HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Computer Vision

Chapter 5: Image segmentation

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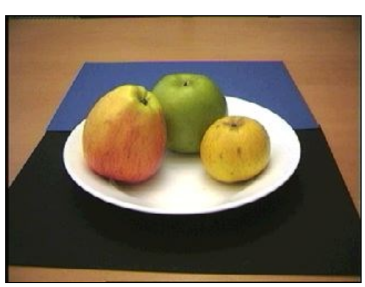
Chapter 5. Segmentation

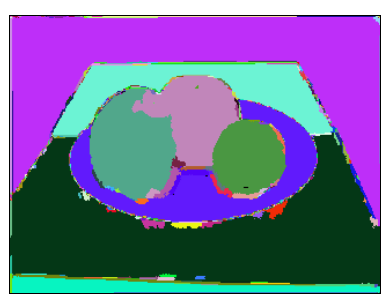
- Introduction to image segmentation
- Segmentation based on pixel classification
  - Thresholding
  - Clustering techniques
- Region-based segmentation
  - Region growing algorithm,
  - Split and merge algorithm
- Edge-based segmentation

Introduction

- Purpose:
  - to partition an image into meaningful regions with respect to a particular application
- Goal:
  - to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects.
- The segmentation is based on the feature measurements taken from the image:
  - grey level, color, texture, depth or motion…

Introduction





Source : Jean-Christophe Baillie, ENSTA, uei.ensta.fr/baillie/assets/ES322%20-%20Segmentation.ppt

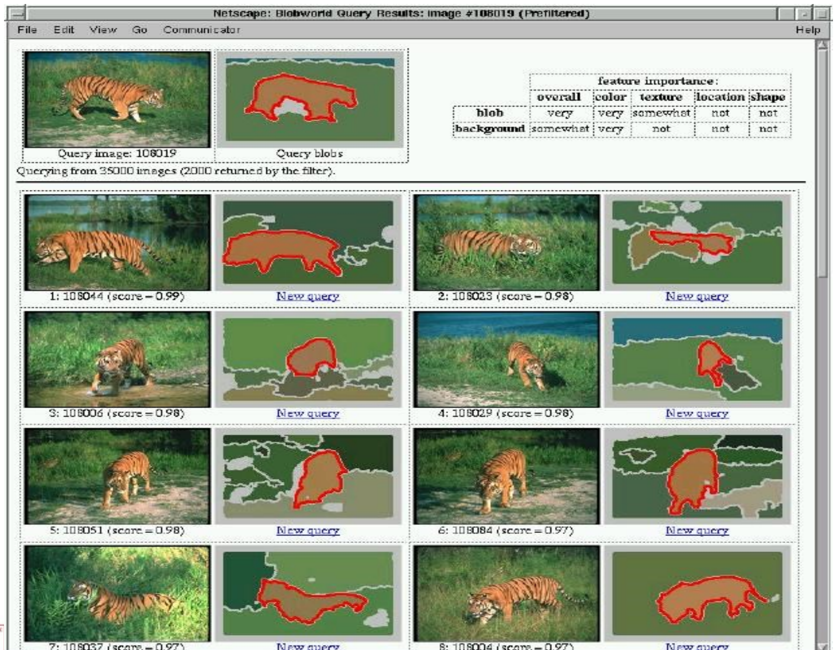
Introduction

- Entity can be extracted from images using mask

Source : Pascal Bertolino, Cours de Traitement d'images. LIS, INPG (France)

Applications

- **Image segmentation**
  - is usually an initial and vital step in a series of processes aimed at overall image understanding of computer vision
- **Segmentation applications**:
  - Object recognition;
  - Image retrieval;
  - Medical image analysis;
  - Boundary estimation within motion or stereo systems;
  - Tracking of objects in a video;
  - Classification of terrains visible in satellite images
  - …

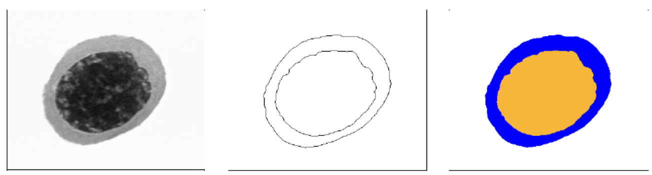


Approaches for image segmentation

- Segmentation is usually based on:
  - discontinuities: edges
    - sudden changes, borders (frontiers) between regions…
  - homogeneous zones: regions
    - same color, texture, intensity, ...

Approaches for image segmentation

- Pixel-based approach
- Region-based approach:
  - look for homogeneous areas in the image
- Edge-based approach :
  - look for discontinuities in the image
  - A closed edge is equivalent to a region
- Hybrid (Dual) approach (region + edge)



Examples

Original images | Segmented images

Pixel-based approach

- Pixel-based approach
  - Thresholding
  - Clustering
- It is not a region segmentation technique
  - But we often in segmentation looking for regions
  - Need some post-processing

Thresholding

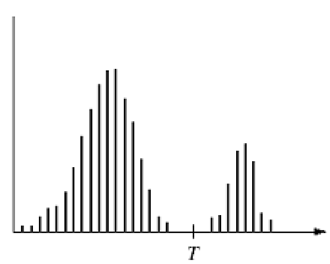
- Thesholding is a *simple and popular* method for object segmentation in digital images
- Thresholding can be
  - *Global:* one threshold for the whole image
  - *Local*: one threshold for a part of the image
  - *Adaptive:* one threshold ajusted according to each image or each image part

Basic global thresholding

- Basic thresholding (2 classes) – main idea :
  - IF value(pixel) >= threshold THEN value(pixel) = 1 (or 255)
  - IF value(pixel) < threshold THEN value(pixel) = 0
- The result is a binary image
- It is also possible to use *n thresholds* to split the image in n+1 classes
- Problem: choosing the threshold(s)!

Basic global thresholding

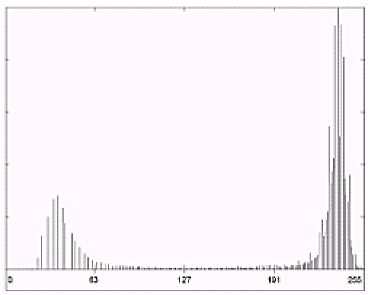
- Find the threshold on histogram of gray level intensity (histogram thresholding)

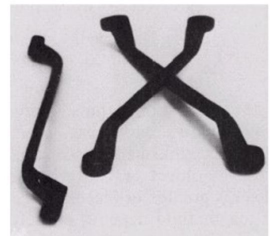


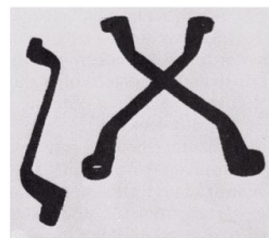
$$g(x,y) = \begin{cases} 0, & f(x,y) < T \\ 1, & f(x,y) \geq T \end{cases}$$

Basic global thresholding

- Threshold value: not difficile if
  – Controled environment
  – Industrial applications





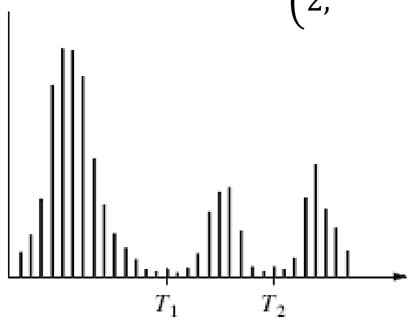


Multi-thresholds

- n thresholds to split the image in n+1 classes:
  – IF value(pixel) < threshold_1
    - THEN value(pixel) = 0
  – IF value(pixel) >= threshold_1 && value(pixel) < threshold_2
    - THEN value(pixel) = 1
  – …
  – IF value(pixel) >= threshold_n
    - THEN value(pixel) = n
- Problems: How many thresholds?

