

# Human Vision, Color and Basic Image Processing

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CS4810

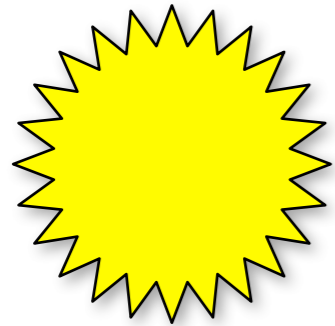
University of Virginia

Acknowledgement: slides by Jason Lawrence, Misha Kazhdan, Allison Klein, Tom Funkhouser, Adam Finkelstein and David Dobkin

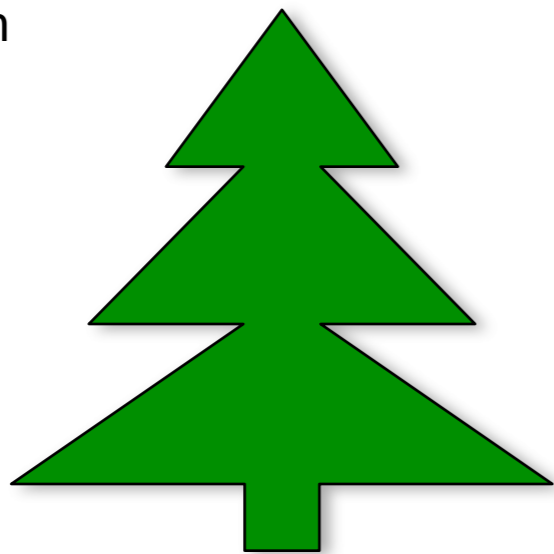
# Outline

- ▶ **Human Vision and Color**
- ▶ Image Representation
- ▶ Reducing Color Quantization Artifacts
- ▶ Basic Image Processing

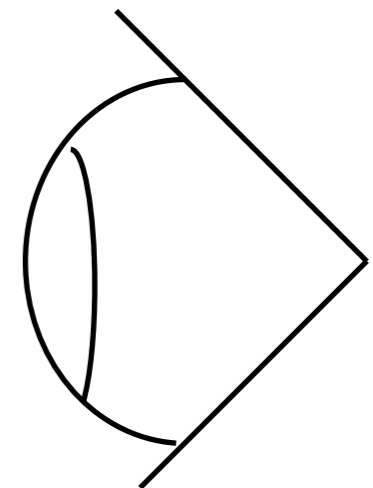
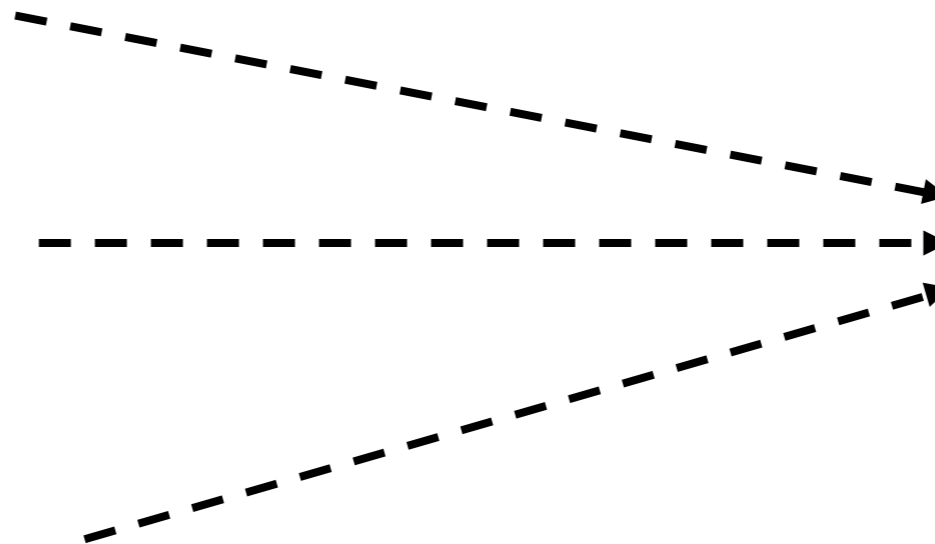
# Human Vision



Sun

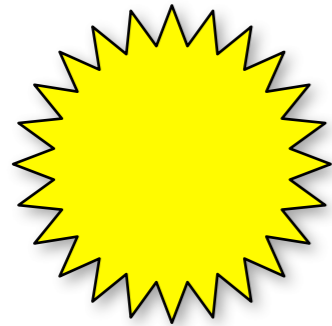


Objects in world

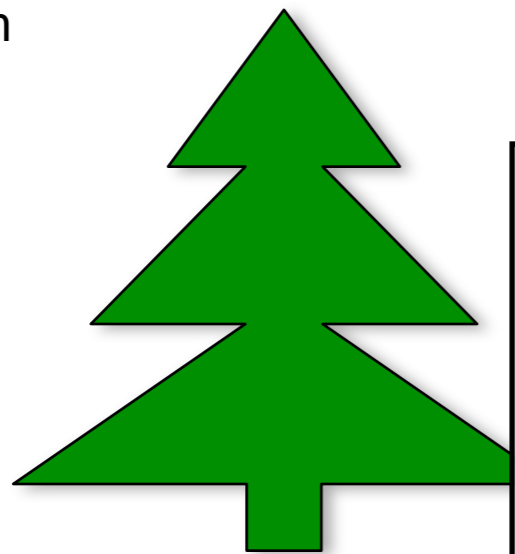


Human eye

# Human Vision



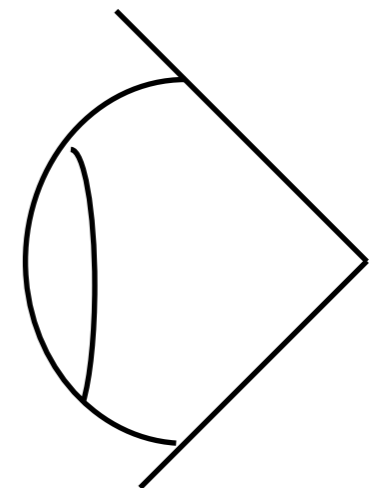
Sun



Objects in world

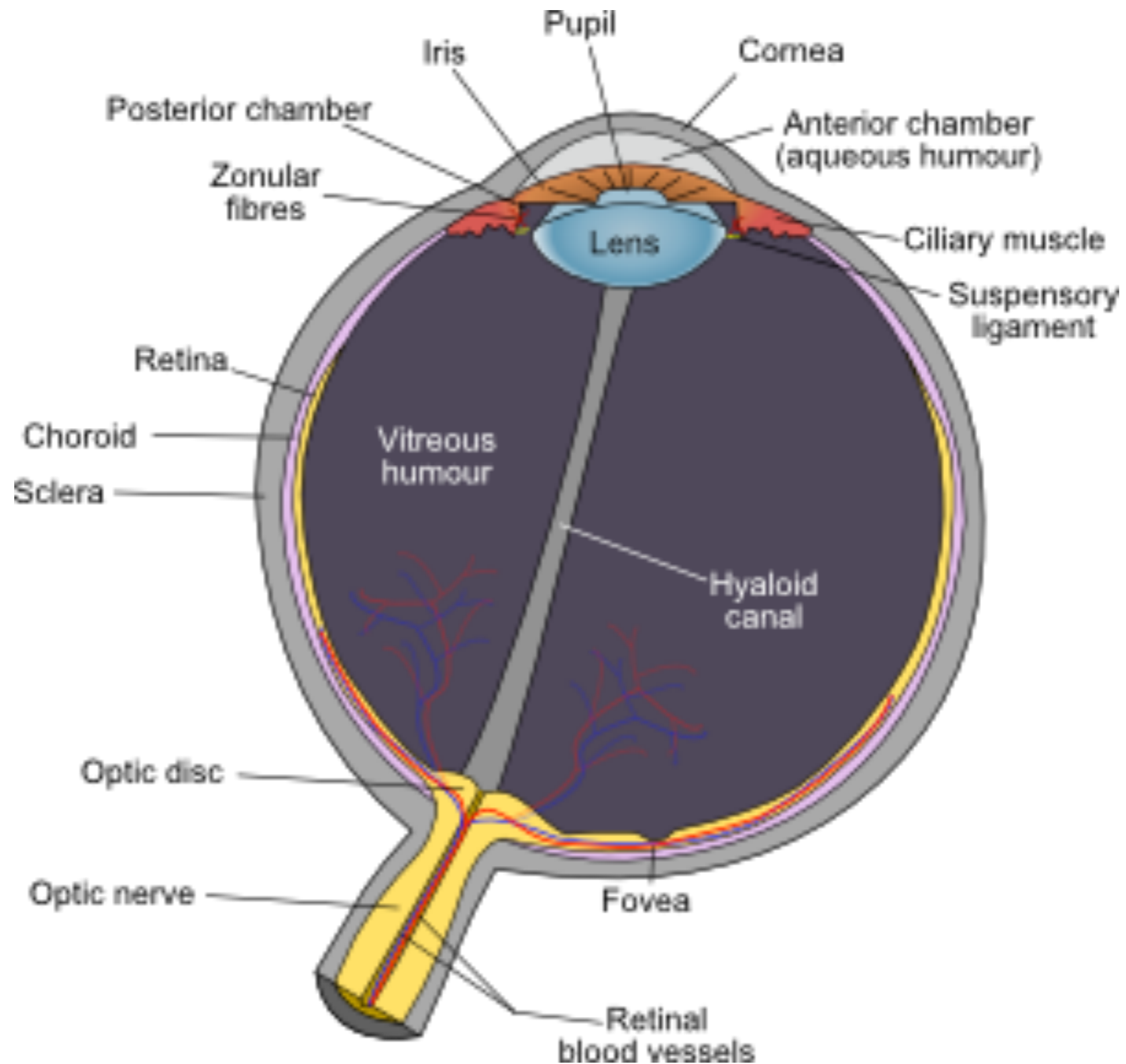
Vision Components:

- Incoming Light
- The Human Eye



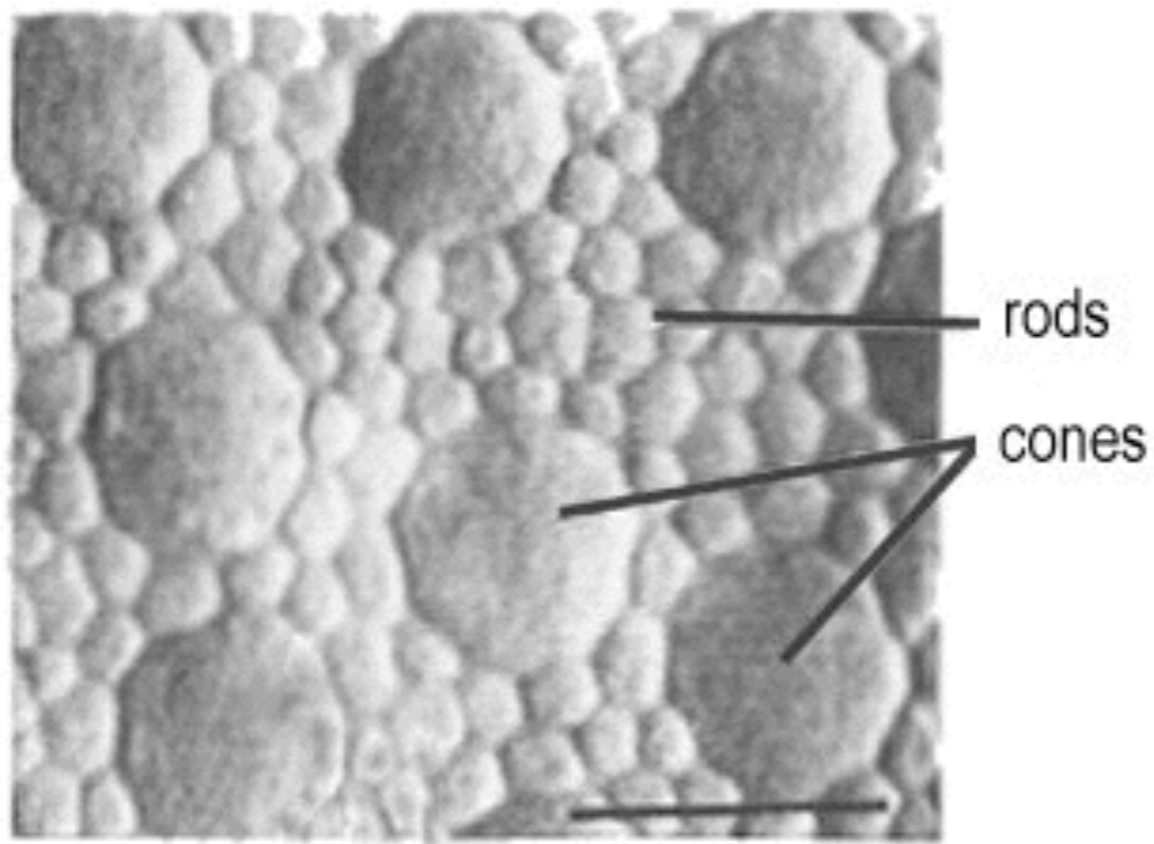
Human eye

# Typical Human Eye

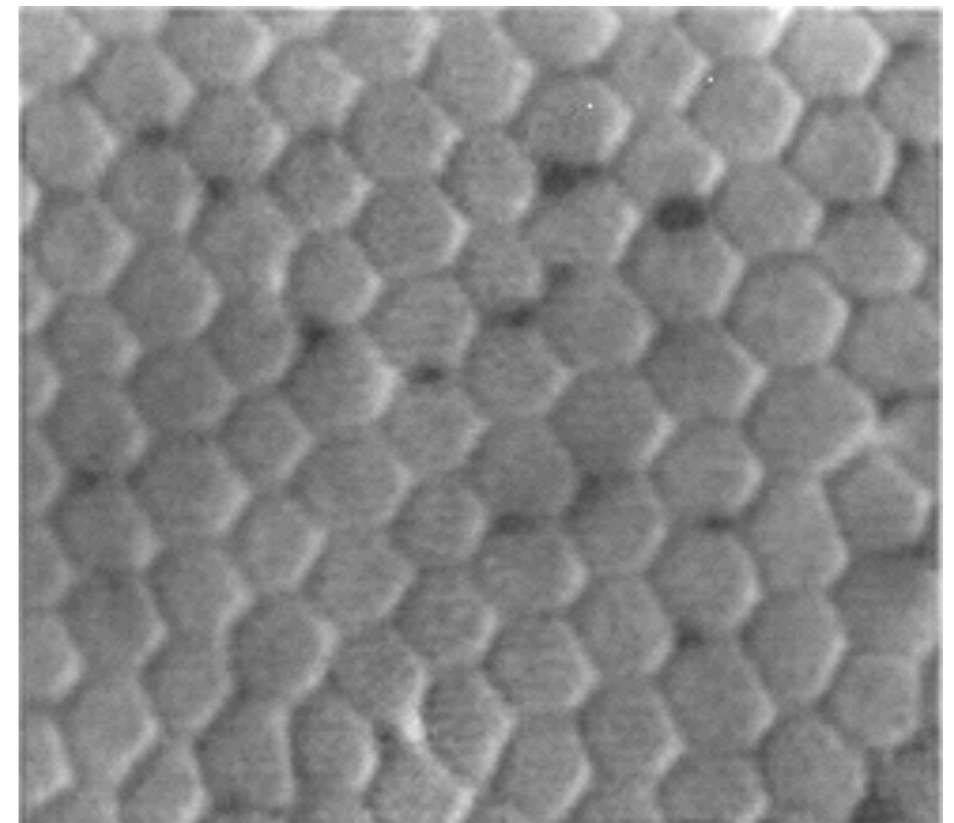


# Color

- Two types of photo-sensitive cells (“photo receptors”)



