Segmentation – Part 1

Thresholding Segmentation Technique

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This material is a modified version of the slides provided by Milan Sonka, Vaclav Hlavac, and Roger Boyle, **Image Processing, Analysis, and Machine Vision**..

Agenda

- What is Segmentation
- Segmentation techniques:

1. **Thresholding**
2. **Edge-based Segmentation**
3. **Region-based Segmentation**
4. **Matching**

Segmentation

- **Goal**: to divide an image into parts that have a strong correlation with objects or areas of the real world, mainly objects and background.
- All pixels in a region **share a common property**, like intensity, texture.
- A complete segmentation of an image *R* is a set of regions *R1, R2, …, Rs*

$$R = \underset{i=1}{\overset{S}{¿}} R_i \qquad R_i \cap R_j = \varphi \qquad i \neq j$$

Segmentation

- **Segmentation may be**
  - **Complete segmentation** - set of disjoint regions uniquely corresponding with objects in the input image
  - **Partial segmentation** - regions do not correspond directly to image objects

image is divided into separate regions that are homogeneous with respect to a chosen property such as brightness, color, etc.
in a complex scene, a set of possibly overlapping homogeneous regions may result. The partially segmented image must then be subjected to further processing, and the final image segmentation may be found with the help of higher level information.

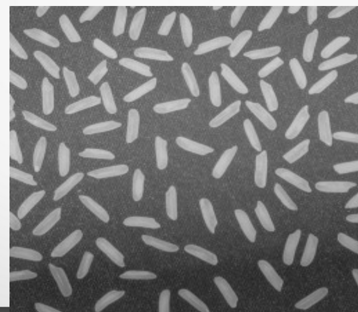
Thresholding Segmentation Technique

- Basic, Band, Multi, Semi-Thresholding
- Threshold detection methods
- **Multi-spectral Thresholding**
- Algorithms
  - Iterative (optimal) Threshold Selection

Advantages

- **Simplest** segmentation process since Many objects or image regions are characterized by constant reflectivity or light absorption of their surface.
- computationally inexpensive and **fast** and can easily be done in **real time**
- **When to use Thresholding:**
  - Objects don’t touch each other
  - Objects’ gray levels are clearly distinct from background’ gray level.



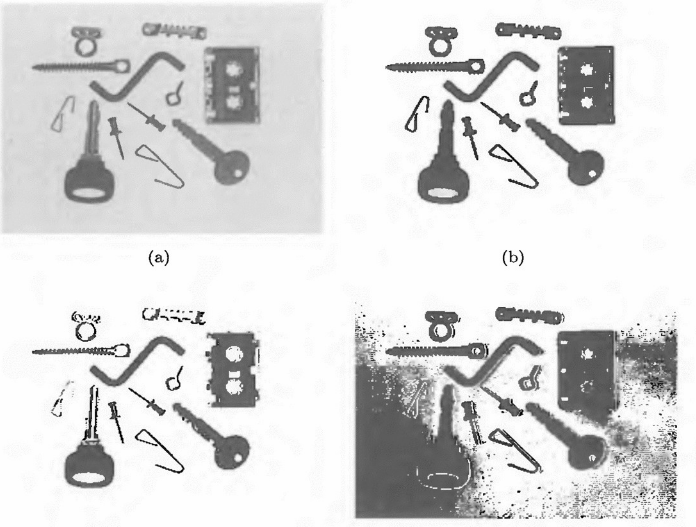


Basic Thresholding

- Basic thresholding of an input image f to an output image g is as follows:

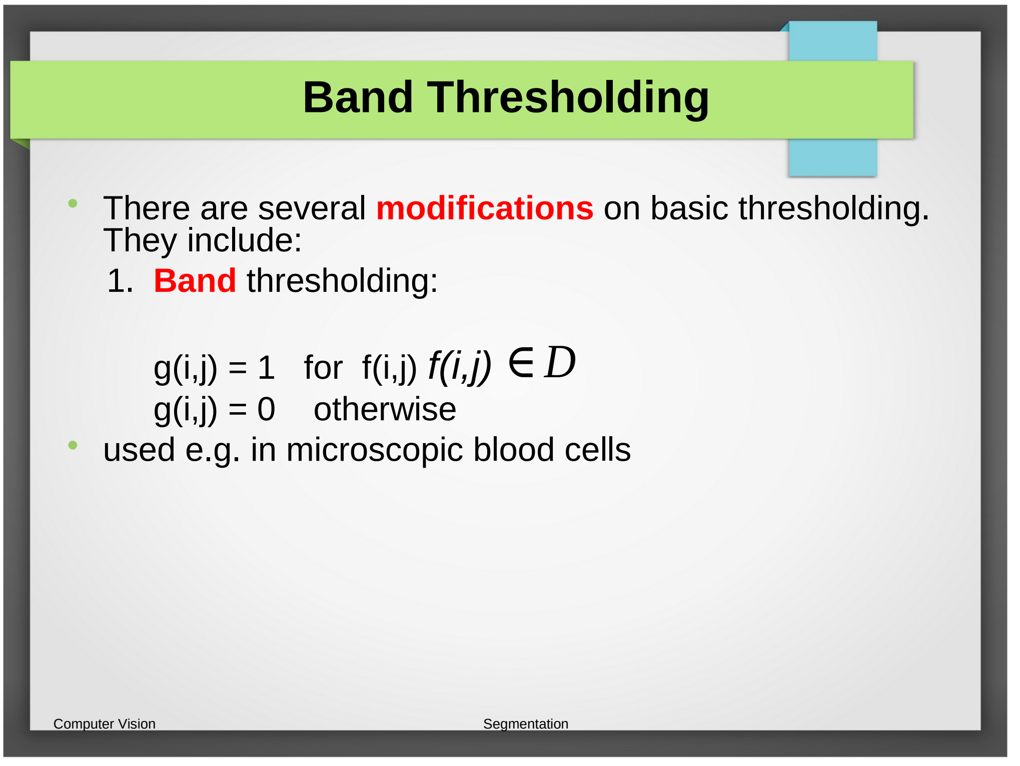
g(i,j) = 1 for *f(i,j)* ¿ T

g(i,j) = 0 for *f(i,j)* ¿ T

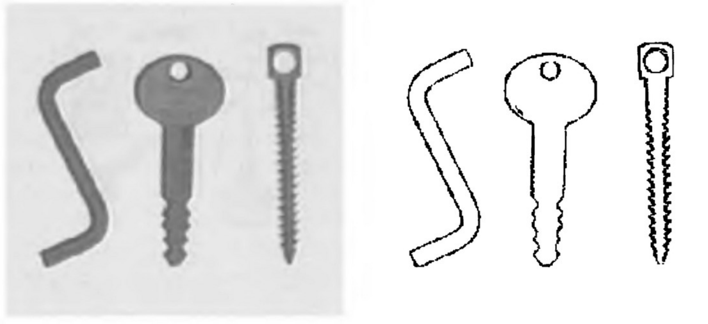


(a) (b) (c) (d)

Figure 6.1: Image thresholding. (a) Original image. (b) Threshold segmentation. (c) Threshold too low. (d) Threshold too high.



Can be used as border detector assuming dark objects in light background , some gray levels between those objects and background only found in the borders



(a) (b)

Figure 6.2: Image thresholding modification. (a) Original image. (b) Border detection using band-thresholding.

Multi-Thresholding

2. **Multi-thresholding**, using limited set of array levels:

g(i,j) = 1	for f(i,j) $\in D_1$
g(i,j) = 2	for f(i,j) $\in D_2$
g(i,j) = 3	for f(i,j) $\in D_3$
.	
.	
.	
g(i,j) = n	for f(i,j) $\in D_n$
g(i,j) = 0	otherwise

Semi-Thresholding

3. **Semi-thresholding**, masks out background

g(i,j) = f(i,j) for f(i,j) ¿ T

g(i,j) = 0 for f(i,j) ¿ T

Threshold Detection techniques

- P-tile thresholding
- Histogram Shape Analysis
- Hysteresis thresholding
- Optimal Thresholding

If the histogram is bi model

Threshold Detection techniques

- **P-tile thresholding**
  - a priori information: **object is brighter/darker than background and occupies a certain known percentile 1/p from the total image area.**
  - We set the threshold by finding the intensity level such that 1/p image pixels are below this value

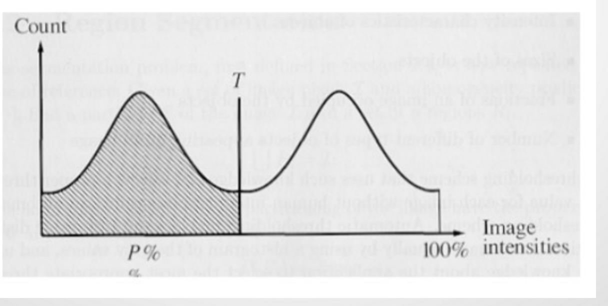
Computer Vision Segmentation

If the histogram is bi model

P-tile thresholding

Threshold is selected such that **1/p** of image pixels has gray values less than T.

