

# Image Segmentation

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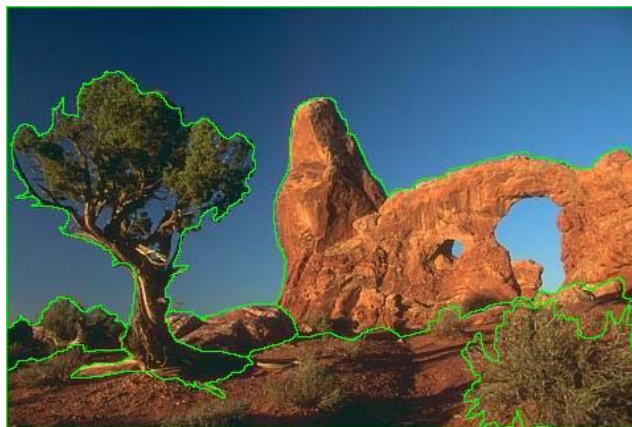
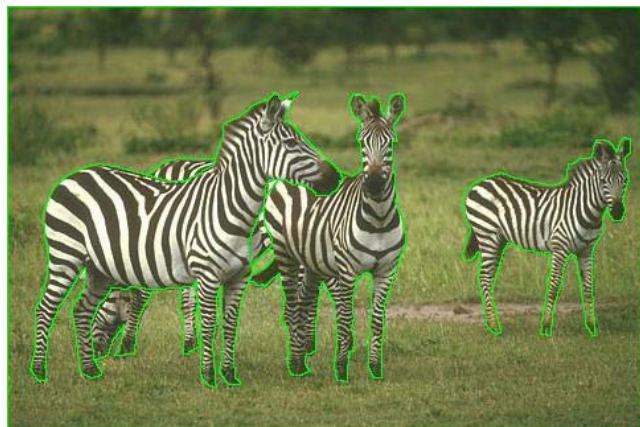
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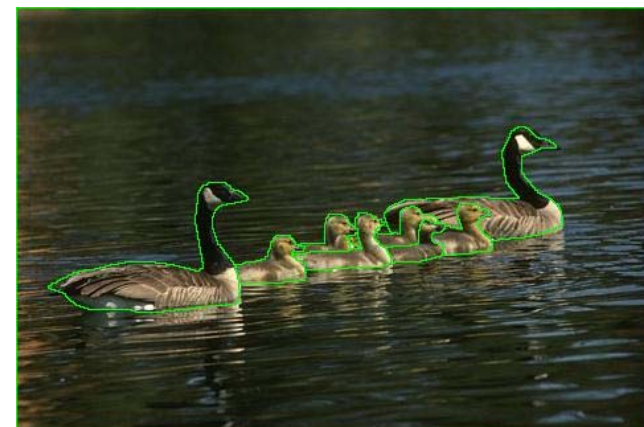
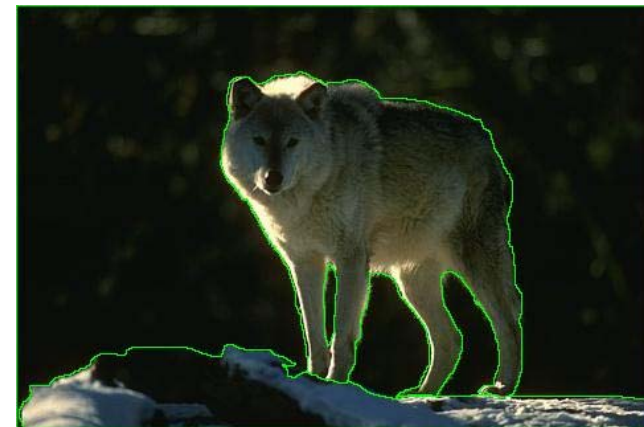
# Image segmentation





# Image segmentation

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# From images to objects

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- “I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of color. Do I have “327”? No. I have sky, house, and trees.”  
-- Max Wertheimer
- What defines an object?
  - Subjective problem, but has been well-studied.
  - Gestalt laws seek to formalize this.
  - “What is interesting and what is not” depends on the application.
  - Broad theory is absent at present.

# Gestalt laws

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- A series of factors affect whether elements should be grouped together.
  - Proximity: tokens that are nearby tend to be grouped.
  - Similarity: similar tokens tend to be grouped together.
  - Common fate: tokens that have coherent motion tend to be grouped together.
  - Common region: tokens that lie inside the same closed region tend to be grouped together.
  - Parallelism: parallel curves or tokens tend to be grouped together.
  - Closure: tokens or curves that tend to lead to closed curves tend to be grouped together.
  - Symmetry: curves that lead to symmetric groups are grouped together.
  - Continuity: tokens that lead to “continuous” curves tend to be grouped.
  - Familiar configuration: tokens that, when grouped, lead to a familiar object, tend to be grouped together.

# Gestalt laws



Not grouped



Proximity



Similarity



Similarity



Common Fate

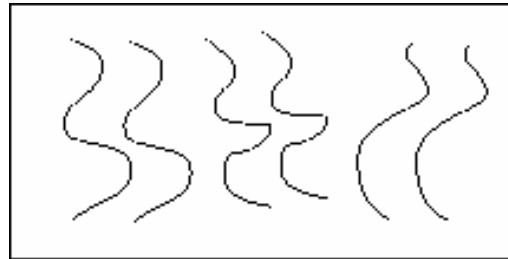


Common Region

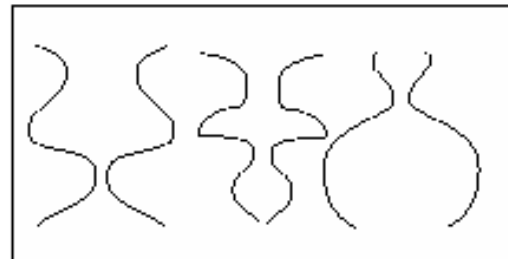


# Gestalt laws

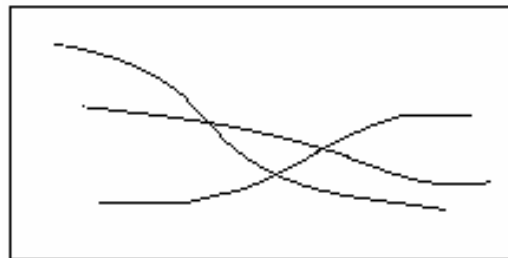
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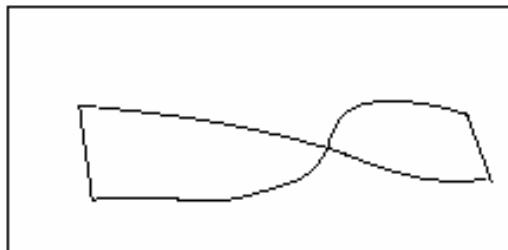
Parallelism



Symmetry



Continuity



Closure

# Image segmentation

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- Image segmentation is the operation of partitioning an image into a collection of connected sets of pixels.
- 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.  $S_i \cap S_j = \emptyset, i \neq j$  No regions intersect.
  3.  $\forall S_i, P(S_i) = \text{true}$  Homogeneity predicate is satisfied by each region.
  4.  $P(S_i \cup S_j) = \text{false},$   
 $i \neq j, S_i \text{ adjacent } S_j$  Union of adjacent regions does not satisfy it.



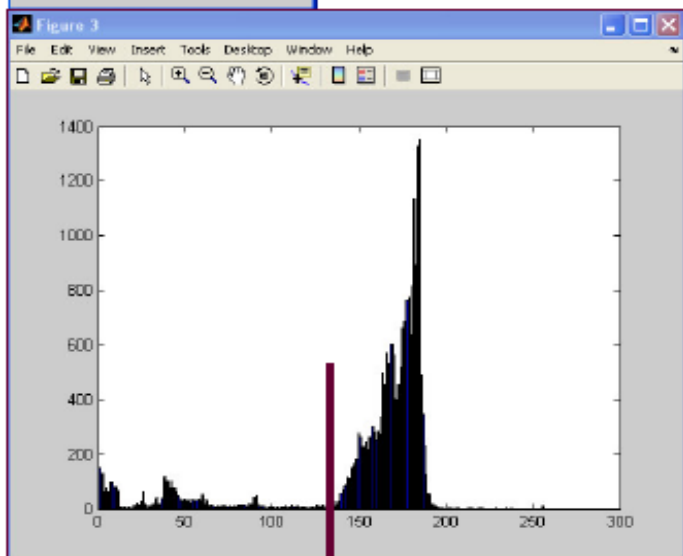
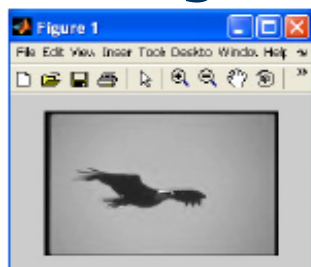
# Image segmentation

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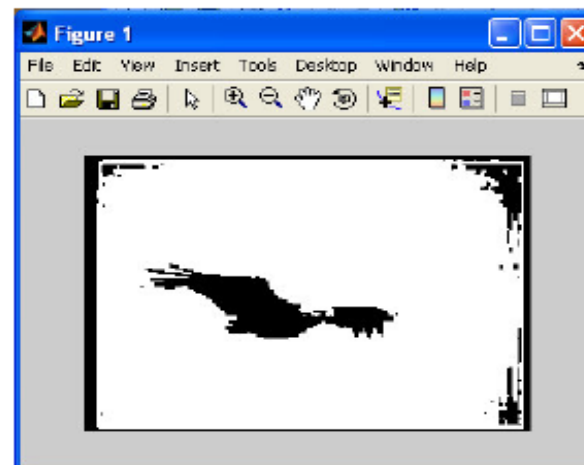
- So, all we have to do is to define and implement the similarity predicate.
  - But, what do we want to be similar in each region?
  - Is there any property that will cause the regions to be meaningful objects?
- Example approaches:
  - Histogram-based
  - Clustering-based
  - Region growing
  - Split-and-merge
  - Morphological
  - Graph-based

