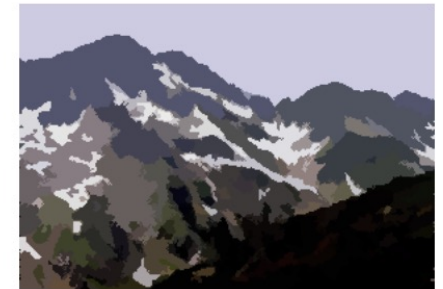


# Segmentation – other\* methods

Three points from the topic:

1. Segmentation by region growing
2. Segmentation by watershed
3. Segmetnation by mean-shift

Monday: split-and-merge



\* - other than thresholding

## Region growing (agglomerative clustering)

- Start from seed pixel(s)
- Compare neighborhood pixels (4-NB or 8-NB etc) to **feature** from region.
  - *Feature* can be mean of intensitiy values from pixels in region etc.
- Include if NB *pixel feature is "close to" feature from region*.
  - "*Close to*" can be a distance function and a threshold.
- Continue until no new NB pixels satisfies criteria.

# Region growing – implementation with boundary stack

- Inputs: Image  $I(x,y)$ , size  $M \times N$ , Seed =  $(x_s, y_s)$ ,
- Initialize:  $L = \text{zeros}(M, N)$ ,  $L(x_s, y_s) = 1$ ,  $\text{stack.push}(x_s, y_s)$ ,  $f(\text{region}) = f(x_s, y_s)$

Keep track of pixels at boundary of region (for example in a stack)

While ( stack is not empty) do:

- Look at NB to a boundary pixel popped from the stack:  $(x_n, y_n)$
- Is feature vector  $f(x_n, y_n)$  similar to  $f(\text{region})$ ?
- If yes  $\rightarrow$  pixel  $I(x_n, y_n)$  is added to the region,  $L(x_n, y_n) = 1$ ,  $(x_n, y_n)$  is pushed to the boundary stack, and  $f(\text{region})$  is updated.

## Region growing, gaussian model

- Let the model be gaussian, the feature is intensity value, but normalized with the st.dev :

## Region growing – more on feature choices

- Feature can be intensity value and mean, but can also include different frequency bands, variance over a local neighbourhood, gradient values, different color bands etc. -> **feature vector  $\mathbf{f}$** .
- The feature vector of the region can be found as **the mean of each of the features in the vector, over the region  $\mathbf{f}_m$** ,.
- Similarity can be measured as inner product:

$O = \text{seed}$

final region

$$\bar{f}_0 = 4$$

0	1	0	0	1	1	0	2	1
1	1	0	0	3	4	3	1	0
0	2	3	4	5	4	3	0	1
0	0	0	4	5	4	4	1	1
1	0	1	3	3	2	0	0	2
0	1	0	2	0	1	1	2	5
1	0	0	1	0	0	1	3	4

include  $q$  in region  
if  $d \leq T$ ,  $T=2$

Use 4NB 

## Example of region growing

Let the intensity level be our feature  $f(q) = \text{intensity}$

$$\text{similarity: } d = |f(q) - \bar{f}|$$

$q$ : position coord.

$\bar{f}$ : mean over region

here: Go through entire boundary  
before update  $\bar{f}$

D = seed

final region

$$\bar{f}_0 = 4$$

0	1	0	0	1	0	2	1
1	1	0	0	3	4	3	1
0	4	3	4	5	4	3	0
0	0	0	4	5	4	4	1
1	0	1	3	3	2	0	0
0	1	0	2	0	1	1	2
1	0	0	1	0	0	1	3
4	3	4	3	4	3	4	3

## Example of region growing

Let the intensity level be our feature  $f(q)$  = intensity

similarity:  $d = |f(q) - \bar{f}|$

$q$ : position coord.

$\bar{f}$ : mean over region

here: Go through entire boundary before update  $\bar{f}$

include  $q$  in region  
if  $d \leq T$ ,  $T=2$

Use 4NB 

$$\begin{array}{|c|c|c|} \hline 4 & & \\ \hline 5 & 4 & 3 \\ \hline 4 & & \\ \hline \end{array} \quad \bar{f}_0 = 4 \Rightarrow \text{include all} \quad \bar{f}_1 = \frac{4+4+4+5+3}{5} = \frac{20}{5} = 4$$

