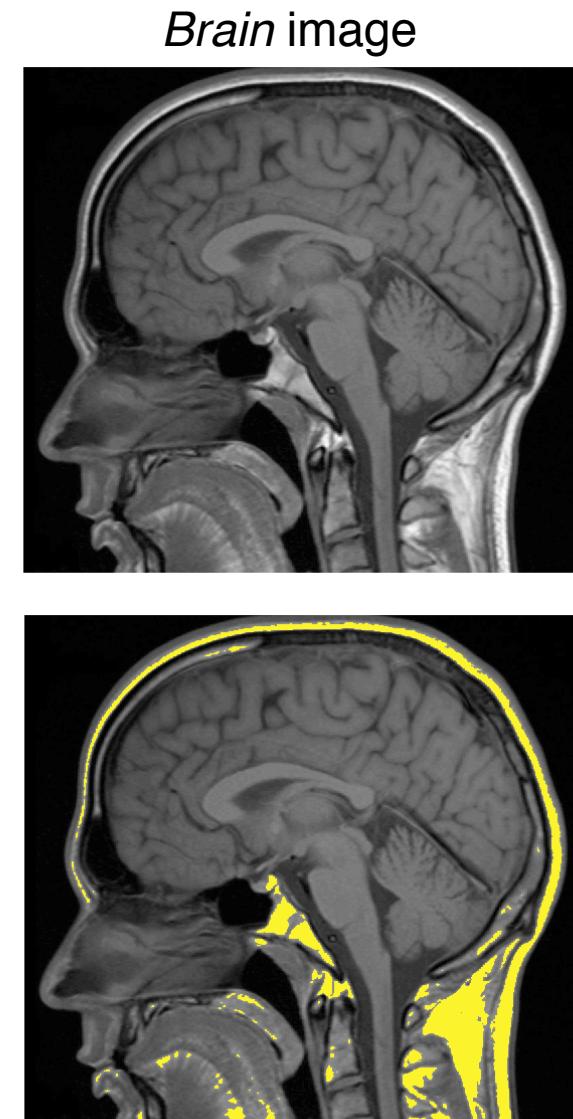
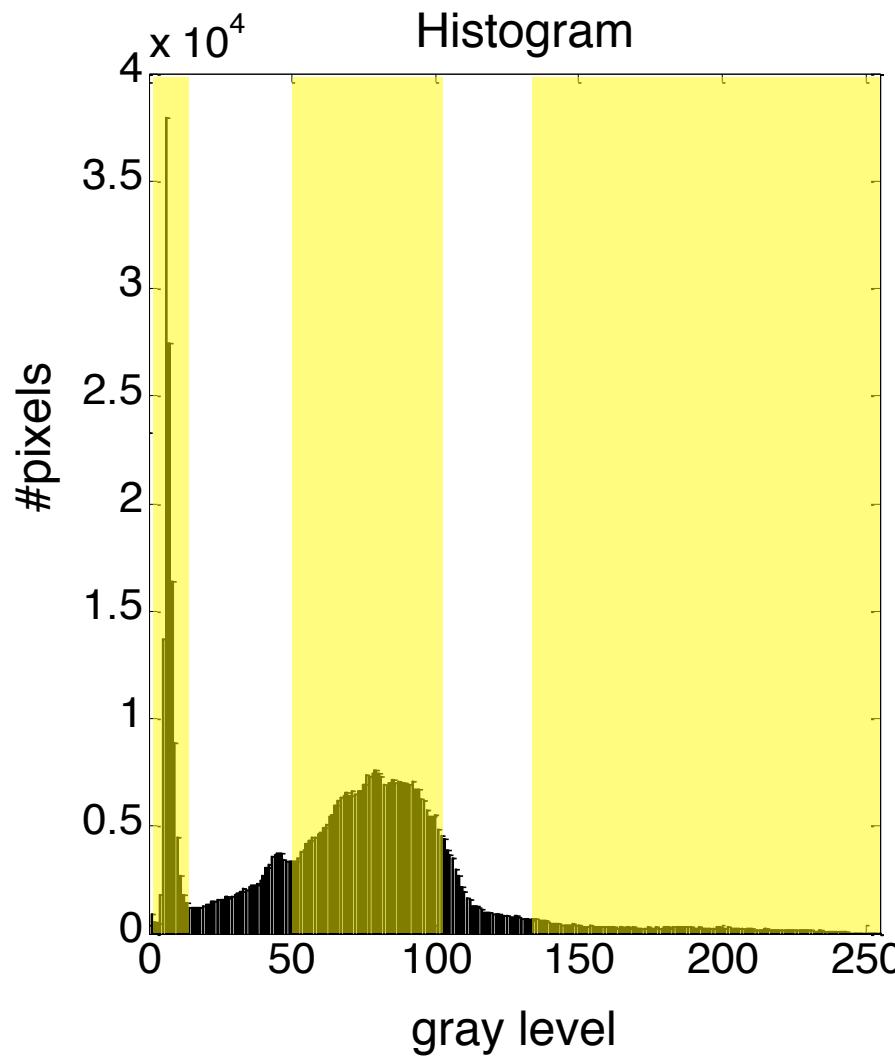
