Announcements

• Assignment 5 is due Jun 5, 11:59 PM
• Final exam
• 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

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 \( P_1 + P_2 = 1 \))

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)
Image smoothing to improve global thresholding

Otsu’s method

Without smoothing

With smoothing
Image smoothing does not always improve global thresholding

Otsu’s method

Without smoothing

With smoothing
Edges to improve global thresholding

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
- Local thresholding using standard deviations
- Global thresholding
- Local standard deviations

CSE 166, Spring 2019
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

Final seed image

Output image

Initial seed 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 predicate \( Q \)

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)
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

1. Specify an initial set of means $m_i, i = 1, 2, \ldots, k$

2. Assign each sample to the cluster whose mean is closest
   (ties are resolved arbitrarily, so samples are assigned to only one cluster)

3. Update cluster means
   \[ m_i = \frac{1}{|C_i|} \sum_{z \in C_i} z \quad i = 1, 2, \ldots, k \]
   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:
   \[ \sum_{i=1}^{k} \| m_i^{(t)} - m_i^{(t-1)} \| \leq T \]
   where $T$ is a specified threshold
Superpixels

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

Superpixel image (100 superpixels)

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

Segmentation using $k$-means, $k = 3$
Images as graphs

Simple graph with edges only between 4-connected neighbors

Stronger (greater weight) edges are darker
Graph cuts for image segmentation

Cut the weak edges
Graph cuts for image segmentation

Input  Smoothed input  Graph cut segmentation
Next Lecture

• Final exam review