### Digital Image Processing

Lecture # 3 B
Image Transformations

#### Contents

- Histograms of:
  - Grayscale Images
  - Colored Images
- Contrast Stretching
- Histogram Equalization

- ◆ Let *I* be a 1-band (grayscale) image.
- I(r,c) is an 8-bit integer between 0 and 255.
- Histogram,  $h_I$ , of I:
  - a 256-element array,  $h_I$
  - $h_I(g)$  = number of pixels in I that have value g. for g = 0,1, 2, 3, ..., 255

◆ Histogram of a digital image with gray levels in the range [0,L-1] is a discrete function

$$h(r_k) = n_k$$

#### Where

- $r_k = k^{th}$  gray level
- $n_k$  = number of pixels in the image having gray level  $r_k$
- $h(r_k)$  = histogram of an image having  $r_k$  gray levels

#### Normalized Histogram

• Dividing each of histogram at gray level  $r_k$  by the total number of pixels in the image, n

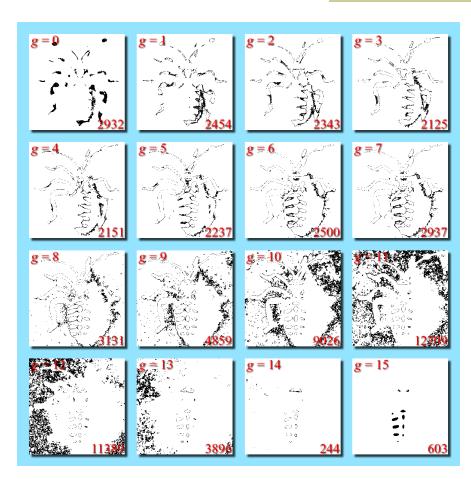


- $p(r_k)$  gives an estimate of the probability of occurrence of gray level  $r_k$
- The sum of all components of a normalized histogram is equal to 1

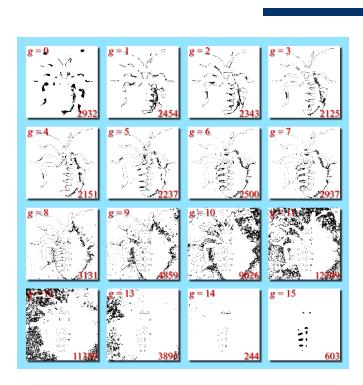


16-level (4-bit) image

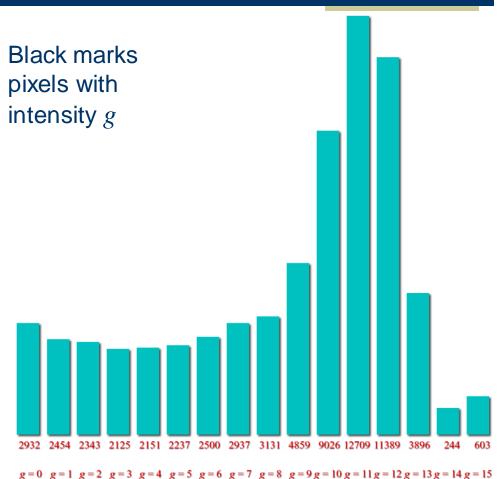
lower RHC: number of pixels with intensity g