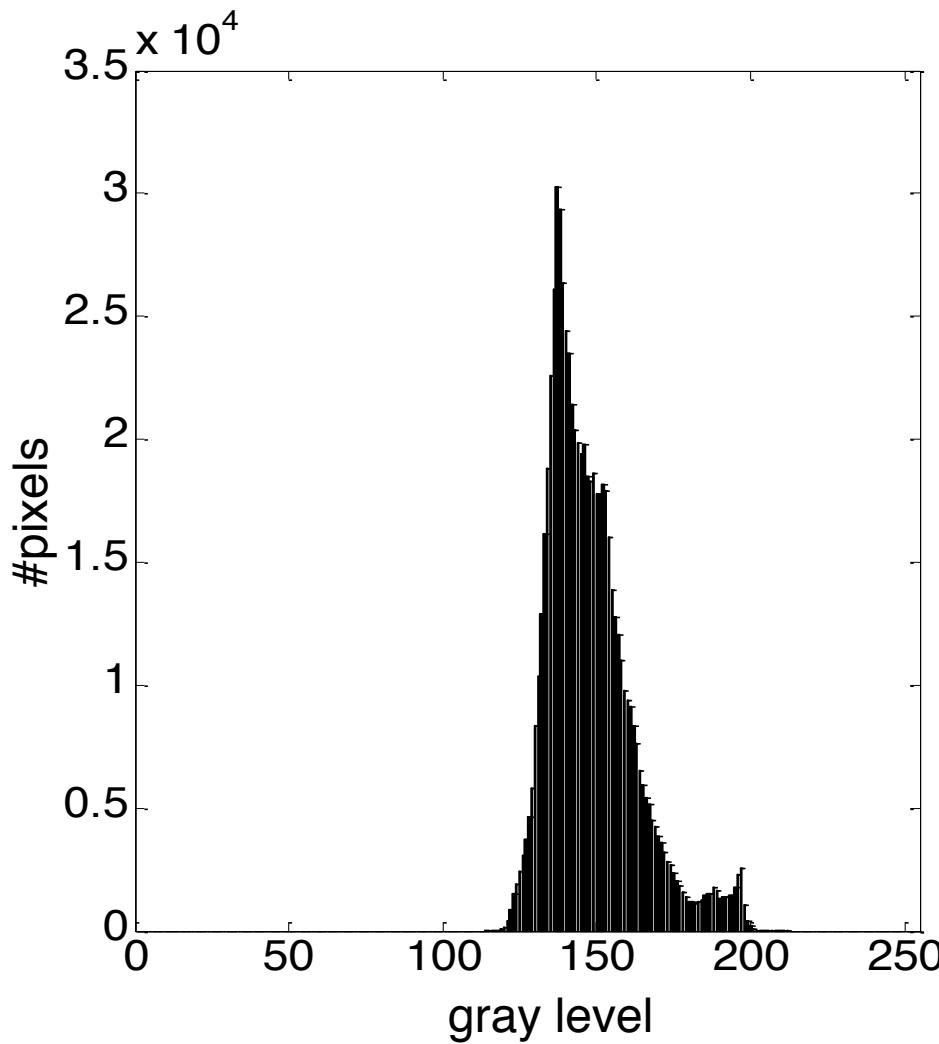


