

# Lecture 21 Region-based Segmentation (chapter 10.4-10.6 )

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# Outline

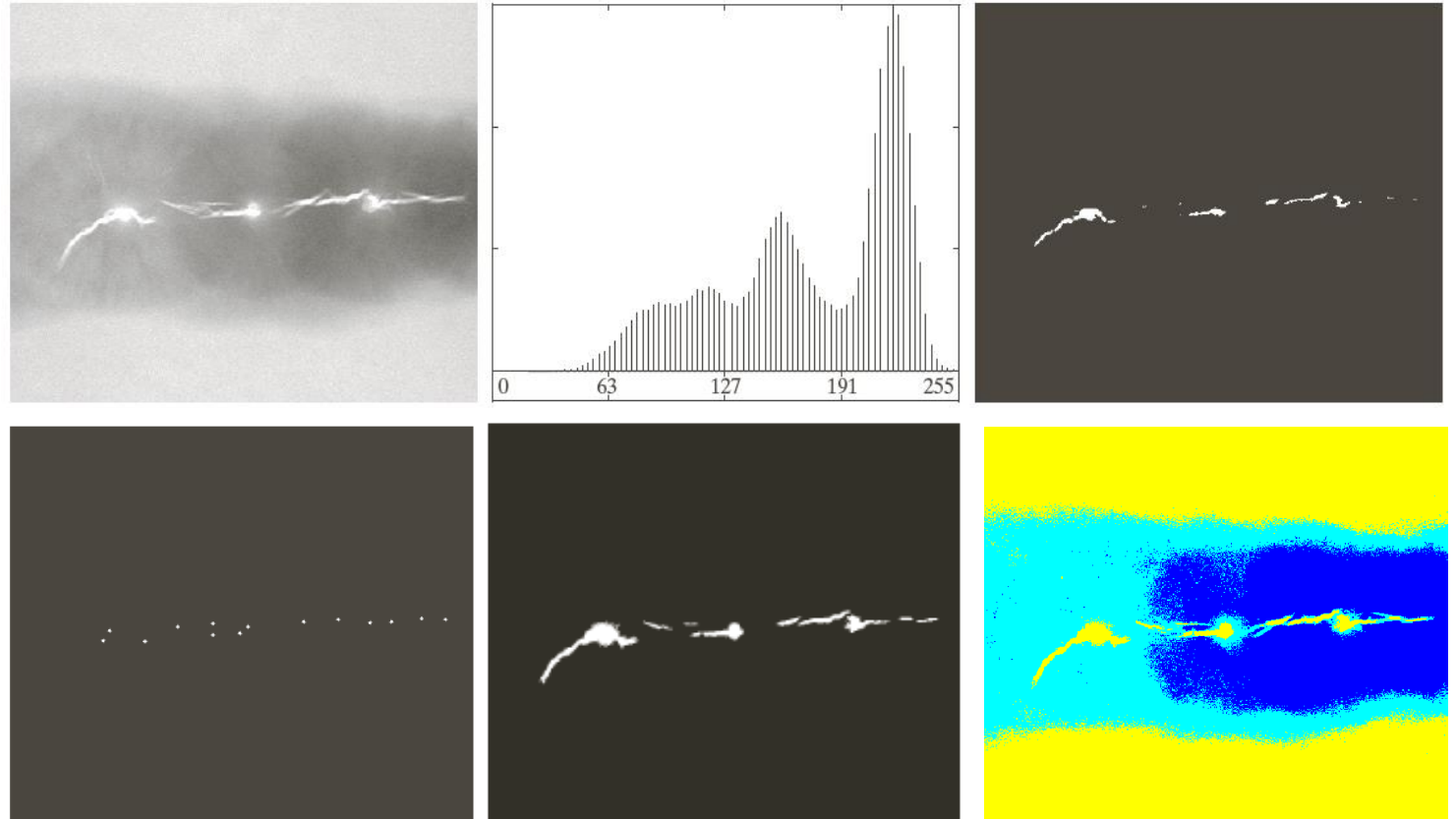
## ➤ Region-based Segmentation

- Region growing
- Region spilt and merge
- Clustering and Super-pixel

# Basic region growing

➤ If we only want “common” pixels near one point.

- 1) from input image  $I(x, y)$  get a binary “seed image”  $S(x, y)$  for locations of interest. (e.g. by thresholding).
- 2) reduce seed connected components down to single point each.
- 3) let  $T(x, y) = 1$  if  $I(x, y)$  satisfies some predicate/condition and 0 else. (e.g.  $(x, y)$  is 8-connected to seed point  $(x_i, y_i)$  and  $|I(x, y) - I(x_i, y_i)| < T$ ).