Rods and cones



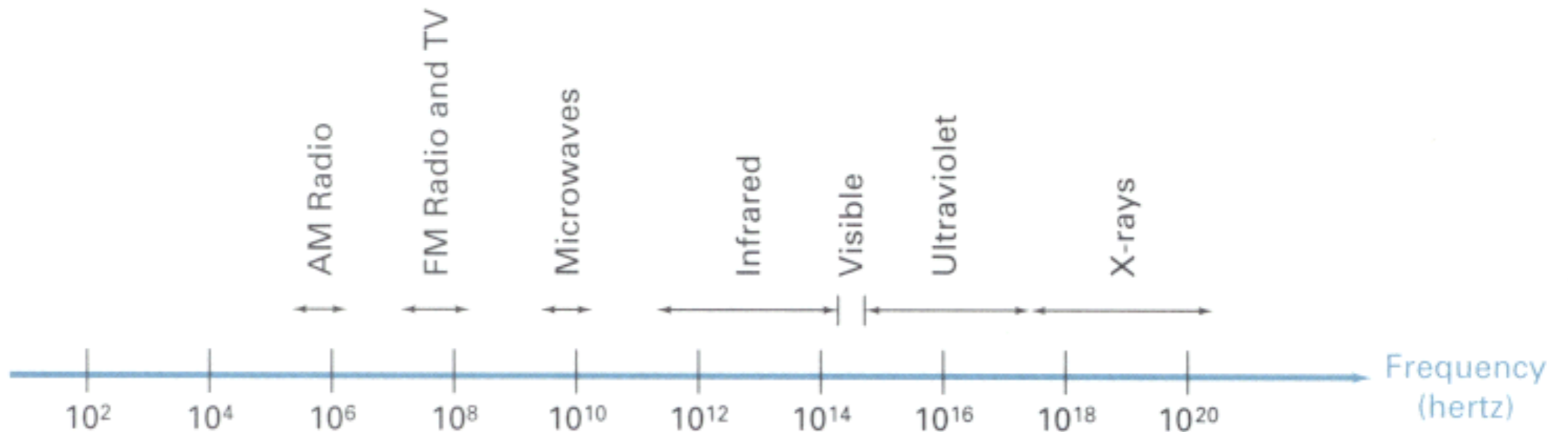
Cones in fovea

# Rods and Cones

- Rods
  - More sensitive in low light: “scotopic” vision
  - More dense near periphery
- Cones
  - Only function with higher light levels: “photopic” vision
  - Densely packed at center of eye: fovea
  - Different types of cones → color vision

# Electromagnetic Spectrum

- ▶ Visible light frequencies range between ...
  - ▶ Red =  $4.3 \times 10^{14}$  hertz (700nm)
  - ▶ Violet =  $7.5 \times 10^{14}$  hertz (400nm)

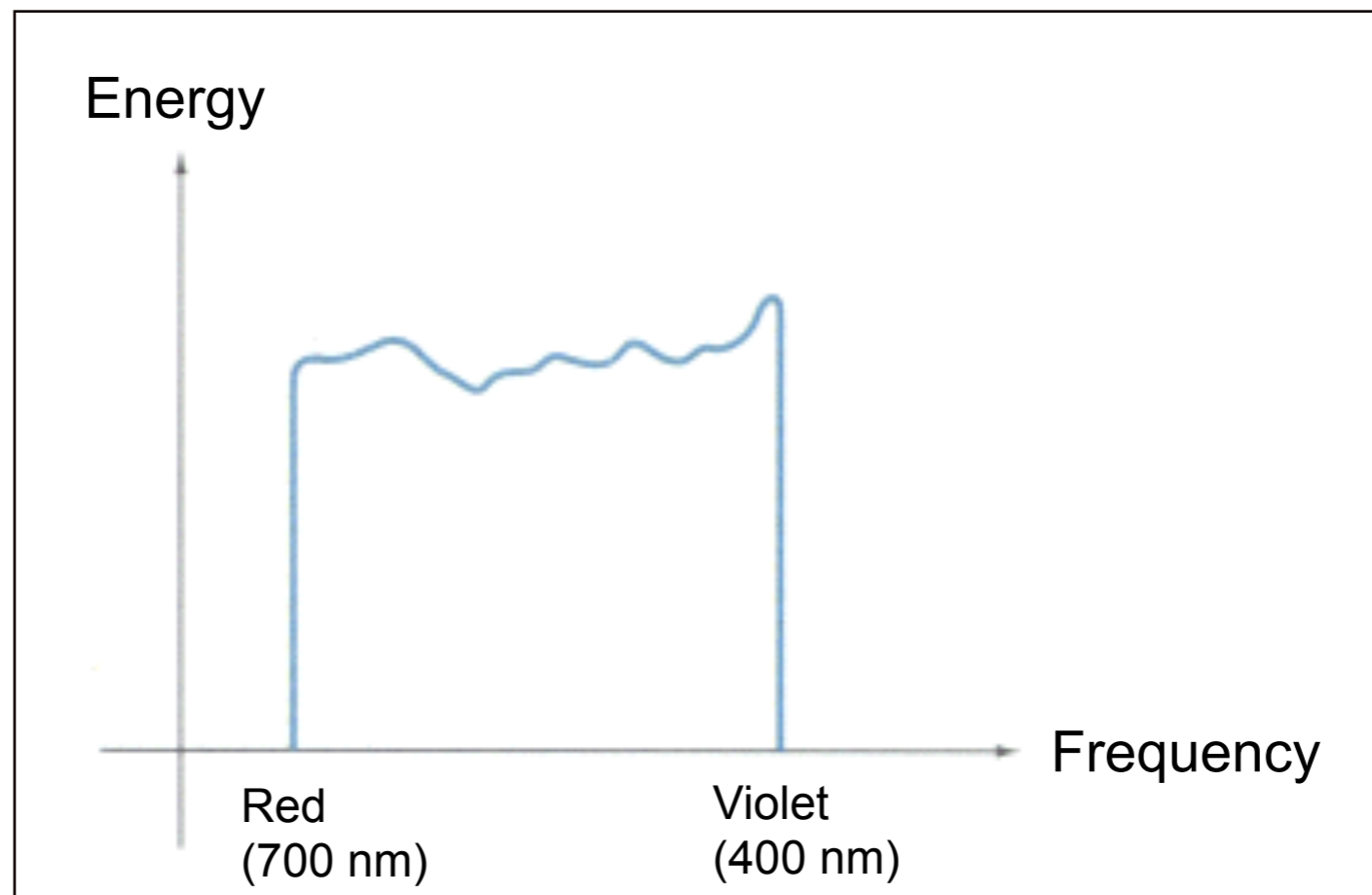


Figures 15.1 from H&B



# Visible Light

- ▶ The human eye can “see” light in the frequency range 400nm – 700nm



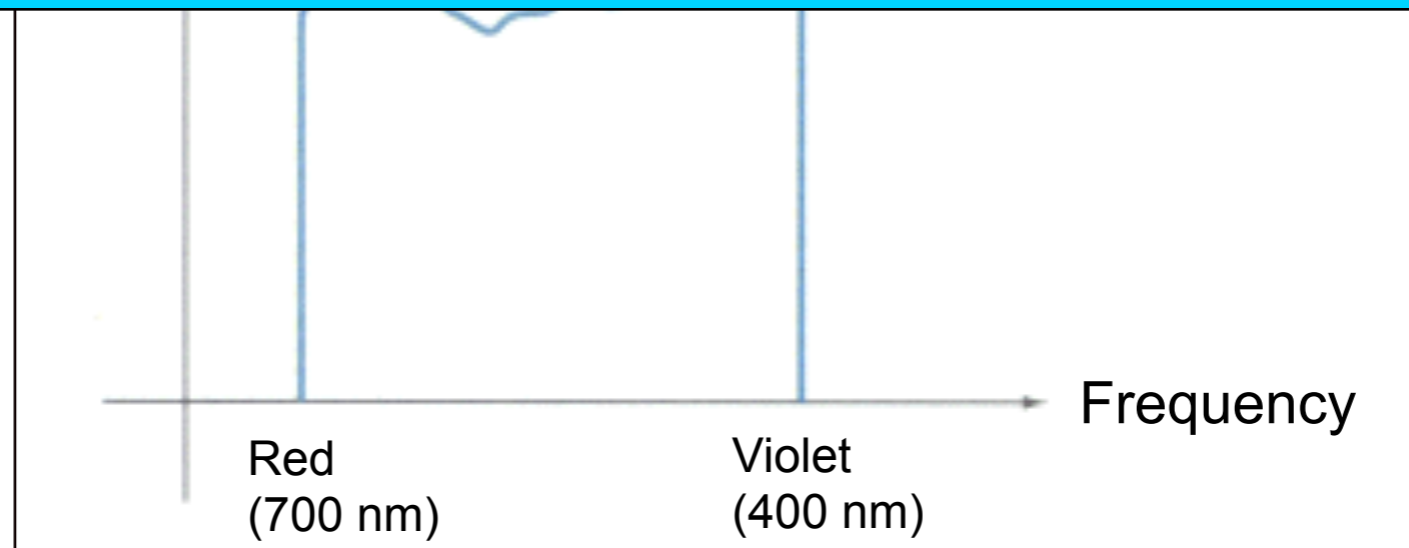
“White” Light

Figure 15.3 from H&B

# Visible Light

- ▶ The human eye can “see” light in the frequency range 400nm – 700nm

**This does not mean that we can see the difference between the different spectral distributions.**

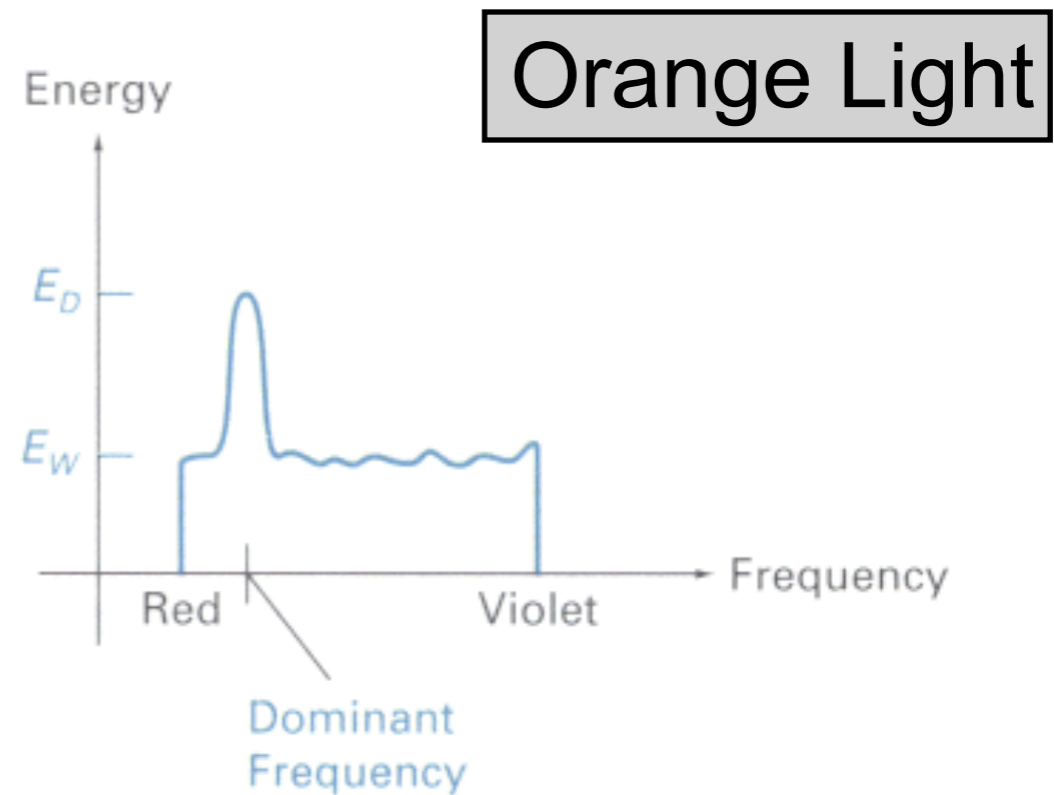
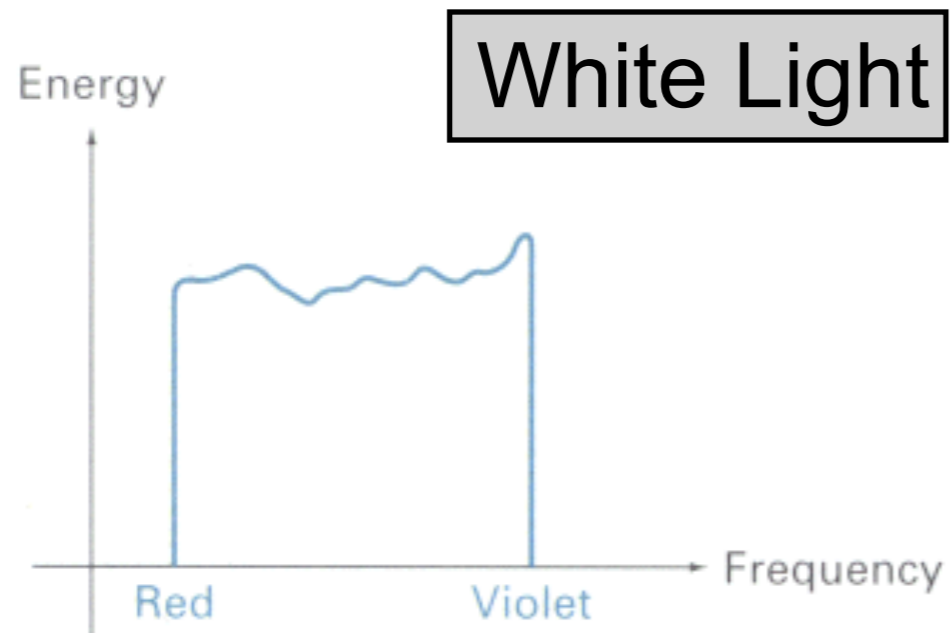


“White” Light

Figure 15.3 from H&B

# Visible Light

- Color may be characterized by ...
  - Hue = dominant frequency (highest peak)
  - Saturation = excitation purity (ratio of highest to rest)
  - Lightness = luminance (area under curve)



# Tristimulus Theory of Color

Spectral-response functions of each of the three types of cones.

