

ECE5554 – Computer Vision

Lecture 2a – Pixel Operations

Creed Jones, PhD

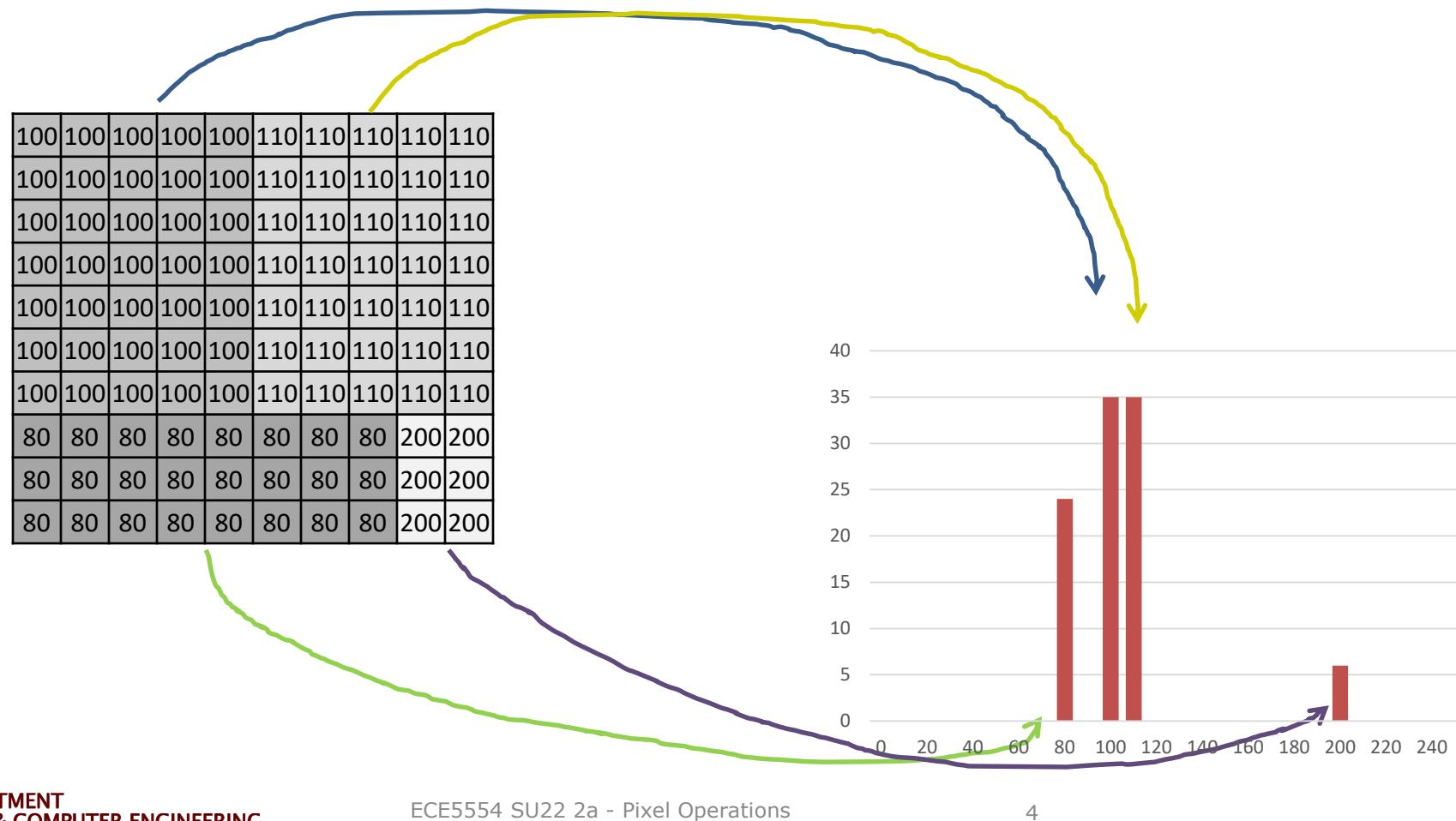
Course updates

- HW1
 - due this Thursday, July 13, 11:59 PM
- Quiz 1 is TOMORROW, July 12 (open 6 PM to 11:59 PM)
 - Covers lectures 1 (1a, 1b & 1c) and 2 (2a, 2b & 2c)
 - Don't forget!
- GTA office hours
 - Dhanush Dinesh will be available via zoom on Monday 6PM - 8PM and on Thursday at 10 AM - 12 PM
 - Meeting ID: 895 5961 7255
 - Passcode: 824650

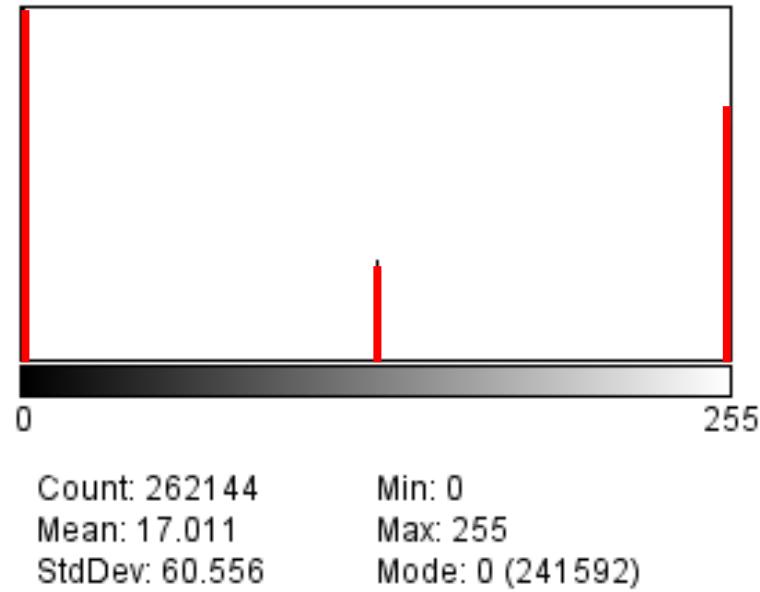
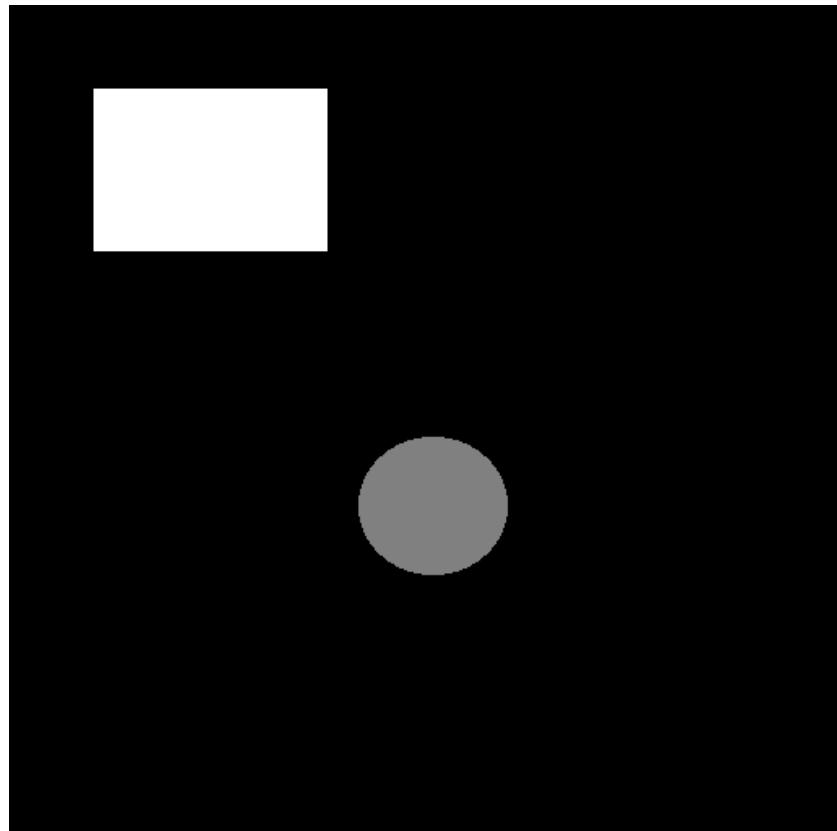
Today's Objectives

- Intensity histograms
- Image Statistics
- Histogram Equalization
- Pixel Operations

