Global Thresholding and Regions based Segmentation

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GIS5060 Geospatial Methods

Outline

- Recap: HOG, LBP
- Image Segmentation
  - Overview
  - Applications
- Threshold and Regions based Segmentation methods

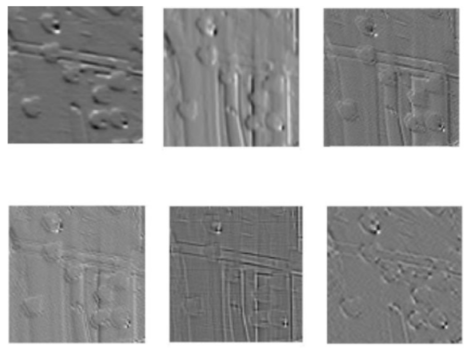
- Lab: Globus Thresholding

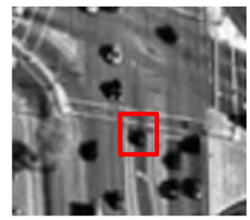
Feature Extraction - example

Data → Feature extraction → Leaning Algorithm

Where is the target?

- Many cars look similar.
- Viewing angle changes
- Occlusion
- Shadow issue

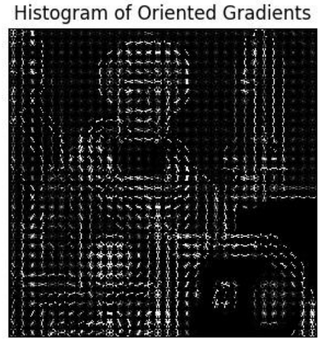




Car detection

Histogram of Oriented Gradients (HOG)

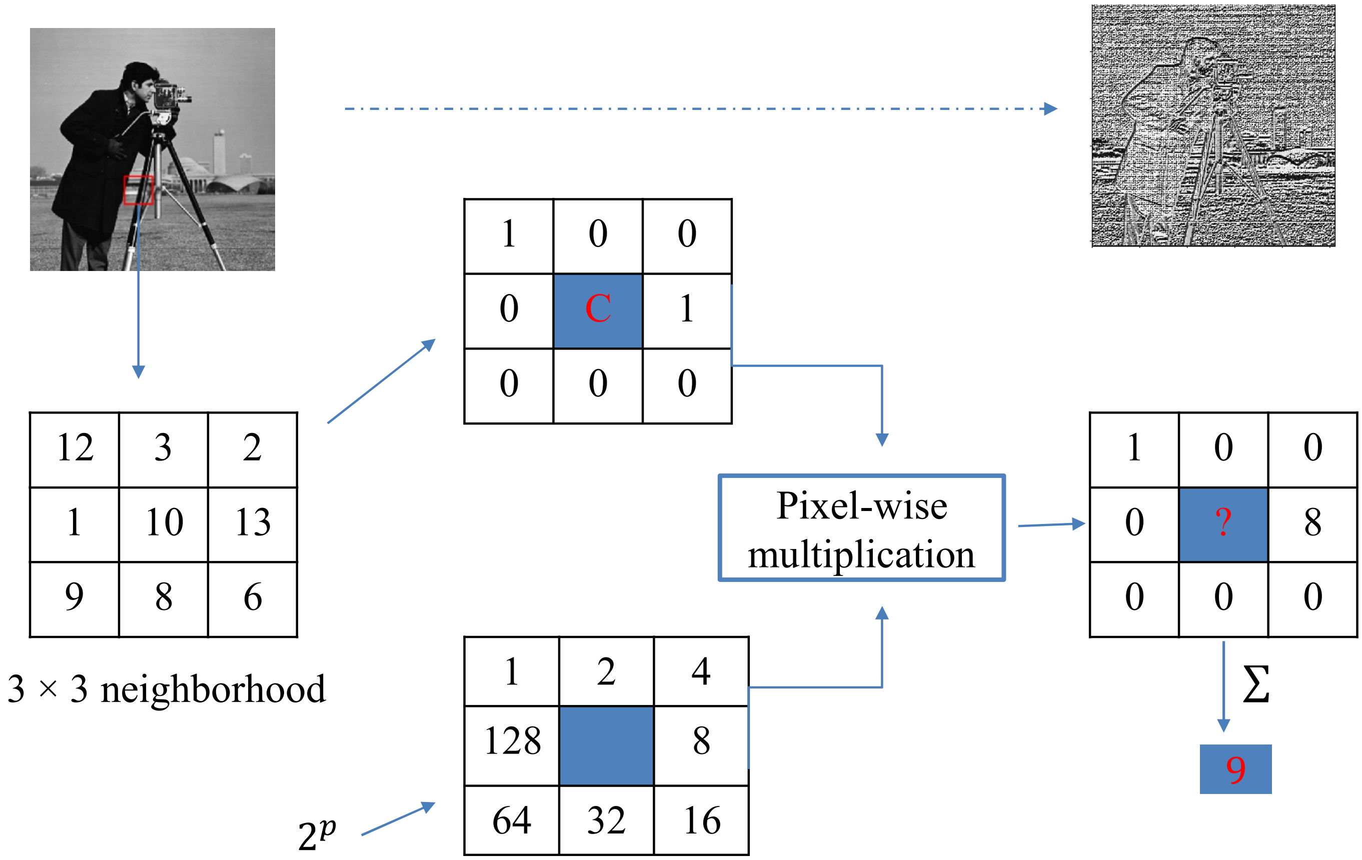
- The method is based on evaluating well-normalized **local histograms** of image **gradient orientations** in a dense **grid**.
- It is essentially a feature descriptor:
  - Formed by histograms of gradients and its orientation.
  - Collected from overlapping spatial local regions




```
from skimage.feature import hog
fd, hog_image = hog(image)
```

Navneet Dalal and Bill Triggs, "Histograms of oriented gradients for human detection." *In Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*, pp.886–893, 2005.

