

Image Segmentation

Overview

- Motivation and Applications
- Segmentation as a clustering problem
 - K-means
 - Mean shift

Image Segmentation

- Goal: break up the image into semantically-meaningful or perceptually-similar regions

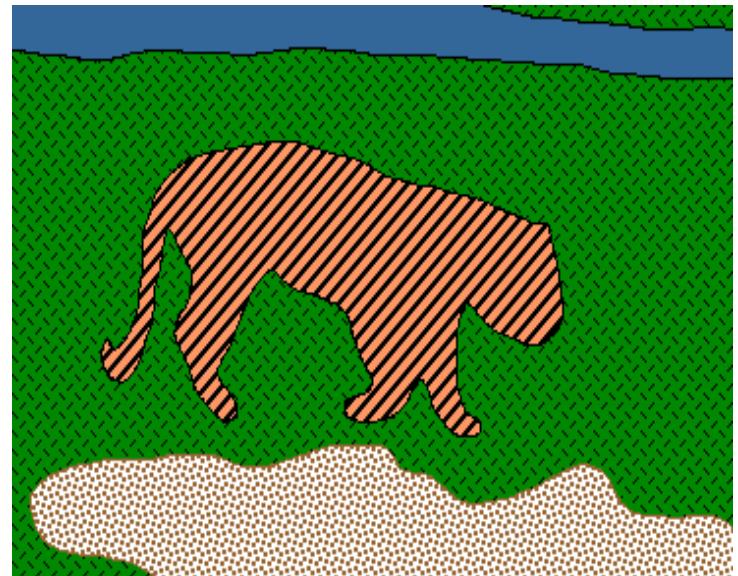
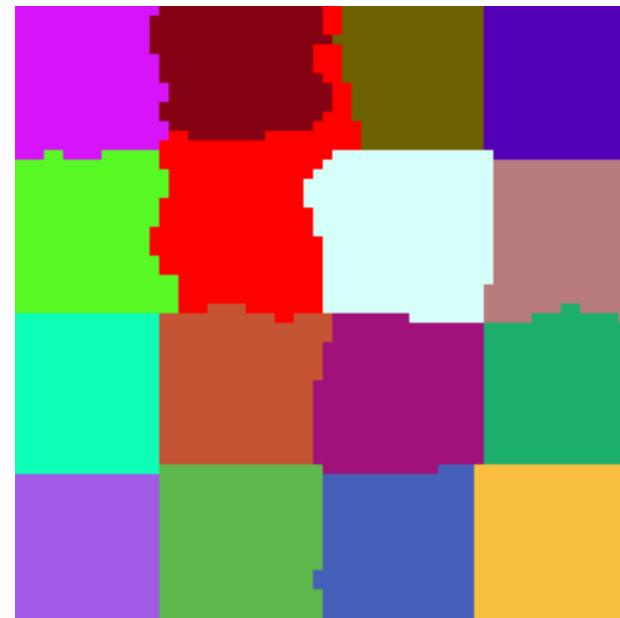
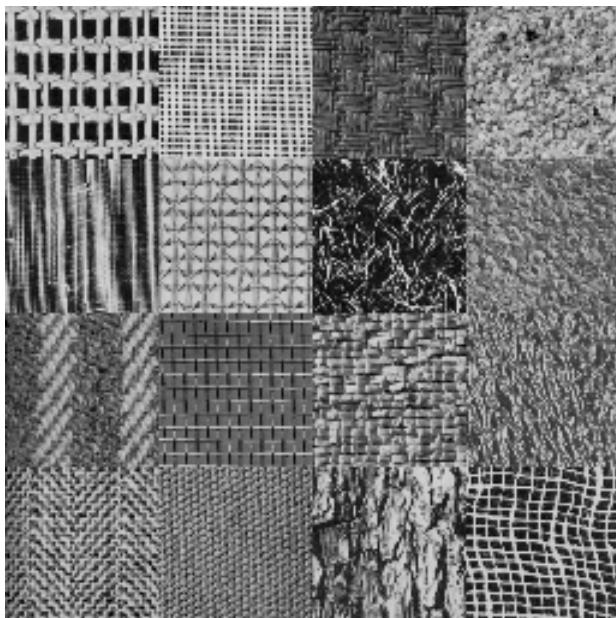


Image segmentation

- Goal: break up the image into semantically meaningful or perceptually similar regions



