15.10.2019

Digital Image Processing (CSE/ECE 478)

Lecture-16: Image Segmentation (contd.)

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Many slides borrowed from Vineet Gandhi @CVIT!

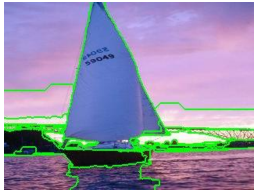
Announcements

- Project proposal review: 19/10 Saturday (tutorial)
- Team ←→ TA mapping
- Project
  - Novelty:
    - Making the method faster
    - More general (can it be applied to other types of data ?)
    - Ultimate: a new method which is faster or more general

Image Segmentation

Partitioning an image into a collection of connected sets of pixels.

1. into regions, which usually cover the image



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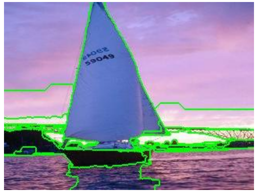
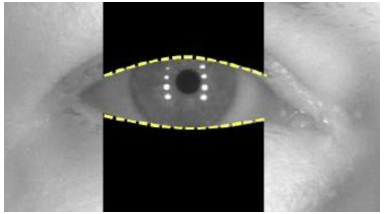


2. into linear structures, such as
   - line segments
   - curve segments



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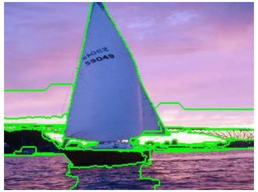

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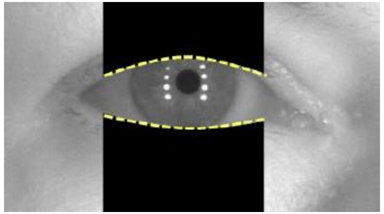


3. into 2D shapes, such as
   - circles
   - ellipses
   - ribbons (long, symmetric regions)

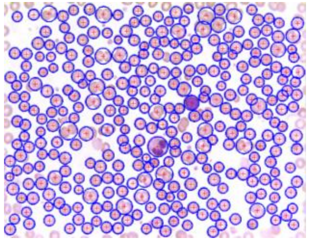


Image Segmentation - Approaches

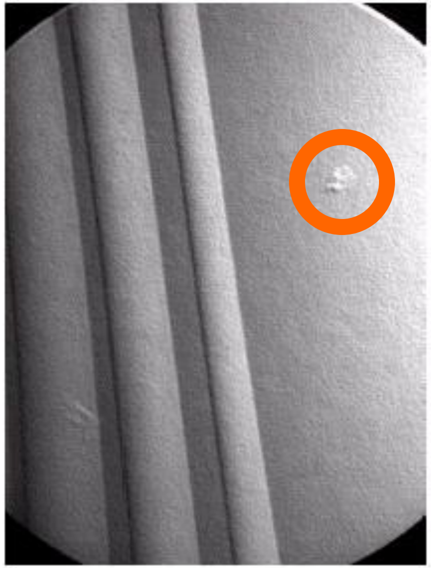
- Edge-based
- Thresholding
- Region-growing
- Morphological Watersheds
- Motion

Edge-based segmentation → Detection of Discontinuities

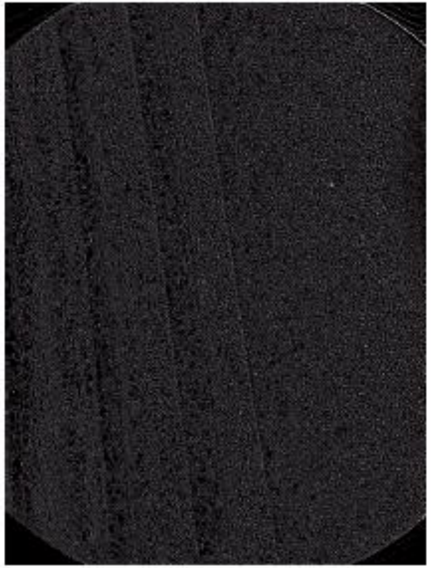
- Three basic types of grey level discontinuities
  - Points / Corners
  - Edges
  - Lines

Point Detection (cont…)

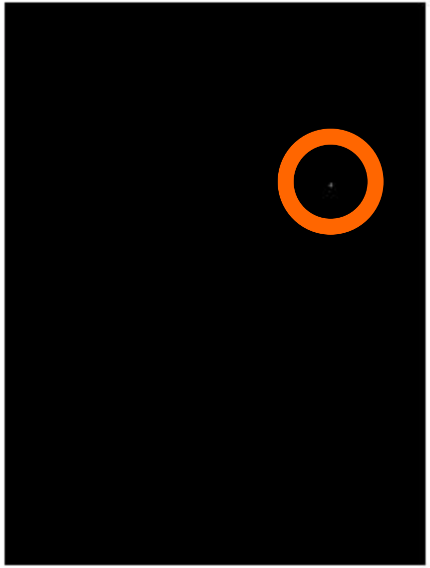
-1	-1	-1
-1	8	-1
-1	-1	-1



X-ray image of a turbine blade



Result of point detection



Result of thresholding

Oriented Line Detection

−1	−1	−1
2	2	2
−1	−1	−1

Horizontal

−1	−1	2
−1	2	−1
2	−1	−1

+45°

−1	2	−1
−1	2	−1
−1	2	−1

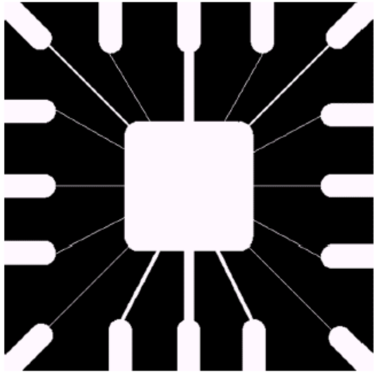
Vertical

2	−1	−1
−1	2	−1
−1	−1	2

−45°

Oriented Line Detection (cont…)

Binary image of a wire bond mask

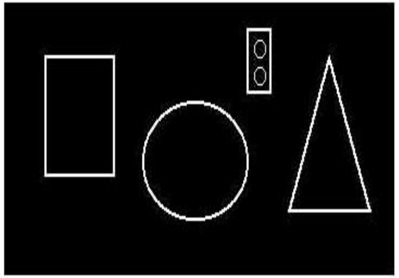


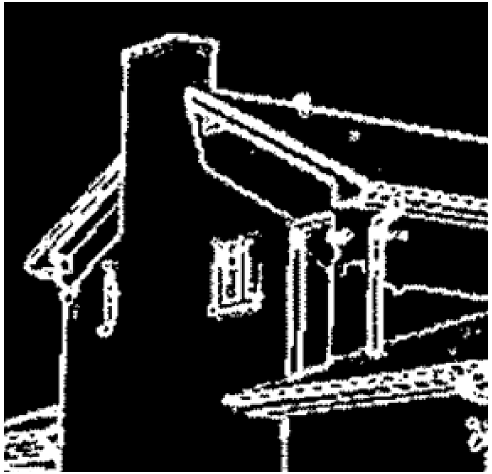
After processing with -45° line detector

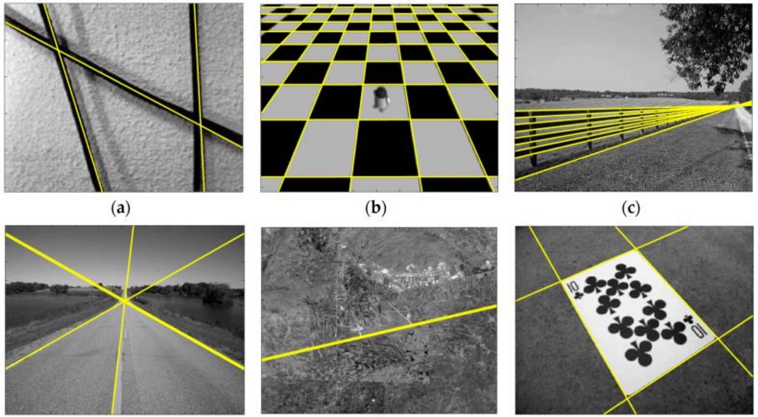
Result of thresholding filtering result

Hough Transform

- Straight lines
- Circles
- Algebraic curves
- Arbitrary specific shapes in an image



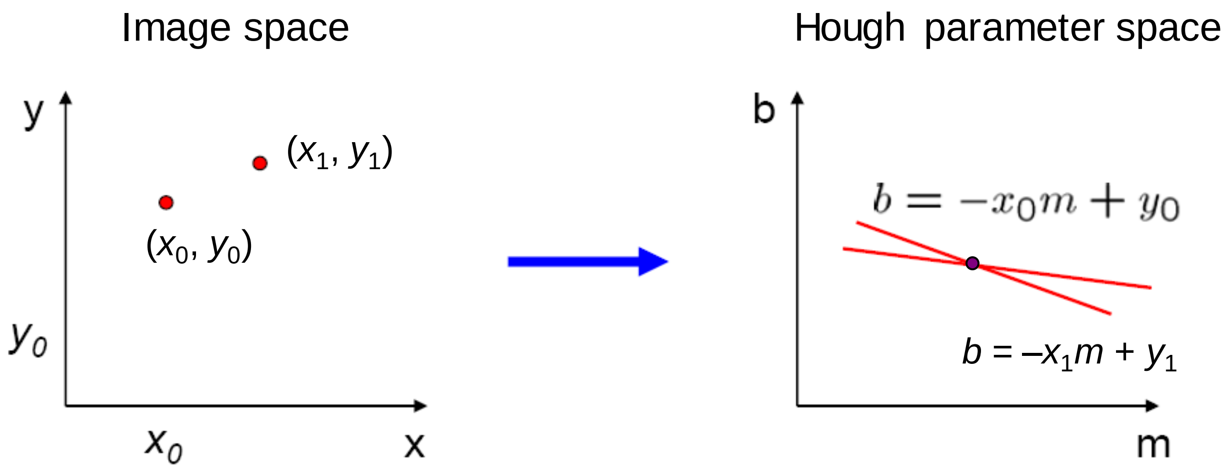


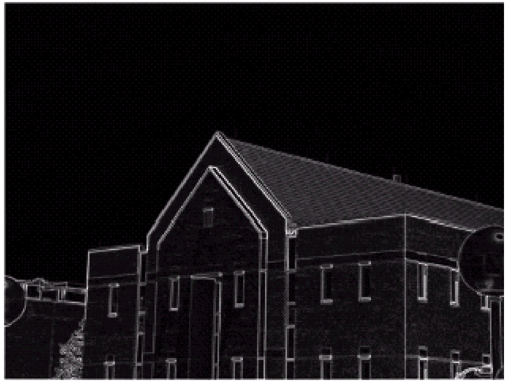


(a) (b) (c) (d) (e) (f)

Parameter space representation

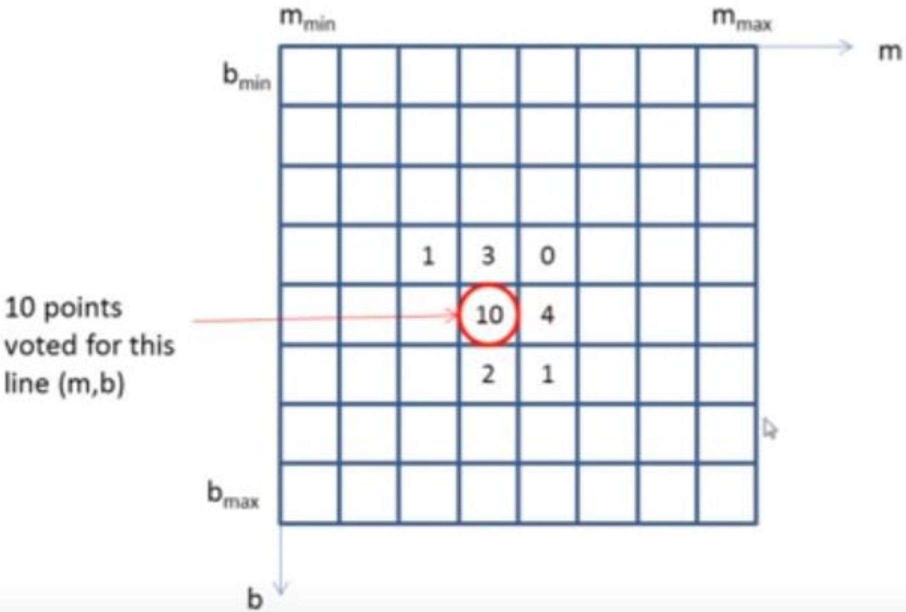
- Where is the line that contains both (x_0, y_0) and (x_1, y_1)?
  - It is the intersection of the lines $b = -x_0m + y_0$ and $b = -x_1m + y_1$





Hough Transform Algorithm

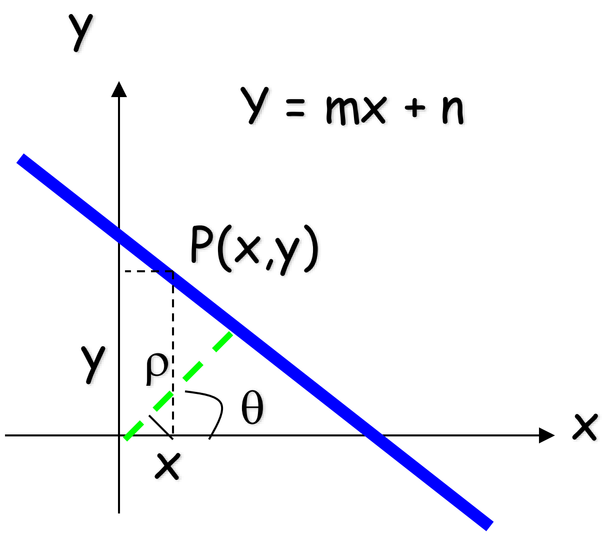
- Initialize an accumulator array A(m,b) to zero
- For each edge element (x,y), increment all cells that satisfy b = -x m + y
- Local maxima in A(m,b) correspond to lines



https://www.youtube.com/watch?v=uDB2qGqnQ1g

Solution:

- Use the “Normal” equation of a line:

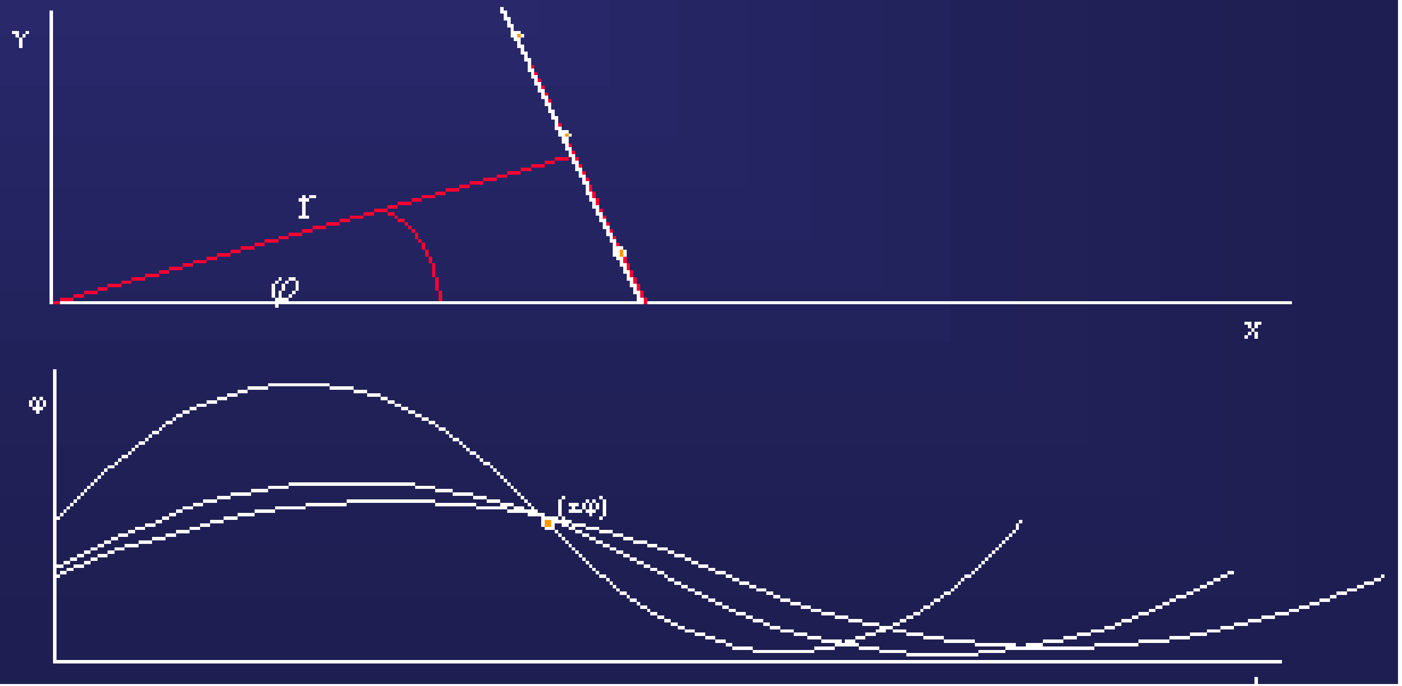


$\rho = x\cos\theta + y\sin\theta$

θ Is the line orientation

ρ Is the distance between the origin and the line

- Finding this intersection we then have the required (r,φ) parameters and therefore the line in the image

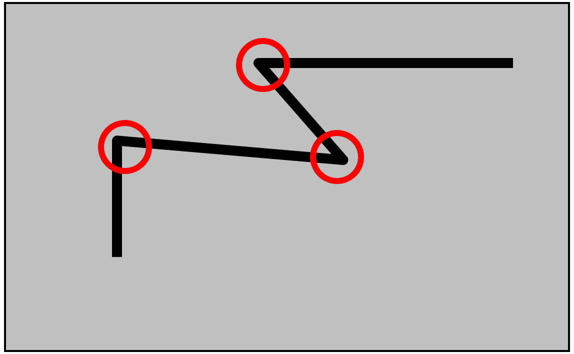


HT for Circles

- Extend HT to other shapes that can be expressed parametrically
- Circle, fixed radius r, centre (a,b)
  - $(x_1-a)^2 + (x_2-b)^2 = r^2$
  - accumulator array must be 3D
  - unless circle radius, r is known
  - re-arrange equation so x_1 is subject and x_2 is the variable
  - for every point on circle edge (x,y) plot range of (x_1,x_2) for a given r

Harris corner detector

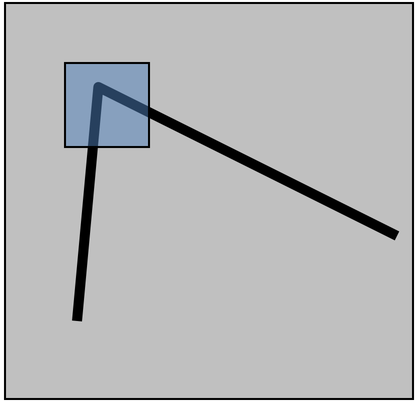
- C.Harris, M.Stephens. “A Combined Corner and Edge Detector”. 1988



from Rick Szeliski’s lecture notes, CSE576, Spring 05

The Basic Idea

- We should easily recognize the point by looking through a small window
- Shifting a window in *any direction* should give *a large change* in intensity



Harris Detector: Summary

- Average intensity change in direction $[u,v]$ can be expressed as a bilinear form:

$$E(u,v) \cong [u,v] \; M \begin{bmatrix} u \\ v \end{bmatrix}$$

- Describe a point in terms of eigenvalues of M: *measure of corner response*

$$R = \lambda_1 \lambda_2 - k\left(\lambda_1 + \lambda_2\right)^2$$

- A good (corner) point should have a *large intensity change* in *all directions*, i.e. R should be large positive

Harris Detector: Workflow

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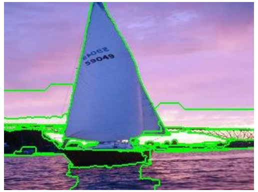

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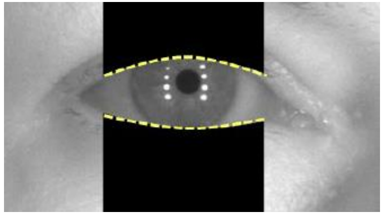

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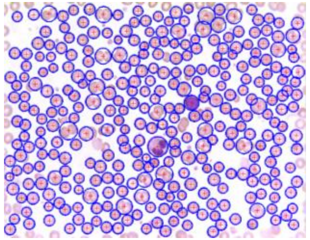
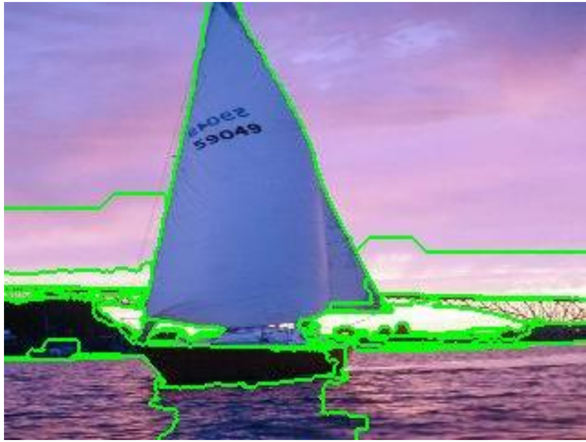


Region Segmentation: Segmentation Criteria

A segmentation is a partition of an image I into a set of regions S satisfying:

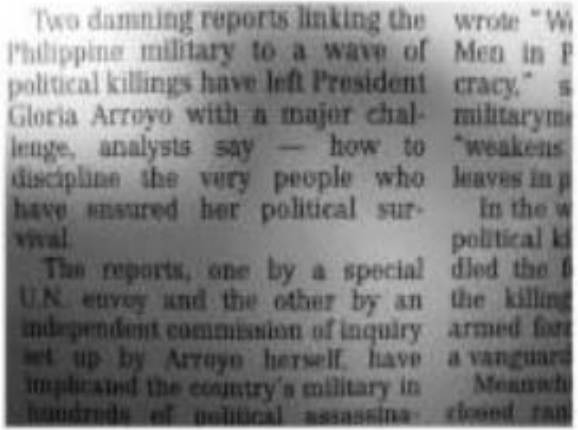
1. $\cup S_i = S$ — Partition covers the whole image.
2. $S_i \cap S_j = \phi,\ i \neq j$ — No regions intersect.
3. $\forall S_i,\ P(S_i) = \text{true}$ — Homogeneity predicate
4. $P(S_i \cup S_j) = \text{false},$ $i \neq j,\ S_i$ adjacent S_j — Union of adjacent regions does not satisfy homogeneity.



Segmentation: Thresholding based approaches

Two class Segmentation: Motivating example

- Separate pixels associated with object of interest from background



Two damning reports linking the Philippine military to a wave of political killings have left President Gloria Arroyo with a major challenge, analysts say — how to discipline the very people who have ensured her political survival.

The reports, one by a special U.N. envoy and the other by an independent commission of inquiry set up by Arroyo herself, have implicated the country's military in hundreds of political assassina-

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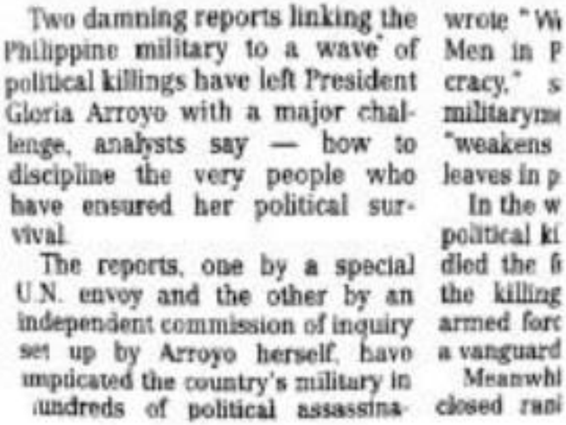

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Thresholding

- Separate pixels associated with object of interest from background

- Given a image f(x,y), the segmented image g(x,y) is given by:

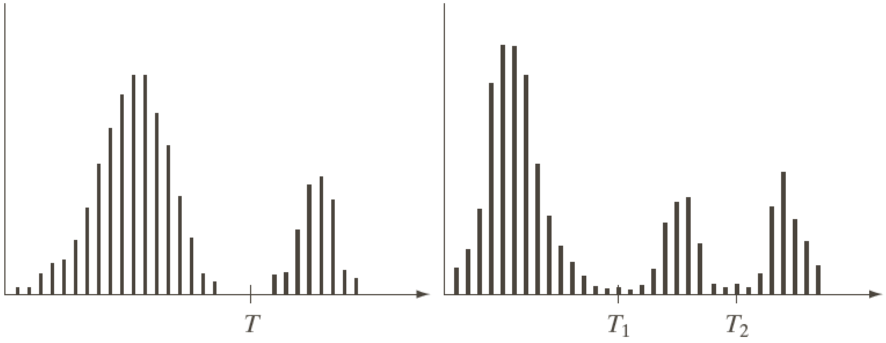
$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T \\ 0 & \text{if } f(x,y) \leq T \end{cases}$$

If T is constant over the entire image → Global Thresholding
If T changes over the image → Variable Thresholding

The main question is: **How to find T?**

Thresholding

- How to find T?
- One Idea is to explore the intensity histograms (if there is clear separation)



a b

FIGURE 10.35 Intensity histograms that can be partitioned (a) by a single threshold, and (b) by dual thresholds.

Thresholding

10. (5 points) Function f is used to convert the 8-bit left image to the binary image on the right. What values of K_1, and K_2 would produce the image on the right? (Assume gray value of IKEA lettering in the left image to be 128.)

$$z' = f(z) = \begin{cases} 0, & \text{if } K_1 < z < K_2 \\ 1, & \text{otherwise} \end{cases}$$

A. $K_1 = 0,\ K_2 = 255$

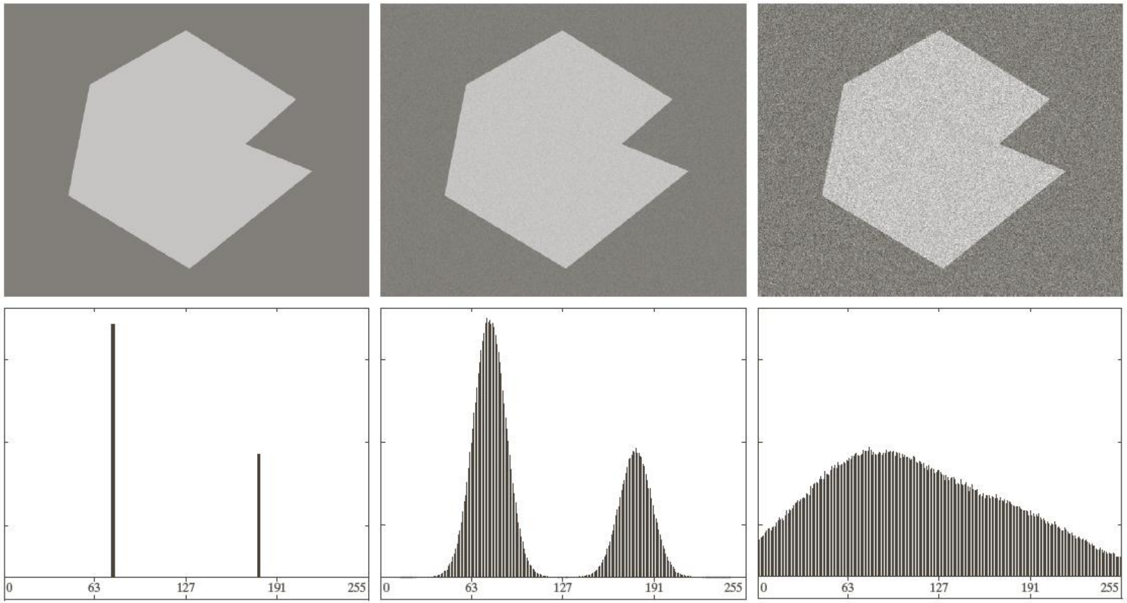
B. $K_1 = 16,\ K_2 = 32$

C. $K_1 = 100,\ K_2 = 200$

D. $K_1 = 200,\ K_2 = 255$

Thresholding: Role of Noise

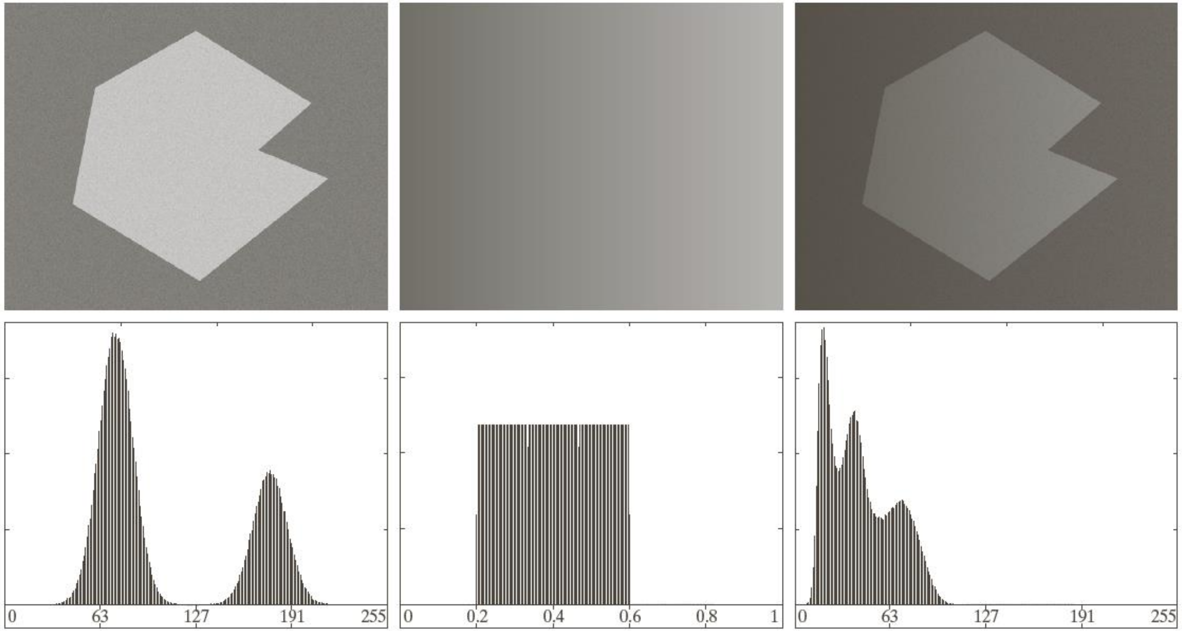
- Clear separation?



a	b	c
d	e	f

FIGURE 10.36 (a) Noiseless 8-bit image. (b) Image with additive Gaussian noise of mean 0 and standard deviation of 10 intensity levels. (c) Image with additive Gaussian noise of mean 0 and standard deviation of 50 intensity levels. (d)–(f) Corresponding histograms.