This motivates encoding color as a combination of red, green, and blue (RGB).

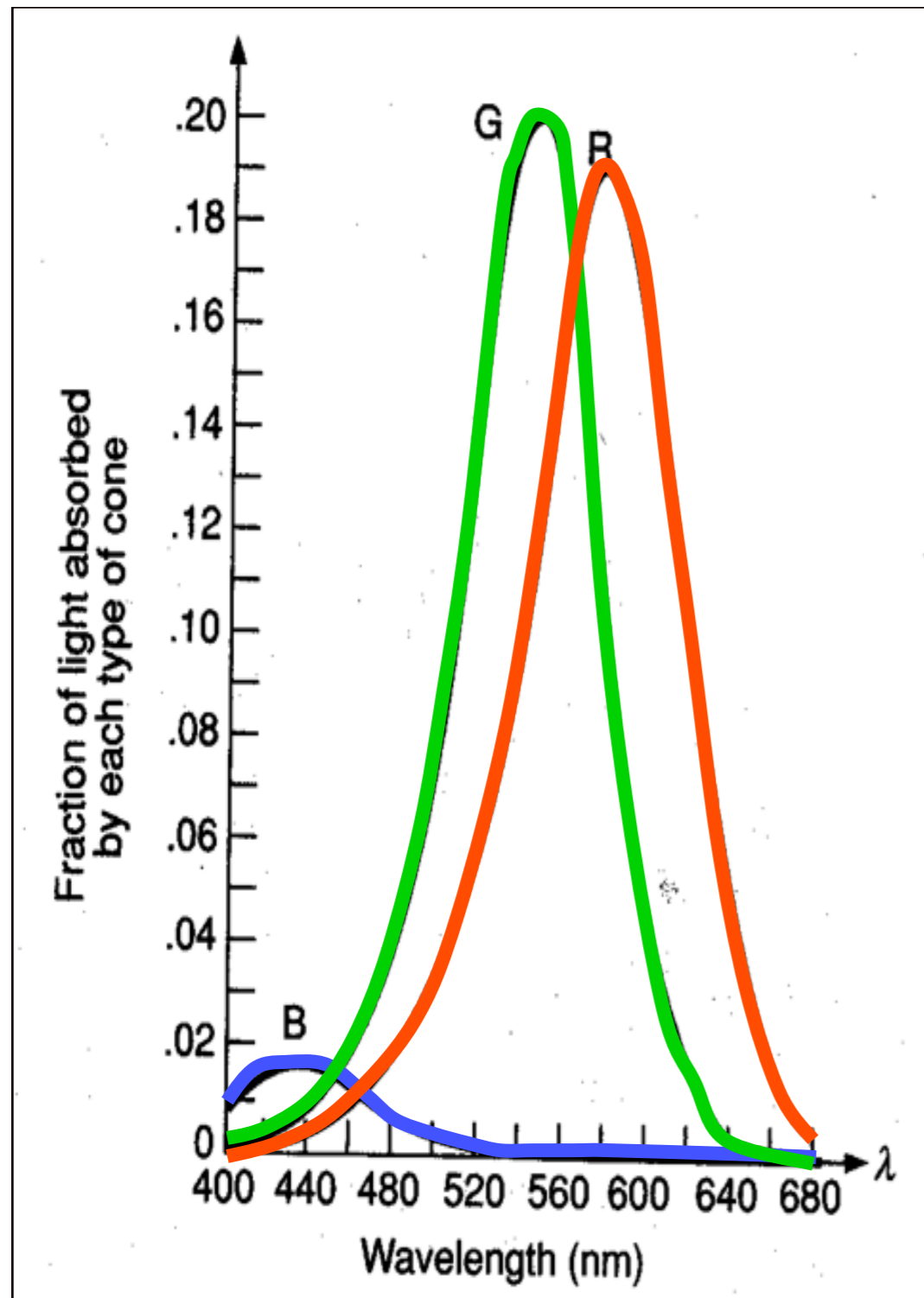


Figure 13.18 from FvDFH

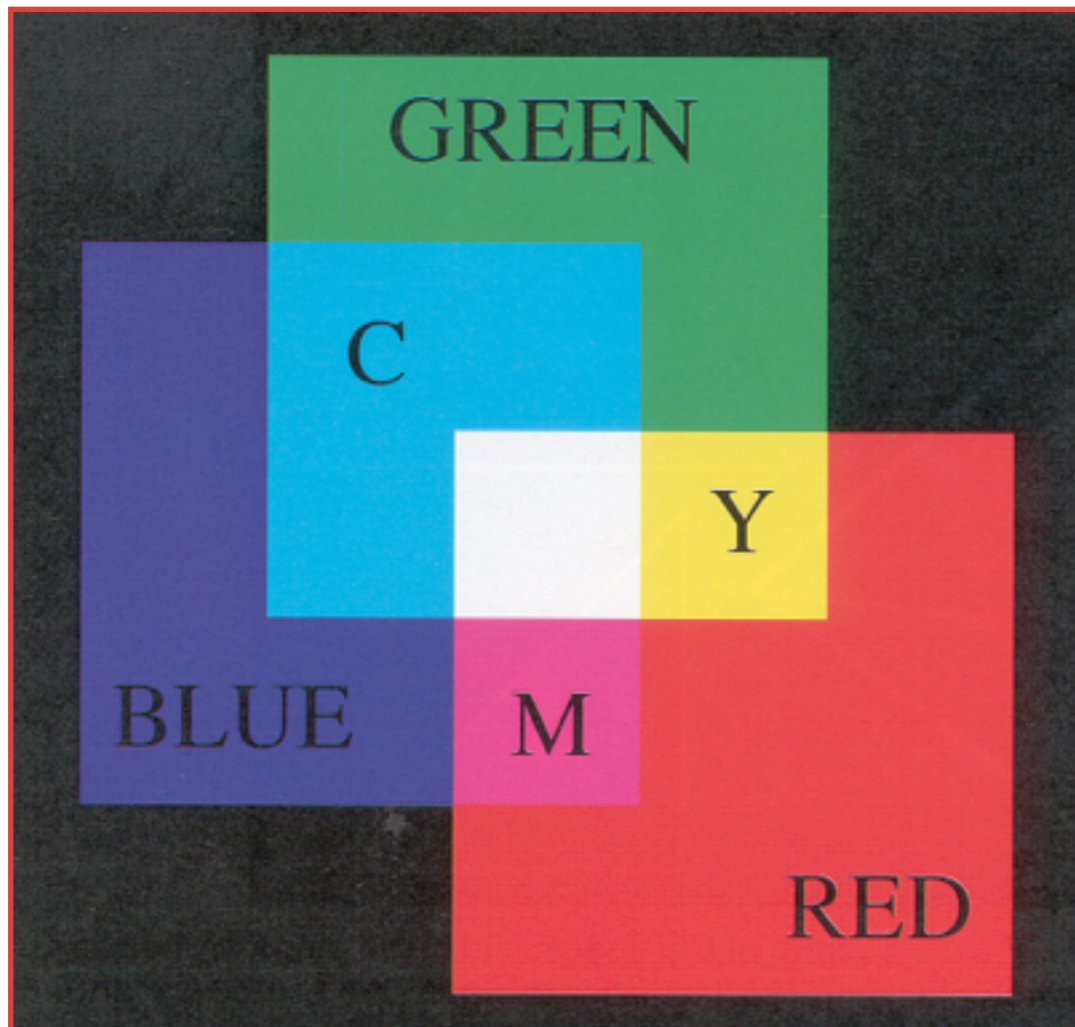
# Tristimulus Color

- Any distribution of light can be summarized by its effect on 3 types of cones
- Therefore, human perception of color is a 3-dimensional space
- Metamerism: different spectra, same response
- Color blindness: fewer than 3 types of cones
  - Most commonly L cone = M cone

# Color Models





- ▶ RGB
  - ▶ XYZ
  - ▶ CMYK
  - ▶ HSV
  - ▶ etc...
- Different ways of parameterizing 3D space.
- RGB most common and used in this class:  
R=645.16nm, G=526.32nm, B=444.44nm

# RGB Color Model

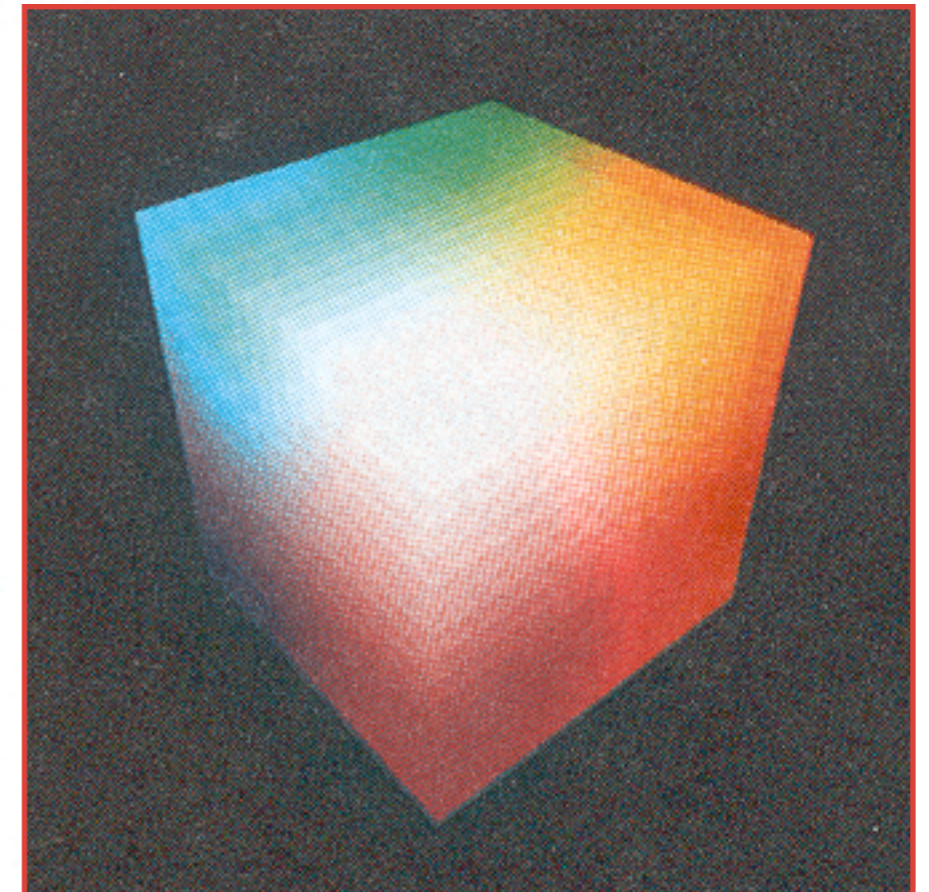
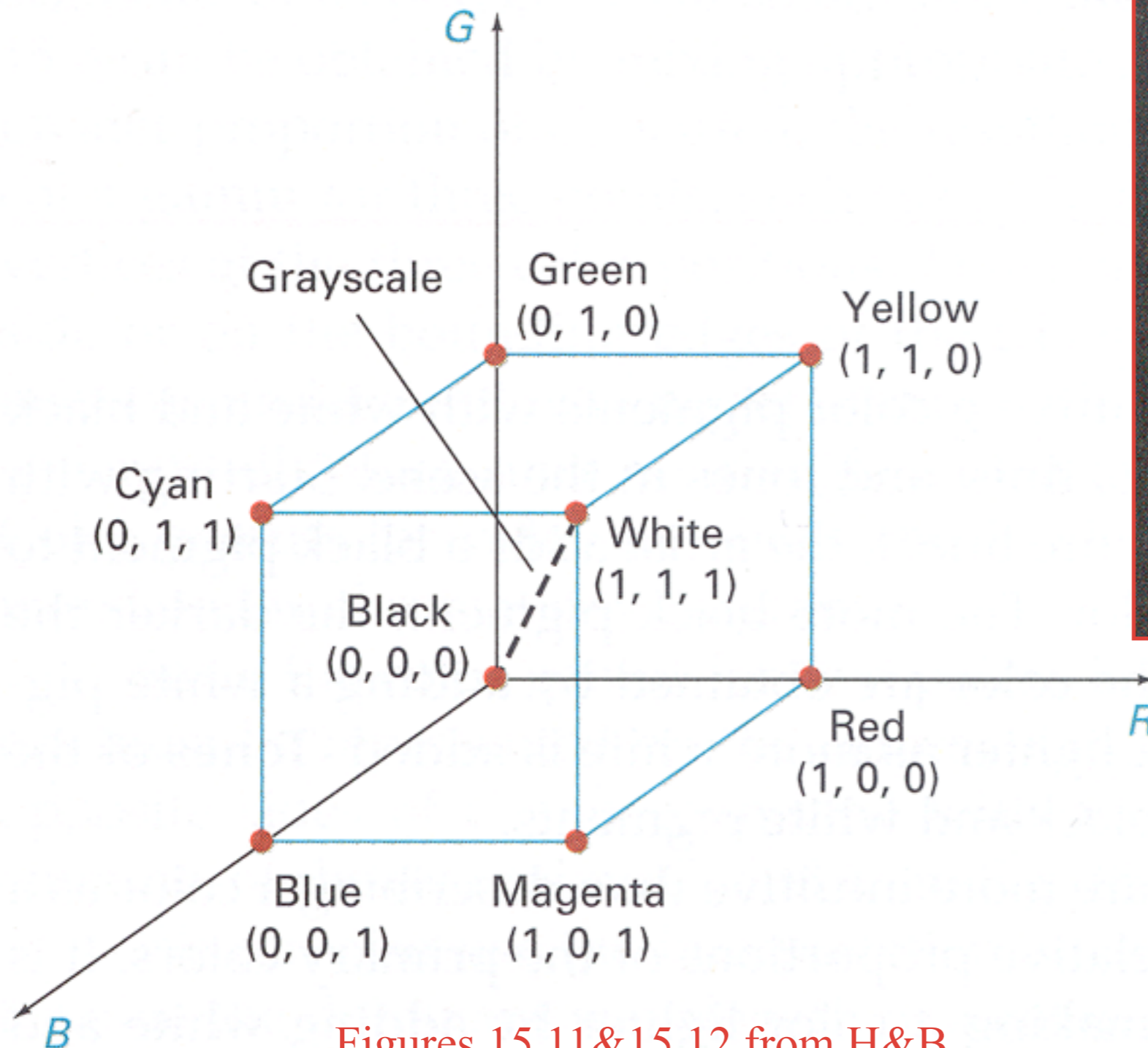


Colors are additive

Plate II.3 from FvDFH

R	G	B	Color
0.0	0.0	0.0	Black
1.0	0.0	0.0	Red
0.0	1.0	0.0	Green
0.0	0.0	1.0	Blue
1.0	1.0	0.0	Yellow
1.0	0.0	1.0	Magenta
0.0	1.0	1.0	Cyan
1.0	1.0	1.0	White
0.5	0.0	0.0	? 
1.0	0.5	0.5	? 
1.0	0.5	0.0	? 
0.5	0.3	0.1	? 

