Watershed-based attribute profiles for remote sensing image analysis

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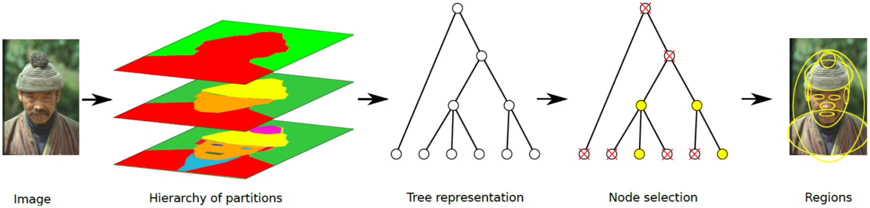
Outlines

1. Hierarchies, watersheds and graphs
2. Attribute Profiles
3. Proposed approach : Watershed Attribute Profiles
4. Experiments on the Zurich dataset

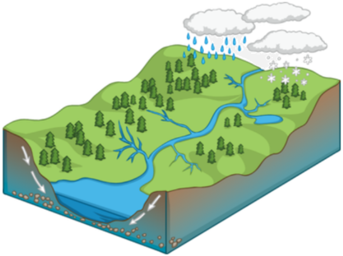
Why hierarchies of partitions ?

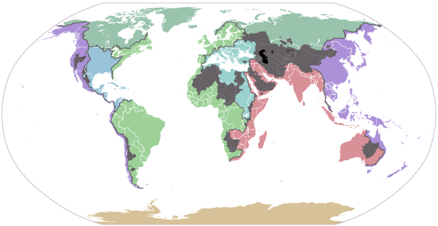
- Regions of interest do not all appear at the same scale
- Several applications on image analysis and processing
  - object detection, image compression, feature extraction...



Catchment basin and watershed

- 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





Watershed segmentation

Gray-scale images 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

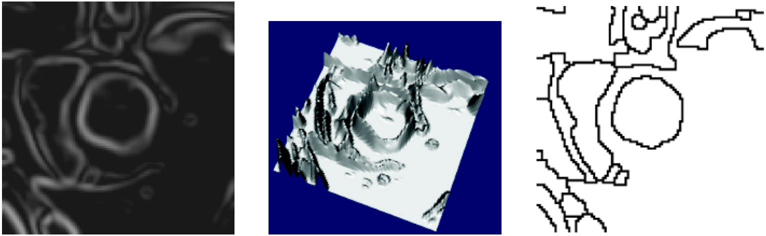
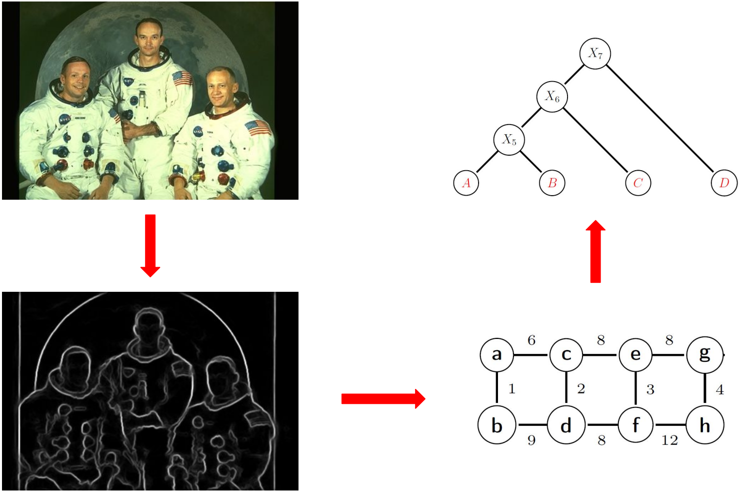


Figure – Watersheds from gray scale images [1]

1. Cousty, J., "Discrete watersheds : theory and applications to cardiac image segmentation", PhD thesis, 2007

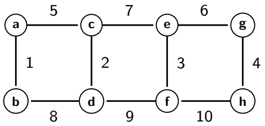
Hierarchical watershed (cuts) on edge-weighted graphs [2]



2. Cousty, J., Bertrand, G., Najman, L., Couprie, M.. Watershed cuts : Minimum spanning forests and the drop of water principle. IEEE PAMI. 2008.