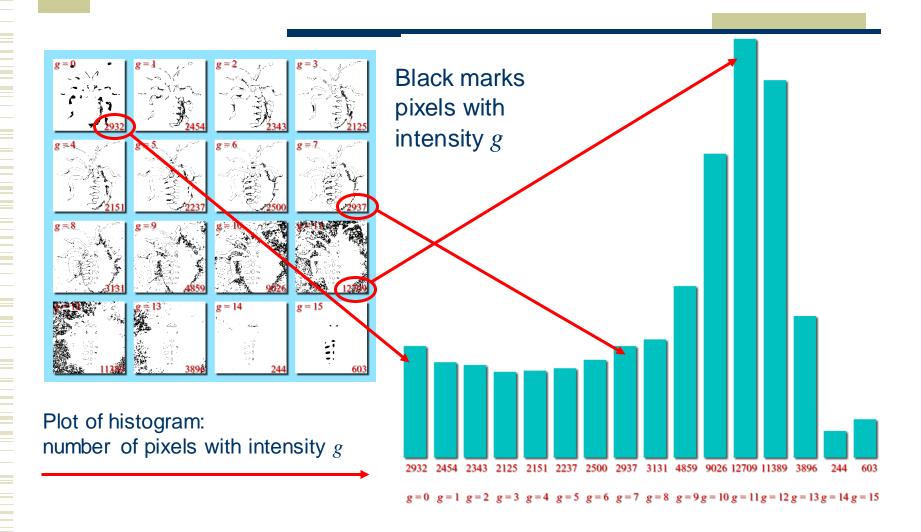


black marks pixels with intensity g



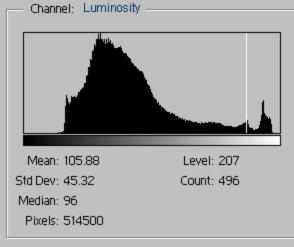
Plot of histogram: number of pixels with intensity *g* 







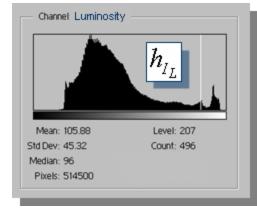
h(g)—then nhar
of pixels in I
vith gaylexel g

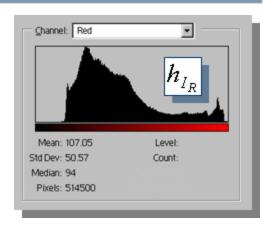


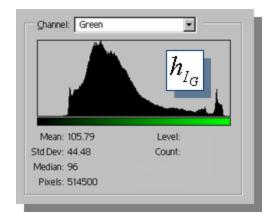
- If I is a 3-band image
- then I(r,c,b) is an integer between 0 and 255.
- I has 3 histograms:
  - $h_R(g) = \#$  of pixels in I(:,:,1) with intensity value g
  - $h_G(g) = \#$  of pixels in I(:,:,2) with intensity value g
  - $h_B(g) = \#$  of pixels in I(:,:,3) with intensity value g

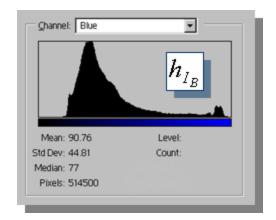
There is one histogram per color band R, G, & B. Luminosity histogram is from 1 band = (R+G+B)/3