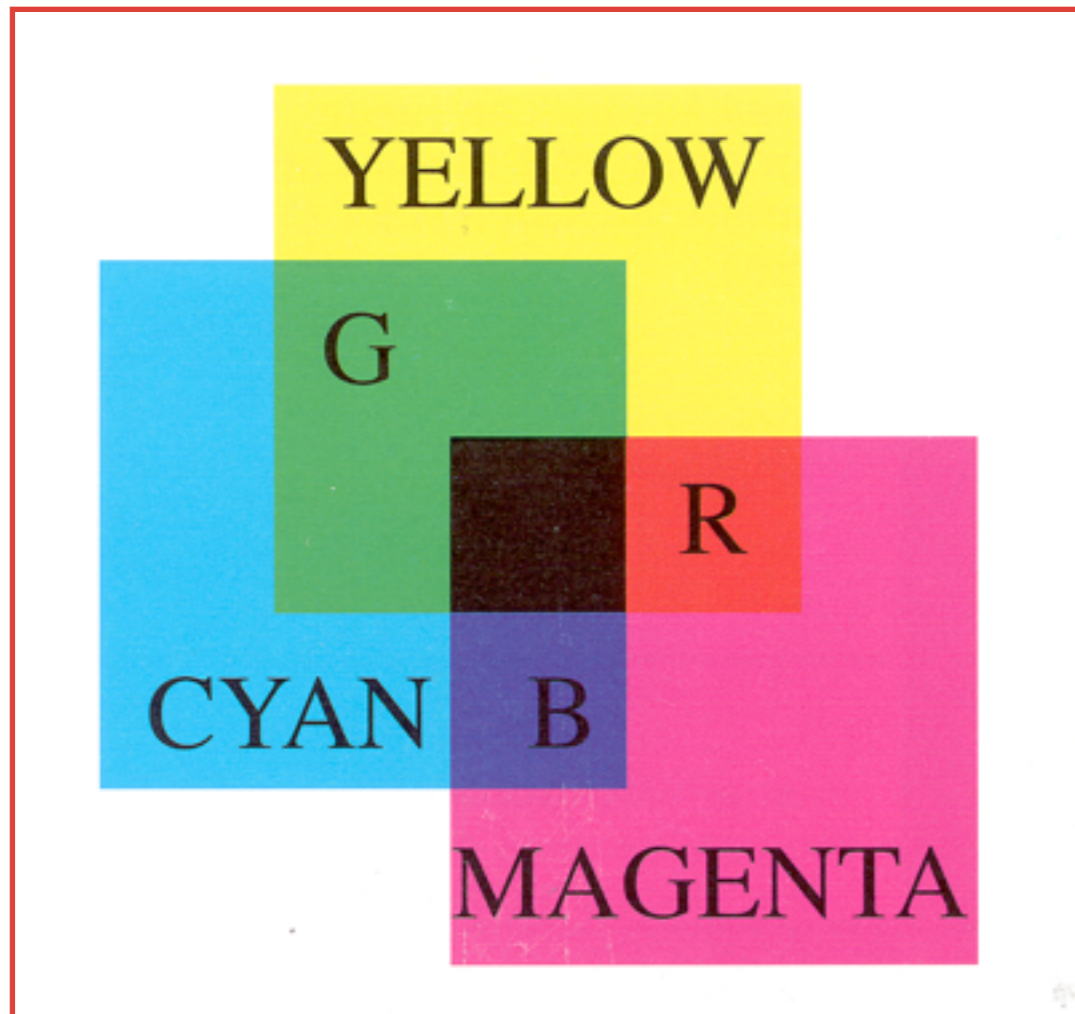
# RGB Color Cube



Figures 15.11&15.12 from H&B

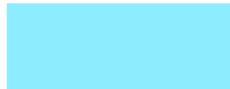




# CMY(K) Color Model



Colors are subtractive

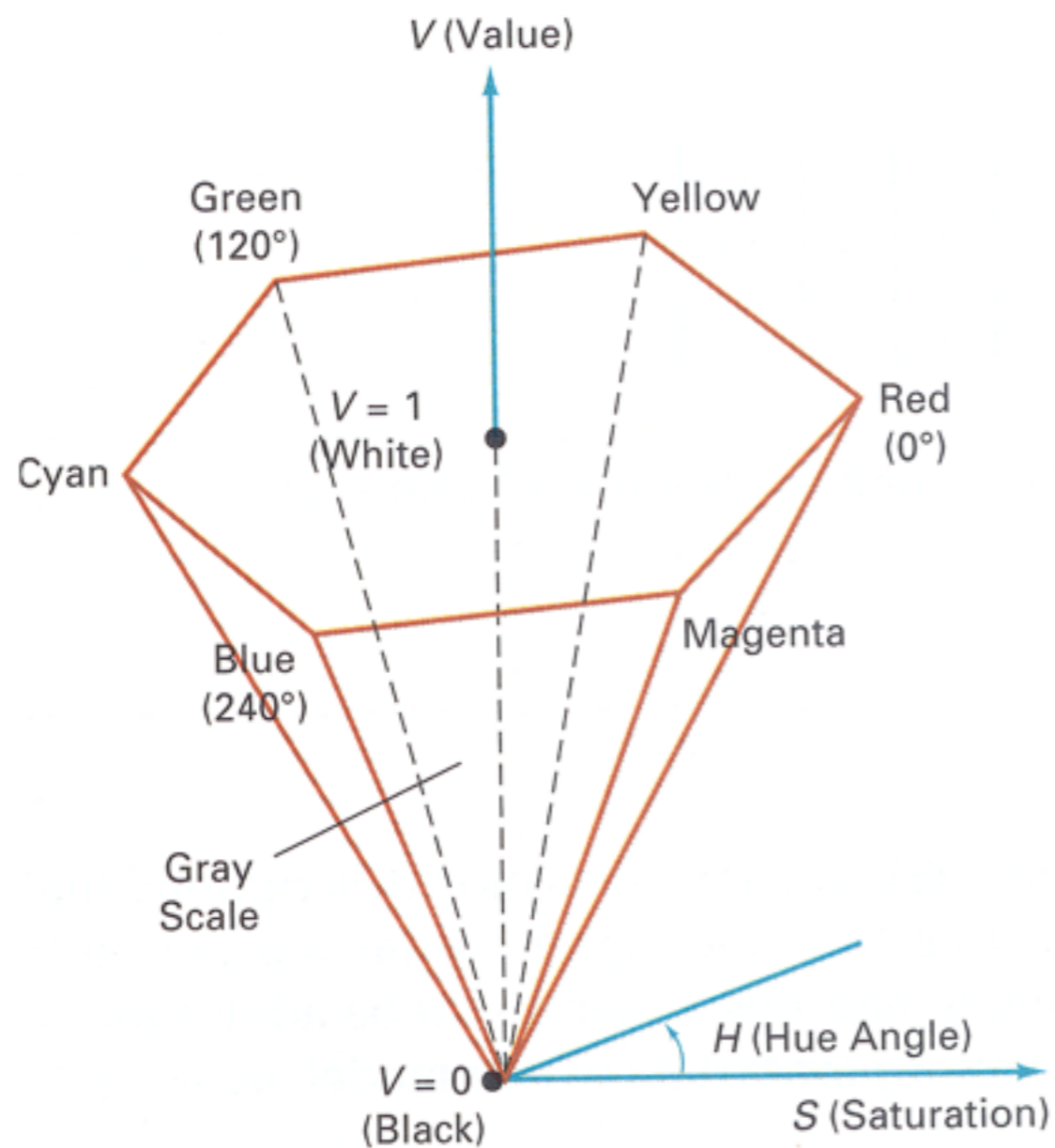
Plate II.7 from FvDFH

C	M	Y	Color
0.0	0.0	0.0	White
1.0	0.0	0.0	Cyan
0.0	1.0	0.0	Magenta
0.0	0.0	1.0	Yellow
1.0	1.0	0.0	Blue
1.0	0.0	1.0	Green
0.0	1.0	1.0	Red
1.0	1.0	1.0	Black
0.5	0.0	0.0	? 
1.0	0.5	0.5	? 
1.0	0.5	0.0	? 

# Discussion question

- ▶ CMY(K) is frequently used for printer ink cartridge colors
- ▶ RGB is frequently used for displays
- ▶ Why would CMY(K) be used for printers and RGB for screens?

# HSV Color Model



H	S	V	Color
0	1.0	1.0	Red
120	1.0	1.0	Green
240	1.0	1.0	Blue
*	0.0	1.0	White
*	0.0	0.5	Gray
*	*	0.0	Black
60	1.0	1.0	? 
270	0.5	1.0	? 
270	0.0	0.7	? 

Figure 15.16&15.17 from H&B

# Outline

- Human Vision and Color
- **Image Representation**
- Reducing Color Quantization Artifacts
- Basic Image Processing

# Image Representation

- What is an image?

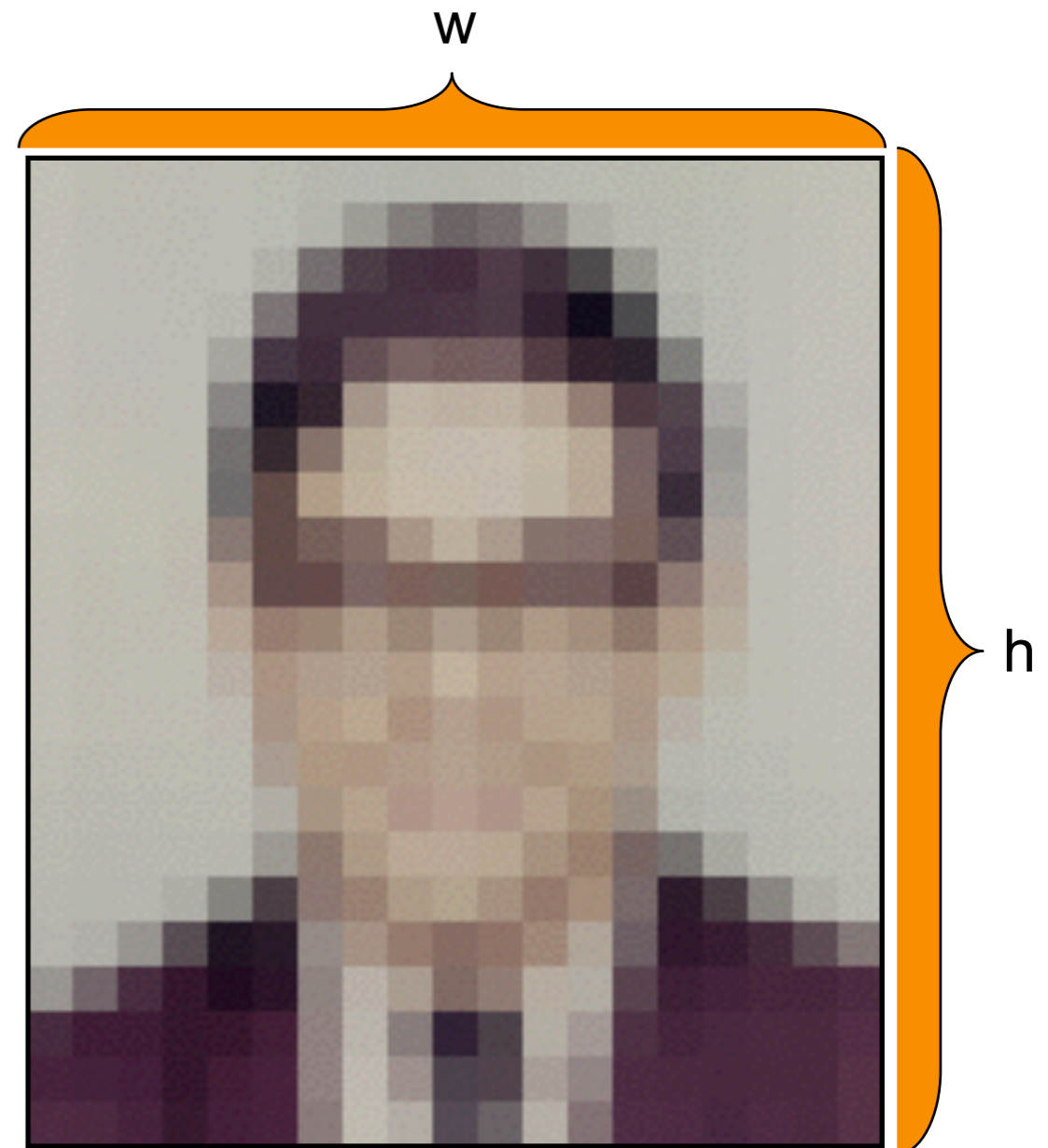


# Image Representation

- An image is a 2D rectilinear array of pixels:
  - A width  $\times$  height array where each entry of the array stores a single pixel.



Continuous image



Digital image

# Image Representation

- What is a pixel?



Continuous image



Digital image

# Image Representation

- A pixel is something that captures the notion of “intensity” and possibly “color”
- Luminance pixels
  - Grey-scale images (aka “Intensity images”)
  - 0 – 1.0 or 0 – 255
- Red, Green, Blue pixels (RGB)
  - Color images
  - 0 – 1.0 or 0 – 255



# Image Resolution

- Spatial resolution: width x height pixels
- Intensity/Color resolution: n bits per pixel
- Temporal resolution: n Hz (fps)

	Width x Height	Bit Depth	Hz
NTSC	640 x 480	8	30
iPhone5	640 x 1136	24	60
Monitor	1920 x 1200	24	75
CCDs	3000 x 2000	36	-
Laser Printer	6600 x 5100	1	-

# Image Quantization Artifacts

- ▶ With only a small number of bits associated to each color channel of a pixel there is a limit to intensity resolutions of an image
  - ▶ A black and white image allocates a single bit to the luminance channel of a pixel.
    - ▶ The number of different colors that can be represented by a pixel is 2.
  - ▶ A 24 bit bitmap image allocates 8 bits to the red, green, and blue channels of a pixel.
    - ▶ The number of different colors that can be represented by a pixel is  $2^{24} = 16.8$  million.

# Outline

- Human Vision
- Image Representation
- **Reducing Color Quantization Artifacts**
  - Halftoning and Dithering
- Basic Image Processing

# Quantization

- Image with decreasing bits per pixel
  - Note contouring!



