Image Segmentation

Image Processing

CSE 166

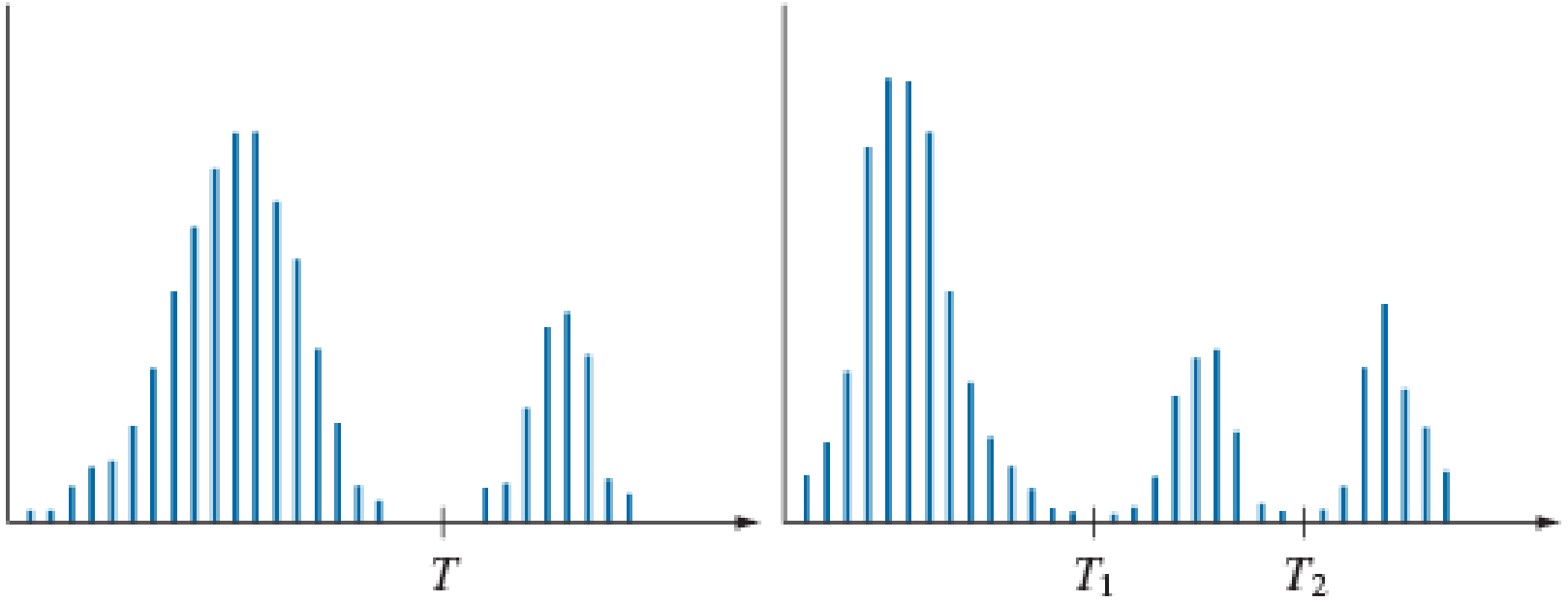
Lecture 15

Announcements

- Assignment 6 will be released today
  - Due Jun 3, 11:59 PM
- Reading
  - Chapter 10: Image segmentation I: edge detection, thresholding, and region detection
    - Sections 10.3, 10.4, 10.5, and 10.6

Thresholding

Histograms



Single threshold

Dual thresholds

Thresholding

- Single threshold

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T \\ 0 & \text{otherwise} \end{cases}$$