# Try this

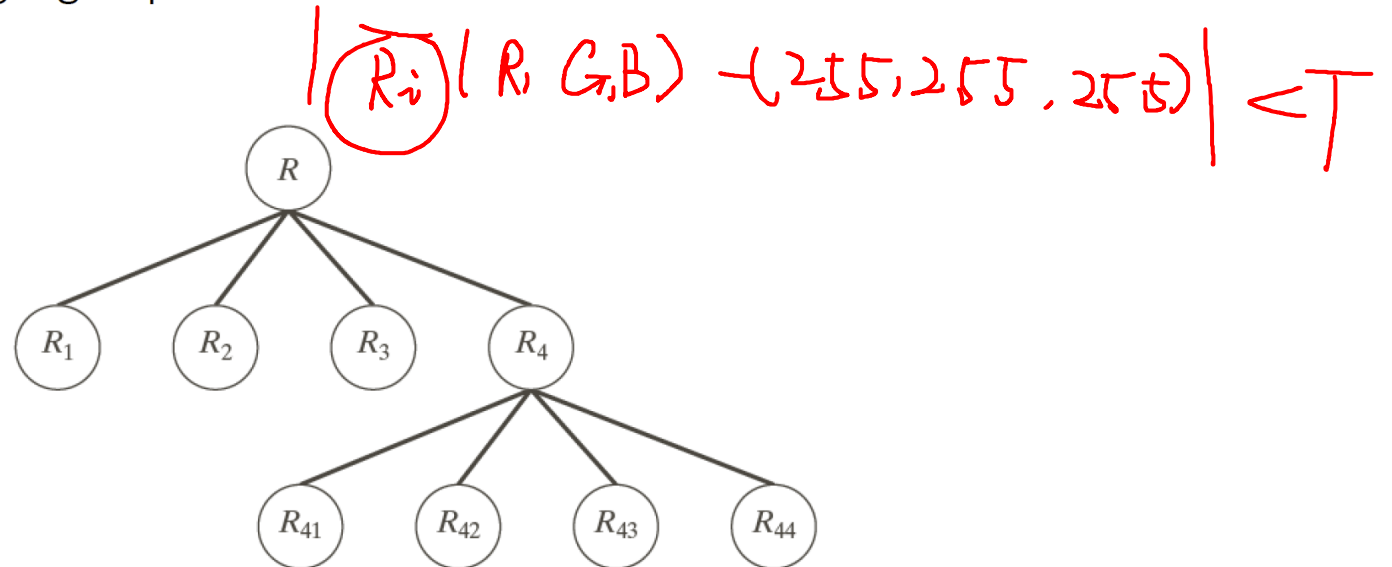
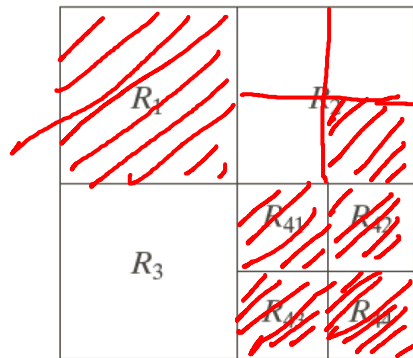
- Check the “regiongrow.m” function in discussion folder.



