34	32	31	37	48
255	237	145	57	24	30	33	28	31	31	39	47	49
255	162	33	28	38	37	36	35	35	37	48	60	59
179	66	33	40	40	43	44	49	51	56	62	67	67
39	23	34	42	45	45	50	55	65	71	72	73	73
28	38	38	41	46	51	61	62	66	71	73	73	76

Matrix generated by the part of the image

Edge Detection

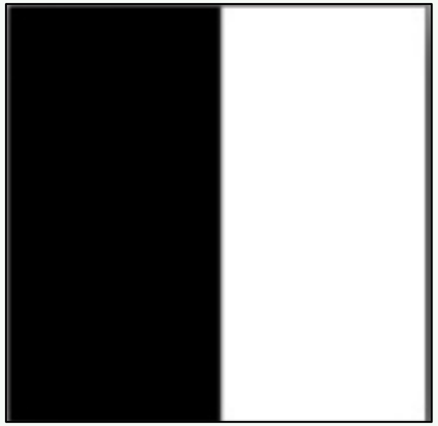
- Process of identifying edges in an image to be used as a fu ndamental asset in image analysis
- Locating areas with strong intensity contrasts
- A kind of filtering that leads to useful features

Edge Detection Usage

- Reduce unnecessary information in the image while preservi ng the structure of the image
- Extract important features of an image
  - Textures and shapes
  - Corners, Lines and Curves
- Recognize objects, boundaries, segmentation
- Part of computer vision and recognition

Edges

- Abrupt changes in the intensity of pixels
- Discontinuity in image brightness or contrast
- Usually edges occur on the boundary of two regions



Differential Operators

- Attempt to approximate the gradient at a pixel via masks
- Threshold the gradient to select the edge pixels

Differencing 1D Signals

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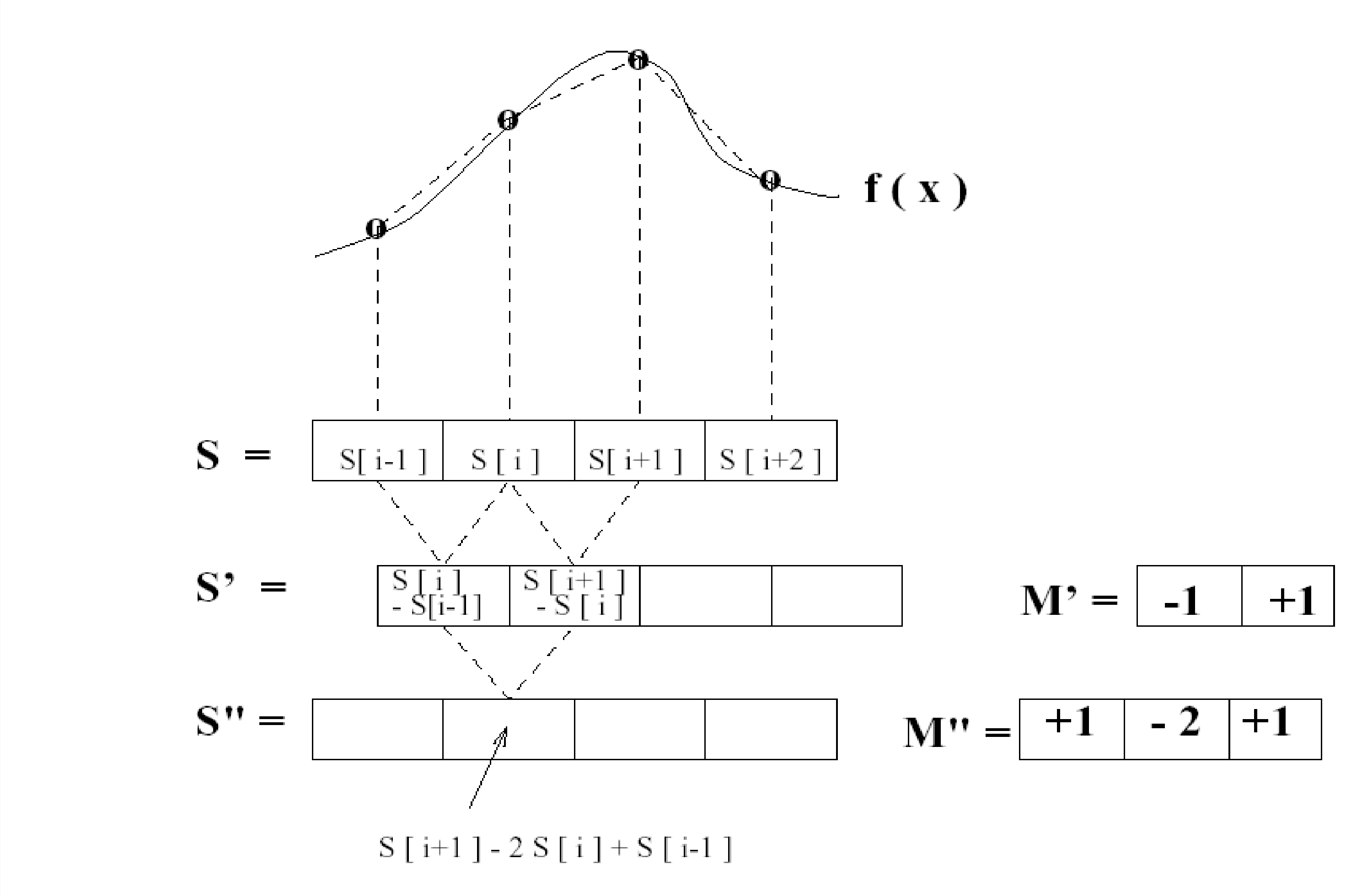