# Histogram-based segmentation

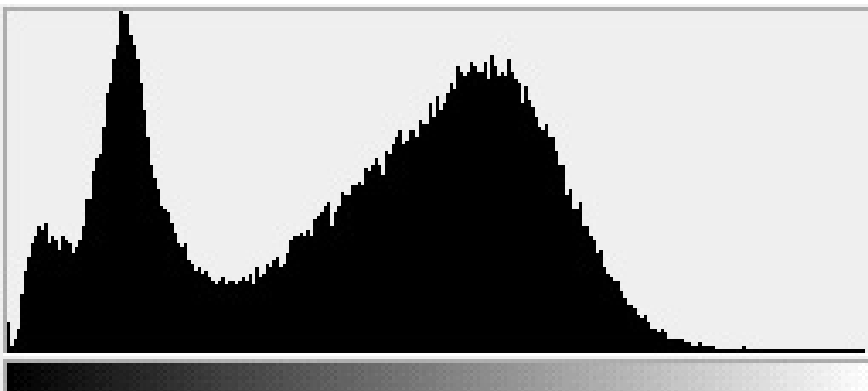
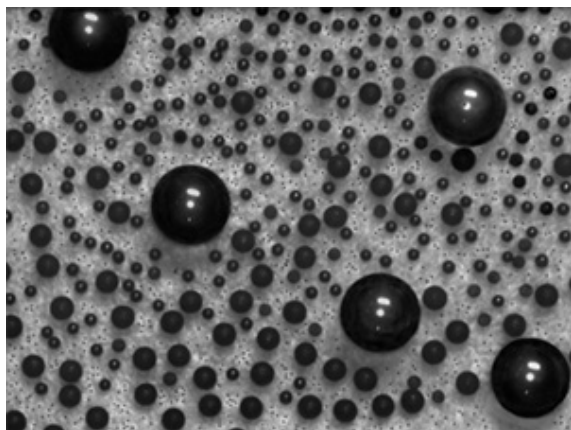
- How many “orange” pixels are in this image?
- This type of question can be answered by looking at the histogram.



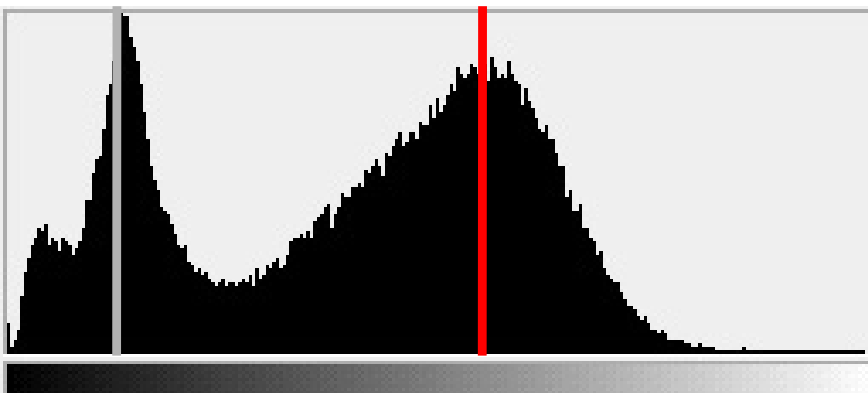
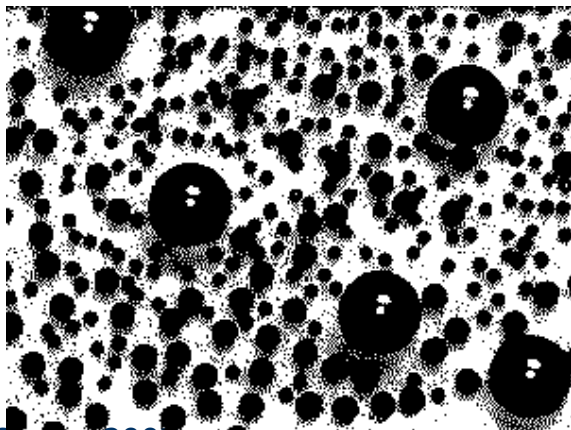
`imshow(B > 140)`



# Histogram-based segmentation

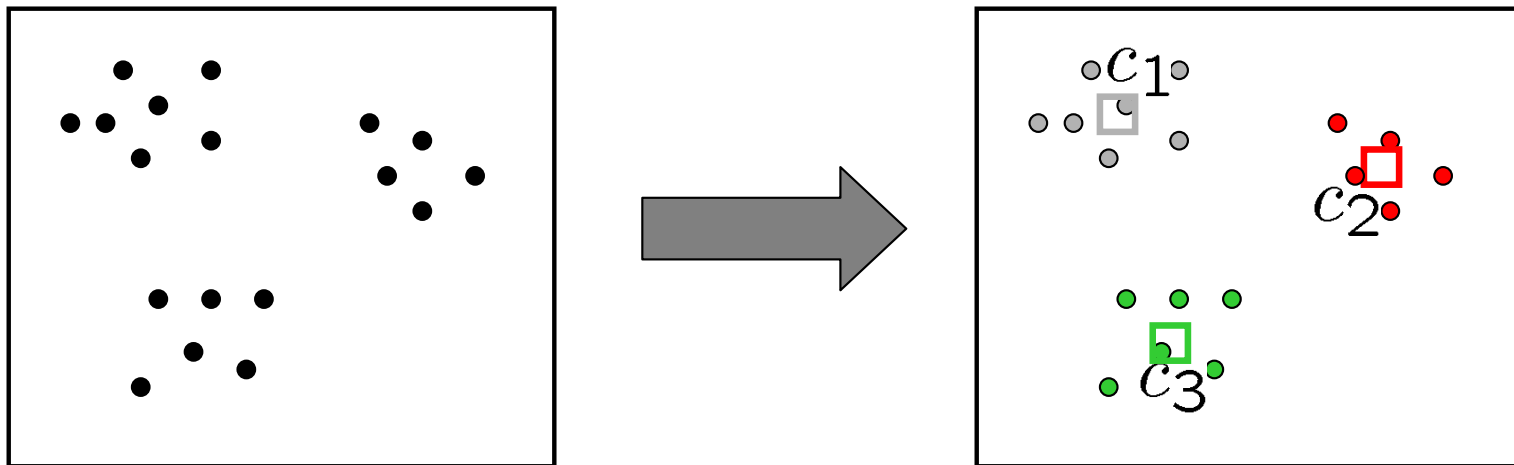


- How many modes are there?
- Solve this by reducing the number of colors to  $K$  and mapping each pixel to the closest color.
- Here's what it looks like if we use two colors.



# Clustering-based segmentation

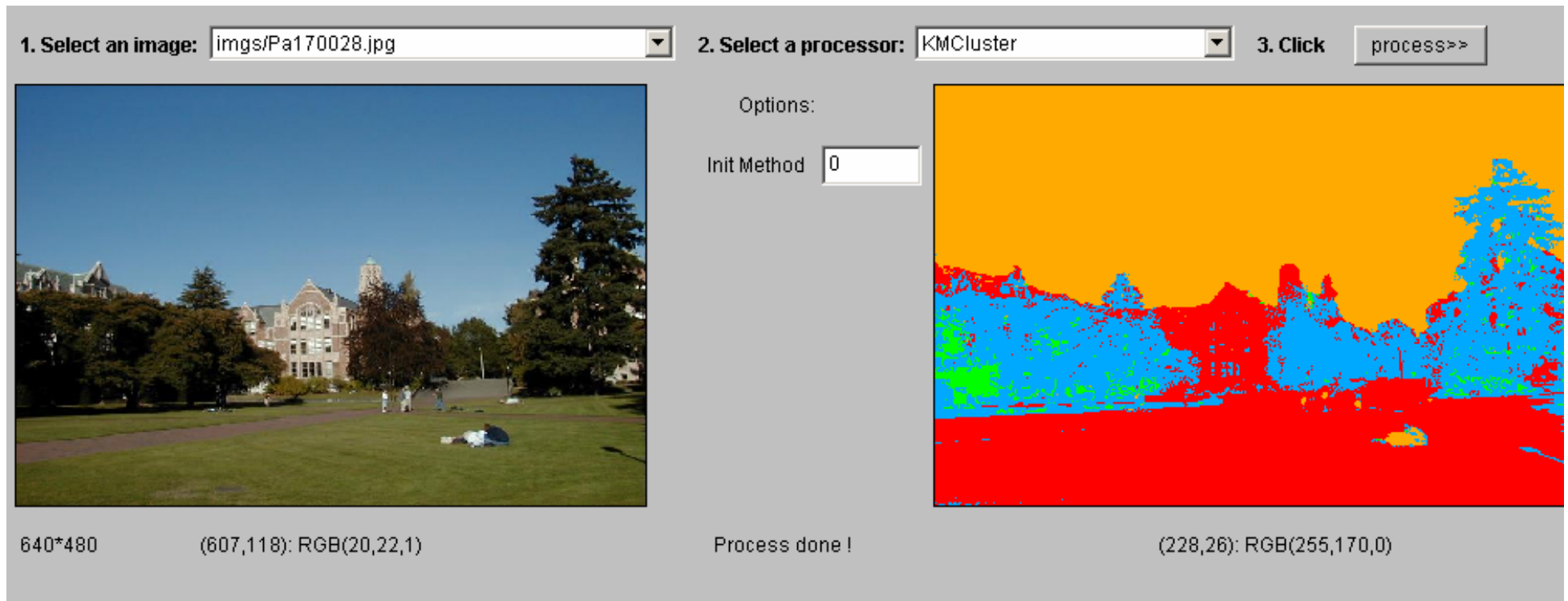
- How to choose the representative colors?
  - This is a clustering problem!



- K-means algorithm can be used for clustering.



# Clustering-based segmentation



K-means clustering of color.