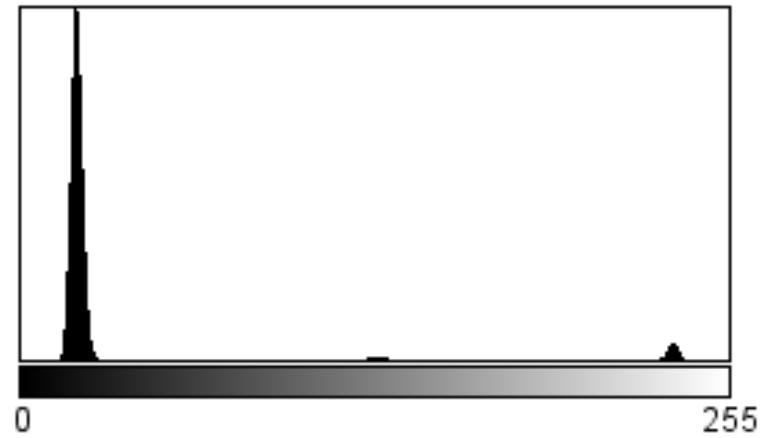
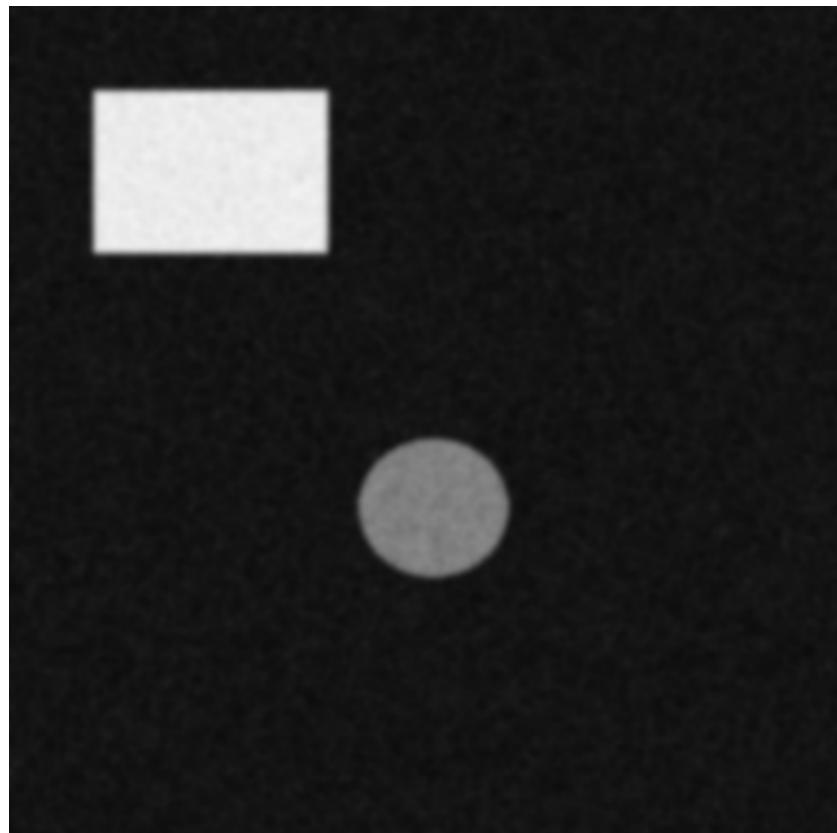
An image histogram is a vector where each entry is the frequency of occurrence of the corresponding gray-level value; it's a bar plot of brightness counts



Regions of distinct intensity are easily seen in the image histogram – note that the area of each region is apparent (the height of the histogram is pixel count)



Noise and image smoothing (blur) cause the lobes in the histogram to spread; the noise that was added to this image is normally distributed



Varying levels of additive Gaussian noise (higher standard deviations, wider distributions) cause more image degradation



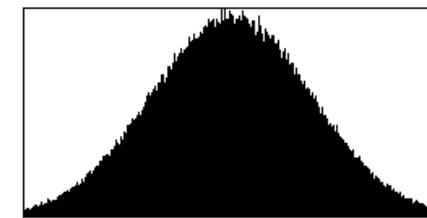
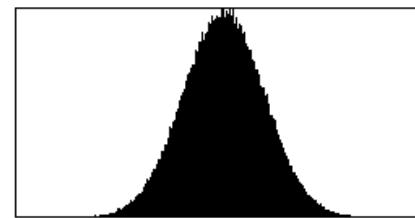
original image



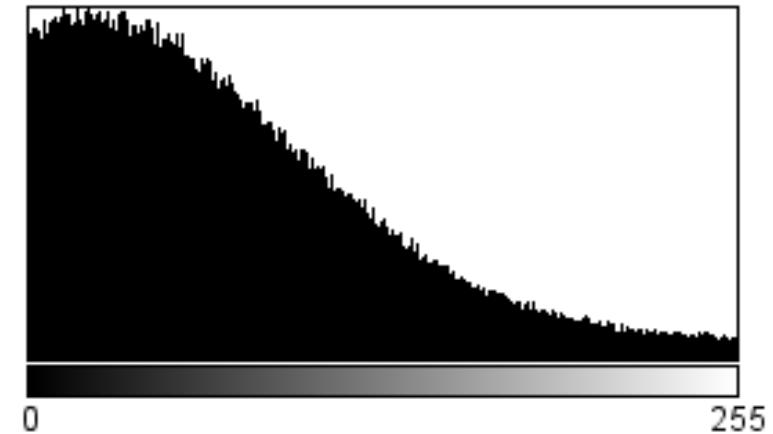
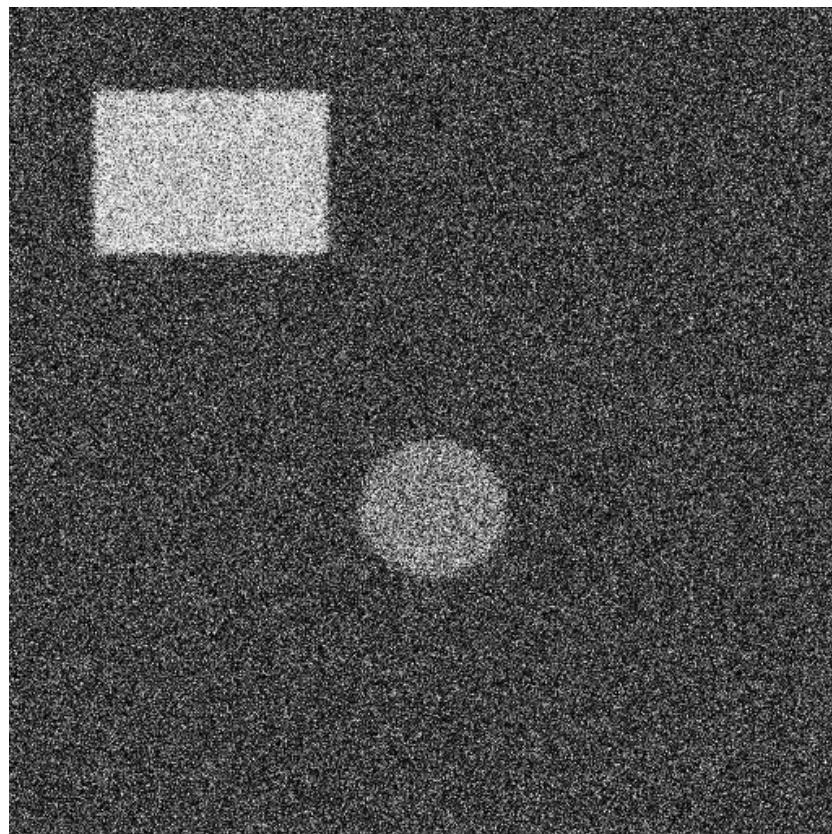
Gaussian noise –
 $\sigma = 25.0$



Gaussian noise –
 $\sigma = 50.0$



A large amount of noise causes the lobes corresponding to regions to spread farther – the Gaussian shape of the noise distribution is easily seen



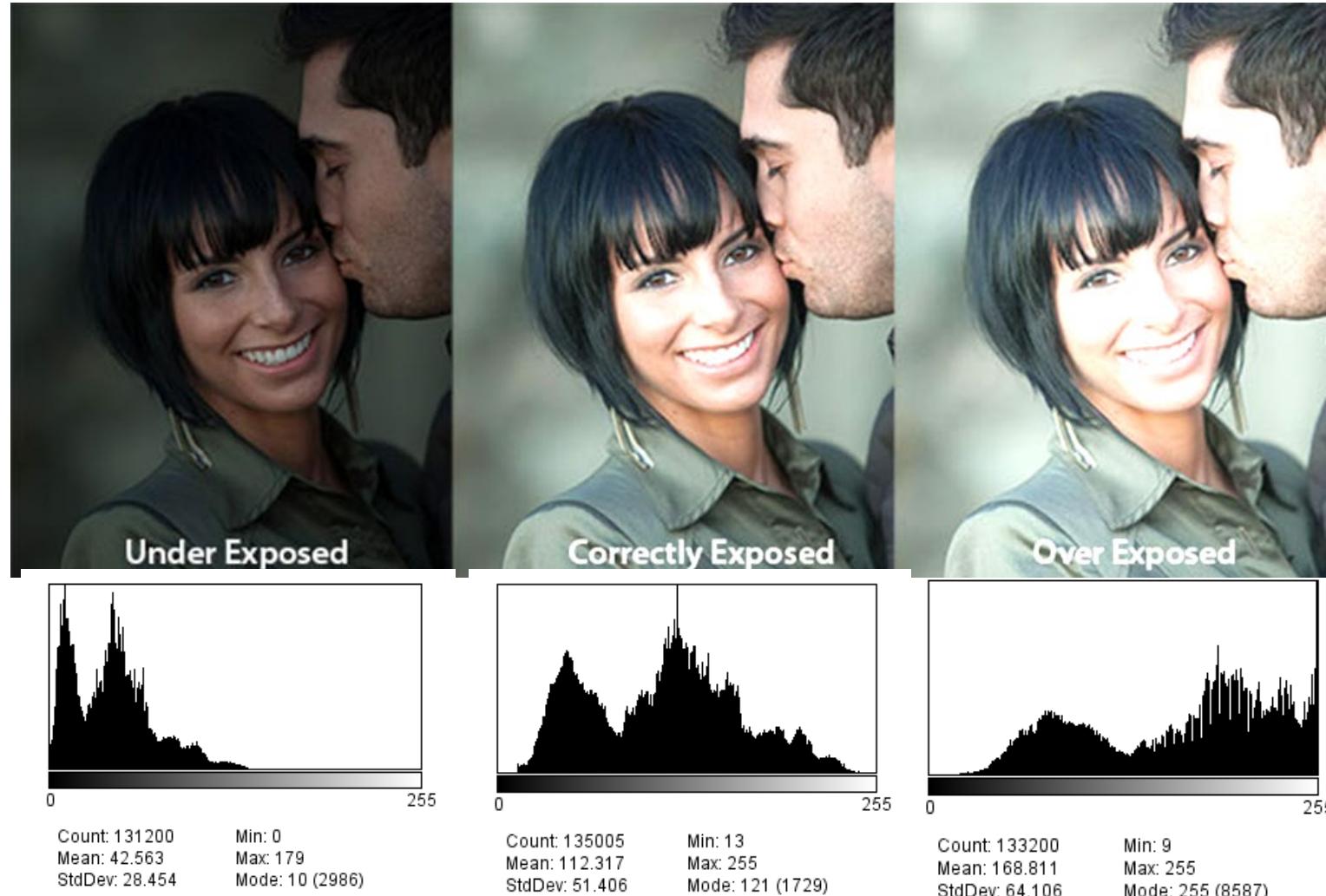
Count: 262144 Min: 0
Mean: 74.958 Max: 255
StdDev: 56.285 Mode: 12 (2194)