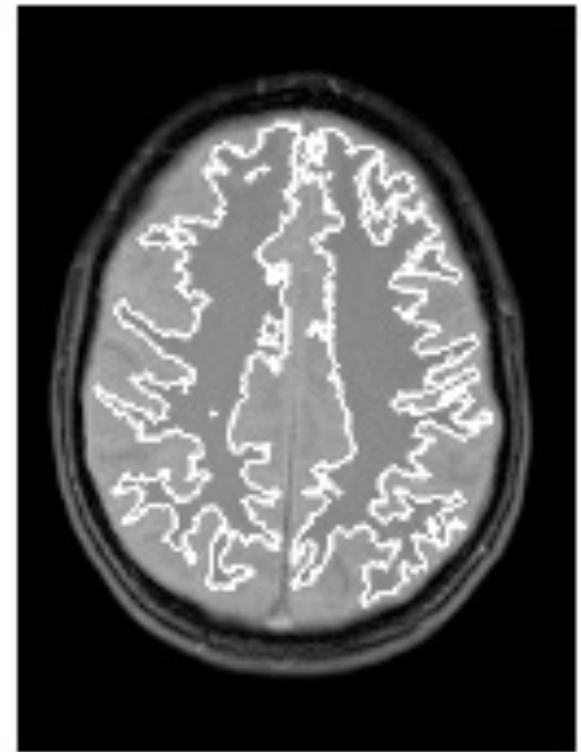
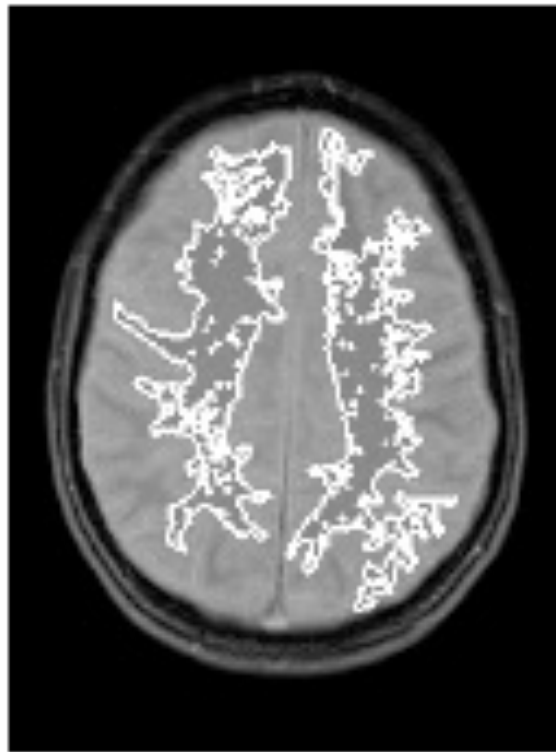
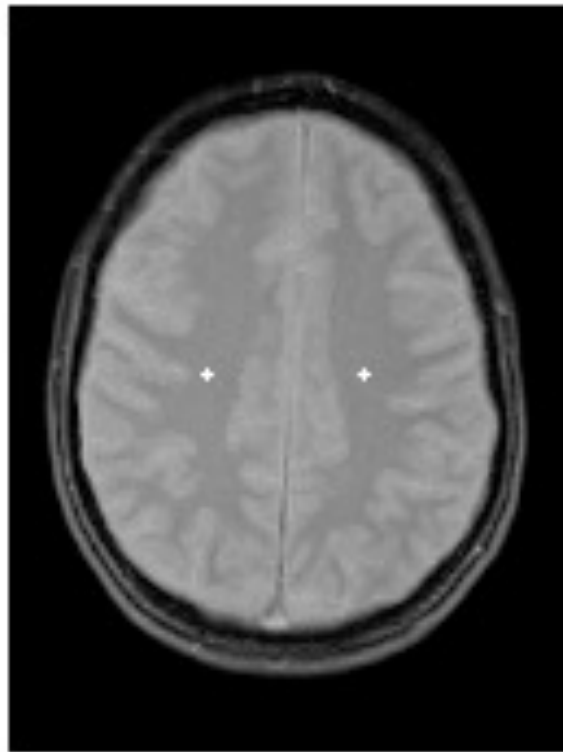
$$\begin{array}{|c|c|c|} \hline 3 & 4 & 3 \\ \hline 4 & 5 & 4 \\ \hline 5 & 4 & 4 \\ \hline \end{array} \quad \bar{f}_1 = 4 \Rightarrow \bar{f}_2 = \frac{20 + \overbrace{3+3+5+4+4}^{\text{new}}}{5+5} = \frac{39}{10} = 3.9$$

$$\begin{array}{|c|c|c|} \hline 2 & 3 & \\ \hline 3 & 4 & \\ \hline 3 & 3 & 2 \\ \hline 2 & & \\ \hline \end{array} \Rightarrow \bar{f}_3 = \frac{39 + 3 + 4 + 3 + 2}{10+4} = \frac{51}{14} = 3.64$$