# Clustering-based segmentation

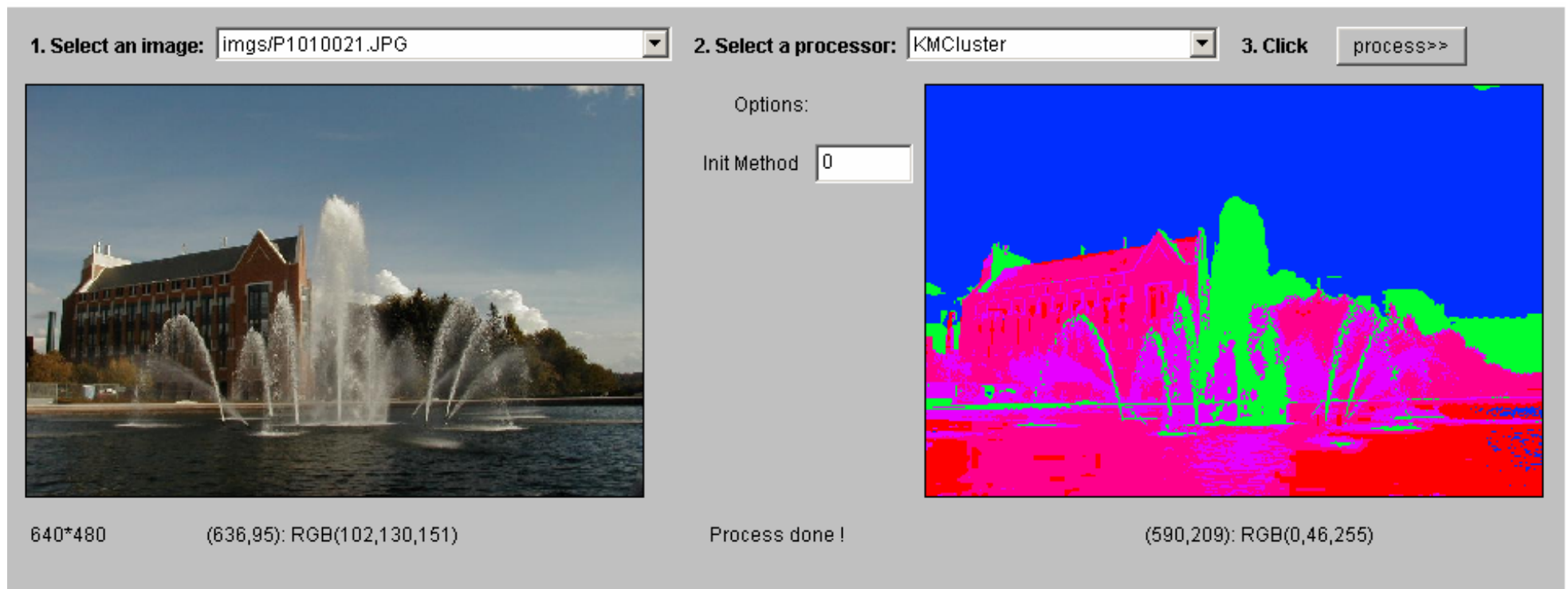
1. Select an image:  2. Select a processor:  3. Click

Options:  
Init Method

640\*480 (636,95): RGB(102,130,151)

Process done !

(590,209): RGB(0,46,255)



K-means clustering of color.

# Clustering-based segmentation

- Clustering can also be used with other features (e.g., texture) in addition to color.

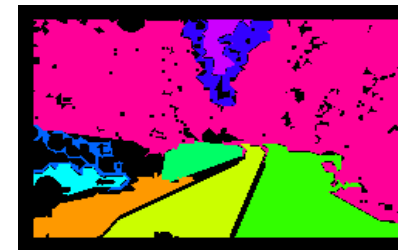
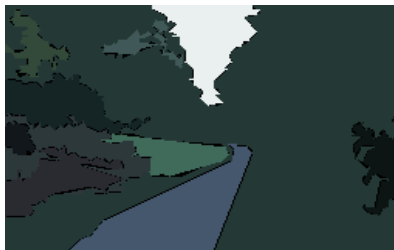
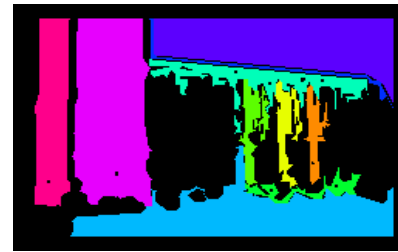
Original Images



Color Regions



Texture Regions



# Clustering-based segmentation

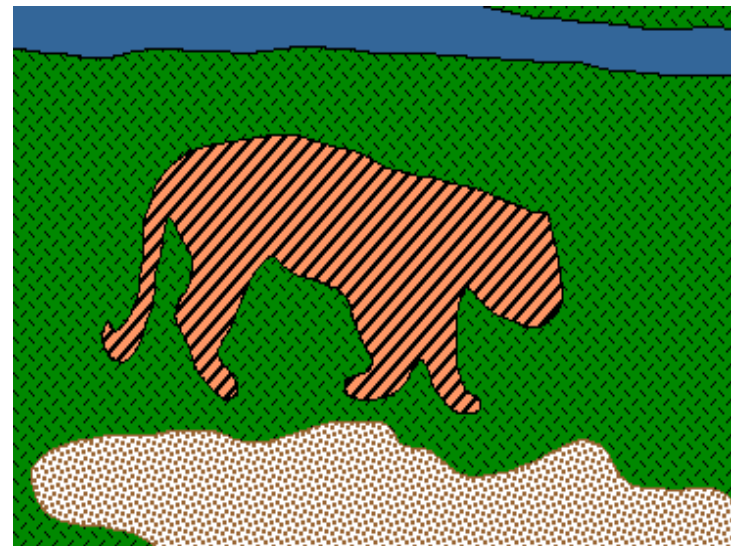
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- K-means variants:
  - Different ways to initialize the means.
  - Different stopping criteria.
  - Dynamic methods for determining the right number of clusters ( $K$ ) for a given image.
- Problem: histogram-based and clustering-based segmentation can produce messy regions.
- How can these be fixed?



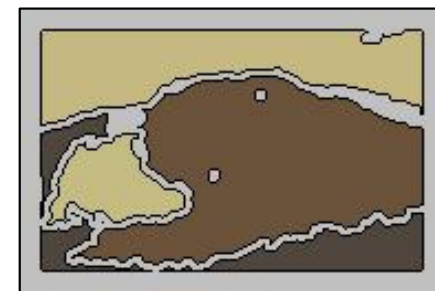
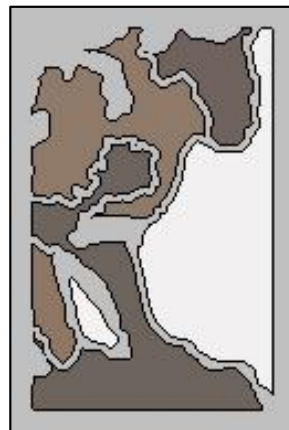
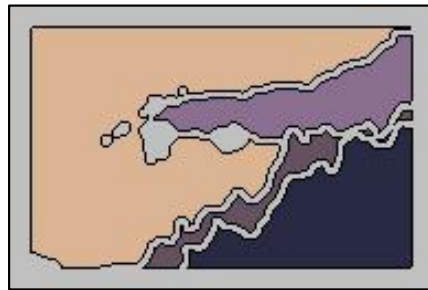
# Clustering-based segmentation

- Expectation-Maximization (EM) algorithm can be used as a probabilistic clustering method where each cluster is modeled using a Gaussian.
- The clusters are updated iteratively by computing the parameters of the Gaussians.



Example from the UC Berkeley's Blobworld system.

# Clustering-based segmentation



Examples from the UC Berkeley's Blobworld system.

# Region growing

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- Region growing techniques start with one pixel of a potential region and try to grow it by adding adjacent pixels till the pixels being compared are too dissimilar.
- The first pixel selected can be just the first unlabeled pixel in the image or a set of seed pixels can be chosen from the image.
- Usually a statistical test is used to decide which pixels can be added to a region.
  - Region is a population with similar statistics.
  - Use statistical test to see if neighbor on border fits into the region population.

# Region growing

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- Let  $R$  be the  $N$  pixel region so far and  $p$  be a neighboring pixel with gray tone  $y$ .
- Define the mean  $\bar{X}$  and scatter  $S^2$  (sample variance) by

$$\bar{X} = \frac{1}{N} \sum_{(r,c) \in R} I(r,c)$$

$$S^2 = \frac{1}{N} \sum_{(r,c) \in R} (I(r,c) - \bar{X})^2$$



# Region growing

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- The T statistic is defined by

$$T = \left( \frac{(N-1)N}{(N+1)} (p - \bar{X})^2 / S^2 \right)^{1/2}$$

- It has a  $T_{N-1}$  distribution if all the pixels in R and the test pixel p are independent and identically distributed Gaussians (i.i.d. assumption).

# Region growing

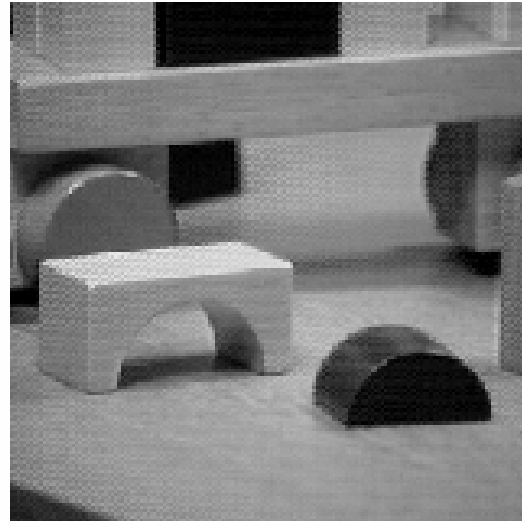
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- For the T distribution, statistical tables give us the probability  $\Pr(T \leq t)$  for a given degrees of freedom and a confidence level. From this, pick a suitable threshold  $t$ .
- If the computed  $T \leq t$  for desired confidence level, add  $p$  to region  $R$  and update the mean and scatter using  $p$ .
- If  $T$  is too high, the value  $p$  is not likely to have arisen from the population of pixels in  $R$ . Start a new region.