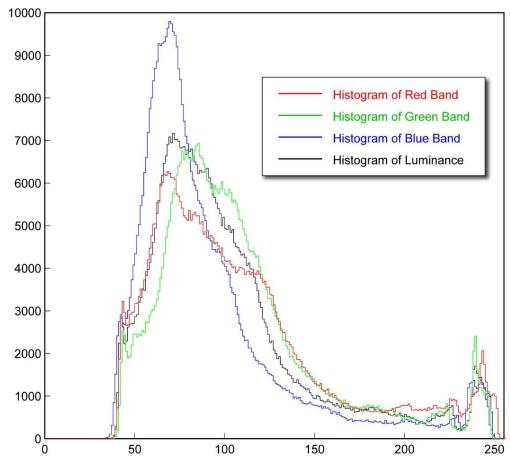


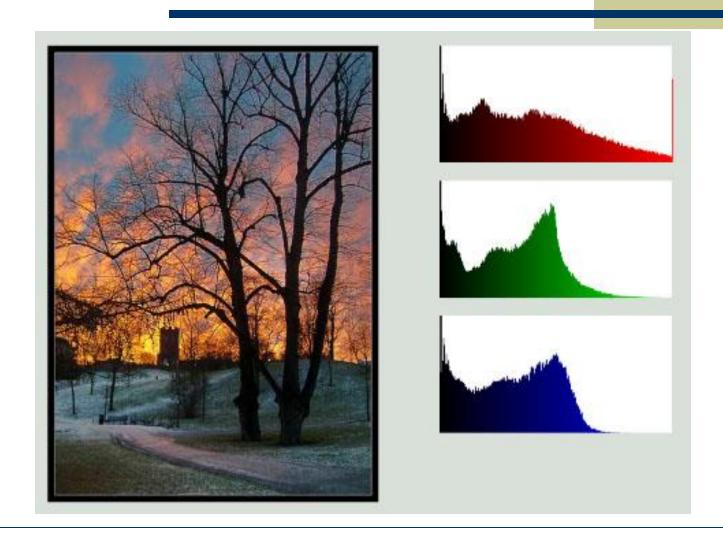


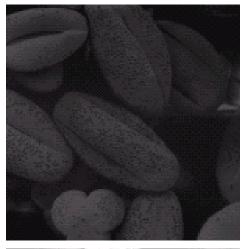








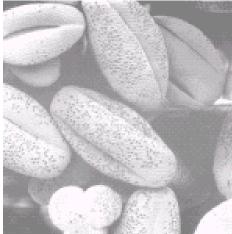




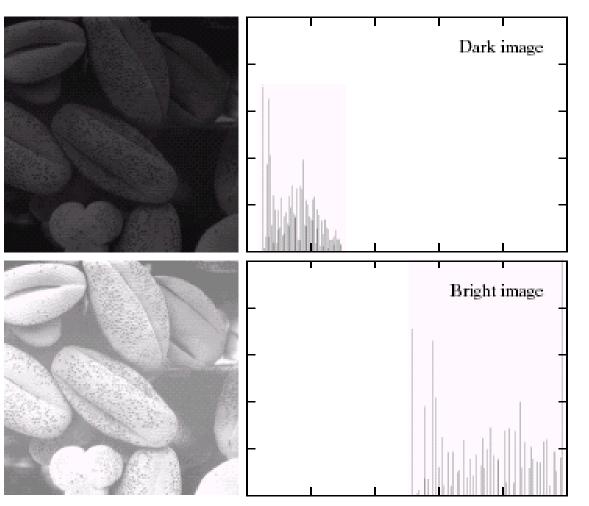


Dark Image

How would the histograms of these images look like?



Bright Image

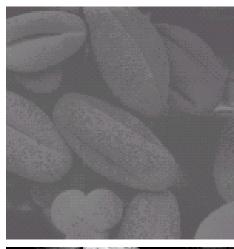


#### **Dark image**

Components of histogram are concentrated on the low side of the gray scale

#### **Bright image**

Components of histogram are concentrated on the high side of the gray scale

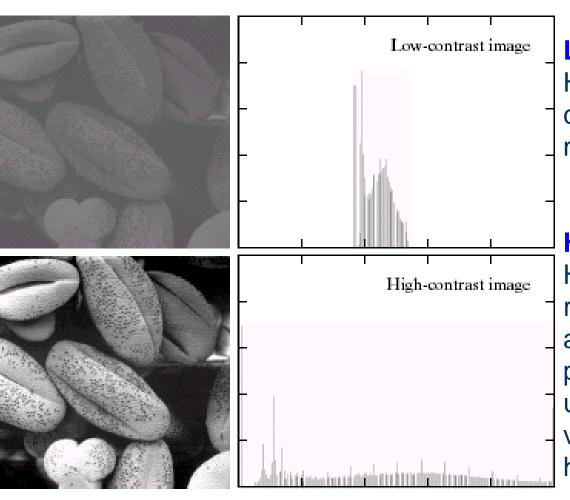






How would the histograms of these images look like?

High Contrast Image



#### Low contrast image

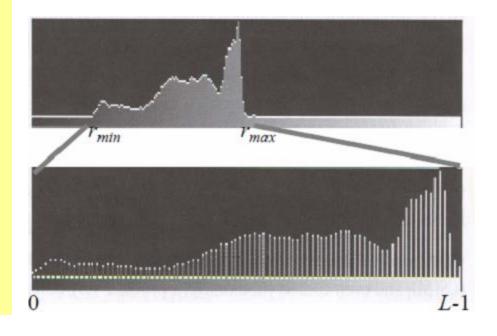
Histogram is narrow and centered toward the middle of the gray scale

#### High contrast image

Histogram covers broad range of the gray scale and the distribution of pixels is not too far from uniform with very few vertical lines being much higher than the others

#### Contrast Stretching

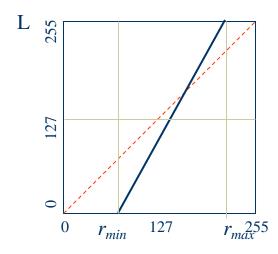
Improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values, *e.g.* the the full range of pixel values



