Image Processing

Segmentation and hierarchical segmentation

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Table of contents

1 Image segmentation

2 Watershed segmentation

3 Graph-based Watershed cuts

4 Hierarchical segmentations

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Table of contents

1 Image segmentation

2 Watershed segmentation

3 Graph-based Watershed cuts

4 Hierarchical segmentations

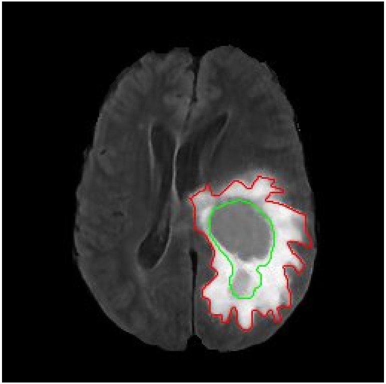
Image segmentation

- Partition of the set of image pixels into regions of interest
  - ◇ Every pixel belongs to a region of interest
- Closed contours around the regions of interest
  - ◇ Pixels may belong to a region of interest or to a contour separating different regions
- Regions of interest are 'homogeneous'
  - ◇ With respect to color, texture, or more complex criteria

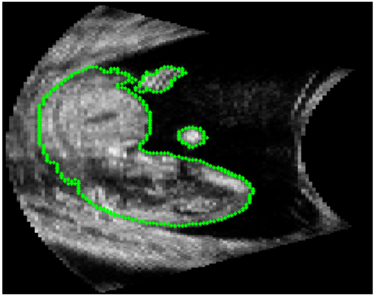
Benefit of image segmentation?

- Simplification of our domain of study:
  - set of pixels $\rightarrow$ set of regions/superpixels
- Pre-processing step for numerous image processing and computer vision tasks
  - Object detection
  - Feature extraction
  - Image simplification
  - Semantic classification
  - Video surveillance
  - Anomaly detection
  - Mapping, cartography, etc.

Application in medicine



tumor detection



Brain

Fetus measurement

Image sources: https://www.researchgate.net/, femonum.telecom-paristech.fr/

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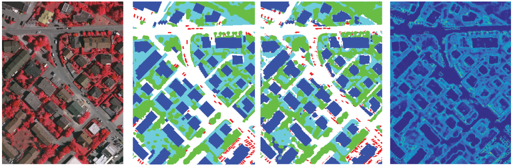
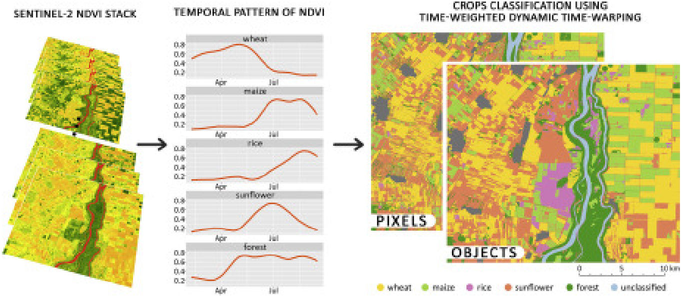
Application in Remote sensing



High-resolution segmentation [1]



Large-scale land-cover/land-use classification [2]

[1] ISPRS 2D Semantic segmentation Dataset.

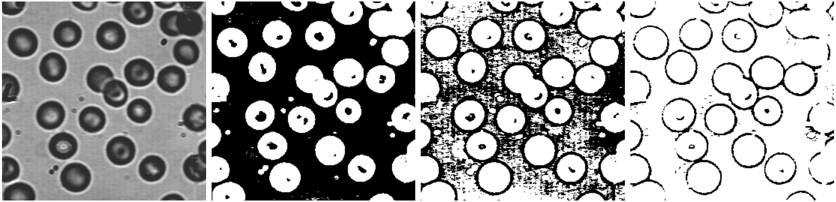
Quick discussion

What are the difference ?