Texture Segmentation

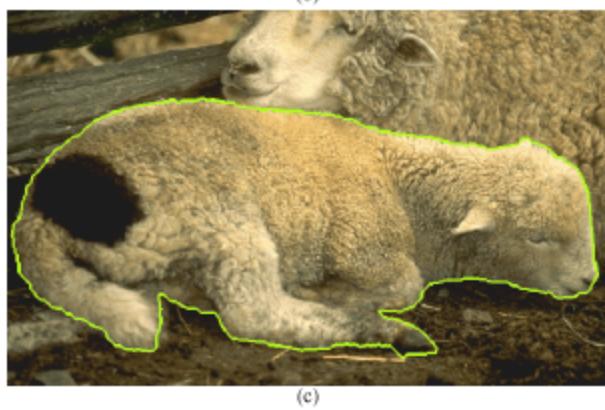


Courtesy Uni Bonn

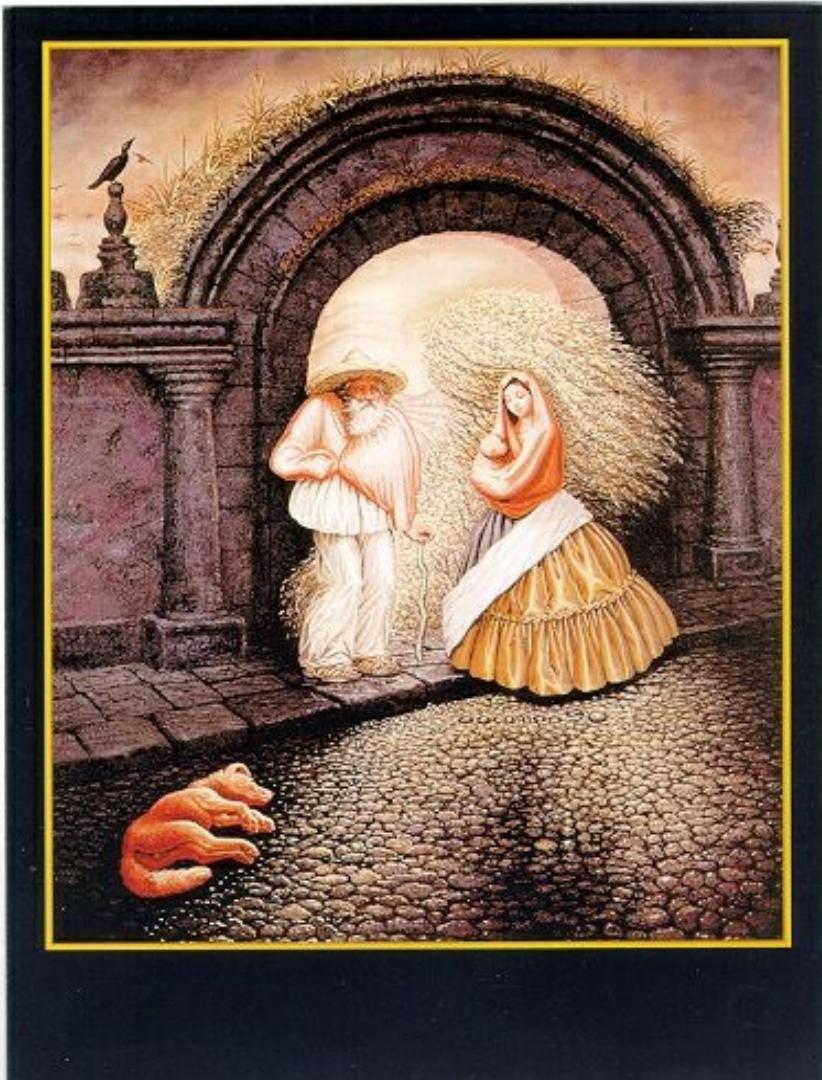
Segmentation for photo editing



Segmentation for photo montage



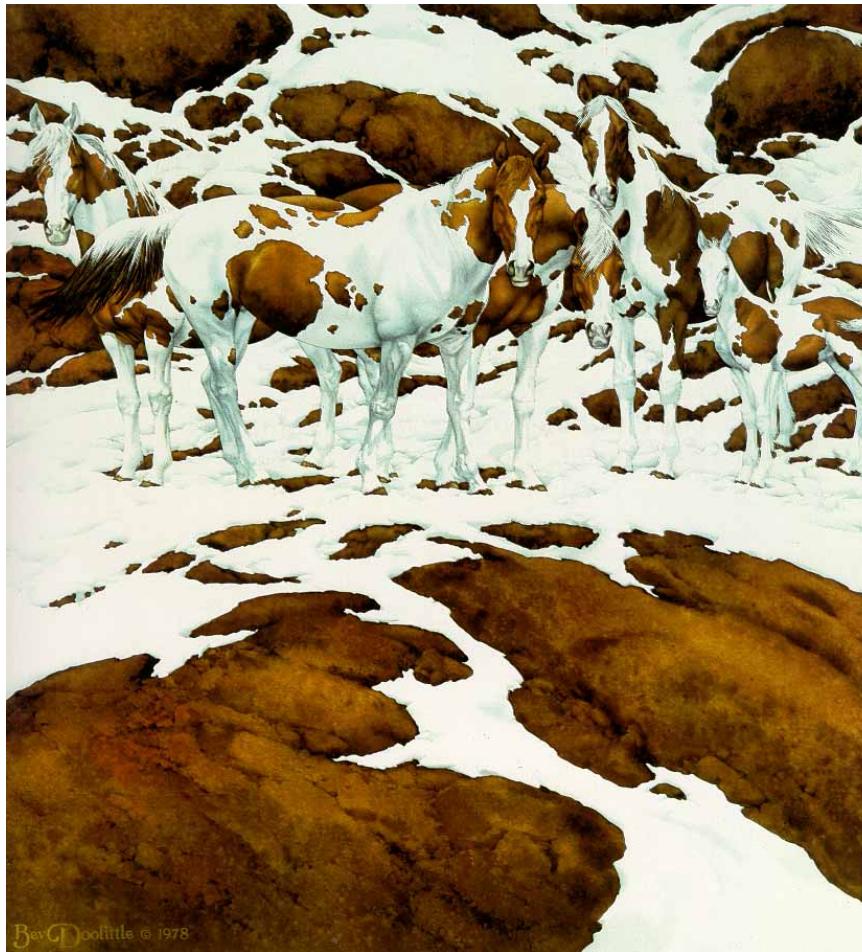
Segment first, or recognise first? (what is the context?)



A portrait of
an old man, or

A couple with
a dog on the street

Segment first, or recognise first? (what is the context?)



Snow and rocks, or

A group of horses
In snow and rocks

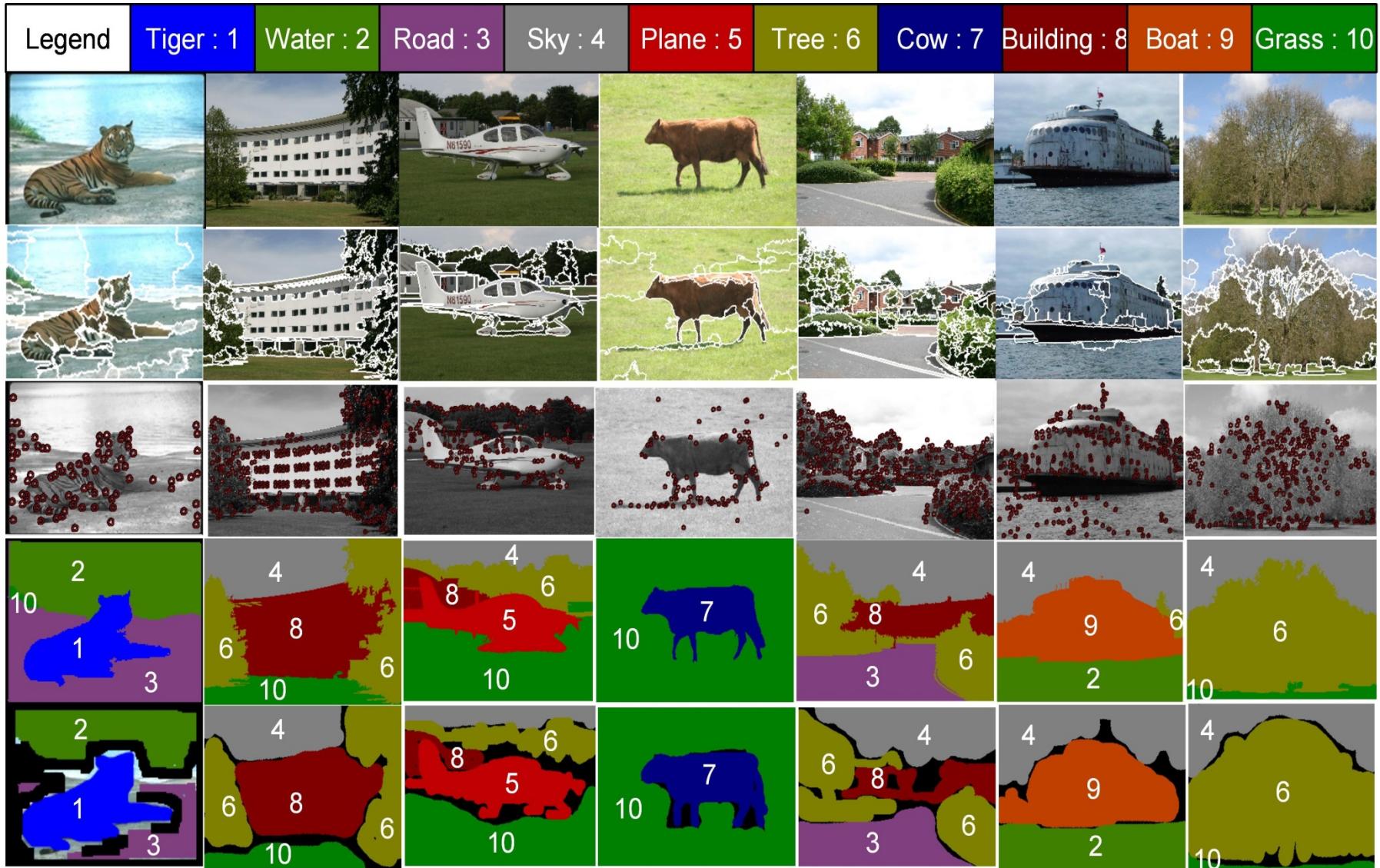
Segmentation and Recognition tasks are coupled

A chicken-and-egg problem?



"Who was first?"

Segmentation for Recognition



We focus on the *bottom-up* approach (i.e. segmentation first)

- Low- and mid-level visual cues for segmentation.
- Partition the image pixels into groups with perceptually homogeneous or similar pixel properties (e.g., intensity, colour, texture, or similar spatial location).
- Grouping pixels into perceptually homogeneous regions.

Histogram-based example: Image Binarization

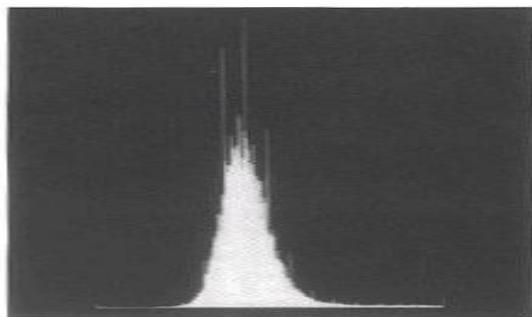
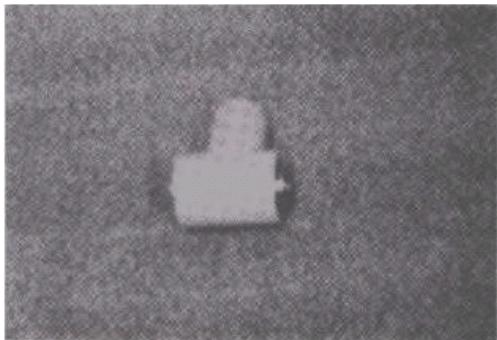
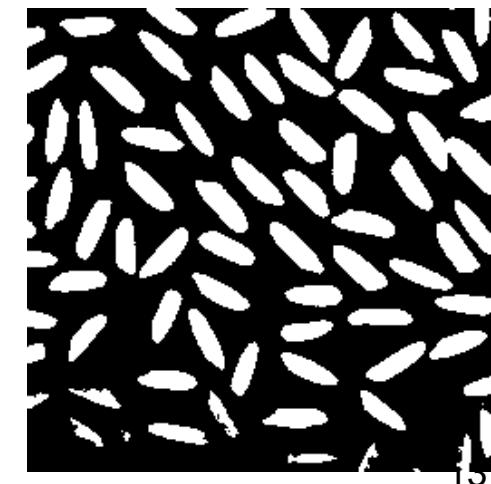
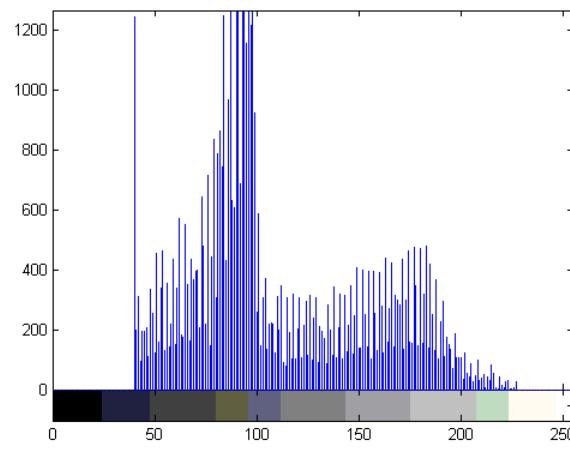
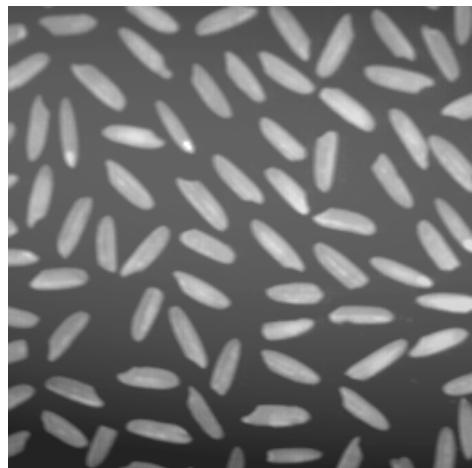
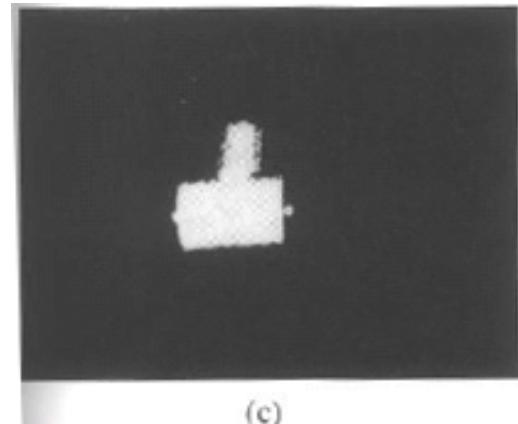