Hierarchical watershed (cuts) on edge-weighted graphs

- (G, w) is an edge-weighted graph
  - which can be a pixel-adjacency graph
  - edge weights can represent a gradient of intensity



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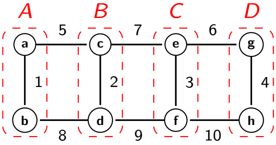
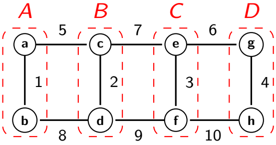


Hierarchical watershed (cuts) on edge-weighted graphs

- (G, w) is an edge-weighted graph
  - which can be a pixel-adjacency graph
  - edge weights can represent a gradient of intensity
- A minimum is a set M of vertices connected by edges of lower weights than the edges adjacent to M
- $\mathcal{S} = (M_0, \ldots, M_\ell)$ is any sequence of the minima of w ranked by importance according to some regional attribute like extinction values



Hierarchical watersheds

- A *hierarchical watershed of* (G, w) *for* $\mathcal{S}$ is a hierarchy of partitions $(\boldsymbol{P}_0, \ldots, \boldsymbol{P}_\ell)$ such that, for any $i \in \{0, \ldots, \ell\}$:
  - $\boldsymbol{P}_i$ is the connected component partition of a minimum spanning forest rooted in the minima ranked after i

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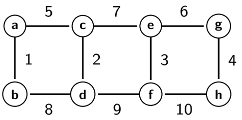

(G, w)

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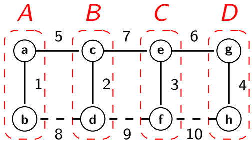

Minima of w

$\mathcal{S} = (\text{B, C, A, D})$

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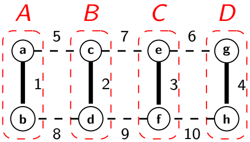

$\{a, b\}$ $\{c, d\}$ $\{e, f\}$ $\{g, h\}$ $\mathbf{P}_0$

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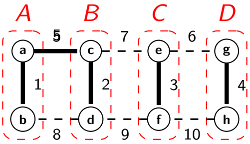

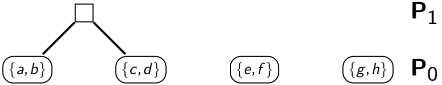

$\mathcal{S} = (\cancel{B,}\ C,\ A,\ D)$

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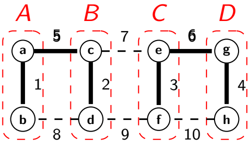

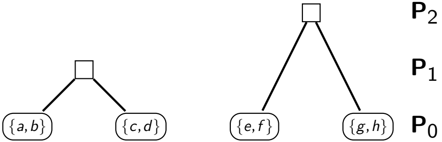

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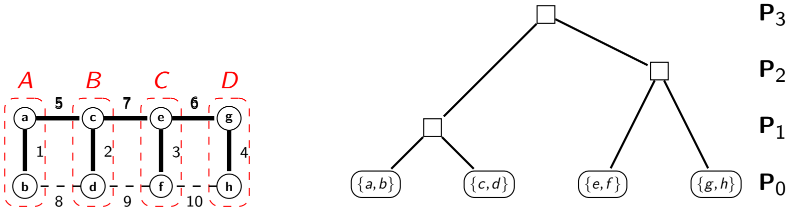

$(\boldsymbol{P}_0, \boldsymbol{P}_1, \boldsymbol{P}_2, \boldsymbol{P}_3)$:
hierarchical watershed of (G, w) for $\mathcal{S} = (B, C, A, D)$