- segmentation
- semantic segmentation
- instance segmentation
- classification in computer vision *vs* classification in remote sensing

Simple method: Threshold-based

- Segment the image based on pixel's intensity or color values



$\lambda = 140$ $\lambda = 160$ $\lambda = 180$

with $\lambda_{red} = 50, \lambda_{green} = 255, \lambda_{blue} = 50$

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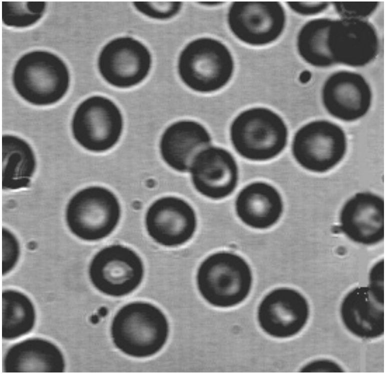
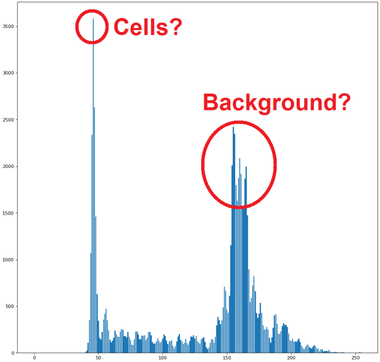
Histogram-based threshold selection

- Peaks in the histogram may indicate the regions of interest $\rightarrow$ help us to automatically define segmentation thresholds





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Histogram-based threshold selection

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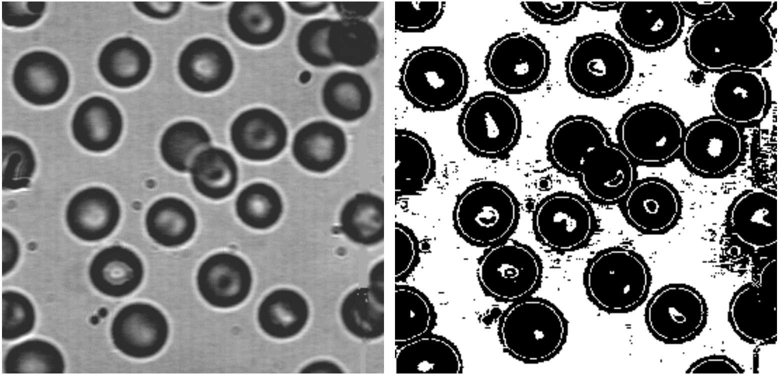
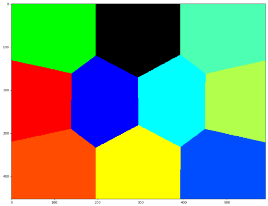


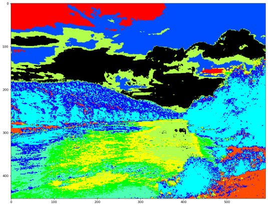
$128 < \lambda < 170$

Clustering methods

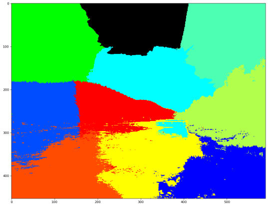
- Iterative clustering methods (K-means, SLIC)
- Combining spatial (x, y) and intensity/color/spectral information



$k = 10$, features= (x, y)



$k = 10$, features= (r, g, b)



$k = 10$, features= (r, g, b, x, y)

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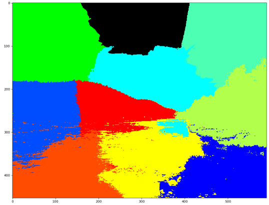
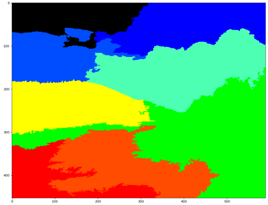
Clustering methods