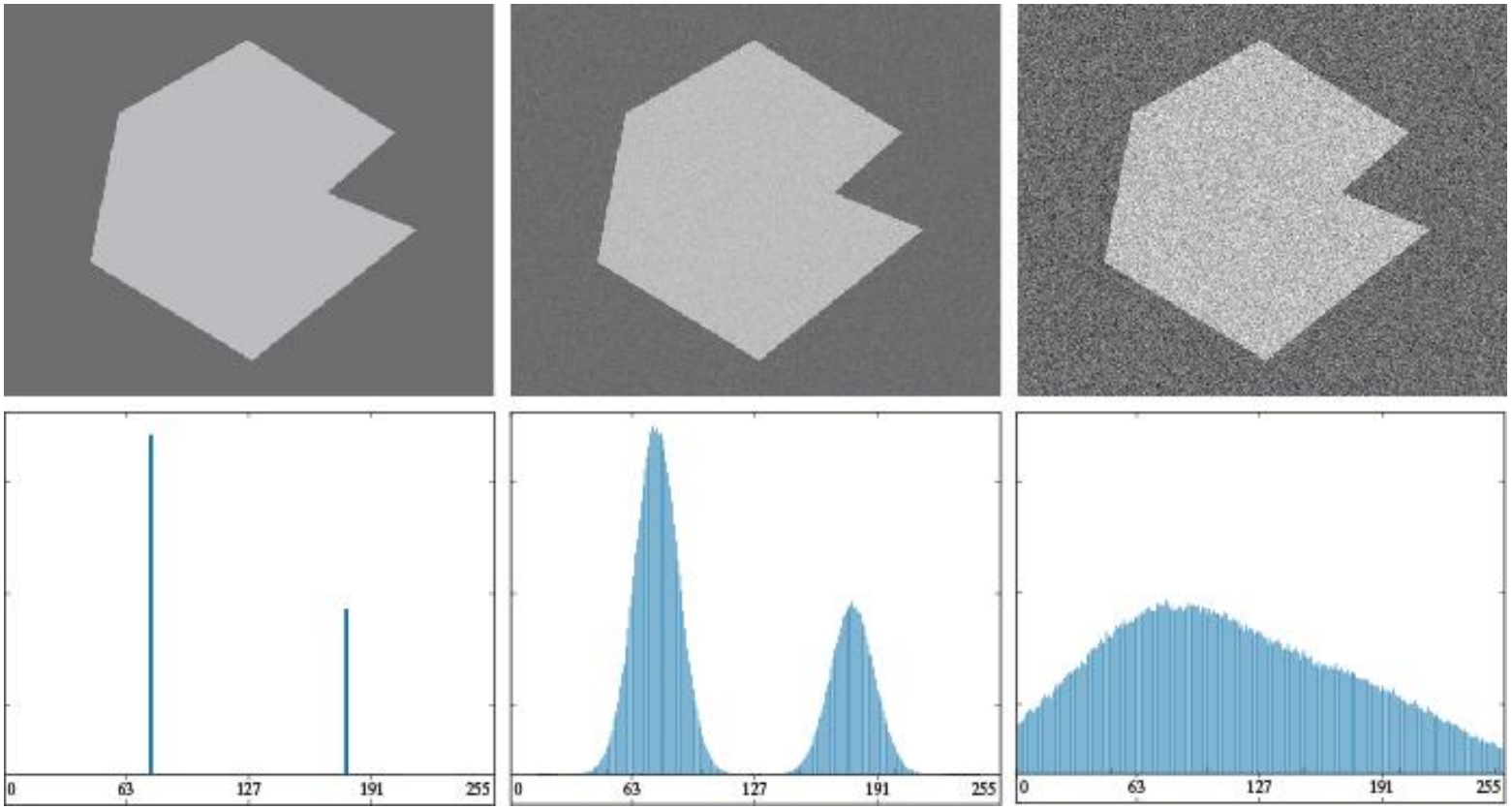
where T is threshold value

- Dual thresholds

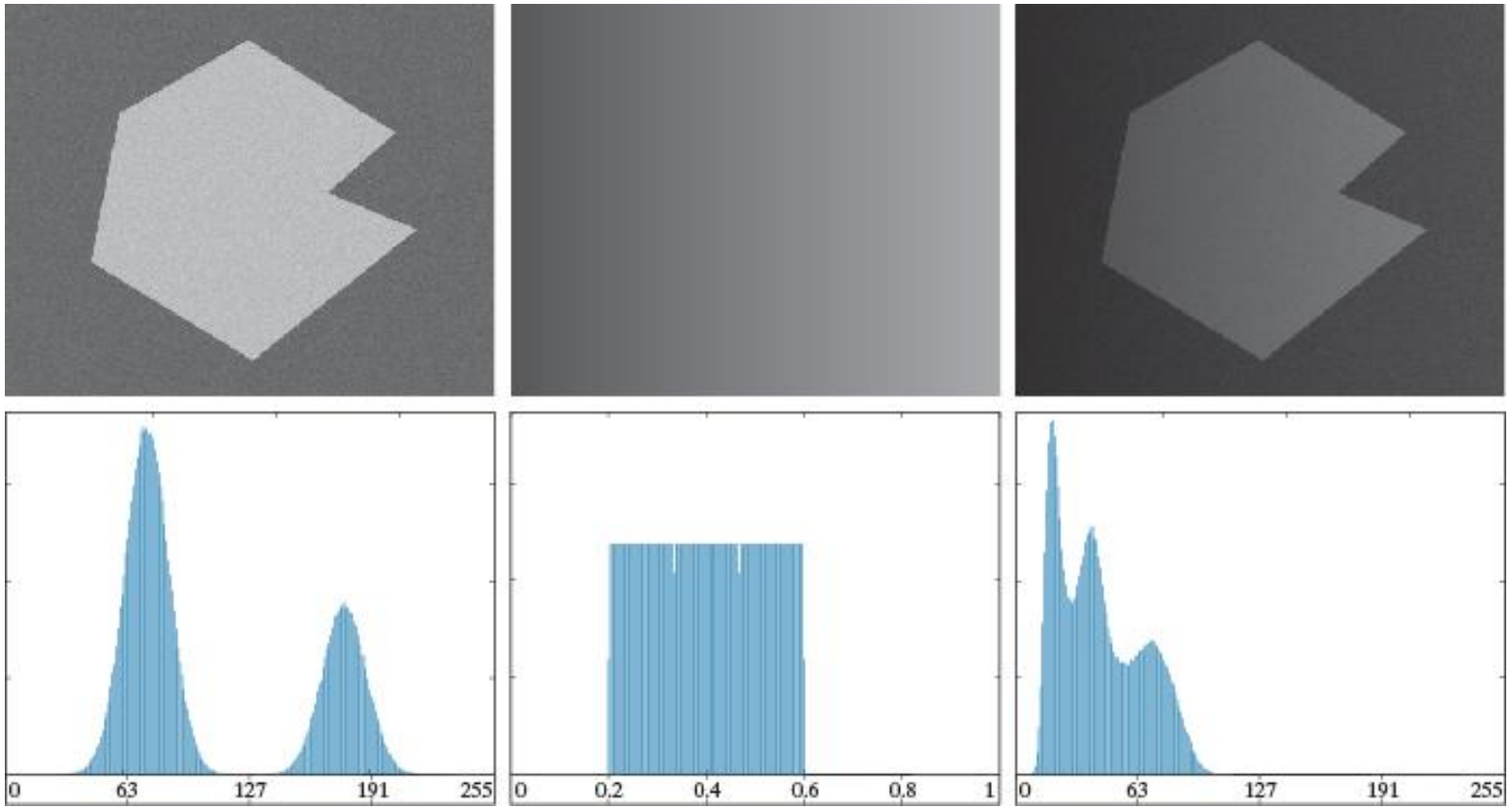
$$g(x,y) = \begin{cases} a & \text{if } f(x,y) > T_2 \\ b & \text{if } T_1 < f(x,y) \leq T_2 \\ c & \text{if } f(x,y) \leq T_1 \end{cases}$$