8 bits



4 bits



2 bits



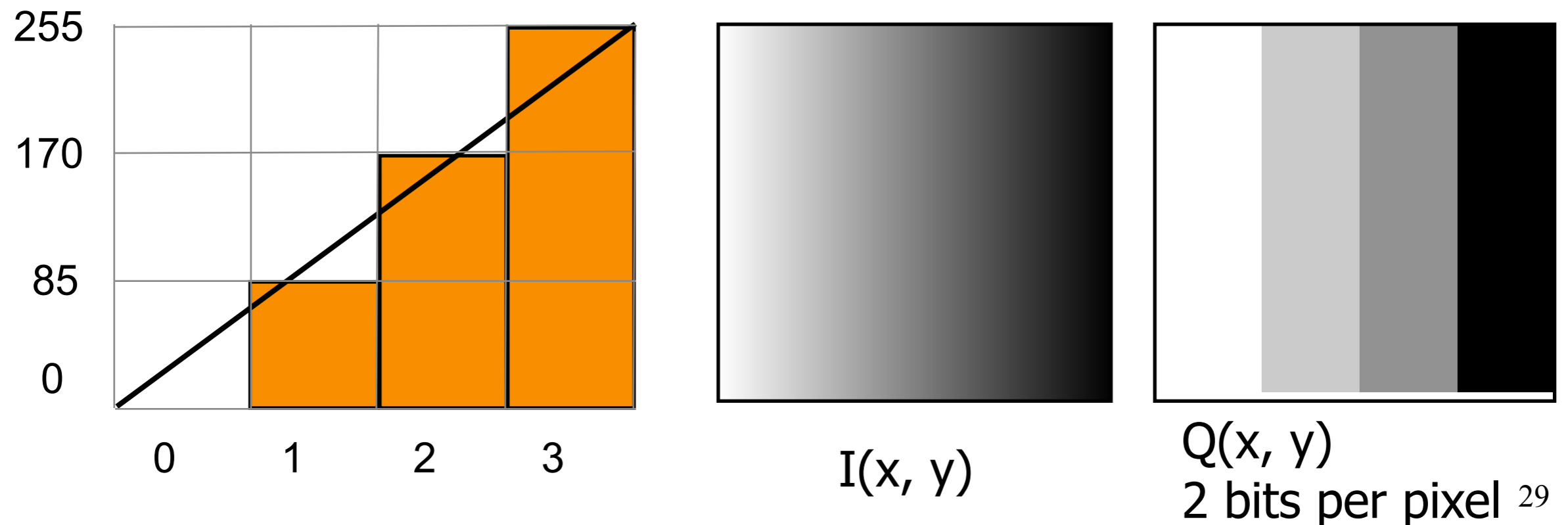
1 bit

# Quantization

- When you have a small number of bits per pixel, you can coarsely represent an image by quantizing the color values:

$$P(x, y) = Q(I(x, y)) = \text{floor} \left( \frac{I(x, y)}{256} 2^b \right)$$

b is the number of bits per pixel

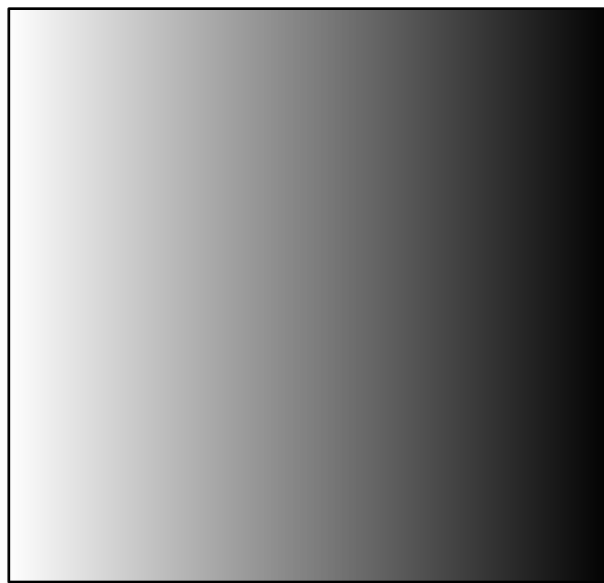


# Reducing Effects of Quantization

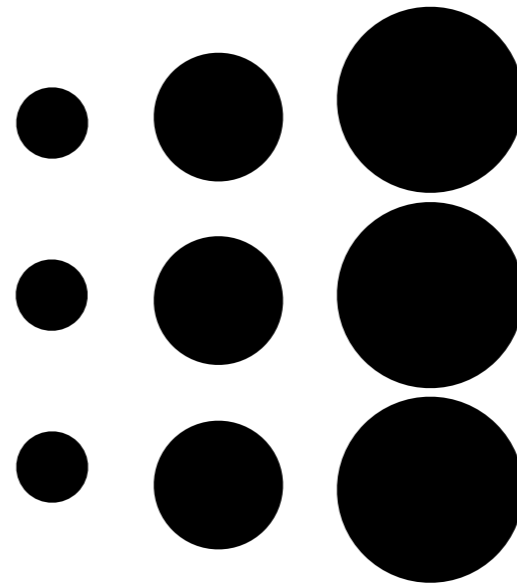
- Trade spatial resolution for intensity resolution
- Halftoning
- Dithering
  - Random dither
  - Ordered dither
  - Error diffusion dither

# Classical Halftoning

- Varying-size dots represent intensities
- Area of dots inversely proportional to intensity

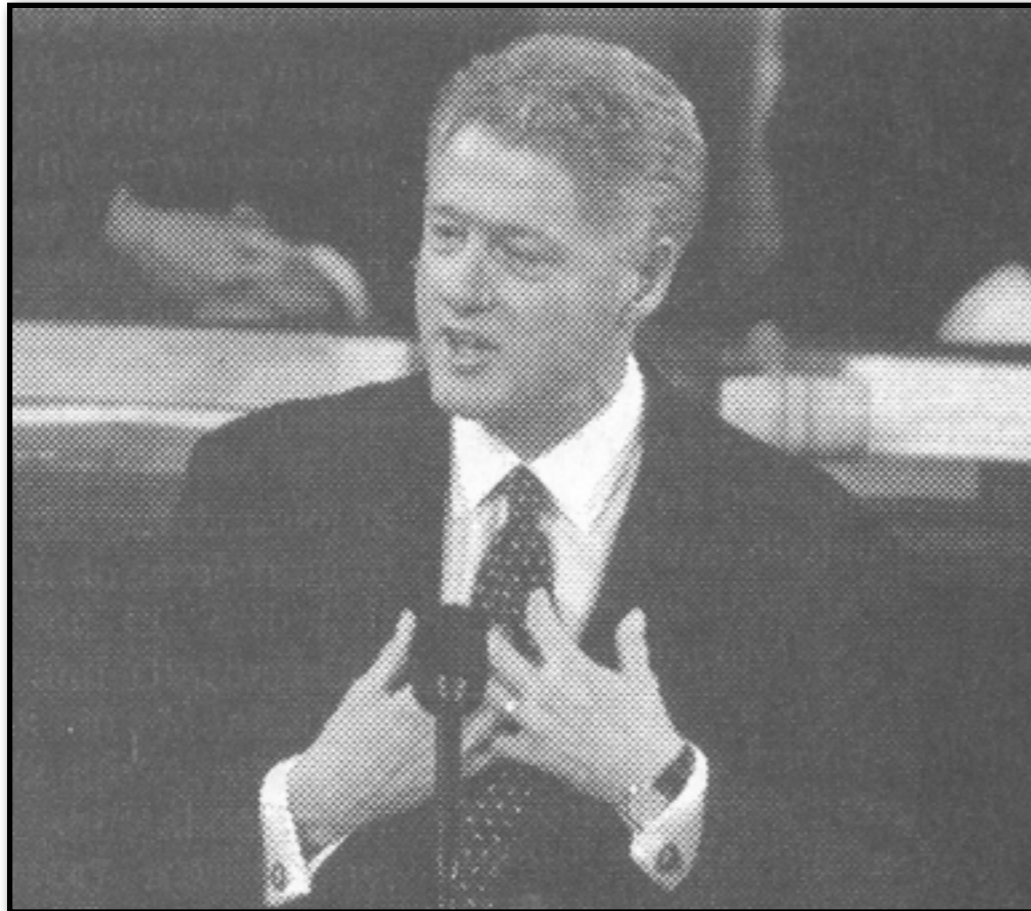


$I(x, y)$

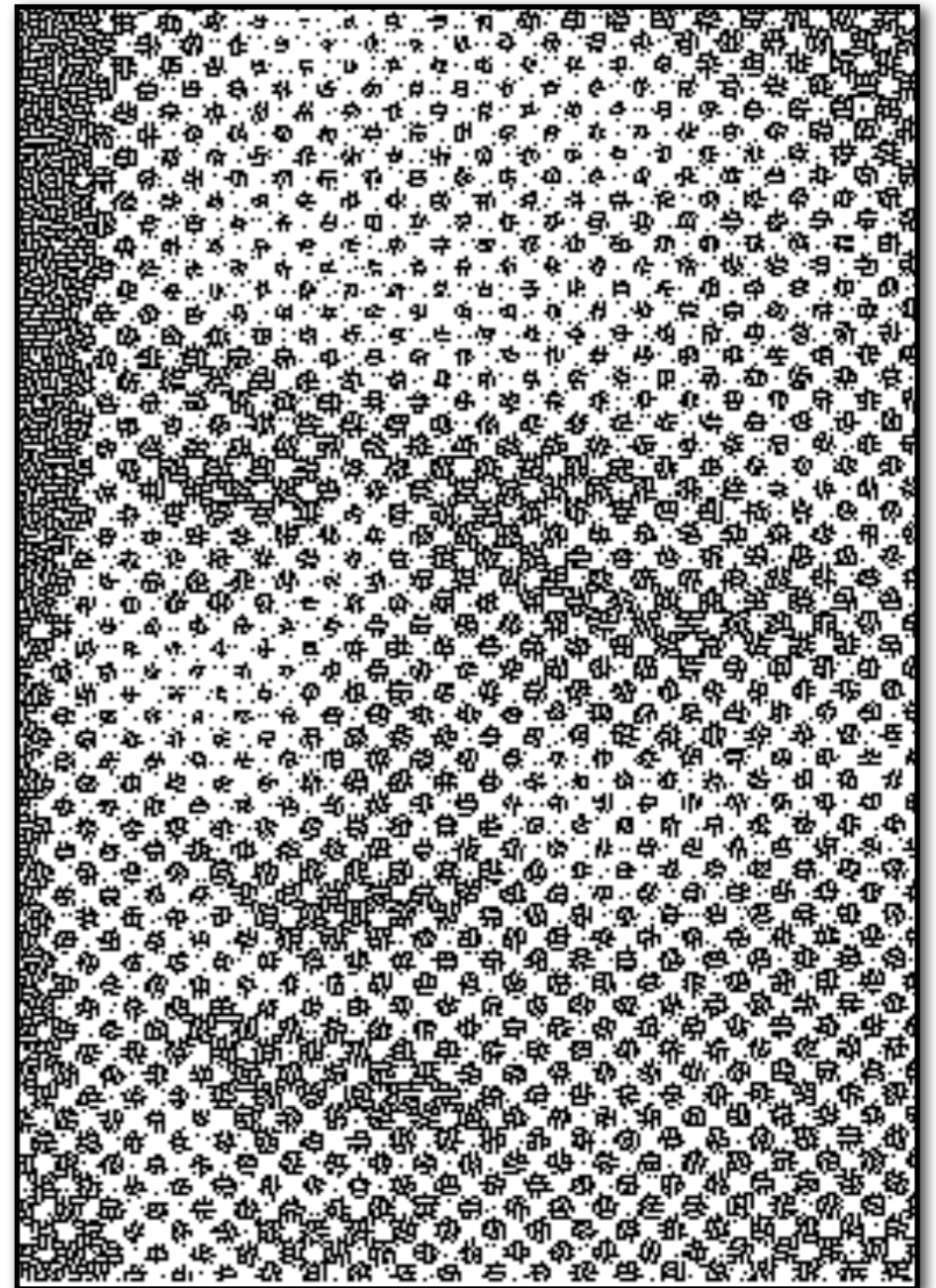


$P(x, y)$

# Classical Halftoning



Newspaper Image



From New York Times, 9/21/99

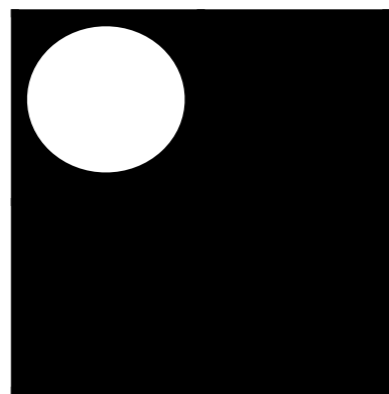


# Digital Halftoning

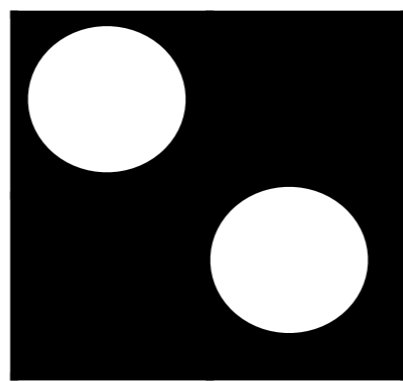
- Use cluster of pixels to represent intensity
- Trades spatial resolution for intensity resolution
- Note that halftoning pattern matters
  - Want to avoid vertical, horizontal lines