# Gray level histograms



# Gray level histograms



*Bay image*



# Gray level histogram in viewfinder



# Gray level histograms

- To measure a histogram:
  - For B-bit image, initialize  $2^B$  counters with 0
  - Loop over all pixels  $x,y$
  - When encountering gray level  $f[x,y]=i$ , increment counter  $\#_i$
- Normalized histogram can be thought of as an estimate of the probability distribution of the continuous signal amplitude
- Use fewer, larger bins to trade off amplitude resolution against sample size.

# Histogram equalization

Idea:

Find a non-linear transformation

$$g = T(f)$$

that is applied to each pixel of the input image  $f[x,y]$ , such that a uniform distribution of gray levels results for the output image  $g[x,y]$ .

flatten the histogram

# Histogram equalization

Analyse ideal, continuous case first ...

Assume

- Normalized input values  $0 \leq f \leq 1$  and output values  $0 \leq g \leq 1$
- $T(f)$  is differentiable, increasing, and invertible, i.e., there exists

$$f = T^{-1}(g) \quad 0 \leq g \leq 1$$

**Goal:** pdf  $p_g(g) = 1$  over the entire range  $0 \leq g \leq 1$

# Histogram equalization for continuous case

- From basic probability theory

$$p_f(f) \xrightarrow{f} T(f) \xrightarrow{g} p_g(g) = \left[ p_f(f) \frac{df}{dg} \right]_{f=T^{-1}(g)}$$

- Consider the transformation function

$$g = T(f) = \int_0^f p_f(\alpha) d\alpha \quad 0 \leq f \leq 1$$

- Then . . .

$$\frac{dg}{df} = p_f(f)$$

$$p_g(g) = \left[ p_f(f) \frac{df}{dg} \right]_{f=T^{-1}(g)} = \left[ p_f(f) \frac{1}{p_f(f)} \right]_{f=T^{-1}(g)} = 1 \quad 0 \leq g \leq 1$$

# Histogram equalization for discrete case

- Now,  $f$  only assumes discrete amplitude values  $f_0, f_1, \dots, f_{L-1}$  with empirical probabilities

$$P_0 = \frac{n_0}{n} \quad P_1 = \frac{n_1}{n} \quad \dots \quad P_{L-1} = \frac{n_{L-1}}{n} \quad \text{where } n = \sum_{l=0}^{L-1} n_l \quad \text{pixel count for amplitude } f_l$$

- Discrete approximation of  $g = T(f) = \int_0^f p_f(\alpha) d\alpha$

$$g_k = T[f_k] = \sum_{i=0}^k P_i \quad \text{for } k = 0, 1, \dots, L-1$$

- The resulting values  $g_k$  are in the range  $[0,1]$  and might have to be scaled and rounded appropriately.

