Hierarchical segmentation of multimodal images

from Earth observation to the analysis of building geo-materials

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Thanks to...

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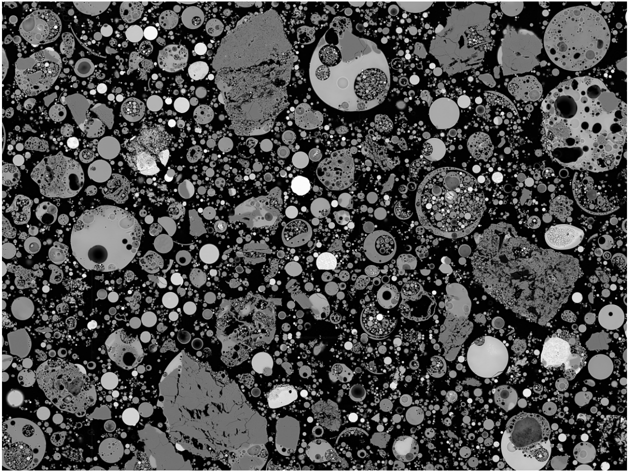
- Miguel Veganzones, GIPSA-lab, France

Overall outline

1. Introduction
2. Analysis of S.E.M. images based on Hierarchical Segmentation
3. Hierarchical segmentation of (EO) multimodal images
4. Conclusion

Images of building materials microstructures

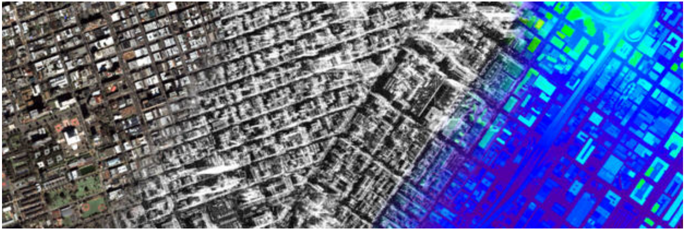


LafargeHolcim

Goal

Measure phase fraction of materials (i.e, localize main chemical elements in fly ashes)

Earth Observation images



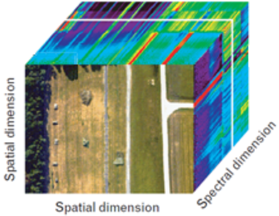
optical SAR LiDAR

Goal

Extract information of the land-cover (e.g., thematic classification, object extraction)

Hyperspectral imagery

Simultaneous acquisition $\mathcal{I} = \{\mathcal{I}_{\lambda_1}, \ldots, \mathcal{I}_{\lambda_N}\}$ of several single band images $\mathcal{I}_{\lambda_i}$ $(i = 1, \ldots, N)$ over N narrow and contiguous wavelengths of the electromagnetic spectrum.



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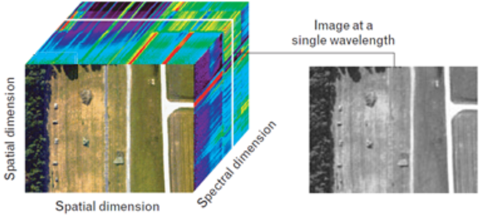

- $\mathcal{I}_{\lambda_i}$: grayscale image $\rightarrow$ spatial information.

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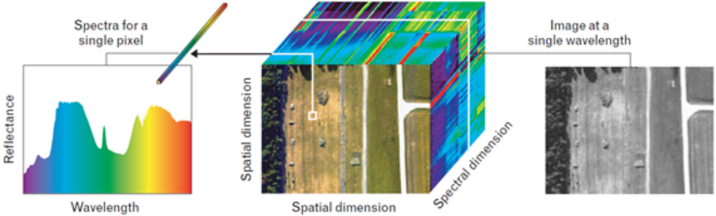
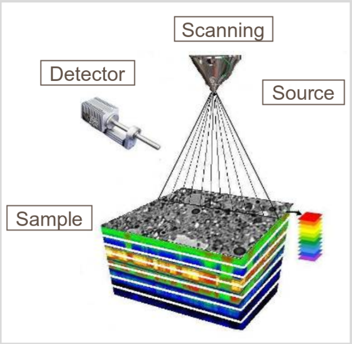
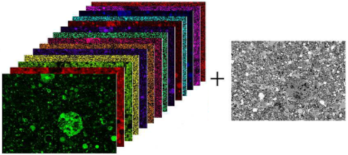