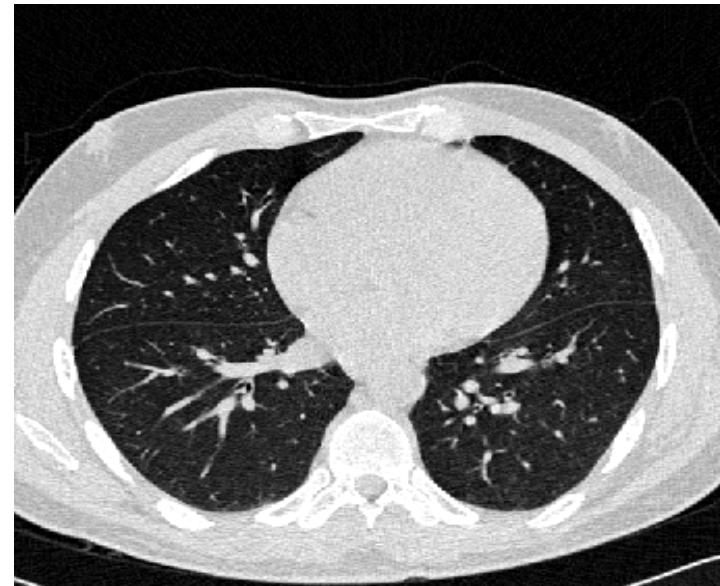
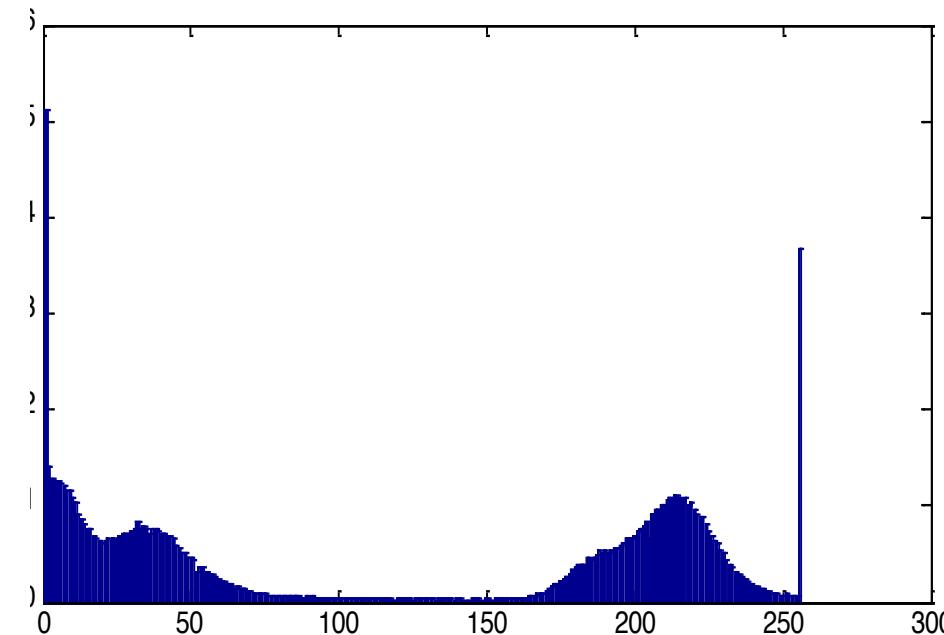
Figure 1.1 Histogram of the BNC ThumbsUp image of Fig. 1.6.



Histogram-based example: Ohlander algorithm

- Input a colour image of a scene
- Starts with the whole image
- Selects the R, G, or B histogram with largest peak and finds clusters from that histogram
- Converts to regions on the image and creates masks for each
- Pushes each mask onto a stack for further histogram clustering

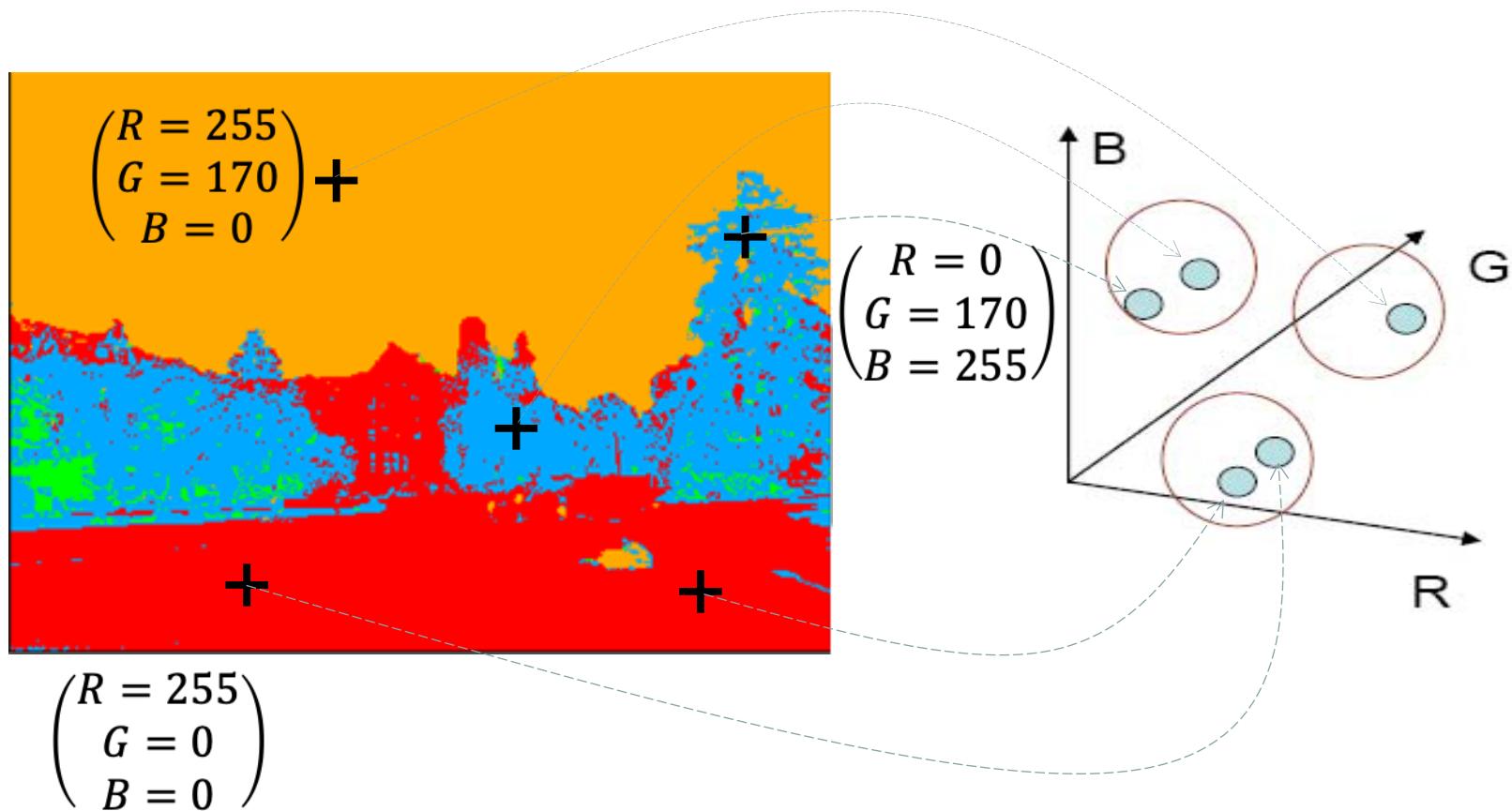
Histogram-based example: Histogram for 3 Clusters