# Histogram equalization example



Original image *Bay*

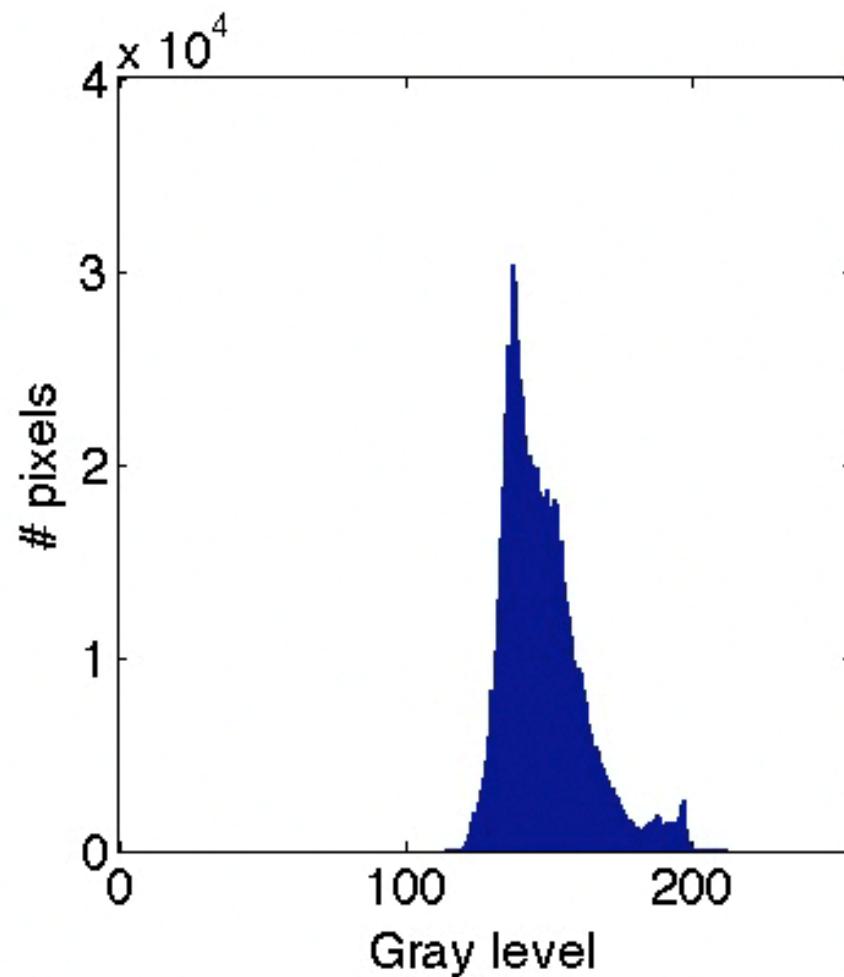


... after histogram equalization

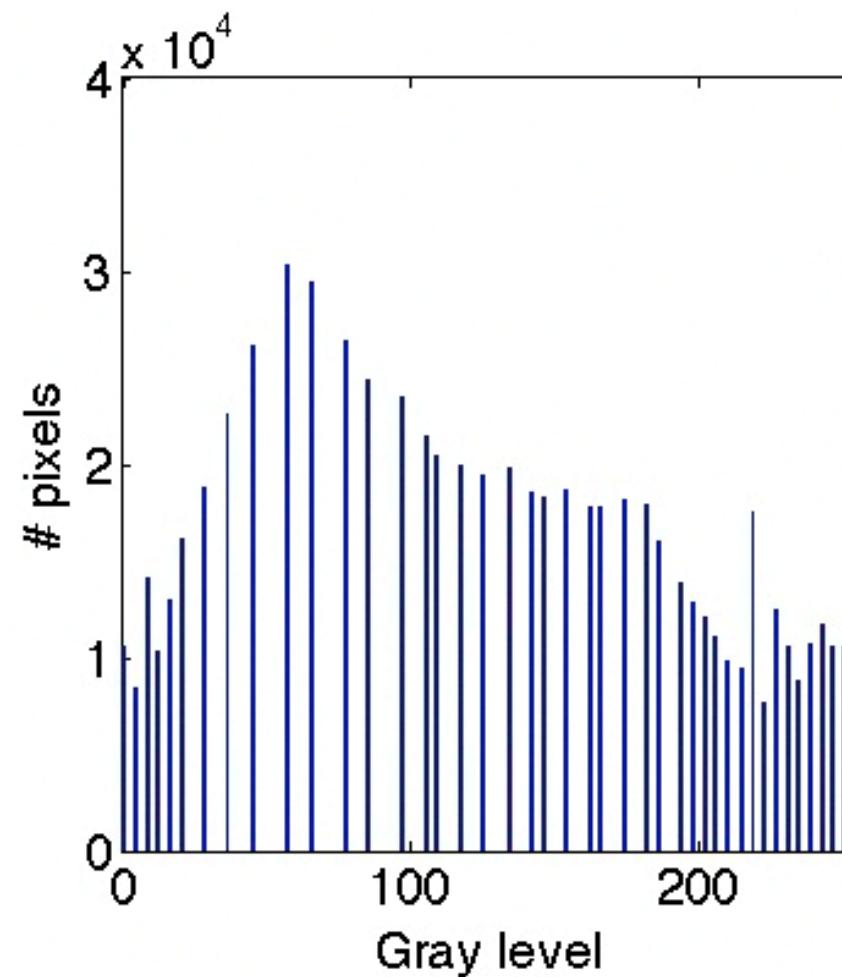