Histograms can be computed by adding the total number of pixels having each distinct gray level – location of the pixels is ignored

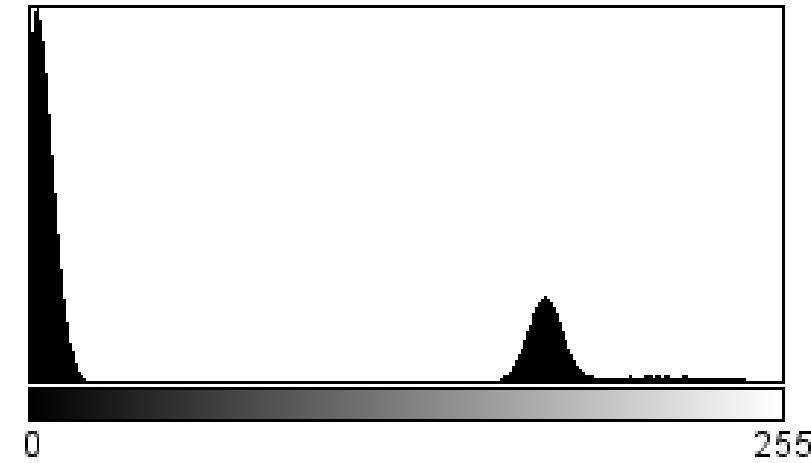
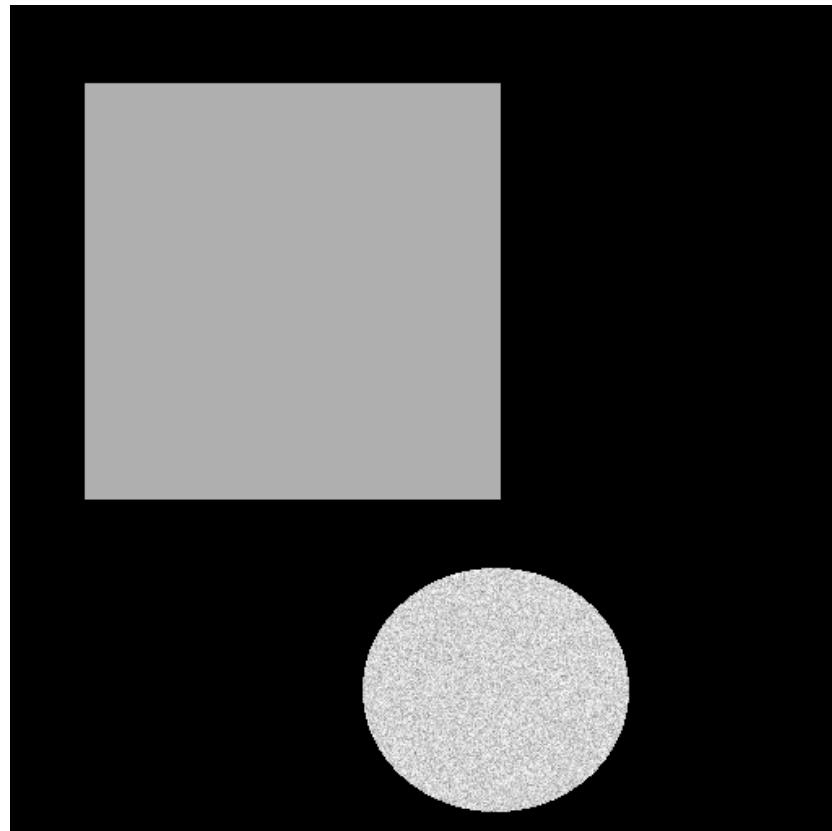
```
def getHist(image, histlen):
    row,col = image.shape
    H = np.zeros((histlen), int)
    for r in range(row):
        for c in range(col):
            H[image[r,c]] = H[image[r,c]] + 1
    return H

...
img = cv2.imread('C:\\Data\\hieroglyphics.png', cv2.IMREAD_GRAYSCALE)
histo = getHist(img, 256)
```

The histogram quickly reveals images that are underexposed, properly exposed or overexposed



When objects in the image are clearly defined by different gray levels, the histogram reveals the areas of the objects in pixel count

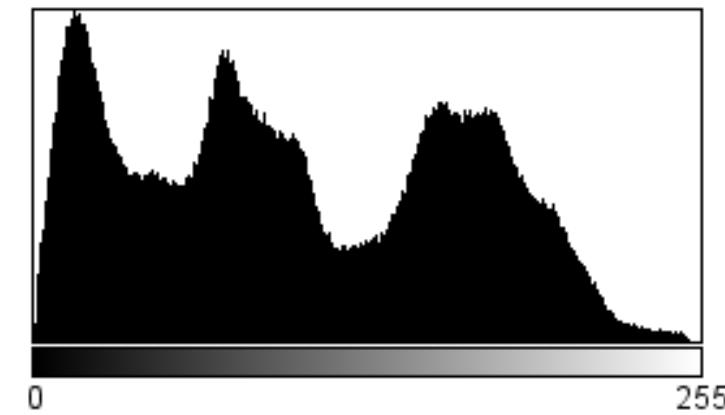
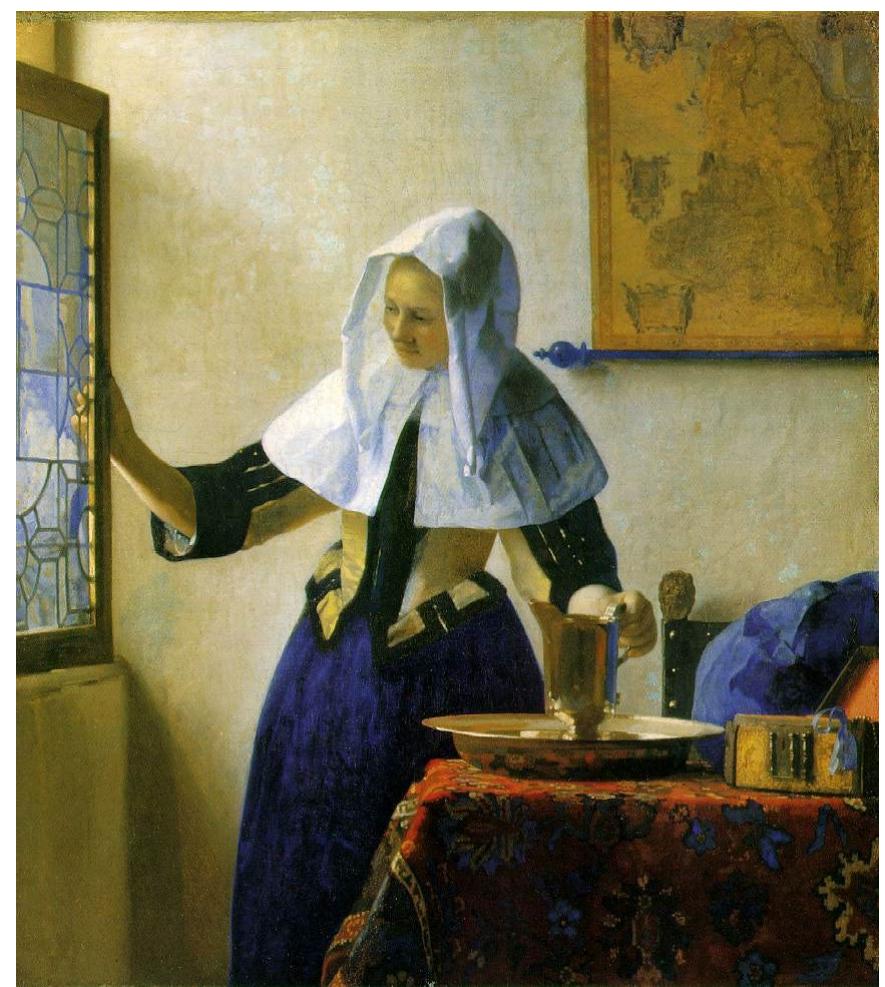




Count: 1225000
Mean: 36.922
StdDev: 39.459

Min: 0
Max: 250
Mode: 10 (94324)

Rembrandt van Rijn, *Jacob blessing the Children of Joseph*



Count: 838614
Mean: 101.429
StdDev: 63.027

Min: 0
Max: 254
Mode: 15 (6891)

Jan Vermeer, *Young Woman with a Water Pitcher*

The gray-level mean and variance can be computed from the image histogram – and we can find the median as well

Mean:

$$\mu = \frac{1}{RC} \sum_{r=0}^{R-1} \sum_{c=0}^{C-1} I(r, c)$$

Variance:

$$\sigma^2 = \frac{1}{RC} \sum_{r=0}^{R-1} \sum_{c=0}^{C-1} [I(r, c) - \mu]^2$$

or

$$\sigma^2 = \left[\frac{1}{RC} \sum_{r=0}^{R-1} \sum_{c=0}^{C-1} [I(r, c)]^2 \right] - \mu^2$$