$$\rightarrow \bar{f}_4 = \frac{51 + 2 + 3}{14+2} = \frac{56}{16} = 3.5$$

$$\rightarrow \bar{f}_5 = \frac{56+2}{16+1} = 3.41$$

# Region growing





# Distance transform – recap from morphology

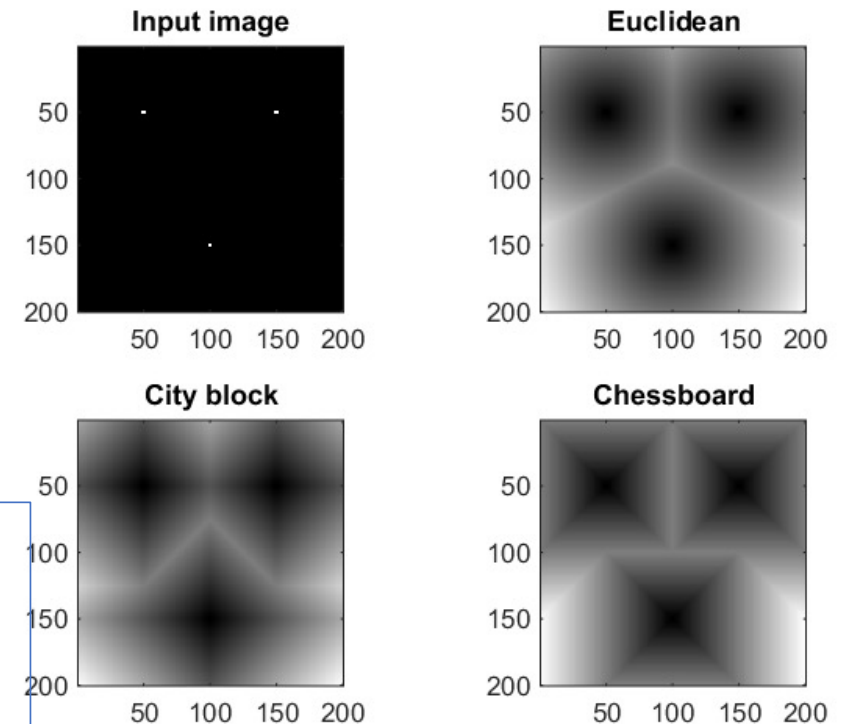
For each pixel in the binary image find the **distance** to the nearest non-zero pixel (or any give feature).

Let two points be defined:  $(x_1, y_1), (x_2, y_2)$

Euclidean distance:  $D_e = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$

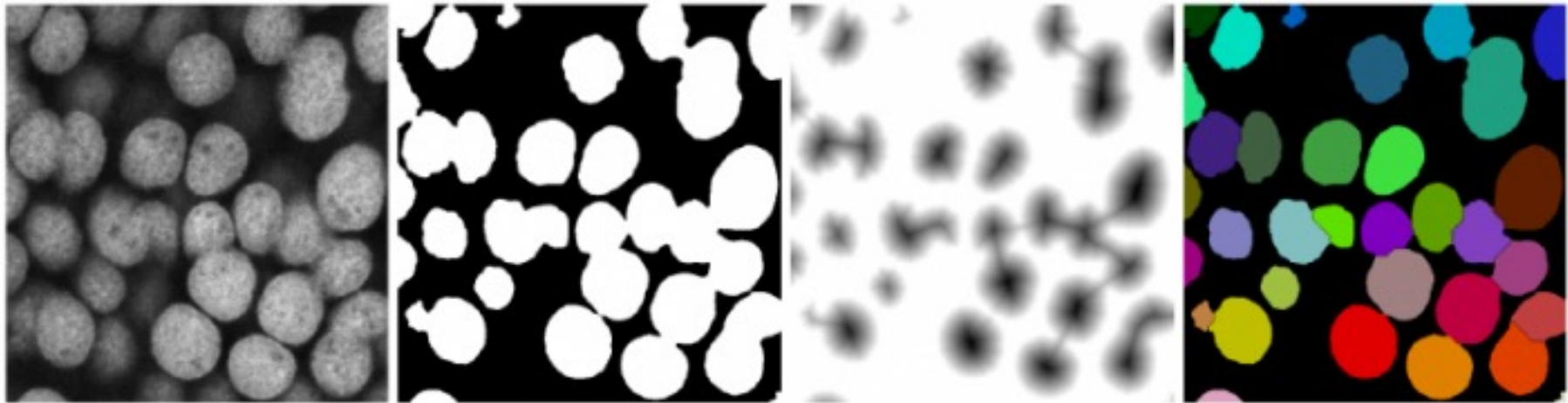
Cityblock distance:  $D_{cb} = |x_1 - x_2| + |y_1 - y_2|$

Chessboard distance:  $D_{chess} = \max(|x_1 - x_2|, |y_1 - y_2|)$

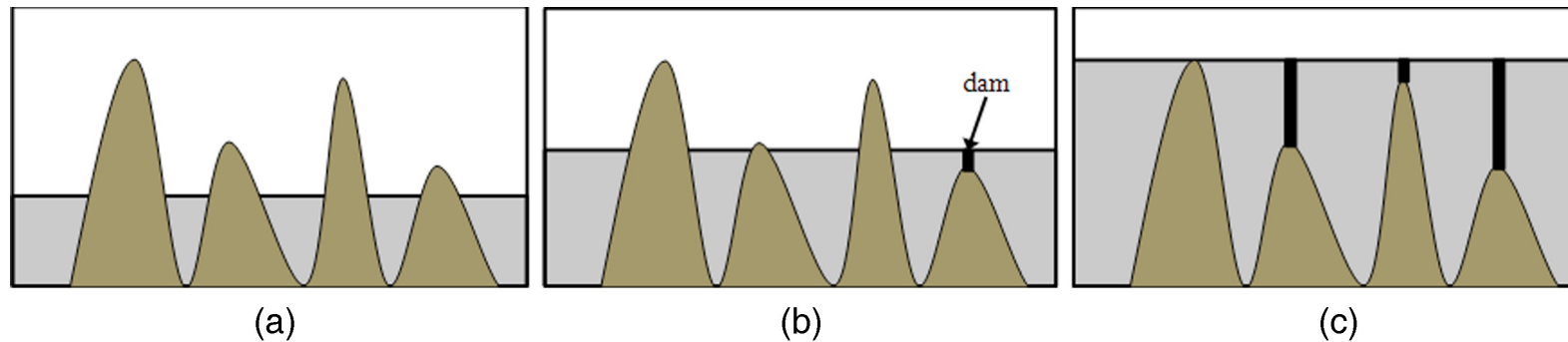


# Distance transform

The distance transform can be used for example for skeletonization, or as input for watershed segmentation



# Watershed- idea



Can not do watershed directly on image, have to find *gradient*, or *distance transform* of image first. Looks at the preprocessed image (gradient or distance) as a **surface**.