- Iterative clustering methods (K-means, SLIC)
- Combining spatial (x, y) and intensity/color/spectral information



K-means algorithm
k = 10, features= (r, g, b, x, y)



SLIC algorithm
$k \approx 10$

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Table of contents

1 Image segmentation

2 **Watershed segmentation**

3 Graph-based Watershed cuts

4 Hierarchical segmentations

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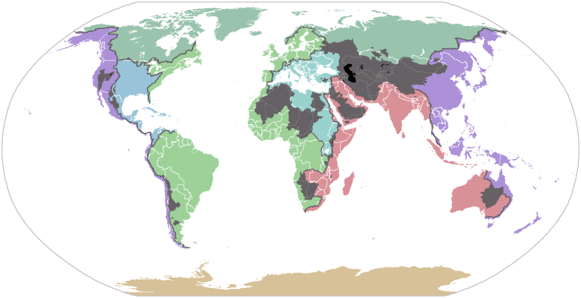
Watershed segmentation

- Based on the topographic notions of catchment basins and watersheds:
  - Studied since the 19th century for topographic purposes
  - Collected precipitation in a catchment basins drains to the same body of water, as a sea
  - Watershed (lines) separate neighbouring catchment basins



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Watershed segmentation

Gray-scale image visualized as a 3D surface:

- Gray-scale values proportional to altitudes
- Local minimum: connected pixels surrounded by pixels of strictly larger gray-levels
- Catchment basin: zone of influence of a minimum
- Watershed lines: frontiers between catchment basins

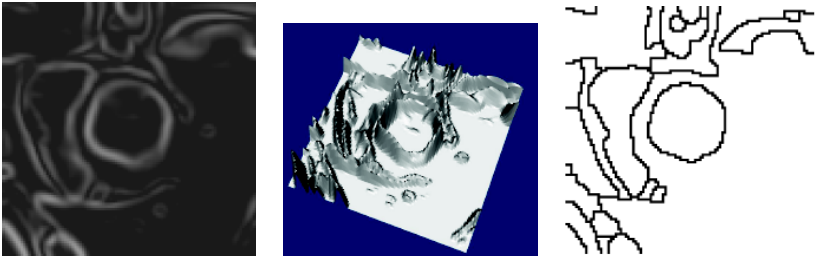


Image source: https://en.wikipedia.org/wiki/Watershed_%28image_processing%29

’Flooding’ algorithm:
Input: gray-scale image I

1. Sort the pixels of I in an increasing order of their gray-levels
2. Find the domain $\{h_{min}, \ldots, h_{max}\}$ of I
3. For each h in $\{h_{min}, \ldots, h_{max}\}$:

   3.1 Find all pixels with gray level less than h
   3.2 Discover and label the local minima of I with altitude h
   3.3 Extend the already labeled catchment basins to the newly discovered pixels with altitude h

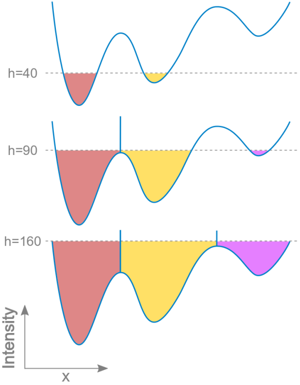
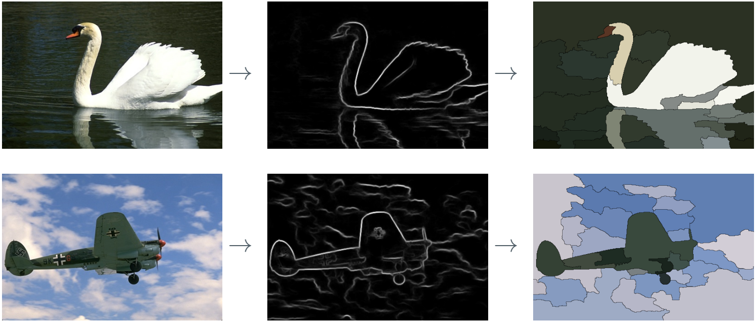