Thresholding: Role of Illumination and Reflectance

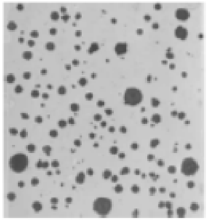


a	b	c
d	e	f

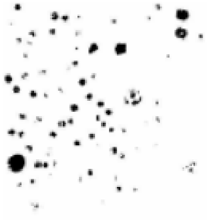
FIGURE 10.37 (a) Noisy image. (b) Intensity ramp in the range [0.2, 0.6]. (c) Product of (a) and (b). (d)–(f) Corresponding histograms.

Choosing a threshold is something of a "black art":

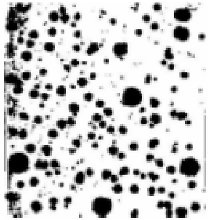
```
n=imread('nodules1.jpg');
figure(1); imshow(n);
n1=im2bw(n,0.35);
n2=im2bw(n,0.75);
figure(2), imshow(n1);
figure(3), imshow(n2);
```



n: Original image



n1: Threshold too low



n2: Threshold too high

Finding T: Basic Global Thresholding

Iterative approach

1. Select an initial estimate of global threshold T
2. Segment the image using T
   – This will produce two groups of pixels (G1 and G2)
3. Compute the average (mean) intensity values m1 and m2 for the pixels in G1 and G2 respectively
4. Compute a new threshold value T_new = (m1+m2)/2
5. If |T_new – T| < eps, stop.
6. Else, set T = T_new. Go to Step 2.

Finding T: Basic Global Thresholding

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Matlab function: `opthr`

Basic Global Thresholding

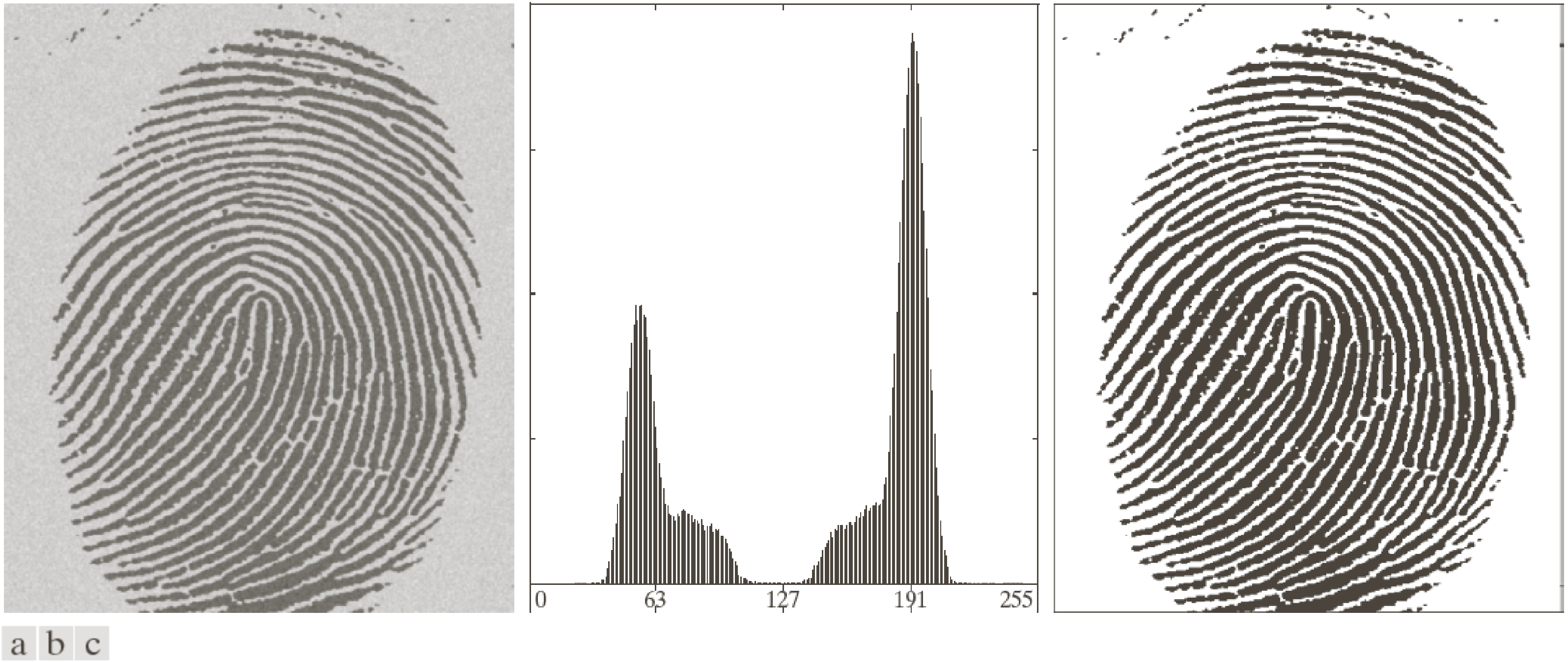
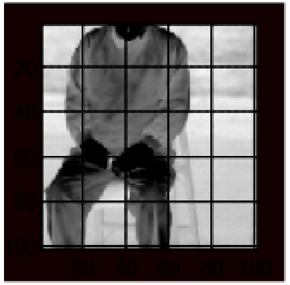
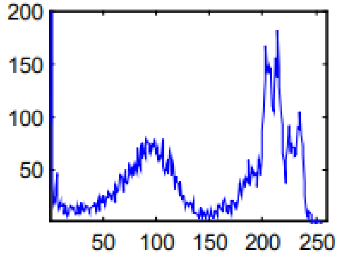


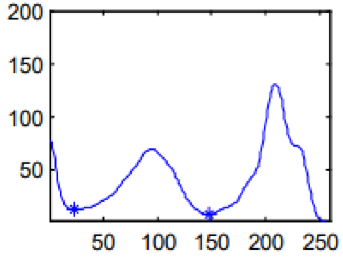
FIGURE 10.38 (a) Noisy fingerprint. (b) Histogram. (c) Segmented result using a global threshold (the border was added for clarity). (Original courtesy of the National Institute of Standards and Technology.)

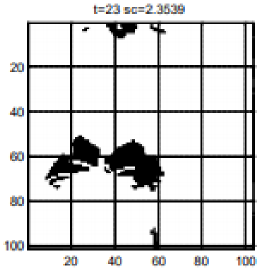
Global Thresholding

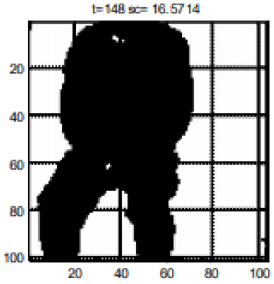
T is usually located at the valley/ one of the valleys



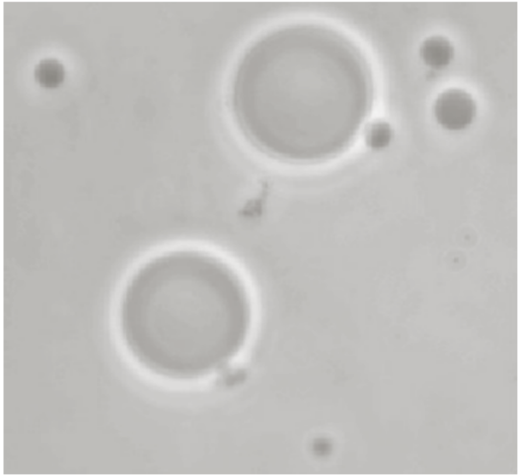


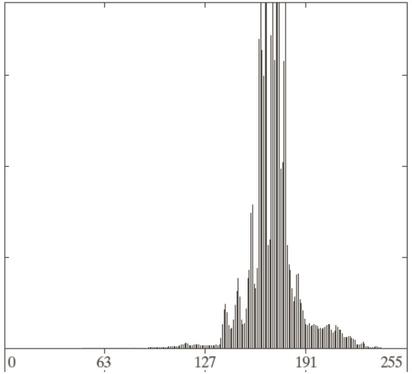






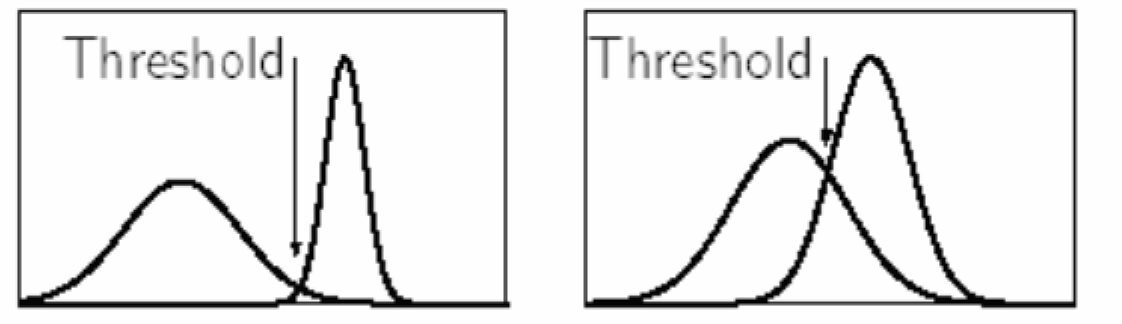
Basic Global Thresholding





- No valleys
- BG intensity close to ROI (region-of-interest) intensity

Determining FG/BG separation

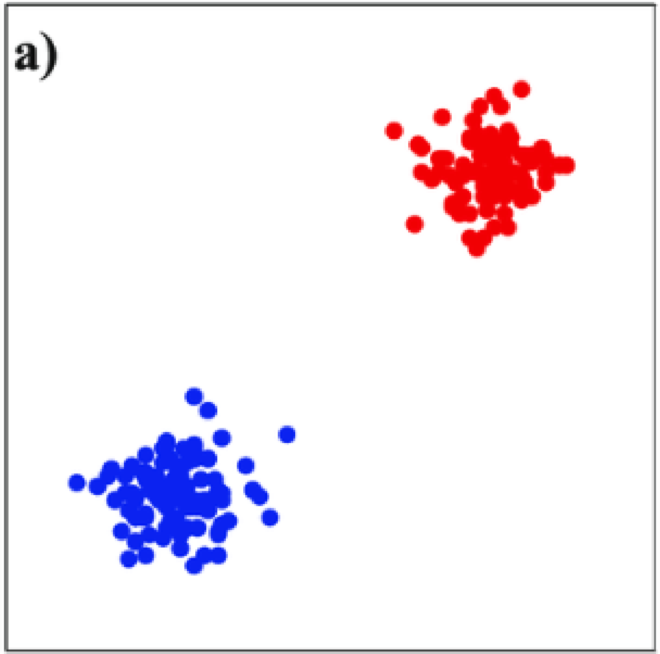


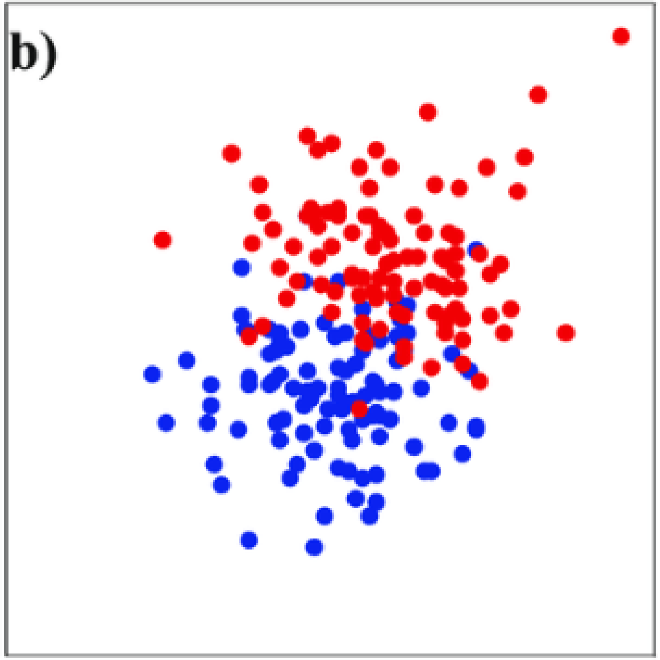
Global Thresholding: Otsu’s Method

- Based on histograms
- Automatically finds the optimal threshold maximizing the between class variance
- Proposed in 1975

- Preliminaries:
  - What is the formula for mean and variance of intensities in an image ?
  - What does variance measure ?
  - A probabilistic / normalized-histogram perspective for mean, variance