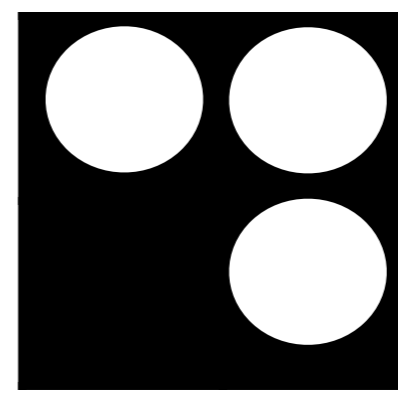
$$0 \leq I \leq 0.2$$



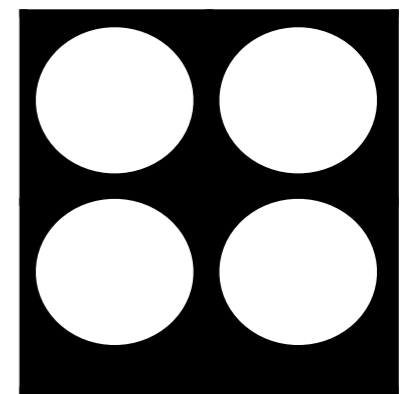
$$0.2 < I \leq 0.4$$



$$0.4 < I \leq 0.6$$



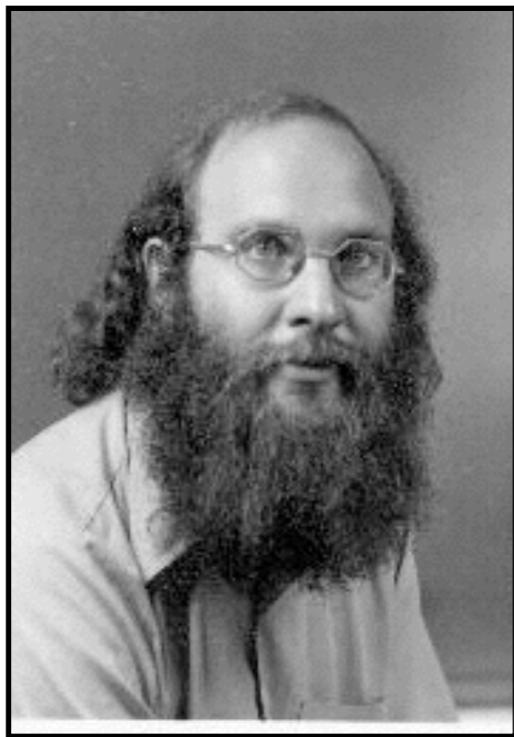
$$0.6 < I \leq 0.8$$



$$0.8 < I \leq 1.0$$

# Digital Halftoning

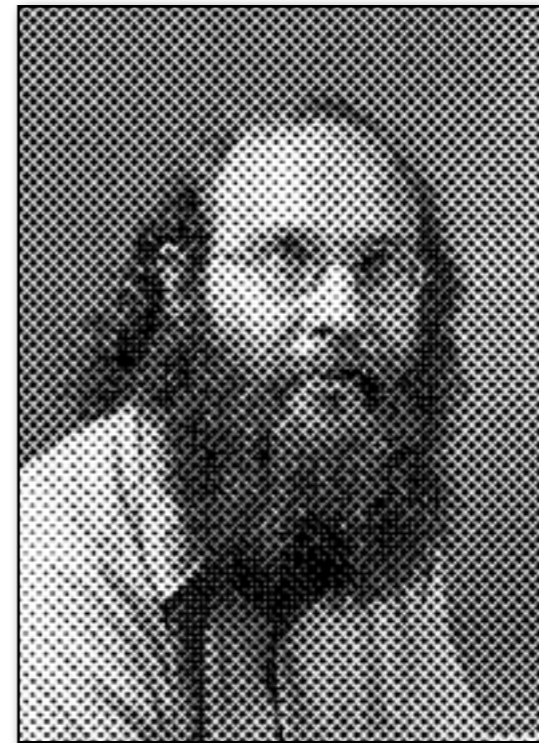
- ▶ Use cluster of pixels to represent intensity
- ▶ Trades spatial resolution for intensity resolution
- ▶ Note that halftoning pattern matters



Original  
(8 bits)



Quantized  
(1 bit)



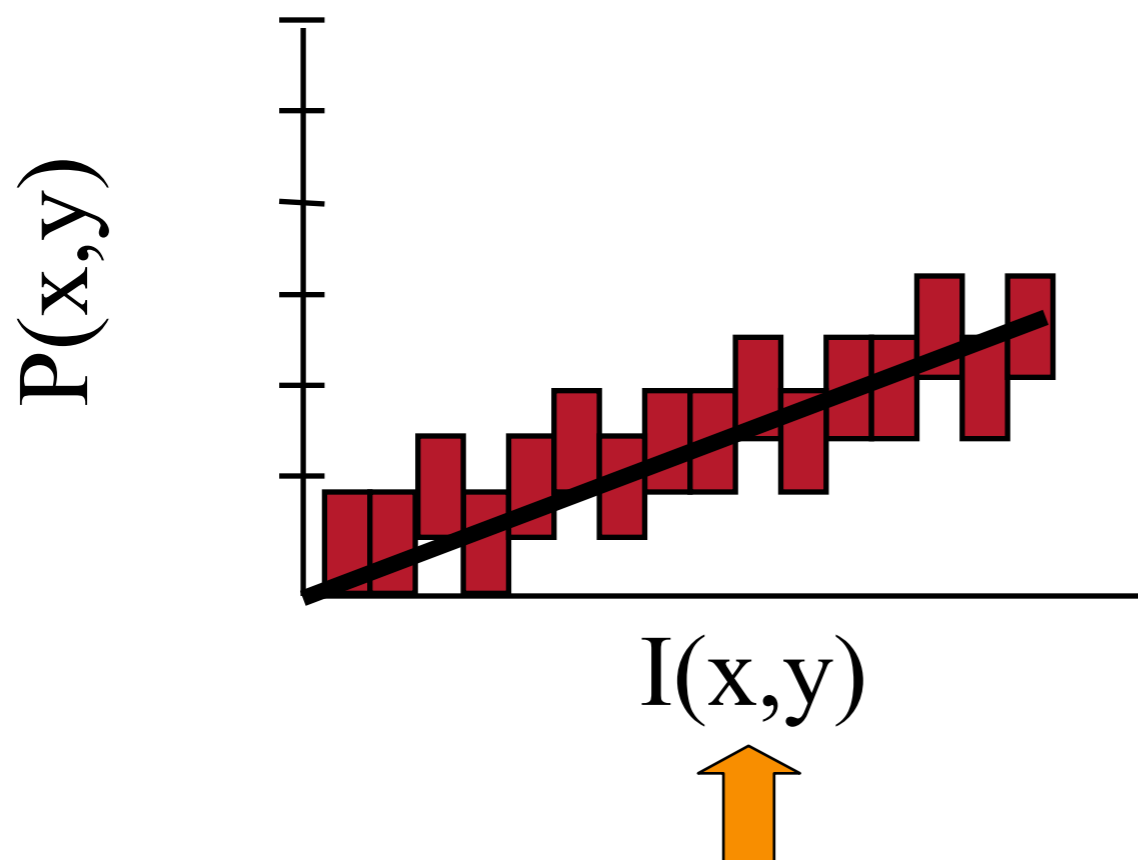
Halftoned  
(1 bit)

# Dithering

- Distribute errors among pixels
  - Exploit spatial integration in our eye
  - Display greater range of perceptible intensities

# Random Dither

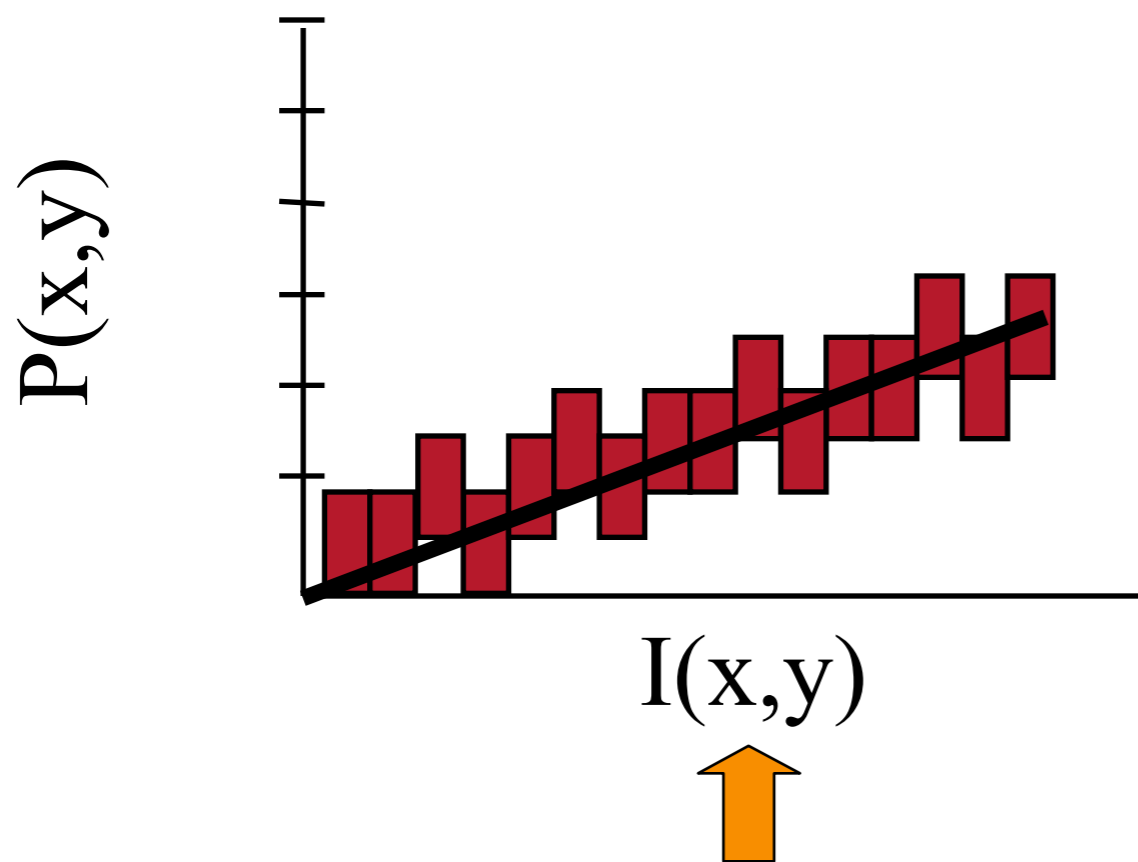
- Randomize quantization errors
- Errors appear as noise



$$P(x, y) = Q(I(x, y) + \text{noise}(x, y))$$

# Random Dither

- Randomize quantization errors
- Errors appear as noise



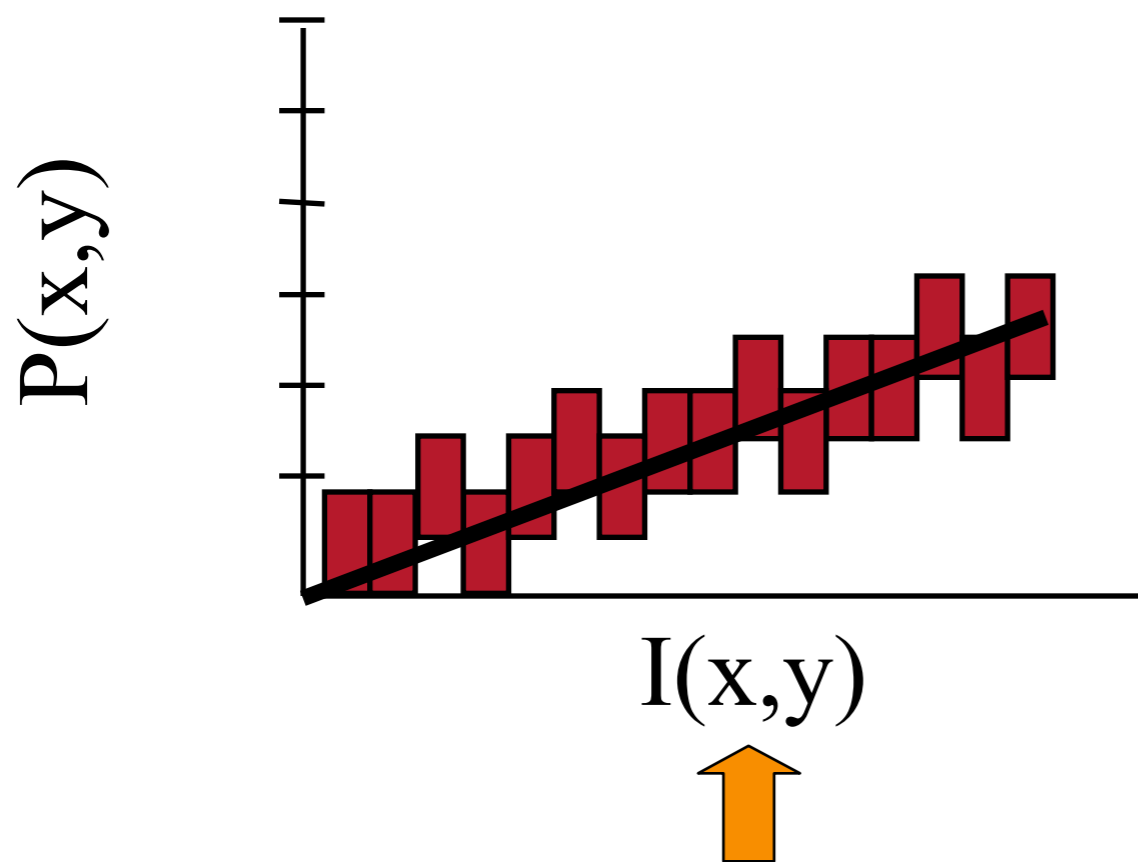
If a pixel is black, then adding random noise to it, you are less likely to turn it into a white pixel than if the pixel were dark gray.

$$P(x, y) = Q(I(x, y) + \text{noise}(x, y))$$

# Random Dither

- Randomize quantization errors
- Errors appear as noise

How much noise should we add?



If a pixel is black, then adding random noise to it, you are less likely to turn it into a white pixel than if the pixel were dark gray.

$$P(x, y) = Q(I(x, y) + \text{noise}(x, y))$$

# Random Dither

- Randomize quantization errors
- Errors appear as noise

How much noise should we add?

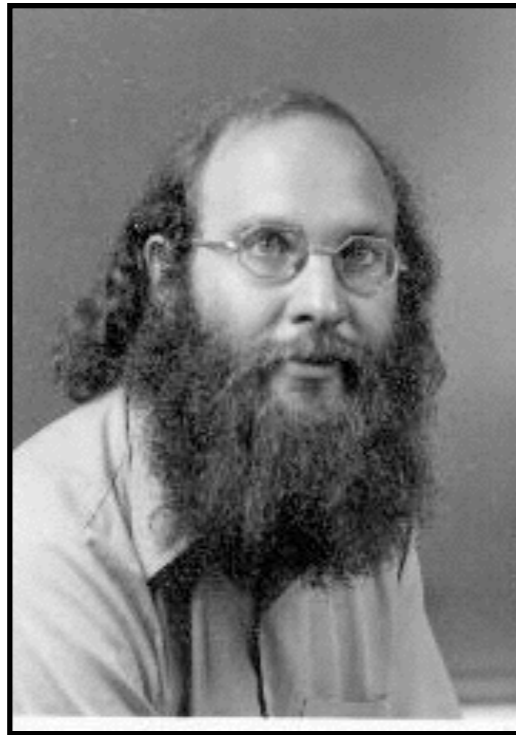
Enough so that we can effect rounding  
but not so much that we overshoot:

$$[-0.5/s, 0.5/s],$$

where  $s$  is the intensity of a single dither  
level in the output:  $s = 2^{(b-1)}$ .

(Note also the assignment uses a color  
range from 0 to 255).