Multi-thresholds

$$g(x,y) = \begin{cases} 0, & f(x,y) < T1 \\ 1, & T2 > f(x,y) \geq T1 \\ 2, & f(x,y) \geq T2 \end{cases}$$

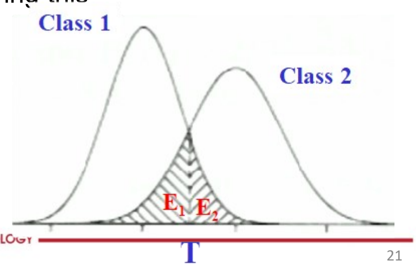


Threshold value

- Global thresholding: How to find the value of the threshold **T** ?
  - Value obtained **by tests**
  - The **mean** value of gray values
  - The **median** value between the min gray level and the max one
  - **One value balancing** both sections of the histogram
    - automatic thresholding

Choice of thresholds (optimal)

- 2 surfaces (background and object) in an image
  - We suppose mathematical models for distributions (gaussians, etc.)
  - We determine the probability of error in the classes 1 and 2 (surfaces 1 et 2)
  - We search for a threshold T resulting in a minimum error
    - Several methods for achieving this



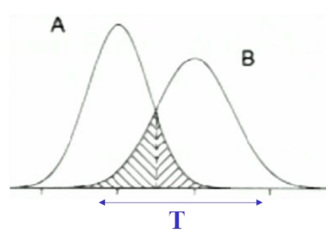
Source : www.iro.umontreal.ca/~dift2730/

Example: Otsu algorithm

- Sweep all possible threshold value for **T**
- For **each value of T**:
  - Compute the mean and variance for each class
  - We look for the intraclass variance
    - Means: μ_1, μ_2
    - Variances: σ_1^2, σ_2^2
    - Intra-class variance:

$$\sigma_w^2 = P_1 * \sigma_1^2 + P_2 * \sigma_2^2$$

- The optimal threshold is the one with the minimum value for σ_w^2
- It is based on the idea that classes are well defined and well grouped



$$\sigma_1^2 = \frac{1}{T} \sum_{i=0}^{T-1} (h(i) - \mu_1)^2$$

$$\sigma_2^2 = \frac{1}{256-T} \sum_{i=T}^{255} (h(i) - \mu_2)^2$$

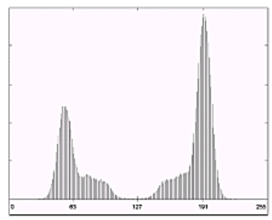
$$\mu_1 = \frac{1}{T} \sum_{i=0}^{T-1} h(i) \qquad P_1 = \frac{1}{N \cdot M} \sum_{i=0}^{T-1} h(i)$$

$$\mu_2 = \frac{1}{256-T} \sum_{i=T}^{255} h(i) \qquad P_2 = \frac{1}{N \cdot M} \sum_{i=T}^{255} h(i)$$

Source : www.iro.umontreal.ca/~dift2730/

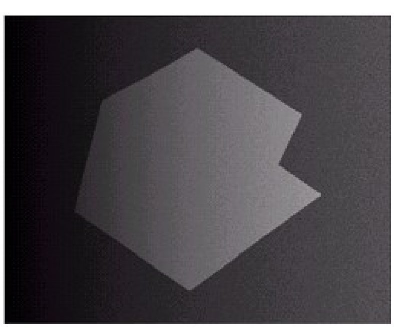
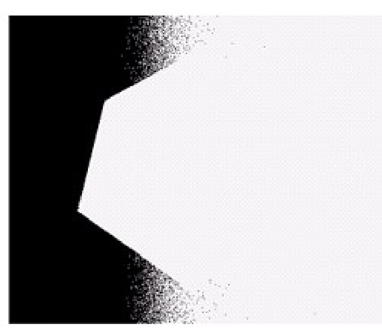
Example: Otsu algorithm

- Threshold found by the algorithm:
  - T = 125

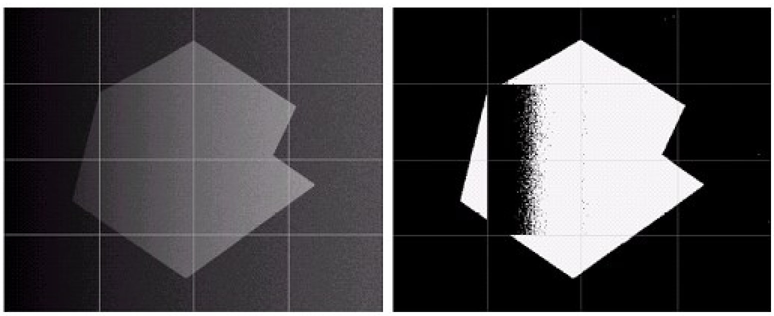
Global threshold: problem

- Problem:
  - Global thresholding cannot be used in that case
  - Solution: adaptive local thresholding

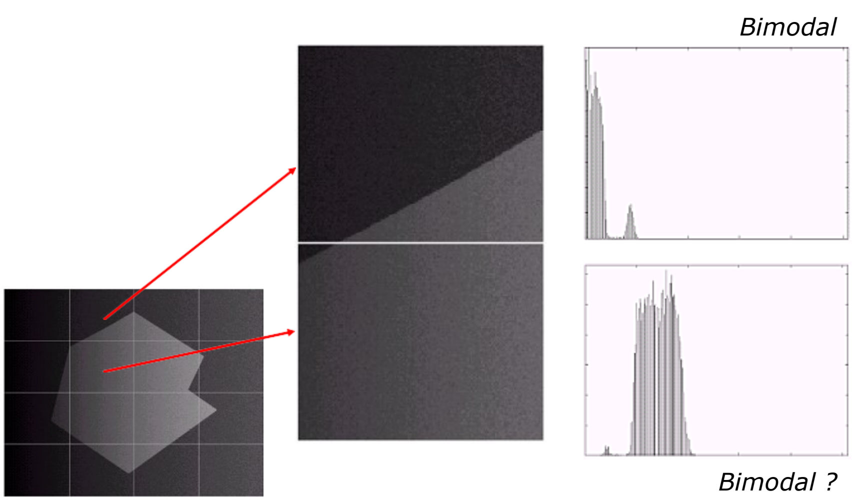



Example of adaptive thresholding

- Split the image in sub-images and process ***each sub-image with its own threshold***
- The main decision is to choose the size of the sub-images
- Before processing each sub-image, ***check the variance*** to make sure that the sub-image contains two regions, and not only one.
  - Example: no thresholding for a sub-image if variance<100