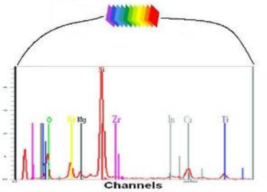
- $\mathcal{I}_{\lambda_i}$: grayscale image $\rightarrow$ spatial information.
- $\mathbf{x} = (x_1, \ldots, x_N)$: reflectance spectrum $\rightarrow$ spectral information.

gipsa-lab



Scanning Electron Microscope





Scanning Electron Microscopy (S.E.M.)

- X-ray diffraction allows to reveal the presence of different chemical elements, providing spectral information
- Backscattered electron imaging is sensitive to the density of the observed pixel, providing spatial information

Image

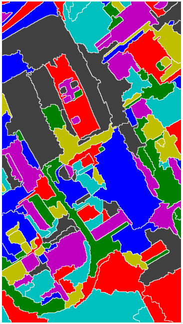
Image

Filtering

Analysis of EO images


Image

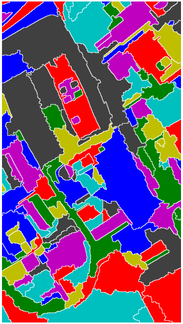

Filtering


Segmentation

Analysis of EO images

Image

Filtering



Segmentation

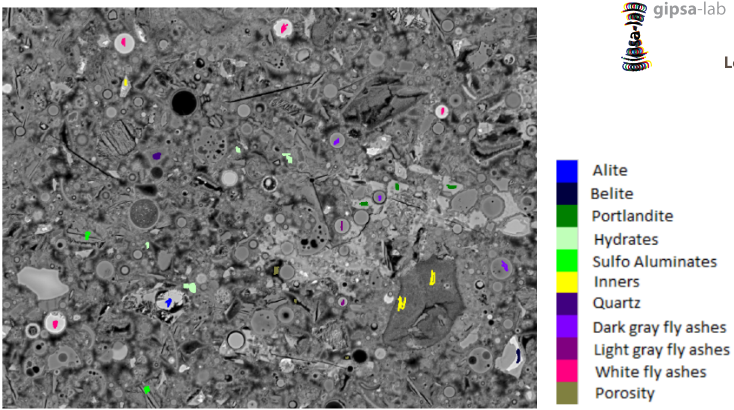
Classification

1 Introduction

2 Analysis of S.E.M. images based on Hierarchical Segmentation

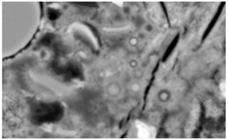
3 Hierarchical segmentation of (EO) multimodal images

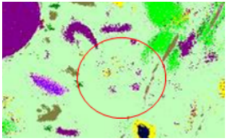
4 Conclusion



Approach

- Supervised classification with Support Vector Machines (SVM)
- Perform spatial regularization by Markov Random Fields (MRF)


BSE image


SVM result


SVM-MRF result

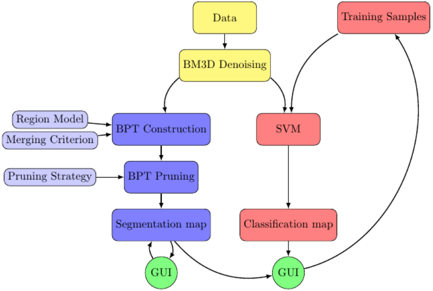
- Overall good results (i.e., main material phases are identified)
- However, the technique does not preserve enough spatial features, or fail for specific types of classes, e.g. micronized fly ashes (important compounds in the cement industry)