# Histogram equalization example

Original image *Bay*



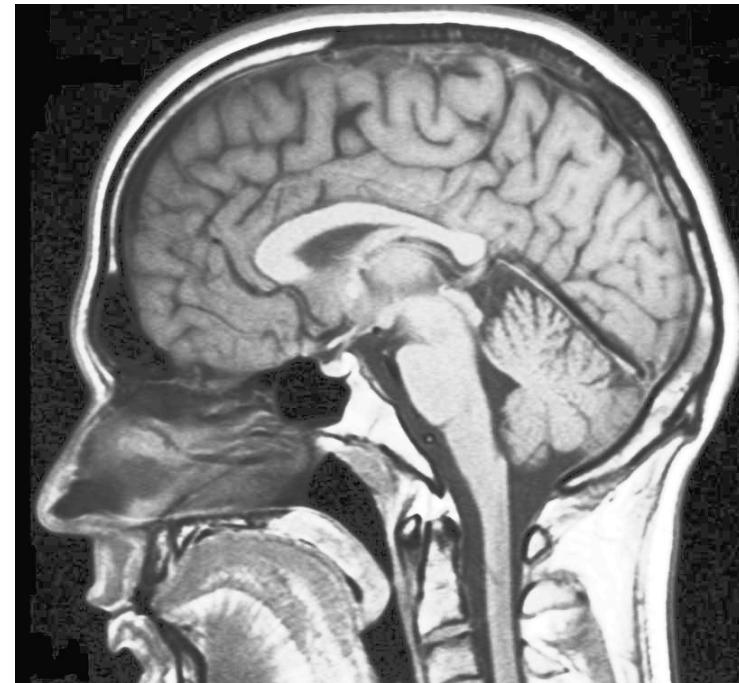
... after histogram equalization