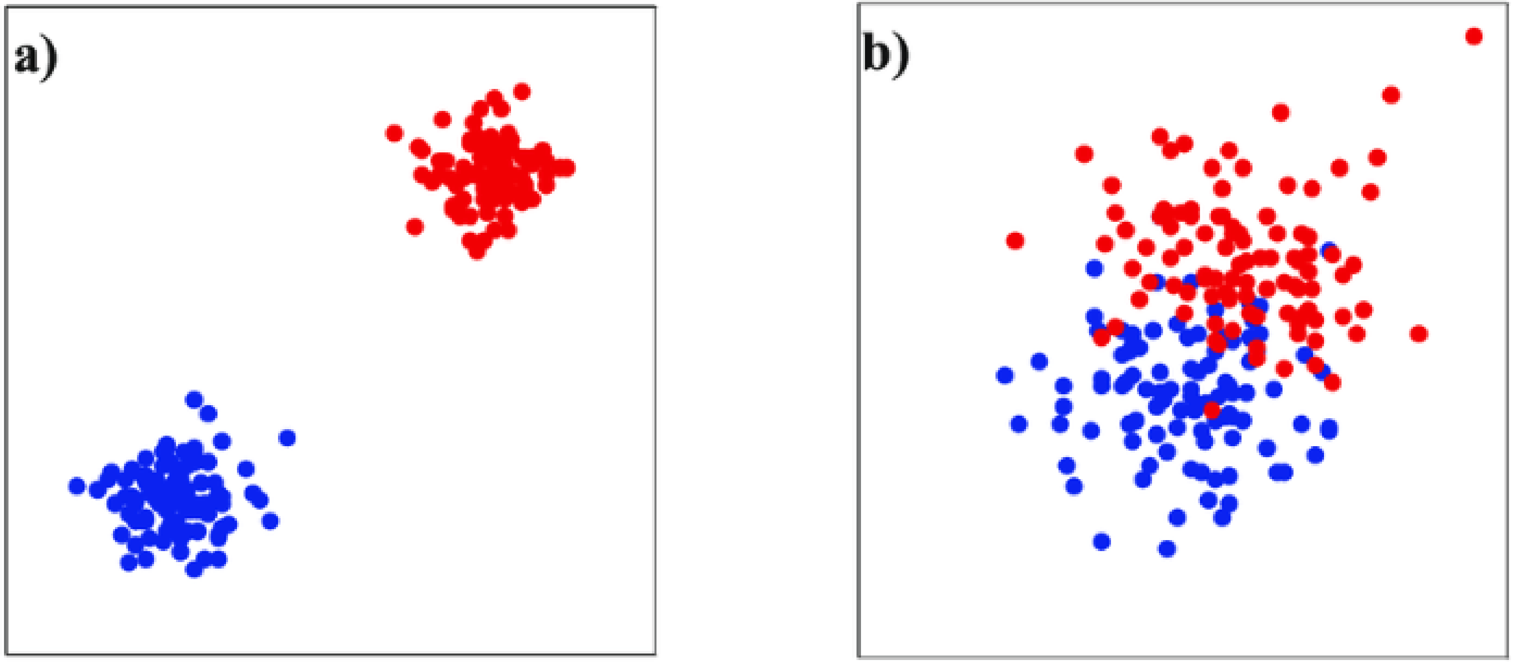
Inter-class and Intra-class variance





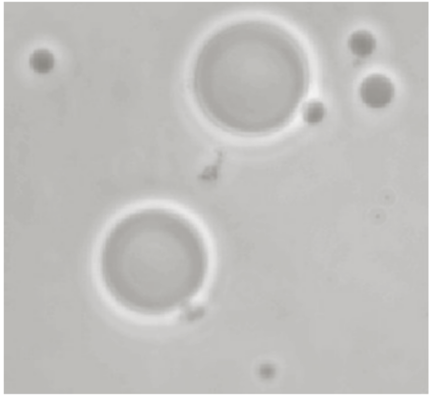
https://www.researchgate.net/figure/Inter-class-and-Intra-class-variances-concept-a-Low-intra-class-variance-and-high_fig2_278382762

Inter-class and Intra-class variance



2: Inter-class and Intra-class variances concept. a) Low intra-class variance and high inter-class variance: compact well separated clusters. b) High intra-class variance and low inter-class variance: wide clusters without a clear frontier.

Insight



- Variance = A measure of region homogeneity
- Regions with high homogeneity will have a low variance.

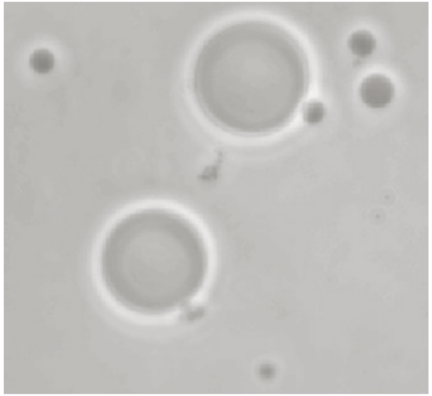
Otsu's algorithm: Find the threshold that <u>minimizes</u> intra-class variance.

1. Consider all possible thresholds T
2. For each threshold t in T
   1. Compute the variance for Class-1 pixels (intensities < t)
   2. Compute the variance for Class-2 pixels (intensities >= t)

Intra-class variance → $\sigma_f^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$

Class-1 probability (fraction of pixels whose intensity < t)

Insight



- Variance = A measure of region homogeneity
- Regions with high homogeneity will have a low variance.

Otsu's algorithm: Find the threshold that <u>minimizes</u> intra-class variance.

1. Consider all possible thresholds T
2. For each threshold t in T
   1. Compute the variance for Class-1 pixels (intensities < t)
   2. Compute the variance for Class-2 pixels (intensities >= t)

Intra-class variance → $\sigma_f^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$

Inter-class variance → $\sigma_i^2 = \sigma^2 - \sigma_f^2(t) = \omega_1(t)\omega_2(t)[\mu_1(t) - \mu_2(t)]^2$

Otsu's Method

- Compute the normalized histogram of the input image. Denote the components of the histogram by $p_i,\ i = 0, 1, 2, 3, \dots, L-1$
- Suppose a threshold is selected $k, 0 < k < L-1$
- C_1 is the set of pixels with levels $[0, 1, 2, 3, \dots, k]$
- C_2 is the set of pixels with levels $[k+1, k+2, k+3, \dots, L-1]$

- Obtain the value of threshold which **maximizes** the between class variance

$$\sigma_B^2(k) = P_1(k)\,(m_1(k) - m_G)^2 + P_2(k)\,(m_2(k) - m_G)^2$$

Otsu's Method

- Compute the normalized histogram of the input image.
- Denote the components of the histogram by $p_i, \ i = 0, 1, 2, 3, \ldots, L-1$
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- Obtain the value of threshold which **maximizes** the between class variance

$$\boxed{\sigma_B^2(k) = P_1(k)\,(m_1(k) - m_G)^2 + P_2(k)\,(m_2(k) - m_G)^2}$$

Otsu’s Method

$$\boxed{\sigma_B^{\ 2}\,(k) = P_1(k)\,(m_1(k) - m_G)^2 + P_2(k)\,(m_2(k) - m_G)^2}$$

- $P_1(k)$ is probability of C_1 occuring

$$P_1(k) = \sum_{i=0}^{k} p_i \;, k = 0,1,2, \dots , k$$

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i \; = 1 - P_1(k)\;, k = 0,1,2, \dots , k$$

- $m_1(k)$ and $m_2(k)$ are means of C_1 and C_2

$$m_1(k) = \frac{\sum_{i=0}^{k} i\; p_i}{P_1(k)} \qquad\qquad m_2(k) = \frac{\sum_{i=k+1}^{L-1} i\; p_i}{P_2(k)}$$

Otsu's Method

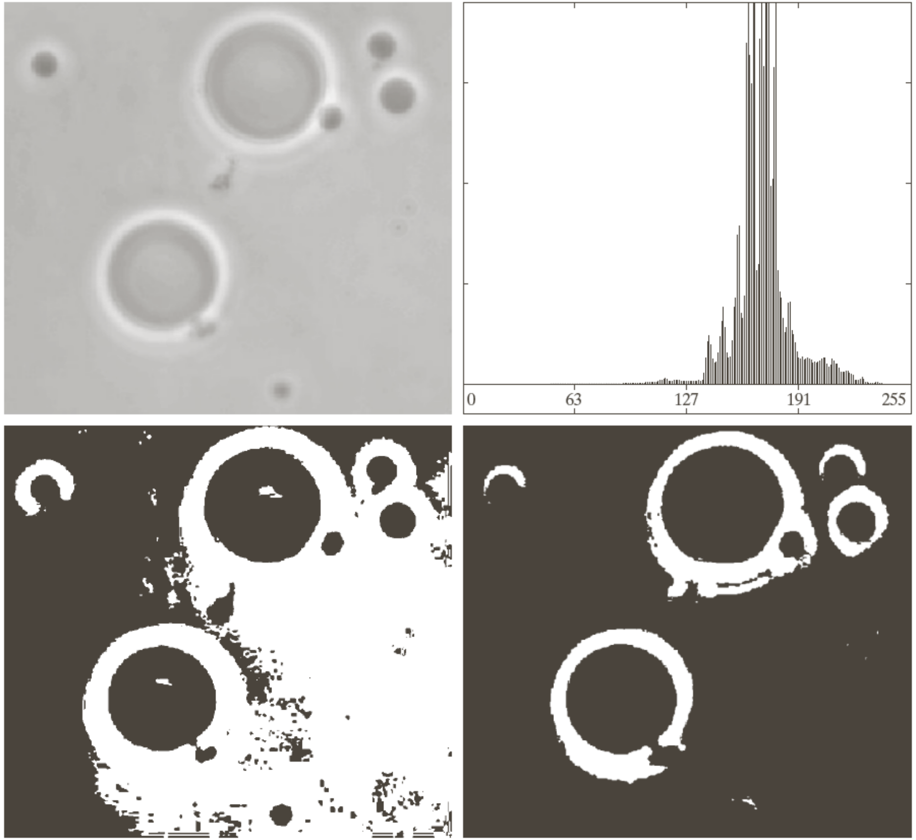
$$\boxed{\sigma_B^2(k) = P_1(k)\,(m_1(k) - m_G)^2 + P_2(k)\,(m_2(k) - m_G)^2}$$

$$\boxed{\sigma_B^2(k^*) = \max_{0 \le k \le L-1} \sigma_B^2(k)}$$

In simple words, we evaluate all values of k and select the value of k that yielded the maximum $\sigma_B^2(k)$

This idea can be easily extended to compute multiple thresholds!

Otsu’s Method

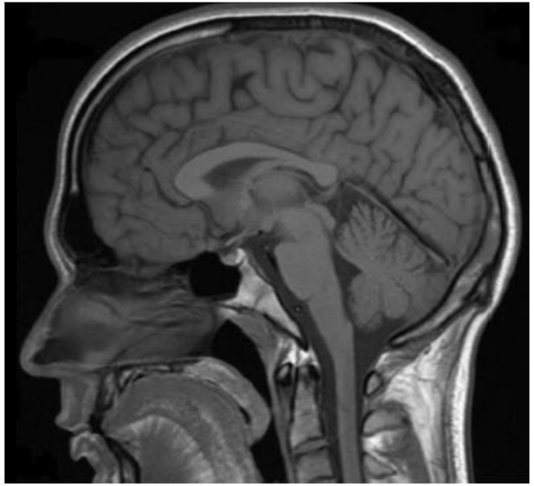


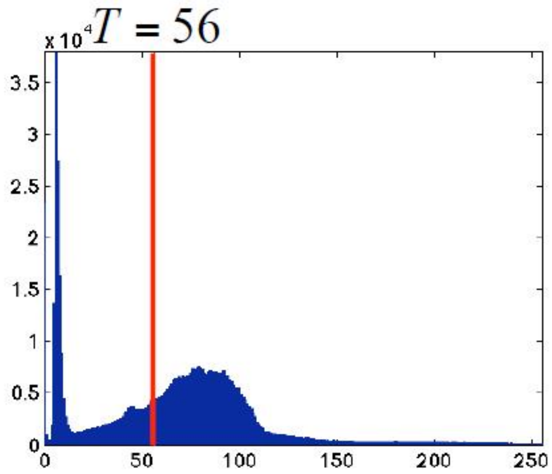
a b
c d

FIGURE 10.39 (a) Original image. (b) Histogram (high peaks were clipped to highlight details in the lower values). (c) Segmentation result using the basic global algorithm from Section 10.3.2. (d) Result obtained using Otsu’s method. (Original image courtesy of Professor Daniel A. Hammer, the University of Pennsylvania.)

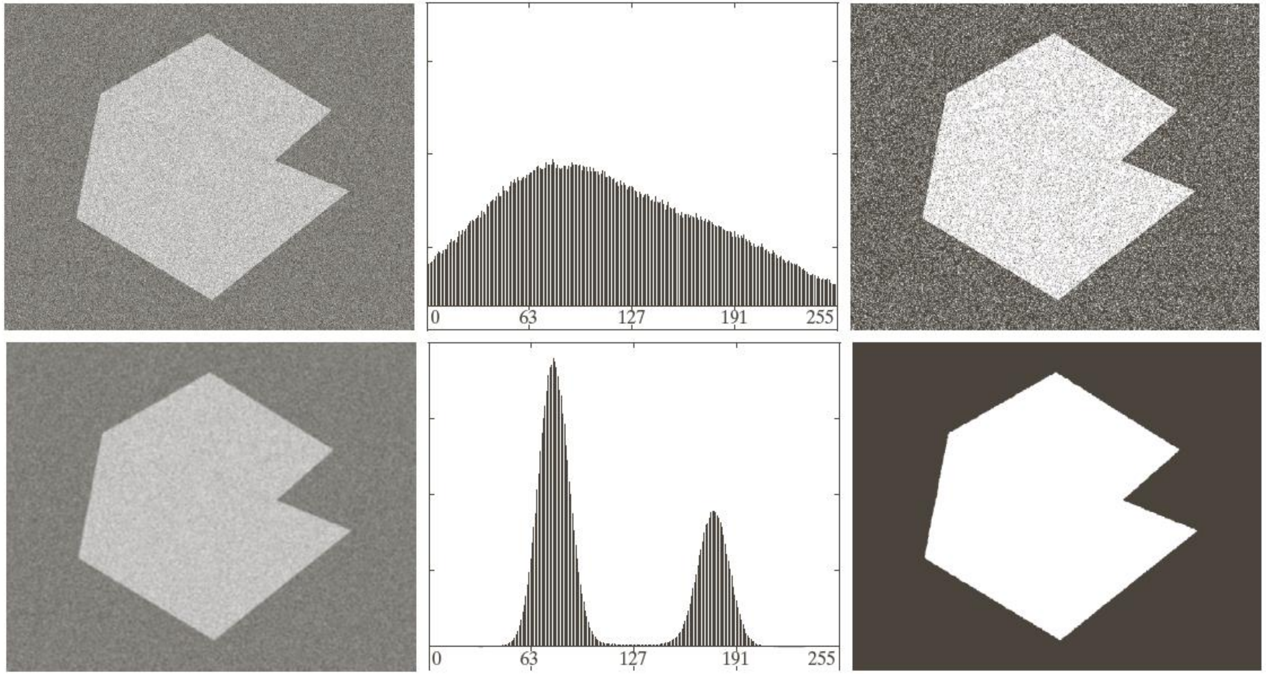
T = 181

Otsu’s Method





Handling Noise



a b c
d e f

FIGURE 10.40 (a) Noisy image from Fig. 10.36 and (b) its histogram. (c) Result obtained using Otsu's method. (d) Noisy image smoothed using a 5×5 averaging mask and (e) its histogram. (f) Result of thresholding using Otsu's method.