K-means clustering

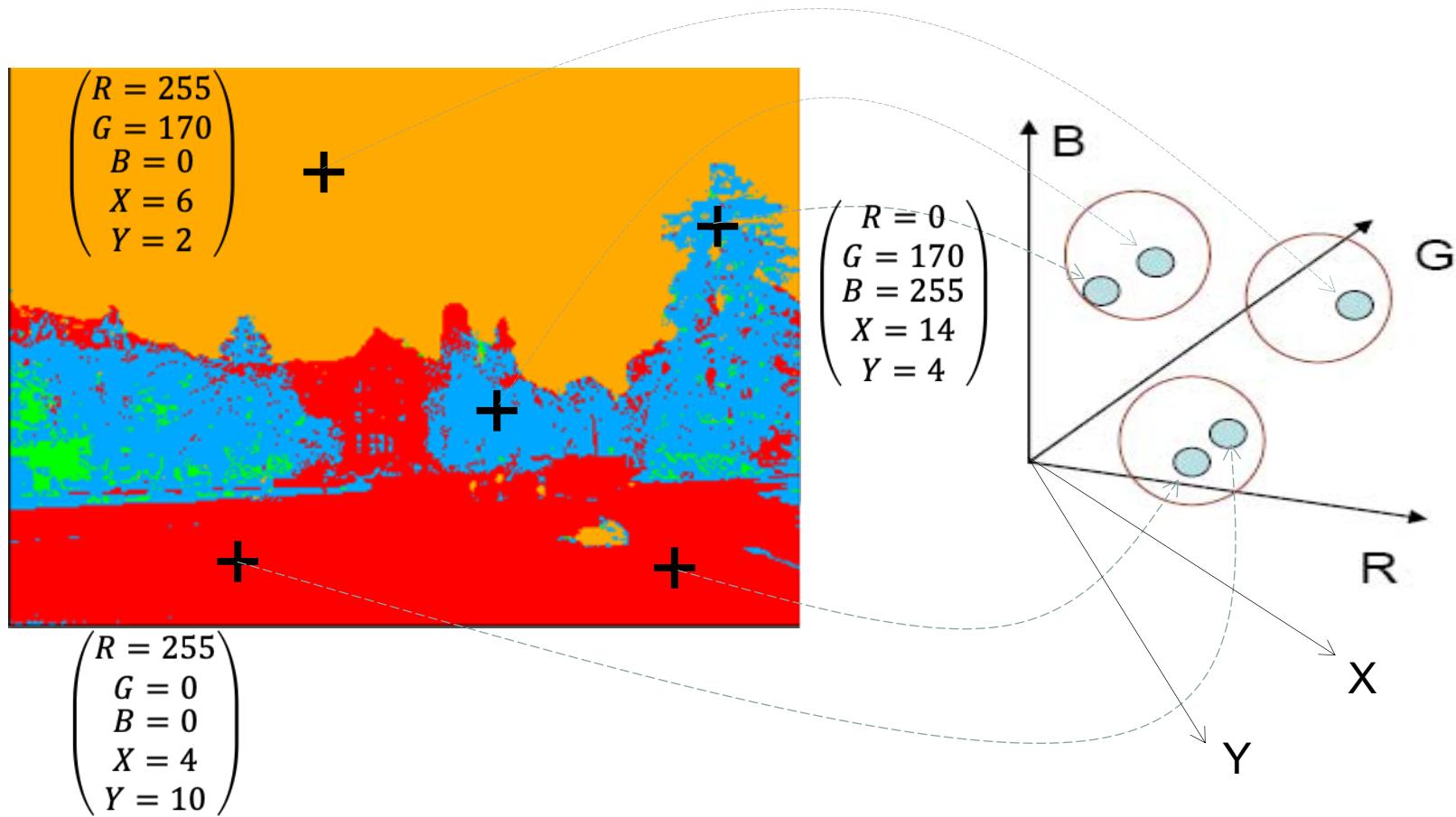
Segmentation as clustering

- Cluster similar pixels using colour features



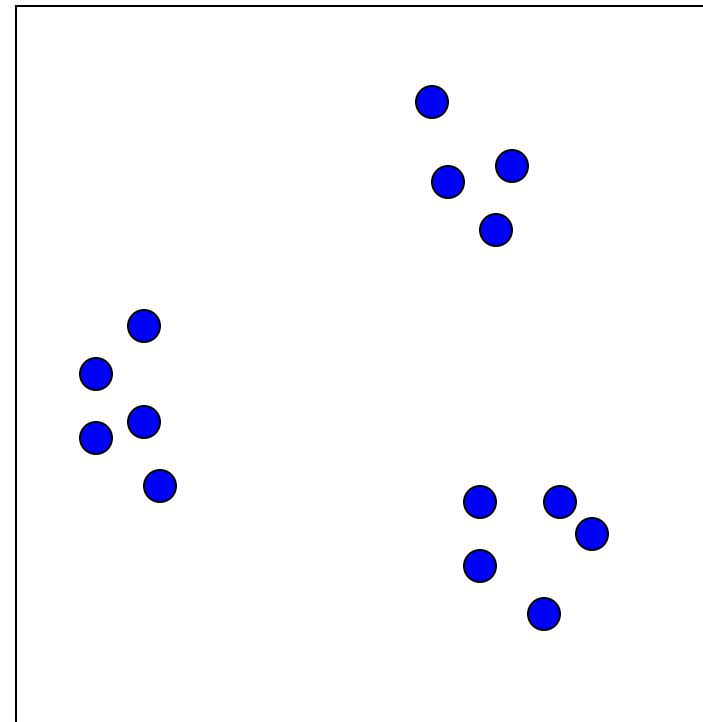
Segmentation as clustering

- Cluster similar pixels together (RGB+ XY)



K-means clustering

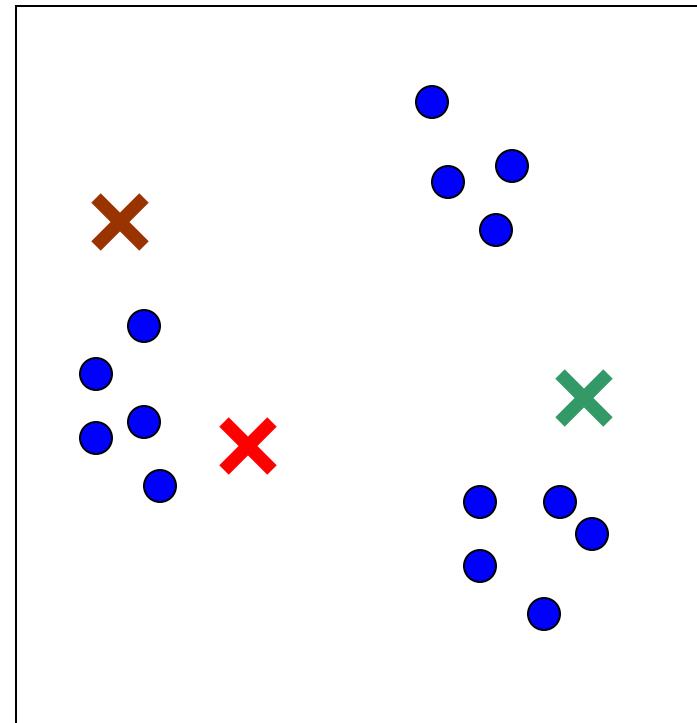
- “Guess” the number of clusters K before start (e.g. K=3)



$K(=3)$ means clustering

- Start with 3 *random* positions of the cluster *centers*.

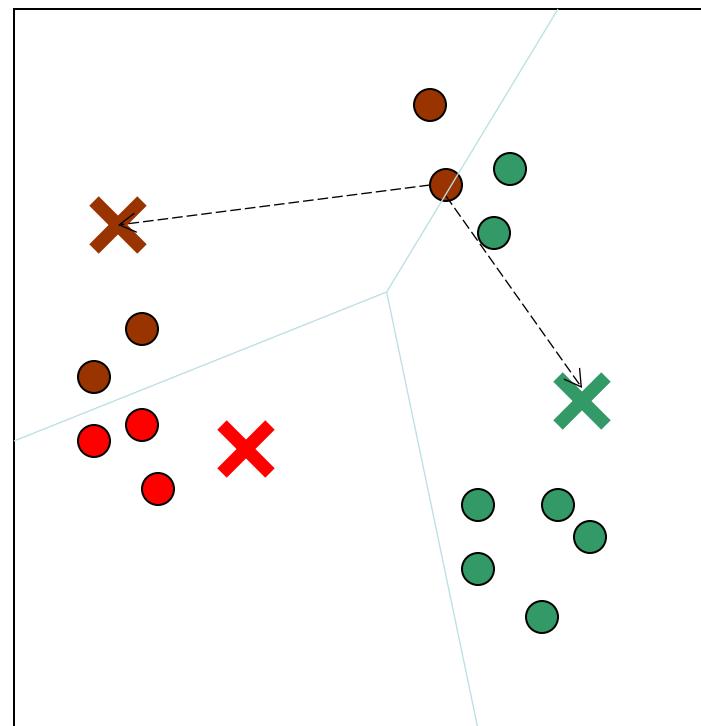
✗ ✗ ✗



Iteration = 0

K-means clustering

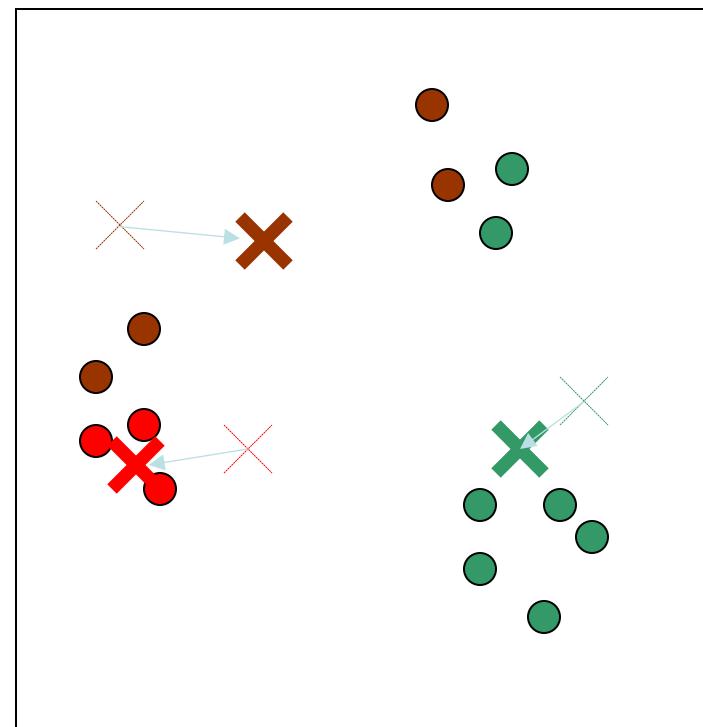
- Start with 3 random positions of the cluster centers.
- By computing the distance, *assign* each data point to the closest center.