# Region growing

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image



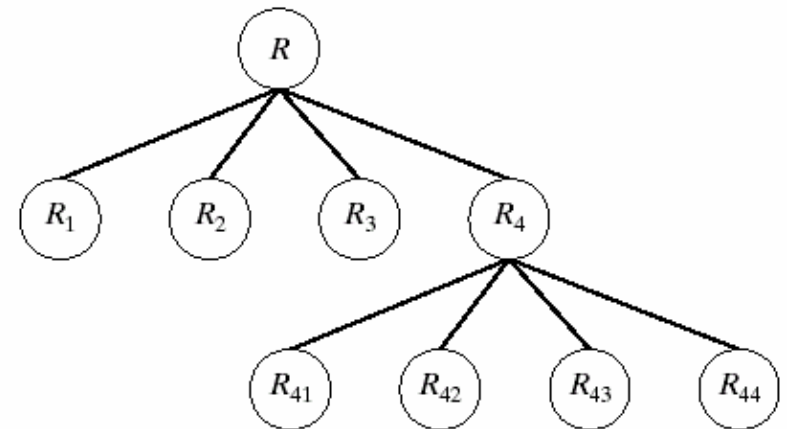
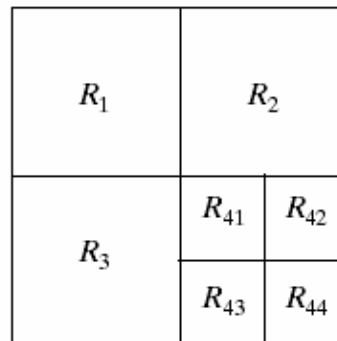
segmentation



# Split-and-merge

1. Start with the whole image.
2. If the variance is too high, break into quadrants.
3. Merge any adjacent regions that are similar enough.
4. Repeat steps 2 and 3, iteratively until no more splitting or merging occur.

→ Idea: good  
Results: blocky



# Split-and-merge

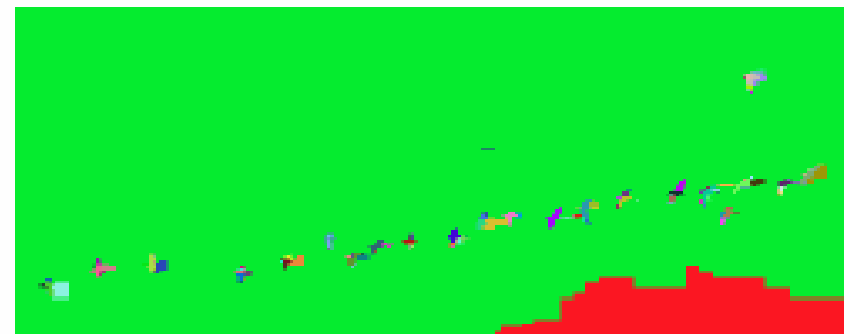
Split and merge example



VIVB004-20CT20CTW001  
Image Processing

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Split and merge example

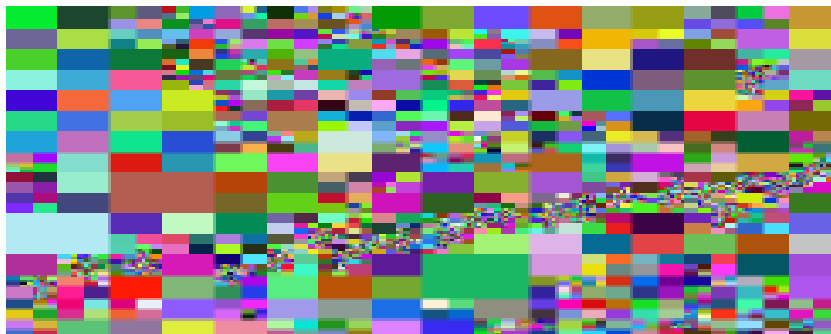


135 regions

VIVB004-20CT20CTW001  
Image Processing

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Split and merge example



4087 regions

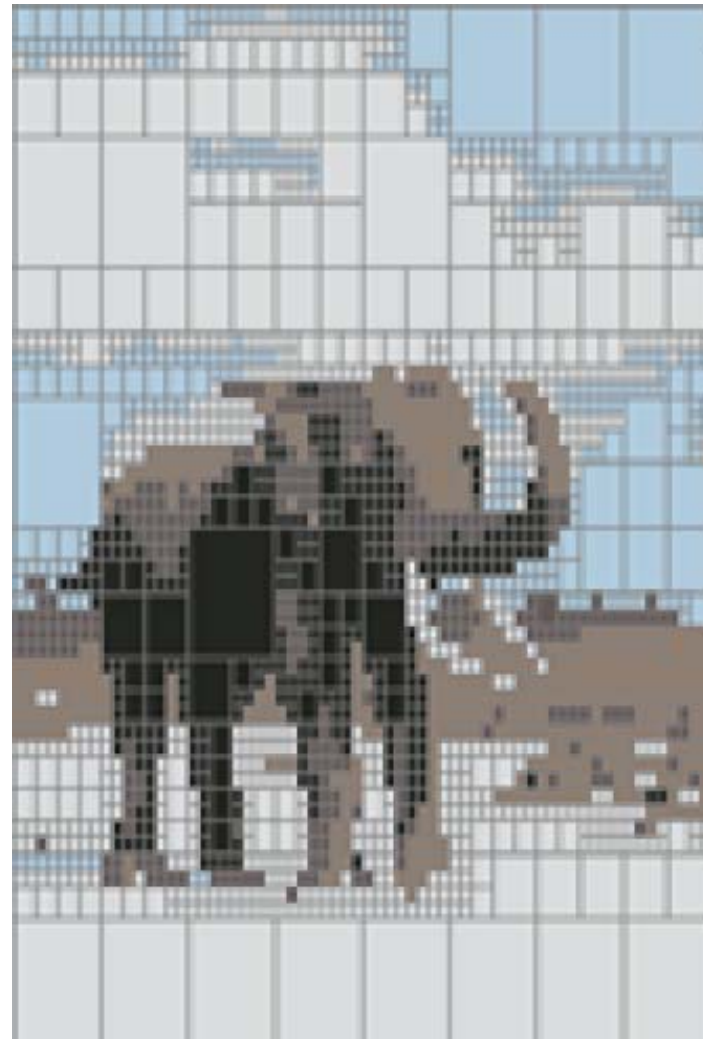
VIVB004-20CT20CTW001  
Image Processing

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# Split-and-merge

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# Split-and-merge

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- Input: result of pixel-based k-means.
- Goal: find compact regions by grouping the pixels.
  1. Merge pixels with identical labels to find the initial set of regions and mark these regions as foreground.
  2. Mark regions with areas smaller than a threshold as background using connected components analysis.
  3. Use region growing to iteratively assign background pixels to the foreground regions by placing a window at each background pixel and assigning it to the label that occurs the most in its neighborhood.
  4. Find individual regions using connected components analysis for each label.

# Split-and-merge

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5. For all regions, compute the erosion transform and repeat:
  1. Threshold erosion transform at steps of 3 pixels in every iteration.
  2. Find connected components of the thresholded image.
  3. Select sub-regions that have an area smaller than a threshold.
  4. Dilate these sub-regions to restore the effects of erosion.
  5. Mark these sub-regions in the output image by masking the dilation using the original image.until no more sub-regions are found.
6. Merge the residues of previous iterations to their smallest neighbors.

# Split-and-merge

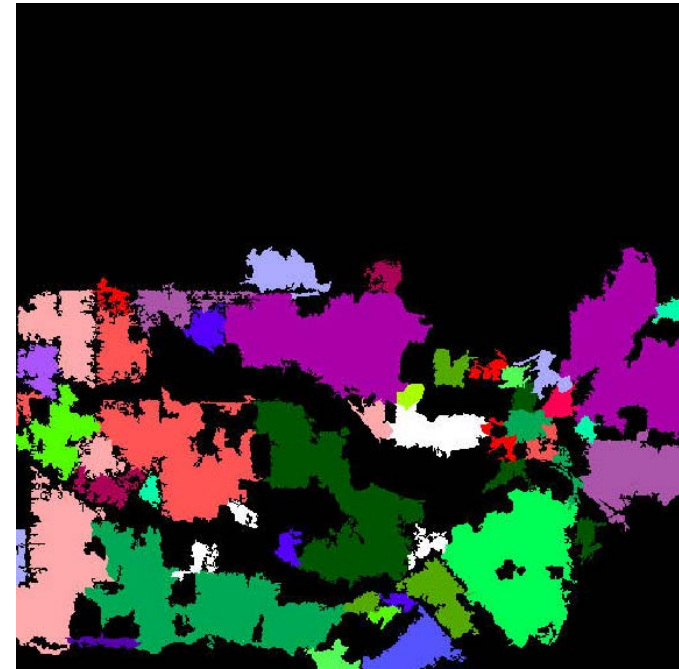
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A satellite image.



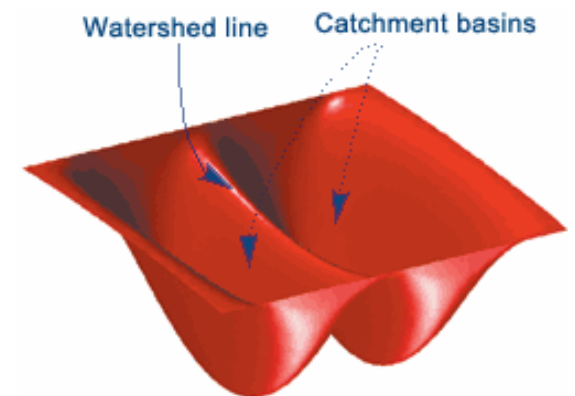
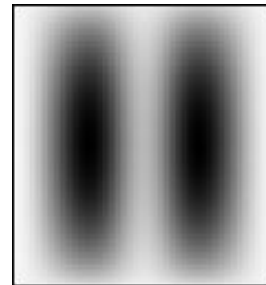
A large connected region formed by merging pixels labeled as residential after classification.