Image source: https://imagej.net/Classic_Watershed

Watershed segmentation

- Usually applied on image gradients, not on the original image
- Regions of interest are expected to have low and homogeneous gray-levels in the gradient



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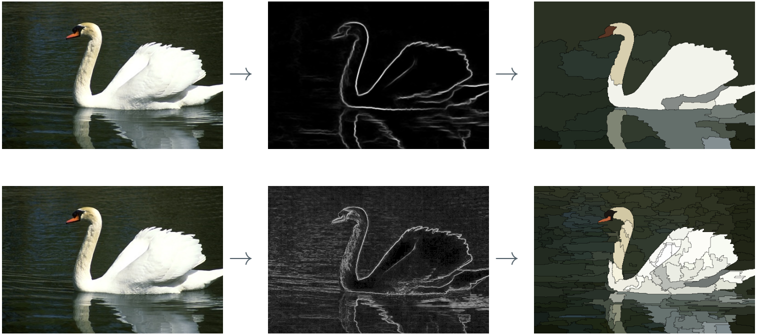
Watershed segmentation

- Quality of watershed segmentation depends on the gradient
- **Ideal scenario:** one local minima per region of interest
- **Common scenario:** several local minima per region of interest, leading to the so-called over-segmentation



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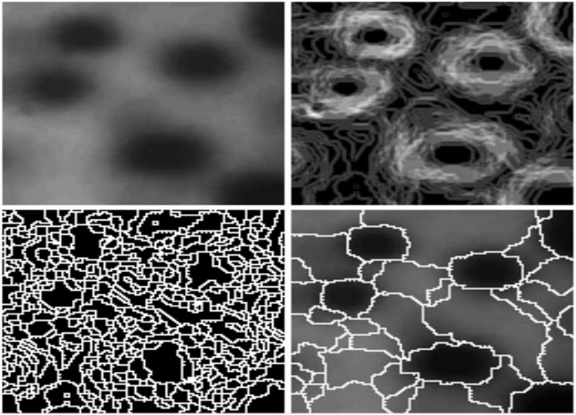
How to deal with over-segmentation?

1. Smoothing of the image gradient
   - ◇ reduces noise and spurious local minima



a b
c d

FIGURE 10.21 (a) Gray-scale image of small blobs. (b) Gradient magnitude image. (c) Watershed transform of (b), showing severe oversegmentation. (d) Watershed transform of the smoothed gradient image; some oversegmentation is still evident. (Original image courtesy of Dr. S. Beucher, CMM/Ecole de Mines de Paris.)

Image source: https://images.slideplayer.com/33/8205913/slides/slide$_6$2.*jpg*

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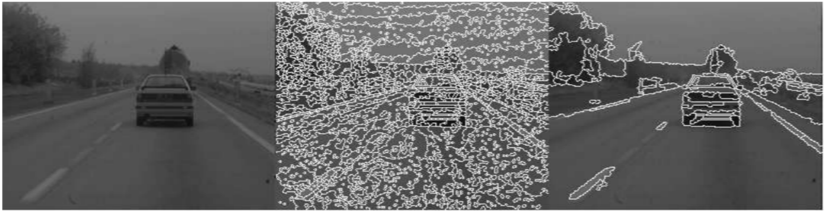
How to deal with over-segmentation?

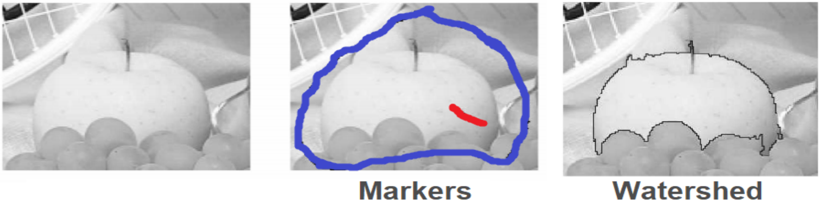
1. Smoothing of the image gradient
   - ◇ reduces noise and spurious local minima
2. Iterative clustering of regions



Beucher. Watershed, hierarchical segmentation and waterfall algorithm. 1994.

