Image Segmentation

DD2423 Image Analysis and Computer Vision

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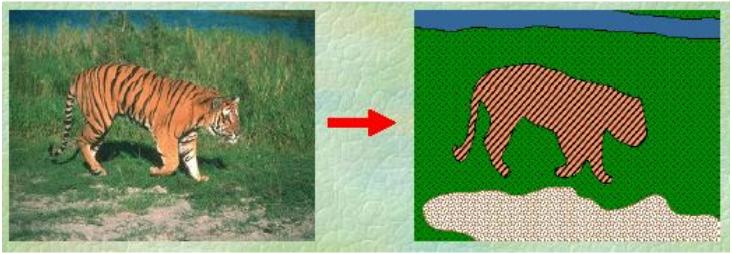
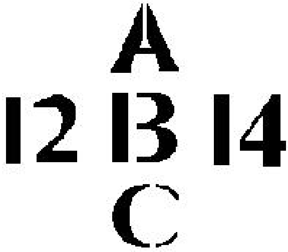
From images to objects

- Image segmentation: Dividing images into semantically meaningful regions.
- Reliable segmentation is possible with prior information, but such information is typically not available.



What is this?

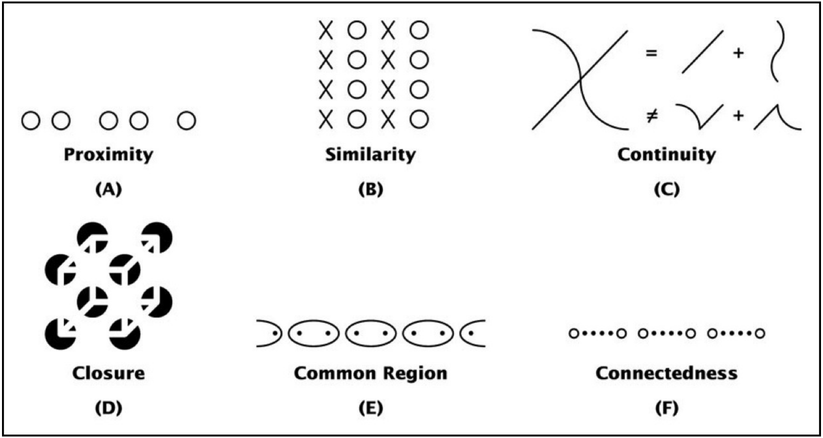


Spot the 'X'

OBCPGDOPDDGQQPCPOCG
PRGPOCBGQRQSSUOPCSR
QCDBPOSCUROOPCDBPOD
POQXGOPQCBBCGPOQDUO
OPQDCBGSOSPQSRCBDOP

KLEFIZKNMLMVKWIYLKMNI
IKLWNMVKAILKHNMVTEFNL
MKLNVKWAVNMKLIYZFENM
NMKLNHKVEYIFKLXNVIWTY
KVNMKLIYWTNMILKMFWEN

Segmentation in humans (Gestalt Theory)



What is this?

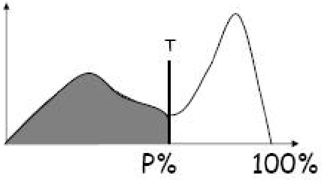
- Figure-ground segmentation: divide image in foreground and background regions. Methods:
  - Thresholding
  - Level-set methods
  - Energy minimization with graphs
- Image segmentation: divide image in regions with pixels of similar qualities. Methods:
  - K-means clustering
  - Split-and-merge
  - Watershedding
  - Mean-shift
  - Normalized cuts

Histogram based segmentation

- Threshold the grey-level values to create a binary image.
- How to find automatically find a good threshold?
- Common problems: measurement noise, non-uniform illumination, non-constant intensity of objects, unknown size of objects, ...

Automatic thresholding

1. P-tile method
   - Use the a priori knowledge about the size of the object: assume an object with size P as fraction of the whole.
   - Choose a threshold such that P% of the overall histogram is determined.



Rather limited use... but can be used as starting point.

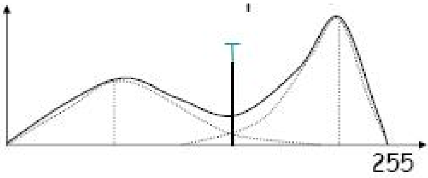
Automatic thresholding

2. Mode method

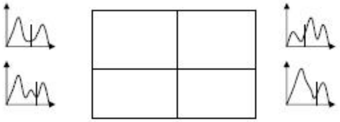
- Find the peaks and valleys of the histogram.
- Set threshold to the pixel value of the valley.
- Non-trivial to find peaks/valleys:

  Ignore small peaks, find largest peaks, find valley between these peaks.