Gradient in images

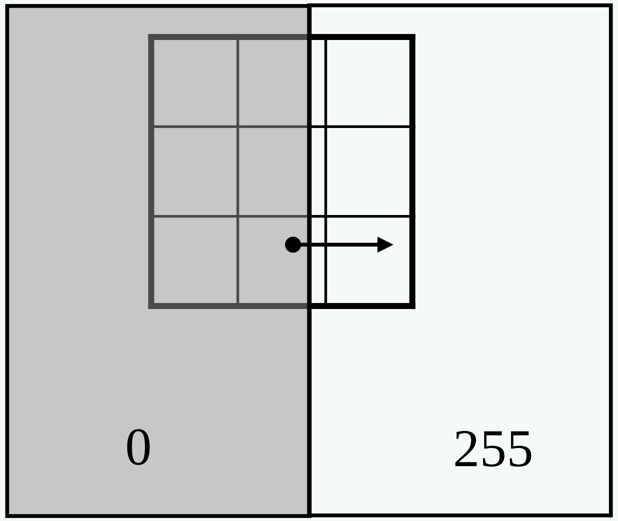
- Two dimensional equivalent of <u>the first order derivative</u>

$$G[f(x,y)] = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

points in the direction of max rate of increase of the function $f(x,y)$

magnitude $G[f(x,y)] = \sqrt{G_x^2 + G_y^2}$

direction $\alpha(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$



Numerical Approximation of Gradient

- For digital images, the derivatives are approximated by differences.

$$G_x \cong f[i, j+1] - f[i, j]$$
$$G_y \cong f[i, j] - f[i+1, j]$$

Differencing masks using first derivatives

$$G_x = \boxed{\begin{array}{|c|c|} -1 & 1 \end{array}} \qquad G_y = \boxed{\begin{array}{c} 1 \\ \hline -1 \end{array}}$$

Differencing masks using second derivatives

$$G_x = \boxed{\begin{array}{c|c|c} 1 & -2 & 1 \end{array}} \qquad G_y = \boxed{\begin{array}{c} 1 \\ \hline -2 \\ \hline 1 \end{array}}$$

Common Masks for Computing Gradient

- Sobel :

$$\begin{array}{|ccc|}\hline -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \\ \hline \end{array} \qquad \begin{array}{|ccc|}\hline 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \\ \hline \end{array}$$