More compact sub-regions after the split-and-merge procedure.

# Watershed segmentation

- The image can be interpreted as a topographic surface, with both valleys and mountains.
- Three types of points can be considered:
  - Points belonging to a regional minimum.
  - Points at which a drop of water, if placed at the location of any of those points, would fall to a single minimum.  
→ **catchment basins**
  - Points at which water would be equally likely to fall to more than one such minimum.  
→ **watershed lines**





# Watershed segmentation

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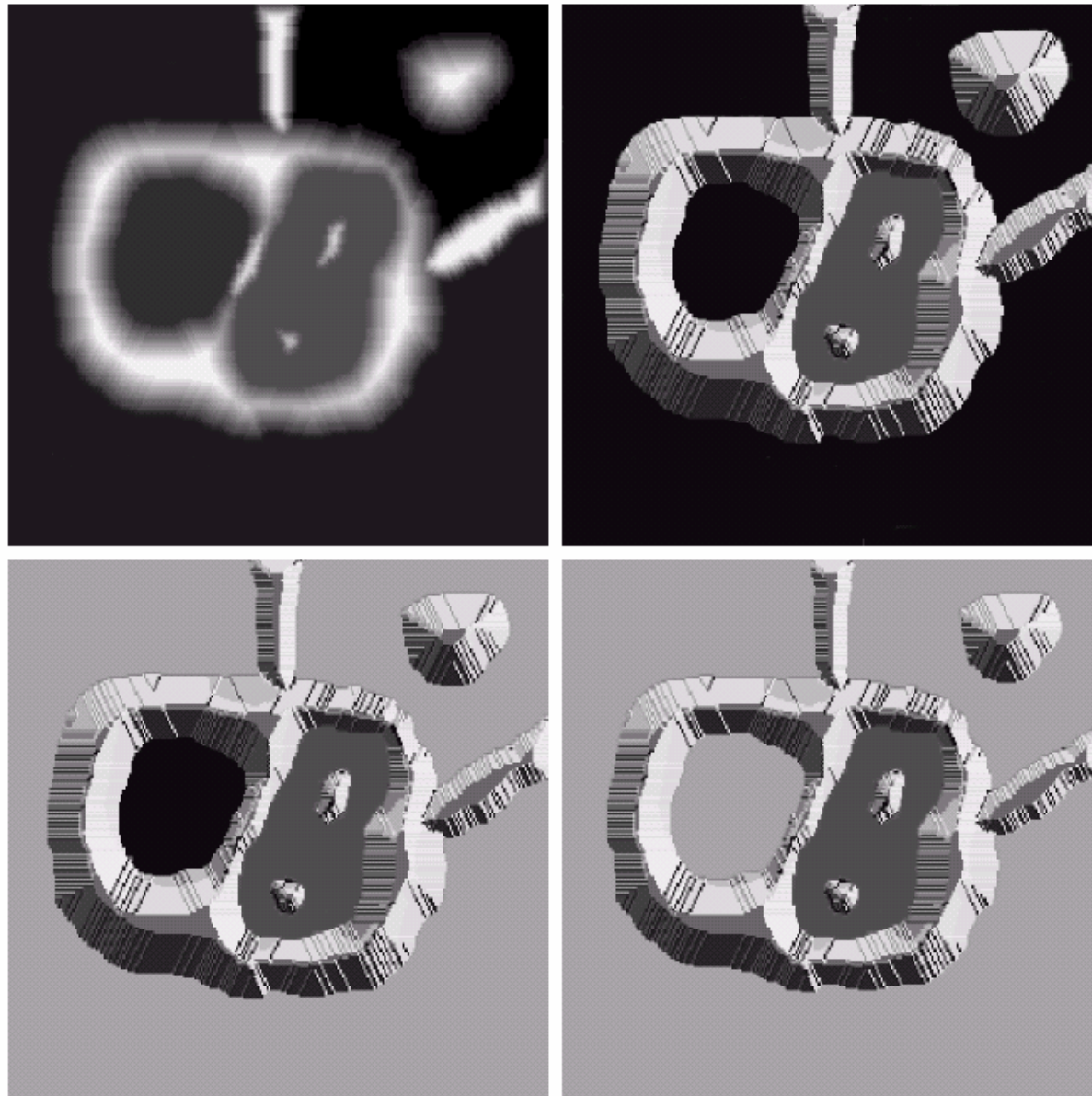
- Assume that there is a hole in each minima and the surface is immersed into a lake.
- The water will enter through the holes at the minima and flood the surface.
- To avoid the water coming from two different minima to meet, a dam is build whenever there would be a merge of the water.
- Finally, the only thing visible of the surface would be the dams. These dam walls are called the watershed lines.

# Watershed segmentation

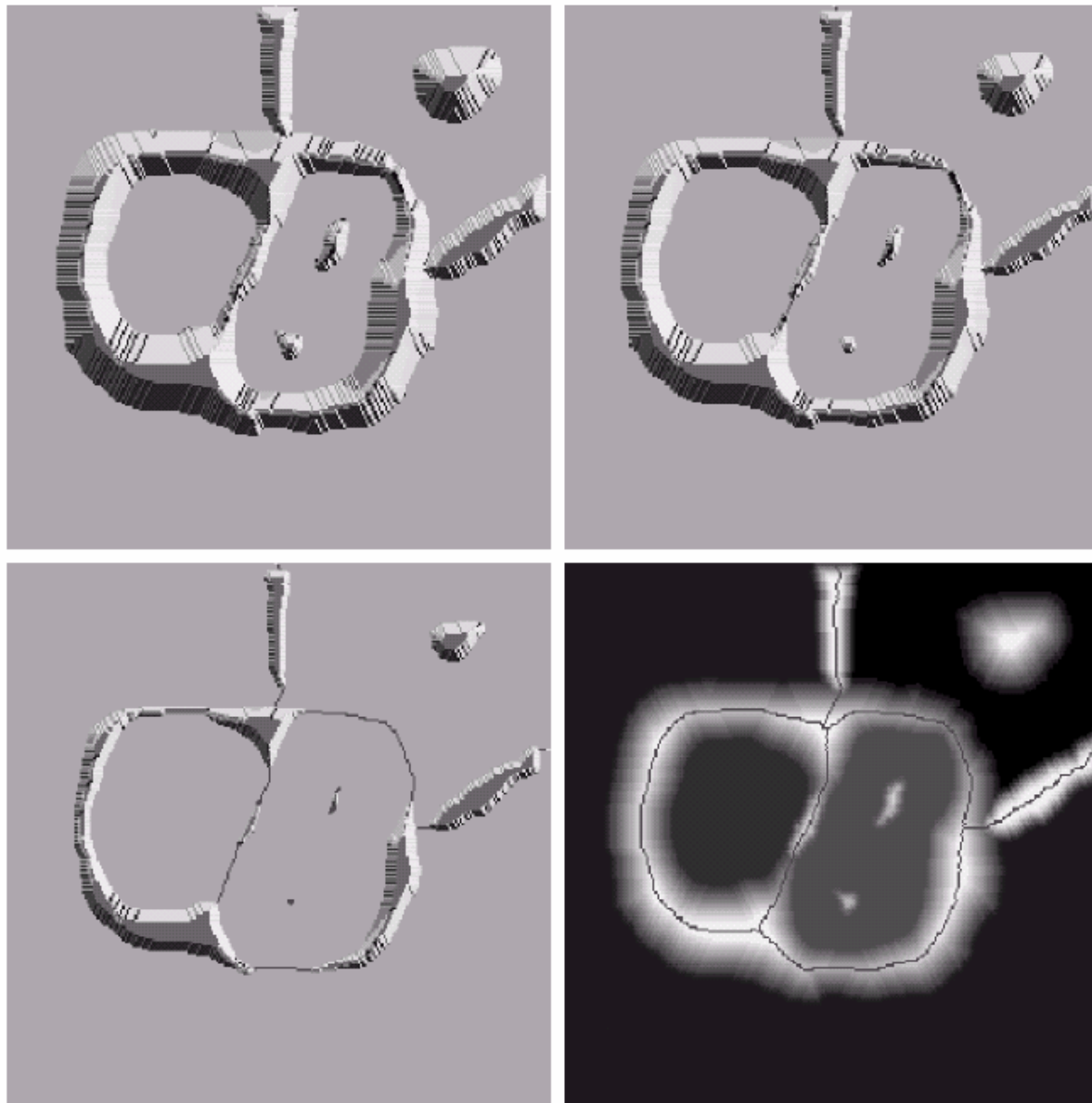
a b  
c d

**FIGURE 10.44**

(a) Original image.  
(b) Topographic view.  
(c)–(d) Two stages of flooding.