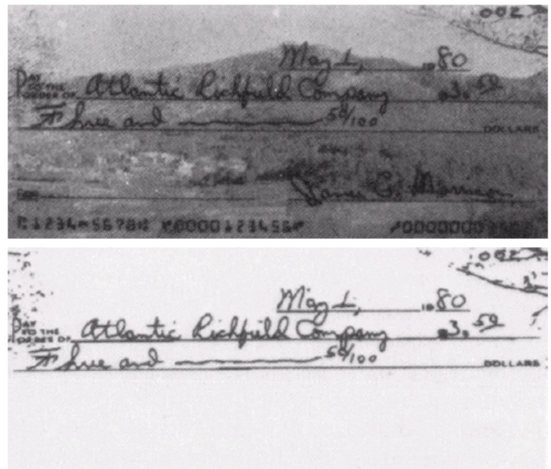
Example of adaptive thresholding



Example of adaptive thresholding

a
b

FIGURE 10.37
(a) Original image. (b) Image segmented by local thresholding. (Courtesy of IBM Corporation.)



Clustering-based segmentation

- Image is considered as a set of N pixels
- Attributes (property) of the pixels:
  - gray level of single-band gray tone images,
  - color values of three-band color images: (r, g, b)
  - values of multi-band images, …
- Based on the similar attribute, pixels classification operators partition an image into homogeneous regions.
  - Clustering provides a grouping of the pixels that is dependent on their values in the image but not necessarily on their locations in the image unless location is a specified property
  - Classifier provide the pixel classes which should be homogeneous regions.

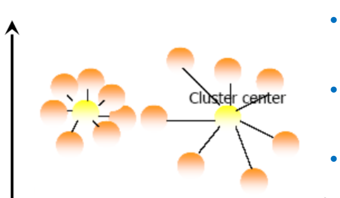
Clustering algorithms

- **Image segmentation approaches including**:
  - Feature space clustering approaches
  - Graph-based approaches

- **Clustering algorithms**:
  - K-Means clustering
  - Mean-Shift Clustering
  - Expectation-Maximization Clustering
  - Watershed Segmentation
  - Graph Cuts (Spectral clustering)
  - Normalized cuts: Jianbo Shi and J. Malik, "Normalized cuts and image segmentation, TPAMI2000
  - …

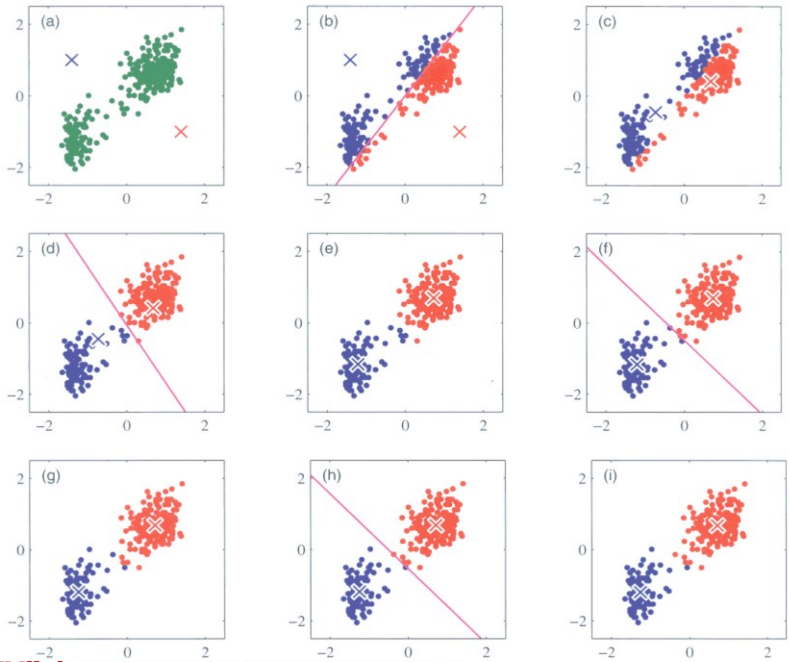
K-means Clustering

- Let X = $\{p_1, \ldots, p_N\}$ be a set of N image pixels:
  - $V(p_i)$: the property vector associated with pixel p_i
  - The clustering algorithm is to partition the image into K clusters (K regions)
- The **K-means** algorithm:
  - Initialization step: An initial property vector of each class C_k is chosen randomly from the set of all property vector, note $\mu_k(0)$
  - Interactive step: Assignment of image pixels to K clusters



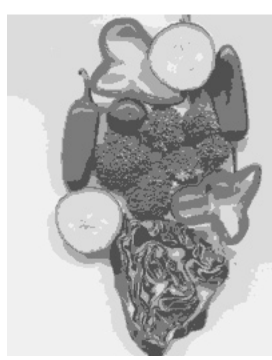
- Pixel p_i is assigned to the closest cluster, using a distance between 2 property vectors.
- Update the property vector of each class: $\mu_k(t)$ is computed as the mean of $\{V(p_i) \mid x_i \in C_k\}$.
- 2 Steps above are repeated until algorithm convergence.

each class C_k should be a region R_k



K-means Clustering

Input image



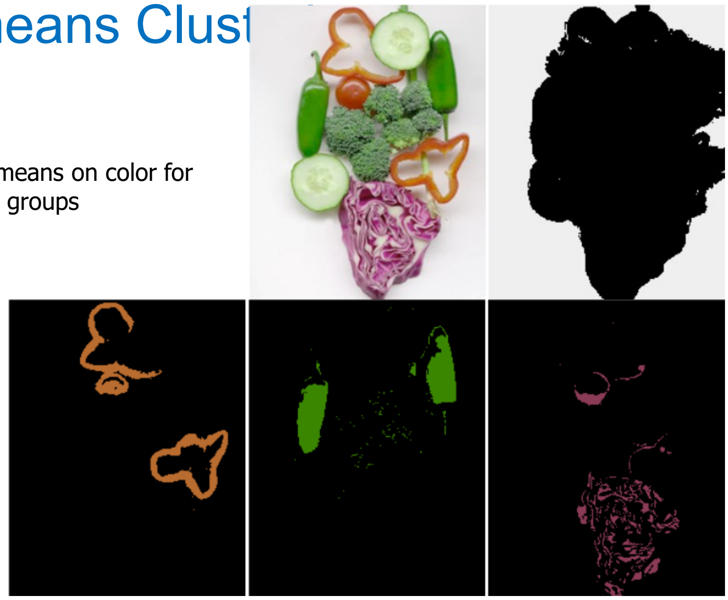
K-means on gray level

K-means on color

Source : D.A. Forsyth and J. Ponce. Computer Vision : A Modern Approach. Prentice-Hall, 2002.