LBP

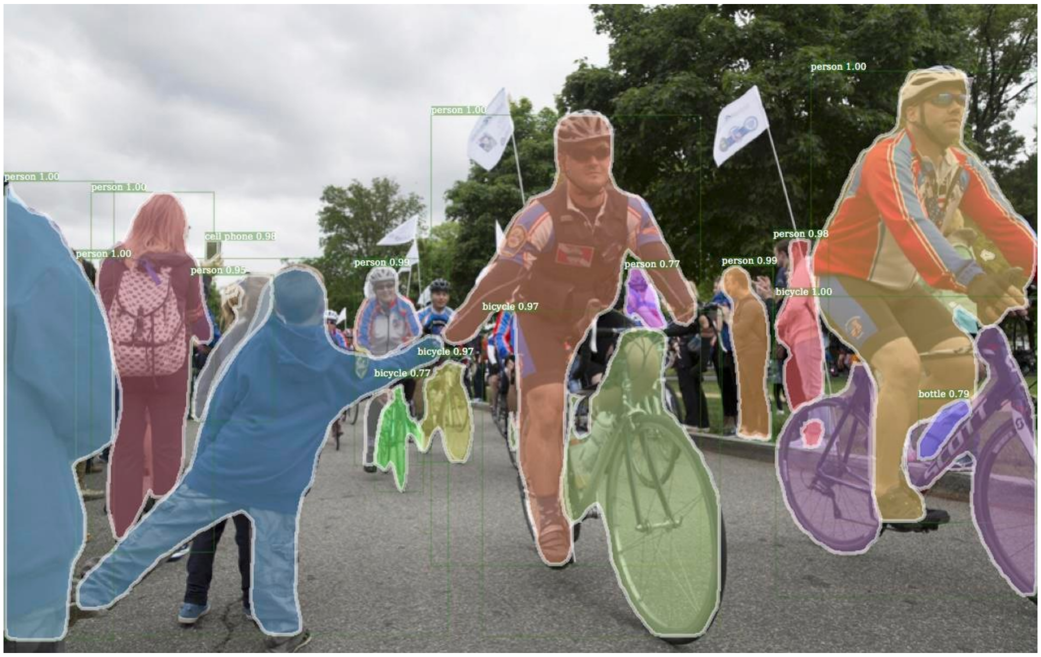


12 3 2
1 10 13
9 8 6
3 × 3 neighborhood
1 0 0
0 C 1
0 0 0
1 2 4
128 8
64 32 16
2^p
Pixel-wise multiplication
1 0 0
0 ? 8
0 0 0
Σ
9

IMAGE SEGMENTATION

Image Segmentation

- How do you identify object?
- Is segmentation involved?



https://github.com/facebookresearch/Detectron

Image Segmentation

- Goal: to partition an image into **a collection of set of pixels -** salient image regions
  - Meaningful, describes objects shapes, structures (line, curve), or natural parts of objects

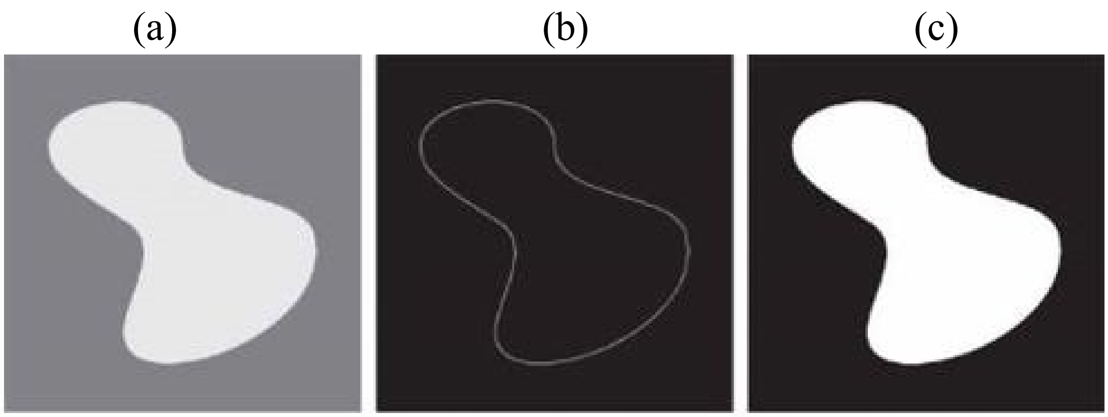
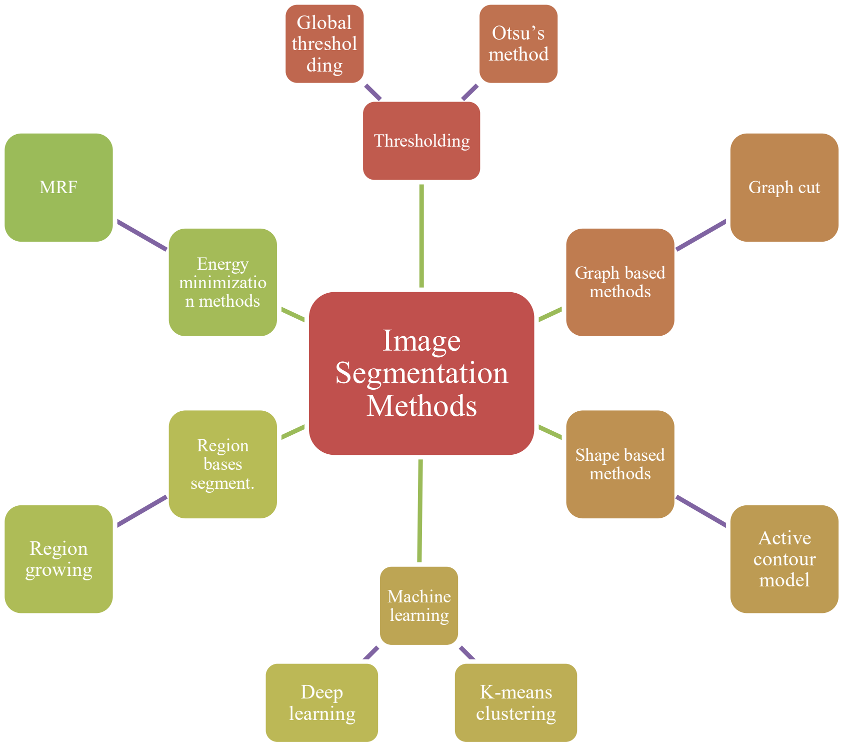


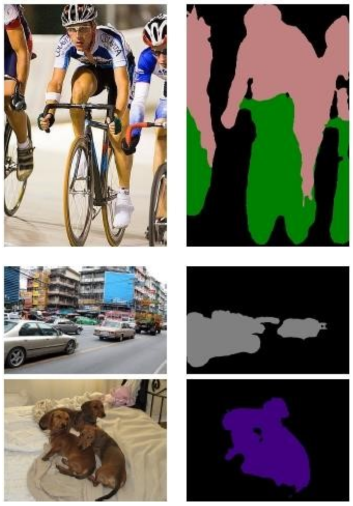
Figure 10.1

(a) Image of a constant intensity region. (b) Boundary based on intensity discontinuities.(c) Result of segmentation.