# Watershed segmentation



e f  
g h

**FIGURE 10.44**

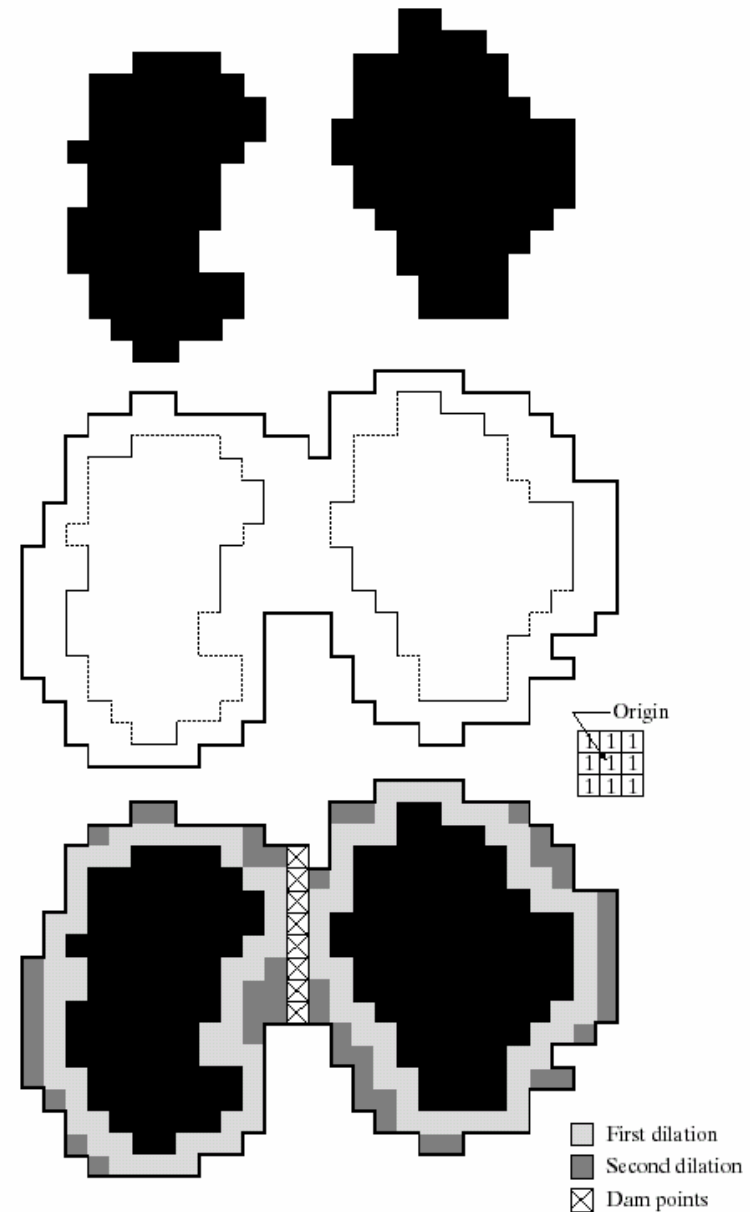
*(Continued)*

(e) Result of further flooding. (f) Beginning of merging of water from two catchment basins (a short dam was built between them). (g) Longer dams. (h) Final watershed (segmentation) lines. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

# Watershed segmentation

a  
b  
d c

**FIGURE 10.45** (a) Two partially flooded catchment basins at stage  $n - 1$  of flooding. (b) Flooding at stage  $n$ , showing that water has spilled between basins (for clarity, water is shown in white rather than black). (c) Structuring element used for dilation. (d) Result of dilation and dam construction.



# Watershed segmentation

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- The key behind using the watershed transform for segmentation is this: change your image into another image whose catchment basins are the objects you want to identify.
- Examples:
  - Distance transform can be used with binary images where the catchment basins correspond to the foreground components of interest.
  - Gradient can be used with grayscale images where the catchment basins should theoretically correspond to the homogeneous grey level regions of the image.

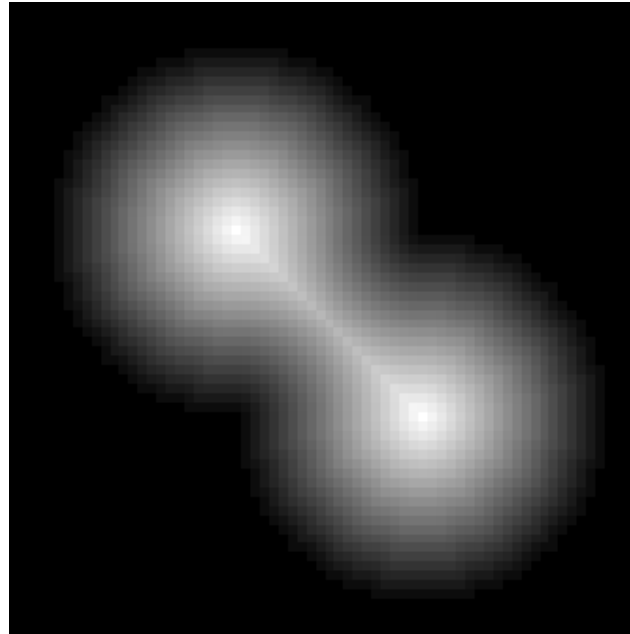


# Watershed segmentation

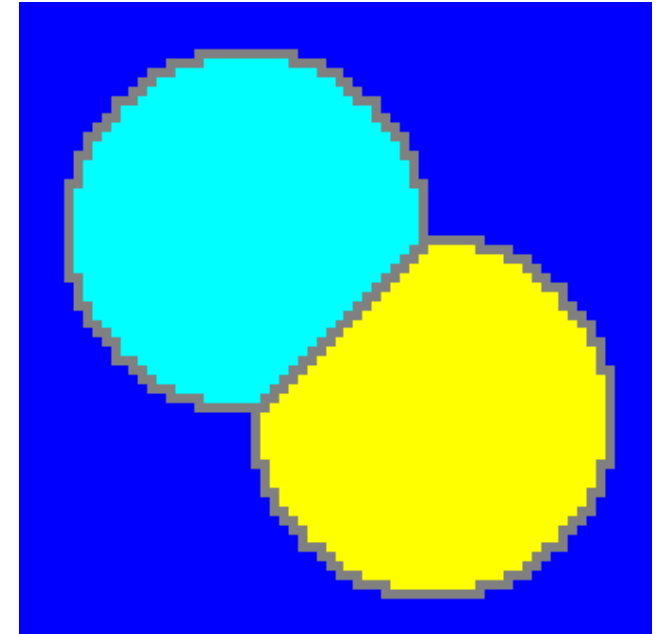
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Binary image.



Distance transform of  
the complement of the  
binary image.



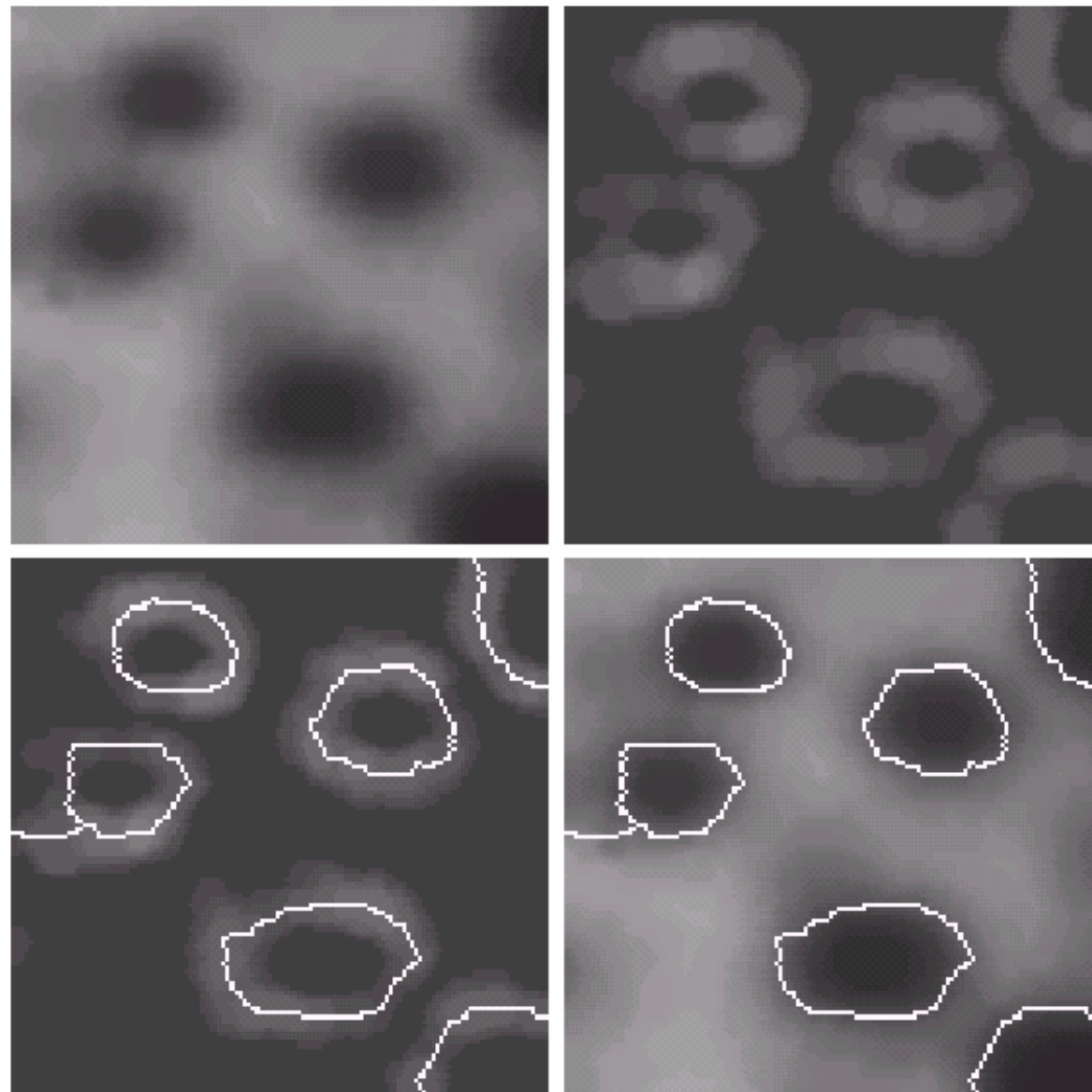
Watershed transform  
after complementing the  
distance transform, and  
forcing pixels that do not  
belong to the objects to  
be at  $-\text{Inf}$ .