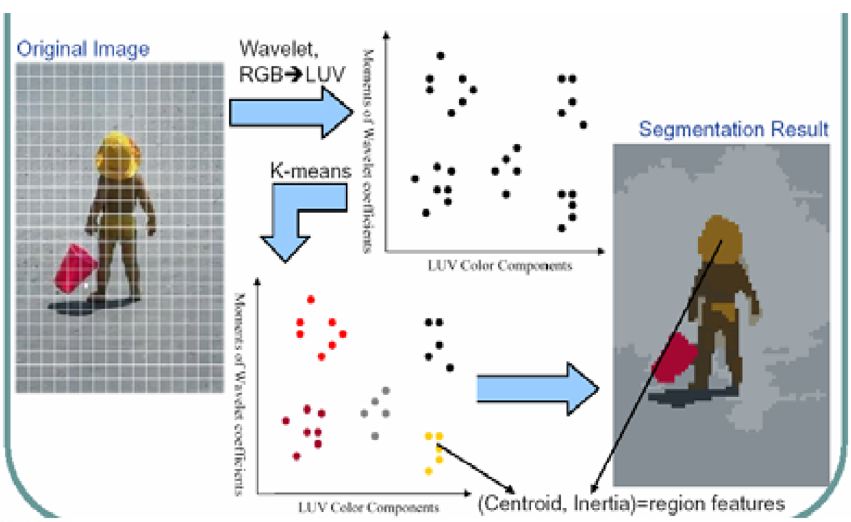
K-means Clust

K-means on color for
11 groups



Source : D.A. Forsyth and J. Ponce. Computer Vision : A Modern Approach. Prentice-Hall, 2002.

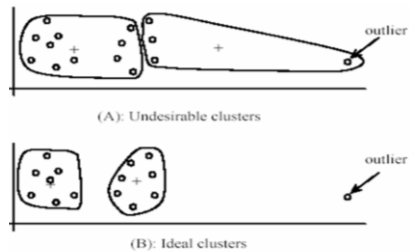
Example

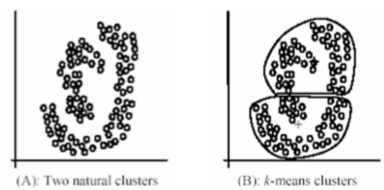


K-means pros and cons

Pros
- Simple
- Converges to local minimum of within-cluster squared error

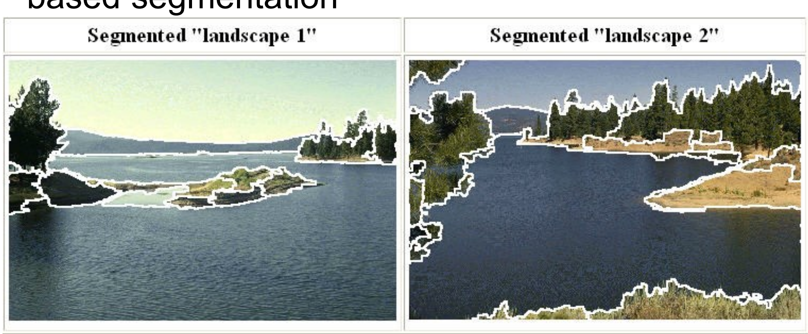
Cons/issues
- Setting k?
- Sensitive to initial centers
- Sensitive to outliers
- Detects spherical clusters
- Assuming means can be computed





Mean shift clustering and segmentation

- An advanced and versatile technique for clustering-based segmentation

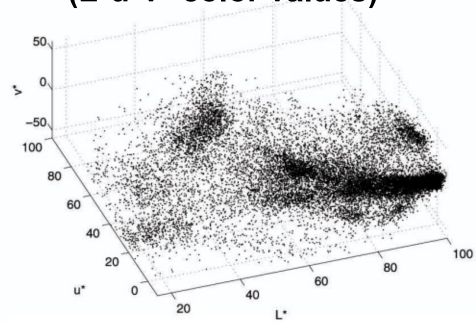


http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

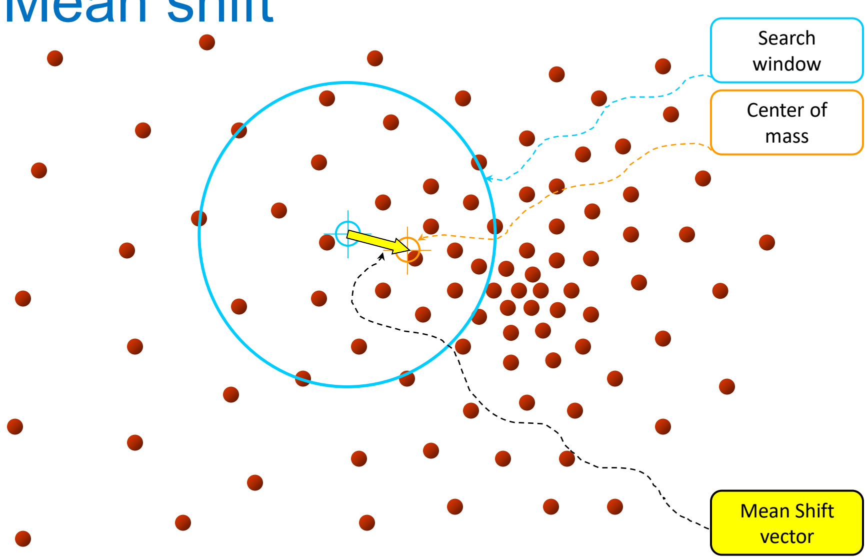
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean shift algorithm

- The mean shift algorithm seeks *modes* or local maxima of density in the feature space