- Prewitt:

$$\begin{array}{|ccc|}\hline -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \\ \hline \end{array} \qquad \begin{array}{|ccc|}\hline 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \\ \hline \end{array}$$

- Roberts:

$$\begin{array}{|cc|}\hline 0 & 1 \\ -1 & 0 \\ \hline \end{array} \qquad \begin{array}{|cc|}\hline 1 & 0 \\ 0 & -1 \\ \hline \end{array}$$

Sx **Sy**

Common Masks for Computing Gradient

On a pixel of the image I

- let G_x be the response to S_x
- let G_y be the response to S_y

Then the gradient is

$$\nabla I = [G_x \ \ G_y]^T$$

And $g = (G_x^2 + G_y^2)^{1/2}$ is the gradient magnitude.

$\theta = \text{atan2}(G_y, G_x)$ is the gradient direction.

Roberts Operator

- Gradient computed across diagonals
- Faster because of 2×2 neighborhood

$$G[f(i,j)] = \left| f(i,j) - f(i+1,j+1) \right| + \left| f(i+1,j) - f(i,j+1) \right| = \left|G_x\right| + \left|G_y\right|$$

<u>Convolution masks</u>

$$G_x = \begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & -1 \\ \hline \end{array} \qquad G_y = \begin{array}{|c|c|} \hline 0 & -1 \\ \hline 1 & 0 \\ \hline \end{array}$$

Prewitt Operator

Convolution masks

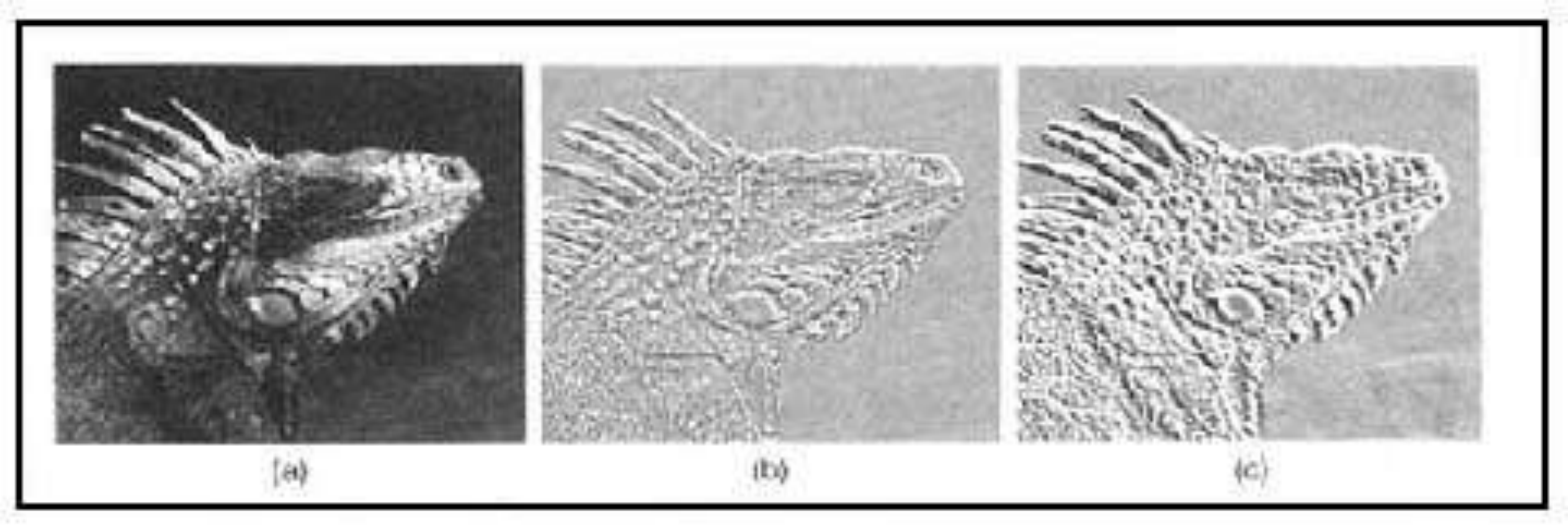
$$S_x = \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array} \qquad S_y = \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -1 & -1 \\ \hline \end{array}$$

Magnitude of the gradient, $M = \sqrt{G_x^2 + G_y^2}$

If $M \geq thresold$, the current pixel is marked as an edge pixel.