Watersheds in the framework of edge-weighted graphs

- Are the solution to a minimum spanning forest optimization problem [3]

3. Cousty, J., Najman, L. and Perret, B., 2013, May. Constructive links between some morphological hierarchies on edge-weighted graphs. In ISMM.
4. Najman, L., Cousty, J. and Perret, B., 2013. Playing with kruskal : algorithms for morphological trees in edge-weighted graphs. In , ISMM 2013.
5. Maia, D. S., Cousty, J., Najman, L., Perret, B. Properties of combinations of hierarchical watersheds. PRL. 2019.

Watersheds in the framework of edge-weighted graphs

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Watersheds in the framework of edge-weighted graphs

- Are the solution to a minimum spanning forest optimization problem [3]
- Can be computed using efficient algorithms [4]
- Satisfy a strong multiscale property
  - not satisfied by min-cut, average-cut and shortest path forest [5]

3. Cousty, J., Najman, L. and Perret, B., 2013, May. Constructive links between some morphological hierarchies on edge-weighted graphs. In ISMM.

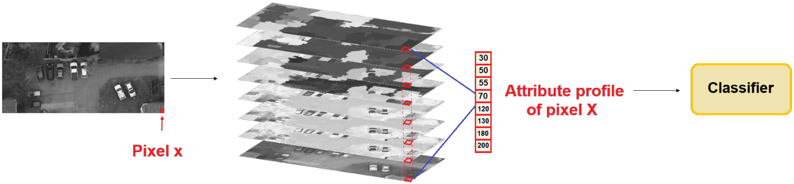
4. Najman, L., Cousty, J. and Perret, B., 2013. Playing with kruskal : algorithms for morphological trees in edge-weighted graphs. In , ISMM 2013.

5. Maia, D. S., Cousty, J., Najman, L., Perret, B. Properties of combinations of hierarchical watersheds. PRL. 2019.

Outlines

Attribute profiles

- Feature extraction from morphological hierarchical representations [6]
- **Main application :** pixel classification of remote sensing images
- Sequence of image reconstructions obtained from attribute filters



6. Dalla Mura, M., Benediktsson, J. A., Waske, B., Bruzzone, L. (2010). Morphological attribute profiles for the analysis of very high resolution images. IEEE Transactions on Geoscience and Remote Sensing, 48(10), 3747-3762.

Attribute profiles

Given an image I :

Image I

Attribute profiles

Given an image I :

1. Compute a hierarchical representation H of I

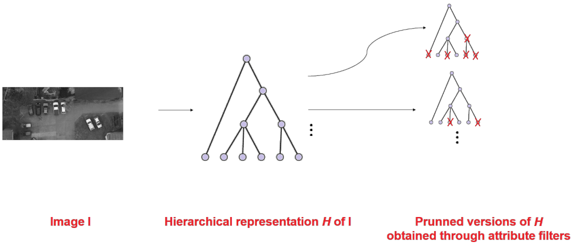
Image I

Hierarchical representation *H* of I

Attribute profiles

Given an image I :

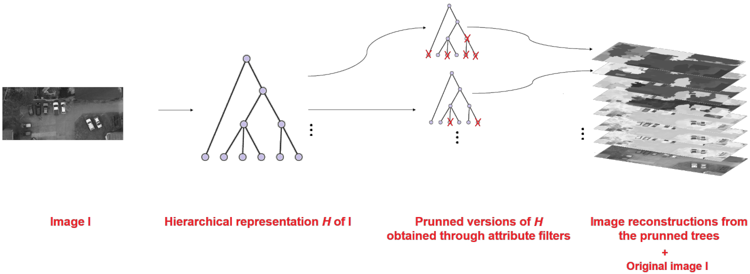
1. Compute a hierarchical representation H of I
2. Perform a sequence of attribute filters on H



Attribute profiles

Given an image I :