where T_1 is first threshold value
T_2 is second threshold value

Noise and thresholding



Varying background and thresholding



Input

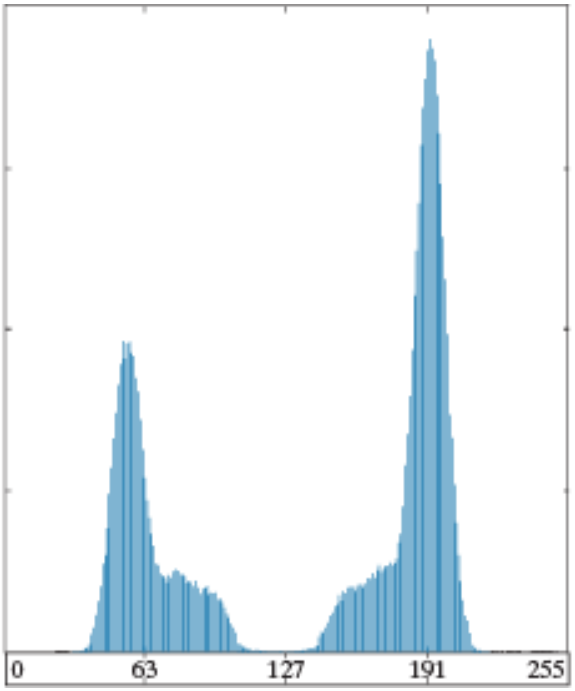
Intensity ramp

Product of input and intensity ramp

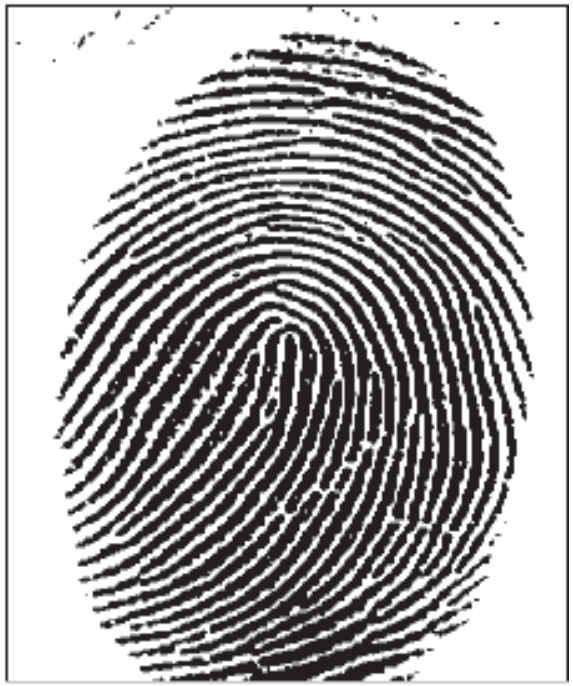
Basic global thresholding



Input



Intensity ramp



Threshold

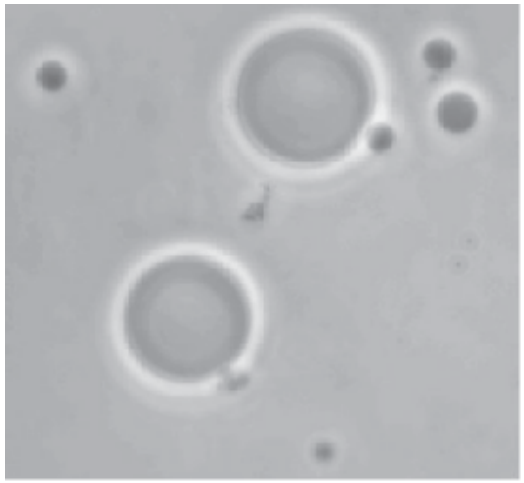
Basic global thresholding

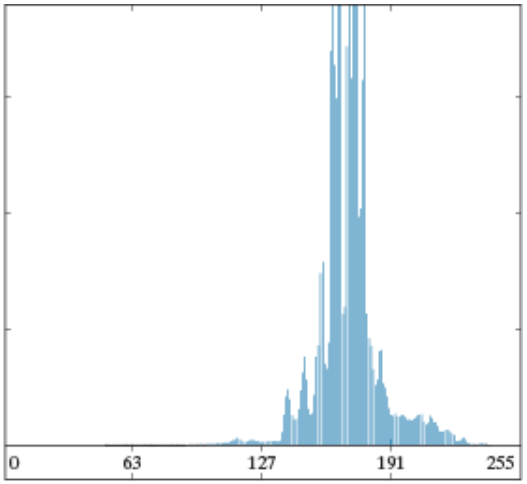
1. Select initial estimate of global threshold T_0
2. Group G_1 if $f(x, y) > T_i$
   Group G_2 if $f(x, y) \leq T_i$
3. m_1 is mean of intensity values in G_1
   m_2 is mean of intensity values in G_2
4. $T_i = \frac{1}{2}(m_1 + m_2)$
5. Repeat steps 2–4 until $|T_i - T_{i-1}| < \Delta T$

Value used to stop iterating

Optimum global thresholding

Input





Histogram

Basic global thresholding



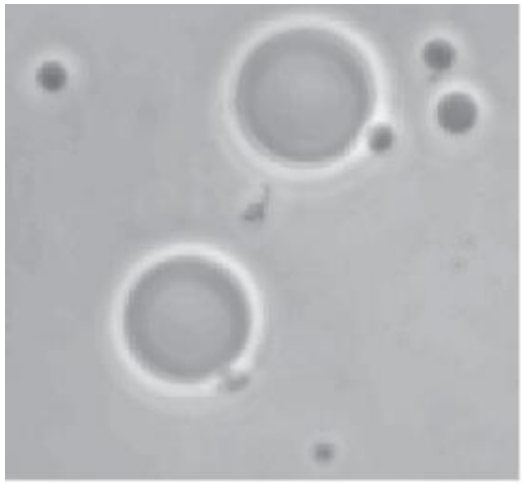


Optimum global thresholding using Otsu's method

Otsu's method

Classes c_1 and c_2
Find threshold T that
minimizes within class variances $\sigma^2_{W_1}$ and $\sigma^2_{W_2}$, which equivalently
maximizes between class variance $\sigma^2_B = P_1 P_2 (m_1 - m_2)^2$,
where P_1 and P_2 and the probabilities of c_1 and c_2, respectively

Input





Optimum global thresholding using Otsu's method

Otsu's method

1. Compute normalized histogram (similar to pdf)
2. Compute cumulative sums $P_1(k) = \sum_{i=0}^{k} p_i \quad k = 0, 1, \ldots, L-1$
   (note $P_2(k) = 1 - P_1(k)$ since $P1 + P2 = 1$)
3. Compute cumulative means $m(k) = \sum_{i=0}^{k} i\, p_i \quad k = 0, 1, \ldots, L-1$
4. Compute global mean $m_G = \sum_{i=0}^{L-1} i\, p_i = m(L-1)$
5. Compute between-class variance $\sigma_B^2(k) = \frac{(m_G P_1(k) - m(k))^2}{P_1(k)(1-P_1(k))} \quad k = 0, 1, \ldots, L-1$
6. Otsu's threshold k^* is the value of k for which $\sigma_B^2(k)$ is maximum
   (average values if multiple maxima)

Otsu's method

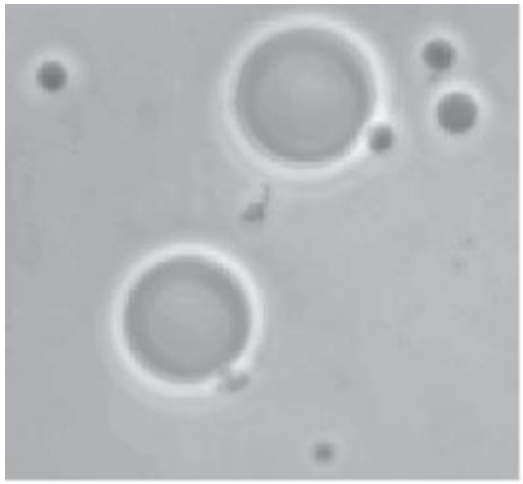
6. Otsu's threshold k^* is the value of k for which $\sigma_B^2(k)$ is maximum (average values if multiple maxima)

Separability measure

$$\eta(k^*) = \frac{\sigma_B^2(k^*)}{\sigma_G^2}$$

where global variance $\sigma_G^2 - \sum_{i=0}^{L-1}(i - m_G)^2 p_i$. $0 \leq \eta(k^*) \leq 1$ (higher is greater separability).
Pixel is in class c_1 if $f(x, y) \leq k^*$
Pixel is in class c_2 if $f(x, y) > k^*$