Standard Deviation:

$$\sigma = \sqrt{\sigma^2}$$

Mean:

$$\mu = \frac{1}{RC} \sum_{i=0}^{G-1} i \cdot H(i)$$

Variance:

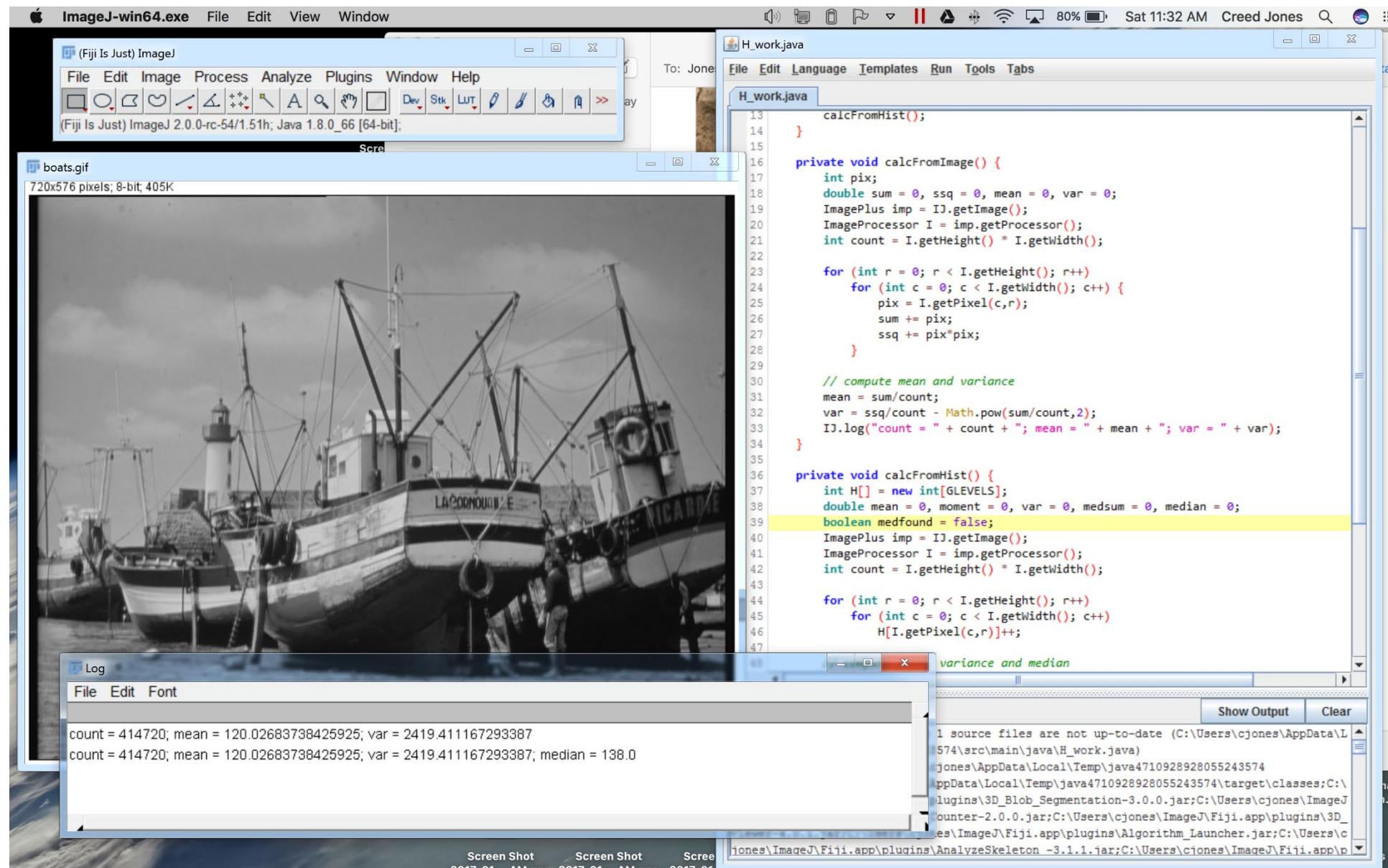
$$\sigma^2 = \left[\frac{1}{RC} \sum_{i=0}^{G-1} i^2 \cdot H(i) \right] - \mu^2$$

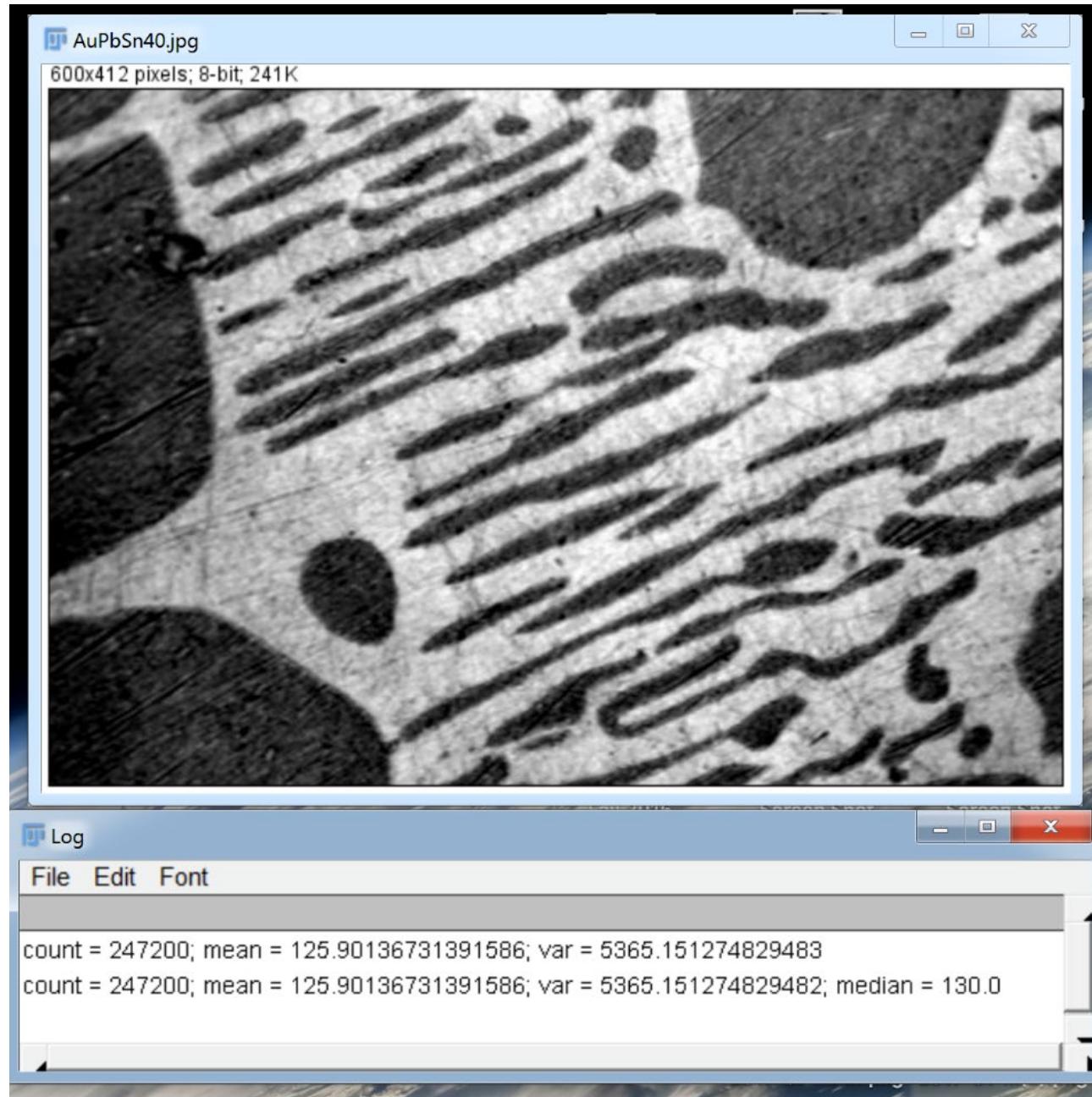
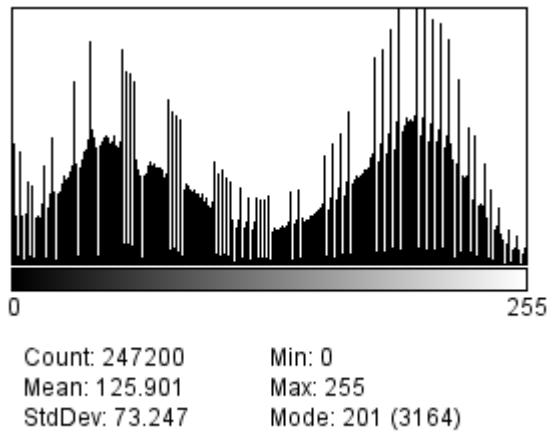
Standard Deviation:

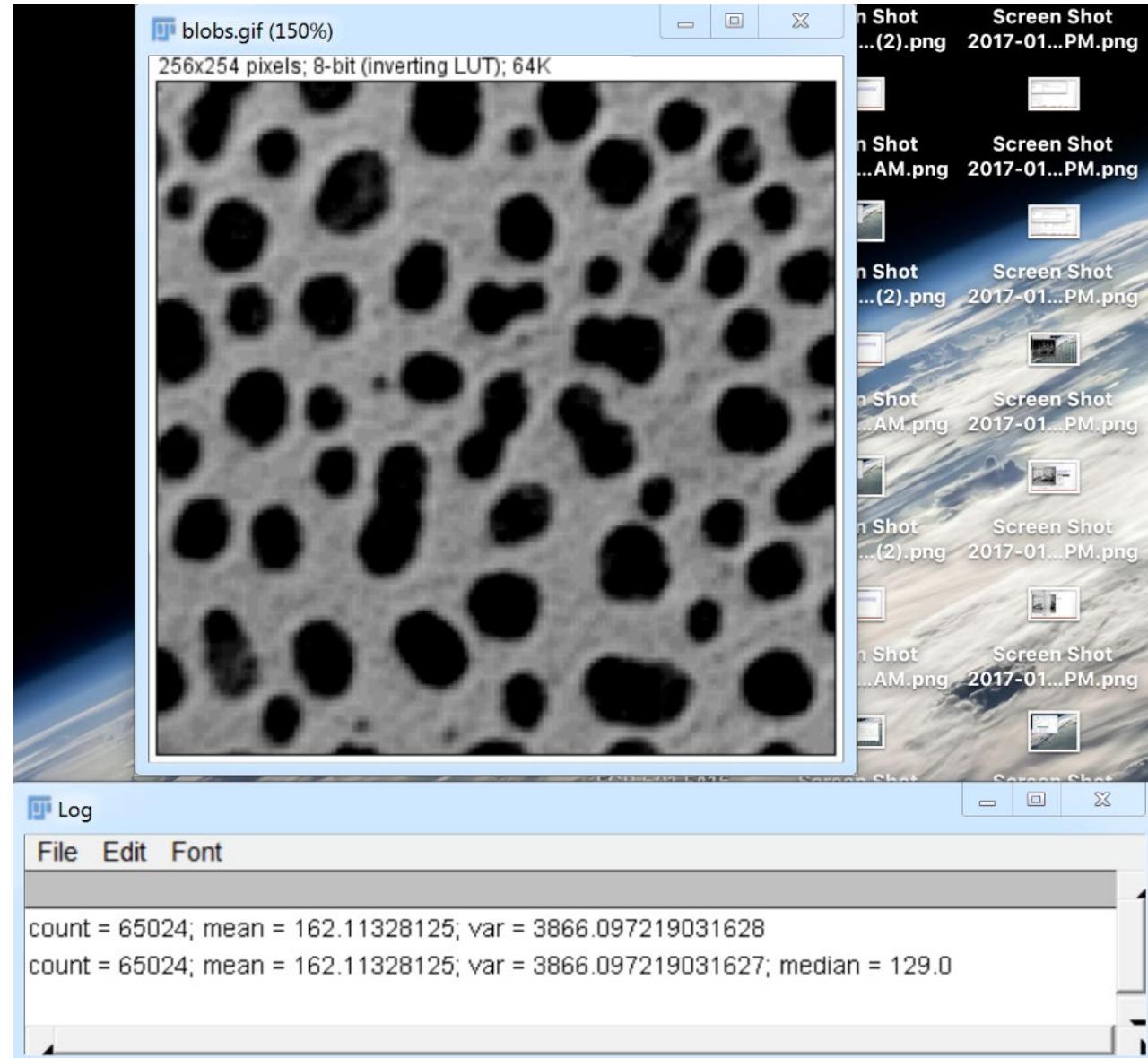
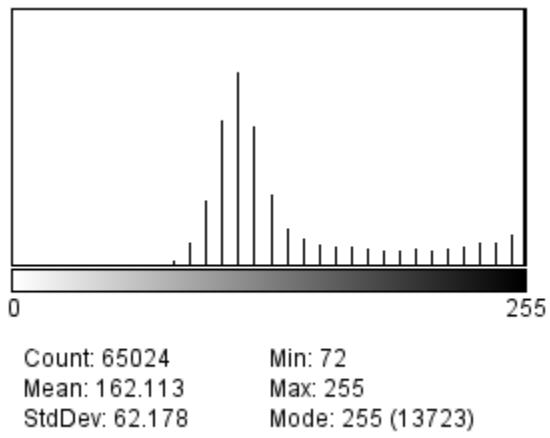
$$\sigma = \sqrt{\sigma^2}$$

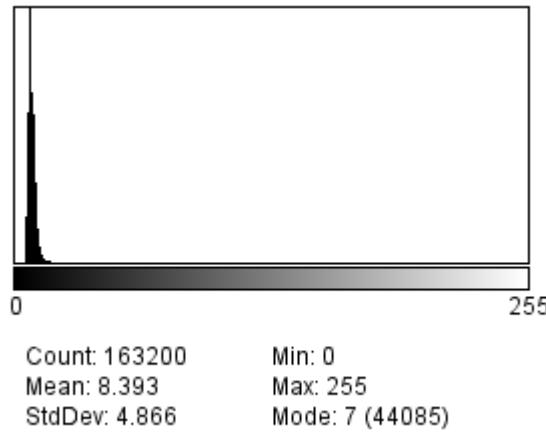
Median:

$$m = \min \left\{ i \left| \sum_{k=0}^i H(k) \geq \frac{RC}{2} \right. \right\}$$





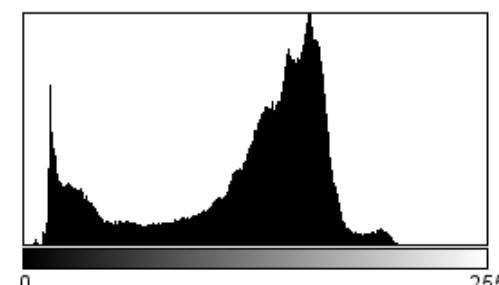
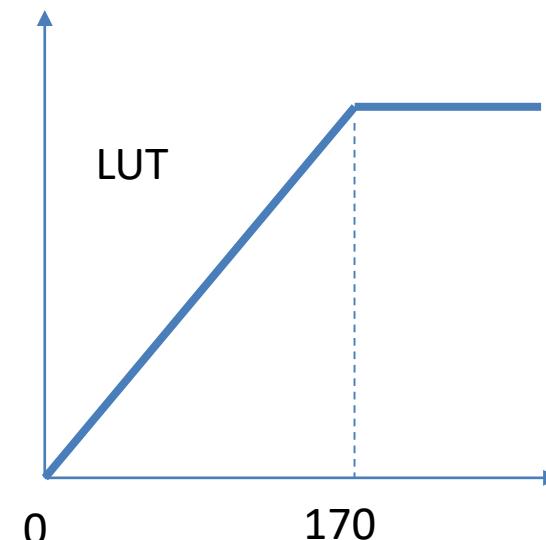




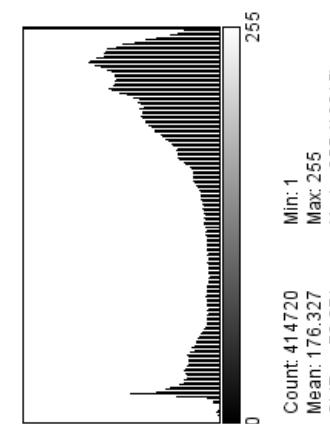
The log window displays the following text:

```
count = 163200; mean = 8.392671568627451; var = 23.680563941152457
count = 163200; mean = 8.392671568627451; var = 23.680563941152446; median = 8.0
```

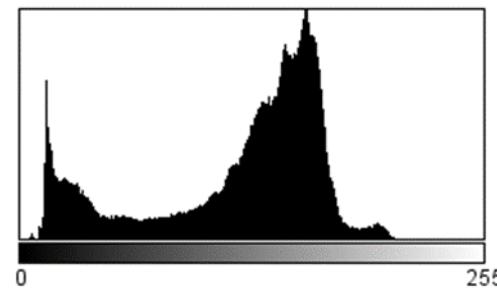
Realize that the output histogram can be computed by transforming the input histogram through the look-up table...



Min: 3
Max: 220
Mode: 157 (7480)

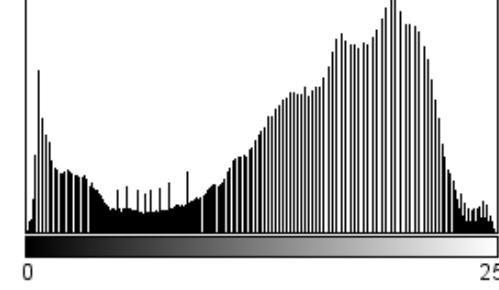


...so we can design a lookup table by specifying what the output histogram should look like; one approach is to make the histogram as flat as possible – this is called histogram equalization



Count: 414720
Mean: 120.027
StdDev: 49.188

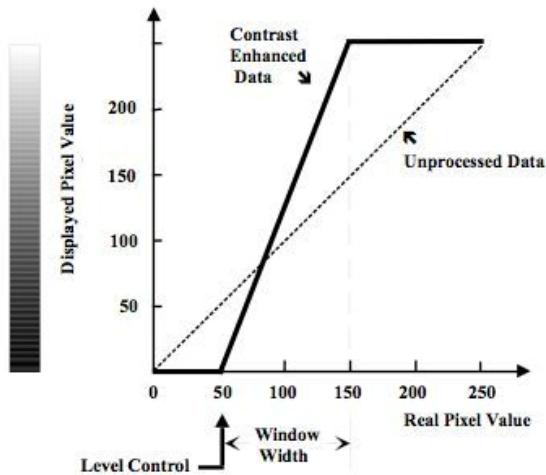
Min: 3
Max: 220
Mode: 157 (7480)



Count: 414720
Mean: 139.107
StdDev: 67.852

Min: 0
Max: 255
Mode: 198 (7480)