# Watershed segmentation

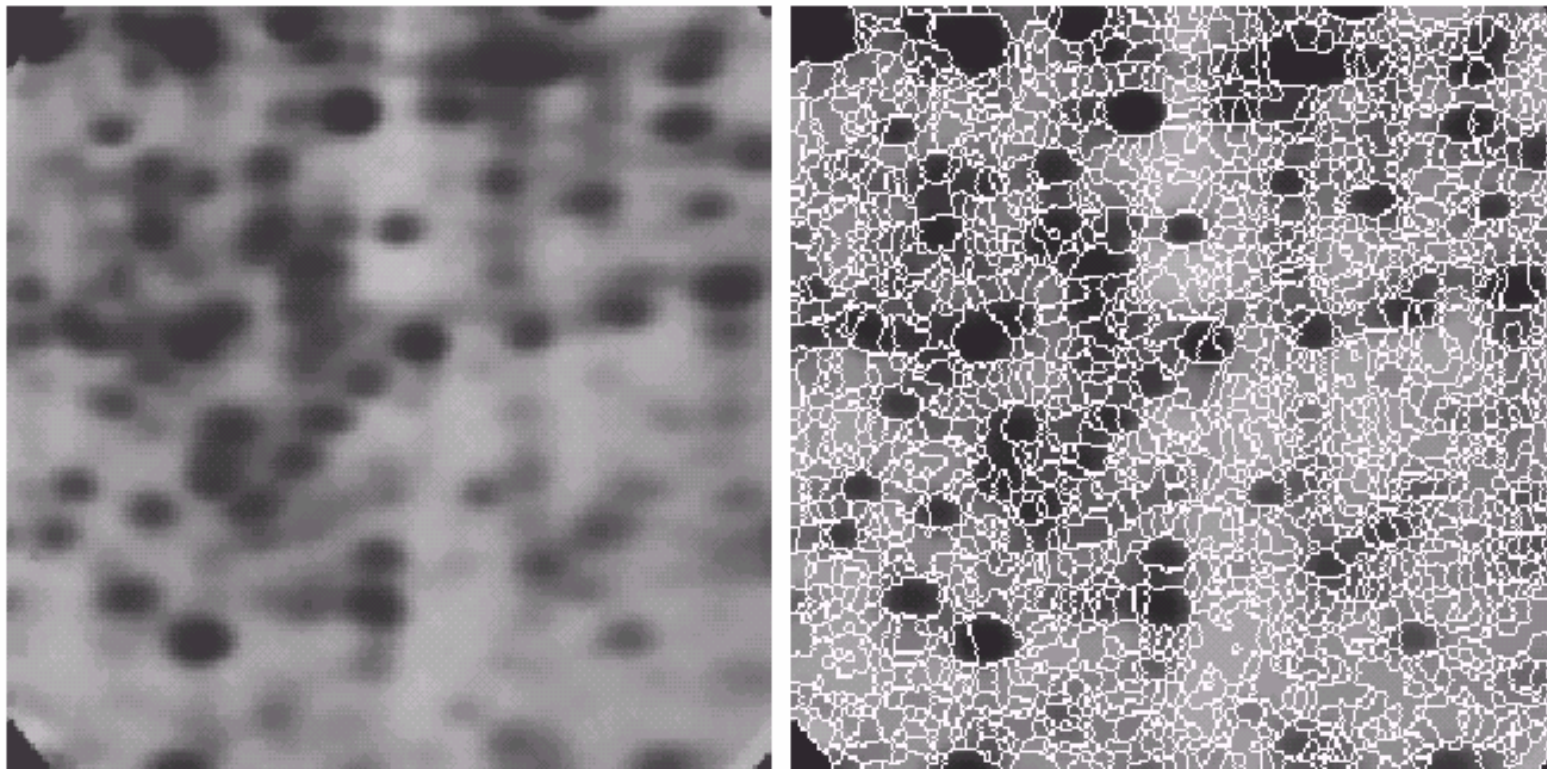
a	b
c	d

**FIGURE 10.46**

(a) Image of blobs. (b) Image gradient.  
(c) Watershed lines.  
(d) Watershed lines superimposed on original image.  
(Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)



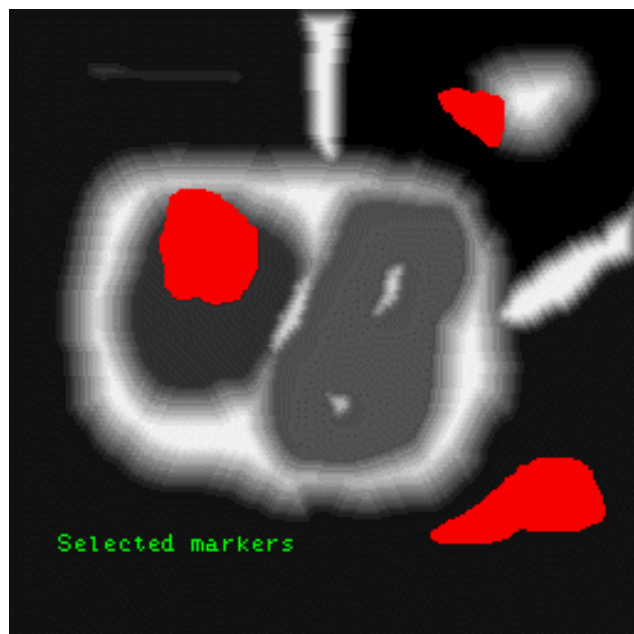
# Watershed segmentation



a b

**FIGURE 10.47**  
(a) Electrophoresis image. (b) Result of applying the watershed segmentation algorithm to the gradient image. Oversegmentation is evident. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

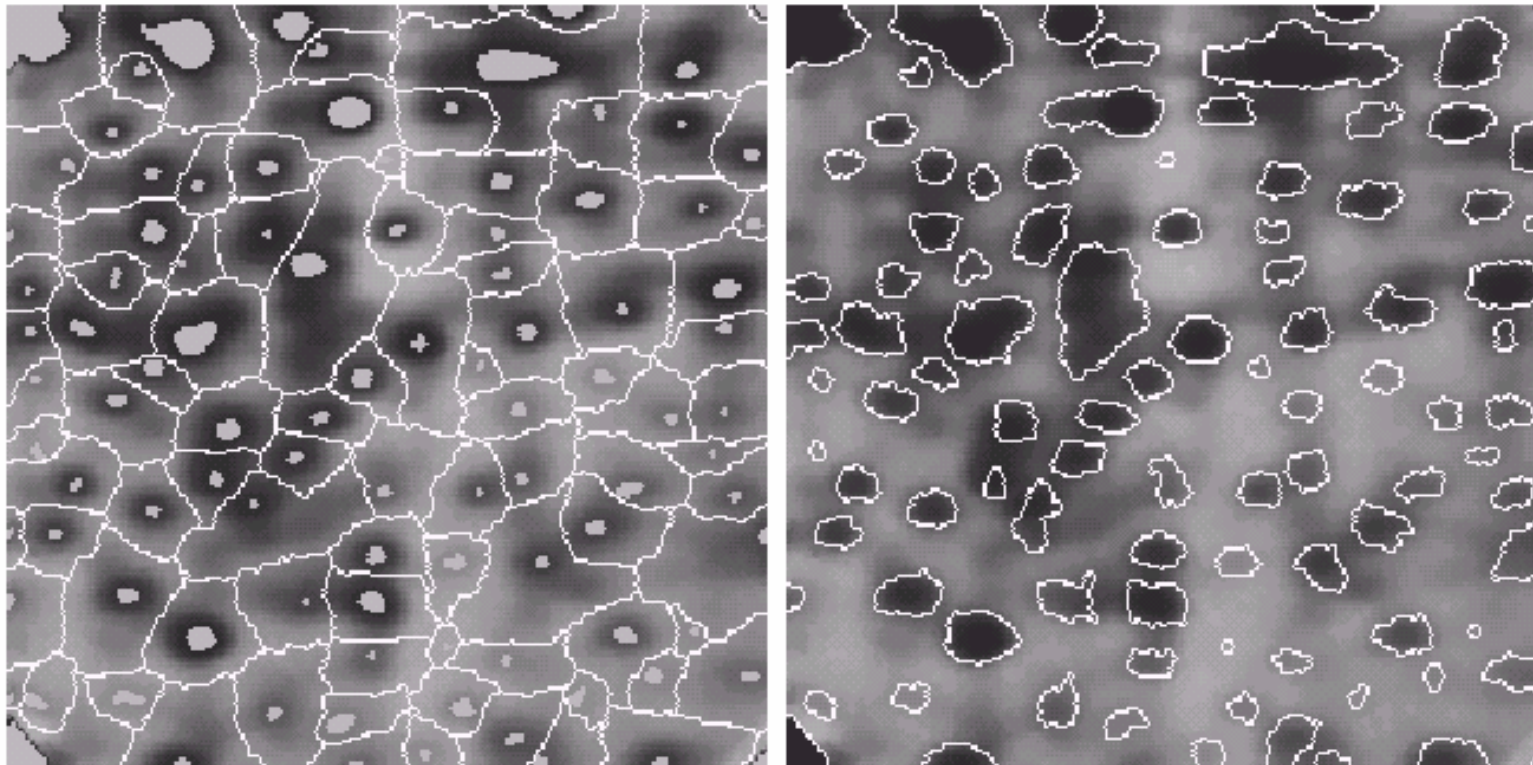
# Watershed segmentation



A major enhancement of the watershed transformation consists in flooding the topographic surface from a previously defined set of markers.