  Maximize 'peakness' (difference between peaks and valleys) to find the threshold as valley.



3. Iterative thresholding
   - Start with an approximate threshold and refine it iteratively, taking into account some goodness measure e.g. $T = (r_1 + r_2)/2$ where r_i is the mean gray value of previous segmented region i.
4. Adaptive thresholding
   - In case of uneven illumination, global threshold has no use.
   - One approach is to divide an image into $m \times m$ subimages and determine a threshold for each subimage.



K-means clustering

- Group pixels based on similarity in colours (or any other measure).
- K-means (or ISODATA) algorithm:
  1) Choose K initial mean values (possibly randomly).
  2) Assign each pixel to the mean that is closest.
  3) Update means as the average of pixels assigned to each mean.
  4) Continue until there is no change in mean values.
- Problem: segments can be splitted up into pieces.

K-means clustering

Spatial coherence

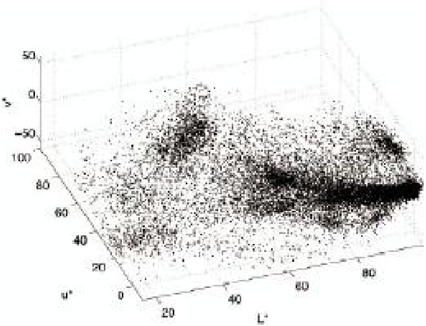
- Methods based on histograms neglect the dependency between neighboring pixels.
- Neglecting dependency may cause segments to be splitted up into different pieces.
- If spatial coherence between pixels is taken into account, this can be avoided.
- Dependency between neighboring pixels or regions could be represented in various ways.

Mean-shift segmentation

- Group pixels both in terms of colours and positions.
- A popular method based on kernel density estimation.

$$\underset{\textit{each pixel}}{\Longrightarrow} \begin{bmatrix} x \\ y \\ R \\ G \\ B \end{bmatrix}$$

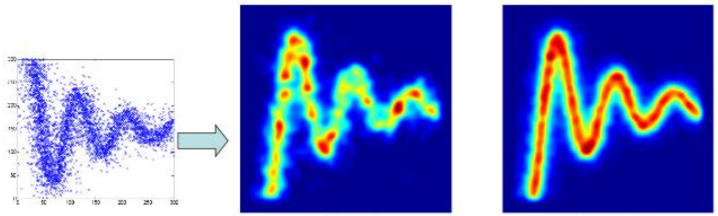
Mean-shift segmentation



Example distribution of colour values in Luv space
(L=luminance, uv=color)

Mean-shift segmentation

- Mean-shift tries to find points (in 5D space) with maximum density.
- Problem: We just have a bunch of samples.
- However, each sample can be assumed to be noisy.
- Solution: We place a small "ball" $K(x - x_i)$ around each sample, with maximum density in the center x_i.



(a) 2000 Samples (b) 20000 Samples

Formally: an iterative scheme

We want to find maxima of the total density function

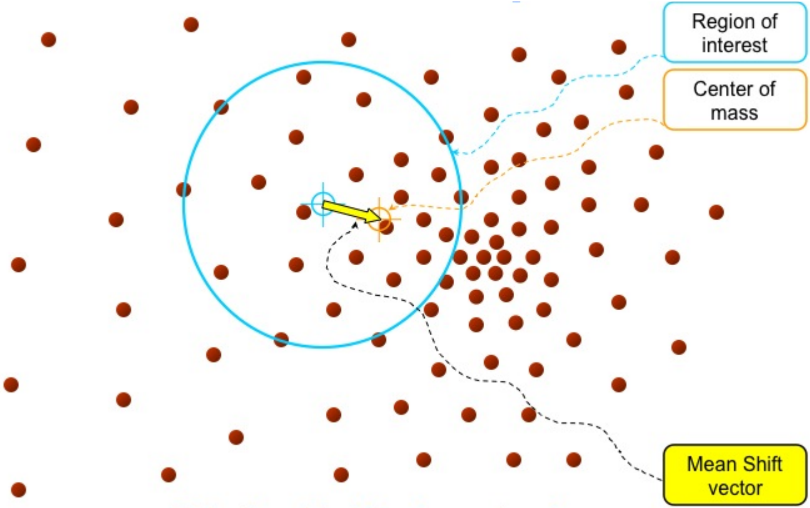
$$f(x) = \frac{1}{n}\sum_{i=1}^{n} K(x - x_i) \quad \text{where} \quad K(x) = C\, k(\|x\|^2)$$