- 1) Find **gradient or distance image**
- 2) Find valleys (local minimas)
- 3) "pinch holes" in the local minimas and «sink surface into water», i.e. flood the valleys.
- 4) Put up a "watershed" (dam) when a basin wants to join another basin.

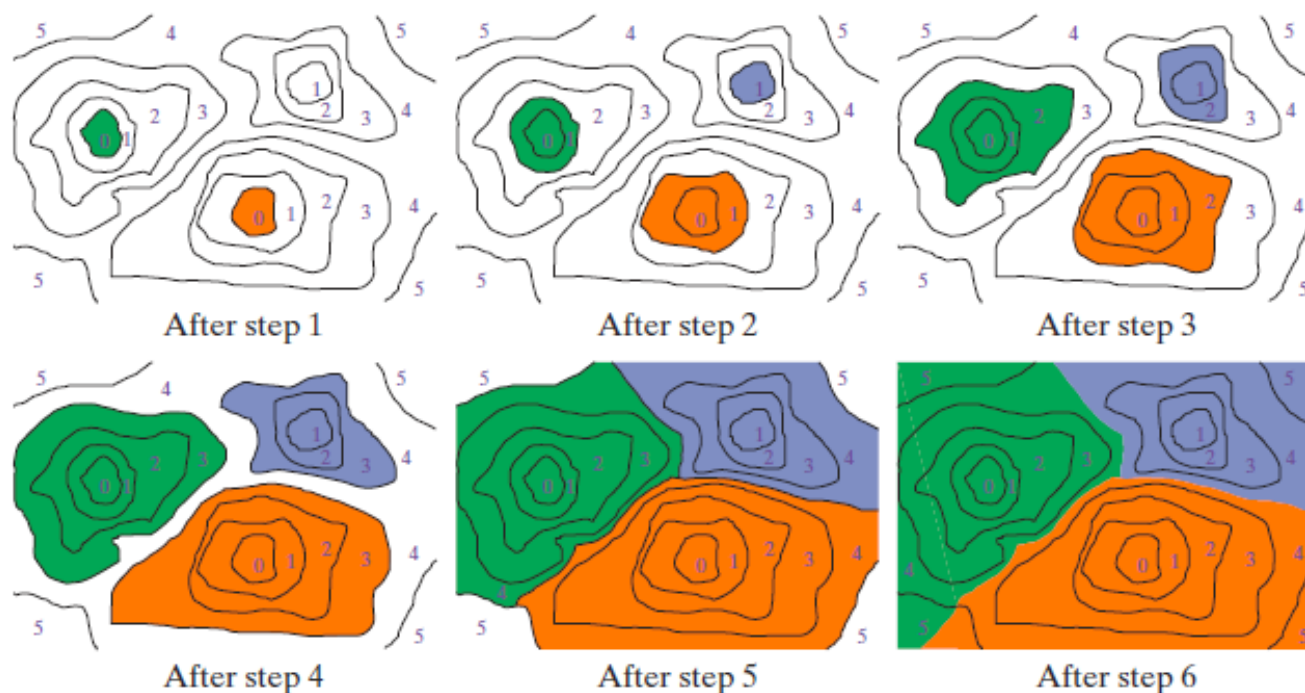
Can **use markers**: only set up sheds if basins from different markers tries to merge.

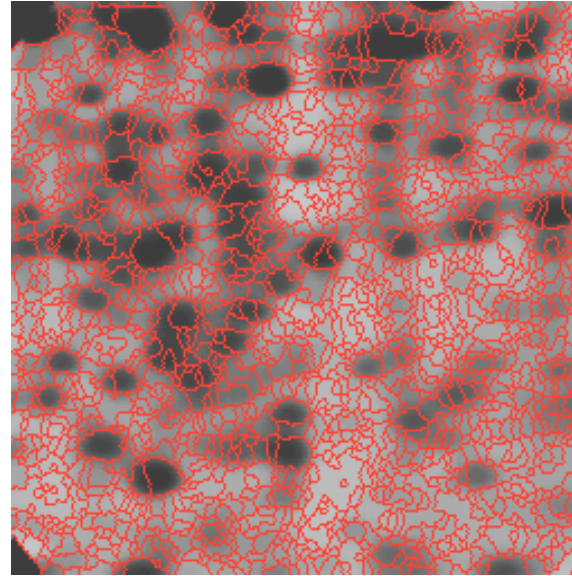
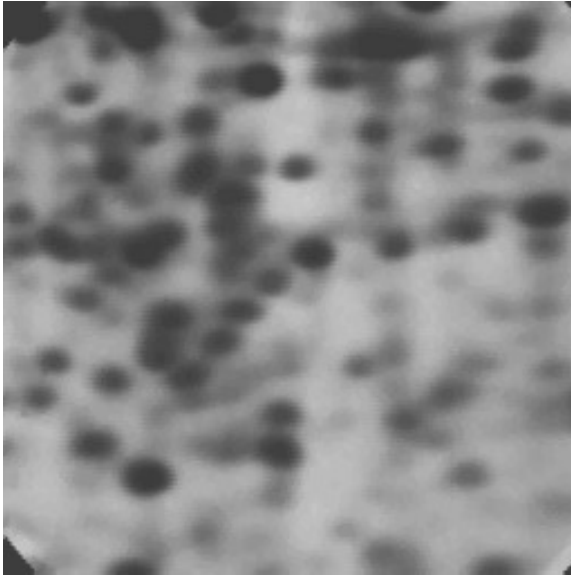
**Geodesic influence zone:** At each level this must be determined for each existing catchment basin. It is the set of **unlabeled pixels** connected to the basin and **closer to that basin** than any other.