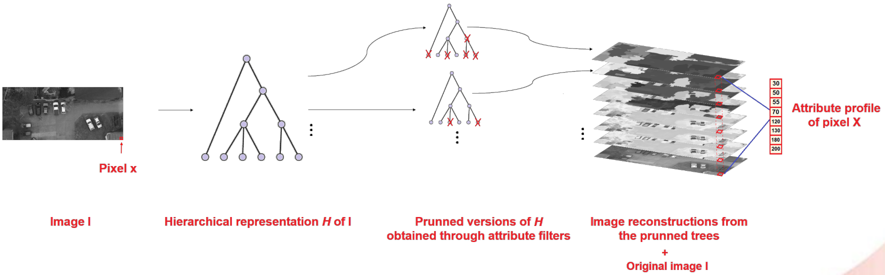
1. Compute a hierarchical representation H of I
2. Perform a sequence of attribute filters on H
3. Reconstruct an image from each pruned version of H



Attribute profiles

Given an image I :

1. Compute a hierarchical representation H of I
2. Perform a sequence of attribute filters on H
3. Reconstruct an image from each pruned version of H
4. For each pixel x, extract its feature vector



Attribute profiles : parameter settings

1. Which hierarchical representation of I to choose ?
   - Max-tree (Max-AP)
   - Min-tree (Min-AP)
   - Min-tree and Max-Tree (AP)[7]
   - Tree-of-shapes : Self-dual AP (SDAP)[8]
   - α-tree (α-AP)[9]
   - ω-tree (ω-AP)[5]

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7. Dalla Mura, M. *et al.* (2010). Morphological attribute profiles for the analysis of very high resolution images. IEEE TGRS, 48(10), 3747-3762.

8. Dalla Mura, M., Benediktsson, J. A., Bruzzone, L. (2011, July). Self-dual attribute profiles for the analysis of remote sensing images. In ISMM (pp. 320-330). Springer, Berlin, Heidelberg.

9. Bosilj, *et al.* (2017, May). Attribute profiles from partitioning trees. In ISMM (pp. 381-392). Springer, Cham.

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What about hierarchical watersheds ? ☺

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7. Dalla Mura, M. *et al.* (2010). Morphological attribute profiles for the analysis of very high resolution images. IEEE TGRS, 48(10), 3747-3762.

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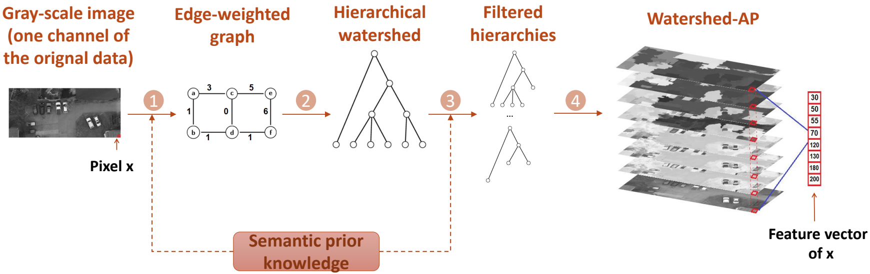
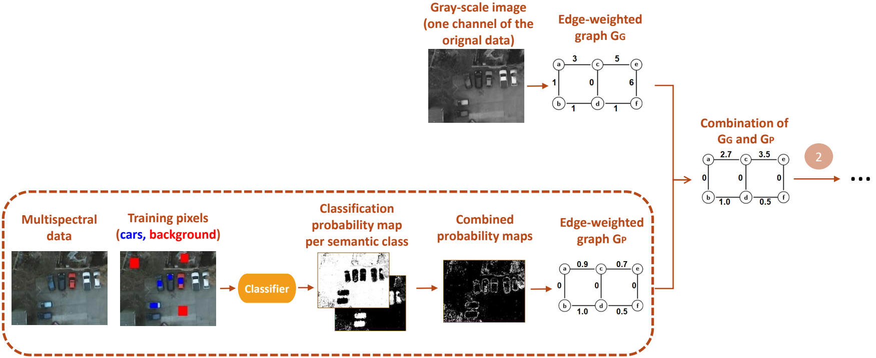
Outlines

Watershed-Based Attribute Profiles (with Semantic Prior Knowledge) [10]



10. Maia, D. S., Pham, M. T., Lefèvre, S. (2022). Watershed-based attribute profiles with semantic prior knowledge for remote sensing image analysis. IEEE JSTARS.