Then the gradient should be

$$\nabla f(x) = \frac{C}{n}\sum_{i=1}^{n}(x - x_i)k'(\|x - x_i\|^2) = 0 \quad \Rightarrow \quad x^{new} = \frac{\sum_{i=1}^{n} x_i\, k'(\|x - x_i\|^2)}{\sum_{i=1}^{n} k'(\|x - x_i\|^2)}$$

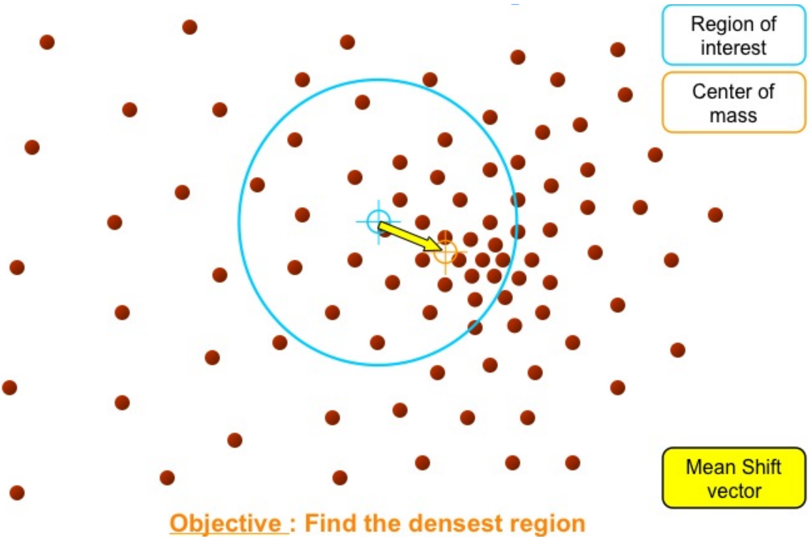
- Most common kernel ('ball'): Gaussian kernel
- Another way to think of it: For each sample
  1. Blur the positions (in 5D space) using a Gaussian kernel.
  2. Move to the new blurred position.
  3. Repeat until convergence.