Input

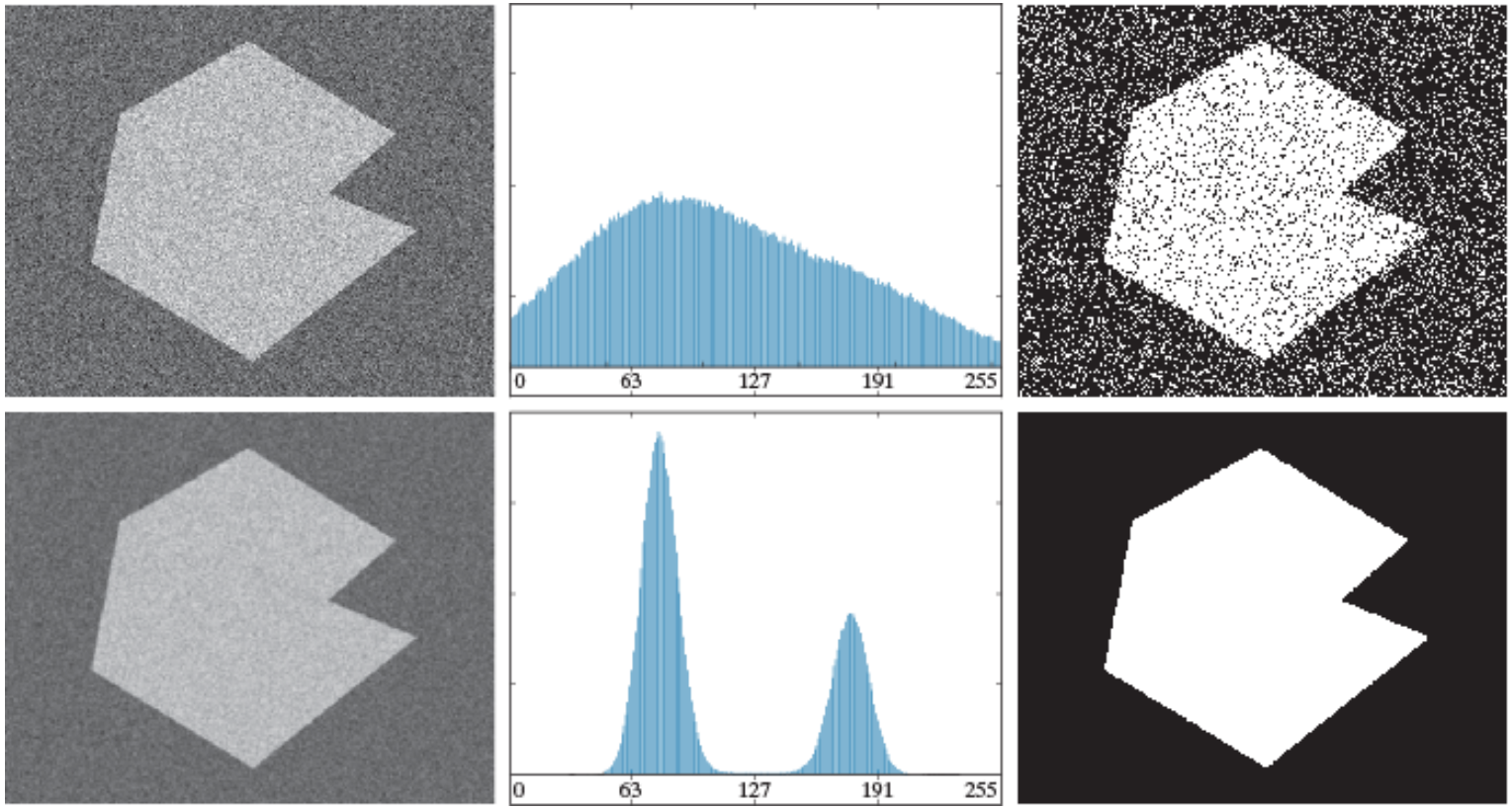




Optimum global thresholding using Otsu's method

Image smoothing to improve global thresholding

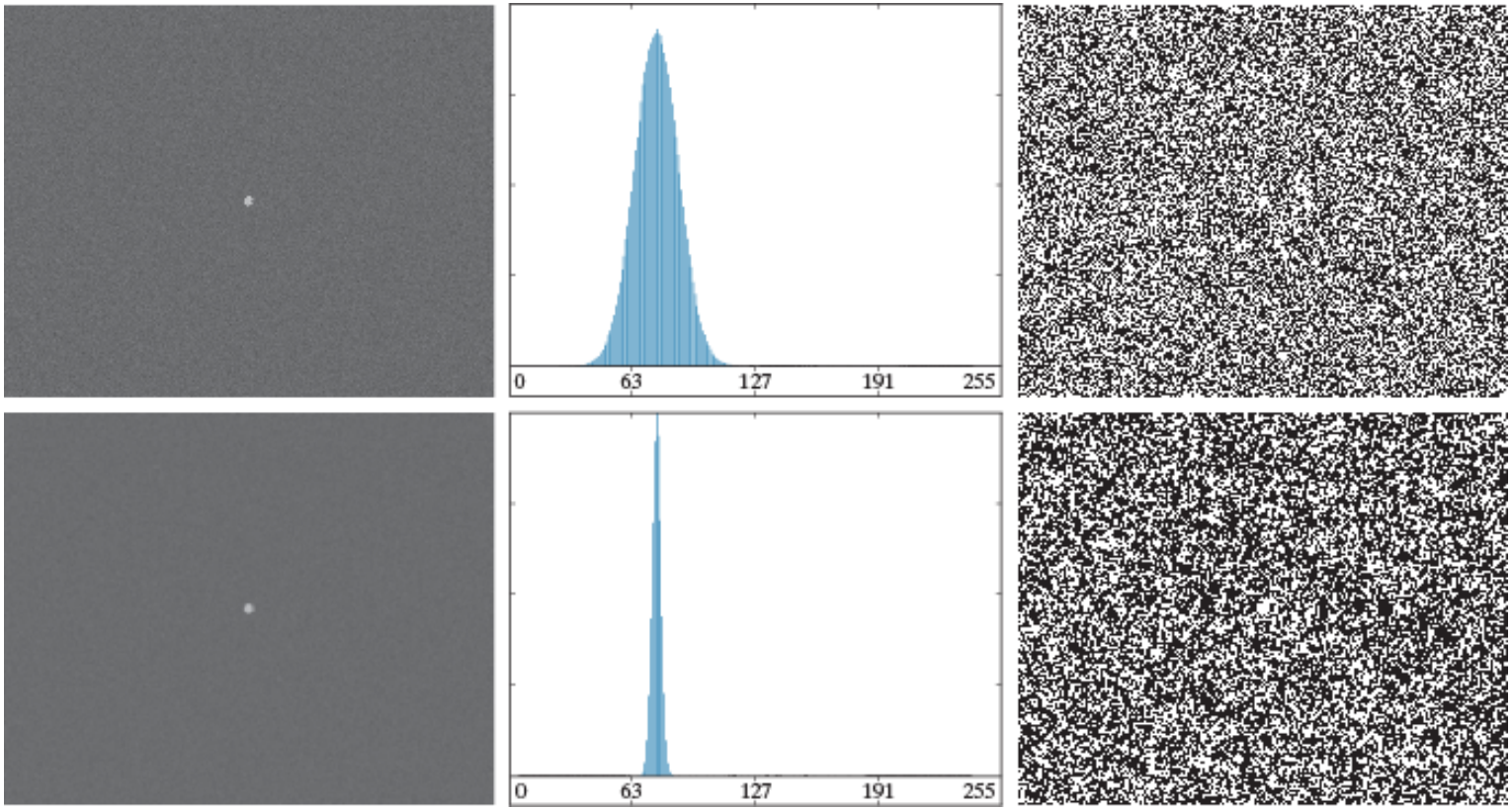
Otsu's method



Without smoothing

With smoothing

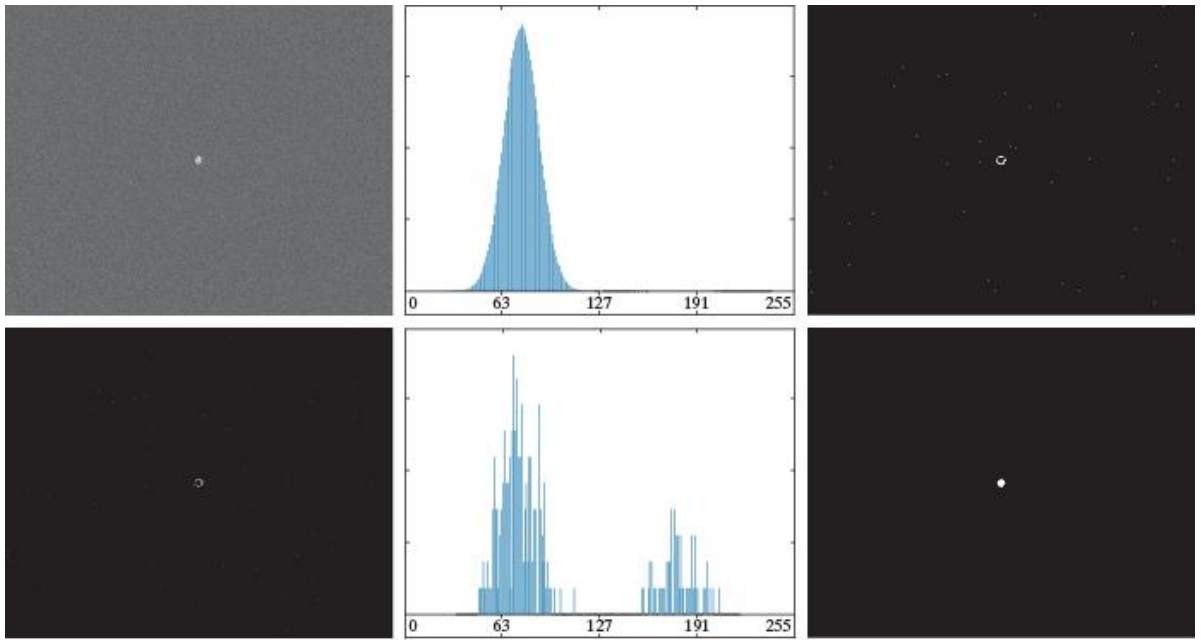