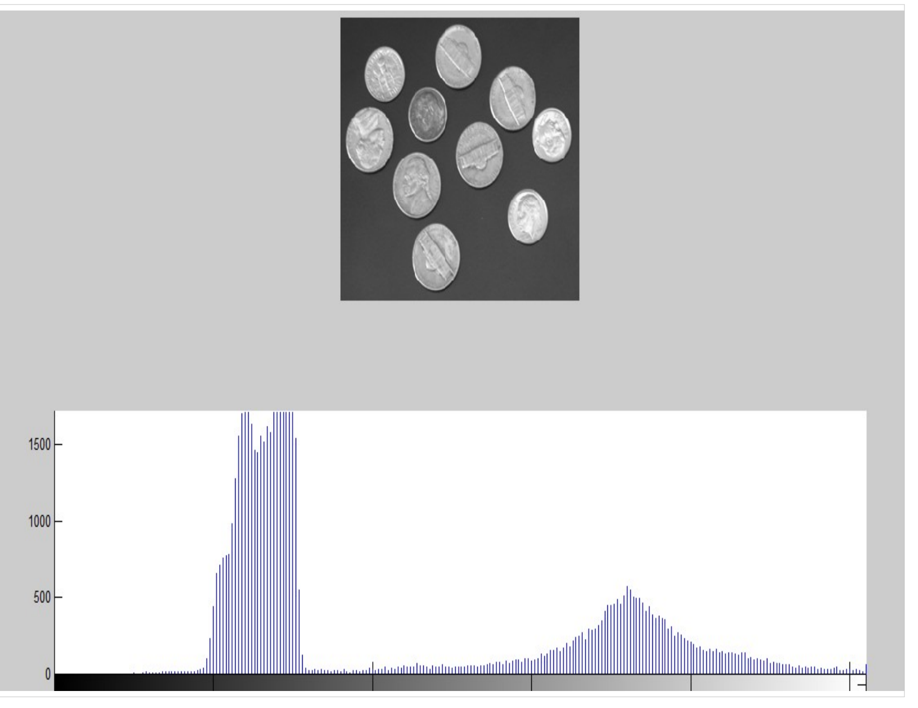
A good example is **processing text pages.**



Thresholding Detection Methods

- **Histogram Shape Analysis**
  - **Bi-modal histogram:** **i**f objects have approximately the same gray level that differs from the gray level of the background