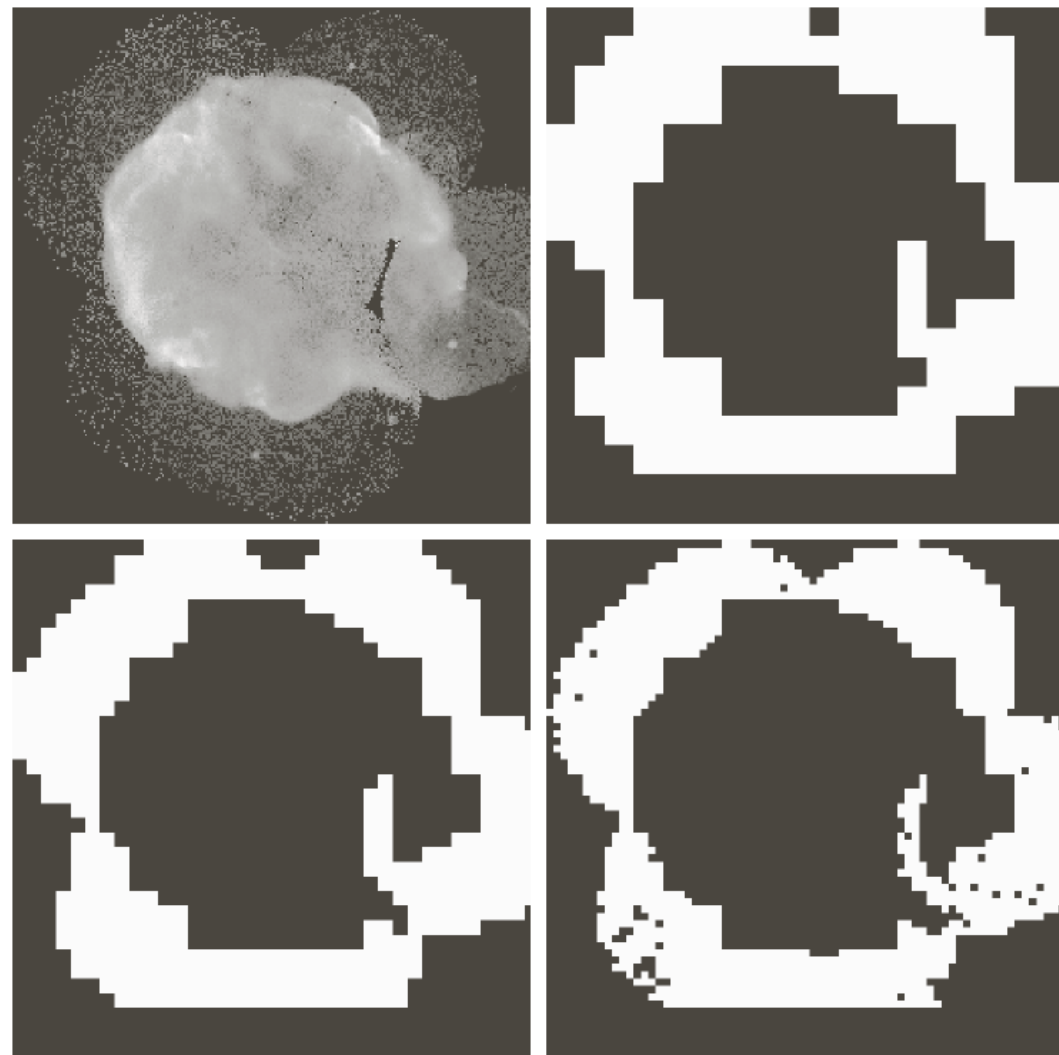
# Region split and merge

## ➤ Steps

1. Split into four disjoint quadrants any region  $R_i$  for which  $Q(R_i) = \text{False}$  (need to specify a minimum quadregion size beyond which no further splitting is carried out);
2. Merge any adjacent regions  $R_j$  and  $R_k$  for which  $Q(R_j \cup R_k) = \text{True}$ ;
3. Stop when no further merging is possible.



# Region Splitting and Merging



# K-means Clustering

➤ Algorithm:

1) Specify an initial set of clusters centers  $m_1, m_2, \dots, m_k \in \mathcal{R}^n$ .

2) For each  $x_i \in \mathcal{R}^n$  in dataset, assign it to closest cluster

$$x_i \in cluster_j \text{ if } \|x_i - m_j\| < \|x_i - m_k\| \quad (k \neq j)$$

3) Update the mean  $m_j = \text{average value of all } x \text{ in cluster } j$ .

$$m_j = \frac{1}{c_j} \cdot \sum_{x \in c_j} x \quad j = 1, 2, \dots, k$$

4) Keeps altering 2) and 3) until stop changing.

E.g. Image histogram

E.g. Color space k-means cluster.