Direction $\theta \approx tan^{-1}(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x})$

Example



a) Input image b) Robert c) Prewitt

Sobel Operator

Convolution masks

$$S_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad S_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

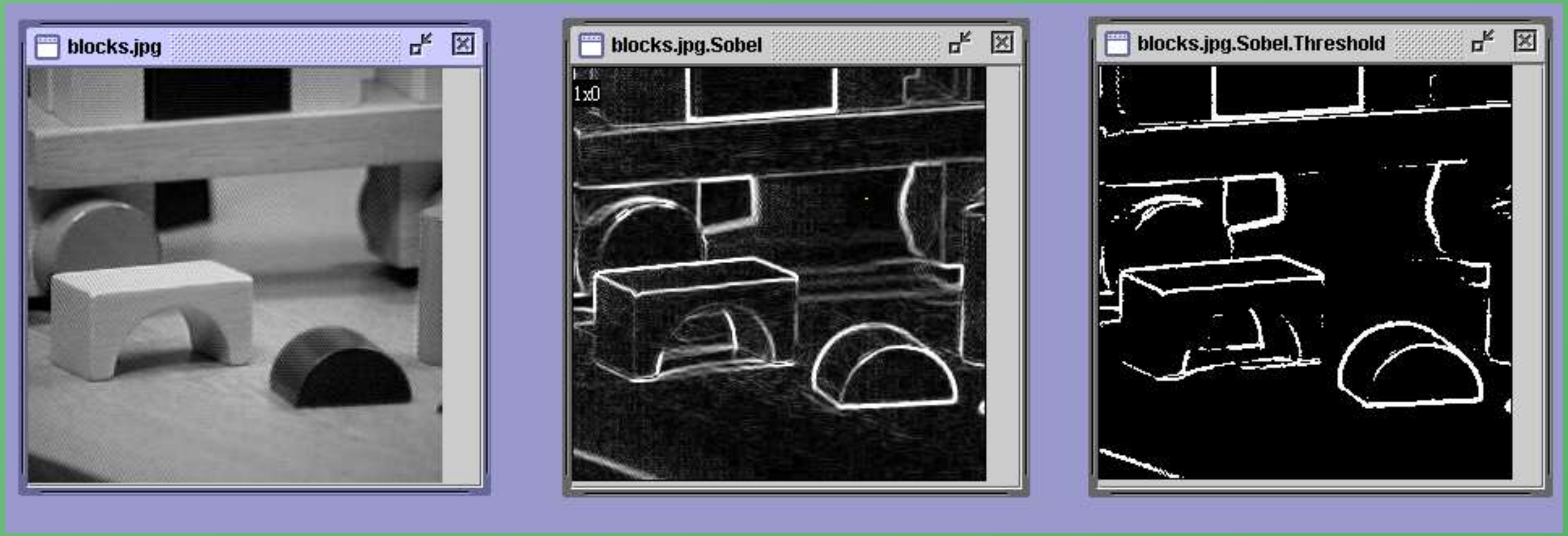
Magnitude of the gradient, *M*

$$M = \sqrt{G_x^2 + G_y^2}$$

If $M \geq thresold$, the current pixel is marked as an edge pixel.

- places an emphasis on pixels closer to the center of the mask.
- most commonly used.