Image smoothing does not always improve global thresholding



Edges to improve global thresholding

Input

Masked input



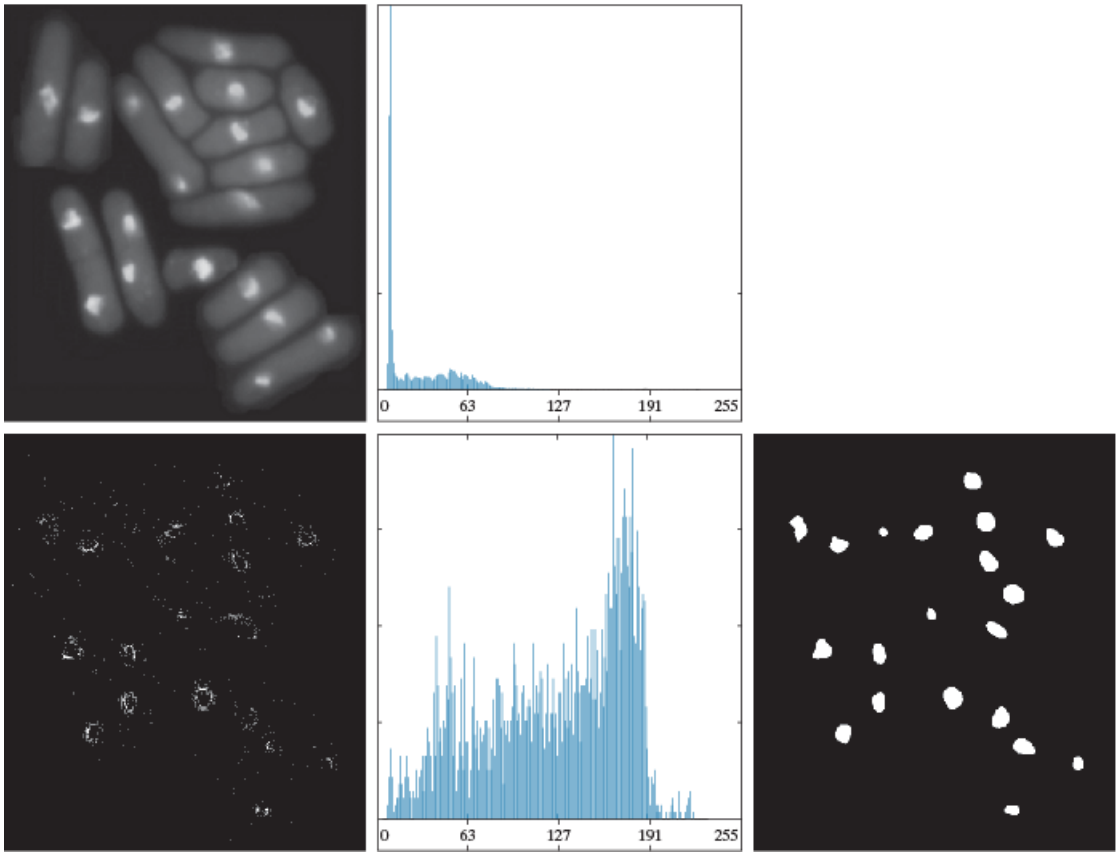
Mask image (thresholded gradient magnitude)

Optimum global thresholding using Otsu's method

Edges to improve global thresholding

Mask image (thresholded absolute Laplacian)