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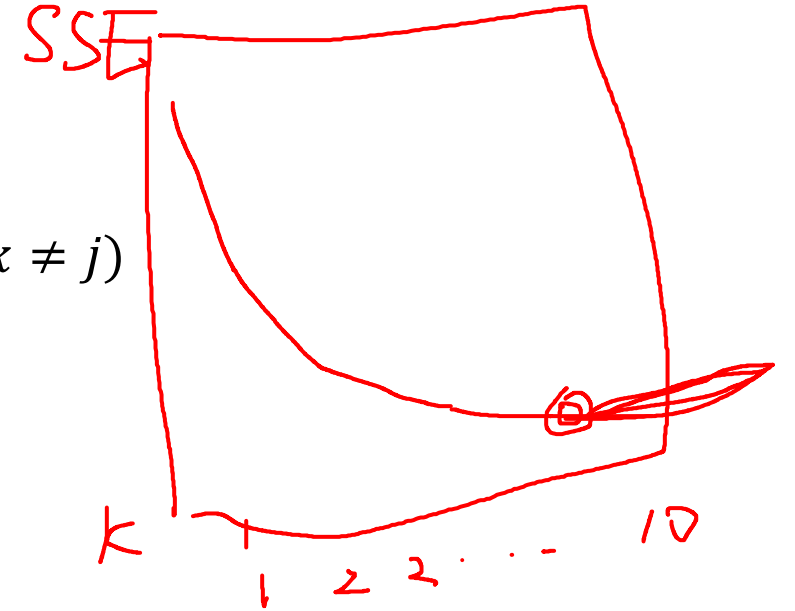
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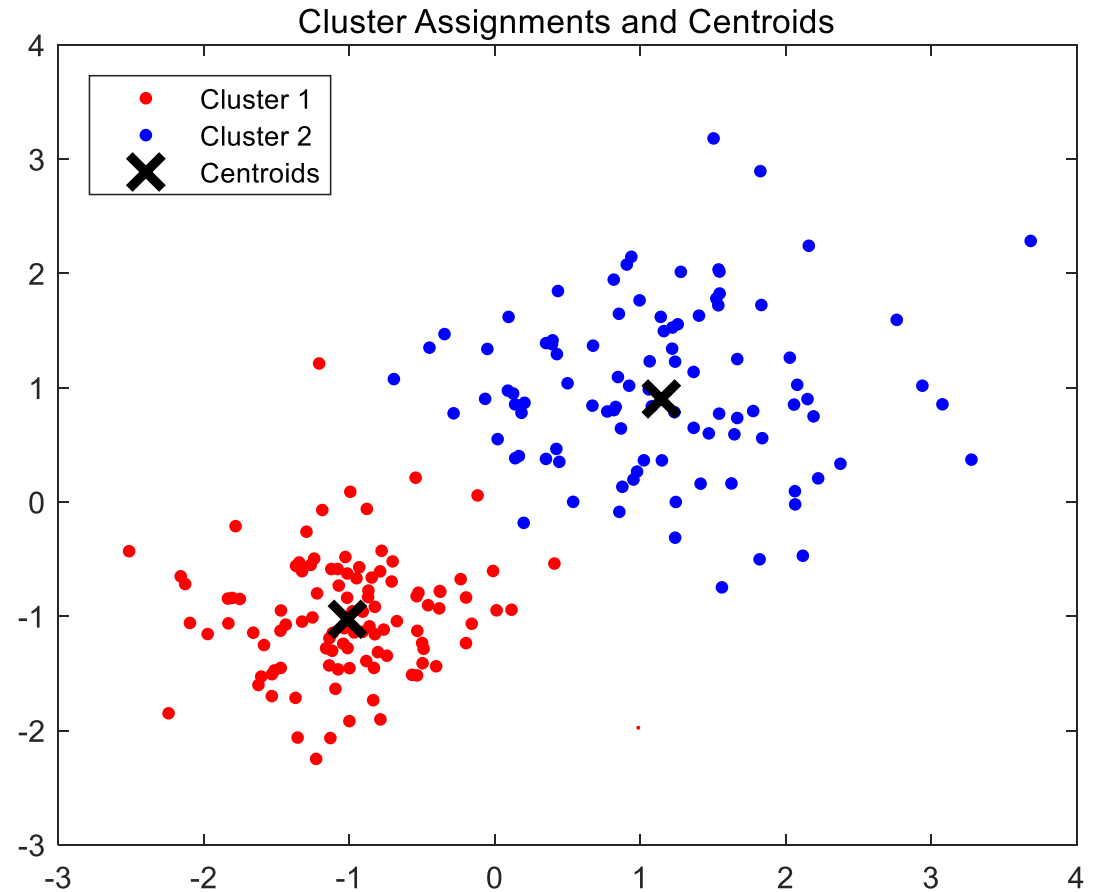
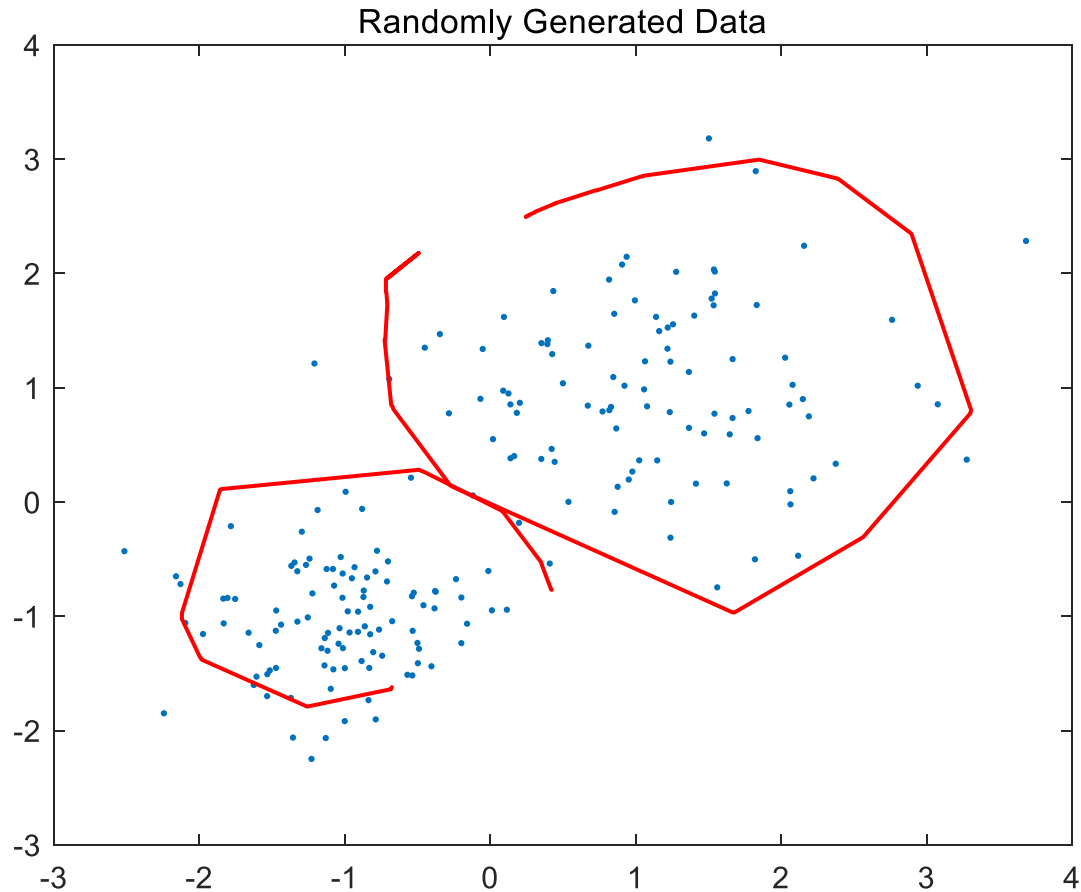