Otsu’s method: Main Limitation

Two damning reports linking the Philippine military to a wave of political killings have left President Gloria Arroyo with a major challenge, analysts say — how to discipline the very people who have ensured her political survival.

The reports, one by a special U.N. envoy and the other by an independent commission of inquiry set up by Arroyo herself, have implicated the country's military in hundreds of political assassina-

Pai et al. PR 2010

No single threshold, may be ideal

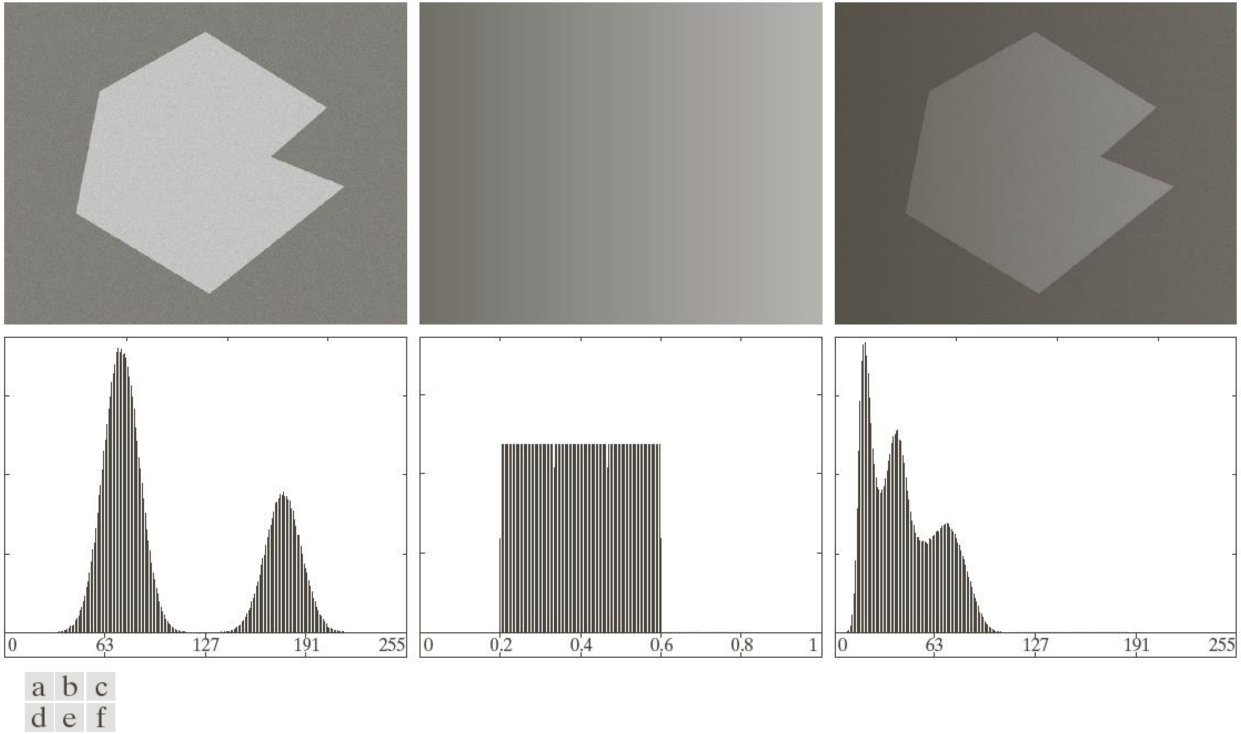


FIGURE 10.37 (a) Noisy image. (b) Intensity ramp in the range [0.2, 0.6]. (c) Product of (a) and (b). (d)–(f) Corresponding histograms.

Global segmentation: main limitation

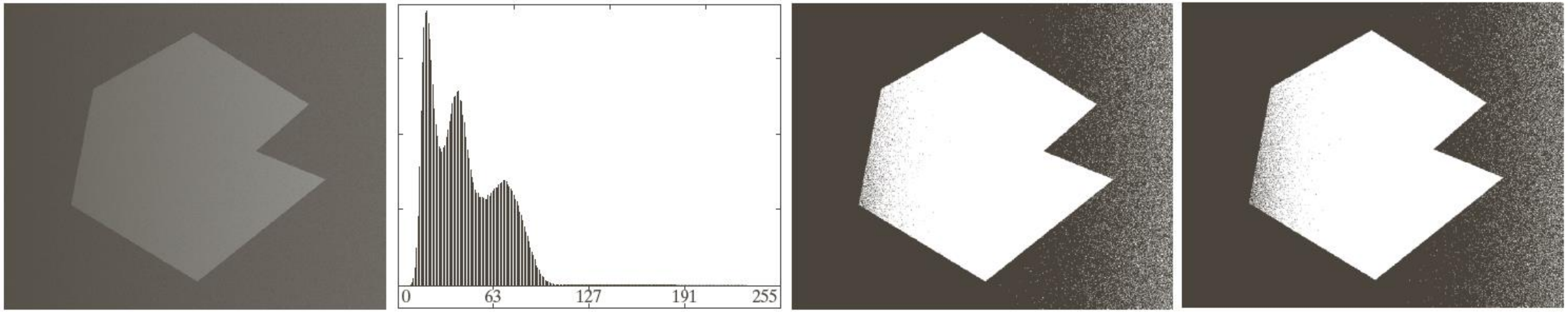


Image subdivision + variable Thresholding

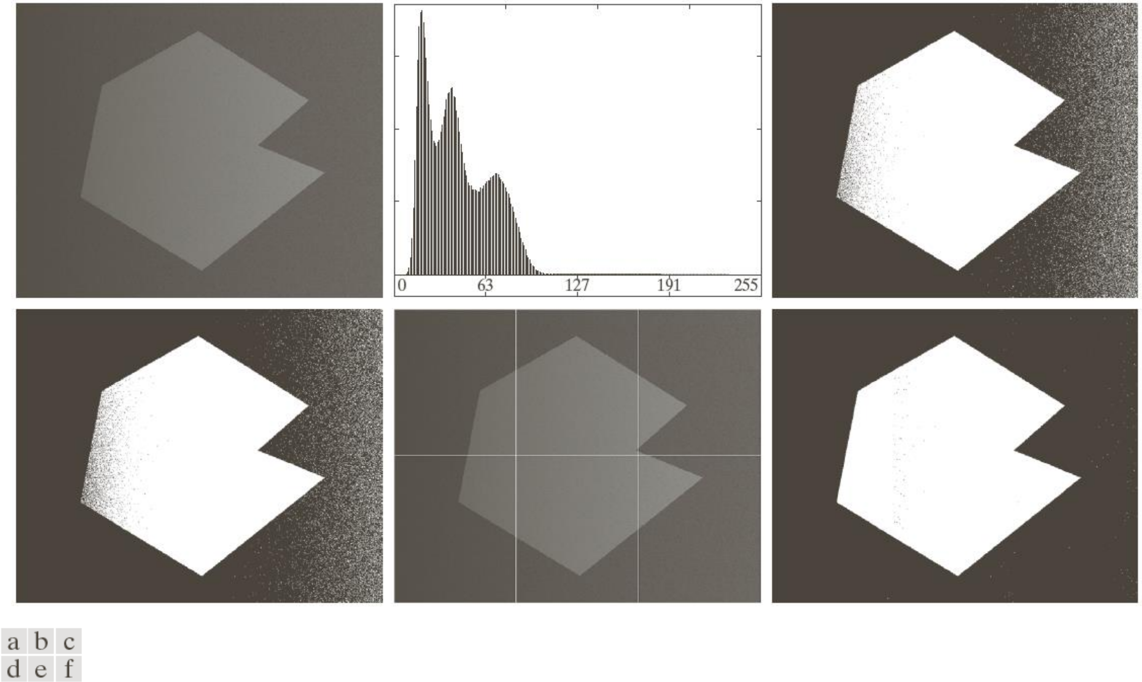


FIGURE 10.46 (a) Noisy, shaded image and (b) its histogram. (c) Segmentation of (a) using the iterative global algorithm from Section 10.3.2. (d) Result obtained using Otsu's method. (e) Image subdivided into six subimages. (f) Result of applying Otsu's method to each subimage individually.

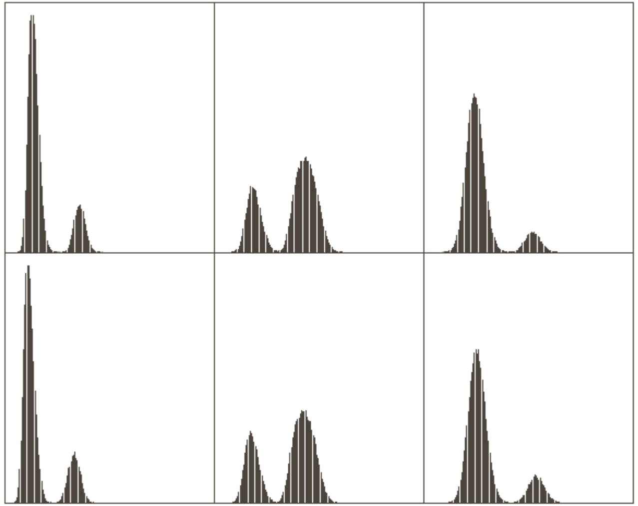


FIGURE 10.47 Histograms of the six subimages in Fig. 10.46(e).

Per pixel variable Thresholding

- Compute standard deviation and mean of each pixel (around local neighborhood)
- Let σ_{xy} , m_{xy} denote the standard deviation and mean value contained in neighborhood S_{xy} centred around (x, y)
- Example threshold function:

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

$$T_{xy} = a\sigma_{xy} + bm_{xy} \quad \text{or} \quad T_{xy} = a\sigma_{xy} + bm_G$$

Per pixel variable Thresholding

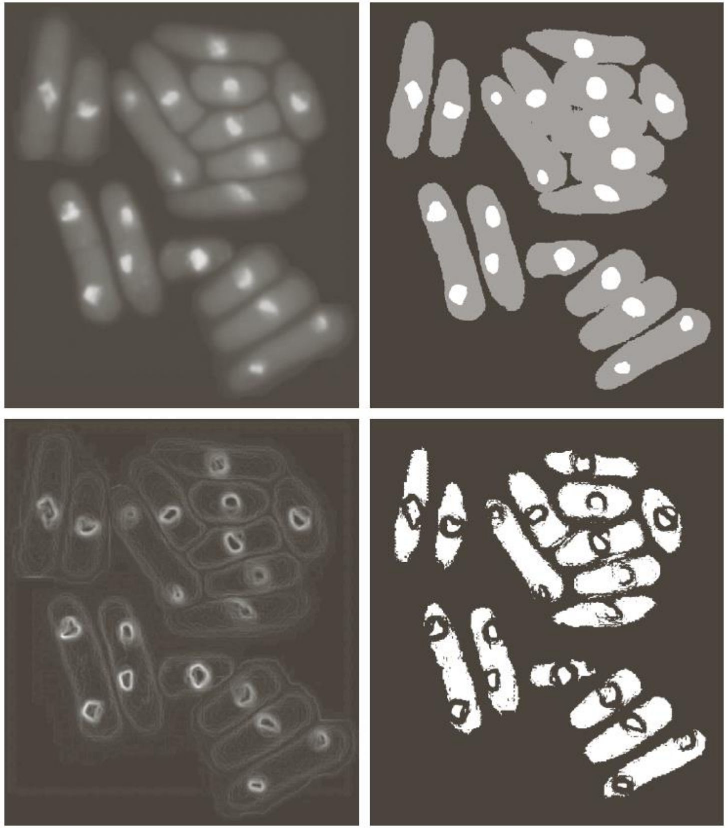
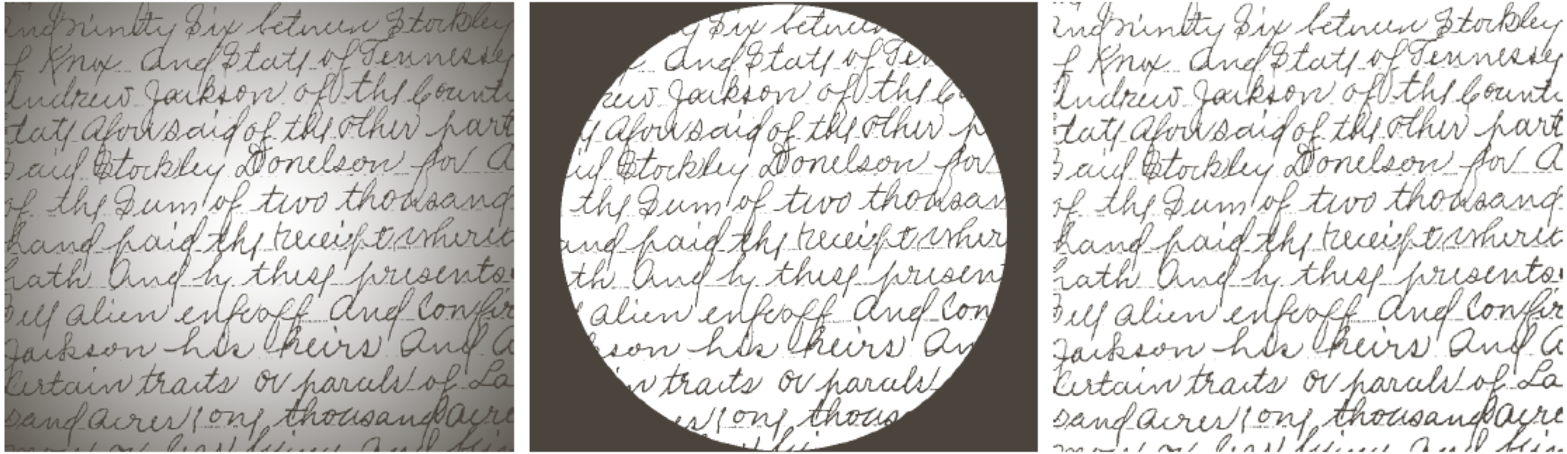


FIGURE 10.48
(a) Image from Fig. 10.43.
(b) Image segmented using the dual thresholding approach discussed in Section 10.3.6.
(c) Image of local standard deviations.
(d) Result obtained using local thresholding.

Per pixel: moving average



a b c

FIGURE 10.49 (a) Text image corrupted by spot shading. (b) Result of global thresholding using Otsu's method. (c) Result of local thresholding using moving averages.

