Binary Image Analysis

A Binary images can be useful for numerous tasks

- ▲ Identifying objects in an image
- ▲ Recognizing text, symbols, drawings
- ▲ Determining orientations of objects in an image

▲ Applications involve

- ▲ Text recognition (mail delivery, text-to-speech, etc..)
- ▲ Quality control systems in manufacturing systems
- ▲ Analysis of satellite imagery

Key Principles

Connectedness

- ▲ Connectedness: how to determine whether two pixels are "connected".
 - ▲ Usually to determine if two pixels belong to the same component.
- ▲ Two common definitions of connectivity
 - ▲ 4 connected and 8 connected
 - ▲ A pixel is connected to P if both P and the pixel of interest X are both 1

	X	
X	P	X
	X	

 $egin{array}{c|cccc} X & X & X \\ \hline X & {m P} & X \\ \hline X & X & X \\ \hline \end{array}$

4 connected

8 connected

Thresholding

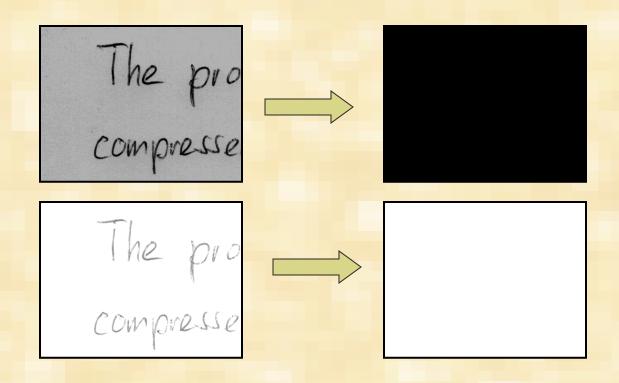
• Global: Based on the intensities of the whole image. Thresholding creates binary images from gray-level ones by turning all pixels below some threshold to zero and all pixels above that threshold to one.

$$g(m,n) = \begin{cases} 1 & \text{if } u(m,n) \ge T \\ 0 & \text{otherwise} \end{cases}$$

• Local: Based on the intensities of a region of the image.

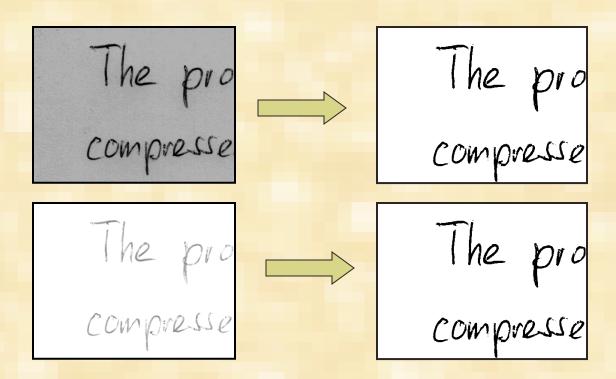
Thresholding

- ▲ Given a gray-scale image, convert it to binary using thresholding. How to separate "objects" from "background"?
 - ▲ Choose a threshold value of 128?



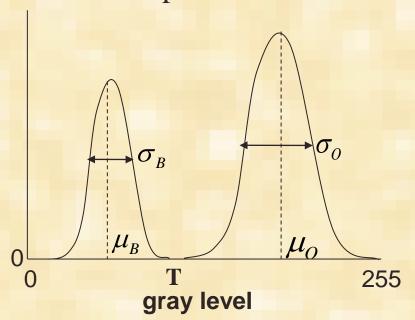
Adaptive Thresholding

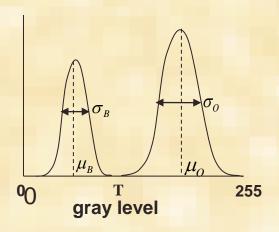
- ▲ Given a gray-scale image, convert it to binary using thresholding. How to separate "objects" from "background"?
 - ▲ Choose a threshold value adaptively.



Adaptive Thresholding Clustering (The Otsu method)

Consider the histogram distribution of an image is in the shape of two clusters. An appropriate threshold can be determined by making each cluster as tight as possible. We can adjust the threshold by increasing the spread of one and decreasing the other. The goal then is to select the threshold that minimizes the combined spread.





The Otsu method

$$\mu = \sum_{i=0}^{N-1} x_i p(x_i) \qquad \eta_B(T) = \sum_{i=0}^{T-1} p(x_i)$$

$$\sigma = \sum_{i=0}^{N-1} (x_i - \mu)^2 p(x_i) \qquad \eta_O(T) = \sum_{i=T}^{N-1} p(x_i)$$

$$\mu = \eta_B(T) \mu_B(T) + \eta_O(T) \mu_O(T)$$

Let define the within-class variance as the weighted sum of the variances of each cluster.

$$\sigma_w^2(T) = \eta_B(T)\sigma_B^2(T) + \eta_O(T)\sigma_O^2(T)$$

Between-class variance can be written as

$$\sigma_B^2(T) = \sigma^2 - \sigma_W^2(T) = \eta_B(T) [\mu_B(T) - \mu]^2 + \eta_O(T) [\mu_O(T) - \mu]^2$$

The optimum threshold is the one that maximizes the between-class variance or, conversely, minimizes the within-class variance.