First, let's look at a formulaic way to express the contents of a linear LUT



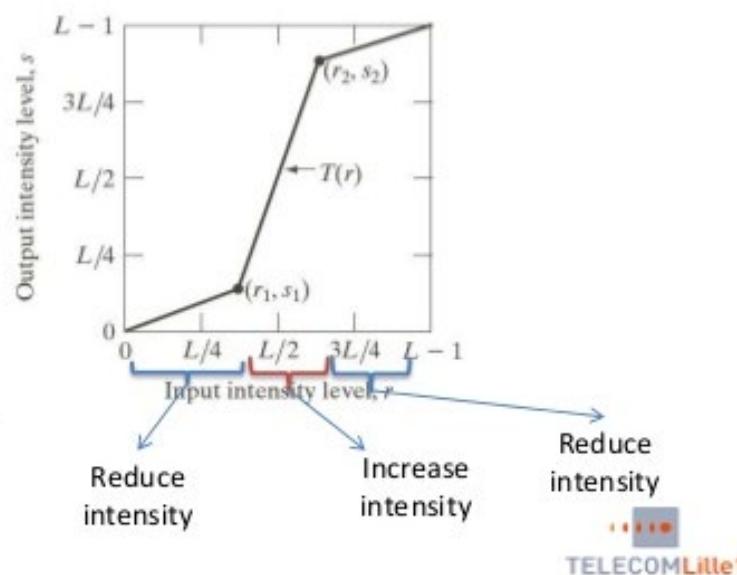
$$LUT[i] = \begin{cases} 0, & \text{if } i < a \\ (i - a) \frac{255}{b - a}, & \text{if } (a \leq i \leq b) \\ 255, & \text{if } i > b \end{cases}$$

<i>idx - input</i>	<i>I(idx) - output</i>
0	0
...	0
50	0
51	$1 * (255/100) = (\text{int})2.55 = 3$
52	$2 * (255/100) = (\text{int})5.1 = 5$
53	$3 * (255/100) = (\text{int})7.65 = 8$
...	...
148	$98 * (255/100) = (\text{int})249.9 = 250$
149	$99 * (255/100) = (\text{int})252.45 = 252$
150	255
...	255
255	255

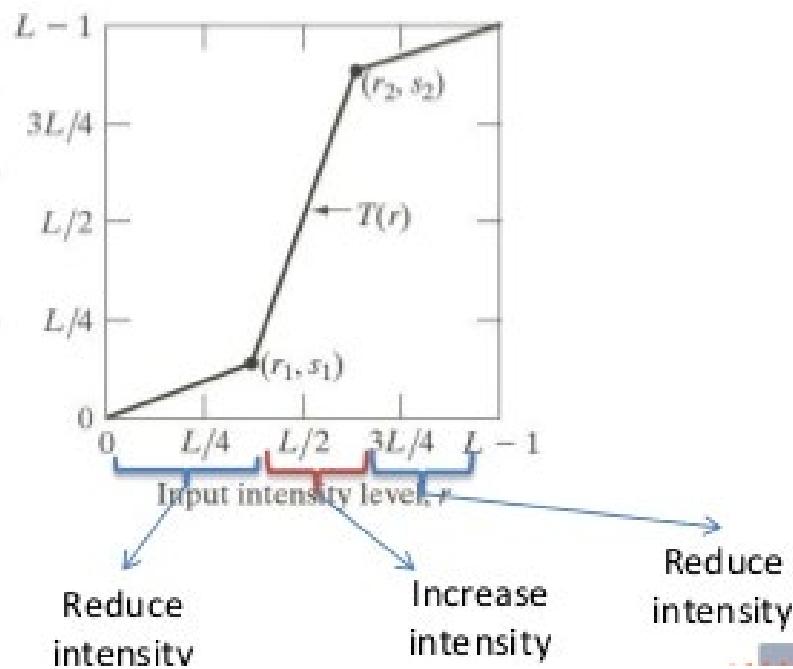
We may want to tailor a piecewise linear transformation to certain gray level regions – to increase contrast in certain ranges

Piecewise linear transformations

- Contrast stretching
 - Low contrast images can result from poor illumination

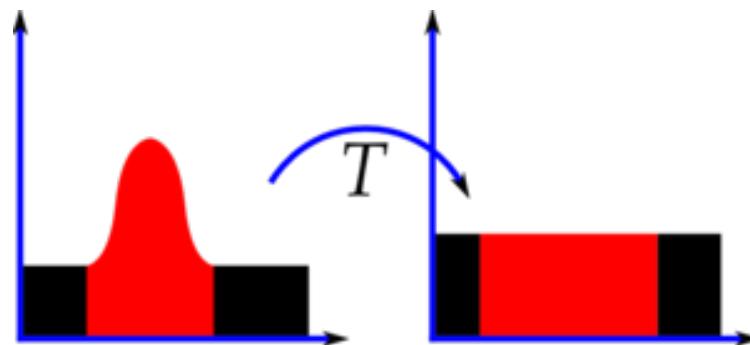


To do this, the LUT is calculated in pieces, using linear interpolation between each known point



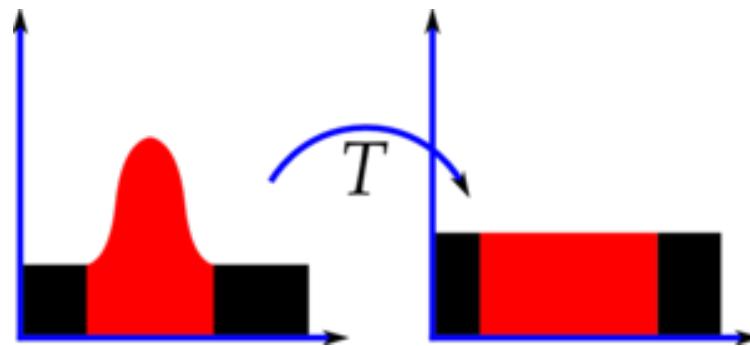
<i>idx - input</i>	<i>I(idx) - output</i>
0	0
1	$(\text{int})(1*s_1/r_1)$
...	...
r_1-1	$(\text{int})((r_1-1)*s_1/r_1)$
r_1	s_1
r_1+1	$(\text{int})(s_1 + (1)*(s_2-s_1)/(r_2-r_1))$
...	...
r_2-1	$(\text{int})(s_1 + (r_2-r_1-1)*(s_2-s_1)/(r_2-r_1))$
r_2	s_2
r_2+1	$(\text{int})(s_2 + (1)*(255-s_2)/(255-r_2))$
...	...
255	255

Histogram equalization is the adjusting of intensity values (usually via LUT) so that the output histogram is equal in height
- ideally



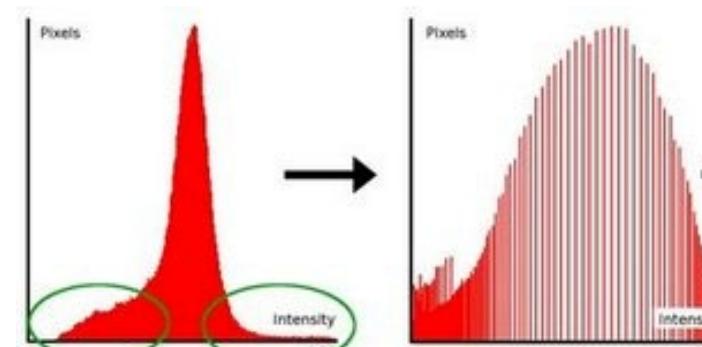
Though this is the idea – with a result that has a flat histogram – this rarely happens because of the limitations of mapping from and to quantized intensity values

Histogram equalization is the adjusting of intensity values (usually via LUT) so that the output histogram is equal in height - ideally

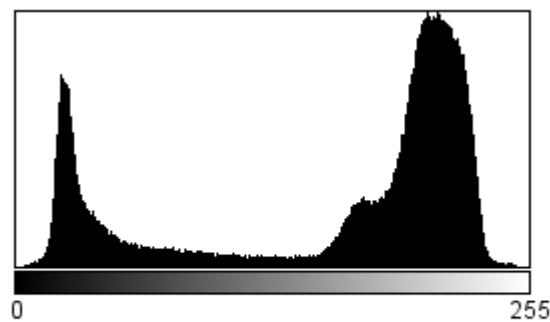
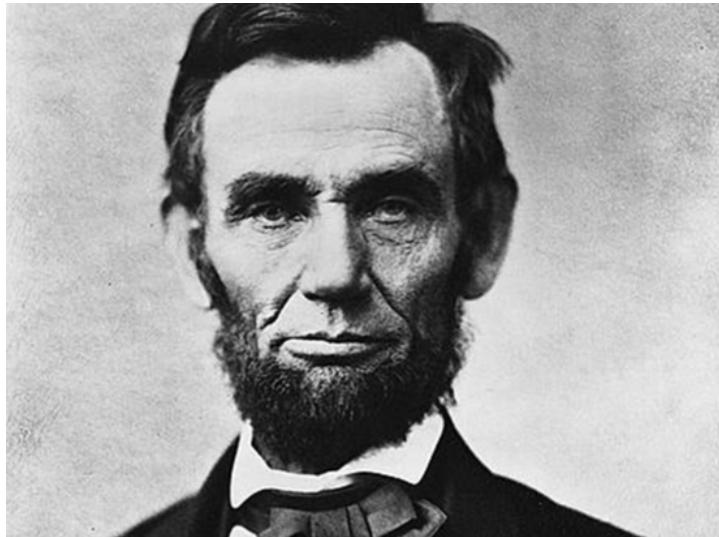


Though this is the idea – with a result that has a flat histogram – this rarely happens because of the limitations of mapping from and to quantized intensity values