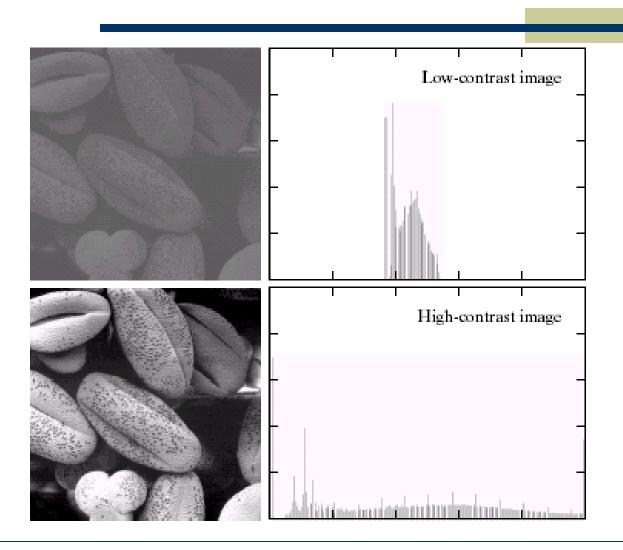
#### Contrast Stretching

If  $r_{max}$  and  $r_{min}$  are the maximum and minimum gray level of the input image and L is the total gray levels of output image, the transformation function for contrast stretch will be

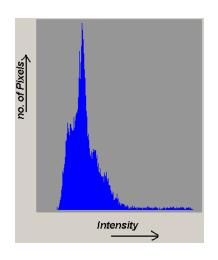


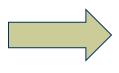


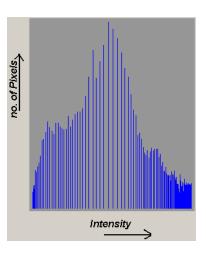
## Contrast Stretching



Histogram equalization re-assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities







# The Probability Distribution Function of an Image

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Rody Chuster ARC

Then,

$$p_{I}(g) = \frac{1}{A}h_{I}(g)$$

This is the probability that an arbitrary pixel from I has value g.

# The Probability Distribution Function of an Image

- p(g) is the fraction of pixels in an image that have intensity value g.
- p(g) is the probability that a pixel randomly selected from the given image has intensity value g.
- Whereas the sum of the histogram h(g) over all g from 0 to 255 is equal to the number of pixels in the image, the sum of p(g) over all g is 1.
- p is the normalized histogram of the image

# The Cumulative Distribution Function of an Image

Let  $\mathbf{q} = I(r,c)$  be the value of a randomly selected pixel from I. Let g be a specific gray level. The probability that  $\mathbf{q} \leq \mathbf{g}$  is given by



where  $h_I(\gamma)$  is the histogram of image I.

This is the probability that any given pixel from *I* has value less than or equal to g.

# The Cumulative Distribution Function of an Image

Let  $\mathbf{q} = I(r,c)$  be the value of a randomly selected pixel from I. Let g be a specific gray level. The probability that  $\mathbf{q} \leq \mathbf{g}$  is given by

Also called CDF for "Cumulative Distribution Function".



where  $h_I(\gamma)$  is the histogram of image I.

This is the probability that any given pixel from I has value less than or equal to g.

# The Cumulative Distribution Function of an Image

- P(g) is the fraction of pixels in an image that have intensity values less than or equal to g.
- P(g) is the probability that a pixel randomly selected from the given band has an intensity value less than or equal to g.
- P(g) is the cumulative (or running) sum of p(g) from 0 through g inclusive.
- P(0) = p(0) and P(255) = 1;

Task: remap image *I* so that its histogram is as close to constant as possible

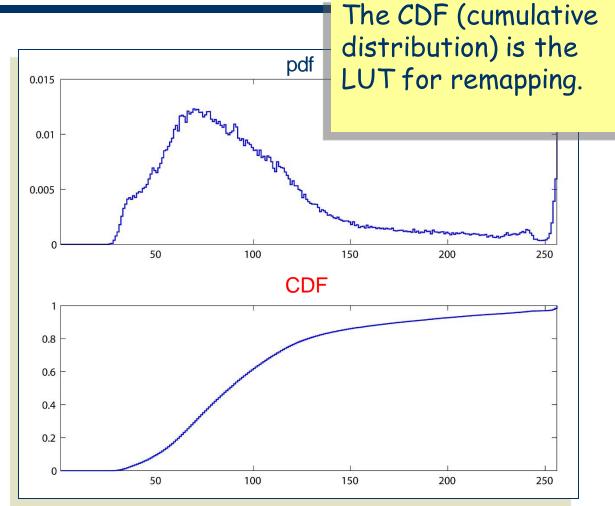
Let 
$$P_I(\gamma)$$

be the cumulative (probability) distribution function of I.