Iteration = 1

K-means clustering

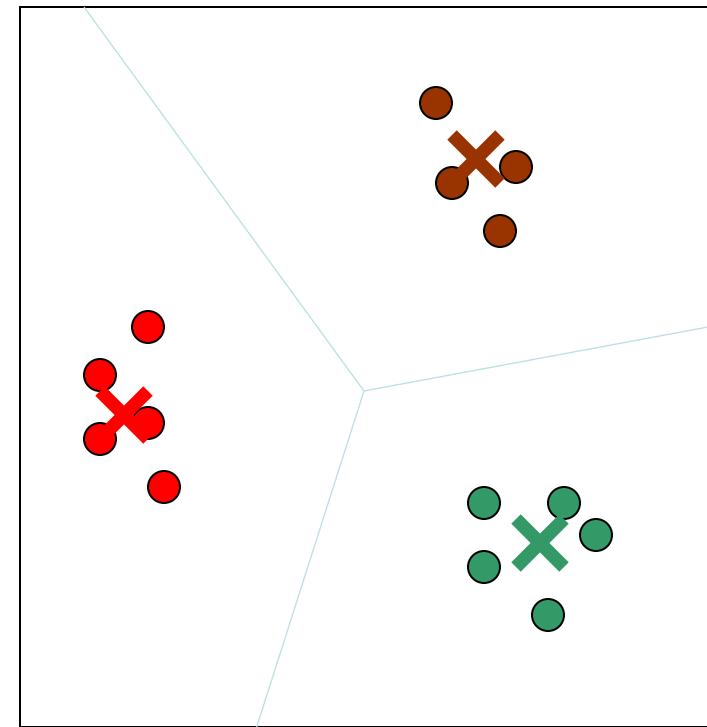
- Start with 3 random positions of the cluster centers.
- By computing the distance, *assign* each data point to the closest center.
- *Re-compute* the centers after the assignments.



Iteration = 1

K-means clustering

- Start with 3 random positions of the cluster centers.
- By computing the distance, *assign* each data point to the closest center.
- Re-compute the centers after the assignments.
- Iterate until no points are reassigned.



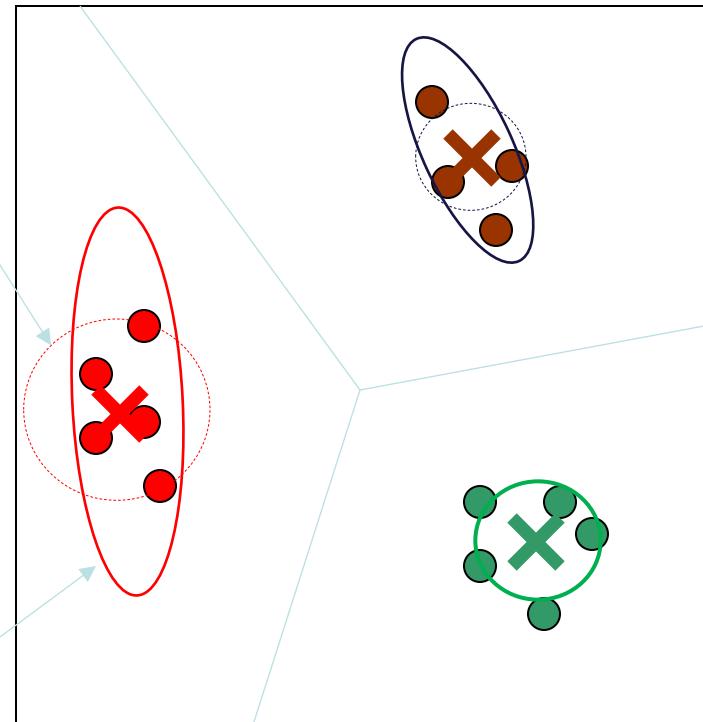
Iteration = 3

K-means clustering

- Question) What have we minimised?
- We have selected the means and membership which minimise the sum of squared distances to the centre means (centroids).
- The sum of squared distances to the means is actually the variance of the cluster

K-means clustering

- Spherical variance is used
- Q) What about the elongated variances?
 - Called Gaussian Mixture Model based clustering



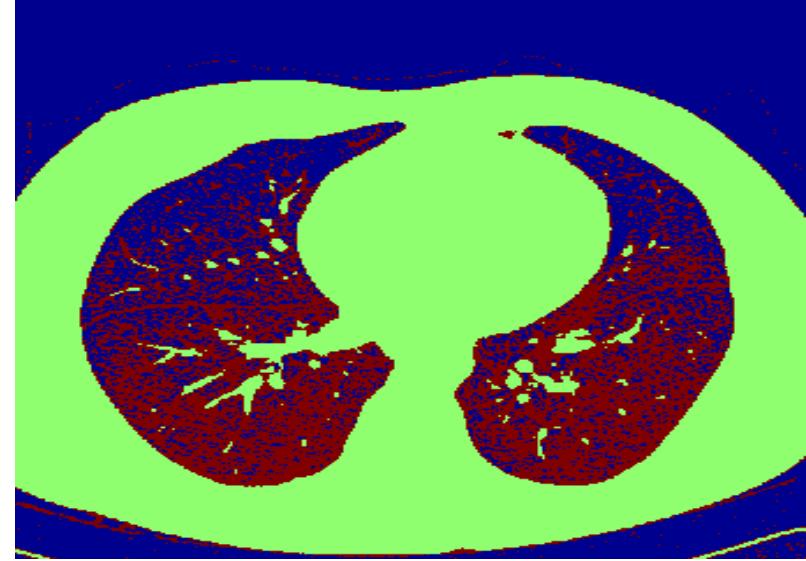
K-means clustering

1. Select a value of K
2. Select a feature vector for every pixel (color, texture, position, or combination of these etc.)
3. Define a similarity measure between feature vectors (Usually Euclidean distance)
4. Apply the K-means algorithm to all the feature vectors

K-means Image Segmentation



Input image (I)



Three-cluster image using the gray levels of *input image*

Matlab code:

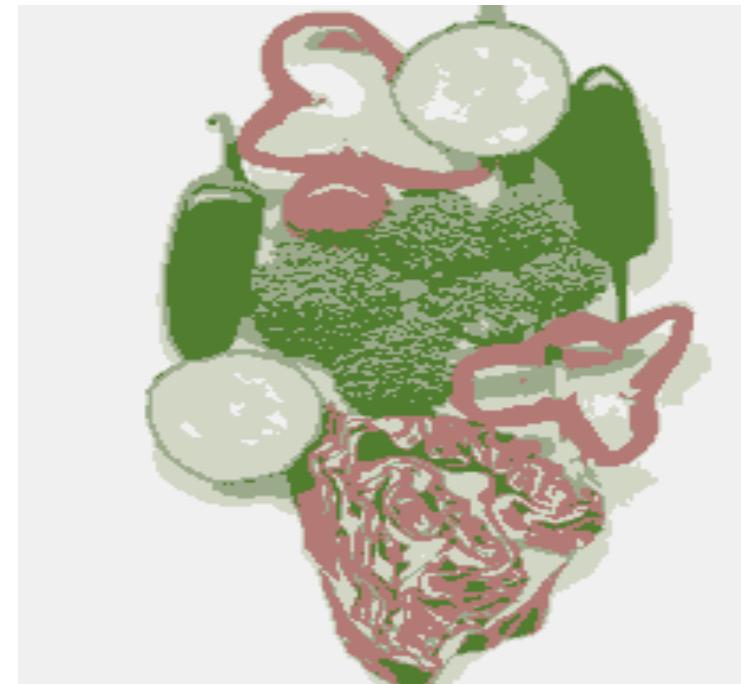
```
I = double(imread('...'));
```

```
J = reshape(kmeans(I(:,3),size(I)); % need statistics toolbox
```

K-means Image Segmentation



Color Image



Segmented on color

- K-means clustering using color information

K-means Pros and Cons

Pros:

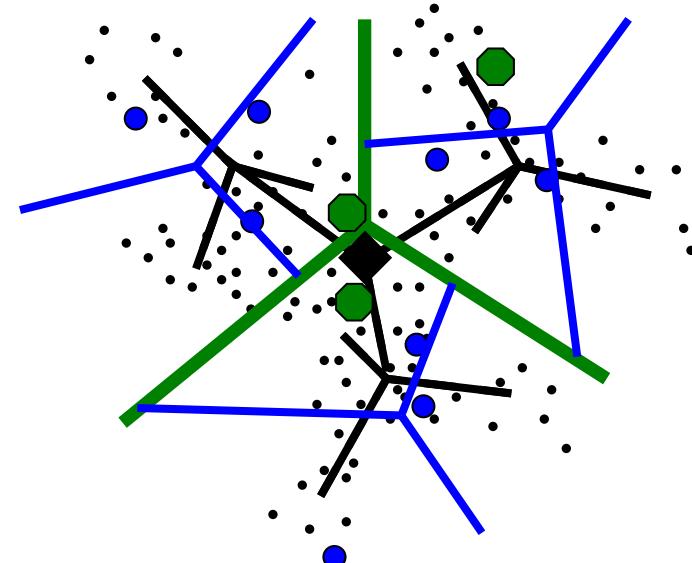
- Finds cluster centers that minimize variance (good representation of data)
- Simple to implement, widespread applications.