Mean-shift segmentation

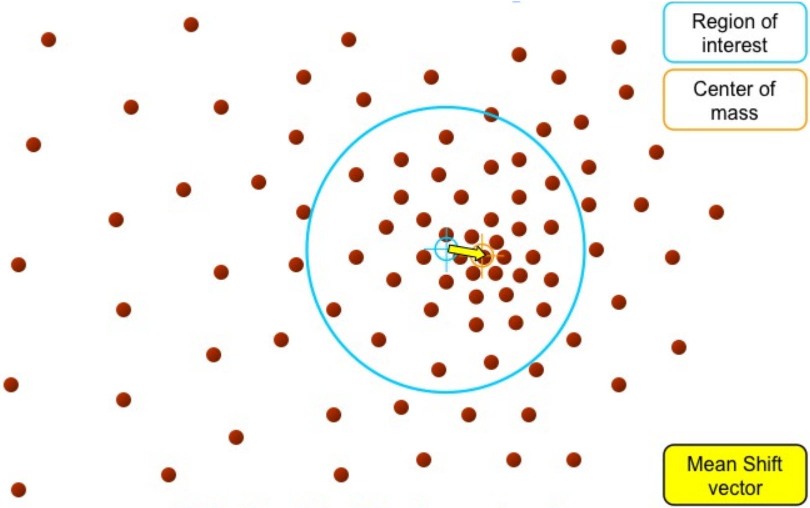


Objective : Find the densest region

Mean-shift segmentation

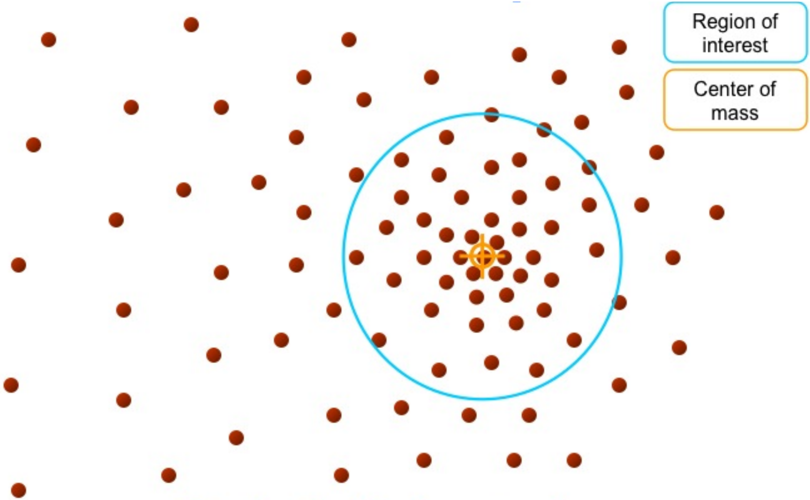


Mean-shift segmentation



Objective : Find the densest region

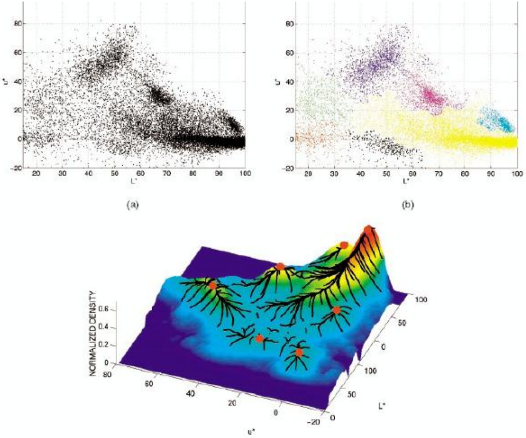
Mean-shift segmentation



Objective : Find the densest region

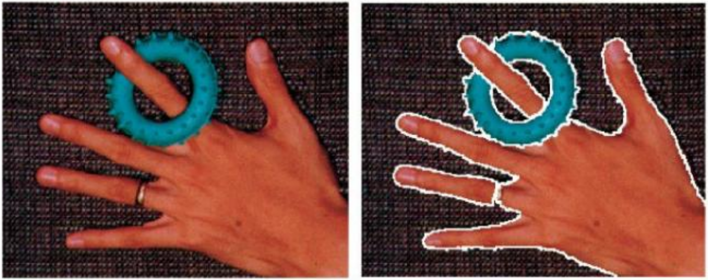
Mean-shift segmentation

- The density will have peaks (also called modes).
- If we start at a particular pixel and do gradient-ascent, we will converge to one of these modes.
- Cluster the image based on which mode a point converges to.



Mean-shift segmentation example

- Get a segmentation by starting with the 5D value of each pixel, iterate and see which peak (mode) you end up with.



(a) (b)

Merging and splitting

The output of many segmentation methods can be improved by simply merging similar neighboring regions together.

Similarity can be measured by

- A simple threshold on difference in mean intensities.
- More sophisticated methods using e.g. variance before and after

$$\sigma_R^2 = \frac{1}{|R|}\sum_{x\in R} f(x)^2 - \left(\frac{1}{|R|}\sum_{x\in R} f(x)\right)^2$$

- Similarly, splitting can be required due to too large variations.

Region Merge (Region growing)

General region merge algorithm:

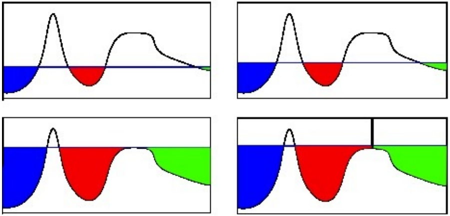
- Beginning from an initial (over)segmentation; for each region check whether its neighboring regions are 'similar'; if so, merge these regions.
- For 'region similarity':
  - Compare their mean intensities. Check with a predetermined threshold.
  - Compare their statistical distributions. Check whether a merge would represent 'observed' values better.
  - Check 'weakness' of the common boundary. Weak boundary: intensities on two sides differ less than a threshold.

Split-and-merge

- First hierarchically split image regions until the variation in each region are small enough.
- Then merge neighbours as long as variations remain small.

Watershedding

- Create some topological map over image domain (using gradient magnitude, distance transform or similar).
- Gradually fill basins with 'water' from the deepest points upwards.
- When two basins meet, create an edge between two segments.
- End when all pixels are either filled or edge pixels.

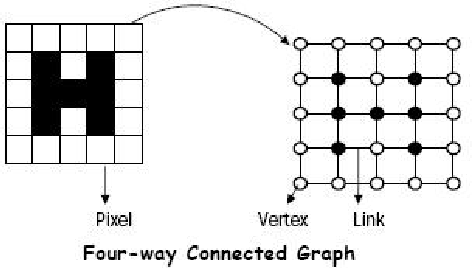


Watershedding

- Usually leads to over-segmentation, unless relevant image regions already have a close to uniform colour.
- However, efficient way to create superpixels (groups of similar pixels) that can be grouped using e.g. merging.