The CDF itself is used as the LUT.

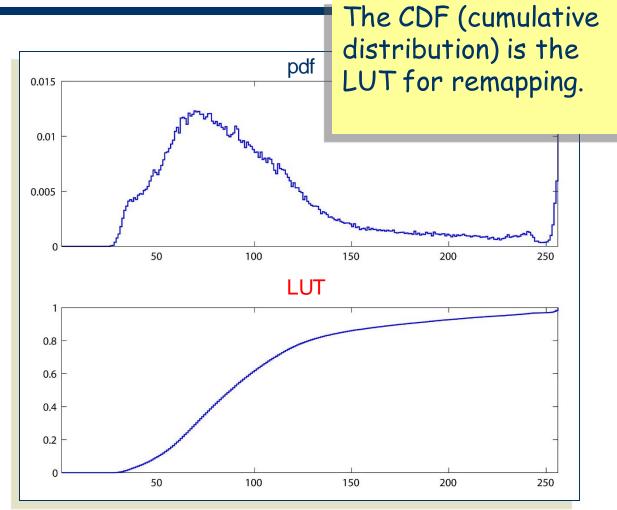






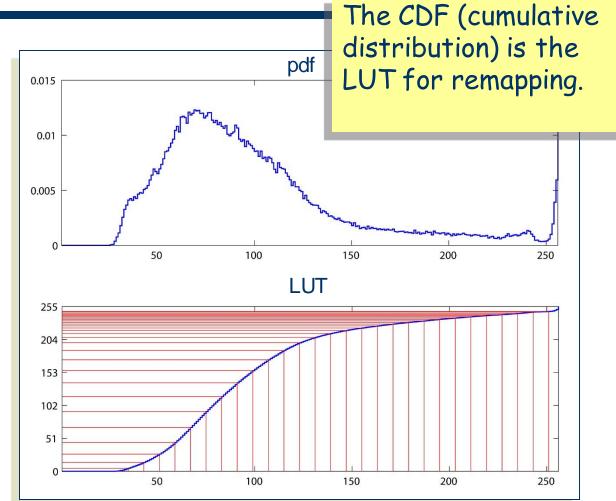






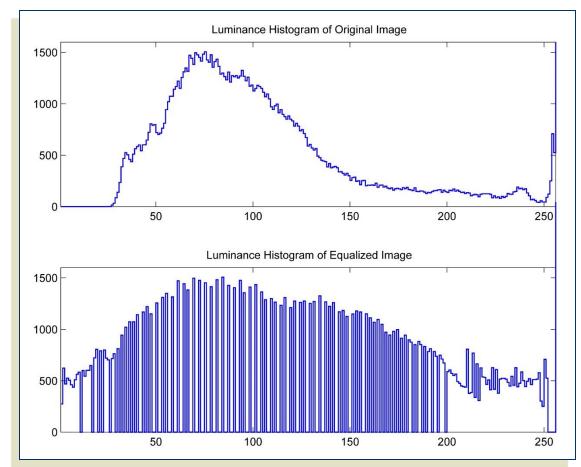


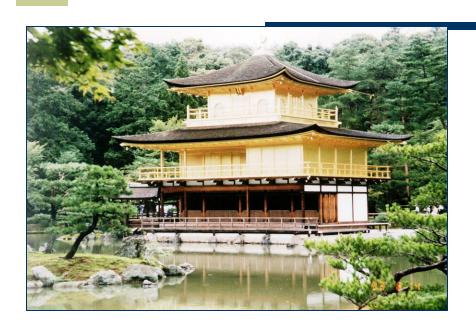




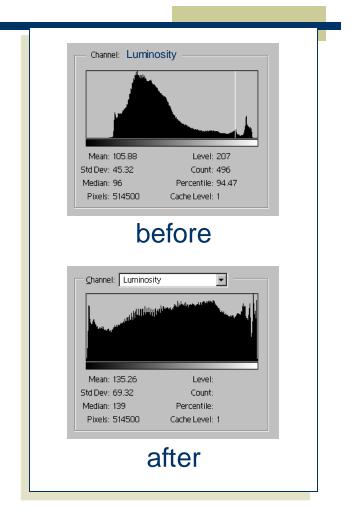


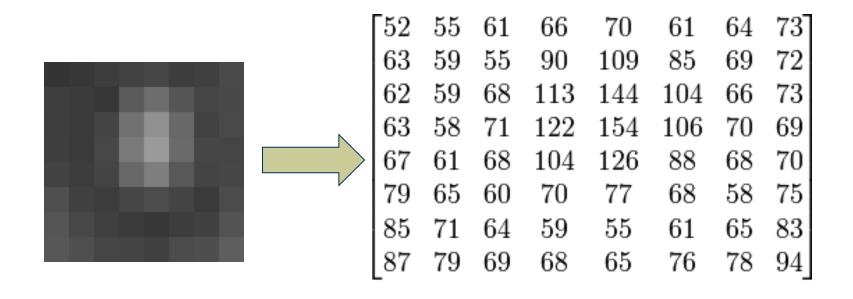












An 8x8 image



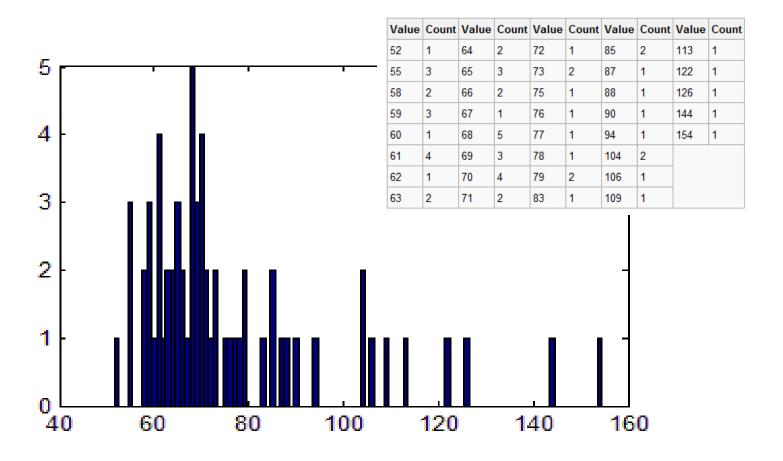
Take out a paper and fill in the following table/histogram

Value	Count								
52		64		72		85		113	
55		65		73		87		122	
58		66		75		88		126	
59		67		76		90		144	
60		68		77		94		154	
61		69		78		104			
62		70		79		106			
63		71		83		109			