Cons:

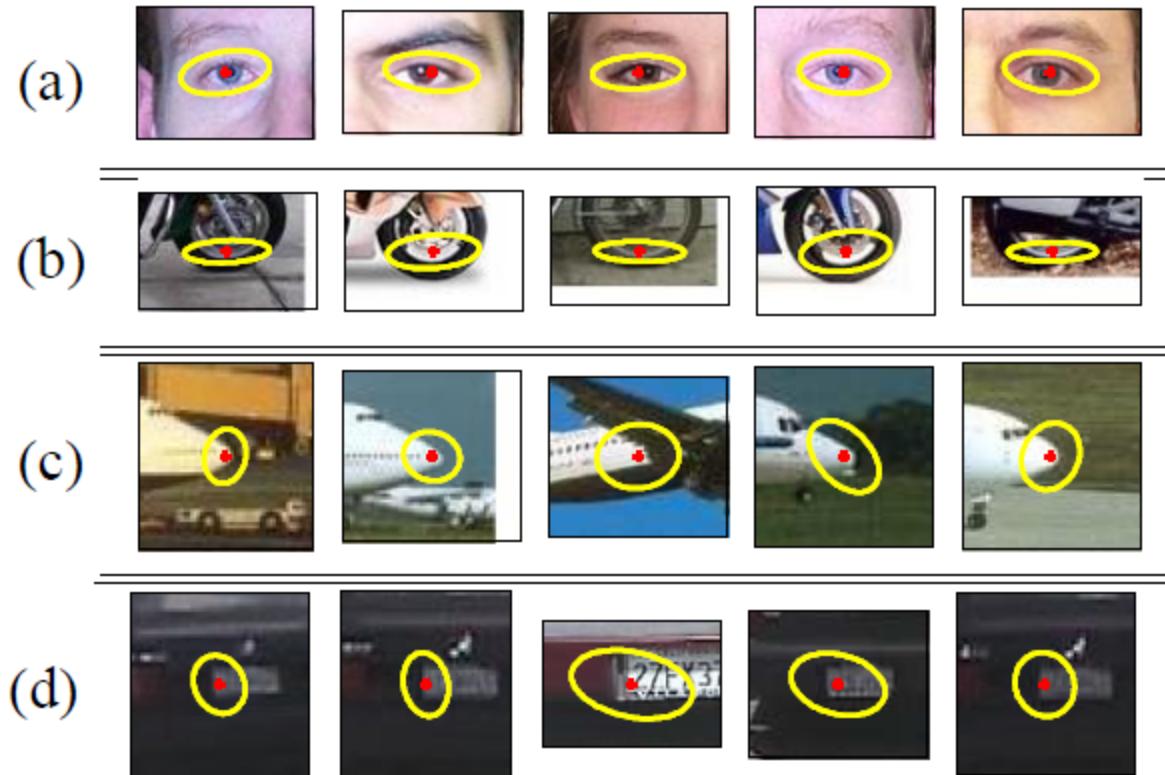
- All clusters have spherical distribution (same to all directions or isotropic)
- Hard membership/assignment (i.e. 1 or 0 membership)
- Prone to local minima
- Need to choose K
- Can be very slow: each iteration is $O(KN)$ for N-dimensional points

Other application of K-means: Building Visual Dictionaries

1. Sample patches from a database
 - E.g., 128 dimensional SIFT vectors
2. Cluster the patches
 - Cluster centers are the dictionary
3. Assign a codeword (number) to each new patch, according to the nearest cluster



Examples of learned visual words



Most likely codewords for 4 learned “topics”
EM with multinomial (problem 3) to get topics

Mean-Shift Clustering

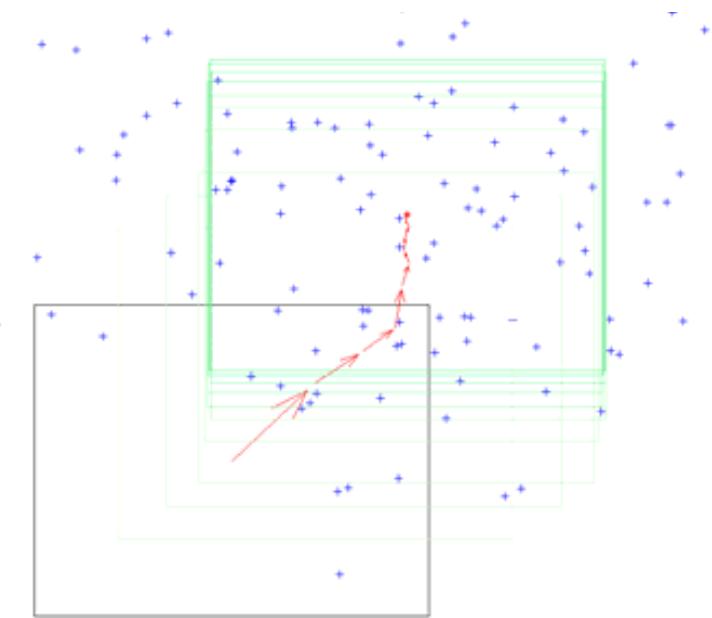
Mean-Shift Clustering

- An advanced and versatile technique for clustering-based segmentation
- The mean shift algorithm seeks a *mode* or local maximum of density of a given distribution
- Perform by computing color histogram, looking for modes

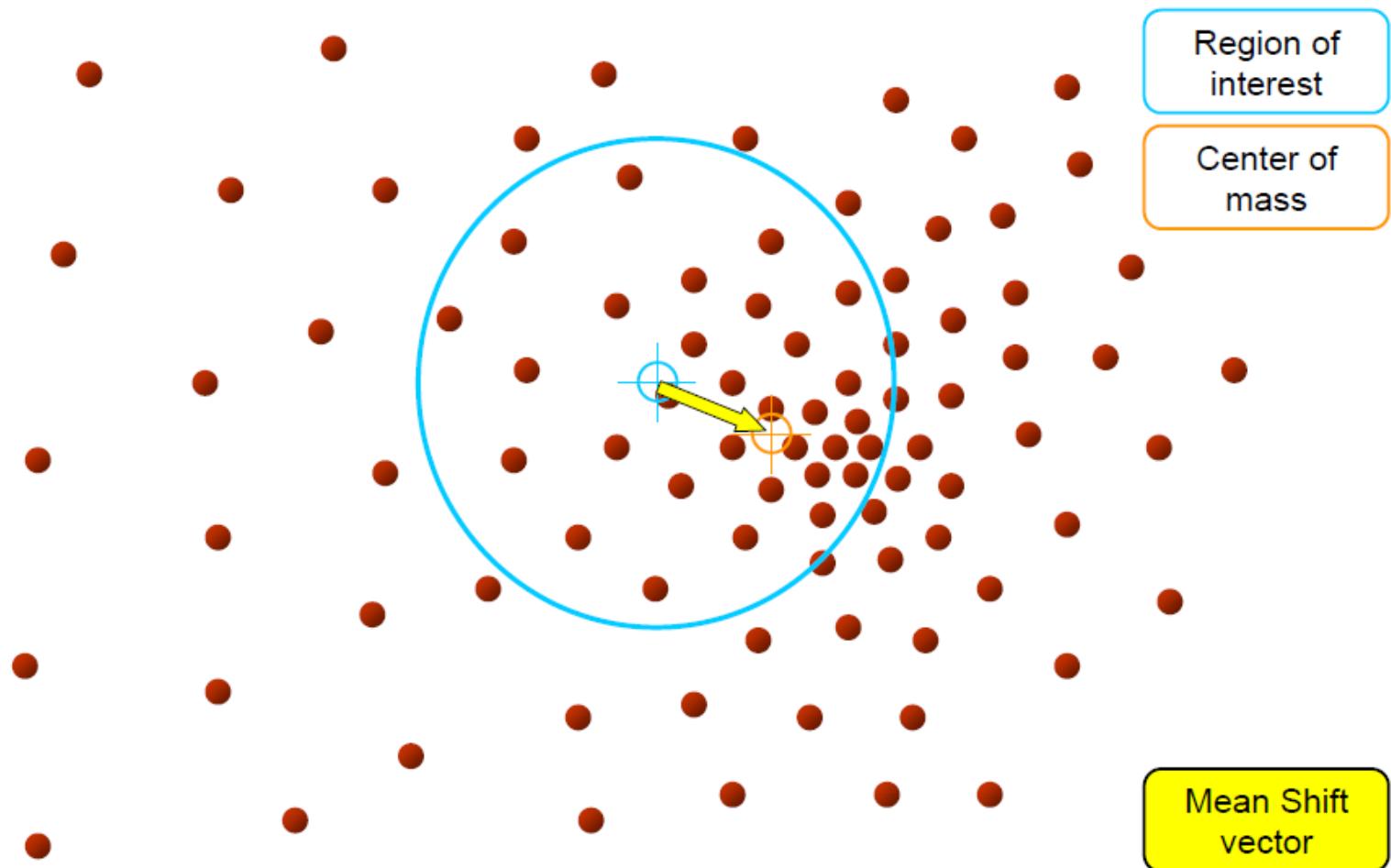
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean-Shift Clustering