Per pixel: moving average

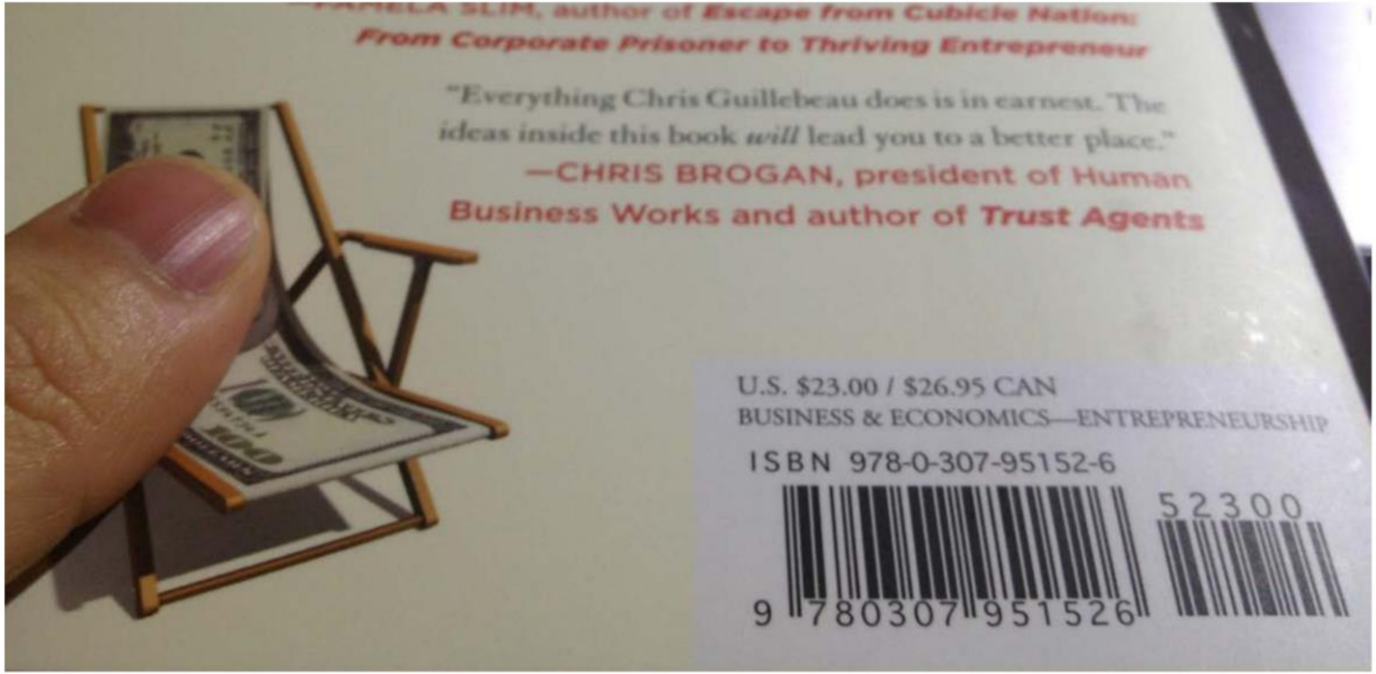
a b c

FIGURE 10.50 (a) Text image corrupted by sinusoidal shading. (b) Result of global thresholding using Otsu's method. (c) Result of local thresholding using moving averages.

Adaptive thresholding: advanced algorithms

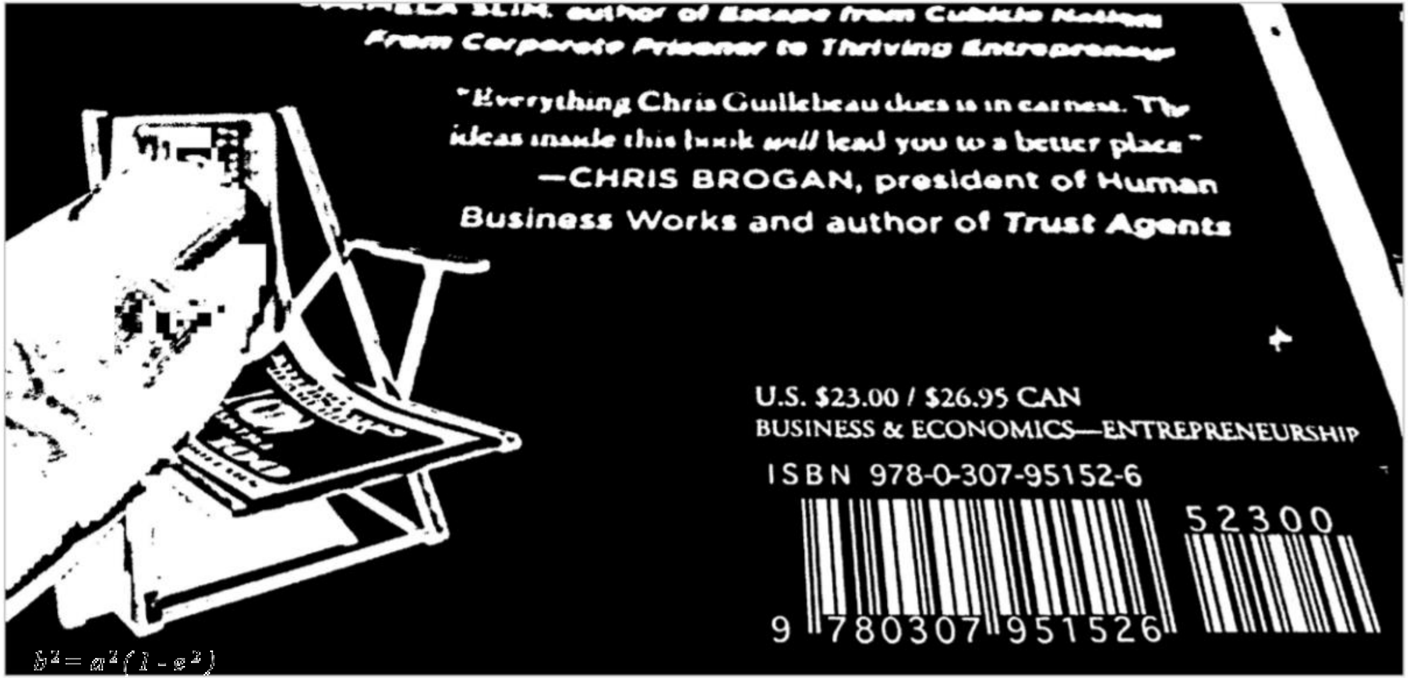
Adaptive thresholding algorithm... Pai et al. PR 2010

Adaptive thresholding: Use case

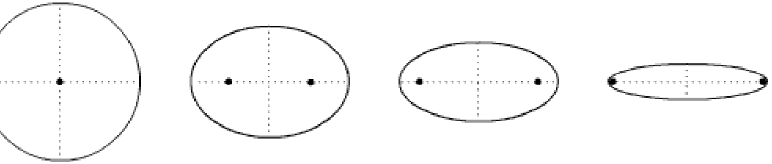


Slide from: Bernd Girod, Stanford

Adaptive thresholding: Use case



$b^2 = a^2(1 - e^2)$



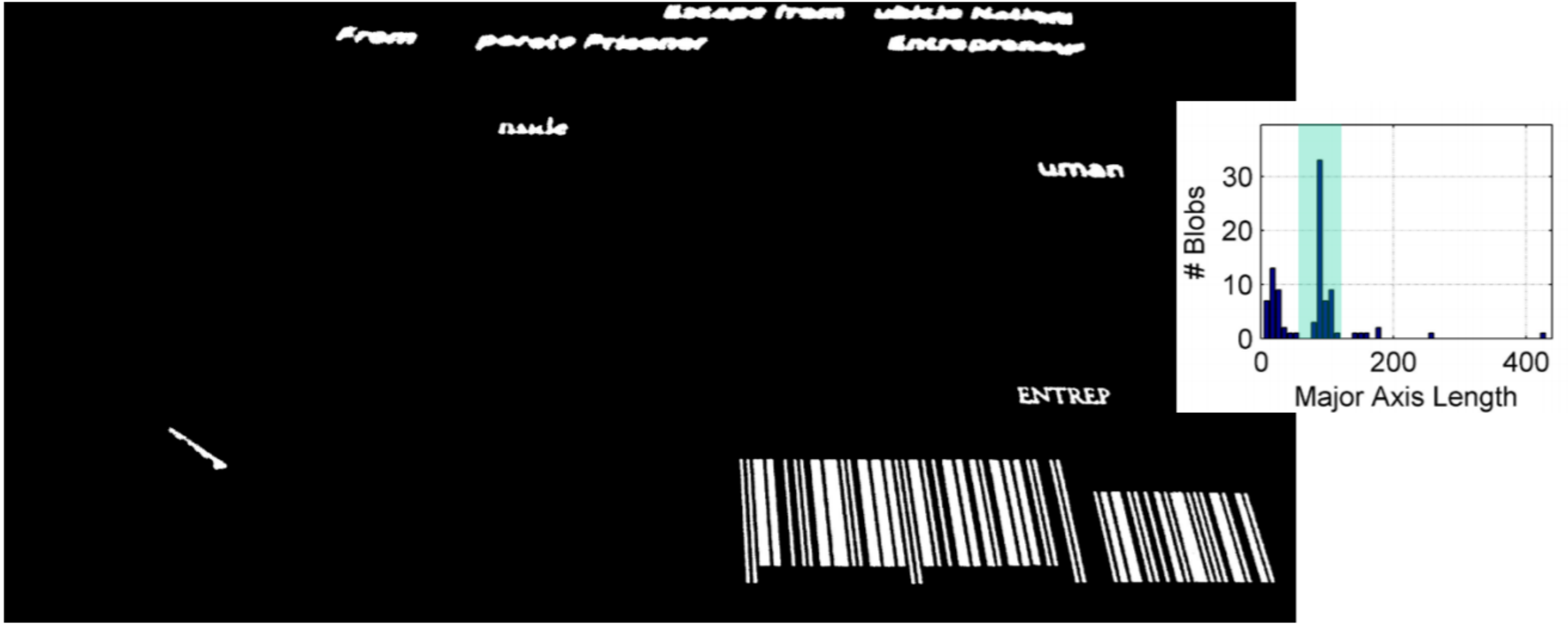
$e = 0$ $e = 0.5$ $e = 0.75$ $e = 0.95$

Slide from: Bernd Girod, Stanford

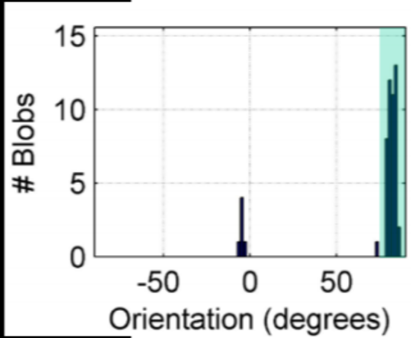
Adaptive thresholding: Use case

Slide from: Bernd Girod, Stanford

Adaptive thresholding: Use case



Adaptive thresholding: Use case



Slide from: Bernd Girod, Stanford

Choosing thresholding algorithms

- Based on typical sizes of objects/regions of interest
  - Small → Adaptive/Local
  - Large → Global

Thresholding: Summary

- Many methods

- Survey

Sezgin, M and Sankur, B (2004), "Survey over Image Thresholding Techniques and Quantitative Performance Evaluation", Journal of Electronic Imaging 13(1): 146-165

- Comparison

http://www.fmwconcepts.com/imagemagick/threshold_comparison/index.php

Segmentation: Region based approaches

Region Based Segmentation

- Basic Formulation: Let R represent the entire image region. Segmentation is the process of partitioning R into subregions $R_1, R_2, \ldots, R_n$, such that:

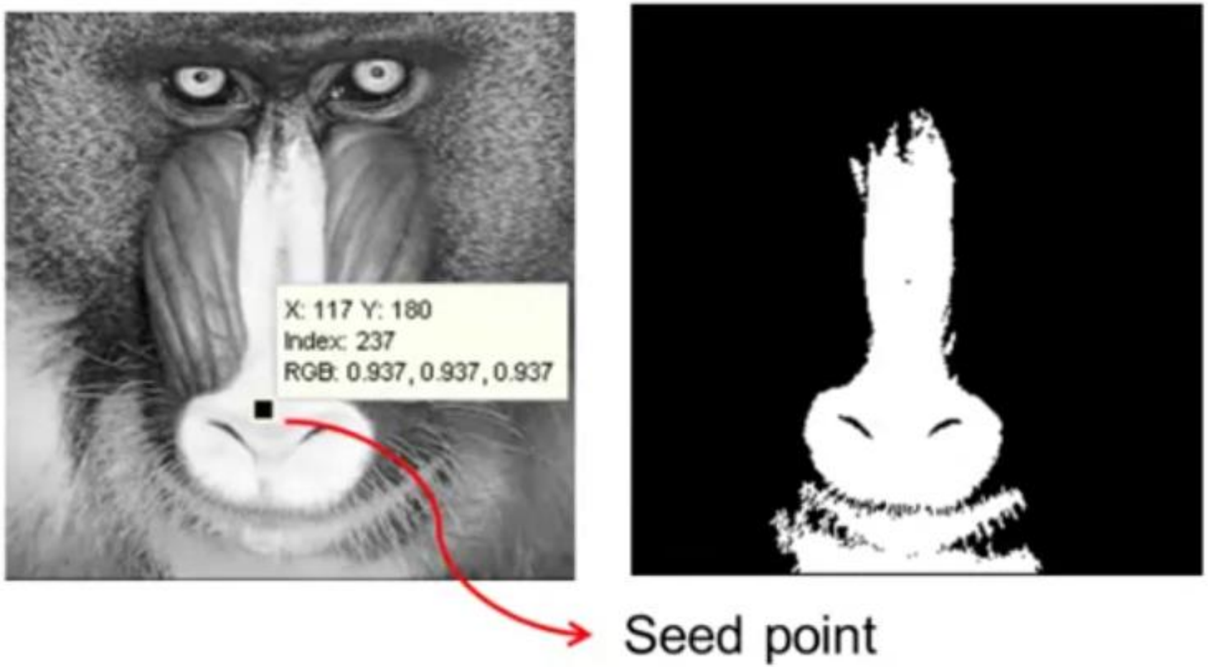
1. $$\bigcup_{i=1}^{n} R_i = R$$
2. R_i is a connected region, for all i
3. $R_i \cap R_j = \emptyset$ for all i and j, i≠j

Region Growing

- Start with a set of seed points
  - Based on prior information
  - Based on some properties calculated at each point

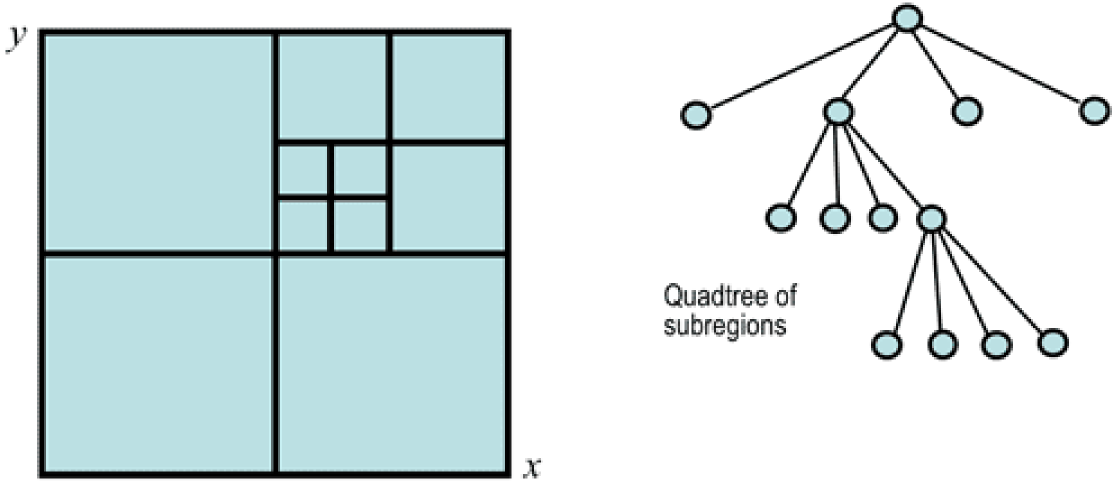
- Grow regions based on a predefined criteria
  - Similarities in color, texture etc.