Image Histogram (Non-zero values)

#### Image Histogram (Non-zero values shown)

Value	Count								
52	1	64	2	72	1	85	2	113	1
55	3	65	3	73	2	87	1	122	1
58	2	66	2	75	1	88	1	126	1
59	3	67	1	76	1	90	1	144	1
60	1	68	5	77	1	94	1	154	1
61	4	69	3	78	1	104	2		
62	1	70	4	79	2	106	1		
63	2	71	2	83	1	109	1		



### Cumulative Distribution Function (cdf)

#### Image Histogram/Prob Mass Function

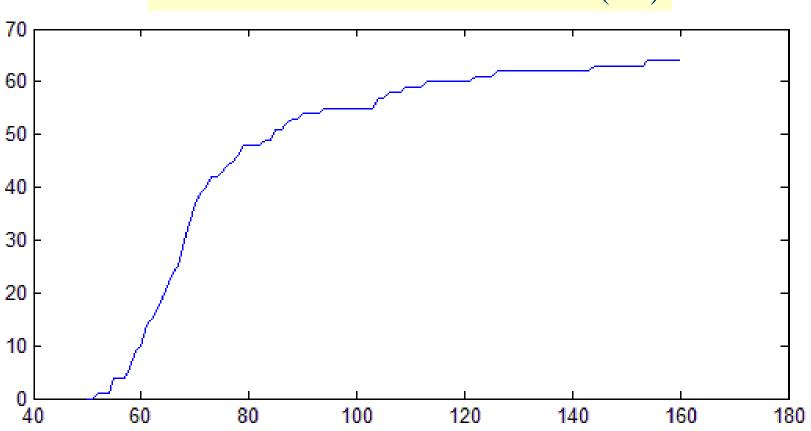
Value	Count								
52	1	64	2	72	1	85	2	113	1
55	3	65	3	73	2	87	1	122	1
58	2	66	2	75	1	88	1	126	1
59	3	67	1	76	1	90	1	144	1
60	1	68	5	77	1	94	1	154	1
61	4	69	3	78	1	104	2		
62	1	70	4	79	2	106	1		
63	2	71	2	83	1	109	1		