Classification of S.E.M. images based on Hierarchical Segmentation

. . . + image filtering and user's interaction

Idea

- Filter the image
- Perform a hierarchical segmentation of the image
- Do classification on top of it
- Allow the user to interact in order to
    - improve the segmentation (i.e., chose an appropriate segmentation in the hierarchy)
    - improve classification (i.e., correct misclassified regions and retrain the classifier)



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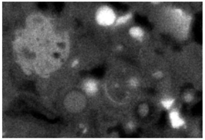
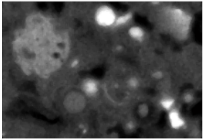
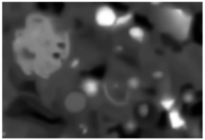


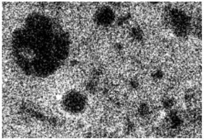
Original image (good SNR)



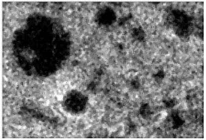
3 × 3 median filter



BM3D



Original image (poor SNR)



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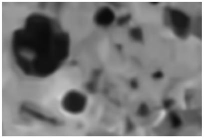

BM3D

L. Drumetz, M. Dalla Mura, S. Meulenyzer, S. Lombard, and J. Chanussot, "**Semiautomatic classification of cementitious materials using scanning electron microscope images**," *Journal of Electronic Imaging*, vol. 24, no. 6, p. 061 109, 2015.

Classification of S.E.M. images based on Hierarchical Segmentation

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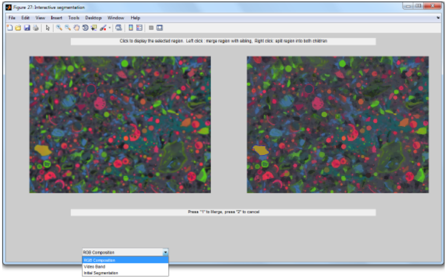
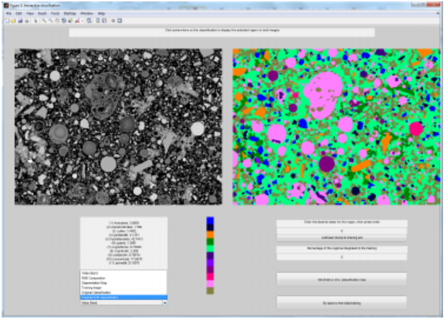


The segmentation interface



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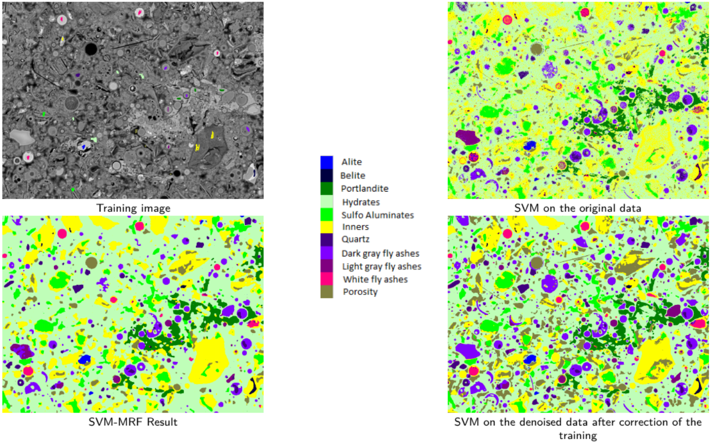

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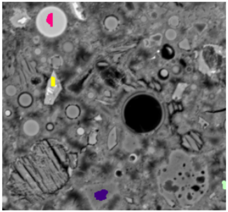
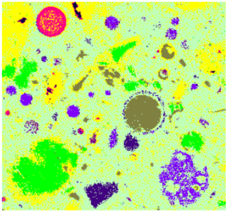
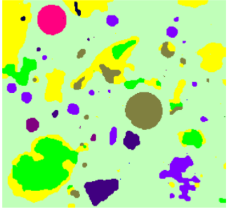