# Histogram equalization example



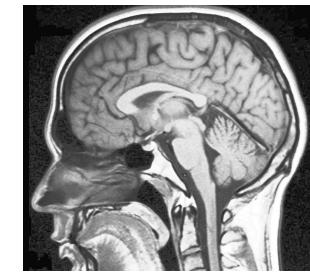
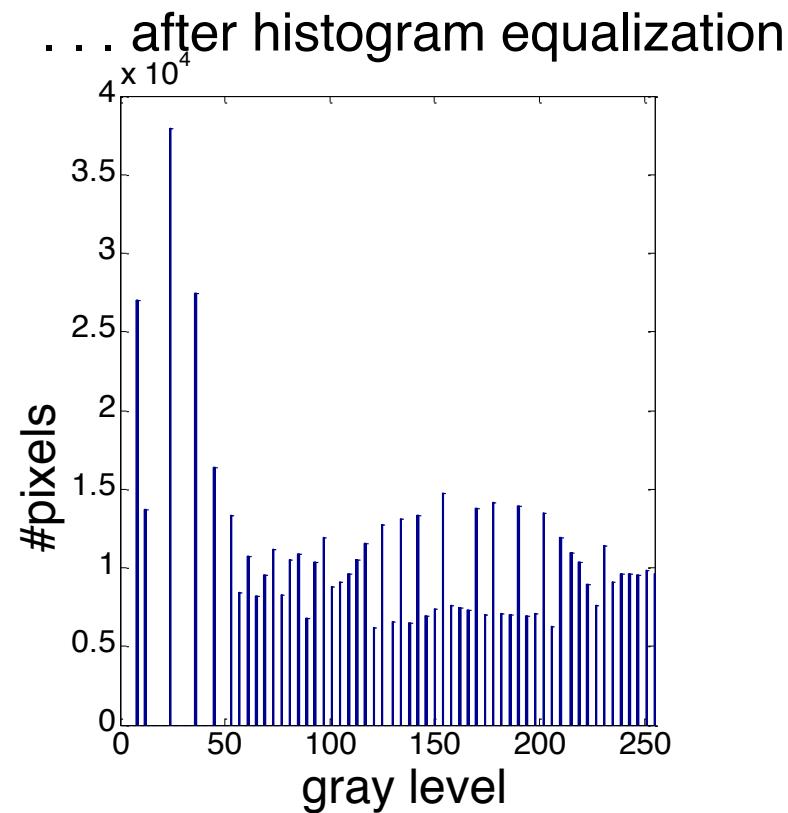
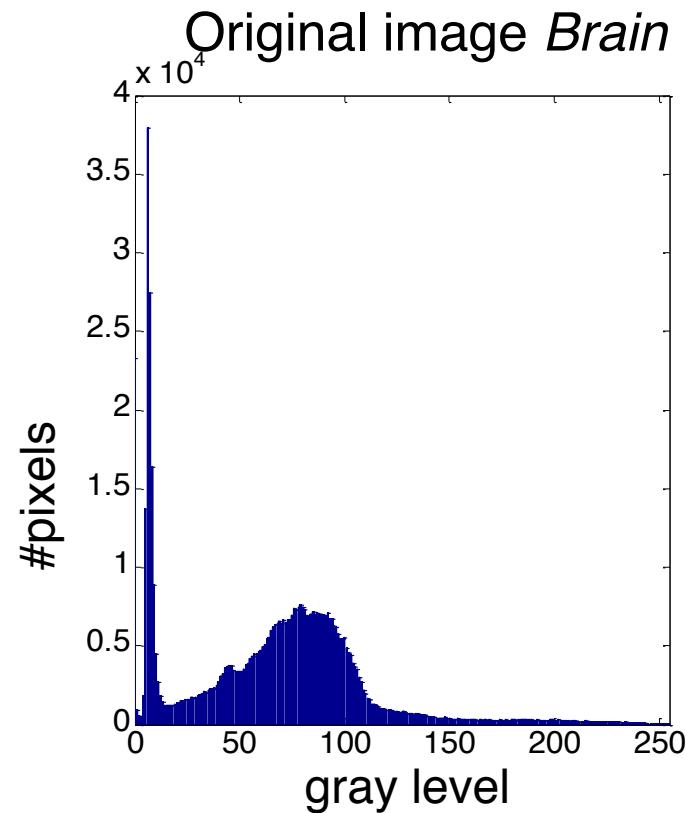
Original image *Brain*