Value	cdf								
52		64		72		85		113	
55		65		73		87		122	
58		66		75		88		126	
59		67		76		90		144	
60		68		77		94		154	
61		69		78		104			
62		70		79		106			
63		71		83	d.	109			

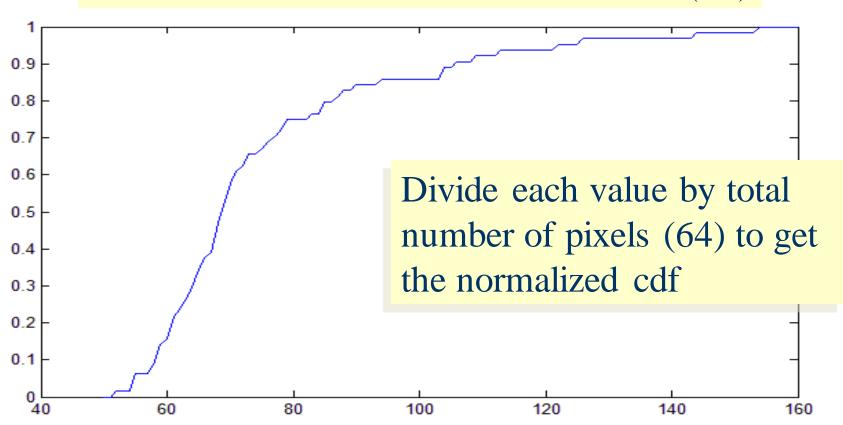
### Cumulative Distribution Function (cdf)

Value	cdf								
52	1	64	19	72	40	85	51	113	60
55	4	65	22	73	42	87	52	122	61
58	6	66	24	75	43	88	53	126	62
59	9	67	25	76	44	90	54	144	63
60	10	68	30	77	45	94	55	154	64
61	14	69	33	78	46	104	57		
62	15	70	37	79	48	106	58		
63	17	71	39	83	49	109	59		









Value	cdf	Value	cdf	Value	cdf	Value	cdf	Value	cdf
52	1	64	19	72	40	85	51	113	60
55	4	65	22	73	42	87	52	122	61
58	6	66	24	75	43	88	53	126	62
59	9	67	25	76	44	90	54	144	63
60	10	68	30	77	45	94	55	154	64
61	14	69	33	<b>78</b> →	46	104	57		
62	15	70	37	79	48	106	58		
63	17	71	39	83	49	109	59		