Input



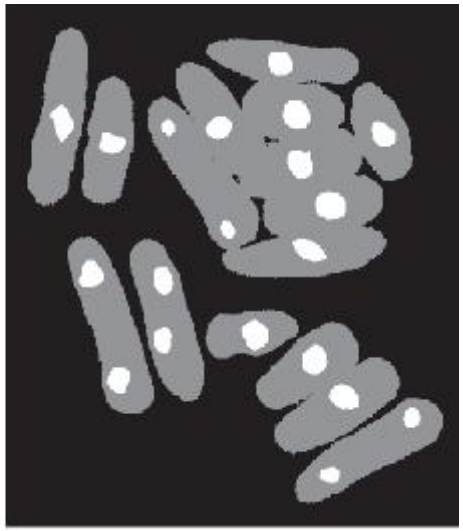
Masked input

Optimum global thresholding using Otsu's method

Variable thresholding

Input

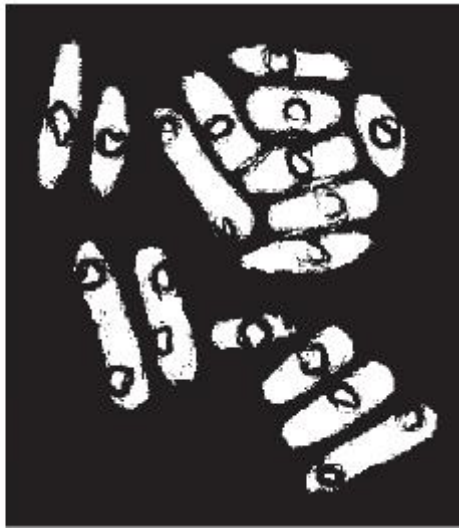




Global thresholding

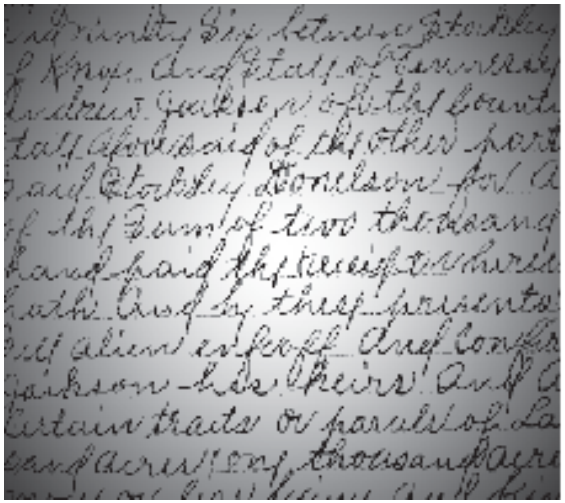
Local standard deviations



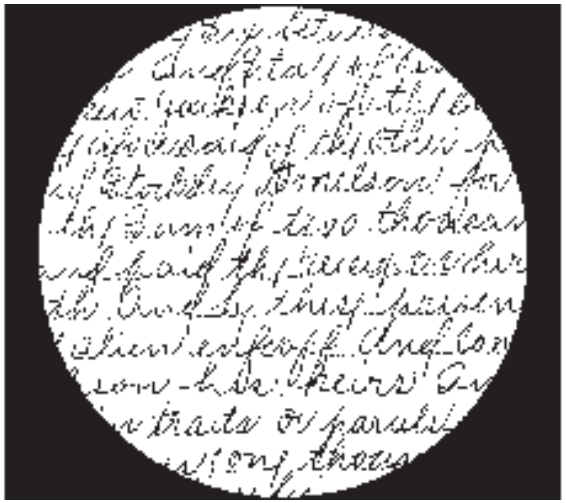


Local thresholding using standard deviations

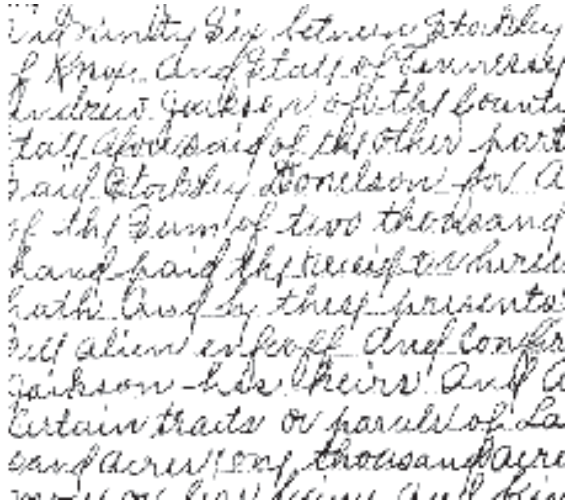
Variable thresholding



Input
(spot shading)

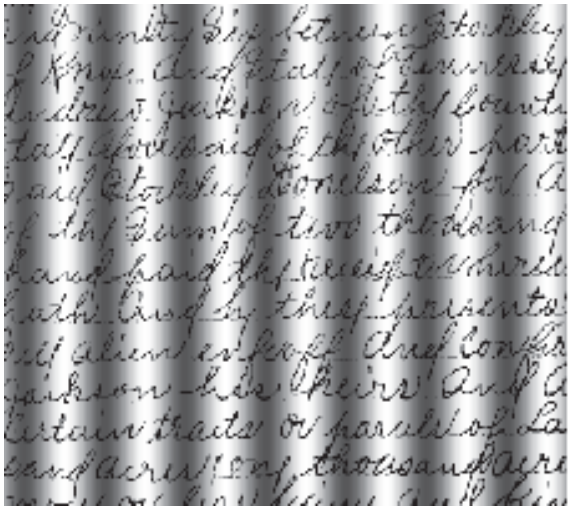


Global
thresholding



Local
thresholding
using moving
averages

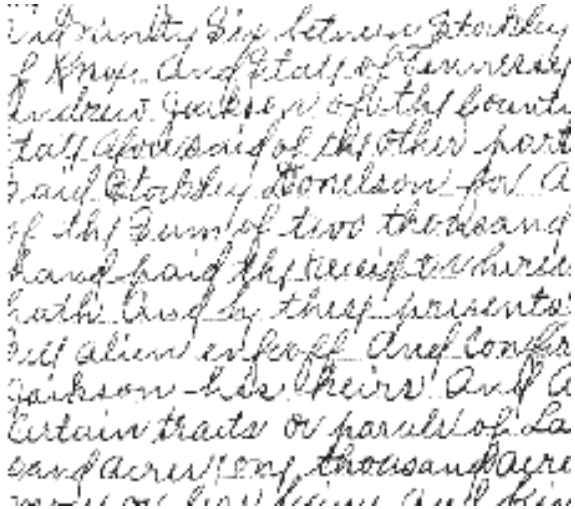
Variable thresholding



Input
(sinusoidal shading)



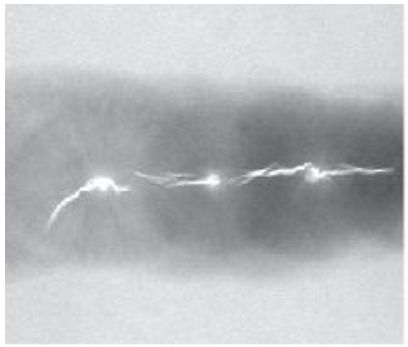
Global
thresholding

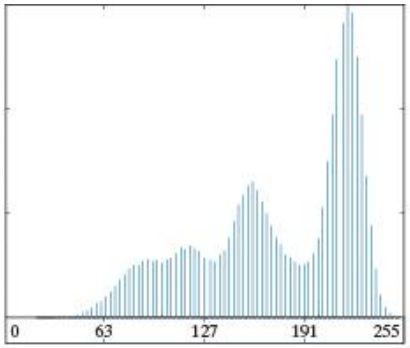


Local
thresholding
using moving
averages

Segmentation by region growing

Input X-ray image







Initial seed image

Final seed image





Output image

Segmentation by region growing

$f(x, y)$ input image

$S(x, y)$ seed image containing ones at locations of seed points and zeros elsewhere

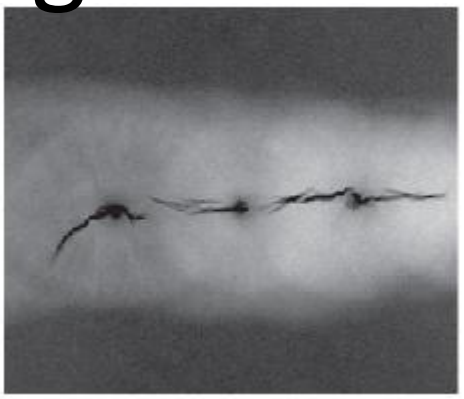
1. Find all connected components in $S(x, y)$ and reduce each connected component to one pixel. Set all such pixels as 1 (all others to zero)
2. Calculate $f_Q(x, y)$ containing results of applying prediate Q
3. Calculate $g(x, y)$ by appending to each seed point in S all 1-valued pixels in f_Q that are 8-connected to that seed point
4. Label each connected component in $g(x, y)$ with a different region label (e.g., integers)