Image Segmentation Methods

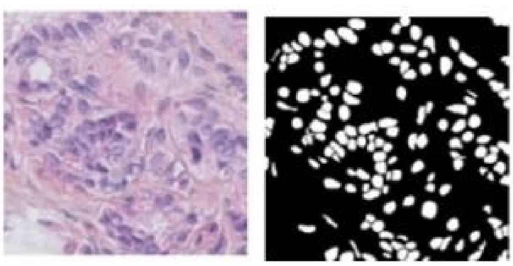


Applications



Semantic segmentation (DeepLab)

Remote Sensing Scene Segmentation (Mou et al. 2018)



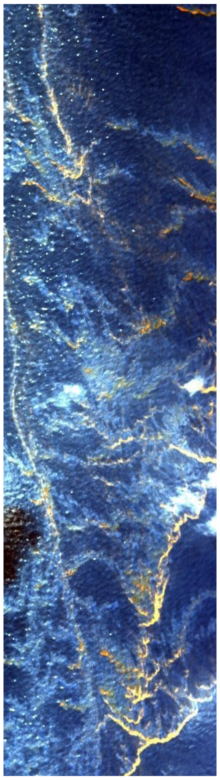
Nuclei segmentation (Alom et al., 2019)

Plant segmentation (Ubbens et al. 2018)

Building Change Detection

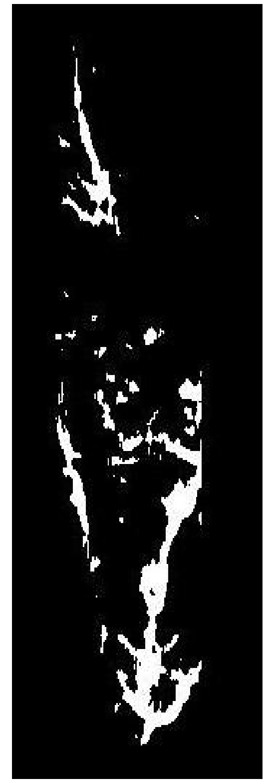
Sidike, et al., IGRASS 2016

Oil Spill Segmentation



RGB representation of image

Segmentation of Oil Slick

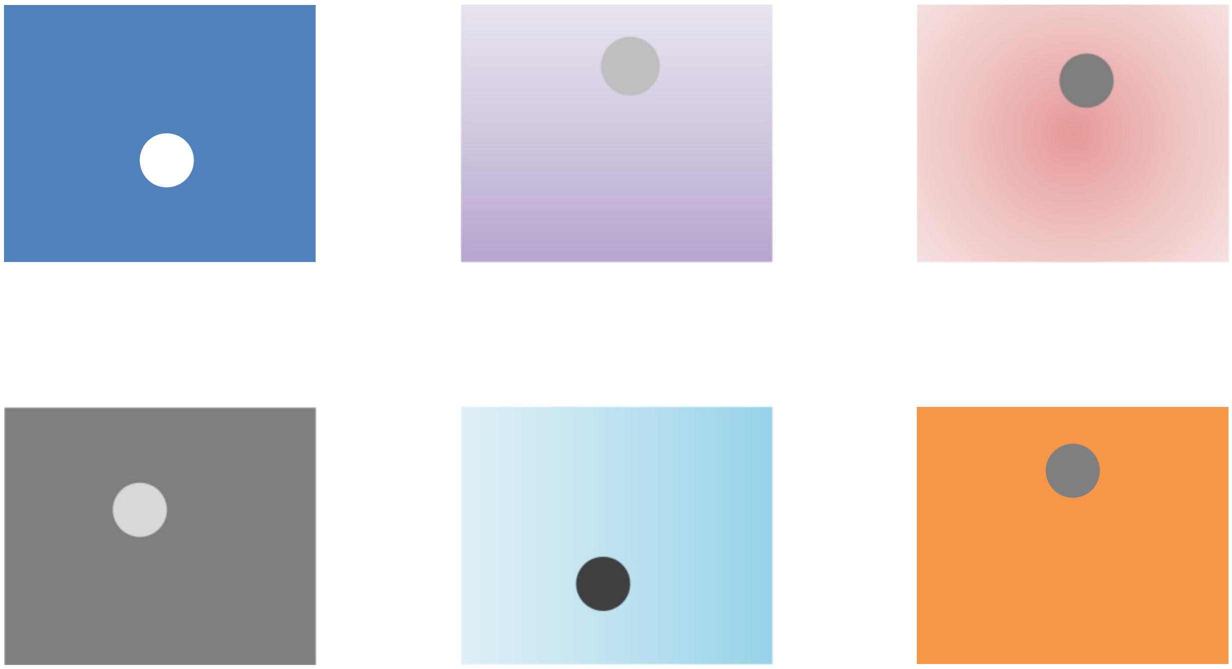


Segmentation mask (area)

Fatema. A., Sidike, P., et al., MEHOC 2017

Segmentation - simple case

- Segment circular region from these images



Segmentation - complex case

- Coherent scene segmentations that contains complex background and more classes

COCO Panoptic Segmentation Task

Thresholding

- Global Thresholding:
  - The threshold T is a constant applicable for entire image.
- Variable Thresholding:
  - The value of T changes over an image
  - Local or regional thresholding:
    - The value of T at any point (x, y) depends on its neighborhood
  - Dynamic or adaptive thresholding