The regions are growed in a breath first manner to ensure regions are met halfway when necessary .

**Watershed** leads to **oversegmentation**. Common solution is **marker-based watershed segmentation**.

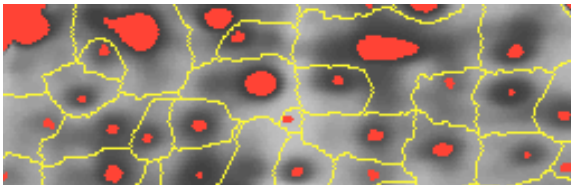
**Figure 10.28** Step-by-step results of immersion-based watershed segmentation on a segmentation function with 6 levels (0 through 5). The different colors indicate the unique labels of the three different regions. The contour lines of the segmentation function are shown, with numbers indicating the levels of the pixels.



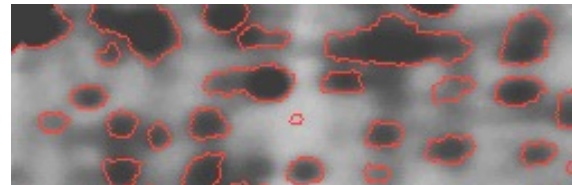


Watershed can produce high degree of oversegmentation

**Marker controlled Watershed** can improve this. Only when basins from different markers are flooded, a watershed is made.



How to find good markers?

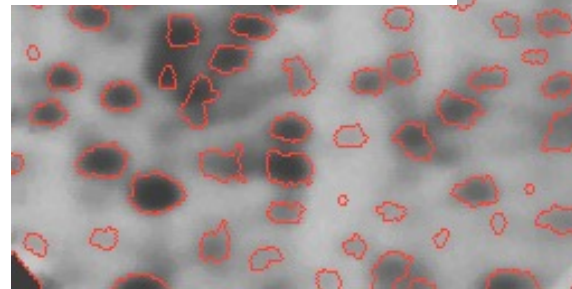
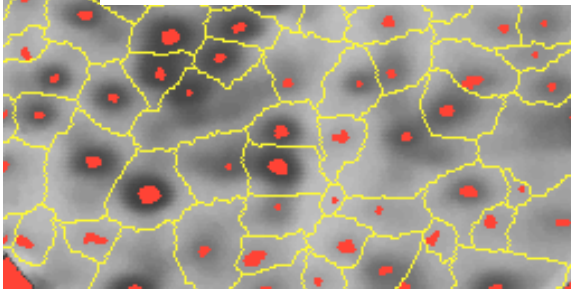