Example predicate

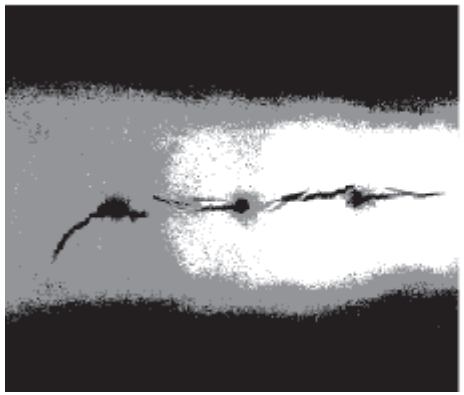
$$Q = \begin{cases} \text{TRUE} & \text{if } |f(x_{\text{seed}}, y_{\text{seed}}) - f(x, y)| \leq T \\ \text{FALSE} & \text{otherwise} \end{cases}$$

where (x, y) is 8-connected to $(x_{\text{seed}}, y_{\text{seed}})$

Segmentation by region growing



Difference image



Difference image thresholded using dual thresholds



Difference image thresholded with the smallest of the dual thresholds

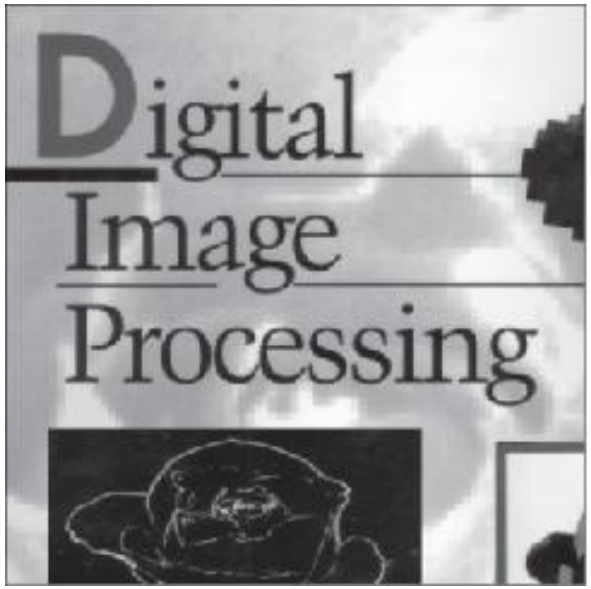


Segmentation by region growing

Advanced segmentation methods

- *k*-means clustering
- Superpixels
- Graph cuts

Segmentation using *k*-means clustering



Input



Segmentation using
k-means, *k* = 3

Segmentation using *k*-means clustering

Set of samples
grayscale: $\{z_1, z_2, \ldots, z_Q\}$, where z_j is grayscale value of j-th pixel
RGB color: $\{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_Q\}$, where $\mathbf{z}_j = (r_j, g_j, b_j)^T$ is the RGB values of the j-th pixel
Partition the set of observations into k clusters $\{C_1, C_2, \ldots, C_k\}$ such that the following is satisfied

$$\arg\min_{C} \left(\sum_{i=1}^{k} \sum_{\mathbf{z} \in C_i} \|\mathbf{z} - \mathbf{m}_i\|^2 \right)$$

where $\mathbf{m}_i$ is the mean vector of the samples in set C_i. That is, find $\{C_1, C_2, \ldots, C_k\}$ such that the sum of squared distances from each point in a set to the mean of that set is minimum.

Segmentation using *k*-means clustering

1. Specify an initial set of means $\mathbf{m}_i \quad i = 1, 2, \ldots, k$
2. Assign each sample to the cluster whose mean is closest
   (ties are resolved aribitrarily, so samples are assigned to only one cluster)
3. Update cluster means

$$\mathbf{m}_i = \frac{1}{|C_i|} \sum_{\mathbf{z} \in C_i} \mathbf{z} \quad i = 1, 2, \ldots, k$$

   where $|C_i|$ is the number of samples in set C_i

4. If mean vectors do not converge, then return to step 2
   Test for convergence:

$$\sum_{i=1}^{k} \|\mathbf{m}_i^{(t)} - \mathbf{m}_i^{(t-1)}\| \leq T$$

   where T is a specificied threshold

Depends on initial set of means

Superpixels

- Group pixels into primitive regions that are more perceptually meaningful that individual pixels. Results in less “pixels” to process.



Input image of 480,000 pixels

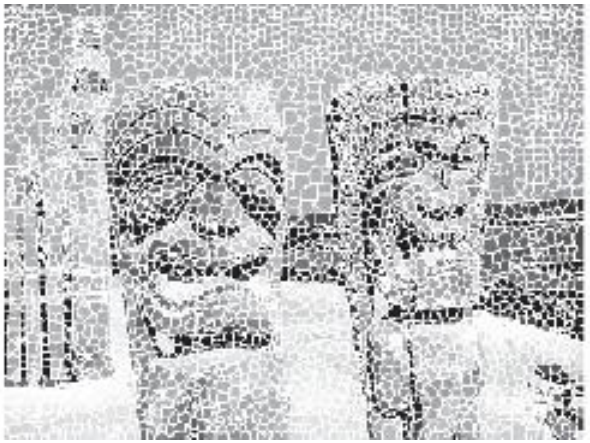
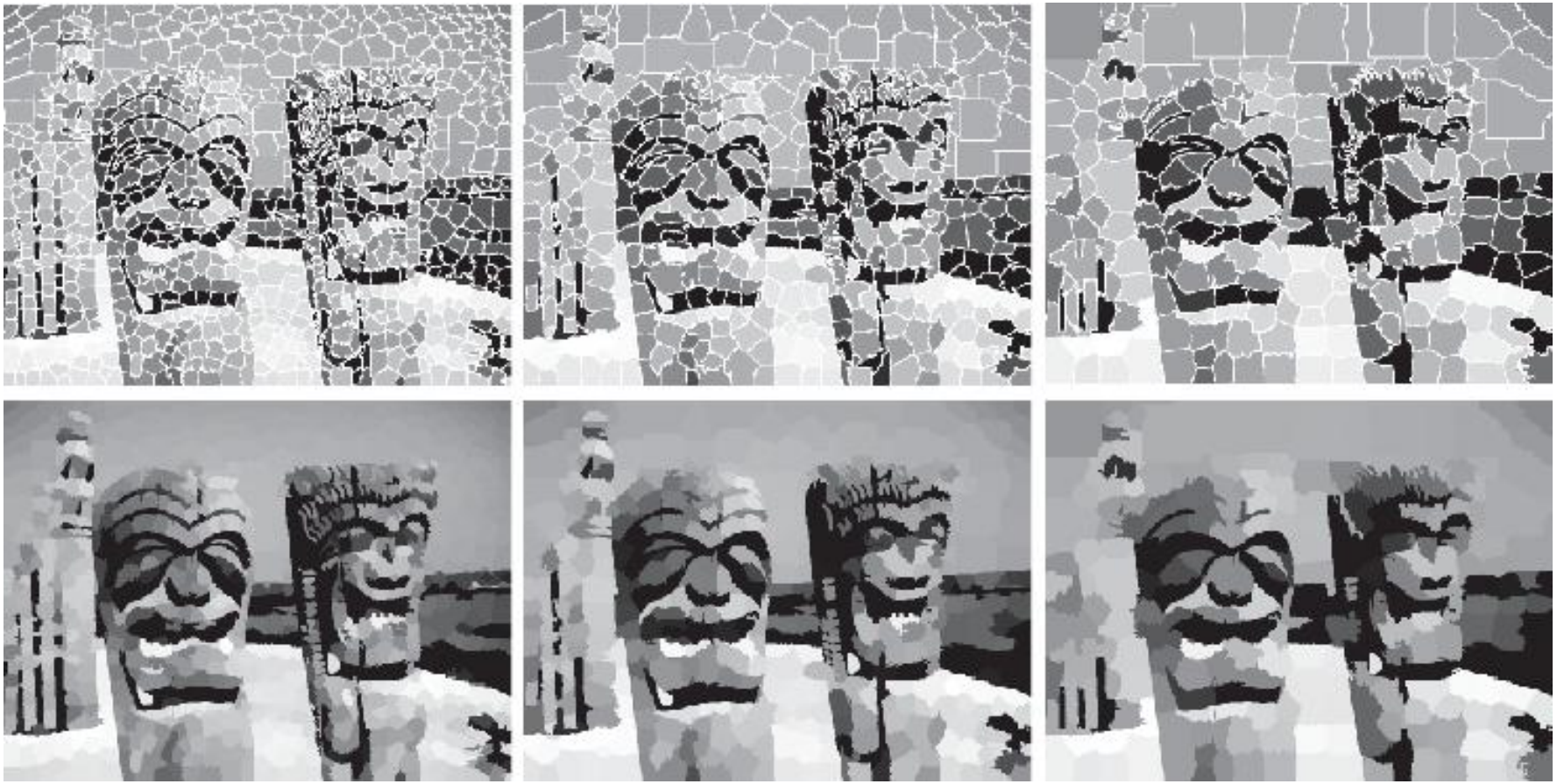