$$SSE = \sum_{k=1}^K \sum_{x \in C_k} |x - m_k|^2$$

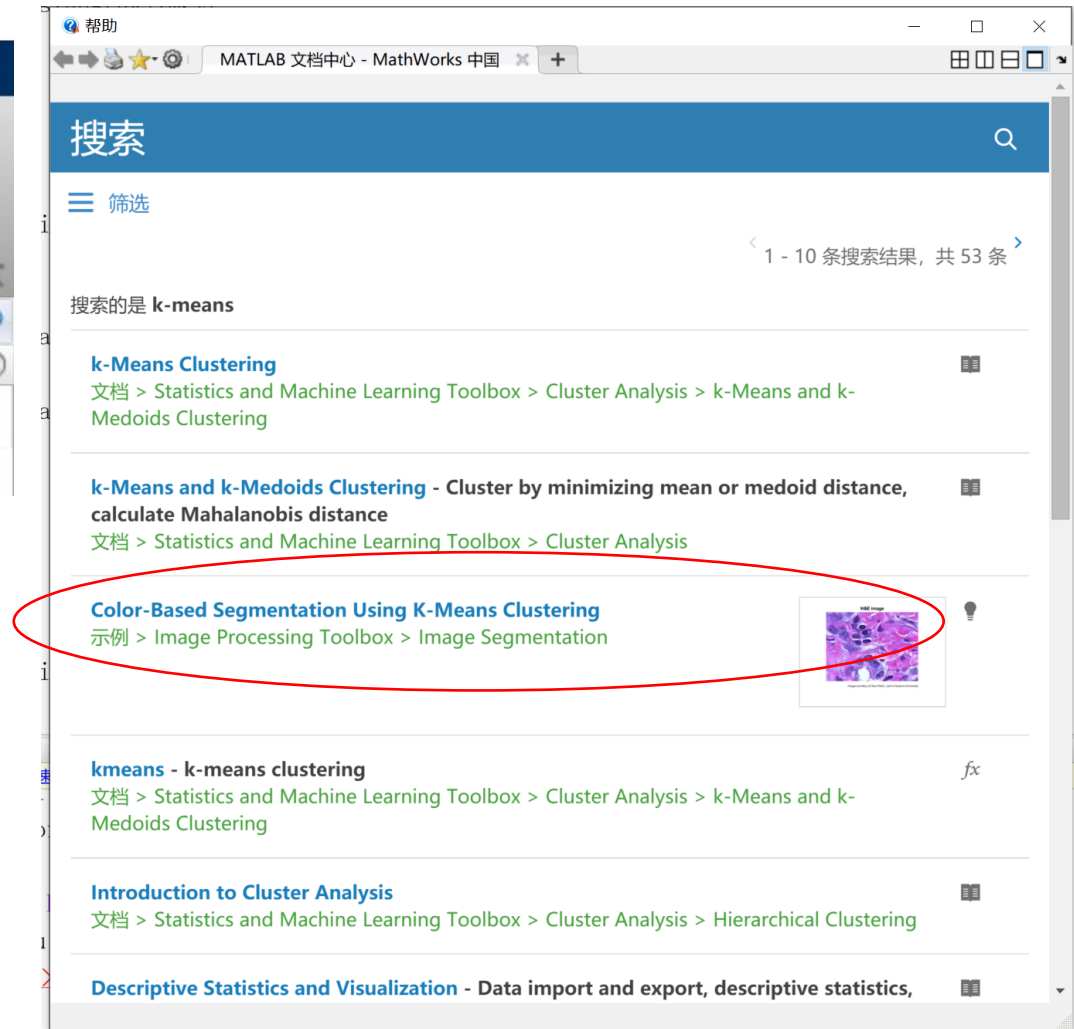
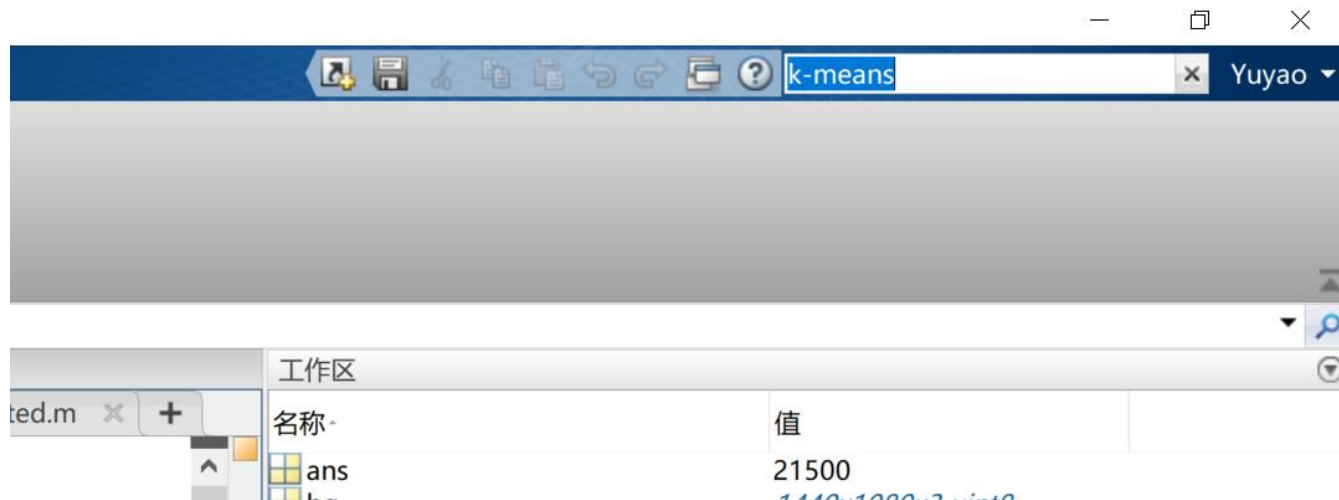
min