Basic Global Thresholding

- Global Thresholding

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

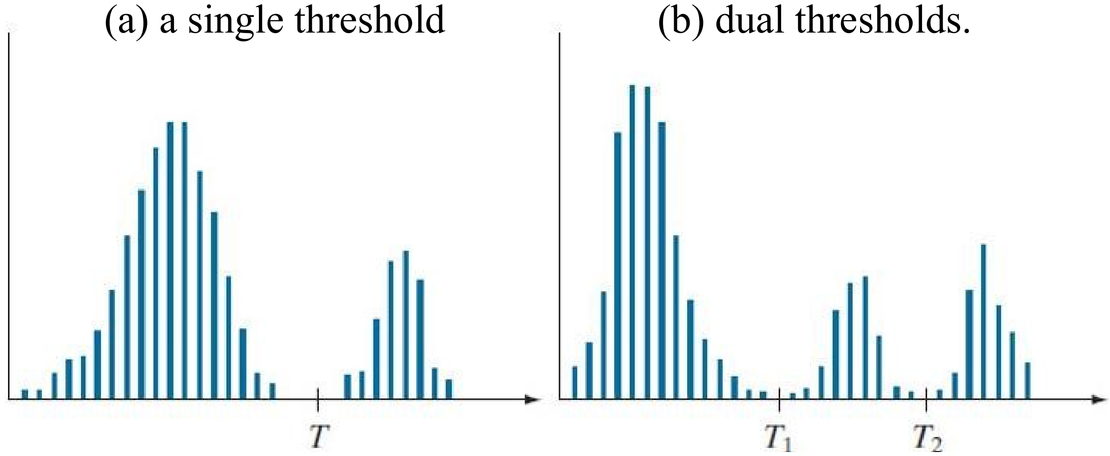
$$g(x,y) = \begin{cases} a & if\ f(x,y) > T_2 \\ b & if\ T_1 < f(x,y) \le T_2 \\ c & if\ f(x,y) \le T_1 \end{cases}$$

(a) a single threshold

(b) dual thresholds.

a b

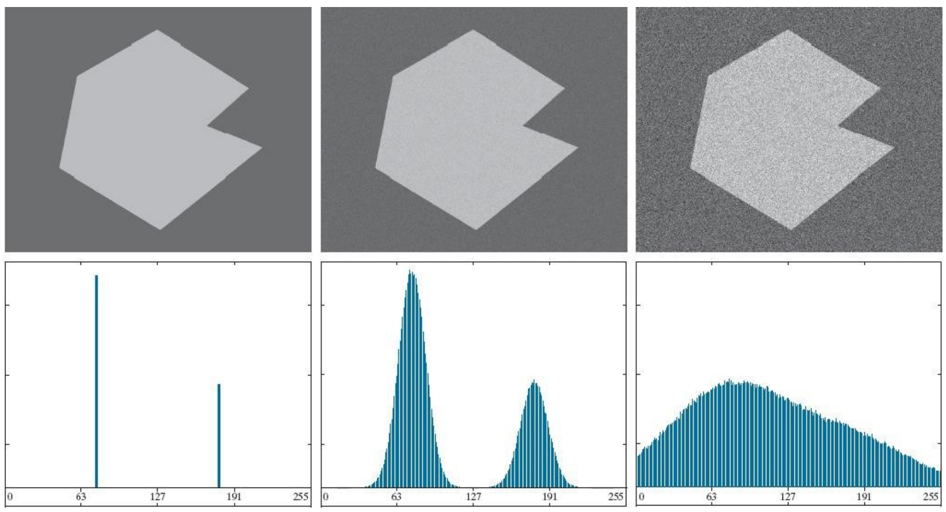
Figure 10.32



Noise Effect on Image Thresholding

- Noise introduces difficulties in finding a proper threshold

Noiseless 8-bit image | Less noise | Sever noise



Histograms

Distinct two modes

Figure 10.33

Illumination Effect on Image Thresholding

(a) Noisy image. (b) Intensity ramp in the range [0.2, 0.6]. (c) Product of (a) and (b).