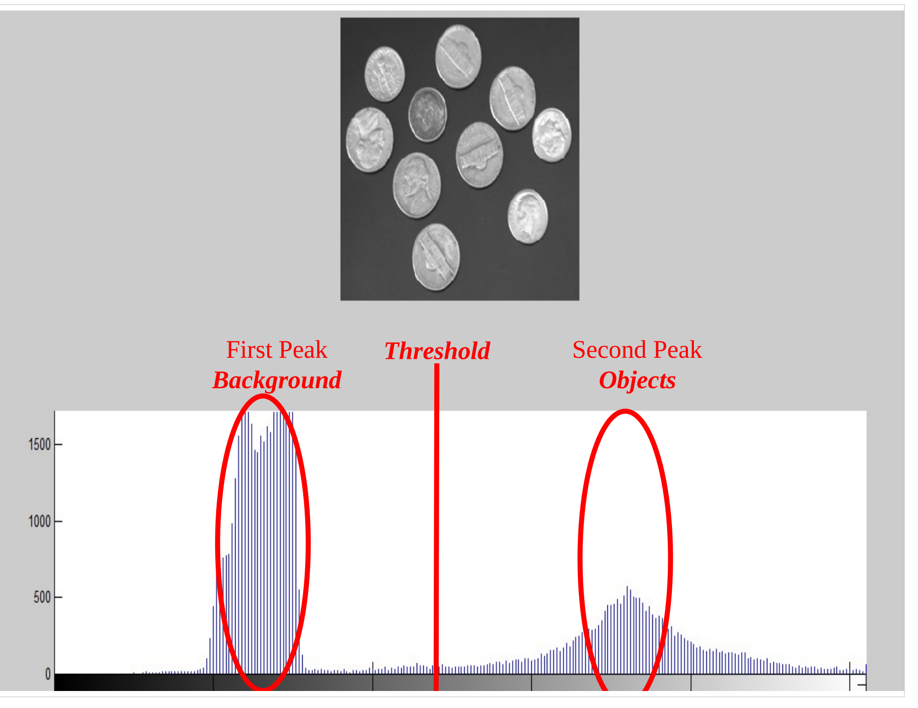
The o/p image is not binary anymore


1500
1000
500
0

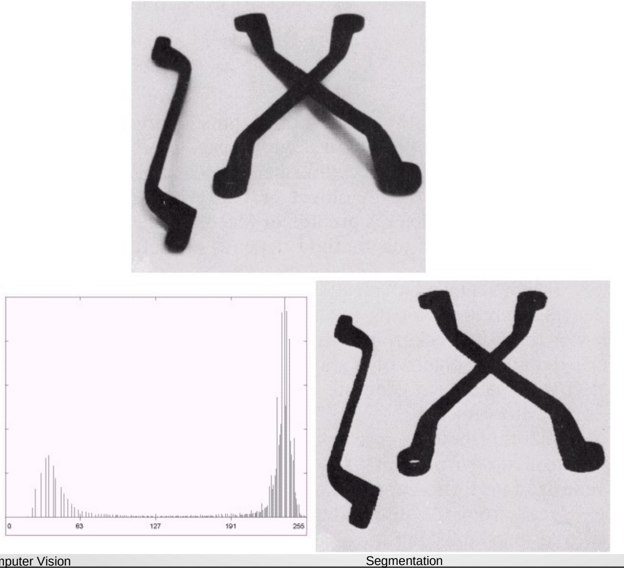
Thresholding Detection Methods

- **Histogram Shape Analysis**
  - **Mode Method:** used for detecting threshold for bi-modal histogram.
    - find the highest local maxima first and detect the threshold as a minimum between them
    - to avoid detection of two local maxima belonging to the same global maximum, a minimum distance in gray levels between these maxima is usually required.

The o/p image is not binary anymore


First Peak
Background
Threshold
Second Peak
Objects
1500
1000
500
0

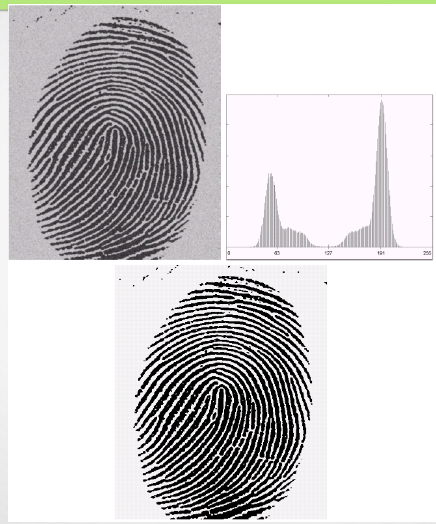
Segmentation Example 1



a
b c

FIGURE 10.28 (a) Original image. (b) Image histogram. (c) Result of global thresholding with T midway between the maximum and minimum gray levels.

Segmentation Example 2



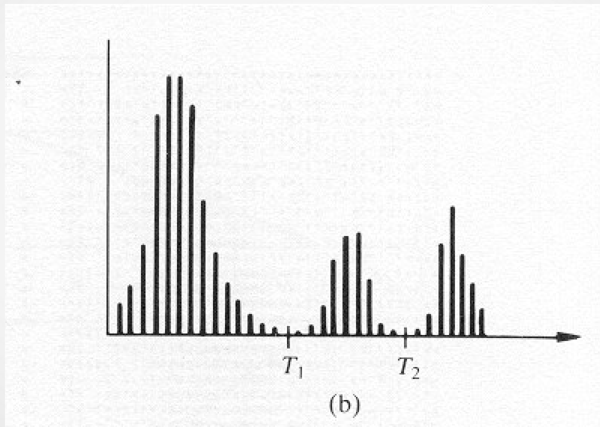
a b
c

FIGURE 10.29 (a) Original image. (b) Image histogram. (c) Result of segmentation with the threshold estimated by iteration. (Original courtesy of the National Institute of Standards and Technology.)