Top left: original image

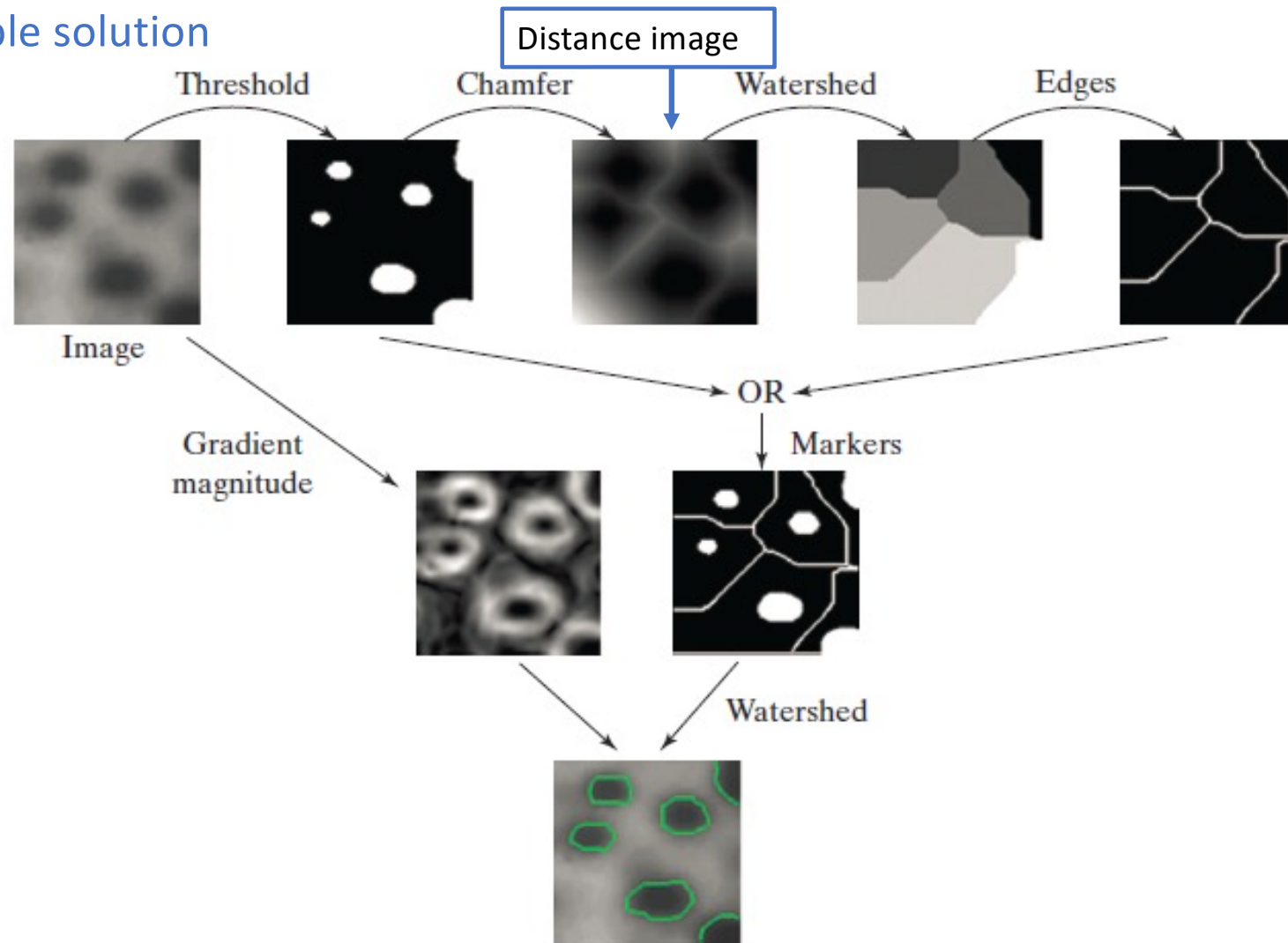
Top right: watershed of gradient image, oversegmented.

Bottom left: red is blob marker, yellow is background marker.

Bottom right: Result after marker controlled watershed.



## One example solution



Gonzalez & Woods, Digital Image Processing, 3rd edition, Prentice Hall India, 2008, credited to S. Beuther

**Figure 10.30** Flowchart of the end-to-end watershed procedure.

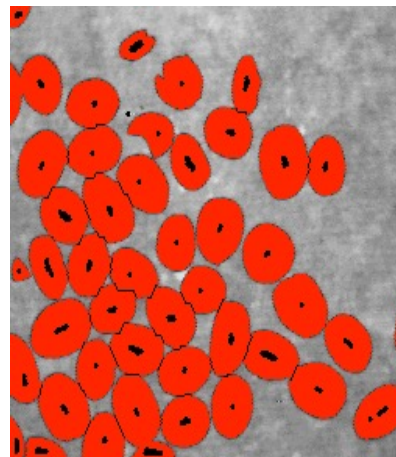
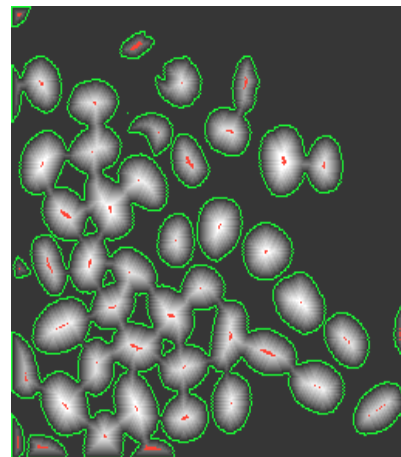
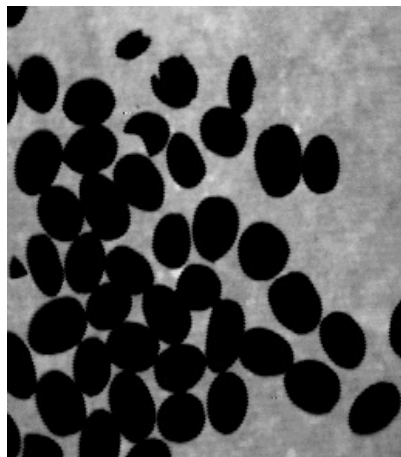
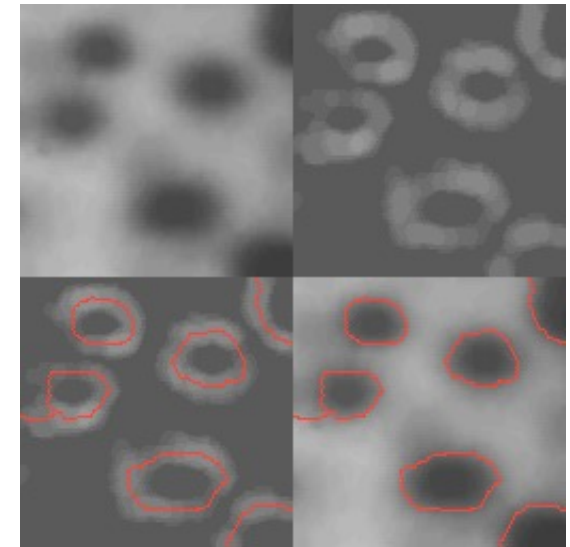


# Watershed example

Watershed from gradient image:

Original image, gradient image

Watershed of the gradient image, Final contours.