# Random Dither



Original  
(8 bits)



Uniform  
Quantization  
(1 bit)



Random  
Dither  
(1 bit)



# Ordered Dither

- Pseudo-random quantization errors
- Matrix stores pattern of thresholds

## For Binary Displays

---

$i = x \bmod n$

$j = y \bmod n$

if  $(I(x,y)/255 > D(i,j) / (n^2+1))$

$P(x,y) = 1$

else

$P(x,y) = 0$

$$D_2 = \begin{bmatrix} 1 & 3 \\ 4 & 2 \end{bmatrix}$$

# Ordered Dither

- Pseudo-random quantization errors
- Matrix stores pattern of thresholds

## For b-Bit Displays

---

$i = x \bmod n$

$j = y \bmod n$

$c = (I(x,y)/255)*(2^b-1)$

$e = c - \text{floor}(c)$

if ( $e > D(i,j) / (n^2+1)$  )

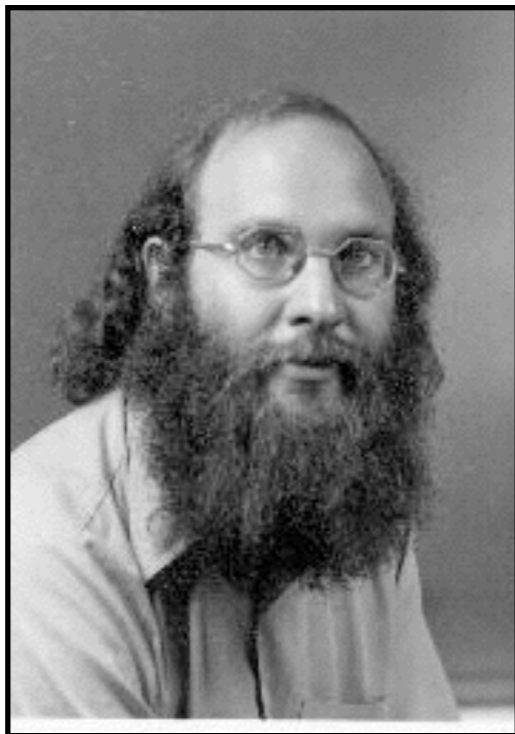
$P(x,y) = \text{ceil}(c)$

else

$P(x,y) = \text{floor}(c)$

$$D_2 = \begin{bmatrix} 1 & 3 \\ 4 & 2 \end{bmatrix}$$

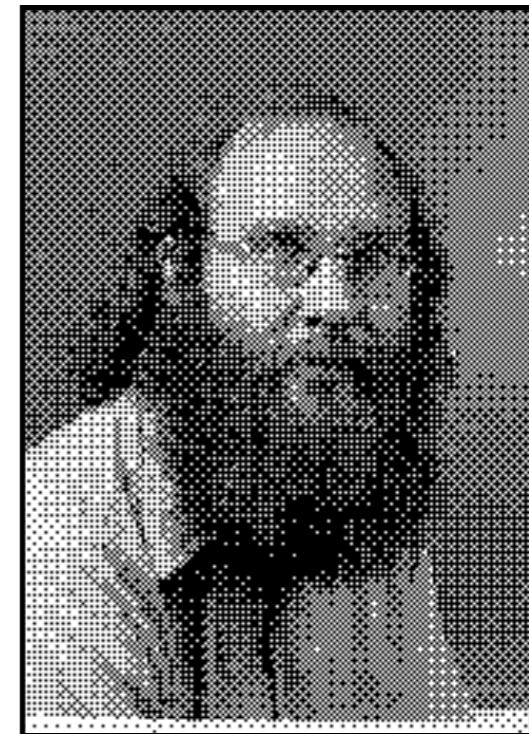
# Ordered Dither



Original  
(8 bits)



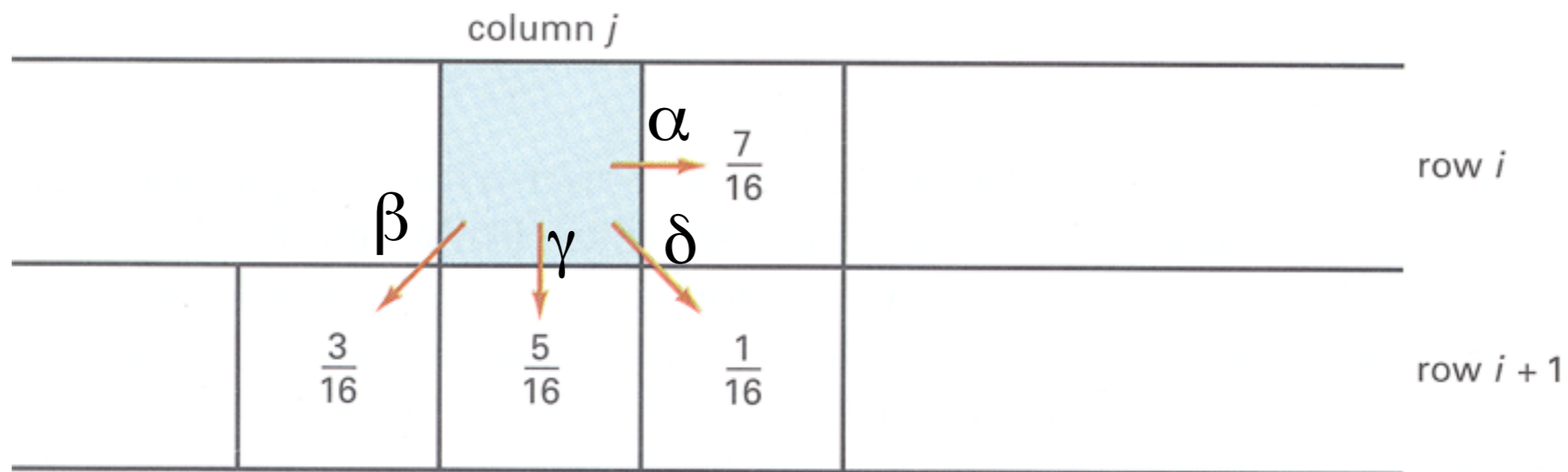
Random  
Dither  
(1 bit)



Ordered  
Dither  
(1 bit)

# Error Diffusion Dither

- Spread quantization error over neighbor pixels
  - Error dispersed to pixels right and below
- Floyd-Steinberg Dither Method:



$$\alpha + \beta + \gamma + \delta = 1.0$$

Figure 14.42 from H&B

# Floyd-Steinberg Dither

```
for (i = 0; i < width; i++)  
  for (j = 0; j < height; j++)  
    Dest[i,j] = quantize(Source[i,j])  
    error = Source[i,j] - Dest[i,j]  
    Source[i,j+1] = Source[i,j+1] +  $\alpha$  * error  
    Source[i+1,j-1] = Source[i+1,j-1] +  $\beta$  * error  
    Source[i+1,j] = Source[i+1,j] +  $\gamma$  * error  
    Source[i+1,j+1] = Source[i+1,j+1] +  $\delta$  * error
```

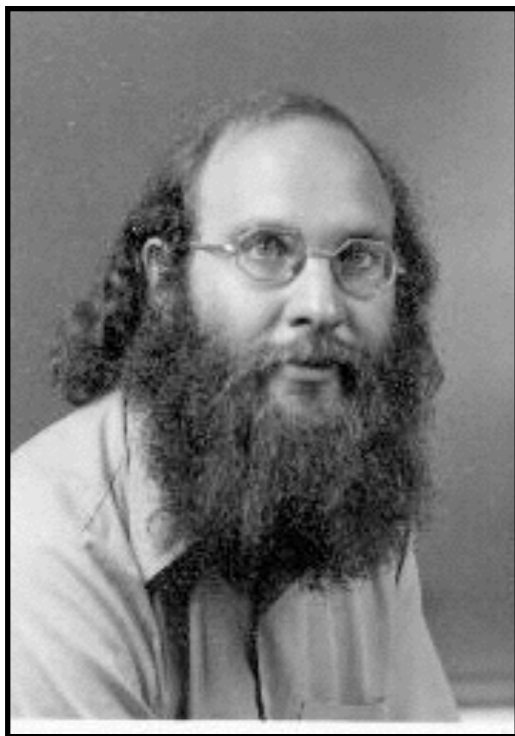
$$\alpha = 7/16$$

$$\beta = 3/16$$

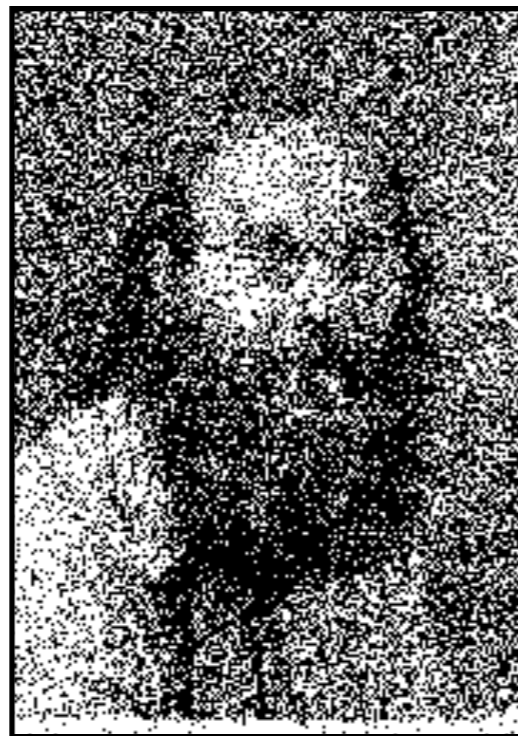
$$\gamma = 5/16$$

$$\delta = 1/16$$

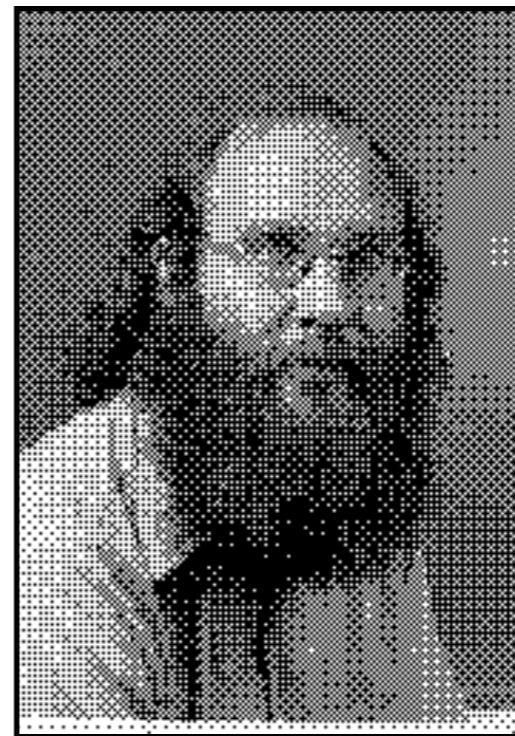
# Floyd-Steinberg Dither



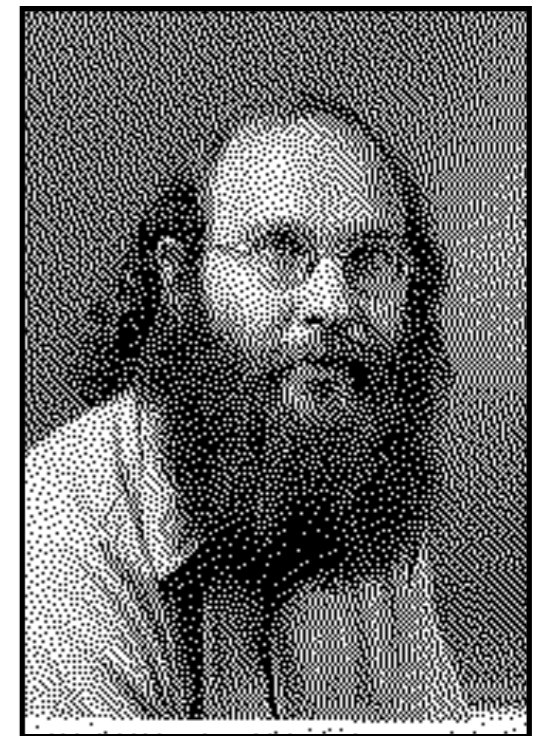
Original  
(8 bits)



Random  
Dither  
(1 bit)



Ordered  
Dither  
(1 bit)

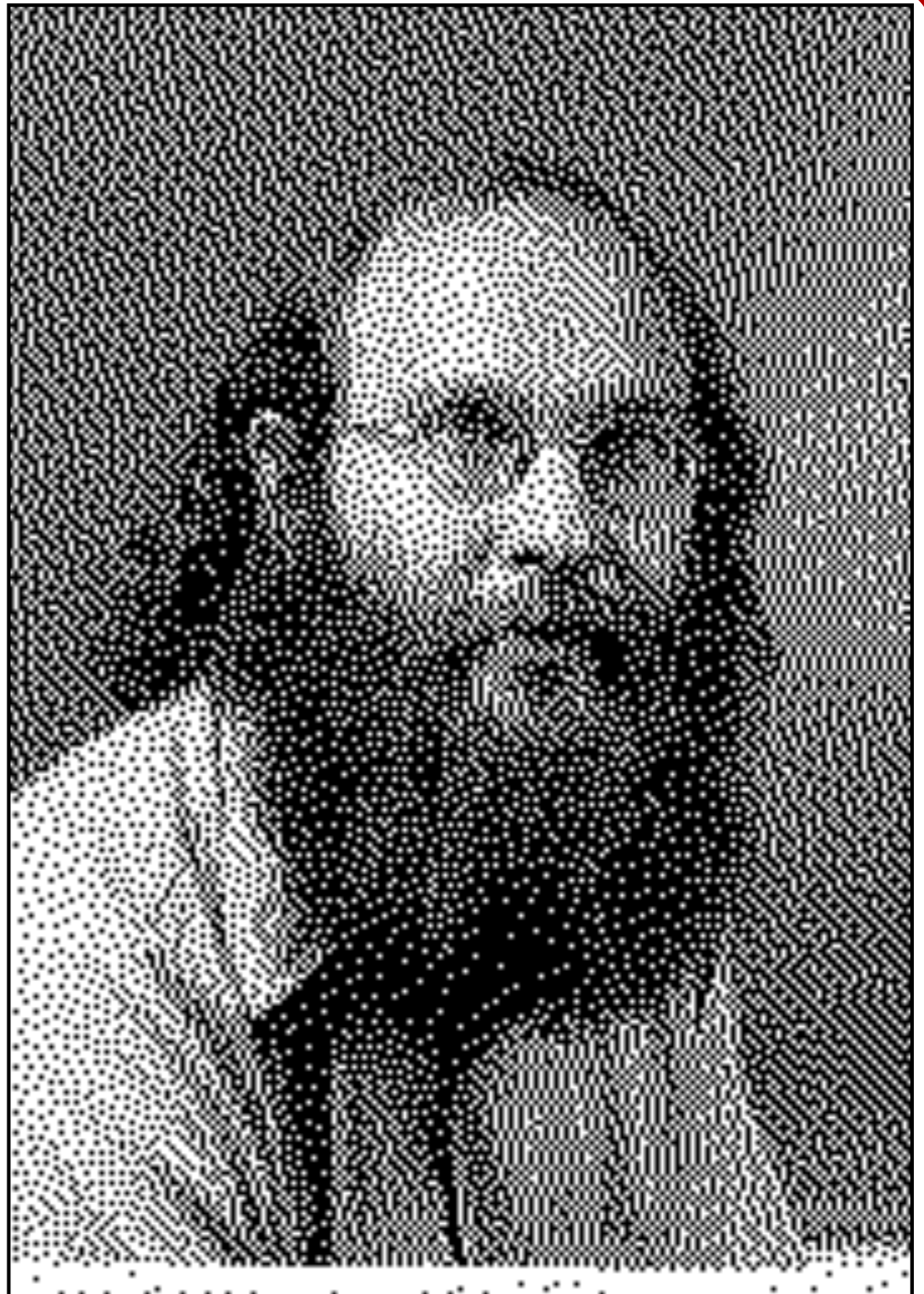


Floyd-Steinberg  
Dither  
(1 bit)

# Discussion Q.

- ▶ How might one get a result even better than Floyd-Steinberg?