How to deal with over-segmentation?

1. Smoothing of the image gradient
   - ◇ reduces noise and spurious local minima
2. Iterative clustering of regions
3. Marked watershed
   - ◇ enforces local minima at the regions of interest
   - ◇ catchment basins are grown only from markers



Cousty *et al*. Watershed cuts: Minimum spanning forests and the drop of water principle. 2008.

Table of contents

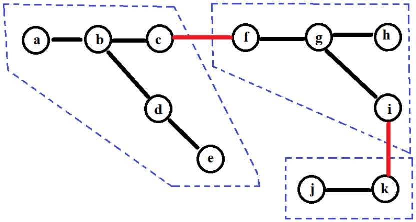
1 Image segmentation

2 Watershed segmentation

3 **Graph-based Watershed cuts**

4 Hierarchical segmentations

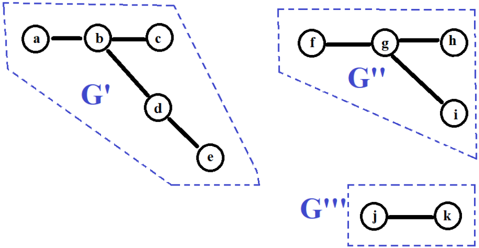
Cuts and partitions



- $G = (V, E)$
- $V = \{a, b, c, \ldots, j, k\}, E = \{\{a, b\}, \{b, d\}, \ldots, \{j, k\}\}$
- $\boldsymbol{E' = \{\{c, f\}, \{i, k\}\}}$ **is a cut** of G:

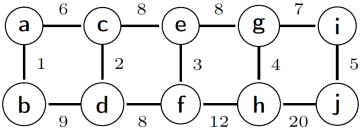
  every edge in E' connects pixels belonging to different connected components of $(V, E \setminus E')$
- $\boldsymbol{E'}$ **induces a partition** of G (resp. V) into three connected components (resp. sub-sets of vertices)

Tree and Forest

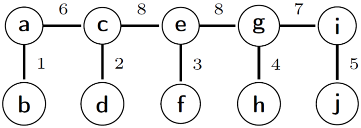


- $G = (V, E)$
- $V = \{a, b, c, \ldots, j, k\}, E = \{\{a, b\}, \{b, d\}, \ldots, \{j, k\}\}$
- G', G'' and G''' are sub-graphs of G
- G', G'' and G''' are trees (no cycles)
- G is a forest

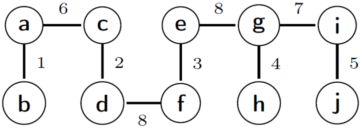
Minimum spanning tree (MST)



G



G'



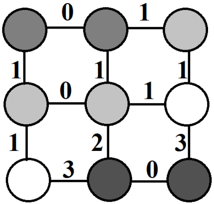
G''

- G' is a **minimum spanning tree (MST)** of G:
  1. $G' = (V, E')$ is a sub-graph of G
  2. G' is a tree
  3. $\sum_{e \in E'} w(e)$ is minimal among all graphs for which 1 and 2 hold true
- **MSTs are not unique!** G'' is also a MST of G

Reminder: Graph for image

- Graph construction based on pixel adjacency, region adjacency
- Pixel: 4 and 8-connected pixels
- Region: neighborhood regions are connected
- Weights: usually defined as the similarity b/w nodes (weighted graph, affinity graph)
- Watershed graph: weight = distance (dissimilarity)