Thresholding Detection Methods

- **Histogram Shape Analysis**
  - **Multi-Modal Histogram:** more thresholds required to segment the image.
    - **Multi thresholding** is used.

Thresholding Examples



Computer Vision Segmentation

In general, good thershold can be selected if the histogram peaks are tall, narrow, symmetric, and separated by deep valleys.

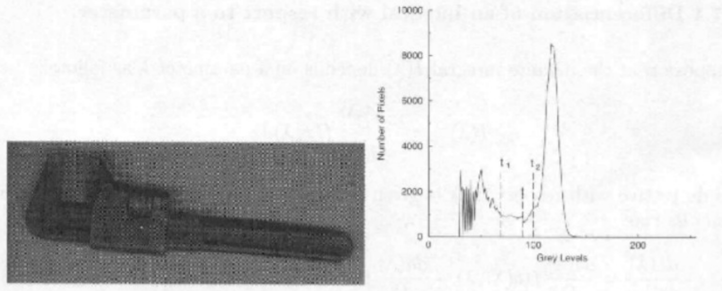
Thresholding Detection Methods

- **Histogram Shape Analysis**
  - **Problem**: noisy histograms .

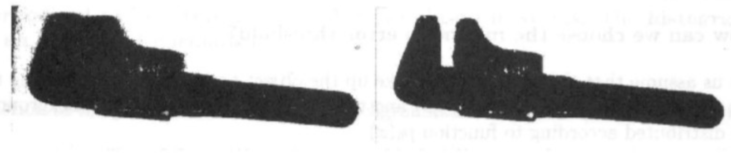
Hysteresis thresholding

- NO clear valley in the histogram of an image
- **Two thresholds** can be used (one at each side of the valley)
  - Pixels **above the high threshold** are classified as **object** and **below the low threshold** as **background**.
  - Pixels between the low and high thresholds are classified as object only if they are adjacent to other object pixels.

it means that there are several background pixels that have similar gray level value with object pixels and vice versa.



(a) Original image (b) Histogram of (a)

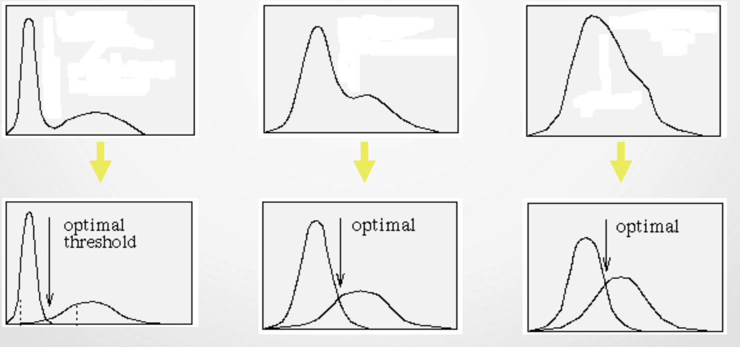


Optimal Thresholding

It approximates histogram using two or more probabilities with **normal distribution**. The threshold is then the min probability between the maxima of the these normal distributions.

It results in **minimum error segmentation**.

Optimal Thresholding



Threshold Detection techniques
Actual Example

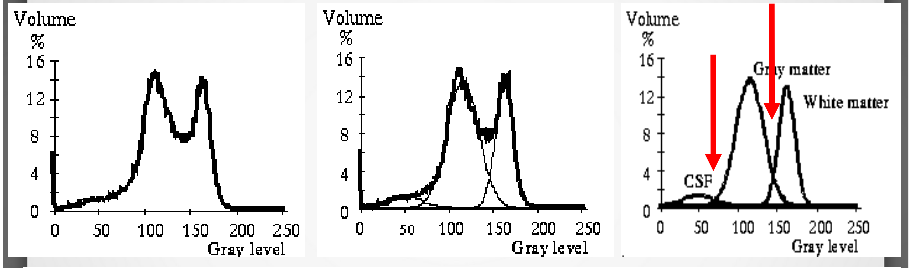


Figure 5.5 *Segmentation of 3-D T1-weighted MR brain image data using optimal thresholding: (a) Local gray level histogram, (b) fitted Gaussian distributions; global 3-D image fit, (c) Gaussian distributions corresponding to WM, GM, and CSF. Courtesy R.J. Frank, T.J. Grabowski, Human Neuroanatomy and Neuroimaging Laboratory, Department of Neurology, The University of Iowa.*