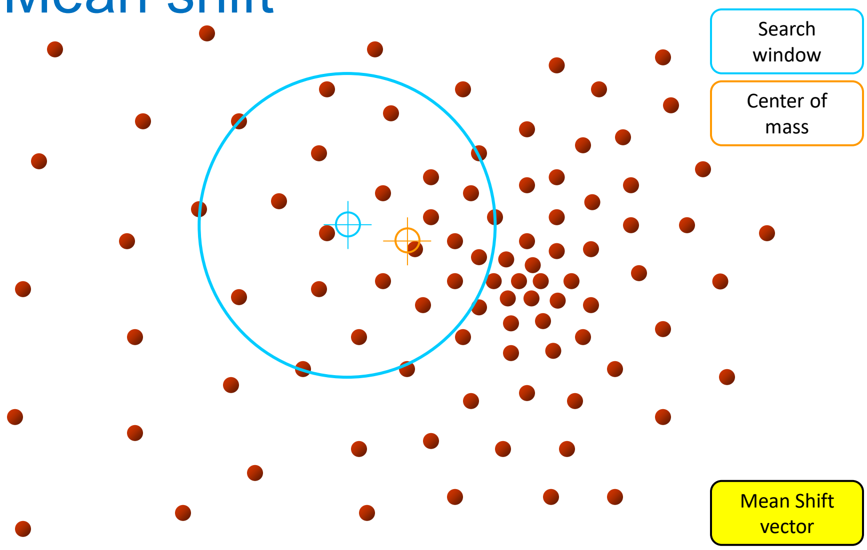


Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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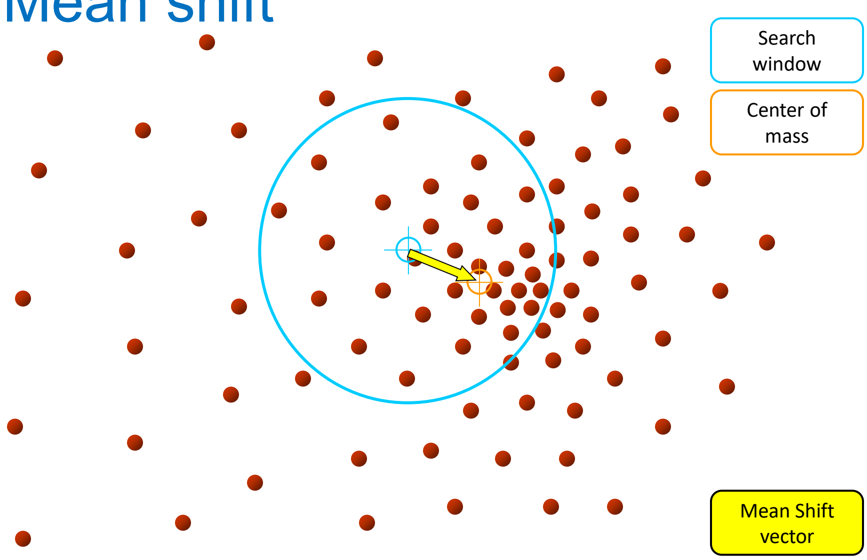
Mean shift



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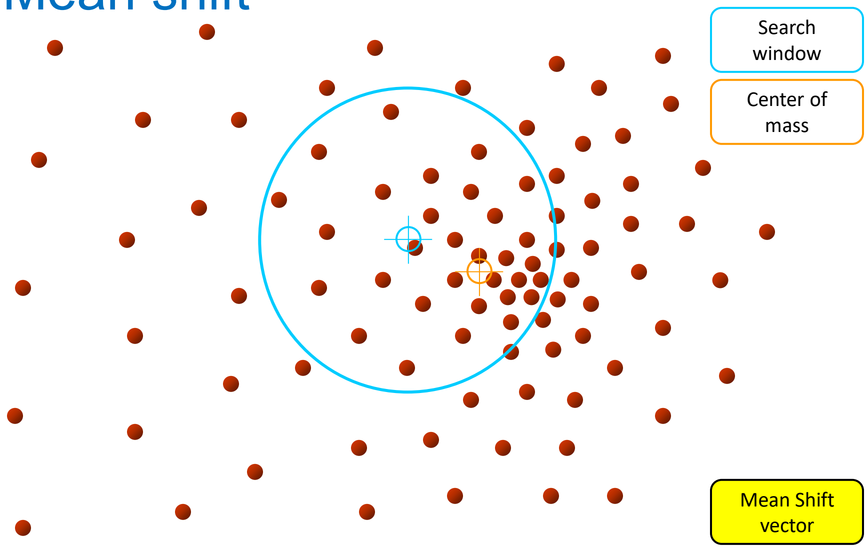
Mean shift



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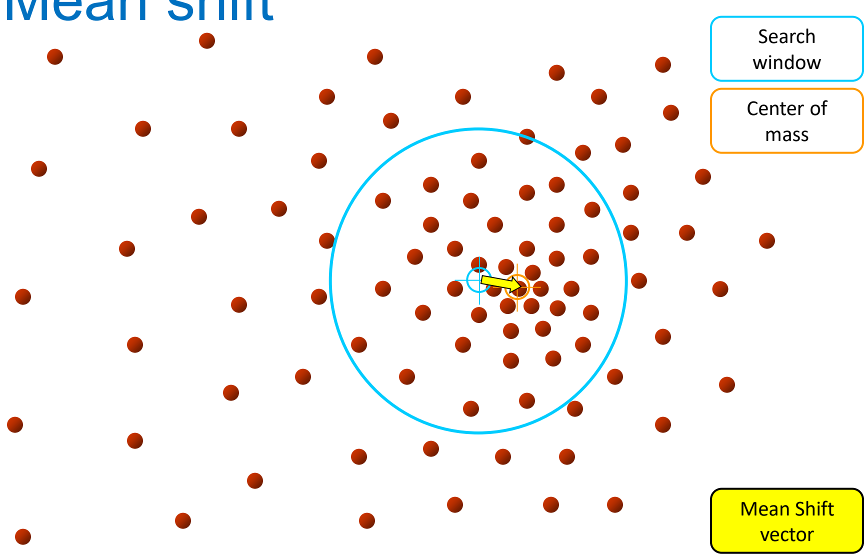
Mean shift



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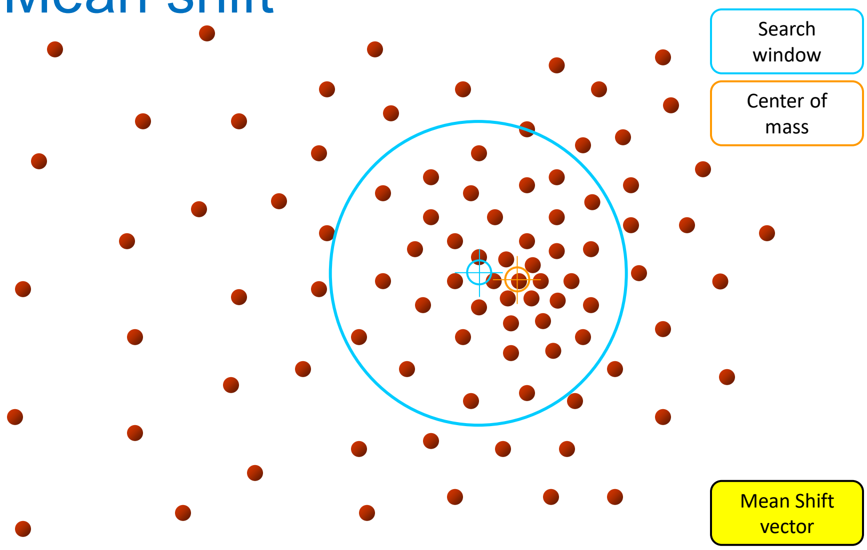
Mean shift



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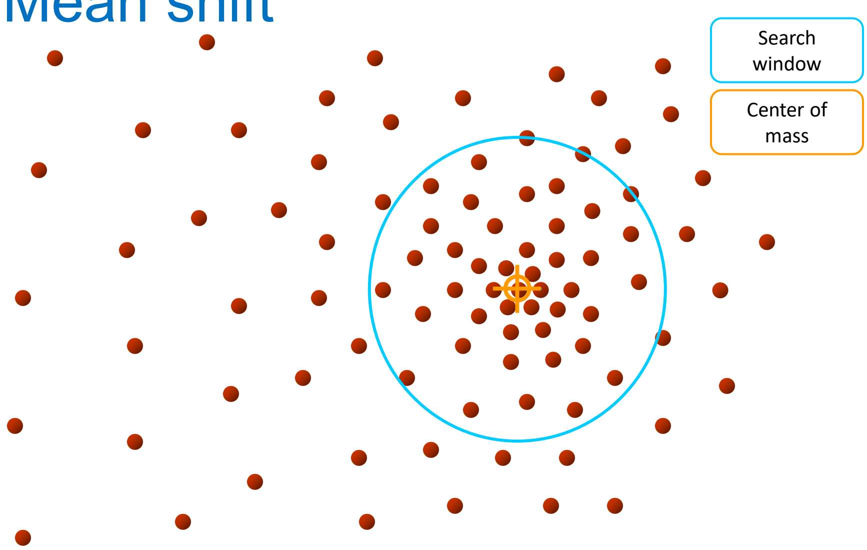
Mean shift