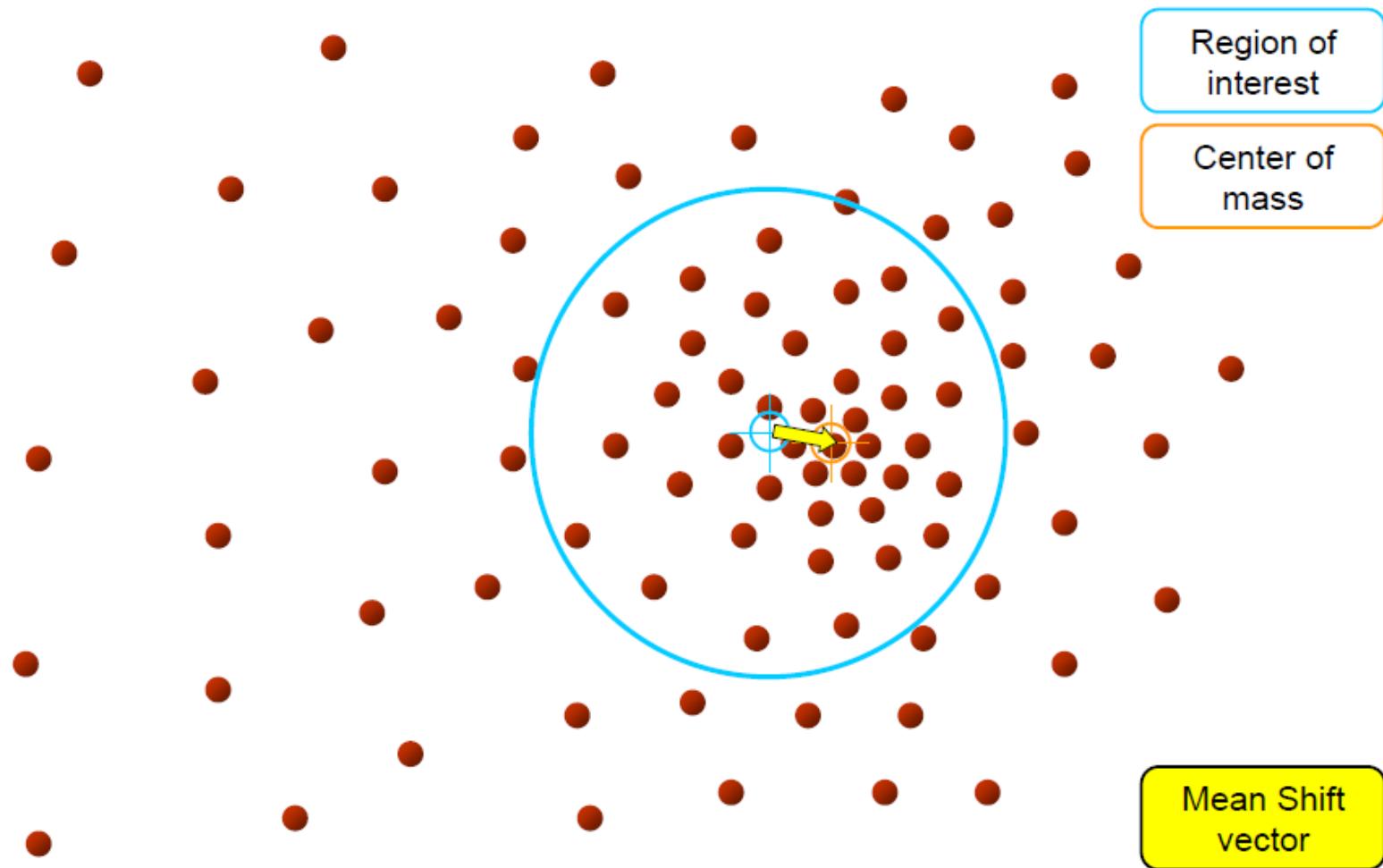
- Choose a search window (width and location)
- Compute the mean of the data in the search window
- Center the search window at the new mean location
- Repeat until convergence