2	2	3
3	3	4
4	1	1

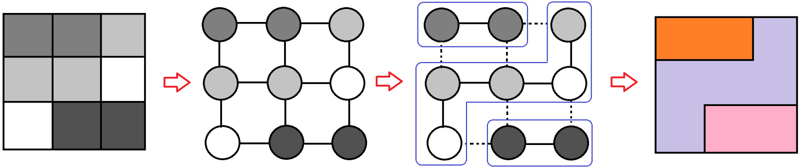


$$w(\{x,y\}) = | f(y)-f(x) |$$

Reminder: Graph-cut for image segmentation

- A graph-cut induces a partition on the set of vertices $\rightarrow$ well adapted to image segmentation
- Many methods/algorithms in the literature
  - ◇ Min-cut/Max-flow
  - ◇ Shortest path
  - ◇ Minimum spanning forest
  - ◇ Normalized cuts

  ...



Original image I — Graph representation of I — Graph-cut E' — Segmentation of I induced by E'

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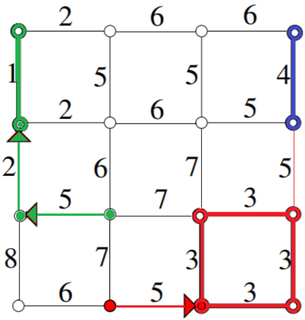
Watershed-cuts

- Same intuition of the watershed segmentation presented previously, but now on graphs
- **Local minimum:** sub-graph of a graph G connected by edges of lower weights than its adjacent edges
- **Steepest descent property:** from each vertex v, there is a minimum M and a path $\pi = (v, v_1, \ldots, v_n)$ *s.t.* v_n is a vertex of M and $w(v, v_1) \leq w(v_1, v_2) \leq \cdots \leq w(v_{n-1}, v_n)$



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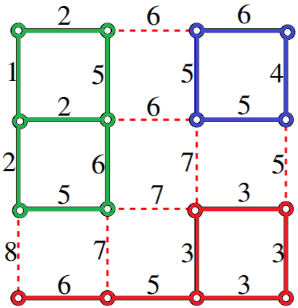
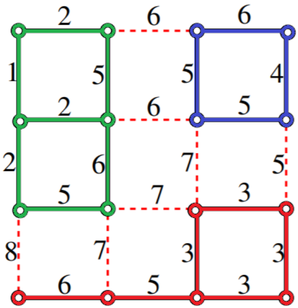
Watershed-cuts

- Watershed-cut: subset of edges S *s.t.*, for any edge $e = (x, y)$ in S, there is a descending path from x and y to two distinct minima of (G, w)
- Watershed segmentation: partition induced by a watershed-cut

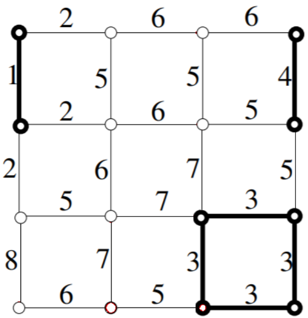


Watershed-cuts

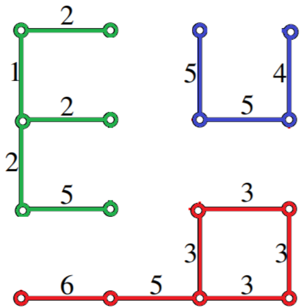
- Watershed-cut: subset of edges S *s.t.*, for any edge $e = (x, y)$ in S, there is a descending path from x and y to two distinct minima of (G, w)
- Watershed segmentation: partition induced by a watershed-cut
- Linked to a well-known optimization problem on graphs:
- **Minimum Spanning Forests**



Minimum Spanning Forest (relative to a set of minima)



(G, w)



(G', w)

- (G', w) **is a MSF** (relative to the minima of (G, w)):
  1. Each connected component of (G', w) contains exactly one minimum of (G, w)
  2. The only cycles of (G', w) come from the minima of (G, w)
  3. $\sum_{e \in E'} w(e)$ is minimal among all graphs for which 1 and 2 hold true