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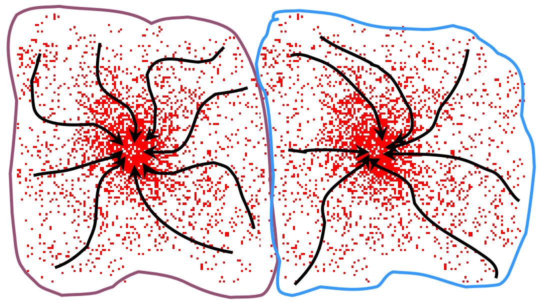
Mean shift clustering

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



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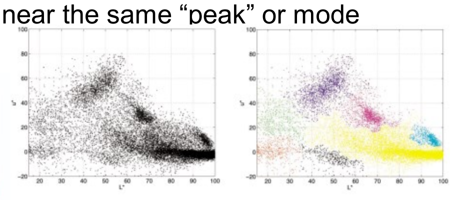
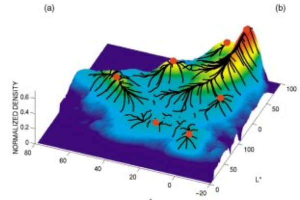
Mean shift clustering/segmentation

- Find features (color, gradients, texture, etc)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode





Mean shift segmentation results

http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

Mean shift segmentation results

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Mean shift

- Pros:
  - Does not assume shape on clusters
  - One parameter choice (window size, aka "bandwidth")
  - Generic technique
  - Find multiple modes
- Cons:
  - Selection of window size
  - Does not scale well with dimension of feature space

Features for segmentation

- Intensity, Color?
- Position
- Texture
- …

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity** similarity

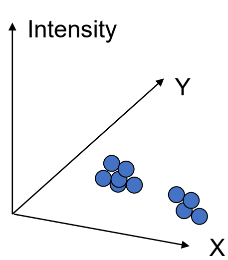
Feature space: intensity value (1-d)

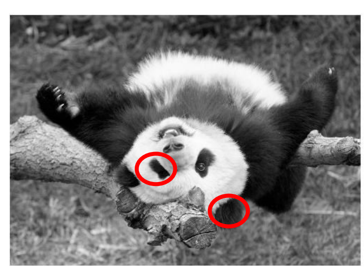
Slide credit: Kristen Grauman

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity+position** similarity





Both regions are black, but if we also include **position (x,y),** then we could group the two into distinct segments; way to encode both ***similarity & proximity.***

Slide credit: Kristen Grauman

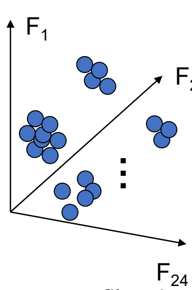
Segmentation as clustering

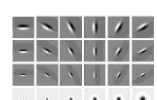
- Color, brightness, position alone are not enough to distinguish all regions…

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **texture** similarity





Filter bank of 24 filters

Feature space: filter bank responses (e.g., 24-d)

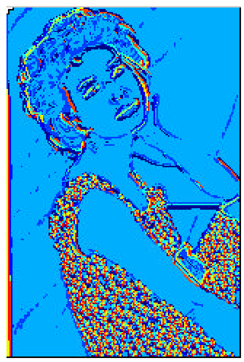
Slide credit: Kristen Grauman

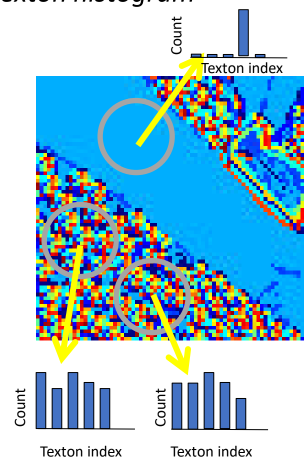
Segmentation with texture features

- Find “textons” by **clustering** vectors of filter bank outputs
- Describe texture in a window based on *texton histogram*

Image

Texton map

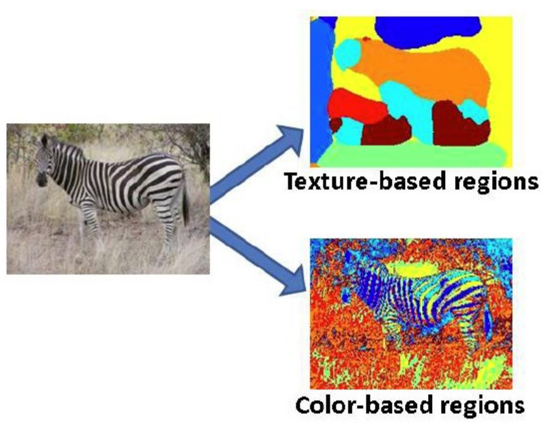




Malik, Belongie, Leung and Shi. IJCV 2001.

Adapted from Lana Lazebnik

Image segmentation example



Slide credit: Kristen Grauman

Pixel-based approach: Pros & cons

- Pros
  – Simple
- Cons: thresholding is mainly an operation on pixels
  – It does not give connected regions ➔ can add more features
  – we need to « clean » the results
    - erase lonely pixels, keep regions
- Other segmentation methods exist
    - that can keep the integrity of regions (connected pixels)

Region-based segmentation

- Finding region based on the criterion of homogeneity and connectivity of pixels (region)
  – Each region is homogeneous (i.e., uniform in terms of the pixel attributes such as intensity, color, range, or texture, etc.)
  – and connected
- **Algorithms**:
  – Region growing
  – Split and merge algorithm
  – Hierarchical clustering
  – …

Region-based segmentation

- Region-based approaches provide :
  - All pixels must be assigned to regions
  - Each pixel must belong to a single region only
  - Each region must be uniform
  - Any merged pair of adjacent regions must be non-uniform
  - Each region must be a connected set of pixels
- Region-based approaches:
  - Different methods
  - Common point: **homogeneity criteria**

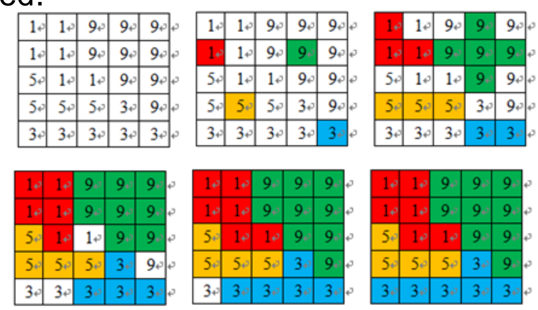
Region growing

- Start from a point (seed) and add neighbor pixels following a given criteria
- The seeds can be manually or automatically chosen
  - automatic seeds in very homogeneous zones for example