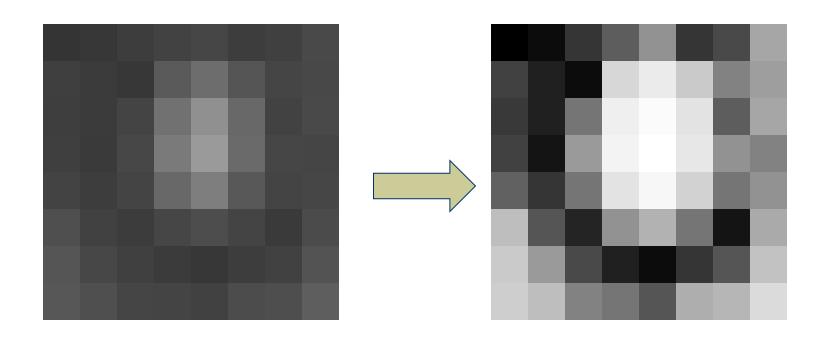
If cdf is normalized



If cdf is NOT normalized

 $s = rand(255 \frac{1}{M} \times N)$  s = rand(255(46/64)) s = 183

Original Image



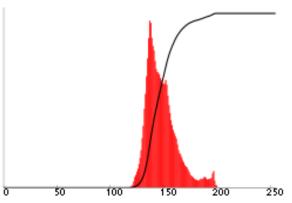
Ahmed



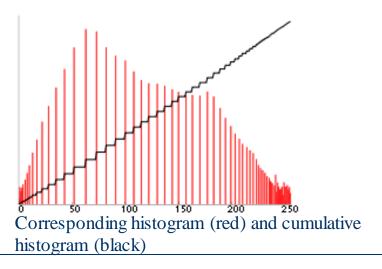
Original Image

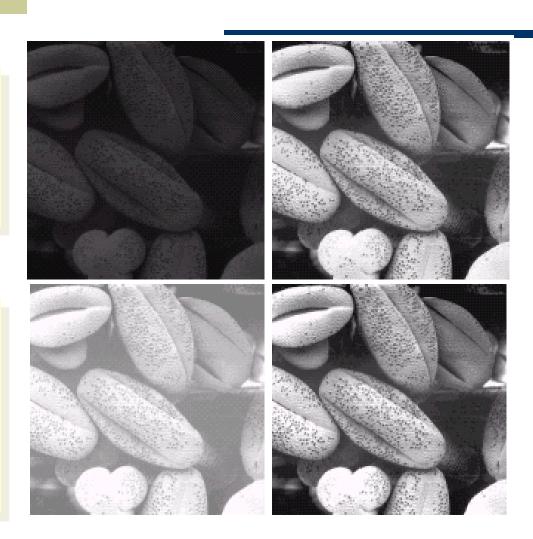


Image after histogram equalization

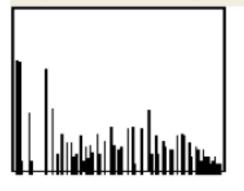


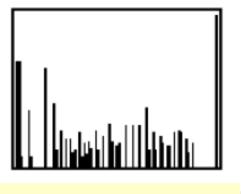
Corresponding histogram (red) and cumulative histogram (black)





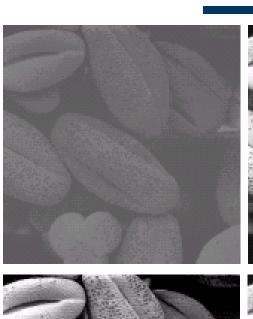
Equalized Histogram



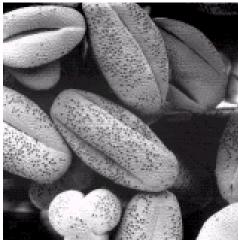


**Equalized Histogram** 

Low contrast

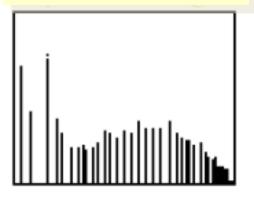


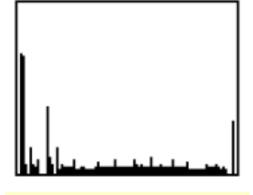






Equalized Histogram





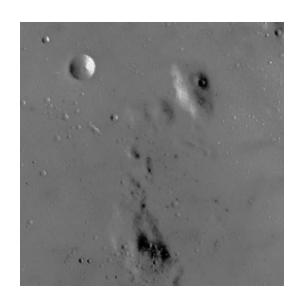
Equalized Histogram

# Histogram Equalization vs. Contrast Stretching

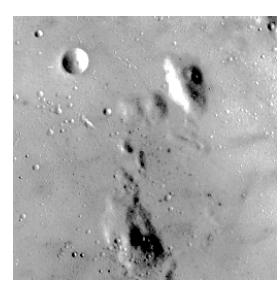
Histogram equalization is sophisticated version of contrast stretching

Contrast Stretching – Linear Transformation Enhancement is less harsh

# Histogram Equalization vs. Contrast Stretching



Original Image



Contrast Stretching



Histogram Equalization

# Acknowledgements

- Digital Image Processing", Rafael C. Gonzalez & Richard E. Woods, Addison-Wesley, 2002
- Peters, Richard Alan, II, Lectures on Image Processing, Vanderbilt University, Nashville, TN, April 2008
- Brian Mac Namee, Digitial Image Processing, School of Computing, Dublin Institute of Technology
- Computer Vision for Computer Graphics, Mark Borg
- Web Resource: HIPR2