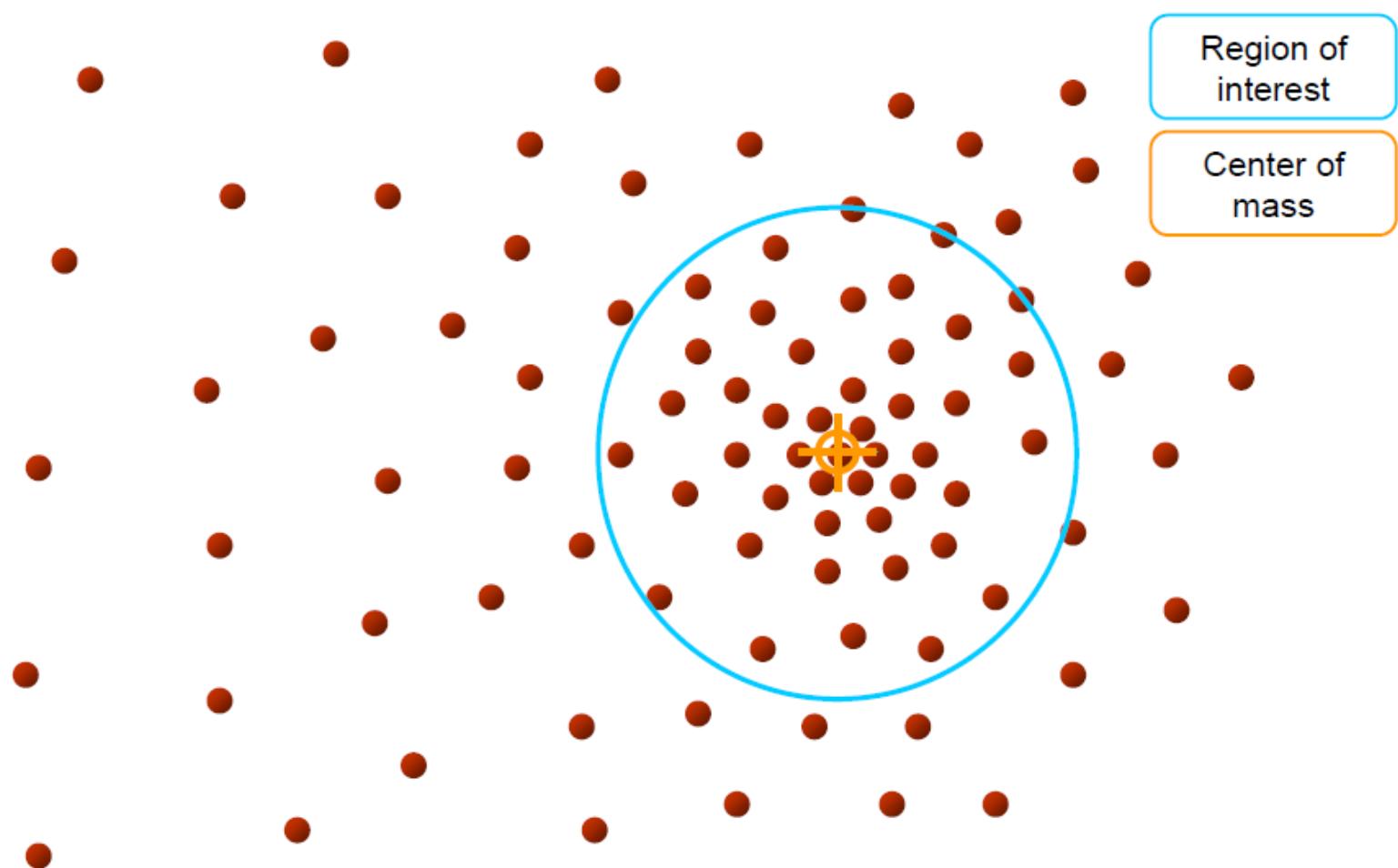
Mean-Shift



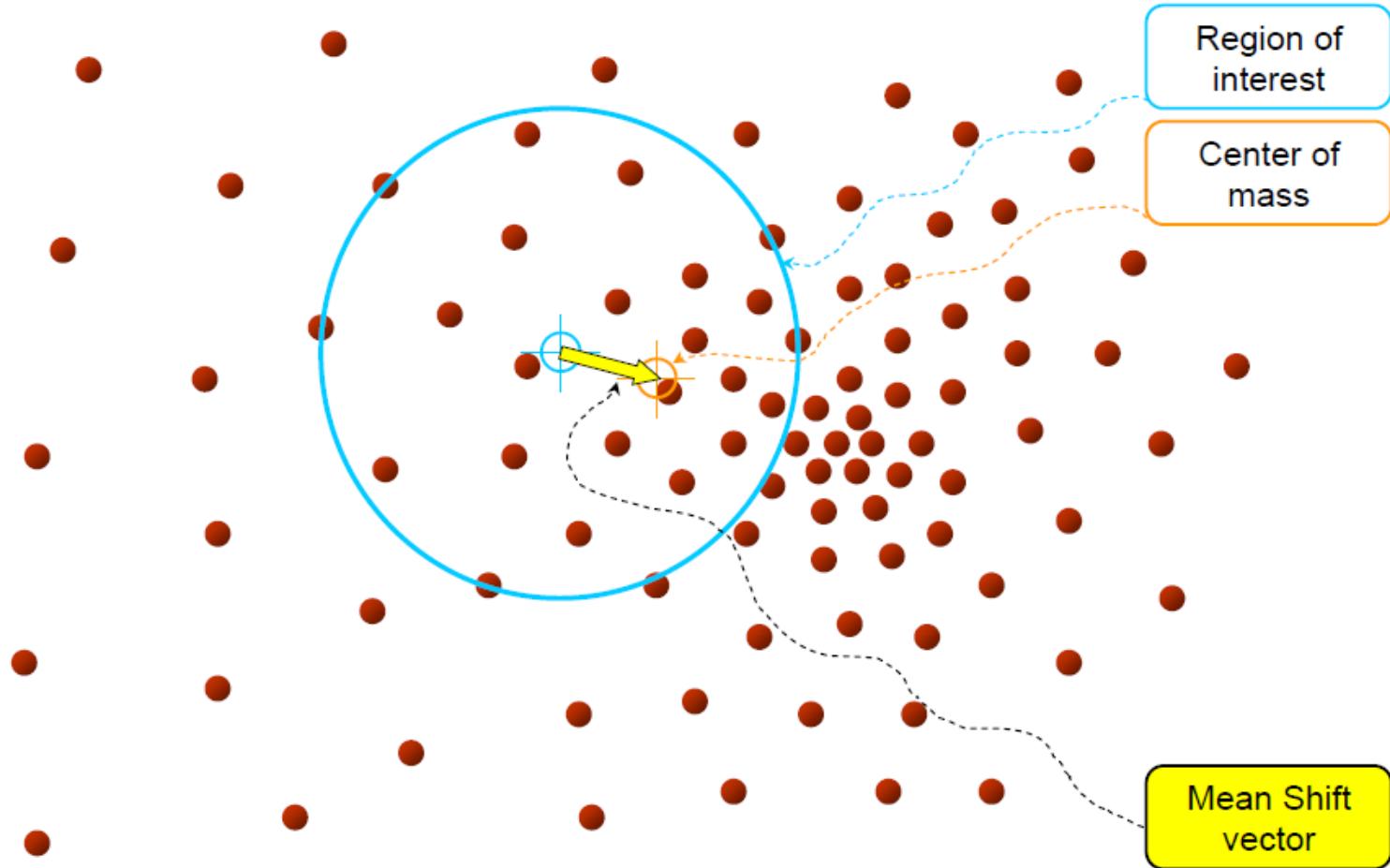
Mean-Shift



Mean-Shift

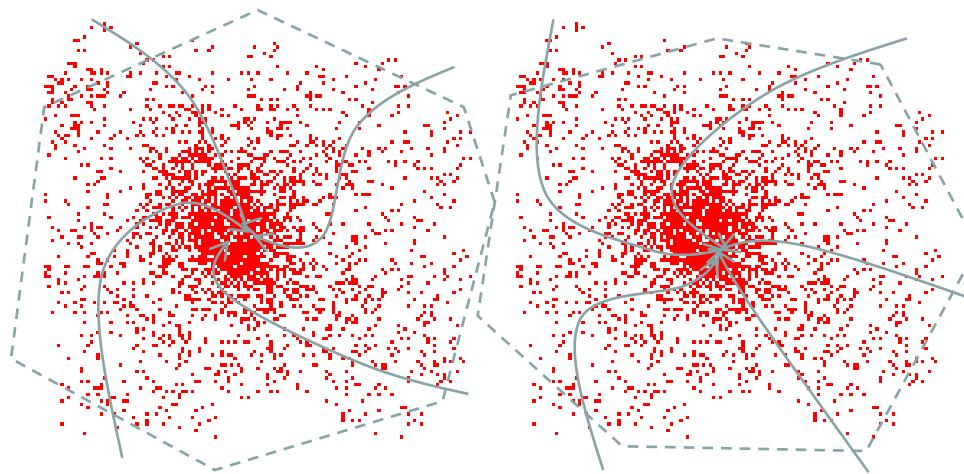


Mean Shift

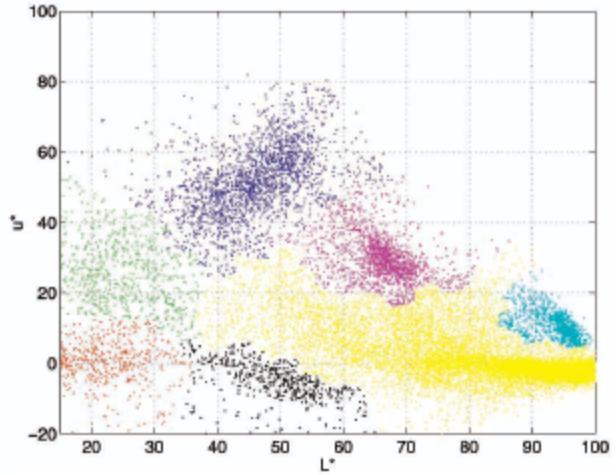
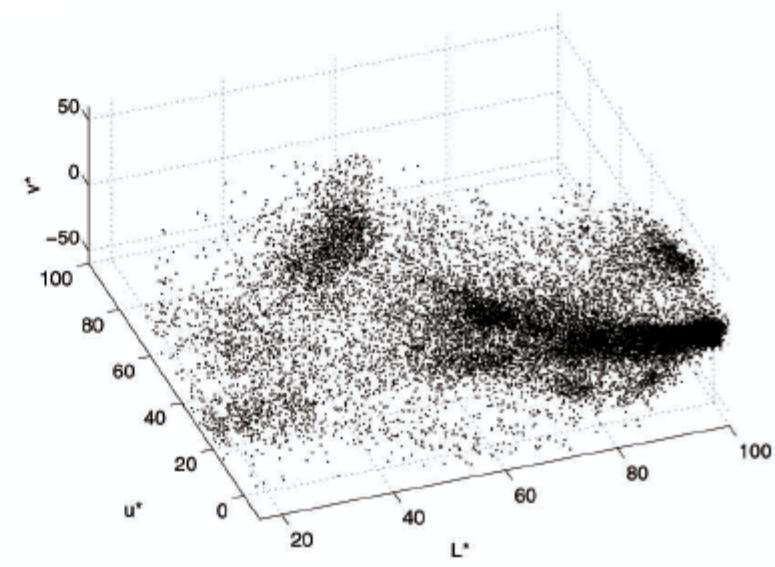
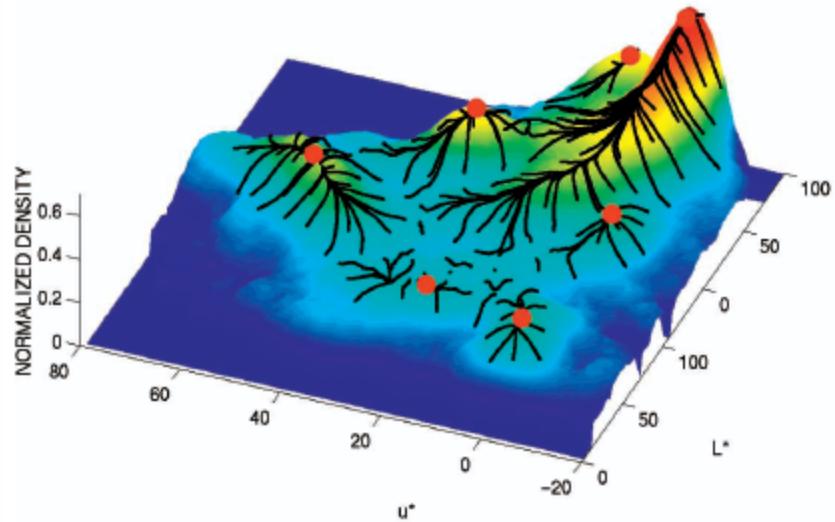
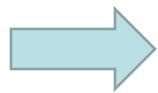


Mean-Shift Clustering

- Attraction basin: the region for which all trajectories lead to the same mode
- Cluster: all data points in the attraction basin of a mode



Mean-Shift Clustering



Summary

- Image segmentation can be done by clustering similar image features.
- K-means and Mean-shift clustering are simple yet practical methods
- There are many advanced methods such as Gaussian mixture models and others.
- Further reading: Chapter 5.2.2 in Szeliski's book