# K-means demo



# Try this



H&E image

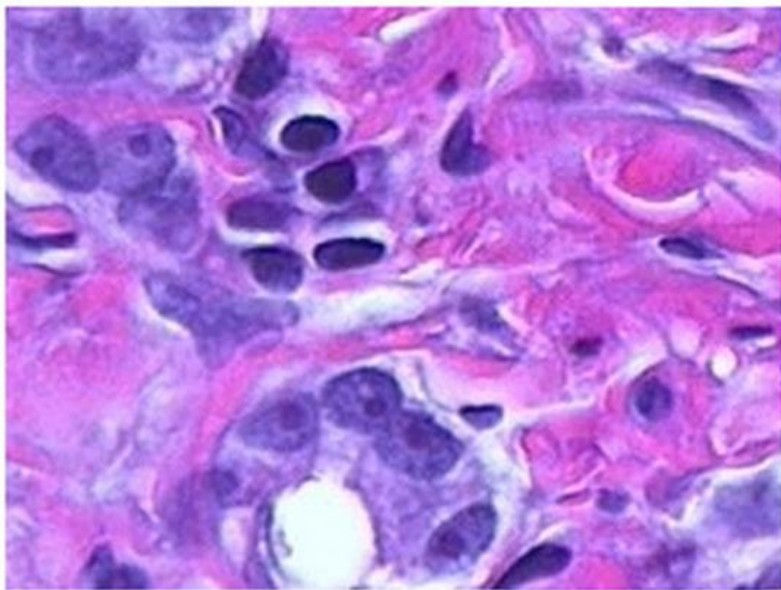
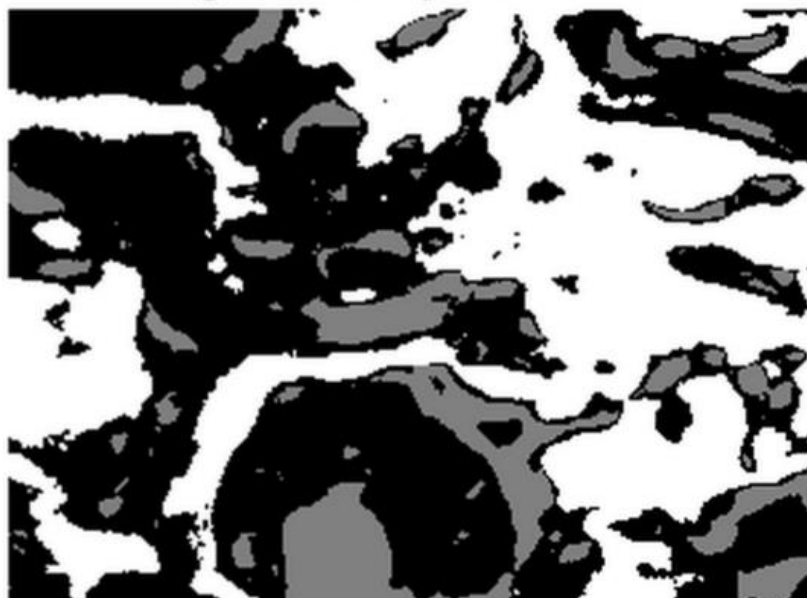
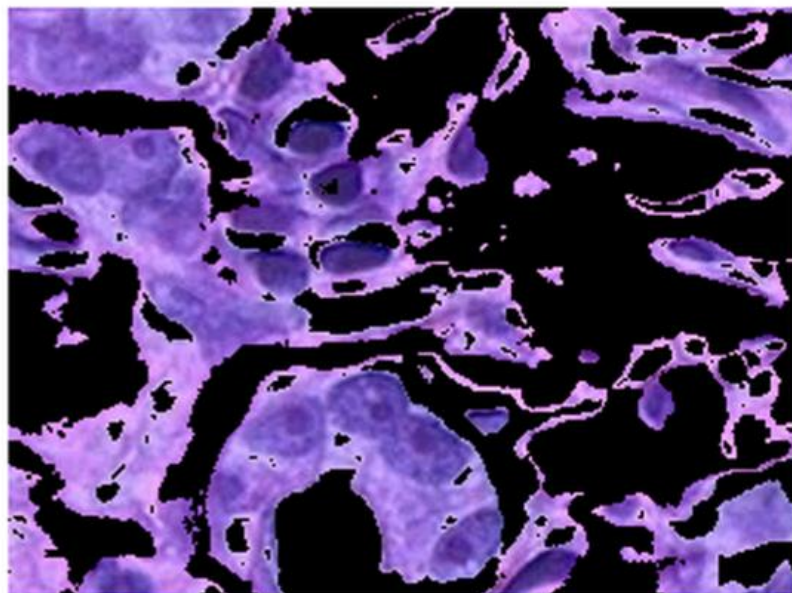