Brain MR Image Segmentation

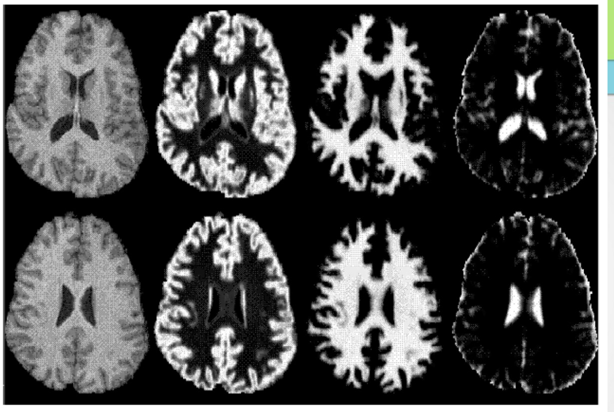


Figure 5.6 *Optimal MR brain image segmentation. Left column: Original T1-weighted MR images, two of 120 slices of the 3-D volume. Middle left: Partial-volume maps of gray matter. The brighter the voxel, the higher is the partial volume percentage of gray matter in the voxel. Middle right: Partial-volume maps of white matter. Right column: Partial-volume maps of cerebro-spinal fluid. Courtesy R.J. Frank, T.J. Grabowski, Human Neuroanatomy and Neuroimaging Laboratory, Department of Neurology, The University of Iowa.*

Algorithm: Iterative Threshold Selection

1. As first iteration consider that the 4 corners contain background pixels only and the remainder contains object pixels.
2. Calculate μ_B^t and μ_O^t as the average intensity of background and object pixels.
3. At step t+1 segmentation is performed using the threshold

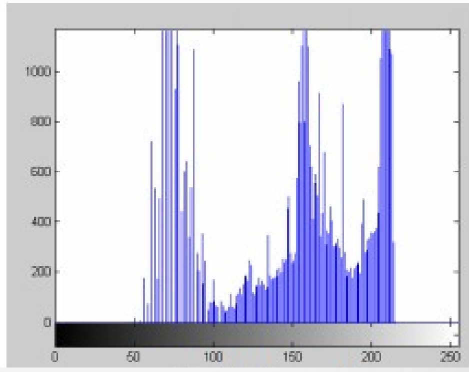
$$T^{(t+1)} = \frac{\mu_B^t + \mu_O^t}{2}$$

Algorithm: Iterative Threshold Selection

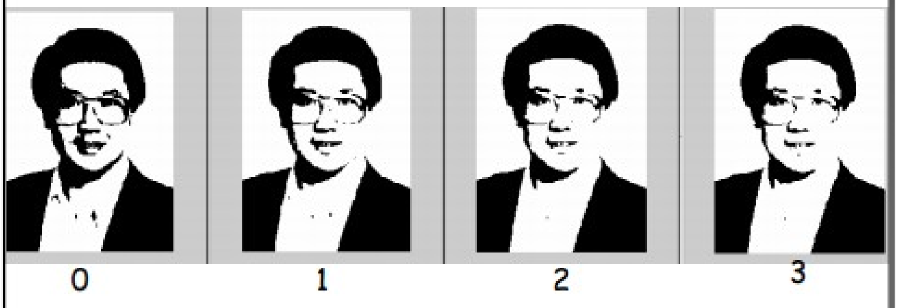
4. Re-calculate μ_B^t and μ_O^t according to new segmentation using:

$$\mu_B^t = \frac{\sum_{(i,j)\in background} f(i,j)}{\#background\_pixels} \qquad \mu_O^t = \frac{\sum_{(i,j)\in objects} f(i,j)}{\#object\_pixels}$$

5. Re-calculate $T^{(t+1)}$
6. Stop if $T^{(t+1)} = T^{(t)}$



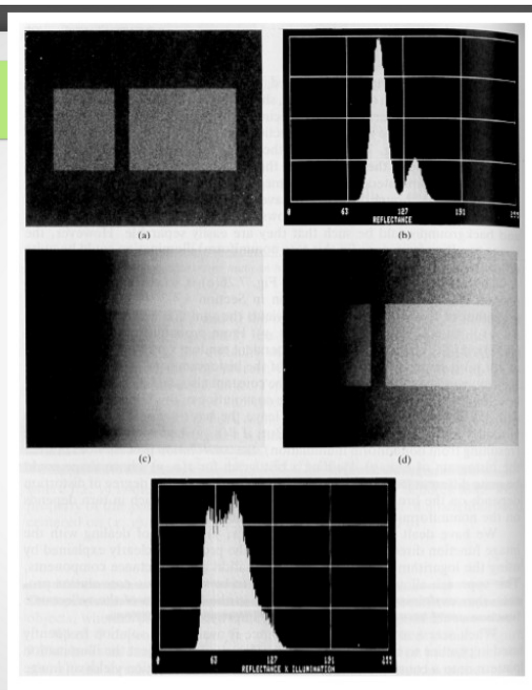
1000
800
600
400
200
0
0
50
100
150
200
250