... after histogram equalization



# Histogram equalization example



# Histogram equalization example



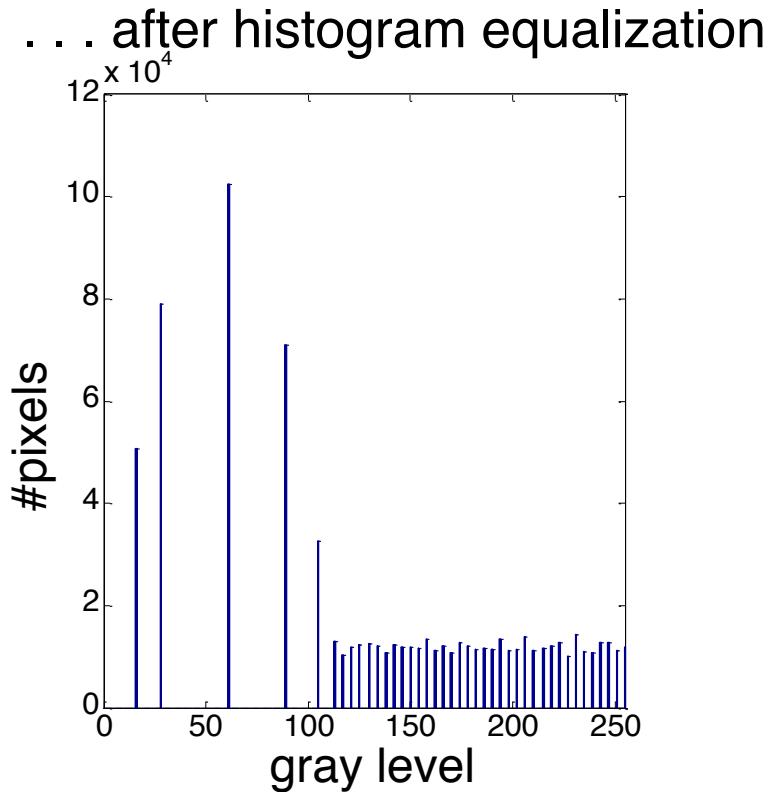
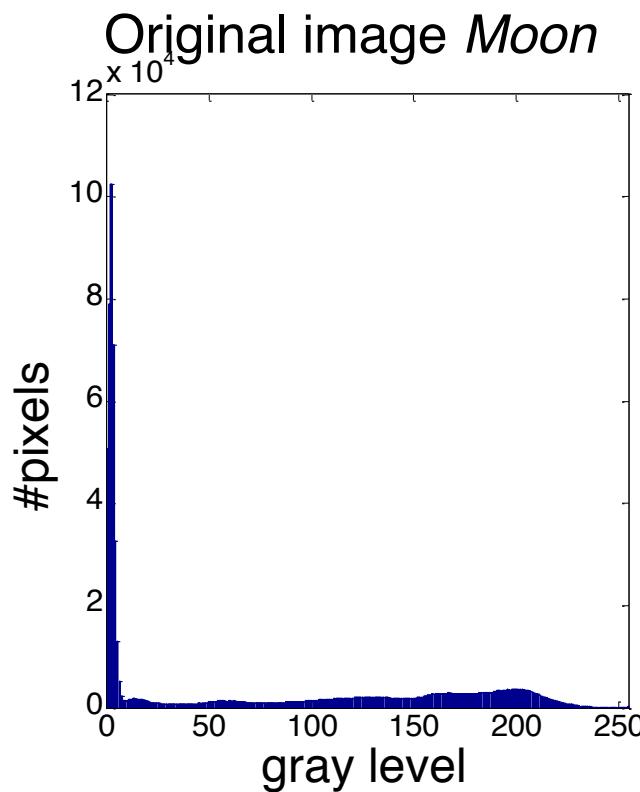
Original image *Moon*