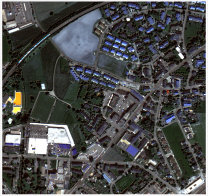
Semantic Prior Knowledge

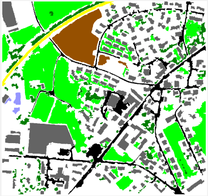


Outlines

Dataset

Zurich dataset





- roads
- buildings
- trees
- grass
- bare soil
- railways
- swiming pools

- 20 images

  15 for training (1% of pixels)

  5 for testing
- Four channels : NIR+RGB
- Width : [622, 1639]
- Height : [782, 1830]

Experimental setup

Hierarchical watersheds :

- area (Area-WS-AP)
- dynamics (Dyn-WS-AP)
- volume (Vol-WS-AP)

Filtering step :

- Ten area thresholds and four moment of inertia thresholds :

  $\lambda_{area} = \{25, 100, 500, 1000, 5000, 10000, 20000, 50000, 100000, 150000\}$

  $\lambda_{moi} = \{0.2,\ 0.3,\ 0.4,\ 0.5\}$

Classification and evaluation :

- Pixel classification with Random Forest
- Evaluation metrics (average over ten runs) :
  - Overall Accuracy (OA)
  - Average Accuracy (AA)

Experiments on the Zurich dataset

- Area-WS-AP and Vol-WS-AP outperform all other attribute profiles [11]

Method	Dim.	Classification result	
		OA (%)	AA (%)
NIR+RGB	4	76.41 ± 0.18	65.16 ± 1.01
AP-maxT	64	81.29 ± 0.17	64.39 ± 0.30
AP-minT	64	76.64 ± 0.32	61.49 ± 0.32
AP	120	81.98 ± 0.14	64.55 ± 0.21
SDAP	64	81.98 ± 0.20	64.16 ± 0.89
α-AP	64	80.37 ± 0.18	63.35 ± 0.80
ω-AP	64	80.35 ± 0.35	63.41 ± 1.36
Area-WS-AP	64	83.12 ± 0.18	65.28 ± 0.11
Dyn-WS-AP	64	80.38 ± 0.12	62.84 ± 0.17
Vol-WS-AP	64	83.36 ± 0.23	65.50 ± 0.13
Watershed-APs computed with semantic prior knowledge			
Area-CPWS-AP	64	85.25 ± 0.20	66.49 ± 0.18
Dyn-CPWS-AP	64	83.46 ± 0.28	65.05 ± 0.32
Vol-CPWS-AP	64	**85.27 ± 0.35**	**66.81 ± 0.24**
Deep learning models :			
FCN-Festa+dCFR [12]	-	78.51 ± 2.21	-
FCN[12]	-	90.51	-

11. Maia, D. S., Pham, M. T., Lefèvre, S. (2022). Watershed-based attribute profiles with semantic prior knowledge for remote sensing image analysis. IEEE JSTARS.

12. Hua, Y., Marcos, D., Mou, L., Zhu, X. X., Tuia, D. Semantic segmentation of remote sensing images with sparse annotations. IEEE Geoscience and Remote Sensing Letters. 2021.

Conclusion

- Watershed-AP as an extension of AP to hierarchical watersheds computed from (edge) weighted graphs
- Applications on land cover classification
- Perspectives : what properties do Watershed-AP computed with prior knowledge preserve ?

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Thank you !