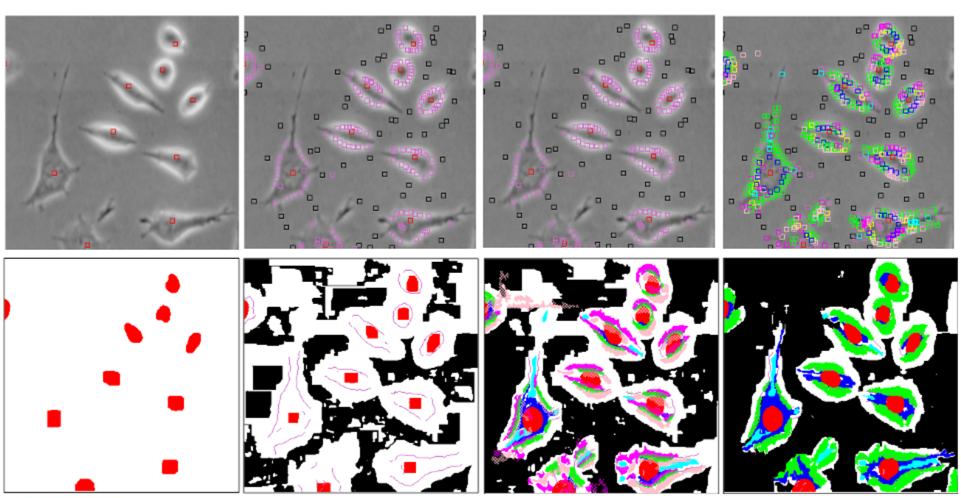
image *Seed* *Region growing* *Final result*

Region growing algorithm

- Algorithm:
  - Choose K random pixels in K regions
  - Use 4(8)-connected and threshold to determine
  - Repeat a and b until almost points are K classified.
- Example illustrated:

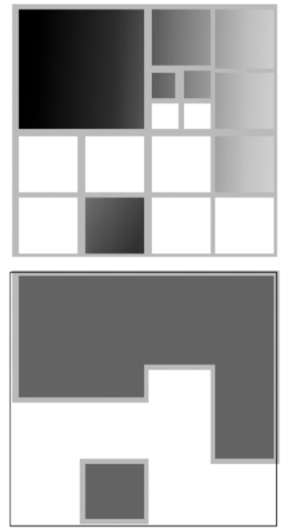


Region growing with multi-seeds

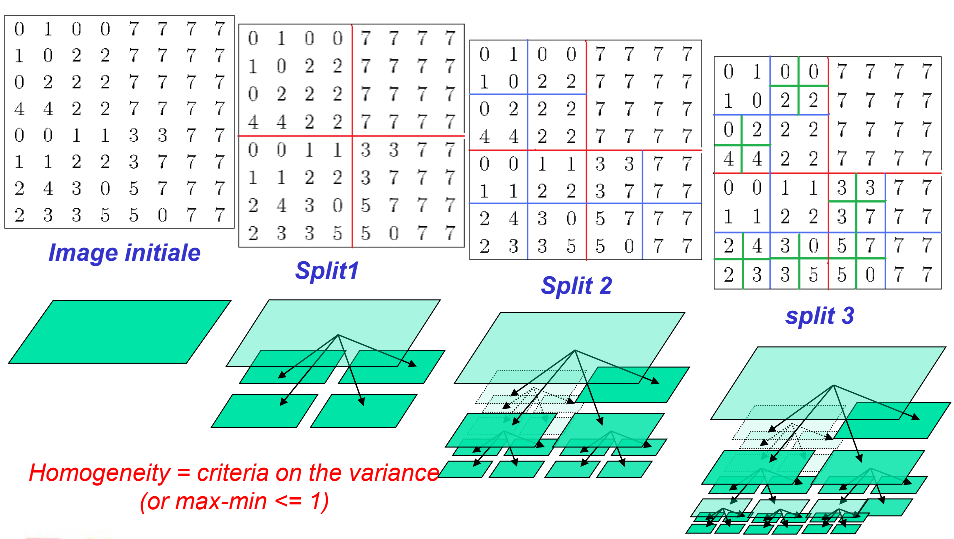


Split-and-merge

- Split (step 1)
  - Recursively split all non-homogeneous regions following a given criteria
    - variance, max-min, …
  - Dividing one region gives 4 subregions
  - Subregion attributes are re-computed
- Merge (step 2)
  - Group all homogeneous adjacent regions following a given criteria



Split-and-merge: split

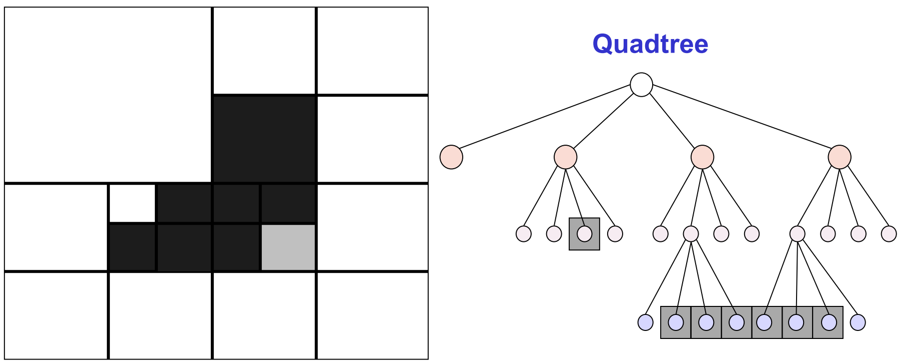


Homogeneity = criteria on the variance
(or max-min <= 1)

Source : Jean-Christophe Baillie. Cours de segmentation. ENSTA ParisTech (France).