Watershed from distance  
image (with markers)

Left to right: Original  
image, Distance function,  
segmentation

[cmm.enscm.fr/~beucher/wtshed.html](http://cmm.enscm.fr/~beucher/wtshed.html)

# Mean-shift segmentation

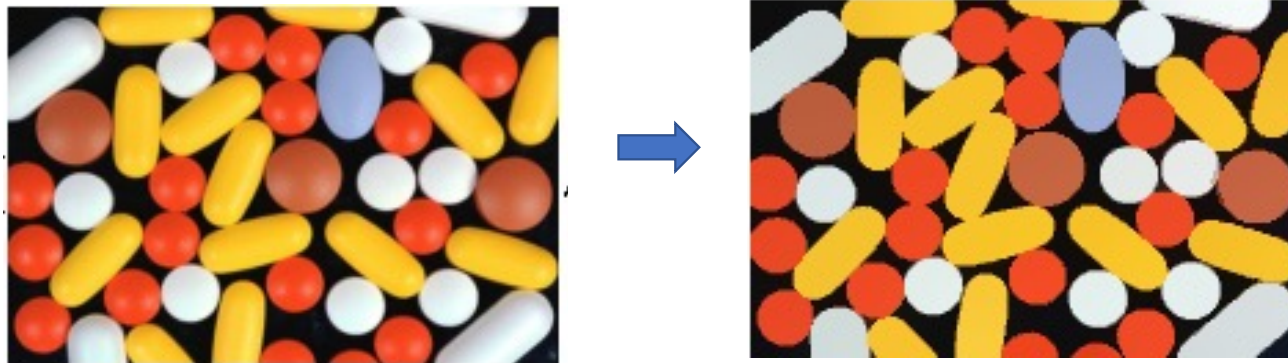
- **Mean-shift segmentation algorithm:**
- involves **first running the mean-shift filter**, then applying some post processing steps to the result.
- Mean-shift clustering is **a non-parametric, density-based clustering algorithm** that can be used to identify clusters in a dataset.
- Particularly useful for datasets where the **clusters have arbitrary shapes and are not well-separated** by linear boundaries.
- mean-shift does **not require specifying the number of clusters** in advance.



## Recap - from non-linear filters

- **Mean-shift filter**

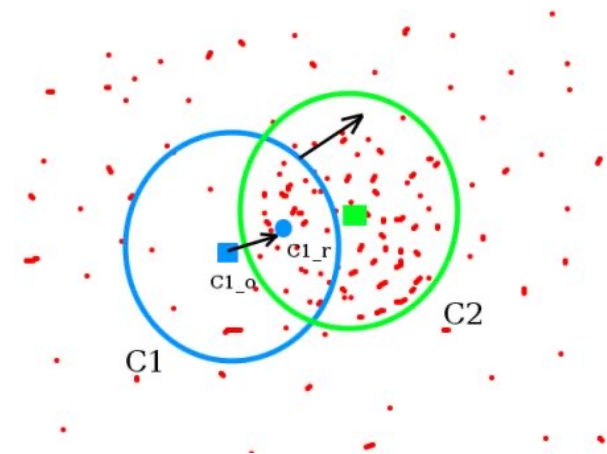
- Clustering both in color values and in distance. Group pixels near in color values AND distance, and recalculate mean according to mean-shift. Iteratively replaces each pixel with the mean of the pixels in a range- $r$  neighborhood and whose value is within a distance  $d$  until mean-shift = 0.



# Mean Shift clustering

The mean shift algorithm seeks modes of the given set of points

1. For each point:
  - a) Center a window on that point
  - b) Compute the mean of the data in the search window
  - c) Center the search window at the new mean location
  - d) Repeat (b,c) until convergence
1. Assign points that lead to nearby modes to the same cluster



Original window C1, center  $c1_o$ , but centroid is  $c1_r$ . -> move region with the "mean-shift" so that center of new region is at  $c1_r$  (C2).

Used for clustering, tracking, segmentation ..

# Mean-shift filter

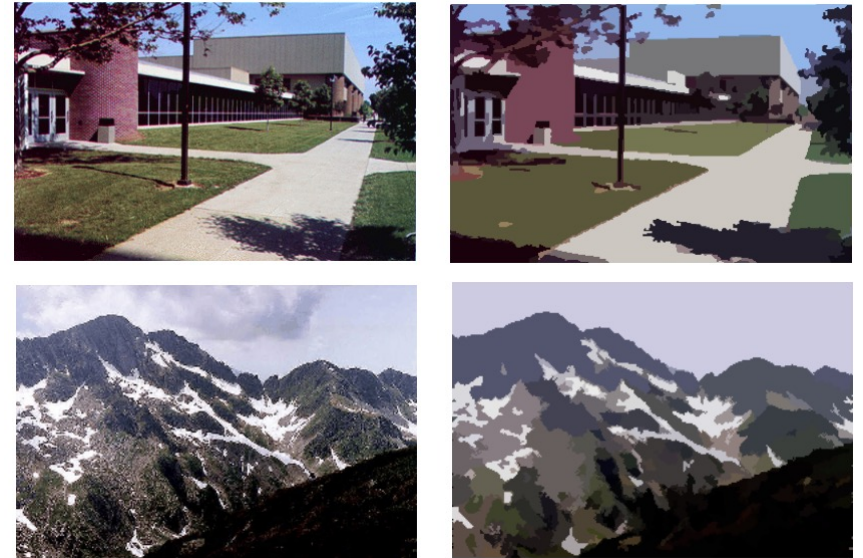
- Mean shift can be seen as locating the maxima – **the modes** - of a density function given discrete data that function