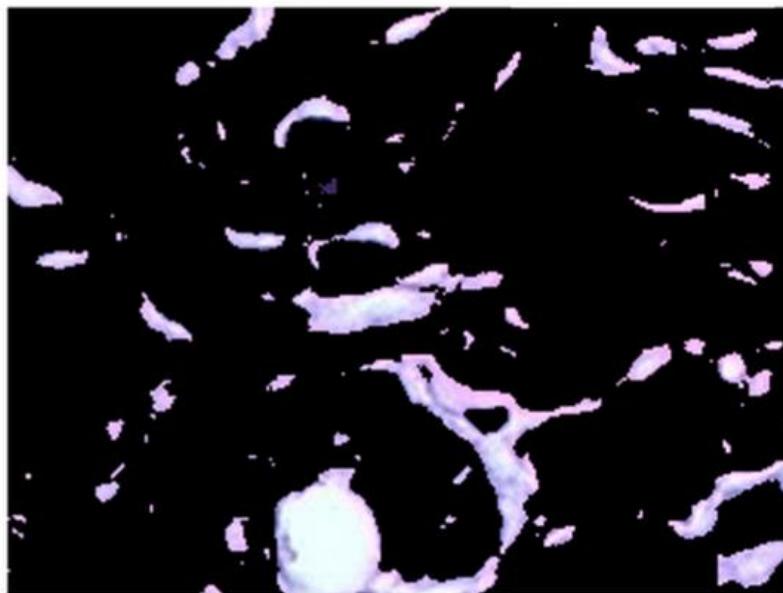
image labeled by cluster index



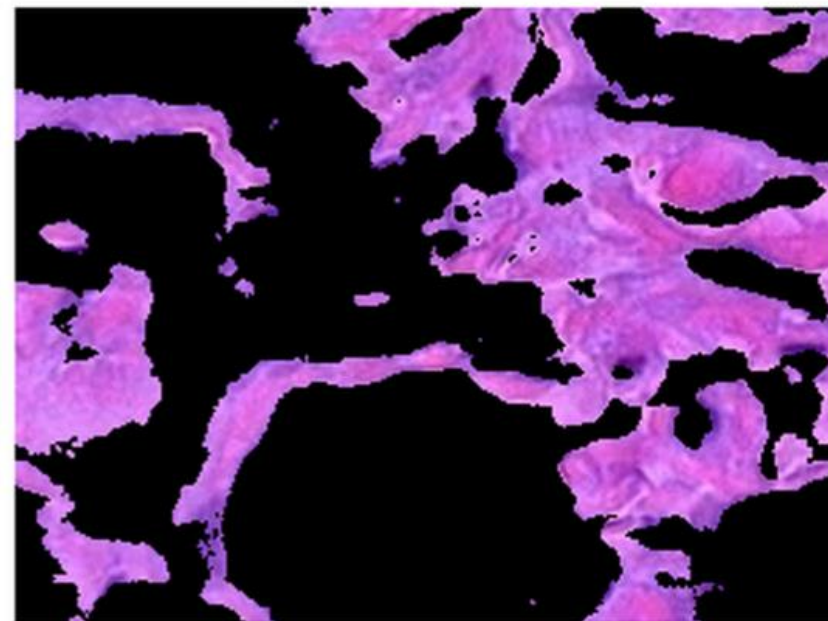
objects in cluster 1



objects in cluster 2



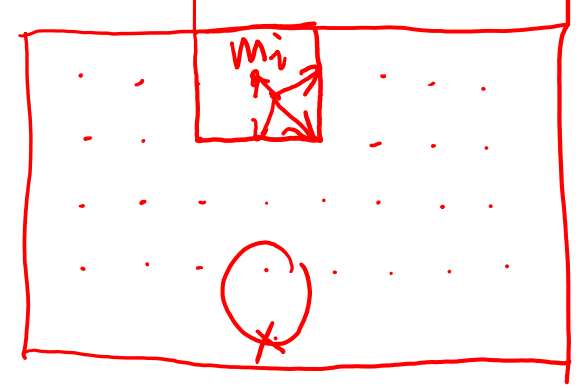
objects in cluster 3



# Super-pixel

- Modification of K-means used in image processing;
- Regions of image that are contiguous and have similar intensity/color.
- Why doing this?
  - More compact (e.g. thousands of super-pixels could represent millions of pixels).
  - “Keeps things together” better for subsequent segmentation; computationally efficient.

# Super-pixel



Idea: Clustering 5-D vectors  $[r, g, b, x, y]$

1) initialize super-pixels center by sampling  $N$  locations on a region grid in image plane.

❖ Move slightly within 3x3 neighborhood to lie on lowest gradient position (Don't want to start on an edge).

2) For each cluster center  $m_i$ , compute distance bwt  $m_i$  and each pixel in a neighborhood of  $m_i$ .

$$\begin{bmatrix} R_{m_i} \\ G_{m_i} \\ B_{m_i} \\ x_{m_i} \\ y_{m_i} \end{bmatrix}$$

$$d_c = \left\| \begin{bmatrix} R \\ G \\ B \end{bmatrix}_i - \begin{bmatrix} R \\ G \\ B \end{bmatrix}_j \right\|_2 \quad \text{color}$$

$$d_s = \left\| \begin{bmatrix} x \\ y \end{bmatrix}_i - \begin{bmatrix} x \\ y \end{bmatrix}_j \right\|_2 \quad \text{spatial}$$

❖ Only search in neighborhood, the region size depends on # of  $N$ .