- Iteration 0: T=146,0 u1=90,1 u2=182,0
- Iteration 1: T=136,0 u1=85,3 u2=179,9
- Iteration 2: T=133,0 u1=83,7 u2=179,2
- Iteration 3: T=131,0 u1=83,1 u2=178,8
- Iteration 4: T=131,0 u1=83,1 u2=178,8

Problems with Global Threshold

- Applies a global threshold
  - Can't handle changing illumination
- Can give poor results for certain types of images
- We may consider a local approach



Illumination effect

Local Thresholding

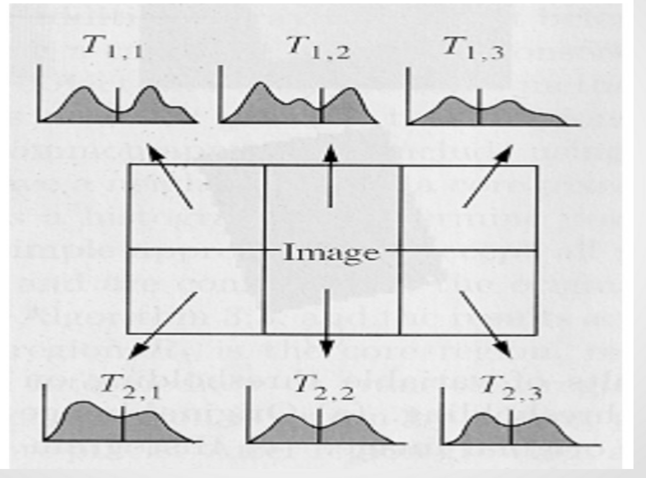
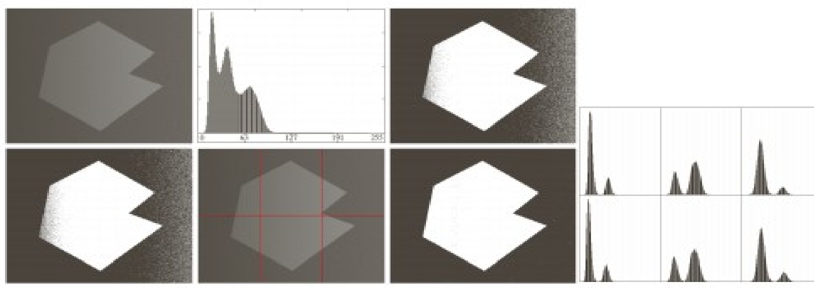
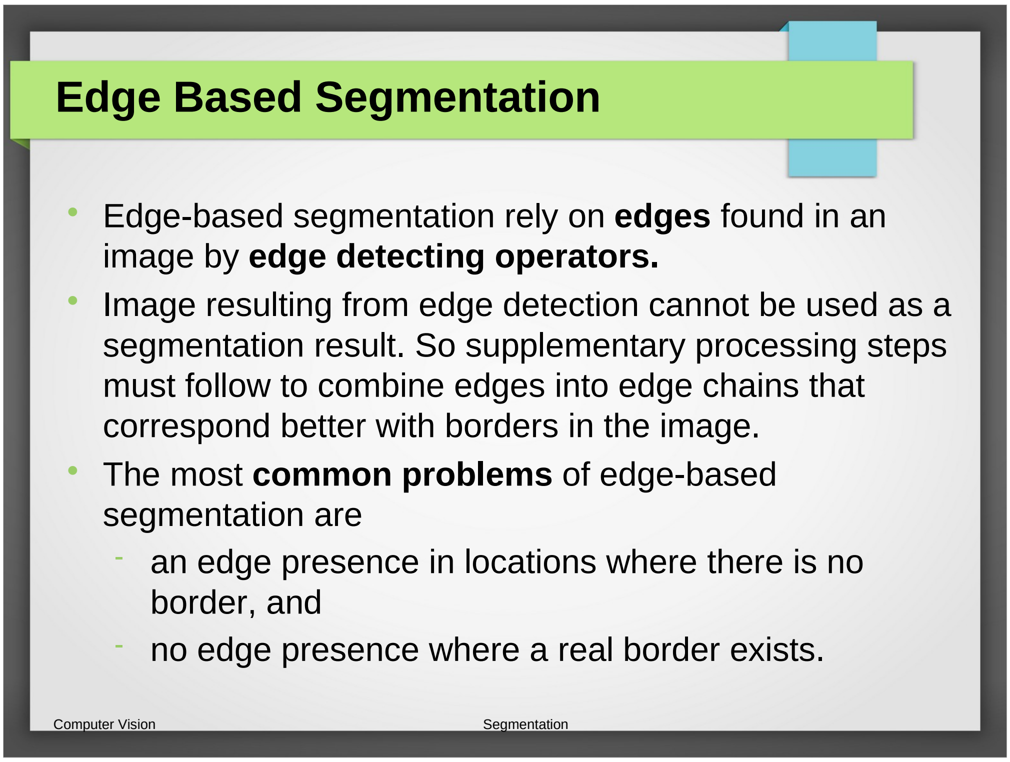