Region Growing: Example



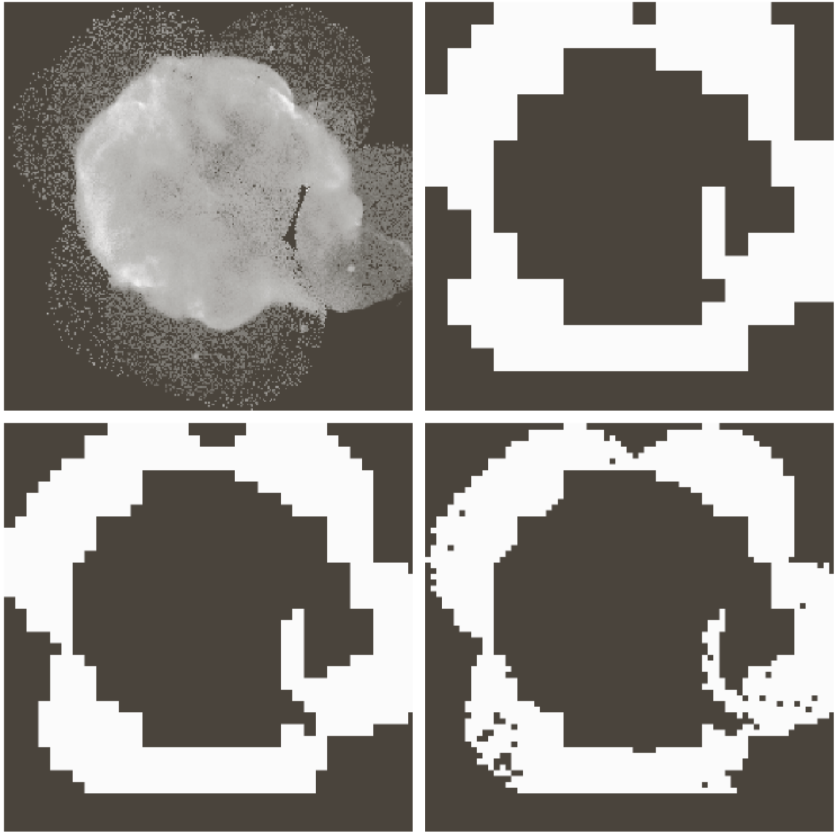
Source: Aggelos K. Katsaggelos

Region Splitting and Merging



Need to define a splitting function and size of the minimum quadrant

Region Splitting and Merging



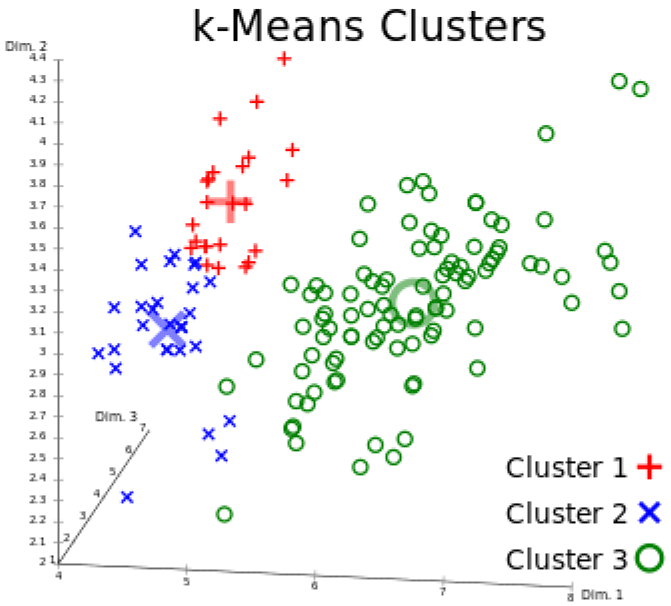
$$Q = \begin{cases} \text{TRUE} & \text{if } \sigma > a \quad \text{AND} \quad 0 < m < b \\ \text{FALSE} & otherwise \end{cases}$$

a b
c d

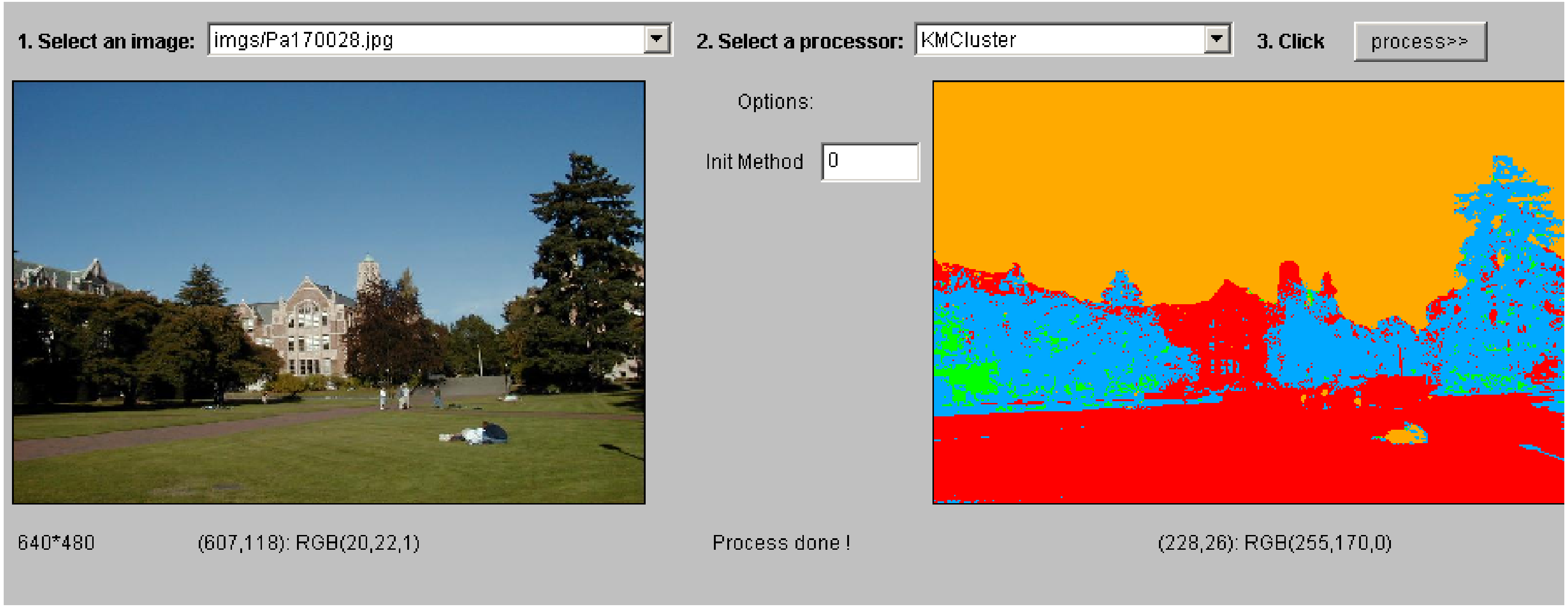
FIGURE 10.53 (a) Image of the Cygnus Loop supernova, taken in the X-ray band by NASA's Hubble Telescope. (b)–(d) Results of limiting the smallest allowed quadregion to sizes of 32×32, 16×16, and 8×8 pixels, respectively. (Original image courtesy of NASA.)

Clustering

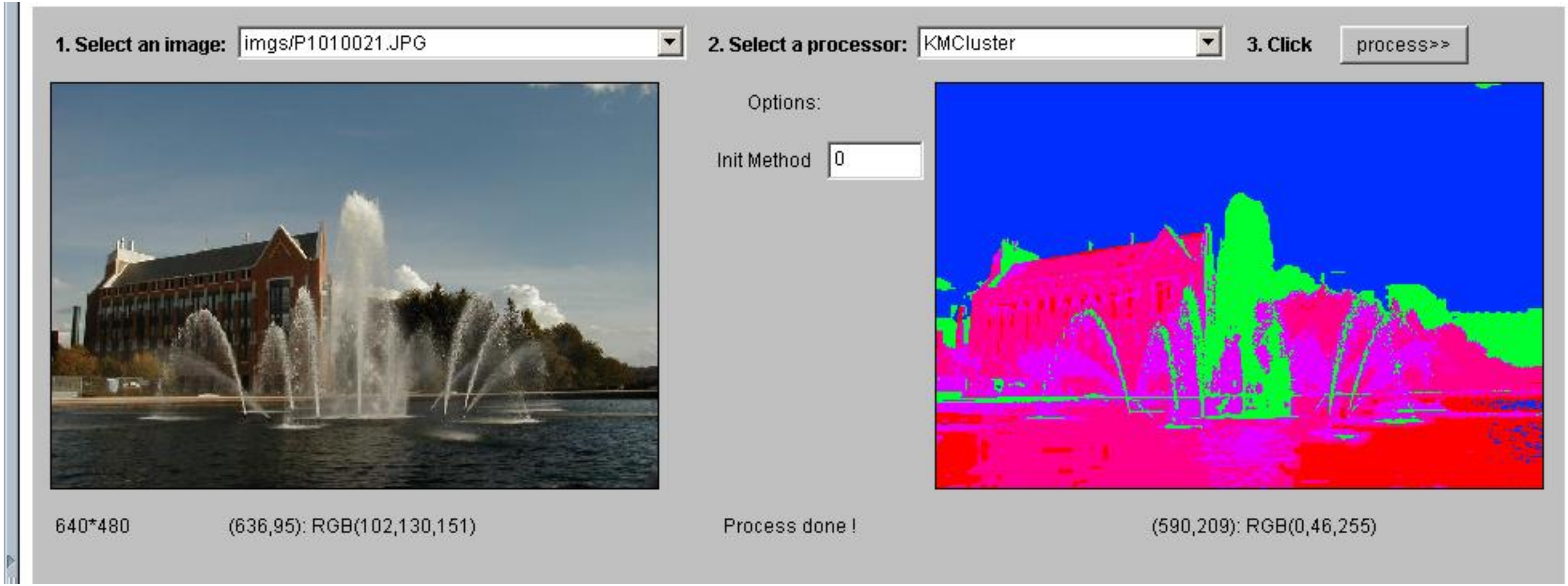
- Clustering using extracted features + spatial coordinates
  - Features like color, texture etc.
  - Algorithms like k-means, agglomerative clustering, spectral clustering etc.



K-Means Example 1



K-Means Example 2



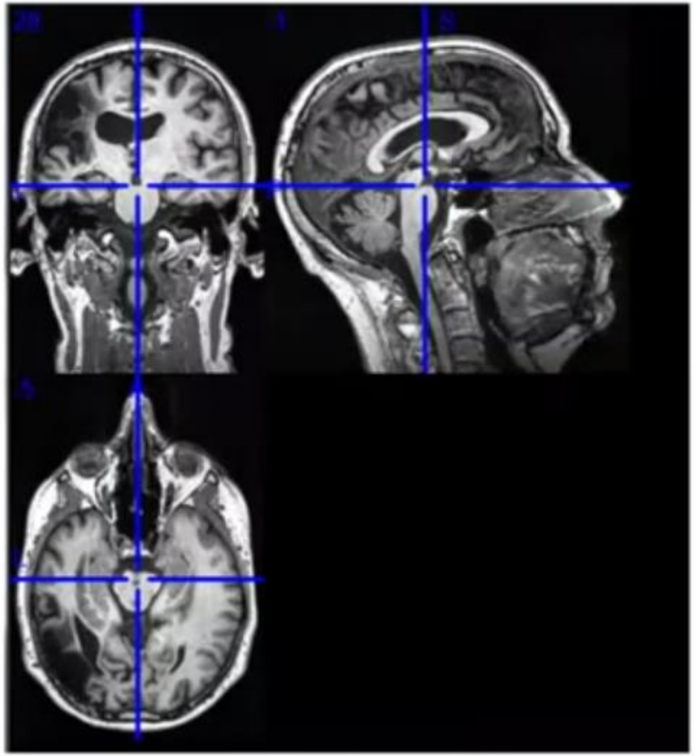
Clustering

- Clustering using extracted features + spatial coordinates
  - Features like color, texture etc.
  - Algorithms like k-means, agglomerative clustering, spectral clustering etc.

Clustering

- Clustering using extracted features + spatial coordinates
  - Features like color, texture etc.
  - Algorithms like k-means, agglomerative clustering, spectral clustering etc.