Graph theory in image segmentation

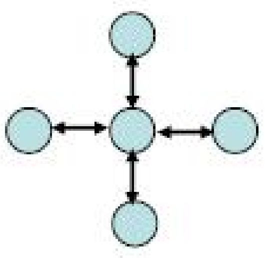
- Graph theory can be used to analyse and segment images.
- Each pixel (or superpixel) in the image corresponds to a node.
- Neighbouring pixels are connected by links.
- All nodes and links have weights.
  - Pixel colour or grey-level value is often assigned to node weight.
  - Link weights are based on some property of the pixels that it connects, such as their intensity differences.

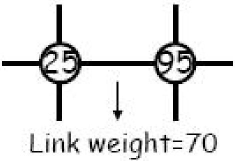


Recursive Shortest Spanning Tree (RSST)

Algorithm of Morris et al. (1986):

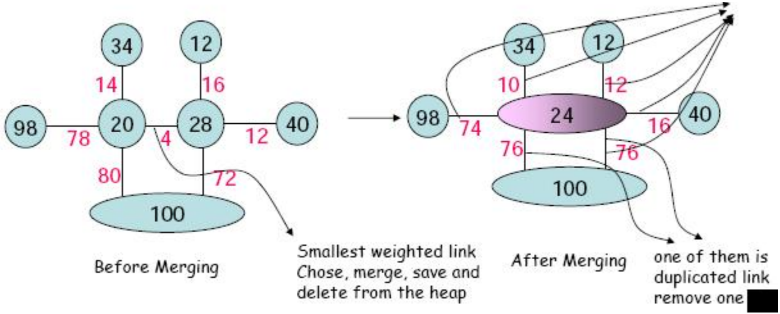
- Image is mapped onto the graph
- Four connected graph is used
- Absolute values of the grey level differences between vertices are assigned to link weights.





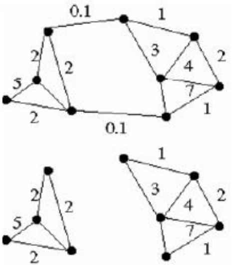
Recursively,

- Find link with smallest value
- Merge two nodes of the link
- Update new node with mean value of two old nodes
- Update links to new node



Graph theoretic clustering

- In graph-theoretic clustering, the links in the graph represents similarities between the nodes.
- These can be summarized as a large affinity (similarity) matrix W.
- Problem: Split the graph in two (or more) pieces so that the cutted links have as low weights as possible.



Meassuring affinity (similarity)

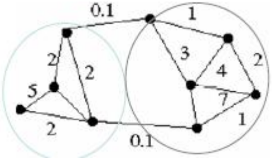
- The affinity matrix can for example have the following elements:
  - Intensity $W(x,y) = \exp\left\{-\|I(x) - I(y)\|^2/(2\sigma^2)\right\}$
  - Distance $W(x,y) = \exp\left\{-\|x - y\|^2/(2\sigma^2)\right\}$
  - Colour $W(x,y) = \exp\left\{-\|c(x) - c(y)\|^2/(2\sigma^2)\right\}$
- Here σ represents a scale factor.
- The best methods combine all possible cues.

Normalized cuts

- Goal: Maximize within cluster similarities, while minimizing across cluster differences.
- Minimize Normalized Cut

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

  - A and B are two disjoint sets of vertices and $V = A \cup B$.
  - $cut(A,B)$ – sum of edges between vertices in A and B.
  - $assoc(A,V)$ – sum of edges connected to any vertex in A.
- Segmentation found by solving a generalized eigenvalue problem.



Normalized cuts

- Let W be affinity matrix and D diagonal matrix with $D_{ii} = \sum_j W_{ij}$.
- Minimizing $Ncut(A, B)$ is equivalent to solving

$$\min_y \frac{y^T(D-W)y}{y^T Dy},$$

where elements in y indicate whether nodes belong to A or B.

- Equivalent to solving generalized eigenvalue problem

$$(D-W)y = \lambda Dy$$

or after normalization

$$(I - D^{-1/2}WD^{-1/2})z = \lambda z, \quad \text{where } z = D^{1/2}y.$$

Normalized cuts

Summary of good questions

- What is the purpose of image segmentation?
- What is Gestalt Theory?
- How to select a threshold for histogram based segmentation?
- How does K-means work?
- Why is spatial coherence important for segmentation?
- What does a mean-shift algorithm try to do and how?
- How does split-and-merge work?
- What is an affinity matrix?
- What does Normalized Cuts try to optimize?

Readings

- Gonzalez and Woods: Chapter 10.3-10.5
- Szeliski: Chapter 5