Split-and-merge: merge

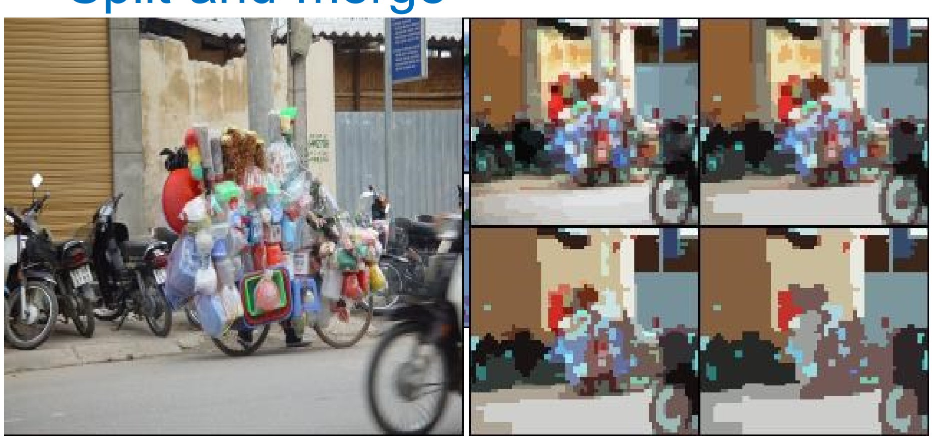
Phase 1: Create homogeneous zones (split)
Phase 2: Group homogeneous zone (merge)



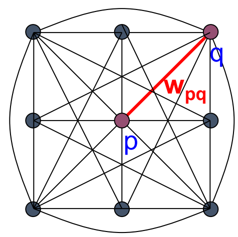
Connect homogeneous adjacent regions

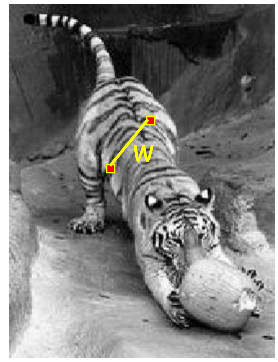
Source : Jean-Christophe Baillie. Cours de segmentation. ENSTA ParisTech (France)

Split-and-merge



Images as graphs

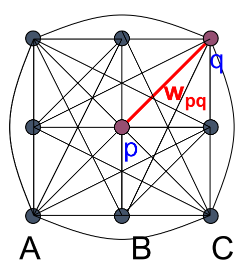




- *Fully-connected* graph
  - node (vertex) for every pixel
  - link between *every* pair of pixels, **p**,**q**
  - affinity weight $\mathbf{w_{pq}}$ for each link (edge)
    - $\mathbf{w_{pq}}$ measures *similarity*
      - similarity is *inversely proportional* to difference (in color and position…)

Source: Steve Seitz

Segmentation by Graph Cuts



- Break Graph into Segments
  - Want to delete links that cross **between** segments
  - Easiest to break links that have low similarity (low weight)
    - similar pixels should be in the same segments
    - dissimilar pixels should be in different segments

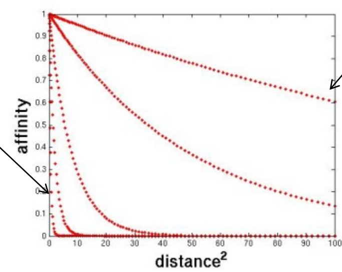
Source: Steve Seitz

Measuring affinity

- One possibility:

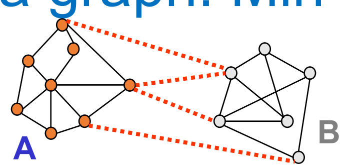
$$aff(x,y) = \exp\left\{-\left(\frac{1}{2\sigma_d^2}\right)\left(\|x-y\|^2\right)\right\}$$

Small sigma: group only nearby points



Large sigma: group distant points

Cuts in a graph: Min cut



- Link Cut
  - set of links whose removal makes a graph disconnected
  - cost of a cut: $$cut(A,B) = \sum_{p \in A, q \in B} w_{p,q}$$

Find minimum cut

- gives you a segmentation
- fast algorithms exist for doing this

Source: Steve Seitz

Minimum cut

- Problem with minimum cut:

  Weight of cut proportional to number of edges in the cut; tends to produce small, isolated components.

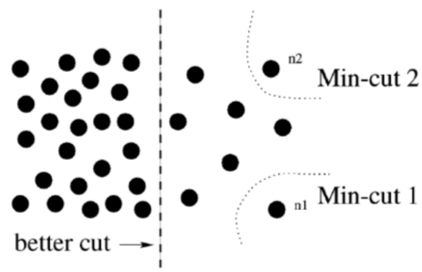
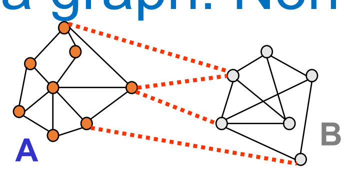


Fig. 1. A case where minimum cut gives a bad partition.

[Shi & Malik, 2000 PAMI]

Cuts in a graph: Normalized cut



Normalized Cut

- fix bias of Min Cut by **normalizing** for size of segments:

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

  assoc(A,V) = sum of weights of all edges that touch A

- Ncut value small when we get two clusters with many edges with high weights, and few edges of low weight between them
- Approximate solution for minimizing the Ncut value : generalized eigenvalue problem.

J. Shi and J. Malik, Normalized Cuts and Image Segmentation, CVPR, 1997

Source: Steve Seitz

Example results

Normalized cuts: pros and cons

Pros:

- Generic framework, flexible to choice of function that computes weights ("affinities") between nodes
- Does not require model of the data distribution

Cons:

- Time complexity can be high
  - Dense, highly connected graphs → many affinity computations
  - Solving eigenvalue problem
- Preference for balanced partitions

Others

- Grabcut: Interactive segmentation
- Watershed
- CRF
- …

Summary

- Segmentation to find object boundaries or mid-level regions, tokens.
- Thresholding
- Segmentation as clustering
  - K-means
  - Mean shift
- Region-based segmentation
  - Region growing
  - Split-and-merge
  - Graph cut, normalized cuts

Segmentation – advices

- Image segmentation
  - No method works for all images
  - No miracle, no warranty!

- One of the main problem is to define the goal of segmentation:
  - What exactly are we looking for in the image?
    - Global regions or small details?
    - Presence or not of persons details in the face?
- It is good to think in advance what we will do with this segmentation results
  - This helps to define the level of precision needed

Segmentation – advices

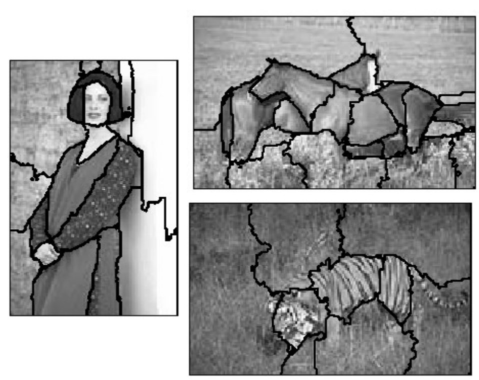
- Image Pre-processing:
  - good selection of sensors and energy source, and controled image acquisition conditions help to make segmentation easier and more efficient
- For some applications, we realize today that we can avoid to segment the image. It is often better like this.

Limits of segmentation

Image segmentation alone cannot find all image objects as we can interpret them

Segmentation vs. grouping

- Term 'segmentation' :
  - less used
  - segmentation, which let think about an exact image splitting into regions
- 'Pixel grouping'
  - which refers only to a notion of similarity between pixels without relation on the content of regions.



Source : [Malik 2001].

Motion segmentation

A.Barbu, S.C. Zhu. Generalizing Swendsen-Wang to sampling arbitrary posterior probabilities, *IEEE Trans. PAMI,* August 2005.

Credit: Kristen Grauman, UT Austin

References

- Kristen Grauman, UT Austin - CS376 Computer Vision – lecture 10
- Alain Boucher, Computer Vision – Segmentation

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Thank you for your attention!

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