Watershed-cuts:

- Obtained using adaptations of MST algorithms
- Efficient computation: quasi-linear time complexity

Algorithm:

Segmentation with watershed-cuts:

Input: weighted grah $((V, E), w)$

1. Create one connected component per vertex in V: $C_0, \ldots, C_{|V|}$
2. Find the set $\mathcal{M}$ of minima of $((V, E), w)$
3. For each edge $e = (x, y)$ in E in increasing order of their weights:
   3.1 Merge the connected components of x (C_x) and y (C_y) if:
      3.1.1 x and y belong to the same minimum; or
      3.1.2 Only C_x contains a minimum; or
      3.1.3 Only C_y contains a minimum;

Cousty *et al*. Watershed cuts: Minimum spanning forests and the drop of water principle. 2008.

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Table of contents

1 Image segmentation

2 Watershed segmentation

3 Graph-based Watershed cuts

4 **Hierarchical segmentations**

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Hierarchical segmentations

- P : set of pixels/vertices
- Sequence $\mathcal{H} = (H_0, \ldots, H_n)$ of nested segmentations of P
- Causality and location principles:
  - any region in H_i, for $i > 0$ is the union of regions from H_{i-1}
  - a contour present at H_i is also in H_j for any $j < i$
- Modeled by a tree structure (e.g. partition tree)

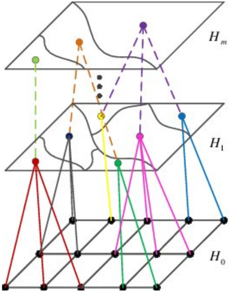
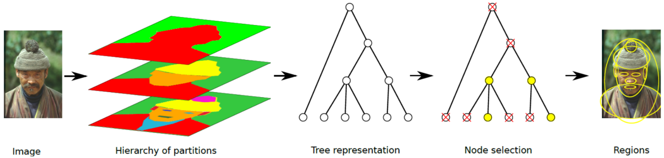


Image souce: T. Lei *et al.* Adaptive morphological reconstruction for seeded image segmentation. 2019.

Why hierarchies of segmentations?

- Regions of interest do not all appear at the same scale
- A cut on tree (by minimizing a defined criterion) could provide a segmentation with better quality



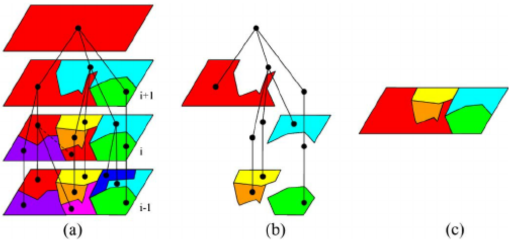
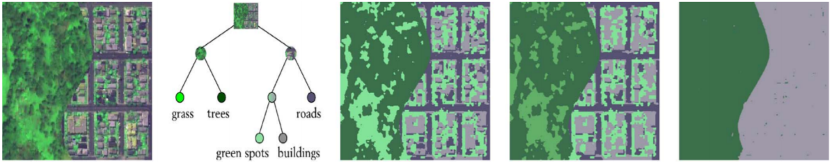


Image souce: B. Perret *et al*. Evaluation of hier-archical watersheds. IEEE TIP. 2017.
A Framework for Land Cover Classification Using Discrete Return LiDAR Data: Adopting Pseudo-Waveform and Hierarchical Segmentation.

Hierarchical segmentations: applications in remote sensing



Hierarchical description of remote sensing images [3]

Extraction of road networks from satellite images [4]

[3] R. Gaetano *et al*. Hierarchical Texture-Based Segmentation of Multiresolution Remote-Sensing Images. 2009.

[4] R. Alshehhi and P. R. Marpu. Hierarchical graph-based segmentation for extracting road networks from high-resolution satellite images. 2017.