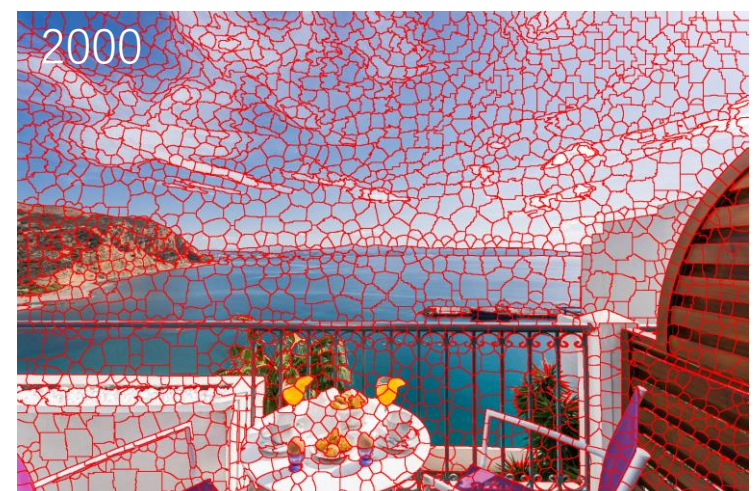
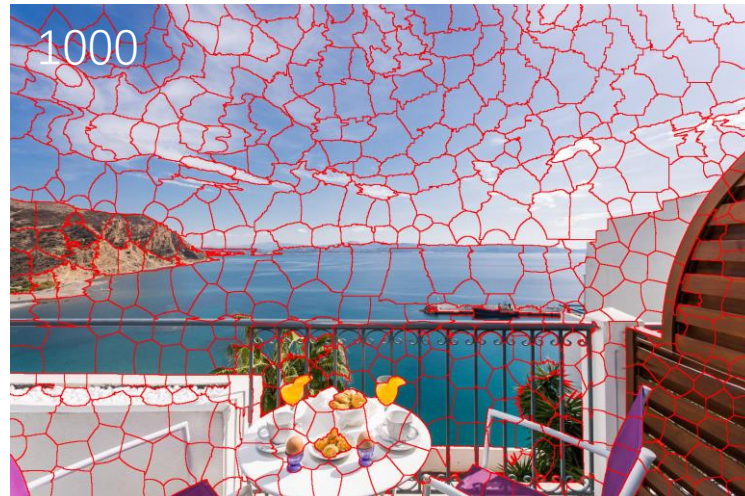
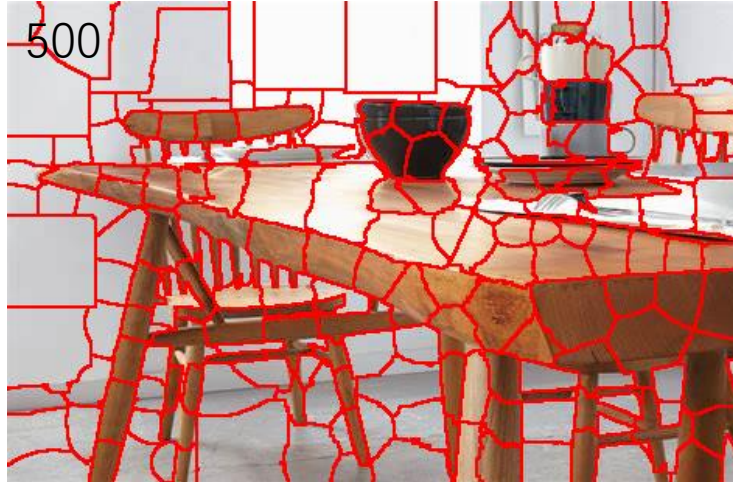
❖ Assign pixel to cluster  $i$  if its distance is better than its current value.

$$D = \sqrt{\left(\frac{d_c}{c}\right)^2 + \left(\frac{d_s}{s}\right)^2}$$



# Try this

- Check the “mysuperpix.m” function in discussion folder.







# Take home message

## ➤ **Pixel-based segmentation:**

each pixel is segmented based on gray-level values, no contextual information, only histogram.

-Example: hough transform

## ➤ **Region-based segmentation:**

considers gray-levels from neighboring pixels by

- including similar neighboring pixels (region growing),
- split-and-merge,
- or super-pixel segmentation.

## ➤ **Edge-based segmentation:**

Detects and links edge pixels to form contours.



# Take home message

- Region based methods are robust because:
  - Regions cover more pixels than edges and thus you have more information available in order to characterize your region
  - When detecting a region you could for instance use texture which is not easy when dealing with edges
  - Region growing techniques are generally better in noisy images where edges are difficult to detect
- The edge based method can be preferable because:
  - Algorithms are usually less complex
  - Edges are important features in an image to separate regions
- The edge of a region can often be hard to find because of noise or occlusions
- Combination of results may often be a good idea