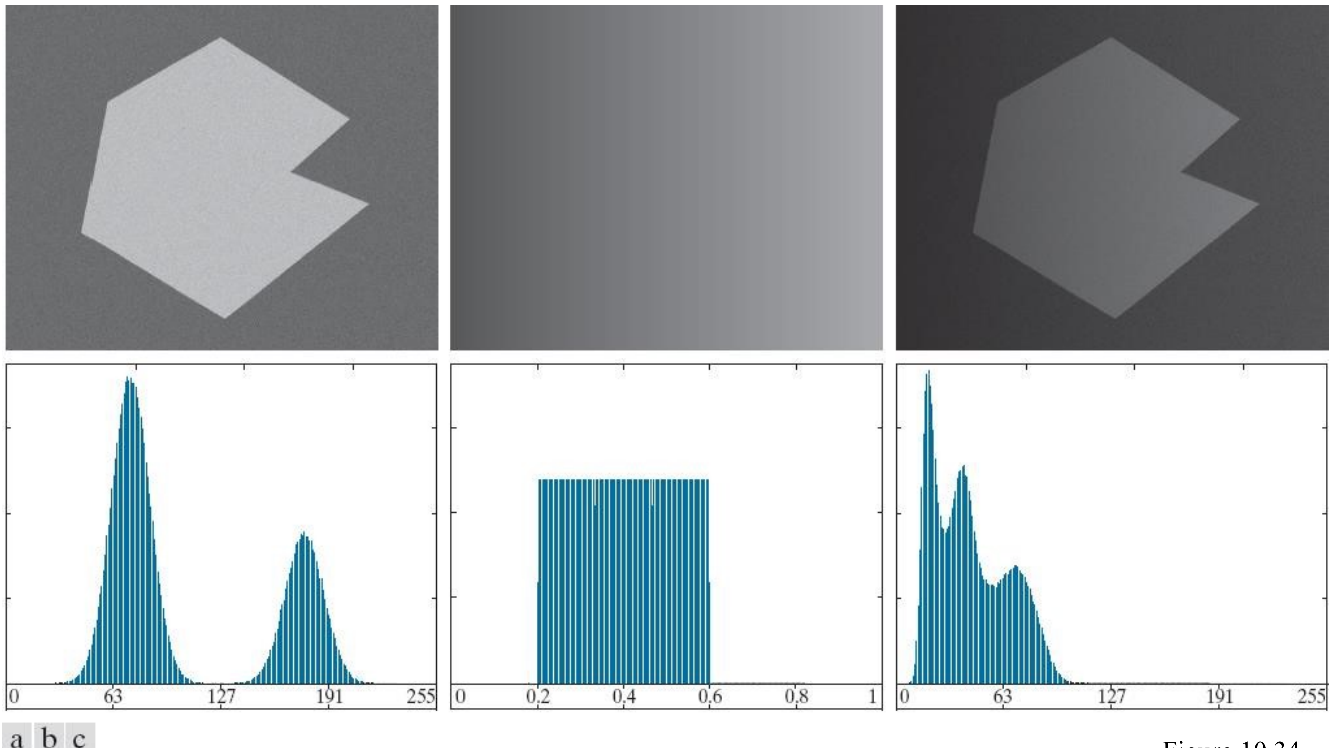


Figure 10.34

Global Thresholding Process

1. Select an initial estimate for the global threshold, T. (e.g., T is the average intensity of input image)

$I =$

10	10	10	10
20	20	20	20
30	30	30	30
40	40	40	40

$\Rightarrow$ $mean(I) = ?$

Global Thresholding Process

2. Segment image using T. This will produce two group of pixels, a and b.

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

3. Computer the average intensity of a and b

$$m_1 = \text{mean}(a)$$

$$m_2 = \text{mean}(b)$$

Global Thresholding Process

4. Computer a new threshold by average of m_1 and m_2

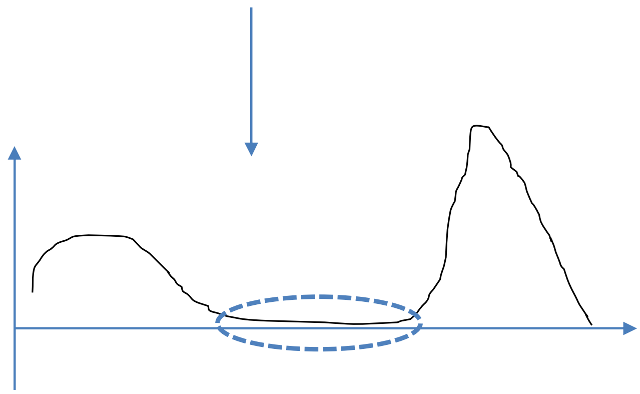
$$m_1 = \text{mean}(a)$$
$$m_2 = \text{mean}(b)$$

$$\Rightarrow \quad T = \frac{(m_1 + m_2)}{2}$$

5. Repeat Steps 2 to 4 until the difference between successive T is less than predefined values, ΔT.

Issues in Basic Global Thresholding

- Noise
- No visible valley
- The valley may be too broad that it is difficulty to intensify optimal *T*



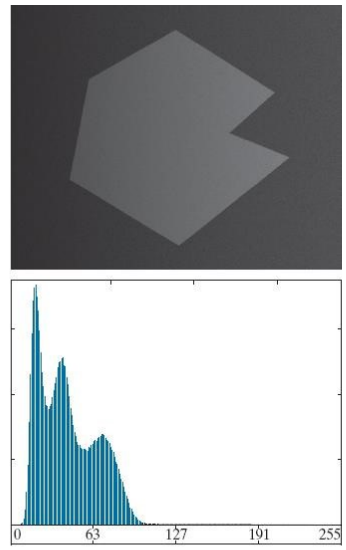


Figure 10.34

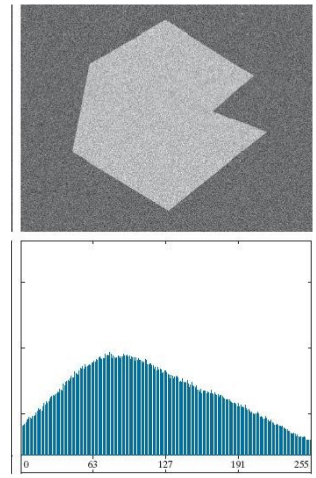


Figure 10.33

Otsu Thresholding

- Otsu's algorithm selects a threshold that maximizes the **between-class variance**
- In the case of two classes:

$$\sigma_B^2 = P_1(\mu_1 - \mu_G)^2 + P_2(\mu_2 - \mu_G)^2$$

- P_1 and P_2 are class probabilities:
  - P_1: accumulate histogram up to gray-level k (i.e., a chosen threshold)
  - P_2: accumulate histogram from gray-level $k+1$ to the maximum graylevel (e.g., 255)
- μ_1 and μ_2 are the means of object classes.

$$\mu_1 = \frac{1}{P_1(k)} \sum_{i=0}^{k} ip(i) \qquad \mu_2 = \frac{1}{P_2(k)} \sum_{i=k+1}^{L-1} ip(i)$$

- μ_G is the global mean – the average intensity of the entire image

Otsu Thresholding - Steps

1. Compute normalization histogram, p_i
2. Compute the cumulative sums, $P_1(k)$
3. Compute cumulative mean, $\mu_1(k)$
4. Compute global mean, μ_G
5. Compute **between-class variance,** σ_B^2
6. To find optimal value of the threshold k, iterate the steps 1-5 for all integer values of k and select the value of k that yields the maximum σ_B^2.

Examples – Otsu's based Seg.