- Let  $\mathbf{x} = (x, y, v) = (x, y, I(x, y))$  for each pixel

- Let a kernel function,  $K(\mathbf{x}_i - \mathbf{x})$  be given. This function determines the weight of nearby points for re-estimation of the mean. Typically a Gaussian kernel on the distance to the current estimate is used
- The weighted mean of the density in the window, determined by  $K$  in a neighborhood around the pixel, is found as  $m(\mathbf{x})$ . The difference  $(m(\mathbf{x}) - \mathbf{x})$  is called the mean shift. Now  $\mathbf{x}$  is set equal to  $m(\mathbf{x})$ , and the process is repeated until convergence.

$$m(\mathbf{x}) = \frac{\sum_{\mathbf{x}_i \in N} K(\mathbf{x}_i - \mathbf{x}) \mathbf{x}_i}{\sum_{\mathbf{x}_i \in N} K(\mathbf{x}_i - \mathbf{x})}$$

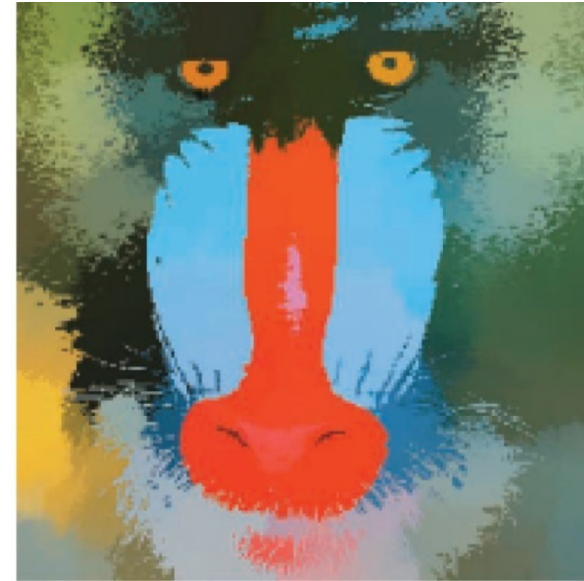
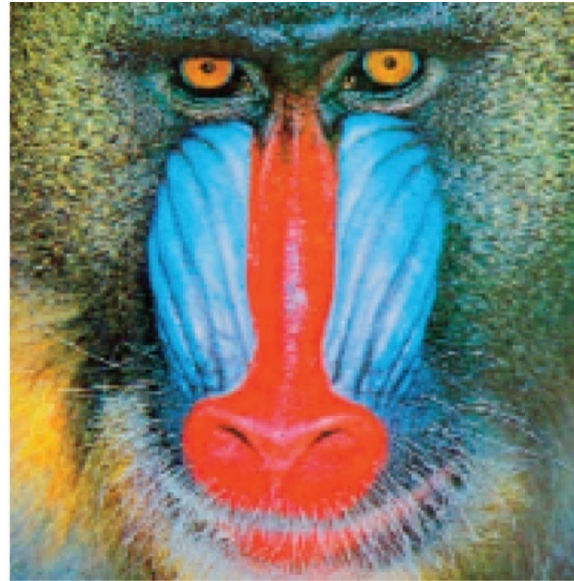
- Output image: value at «start position»  $(x', y')$  is set to the «end value» in  $m(\mathbf{x})$ .



# Mean-shift segmentation

- **Postprocessing**: Any two pixels that are nearby in both spatial coordinates and range are merged, and finally small regions are merged with nearby larger regions.
- Good results – computationally expensive.
- **Links Segmentation to edge-preserving smoothing! Any edge-preserving smoothing can be done instead.**

**Figure 5.22** An image (left) and the cartoon-like result of mean-shift filtering (right), using  $h_s = 32$  and  $h_r = 16$ .



© 2002 IEEE. Reprinted, with permission, from D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(5):603-619, May 2002.

**Figure 10.31** Result of the mean-shift segmentation algorithm on an image of a clown.

( First run mean-shift filter, then apply postprocessing steps. )



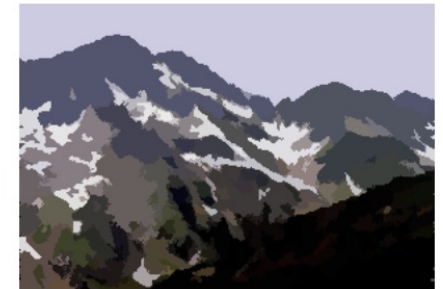
Stan Birchfield



# Segmentation – other\* methods

Three points from the topic:

1. Segmentation by region growing
2. Segmentation by watershed
3. Segmetnation by mean-shift



\* - other than thresholding