Example



original image

gradient magnitude

thresholded gradient magnitude

Example

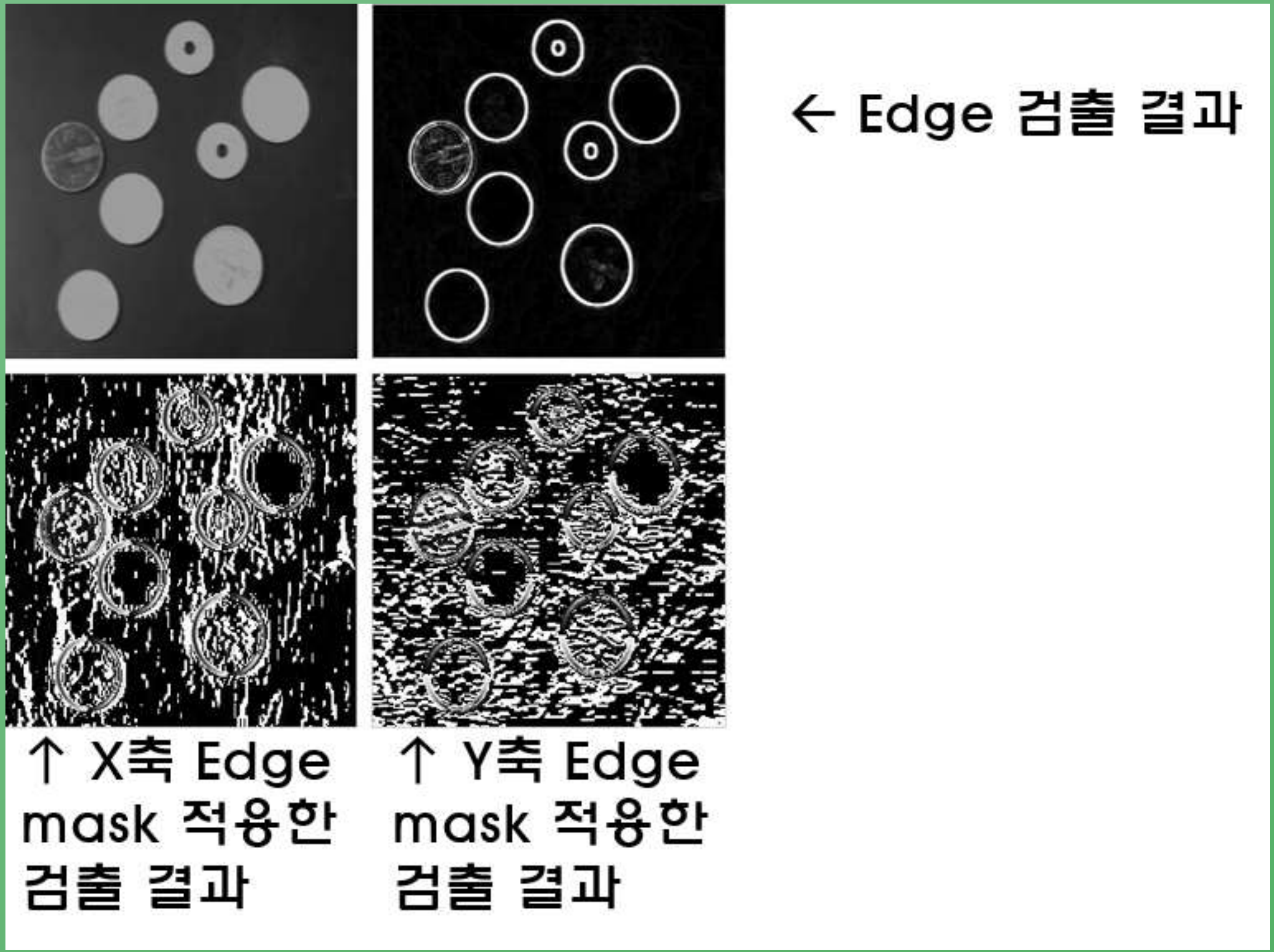
Input Image

Roberts Operator

Sobel Operator

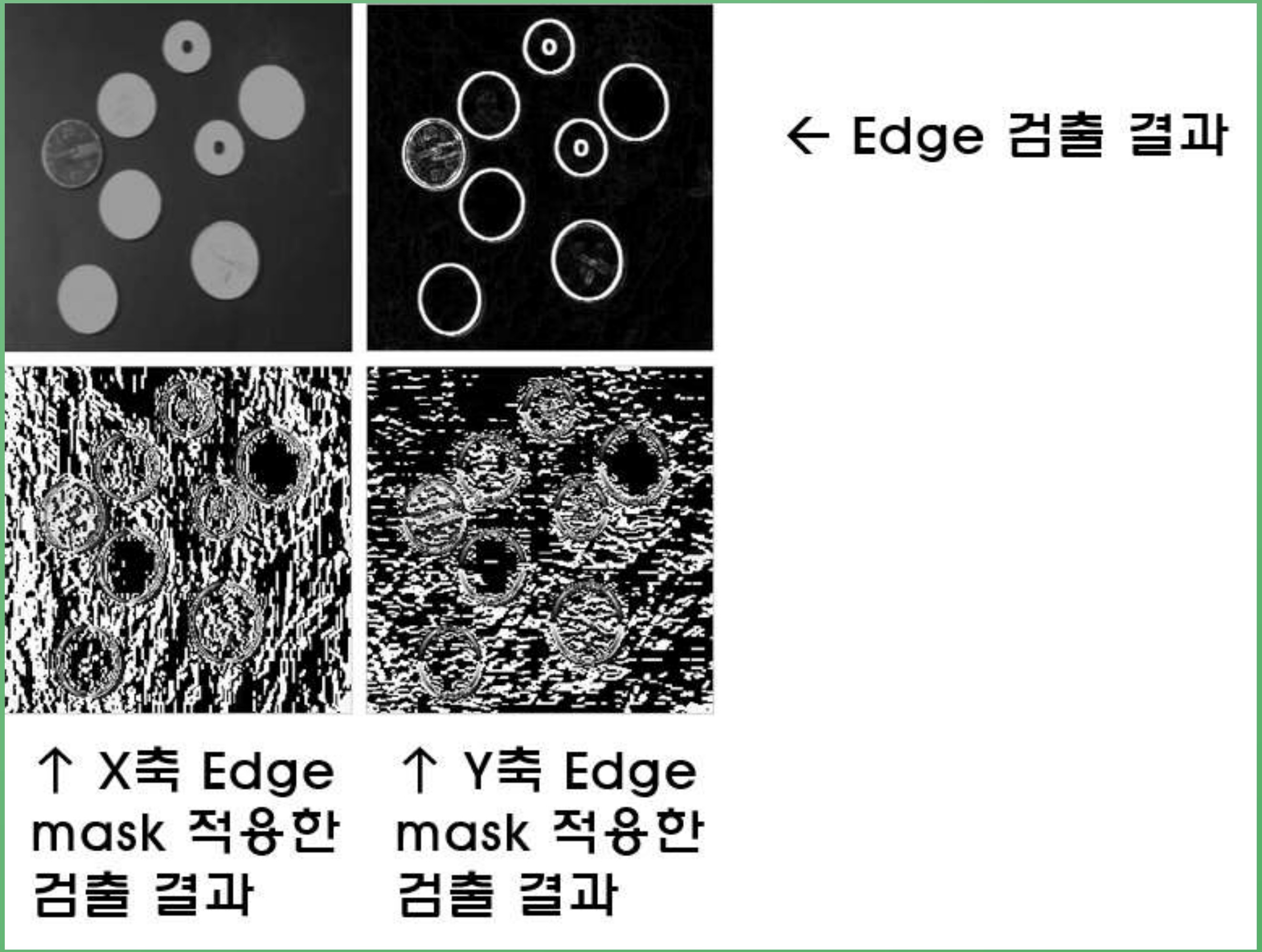
Prewitt Operator

Example



Prewitt operator + Edge thresholding

Example



Sobel operator + Edge thresholding

Common Masks for Computing Gradient

- Sobel : $\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ $\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$

- Prewitt: $\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ $\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$

- Roberts: $\begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ $\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$

Sx **Sy**