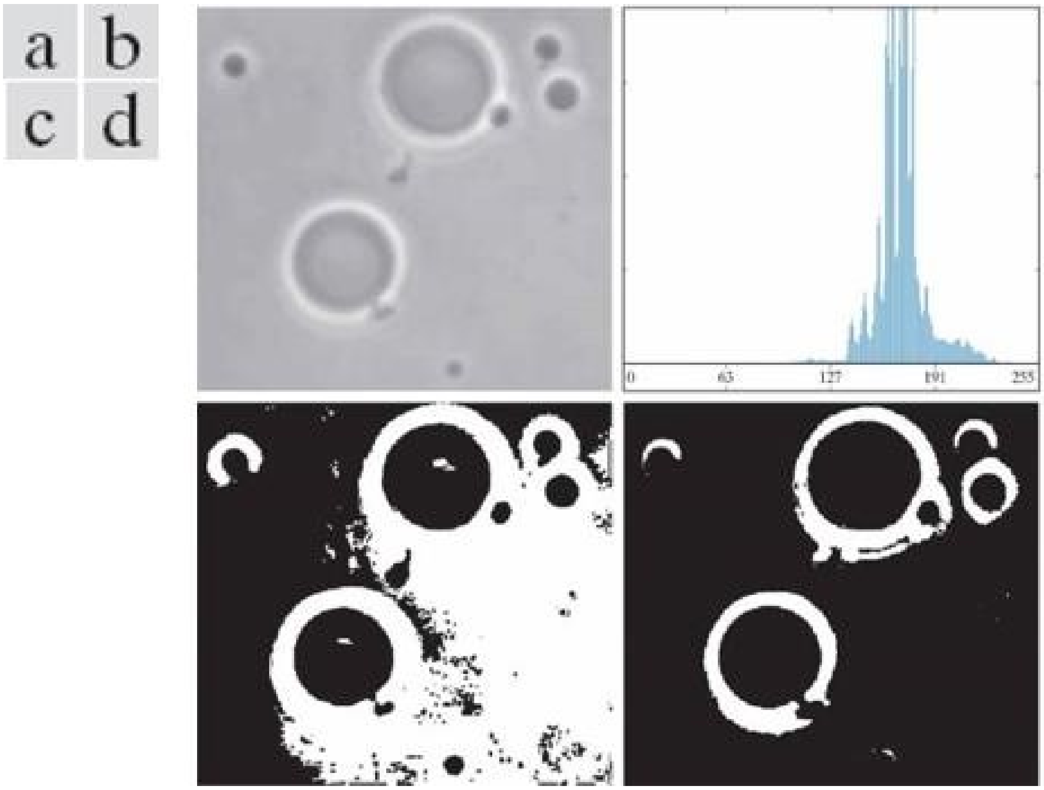
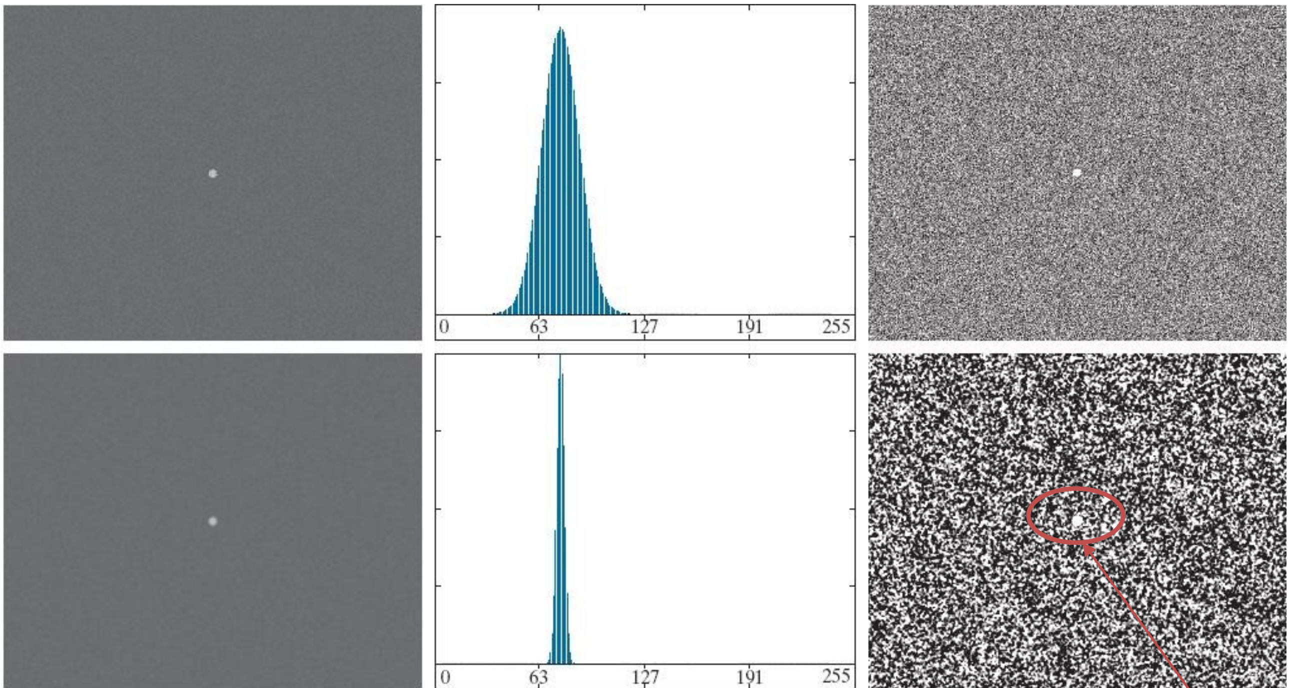


Figure 10.36 in Textbook

(a) Original image.
(b) Histogram
(c) Segmentation result using the basic global algorithm
(d) Result using Otsu's method.

Failing case: Smoothing + Otsu's based Seg.