Close up view:



# Outline

- Human Vision
- Image Representation
- Reducing Color Quantization Artifacts
- **Basic Image Processing**
  - Single Pixel Operations
  - Multi-Pixel Operations



# Computing Grayscale

- ▶ The human retina perceives red, green, and blue as having different levels of brightness.
- ▶ To compute the luminance (perceived brightness) of a pixel, we need to take the weighted average of the RGBs:  $L = 0.30*r + 0.59*g + 0.11*b$



Original



Grayscale

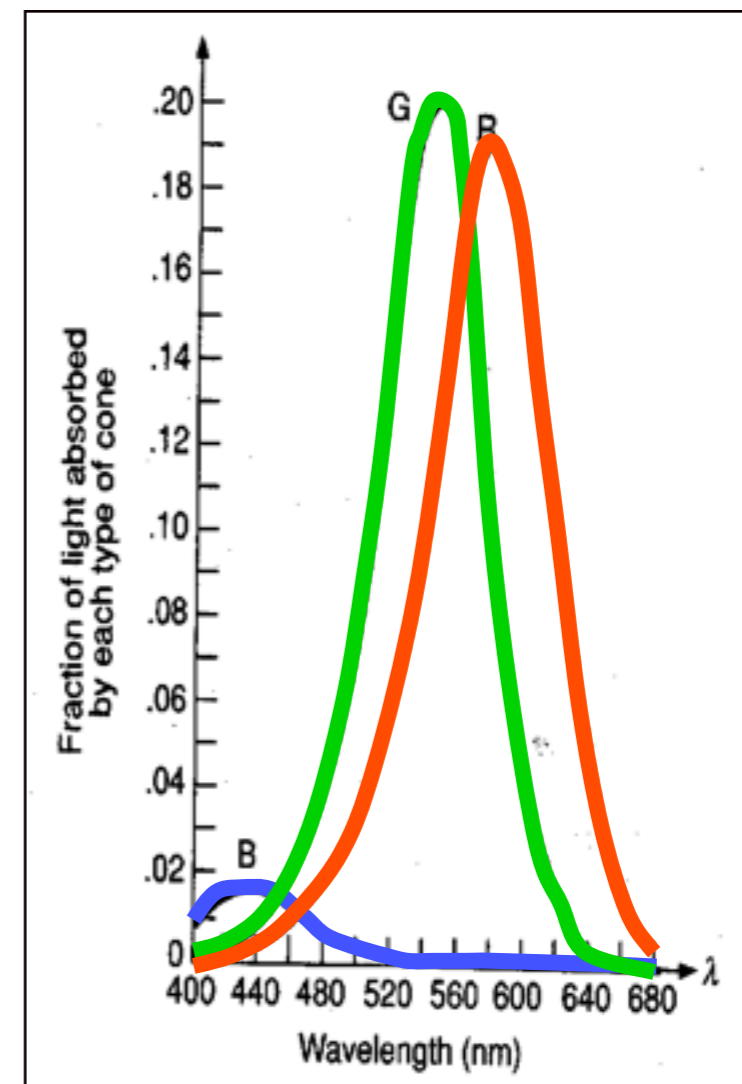


Figure 13.18 from FvDFH

# Adjusting Brightness

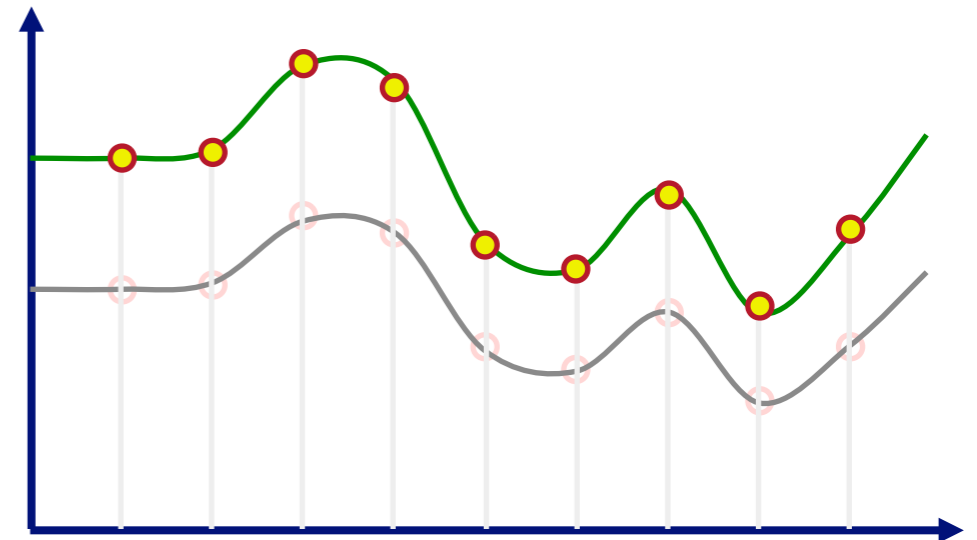
- Simply scale pixel components
  - Must clamp to range (e.g., 0 to 255)



Original



Brighter



# Adjusting Contrast

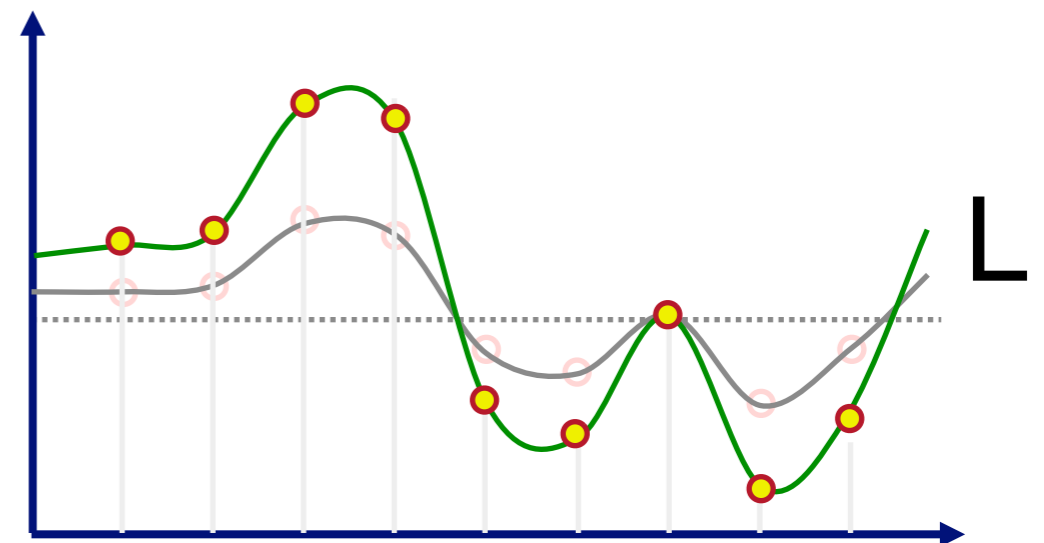
- Compute mean luminance  $L$  for all pixels
  - $L = 0.30*r + 0.59*g + 0.11*b$
- Scale deviation from  $L$  for each pixel color component (RGB)
  - Must clamp to range (e.g., 0 to 255)



Original



More Contrast

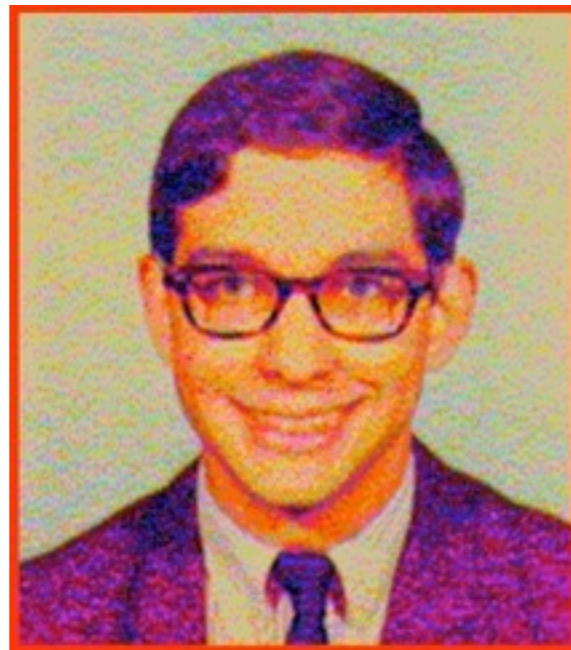


# Adjusting Saturation

- Compute luminance  $L(p)$  for each pixel  $p$ 
  - $L(p) = 0.30*r(p) + 0.59*g(p) + 0.11*b(p)$
- Scale deviation from  $L(p)$  for each pixel component (RGB)
  - Must clamp to range (e.g., 0 to 255)



Original



More Saturation

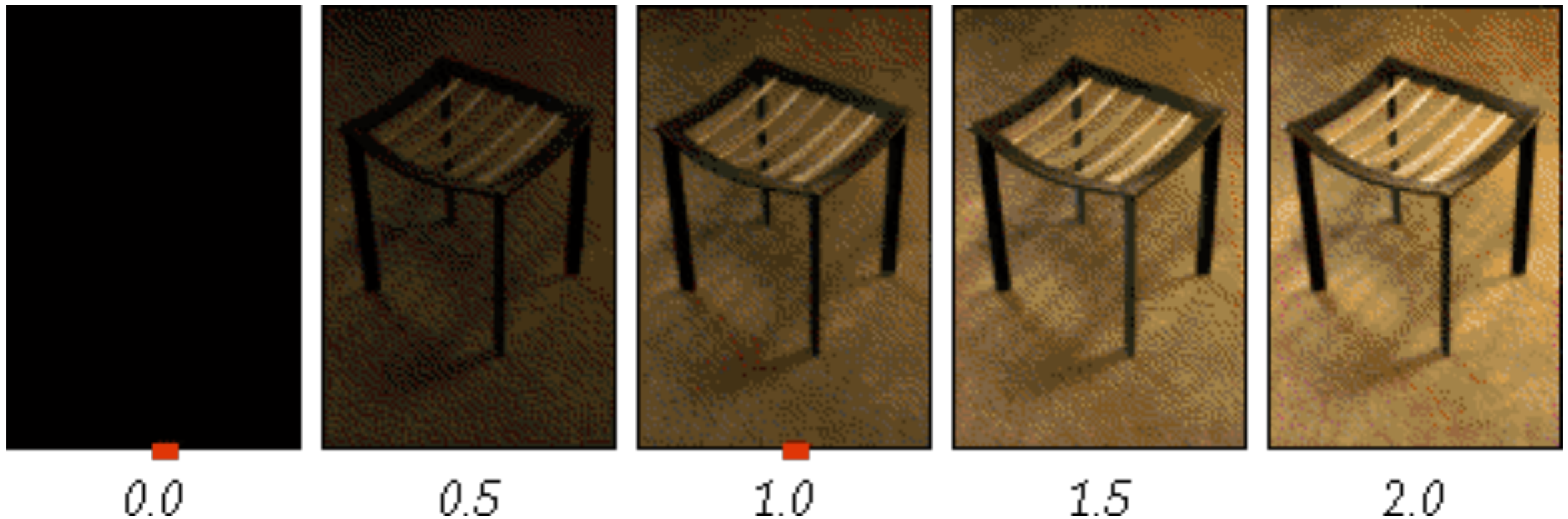
# Image Processing by Interpolation

- Nice discussion of these operations:  
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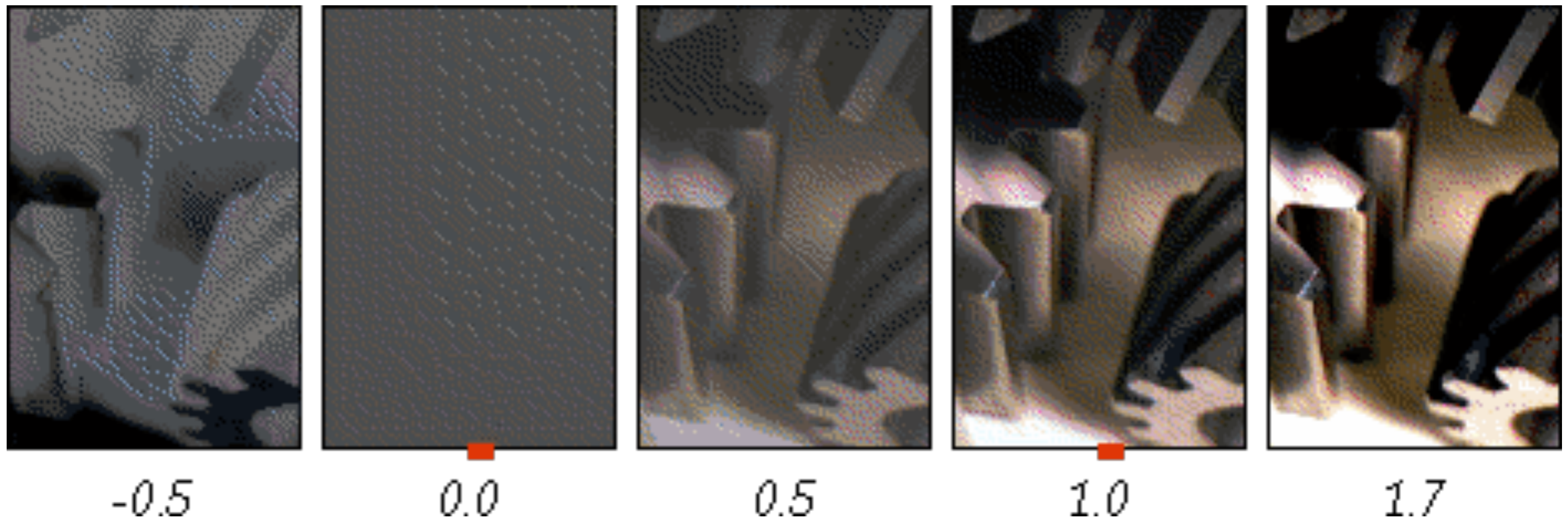
$$\text{out} = (1-\alpha)*\text{in0} + \alpha*\text{in1}$$



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-1.0



0.0



0.5



1.0



2.5