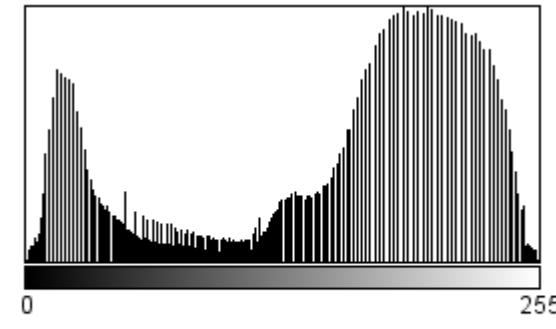
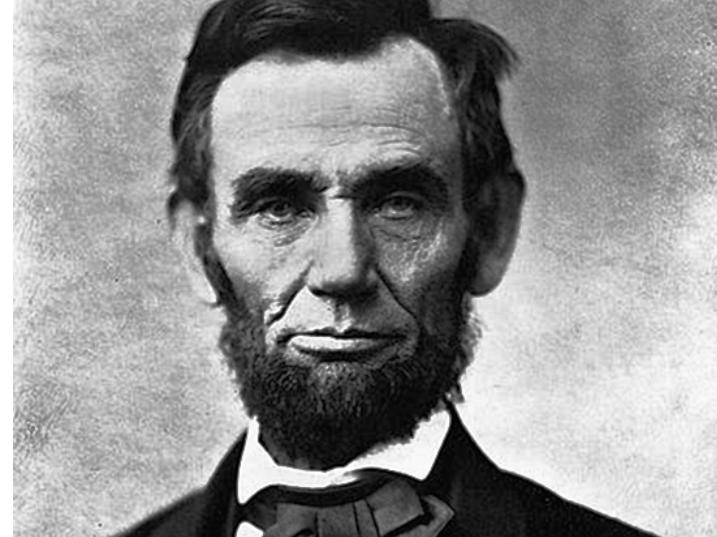
This is more
usually the
result



The precise objective is a resulting image where the histogram has equal area over each (reasonably sized) portion of the intensity range

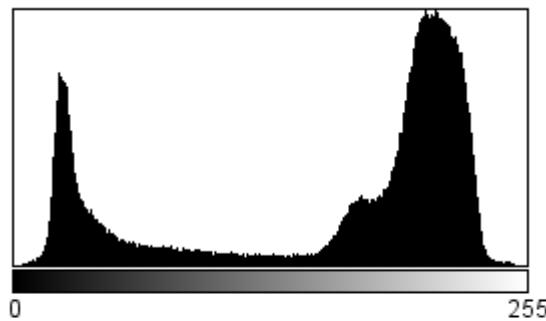


Count: 227150
Mean: 157.677
StdDev: 74.624
Min: 0
Max: 255
Mode: 210 (3775)

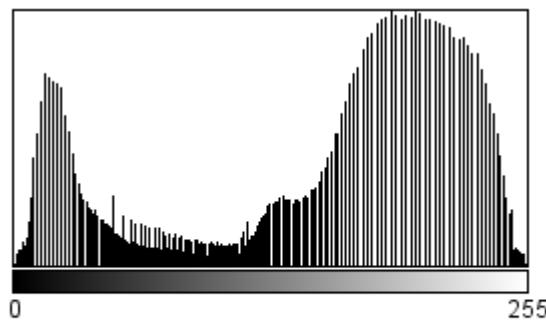


Count: 227150
Mean: 145.341
StdDev: 74.390
Min: 0
Max: 255
Mode: 200 (3775)

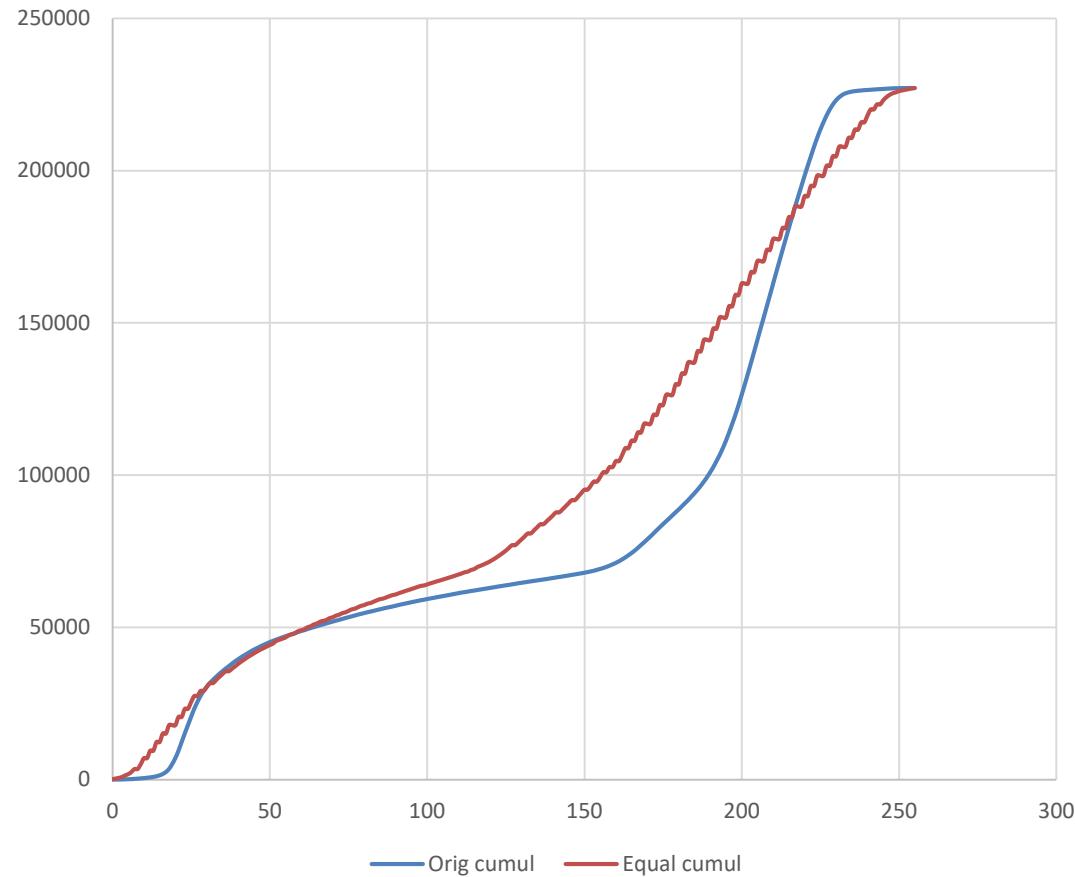
The cumulative histogram (where $CH[i] = \sum_{k=0}^i H[k]$) of the equalized image will be close (well, closer) to a line



Count: 227150
Mean: 157.677
StdDev: 74.624



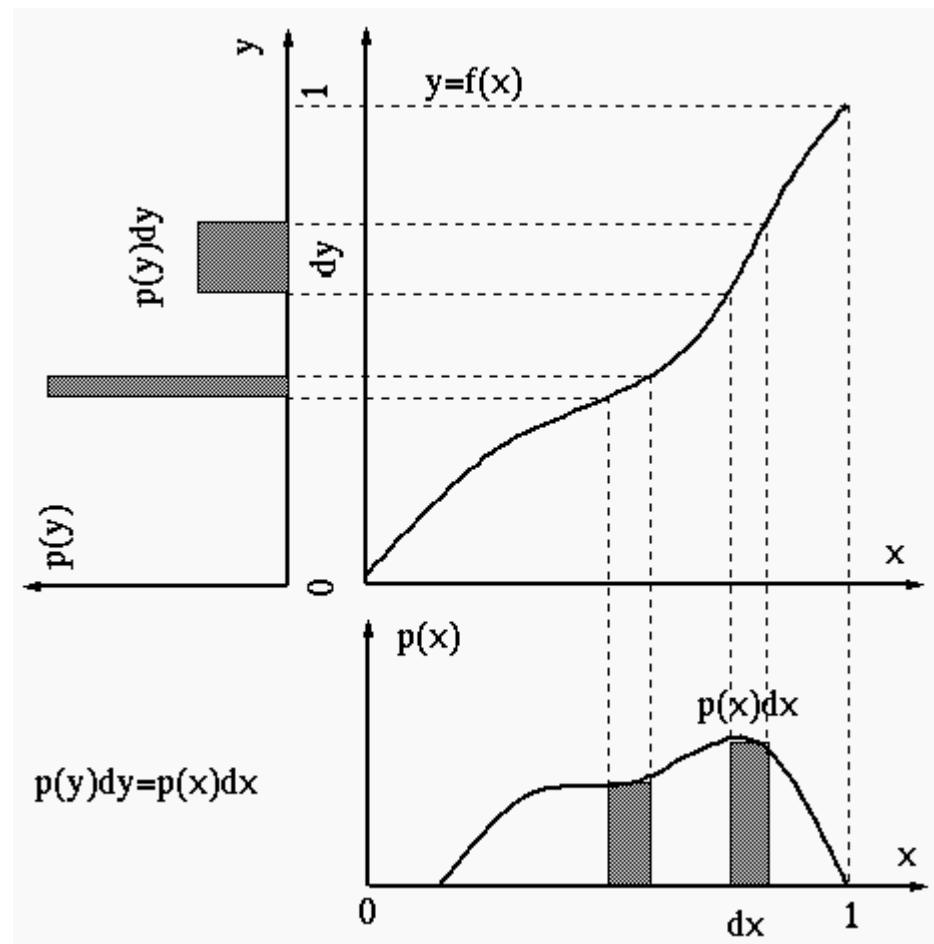
Count: 227150
Mean: 145.341
StdDev: 74.390