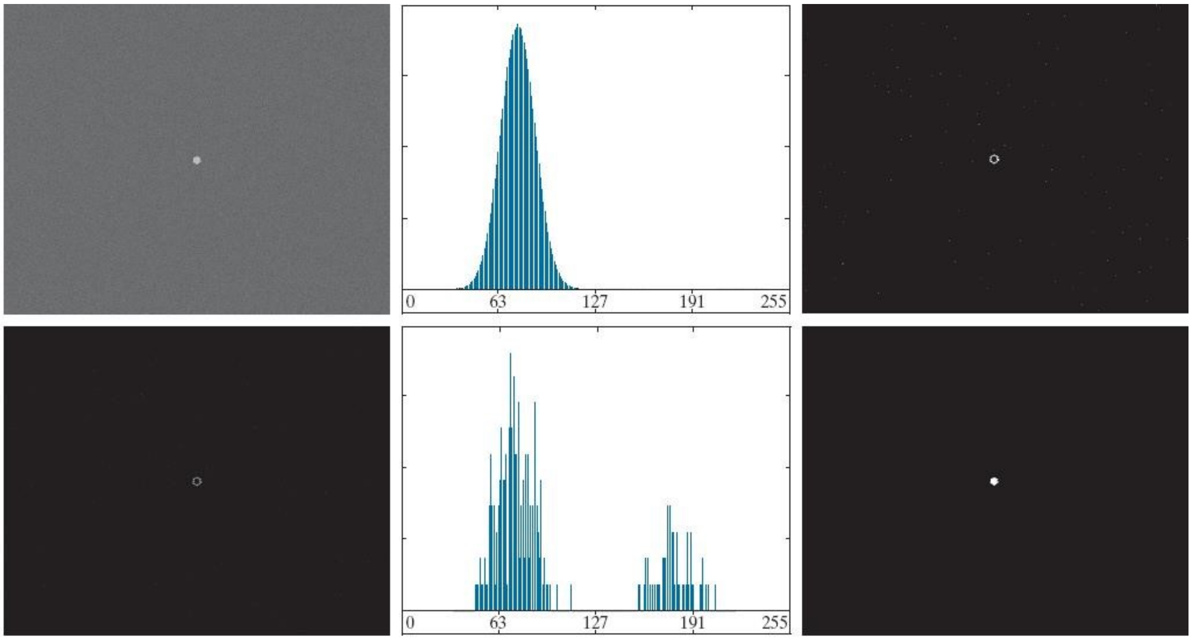
a b c
d e f

(a) Noisy image
(b) Its histogram.
(c) Result obtained using Otsu's method.
(d) Noisy image smoothed using a 5 × 5 averaging kernel
(e) The histogram of (d)
(f) Result obtained using Otsu's method for (d)

Figure 10.38 in the Textbook

Fail to segment

Solution: Gradient + Otsu's Seg.



a b c
d e f

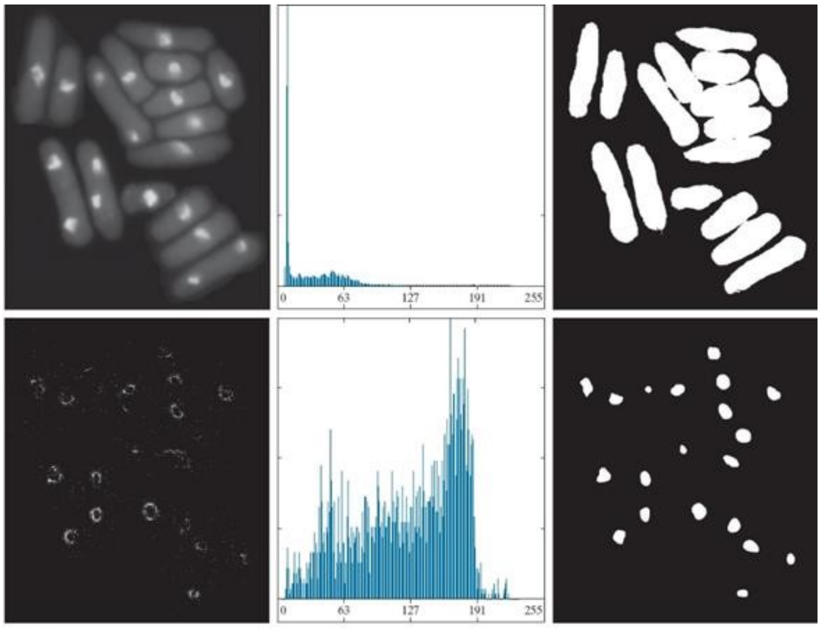
Figure 10.39 in the Textbook

(a) Noisy image
(b) The histogram of (a).
(c) Gradient magnitude image.
(d) Image formed as the product of (a) and (c).
(e) Histogram of the nonzero pixels in the image in (d).
(f) Result of segmenting image (a) with the Otsu threshold based on the histogram in (e).

Lecture_4

```
from skimage.data import camera
from skimage.filters
import roberts, sobel, scharr, prewitt
image = camera()
edge_roberts = roberts(image)
edge_sobel = sobel(image)
```

Laplacian + Otsu's Seg.



a b c
d e f

Figure 10.40 in the Textbook

(a) Image of yeast cells.

(b) The histogram of (a).

(c) Segmentation of (a) with Otsu's method

(d) Mask image formed by thresholding the absolute Laplacian image.

(e) Histogram of the nonzero pixels in the product of (a) and (d).

(f) Original image thresholded using Otsu's method based on the histogram in (e).

Laplacian operator (Lecture 4)

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Variable Thresholding (VT)

- Smoothing and edge information can help in object segmentation, but may ineffective in many practical scenarios.
- **Variable Thresholding**: compute a threshold at every pixel (x, y) within its neighborhood in an image.
- Common form: $T_{xy} = a\sigma_{xy} + b\mu_{xy}$

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

a and b are nonnegative constants

σ_{xy} and μ_{xy} are the standard deviation and mean of the set of pixel values in a neighborhood

VT based on Moving Averages

- A special case of the local thresholding
  - Computing a moving average along scan lines of an image

- Carried out line by line in a **zigzag pattern** to reduce illumination bias

- Especially useful in document processing

VT based on Moving Averages

- Moving average at the pixel $k+1$ is formed by averaging the intensities of that pixel and its $n-1$ preceding neighbors.

$$\mu(k+1) = \frac{1}{n} \sum_{i=k+2-n}^{k+1} z_i \qquad \qquad for\ k \geq n-1$$

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

Moving Average

$\mathbf{f(x,y)}$

$a1$	$a2$	$a3$
$a6$	$a5$	$a4$
$a7$	$a8$	$a9$

zigzag pattern:

$a1$	$a2$	$a3$	$a4$	$a5$	$a6$	$a7$	$a8$	$a9$

If $\boldsymbol{n = 3}$:

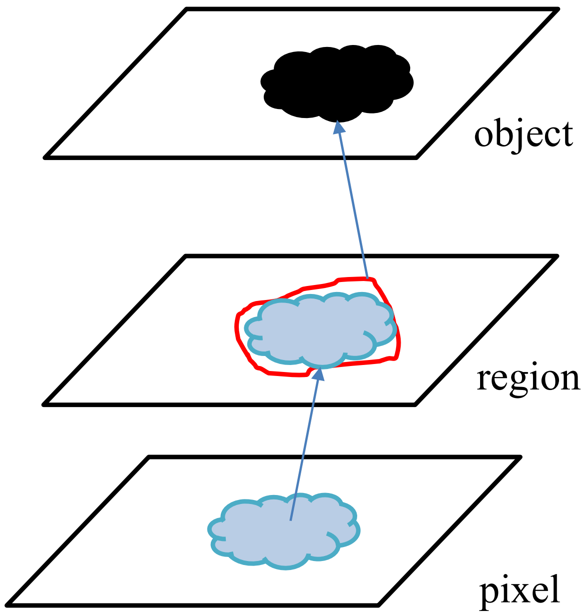
			μ					

$$\frac{a2 + a3 + a4}{3} \rightarrow \quad g(x,y) = \begin{cases} 1 \ \ if\ f(x,y) > c\mu_{xy} \\ 0 \ \ if\ f(x,y) \leq c\mu_{xy} \end{cases}$$

for each position, compute the local average as the threshold

Region based segmentation

The fundamental drawback of histogram-based segmentation: **histograms provide no spatial information**.



- Region:
  - A Group of connected pixels with similar properties
  - Regions may indicate objects or its parts in a scene
  - Regions segmentation is based in similarity

Region Growing

- Group pixels or subregions into larger regions based on predefined criteria for growth.
- Exploit the important fact that pixels which are close together have similar gray values
- Seeded Segmentation
  1. Choose one or more seed pixels
  2. Using a similarity criteria to determine if its neighboring pixels share similar property with the selected seed pixel
  3. Repeat step 2 till no new pixel can be added

$$|\text{neighboring pixels} - seed\ pixel| < threhold$$

Region Growing

Seed, and set T = 3

1	7	4	8
2	1	**6**	5
1	2	6	8

⇨

0	1	1	1
0	0	1	1
0	0	1	1

Clustering based Segmentation

❖ Performs *K*-means clustering

- **Initialization**:
  - choose *k* cluster centers at random locations
- **Repeat**:
  - Assign each pixel to its closet cluster center using Euclidian Distance
  - Recompute the new cluster centers as the mean of its all assigned points
- **Until**:
  - The maximum number of iterations is reached, or
  - No changes during the assignment step, or

```
from skimage.segmentation import slic
```

K-means Clustering

(a) – (f) Iterative Process for $k = 2$

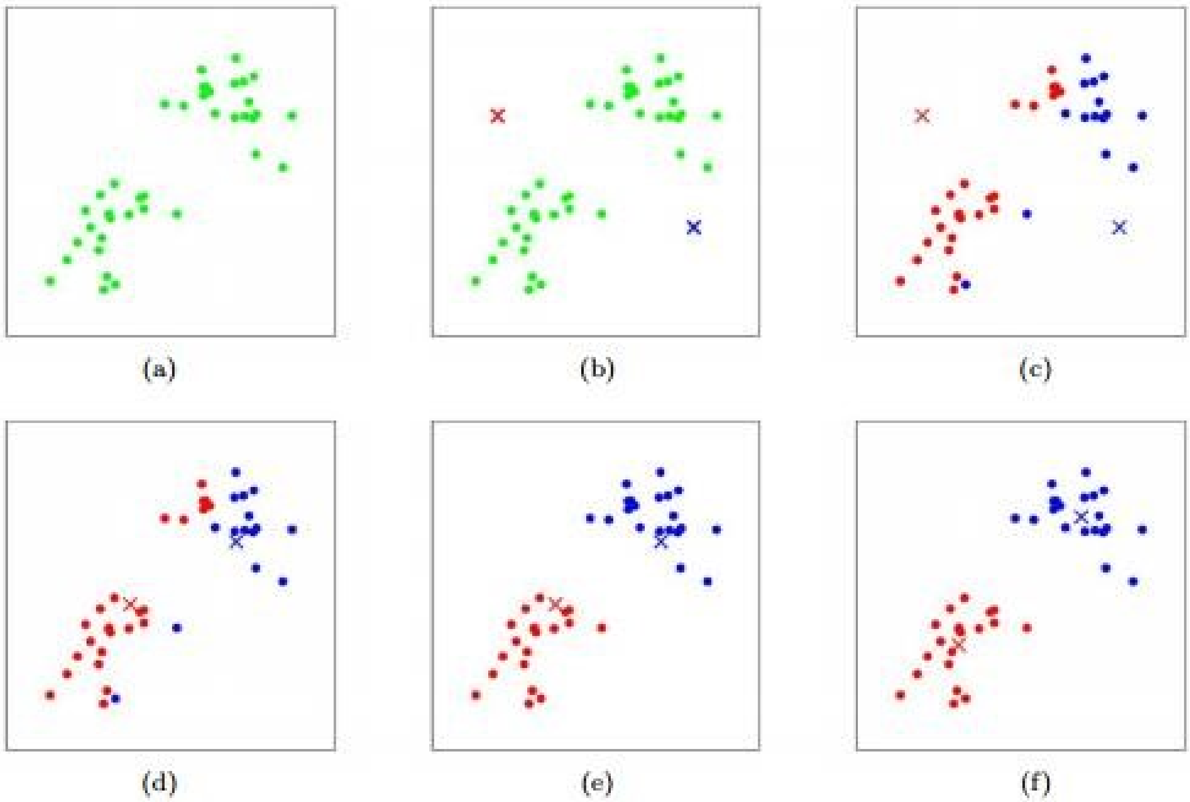


Figure credit: Chris Piech

Active Contour Model (ACM)

- Deformable models confined to the plane.
- **Active** contour:
  - The curves are dynamic that are attracted to region boundaries.
- Expression

$$E_{\boldsymbol{snake}} = E_{internal} + E_{external} + E_{img}$$

Movement of curve

  - The **internal term** stands for regularity/smoothness along the curve
  - The **image term** guides the active contour towards the strong gradients
  - The **external term** can be used to account for user-defined constraints
  - The lowest potential of such a cost function refers to an equilibrium of these terms

- **Level set**: sets of points of a 2-D curve formed by the intersection of a plane and a 3D surface.

```
from skimage.segmentation import chan_vese
```

```
from skimage.segmentation import active_contour
```