Reading for discussion 1 Hierarchical graph-based segmentation for extracting road networks from high-resolution satellite images (Alshehhi et al., 2017).

- summary of the proposed methodology and the obtained results
- which techniques you have learned/known from the Computer Vision course
- pros/cons of the proposed approaches

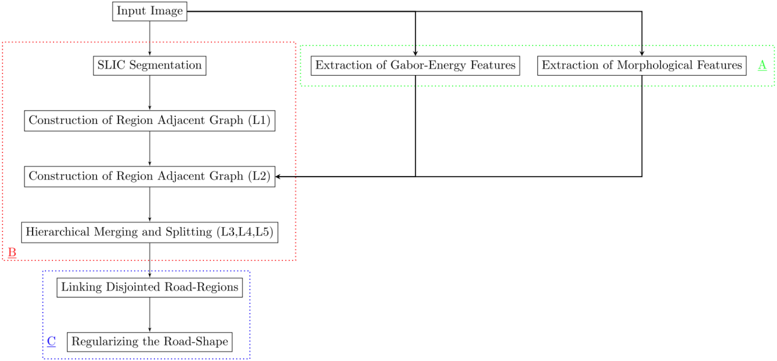
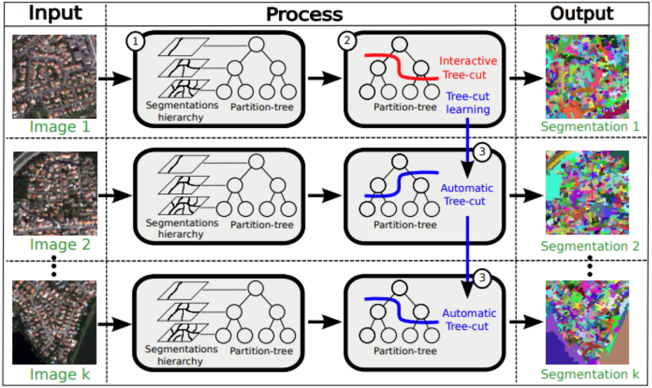


Fig. 1. Flowchart of the proposed method. It consists of (A) Pre-processing, (B) Graph-based segmentation, and (C) Post-processing.

Hierarchical segmentation: applications in remote sensing

Reading for discussion 2 Hierarchical segmentation of multiresolution remote sensing images (Camille Kurtz et al., 2018)

- **multi-resolution** hierarchical segmentation
- Iterative approach



Lab (for assignment)

Threshold, histogram, watershed and graph-based segmentation

- Download the notebook file and images from Moodle
- Exo 1: Manual thesholding and histogram-based thresholding for segmentation
- Exo 2: Clustering-based segmentation
- Exo 3: Watershed segmentation and dealing with over-segmentation
- Exo 4: Efficient Graph-Based Image Segmentation by Felzenszwalb Huttenlocher (paper that you like alot !!!)
- **Submit your work on Moodle by November 20 !!!**

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References I

1. A big thank to Deise Santana Maia for her materials to prepare this lecture
2. Guimaraes *et al*. A hierarchical image segmentation algorithm based on an observation scale, 2012.
3. Wikipedia: `https://en.wikipedia.org/wiki/Image_segmentation`
4. B. Perret *et al*. Evaluation of hierarchical watersheds. IEEE TIP. 2017.
5. T. Lei *et al*. Adaptive morphological reconstruction for seeded image segmentation. 2019.
6. Felzenszwalb, P. F., Huttenlocher, D. P. Efficient graph-based image segmentation. 2004.
7. Cousty *et al*. Watershed cuts: Minimum spanning forests and the drop of water principle. 2008.
8. R. Gaetano *et al*. Hierarchical Texture-Based Segmentation of Multiresolution Remote-Sensing Images. 2009.
9. R. Alshehhi and P. R. Marpu. Hierarchical graph-based segmentation for extracting road networks from high-resolution satellite images. 2017.