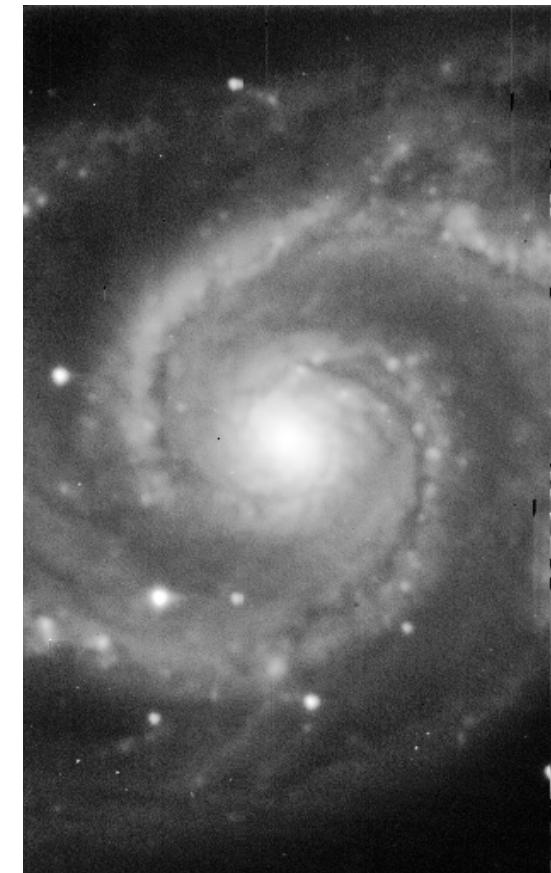
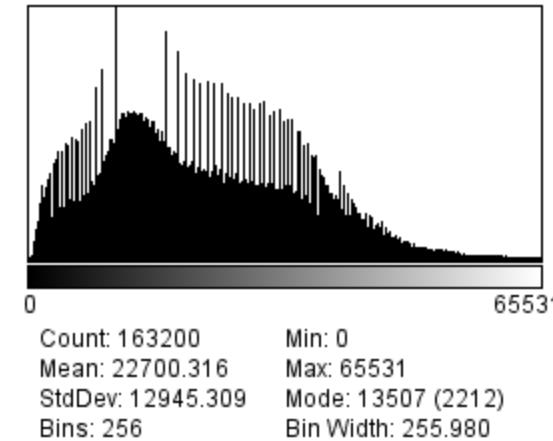
— Orig cumul — Equal cumul

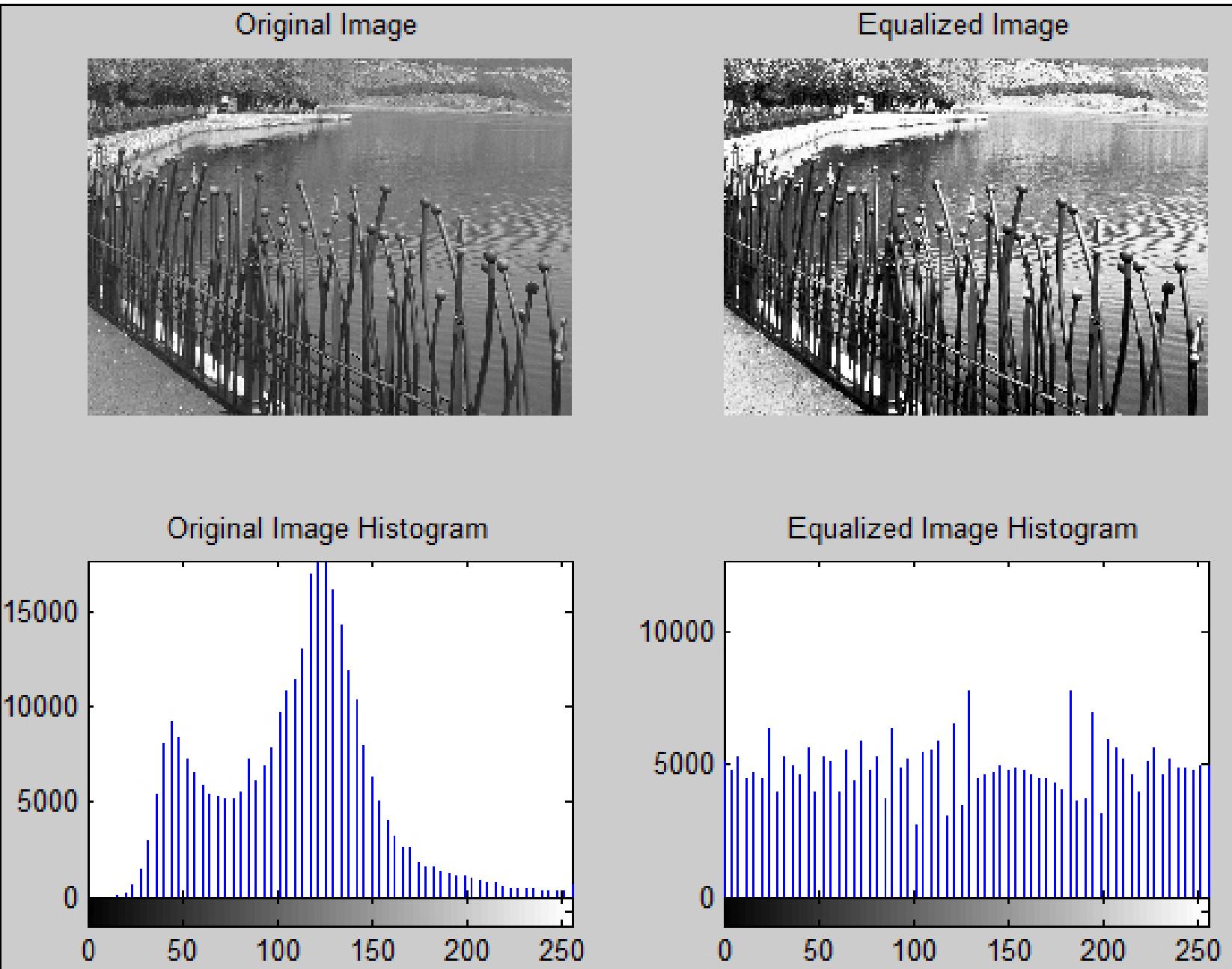
One way to fill the LUT to accomplish histogram equalization: successive piecewise linear functions for a set of regions in the input histogram

- The bottom $1/n$ of the output range should be a linear progression through whatever portion of the input range contains $1/n$ of the image pixels
- The next $1/n$ should progress through the portion of the input range containing the next $1/n$ of the image pixels
- and so on...



When we perform histogram equalization on the 16-bit image, the comb effect on the output is much reduced and visual result is better (though the improvement may be difficult to see)

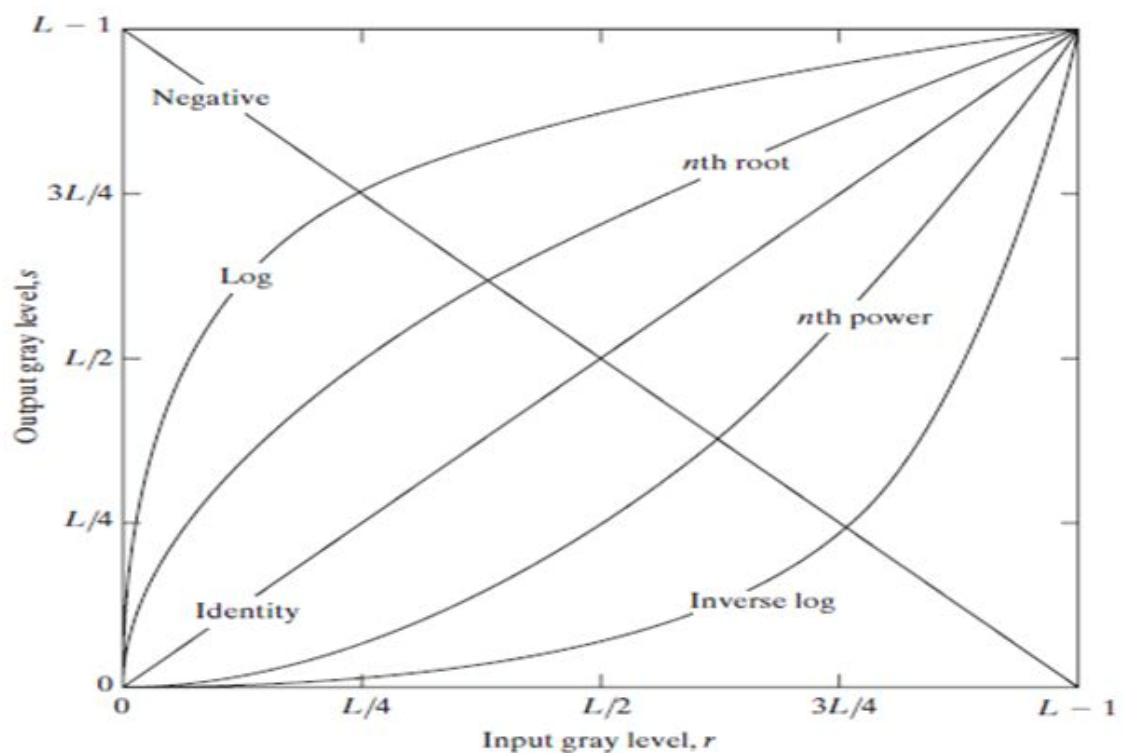




Some Basic Intensity (Gray-level) Transformation Functions

Consider the following figure, which shows three basic types of functions used frequently for image enhancement:

FIGURE 3.3 Some basic gray-level transformation functions used for image enhancement.



Today's Objectives

- Intensity histograms
- Image Statistics
- Histogram Equalization
- Pixel Operations