Clustering-Medical Images



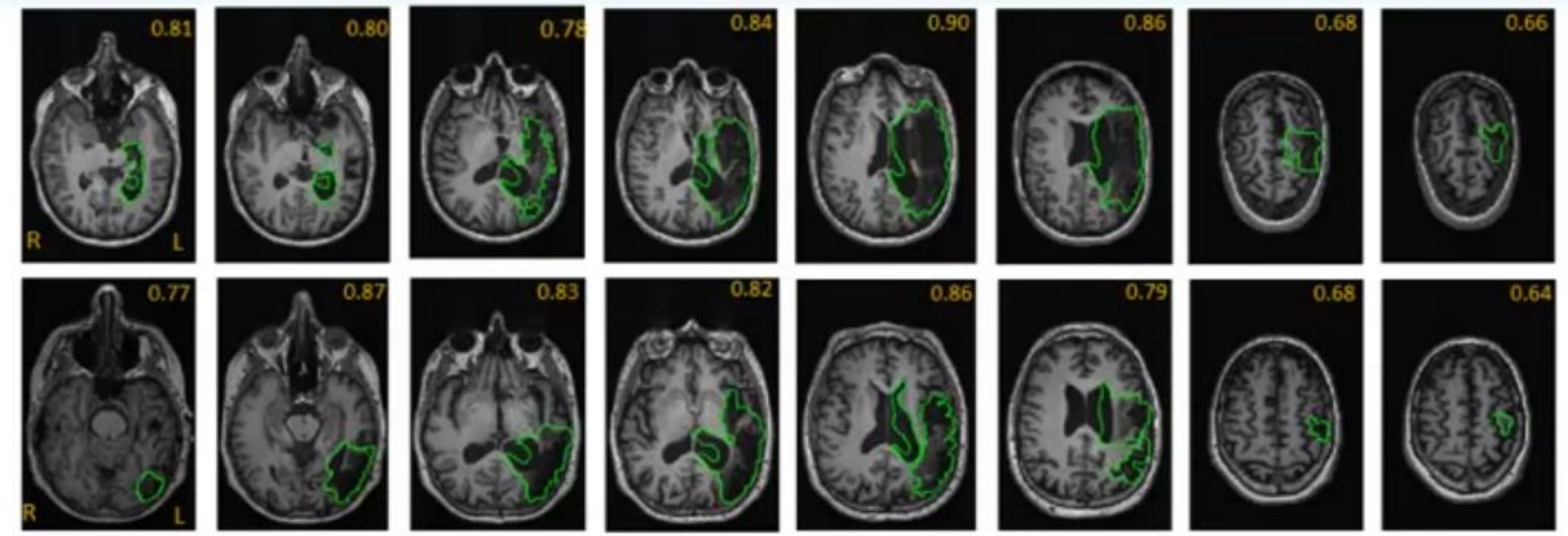
Voxels i.e 3D pixels

Clustering in 4 dimensional space i.e
[x, y, z, I(x,y,z)]

There are three groups: White matter, Gray matter and CSF

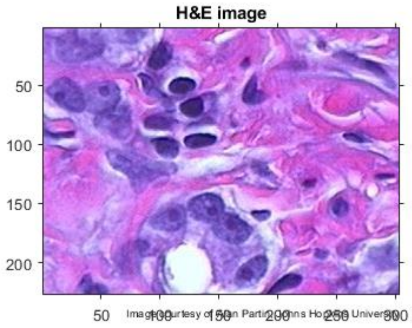
Source: Aggelos K. Katsaggelos

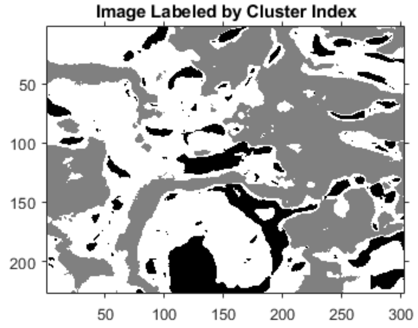
Clustering-Medical Images

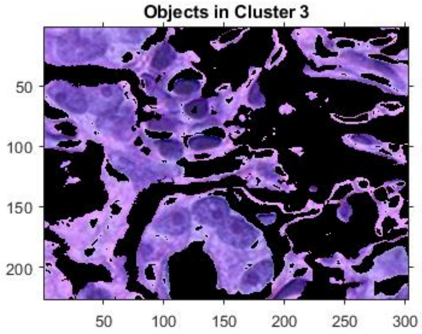


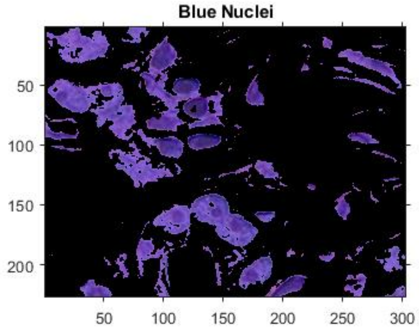
Important both for diagnosis + analysis of recovery

Source: Aggelos K. Katsaggelos









RGB -> L*a*b

Clustering on a,b

Get intensity

Threshold L

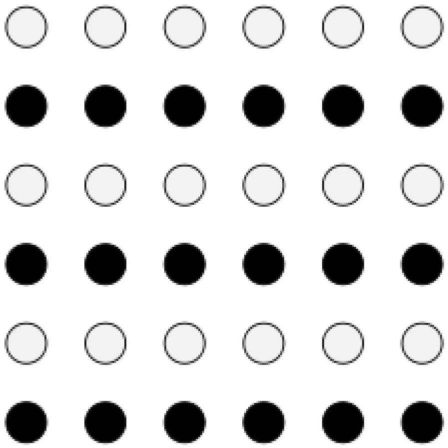
https://in.mathworks.com/help/images/color-based-segmentation-using-k-means-clustering.html

Advanced algorithms

- Mean Shift, Graph cut etc.
- Will be covered in computer vision course

Image Segmentation: How humans do it?

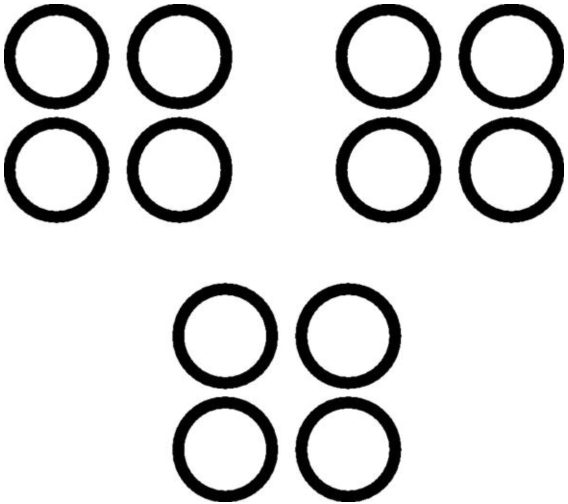
- Gestalt Principles of grouping

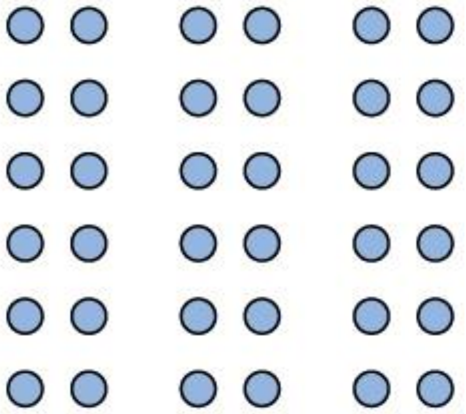


1. Similarity

Image Segmentation: How humans do it?

- Gestalt Principles of grouping

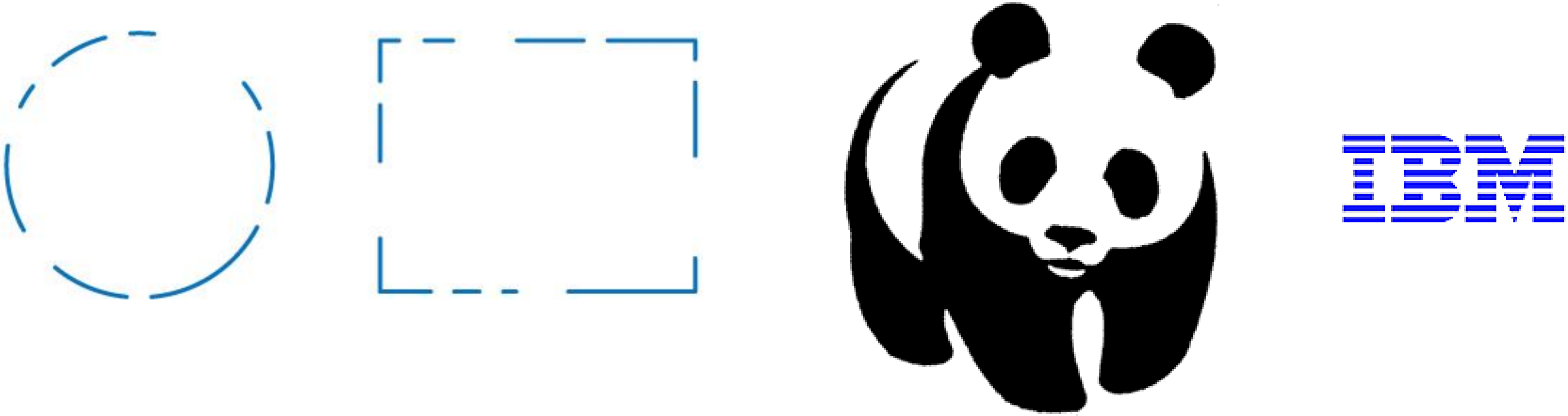




2. Proximity

Image Segmentation: How humans do it?

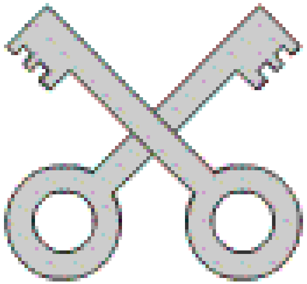
- Gestalt Principles of grouping

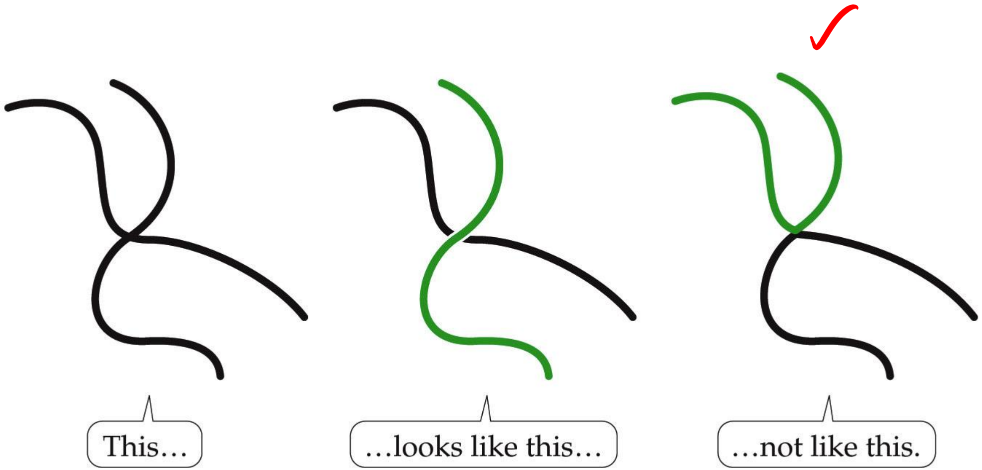


3. Closure

Image Segmentation: How humans do it?

- Gestalt Principles of grouping

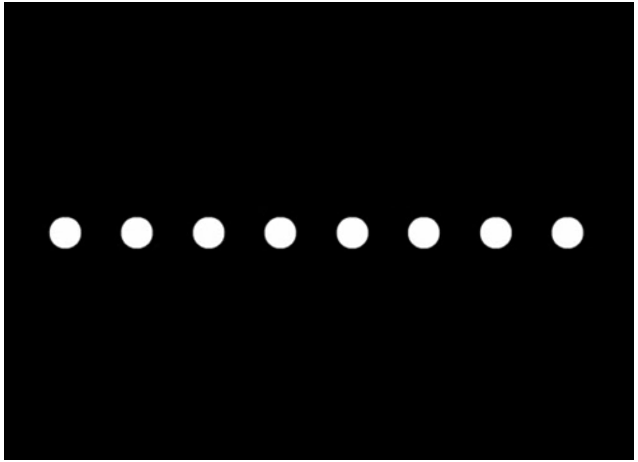




4. Good Continuation

Image Segmentation: How humans do it?

- Gestalt Principles of grouping



5. Common Fate

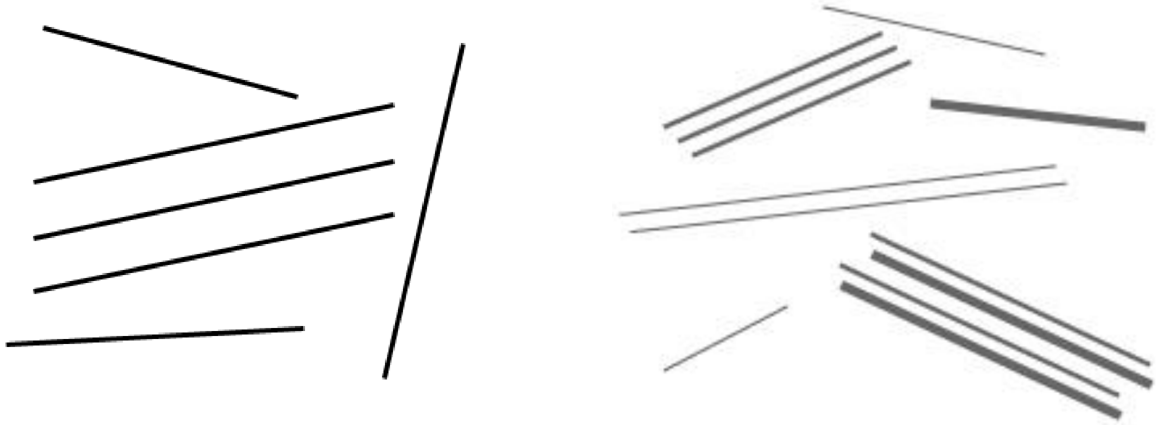
Image Segmentation: How humans do it?

- Gestalt Principles of grouping

6. Symmetry

Image Segmentation: How humans do it?

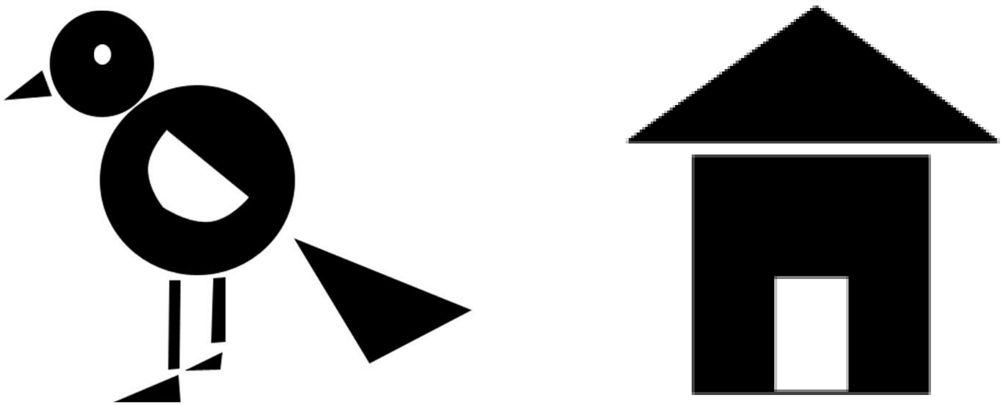
- Gestalt Principles of grouping



7. Parallelism

Image Segmentation: How humans do it?

- Gestalt Principles of grouping



8. Familiarity

Image Segmentation: How humans do it?

- Gestalt Principles of grouping
  1. Similarity
  2. Proximity
  3. Good continuity
  4. Closure
  5. Common Fate
  6. Symmetry
  7. Parallelism
  8. Familiarity

Additional References

- G&W textbook
  - 10.3, 10.4