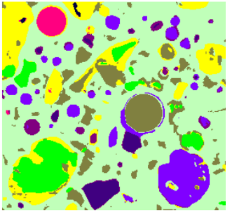
Training image



SVM on the original data



SVM-MRF Result

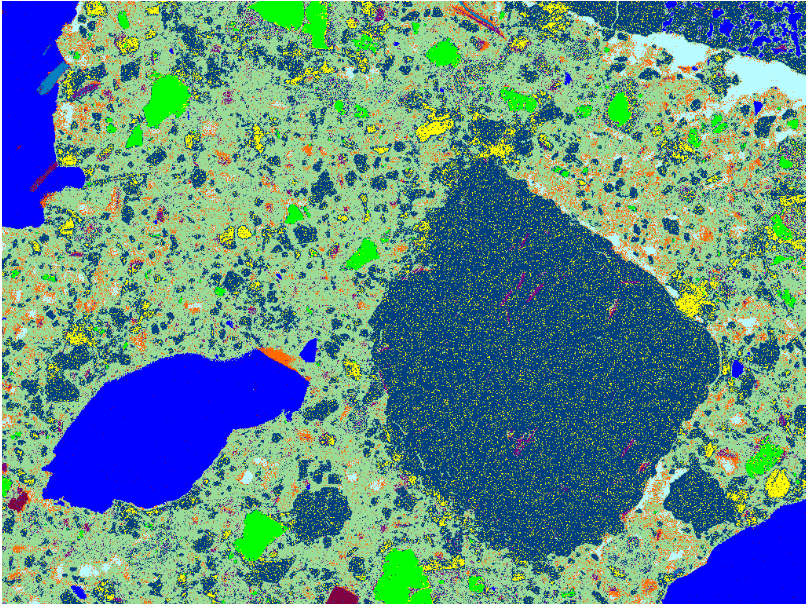


SVM on the denoised data after correction of the training

L. Drumetz, M. Dalla Mura, S. Meulenyzer, S. Lombard, and J. Chanussot, "**Semiautomatic classification of cementitious materials using scanning electron microscope images**," *Journal of Electronic Imaging*, vol. 24, no. 6, p. 061 109, 2015.

Classification of S.E.M. images based on Hierarchical Segmentation

...on concrete too!



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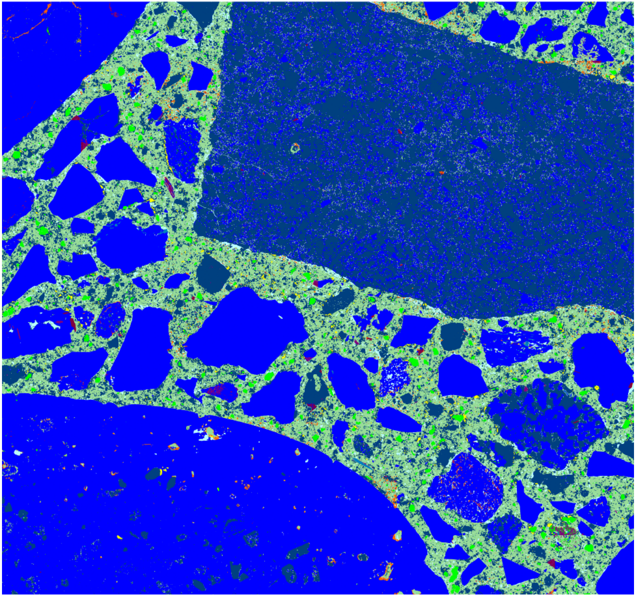

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2 Analysis of S.E.M. images based on Hierarchical Segmentation

3 Hierarchical segmentation of (EO) multimodal images
- Preliminaries
- Segmentation of multimodal images
- Results

4 Conclusion

Why hierarchies?

Regions/features of interest can often be defined at different scales.