Image of 4,000 superpixels with boundaries



Image of 4,000 superpixels

Superpixels



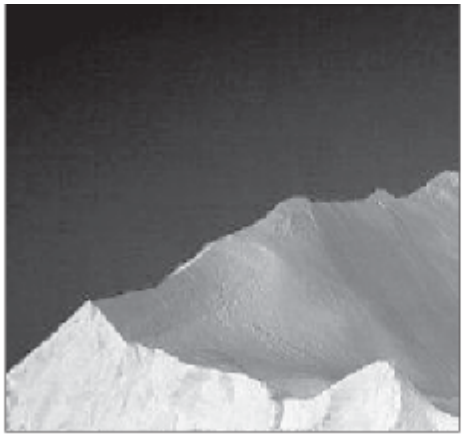
1,000 superpixels

500 superpixels

250 superpixels

Superpixels for image segmentation

Input image of 301,678 pixels





Segmentation using *k*-means, *k* = 3





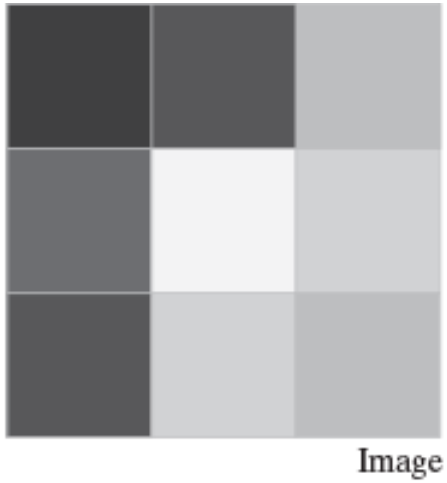


Superpixel image (100 superpixels)

Segmentation using *k*-means, *k* = 3

Images as graphs

- Pixels in the image as nodes in a graph with edges connecting every pair of nodes
  - Use a weighted graph, where the weight of each edge is a function of the similarity between the nodes
  - Typically, weights are formed from spatial relationships (e.g., distance between pixels) and intensity measures (e.g., texture and color)

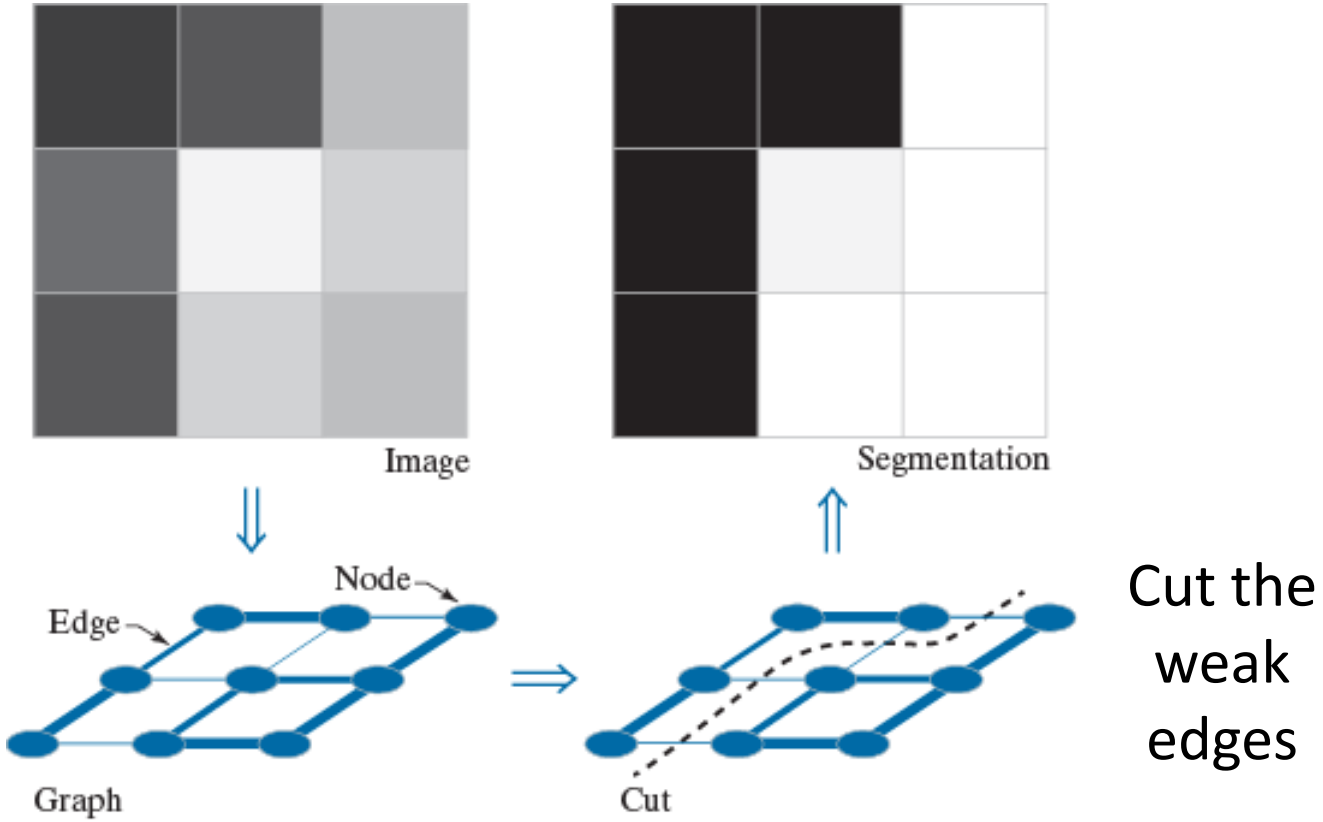


Simple graph with edges only between 4-connected neighbors

Stronger (greater weight) edges are darker

Graph cuts for image segmentation

- The nodes are partitioned into two subsets by a cut of the graph



Graph cuts for image segmentation



Input



Smoothed input



Graph cut segmentation

Next Lecture

- Feature extraction
- Reading
  - Chapter 12: Feature extraction
    - Sections 12.1, 12.4, and 12.6