# Watershed segmentation



a b

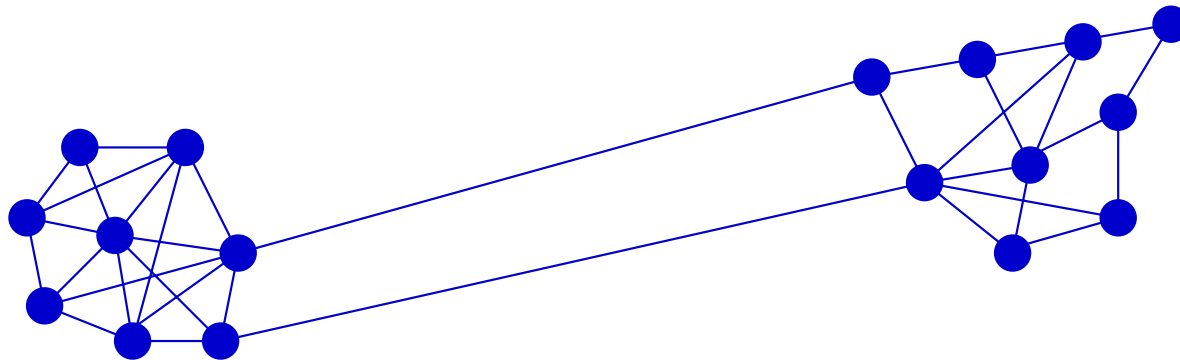
**FIGURE 10.48**  
(a) Image showing internal markers (light gray regions) and external markers (watershed lines).  
(b) Result of segmentation. Note the improvement over Fig. 10.47(b).  
(Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)



# Graph-based segmentation

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- An image is represented by a graph whose nodes are pixels or small groups of pixels.
- The goal is to partition the nodes into disjoint sets so that the similarity within each set is high and across different sets is low.

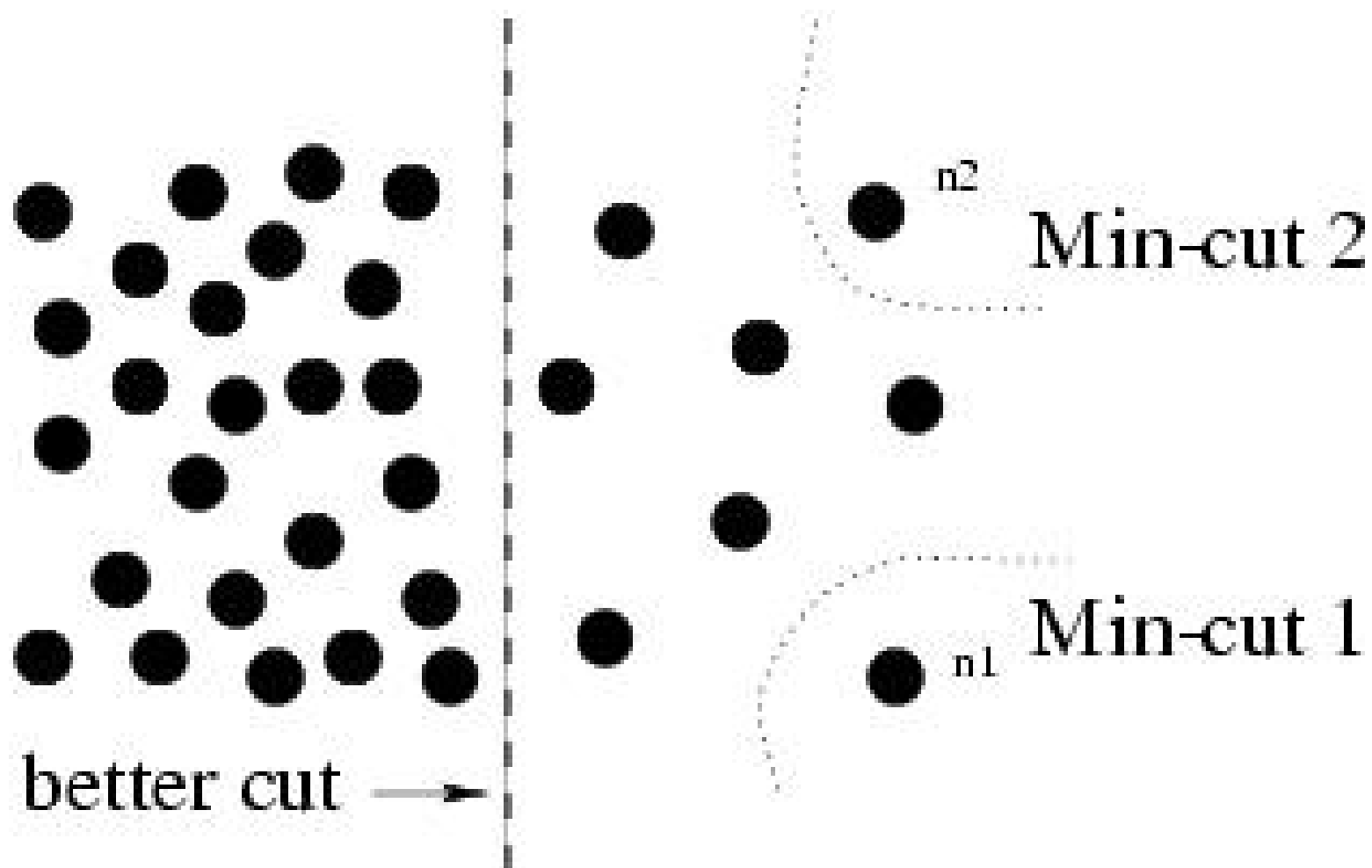


# Graph-based segmentation

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- Let  $G = (V, E)$  be a graph. Each edge  $(u, v)$  has a weight  $w(u, v)$  that represents the similarity between  $u$  and  $v$ .
- Graph  $G$  can be broken into 2 disjoint graphs with node sets  $A$  and  $B$  by removing edges that connect these sets.
- Let  $\text{cut}(A, B) = \sum_{u \in A, v \in B} w(u, v)$ .
- One way to segment  $G$  is to find the minimal cut.

# Graph-based segmentation



# Graph-based segmentation

- Minimal cut favors cutting off small node groups, so Shi and Malik proposed the **normalized cut**.

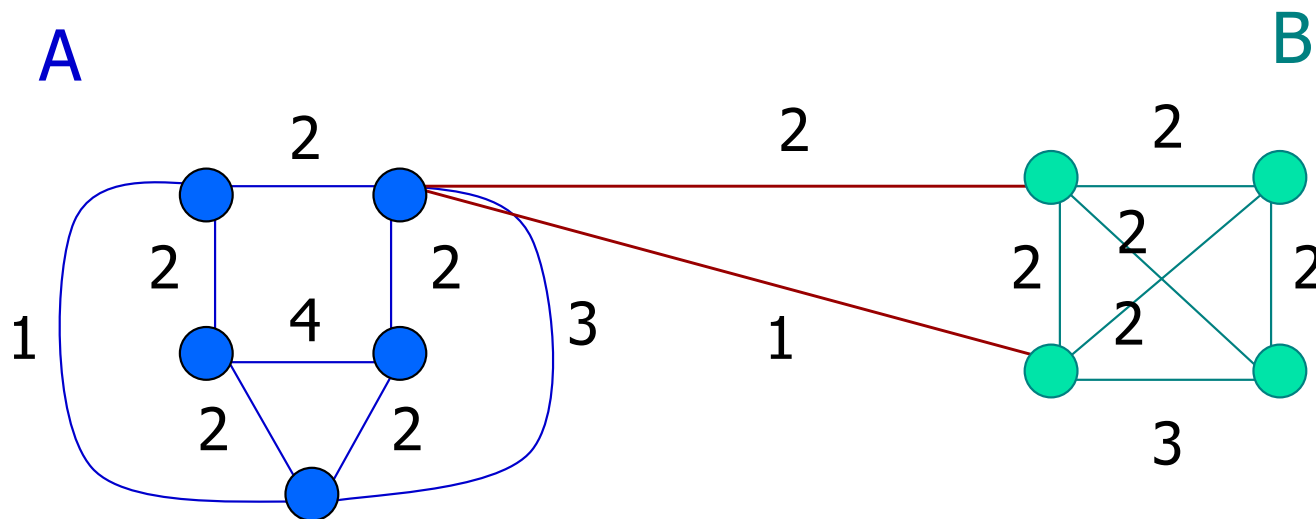
$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

Normalized cut

$$assoc(A,V) = \sum_{u \in A, t \in V} w(u,t)$$

How much is A connected to the graph as a whole

# Graph-based segmentation



$$\text{Ncut}(A,B) = \frac{3}{21} + \frac{3}{16}$$

# Graph-based segmentation

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- Shi and Malik turned graph cuts into an eigenvector/eigenvalue problem.
- Set up a weighted graph  $G=(V,E)$ .
  - $V$  is the set of  $(N)$  pixels.
  - $E$  is a set of weighted edges (weight  $w_{ij}$  gives the similarity between nodes  $i$  and  $j$ ).
  - Length  $N$  vector  $d$ :  $d_i$  is the sum of the weights from node  $i$  to all other nodes.
  - $N \times N$  matrix  $D$ :  $D$  is a diagonal matrix with  $d$  on its diagonal.
  - $N \times N$  symmetric matrix  $W$ :  $W_{ij} = w_{ij}$ .



# Graph-based segmentation

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- Let  $x$  be a characteristic vector of a set  $A$  of nodes.
  - $x_i = 1$  if node  $i$  is in a set  $A$
  - $x_i = -1$  otherwise

- Let  $y$  be a continuous approximation to  $x$

$$y = (1 + x) - \frac{\sum_{x_i > 0} d_i}{\sum_{x_i < 0} d_i} (1 - x).$$

- Solve the system of equations
$$(D - W) y = \lambda D y$$
for the eigenvectors  $y$  and eigenvalues  $\lambda$ .
- Use the eigenvector  $y$  with second smallest eigenvalue to bipartition the graph ( $y \rightarrow x \rightarrow A$ ).
- If further subdivision is merited, repeat recursively.

# Graph-based segmentation

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- Edge weights  $w(i,j)$  can be defined by

$$w(i,j) = e^{\|F(i)-F(j)\|^2 / \sigma_I^2} * \begin{cases} e^{\|X(i)-X(j)\|^2 / \sigma_X^2} & \text{if } \|X(i)-X(j)\|^2 < r \\ 0 & \text{otherwise} \end{cases}$$

where

- $X(i)$  is the spatial location of node  $I$
- $F(i)$  is the feature vector for node  $I$   
which can be intensity, color, texture, motion...
- The formula is set up so that  $w(i,j)$  is 0 for nodes that are too far apart.

# Graph-based segmentation