Image Partitioning Based Thresholding (Local Thresholding)

- In order to face non uniform illumination or reflectance, the image is partitioned and the thresholding is operated on each partition.
  - In each partition, the illuminance and reflectance is supposed uniform.
  - In each partition, objects and background have to be equally represented.



Local thresholding or Adaptive thresholding



The final aim is to reach at least a partial segmentation -- that is, to group local edges into an image where only edge chains with a correspondence to existing objects or image parts are present.

Edge Based Segmentation

- **Edge Image Thresholding**
  - Almost no zero-value pixels are present in an edge image, but small edge values correspond to non-significant gray level changes resulting from quantization noise, small lighting irregularities, etc.
  - **Selection of an appropriate global threshold is often difficult and sometimes impossible;**

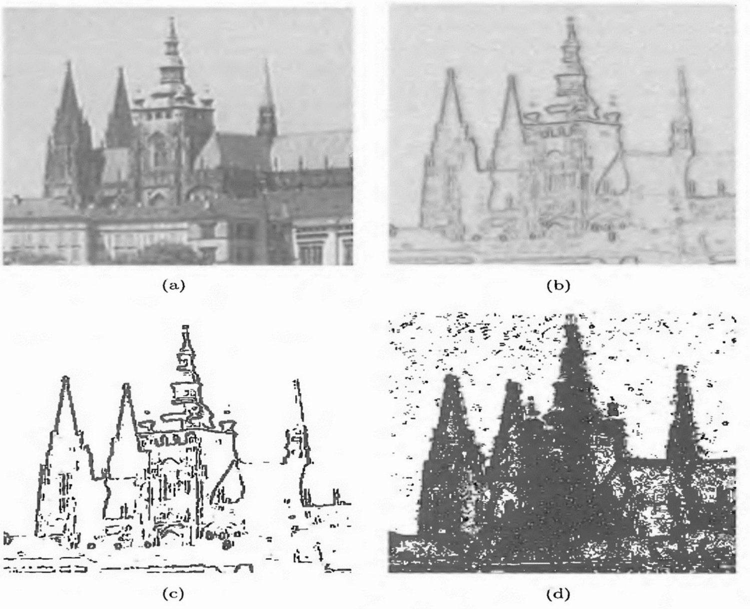


Figure 6.8: Edge image thresholding. (a) Original image. (b) Edge image (low contrast edges enhanced for display). (c) Edge image thresholded at 30. (d) Edge image thresholded at 10.

Edge Based Segmentation

- **Edge Image Thresholding**
  - Alternatively, **non-maximal suppression** and **hysteresis thresholding** can be used as was introduced in the Canny edge detector.

(a) (b)

Figure 6.9: (a) Non-maximal suppression of the data in Figure 6.8a. (b) hysteresis applied to (a); high threshold 70, low threshold 10.

Summary

- Basic, Band, Multi, Semi-Thresholding
- Threshold detection methods
- Multi-spectral thresholding
- Hierarchical Thresholding
- Algorithms
  - Iterative Threshold Selection
- Edge based Segmentation
  - Edge Thresholding