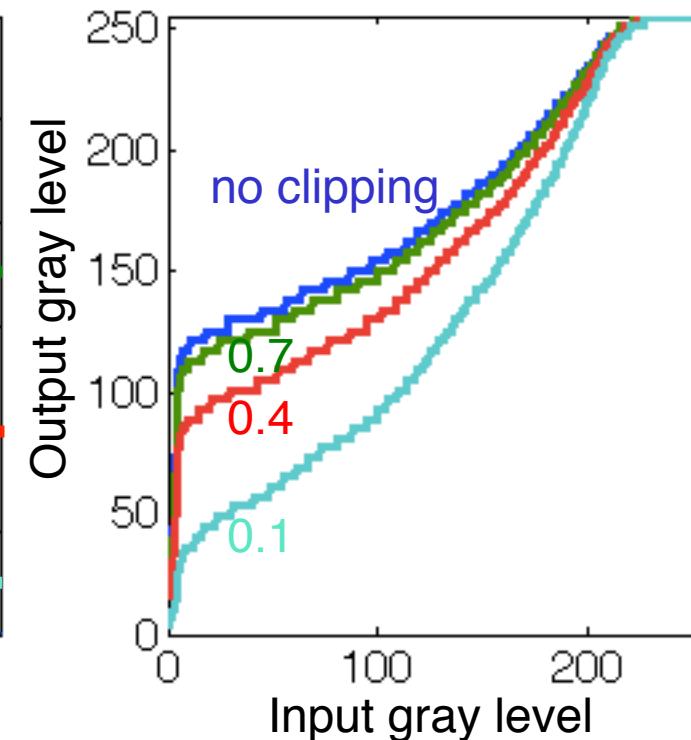
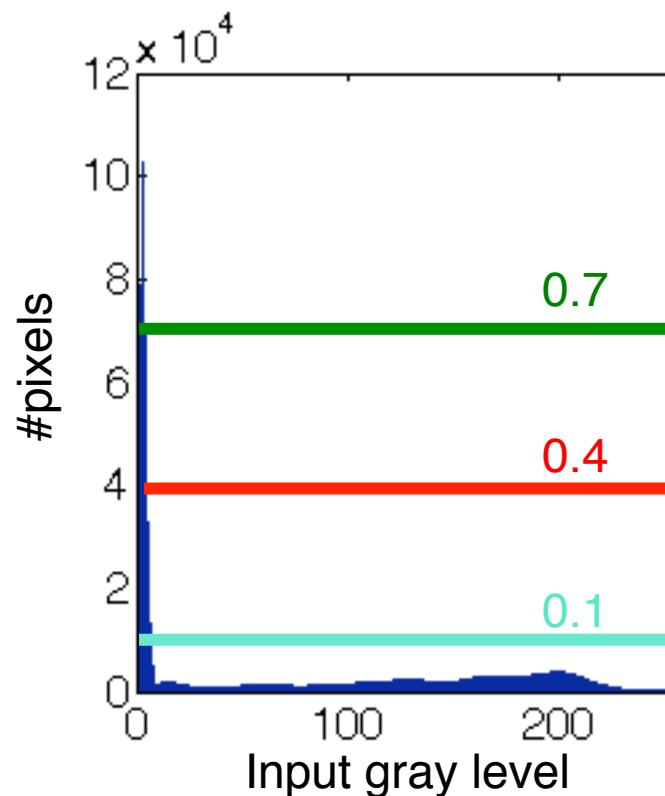
... after histogram equalization



# Histogram equalization example

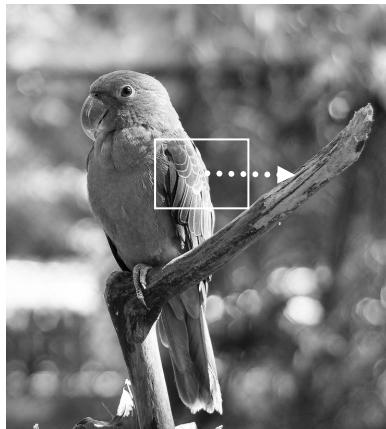


# Contrast-limited histogram equalization



# Adaptive histogram equalization

- Histogram equalization based on a histogram obtained from a portion of the image



Sliding window approach:  
different histogram (and  
mapping) for every pixel



Tiling approach:  
subdivide into overlapping  
regions, mitigate blocking  
effect by smooth blending  
between neighboring tiles

- Limit contrast expansion in flat regions of the image,  
e.g., by clipping histogram values.  
("Contrast-limited adaptive histogram equalization")

[Pizer, Amburn et al. 1987]

# Adaptive histogram equalization

Original image  
*Parrot*



Global histogram  
equalization



Adaptive histogram  
equalization, 8x8 tiles



Adaptive histogram  
equalization, 16x16 tiles



# Adaptive histogram equalization

Original image  
*Dental Xray*



Global histogram  
equalization



Adaptive histogram  
equalization, 8x8 tiles



Adaptive histogram  
equalization, 16x16 tiles



# Adaptive histogram equalization

Original image  
*Skull Xray*



Global histogram  
equalization



Adaptive histogram  
equalization, 8x8 tiles



Adaptive histogram  
equalization, 16x16 tiles