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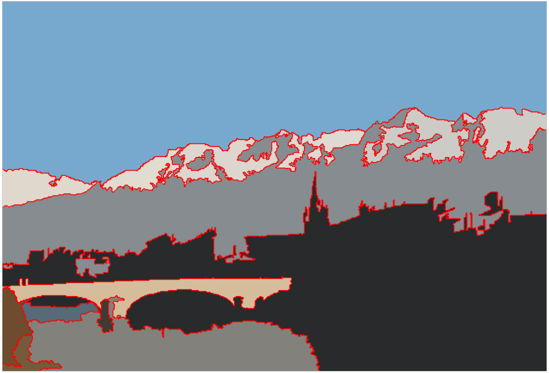

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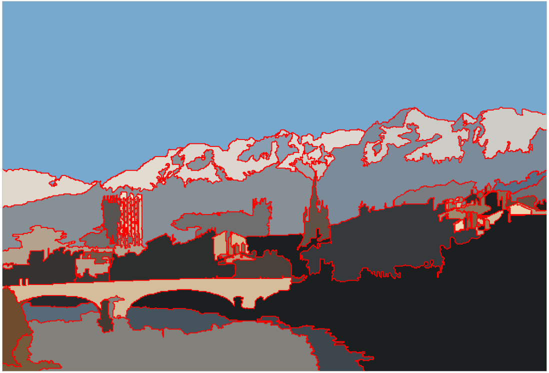

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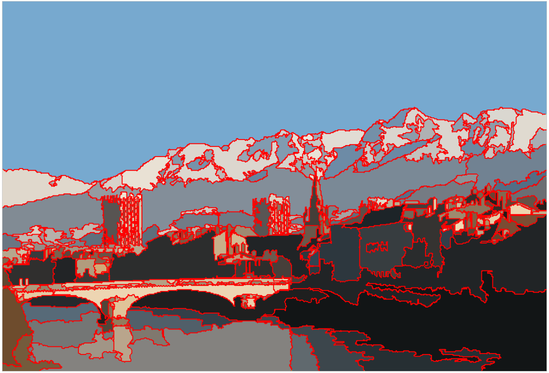


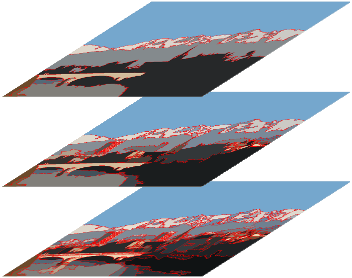
Why hierarchies?

Solution: represent them all in a hierarchical structure.

→ Can be built once, regardless of the application.

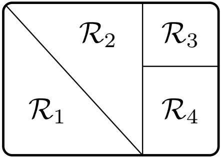
→ Flexible analysis, tuned afterwards depending on the goal.

hierarchical
⟹
representation



Partition π of E:

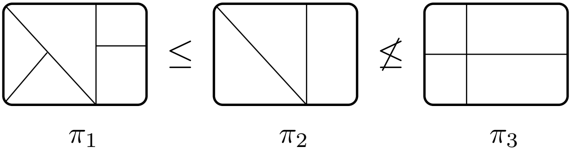
→ Collection of disjoint regions $\mathcal{R} \subseteq E$ whose union cover E.
Π_E : set of all partitions of E.



$$\mathcal{R}_i \cap \mathcal{R}_j = \emptyset$$
$$E = \bigcup_i \mathcal{R}_i$$

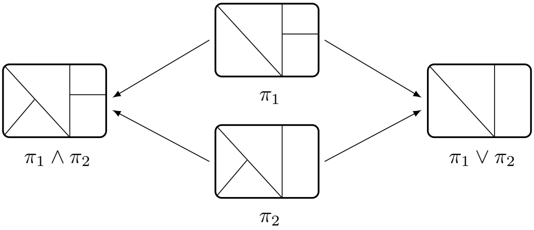
Partition π of E:

- → Collection of disjoint regions $\mathcal{R} \subseteq E$ whose union cover E.
  Π_E : set of all partitions of E.
- → Any two partitions may (or may not) be comparable with the refinement ordering $\leq$.



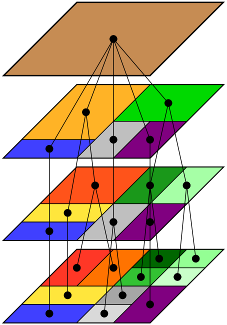
Partition π of E:

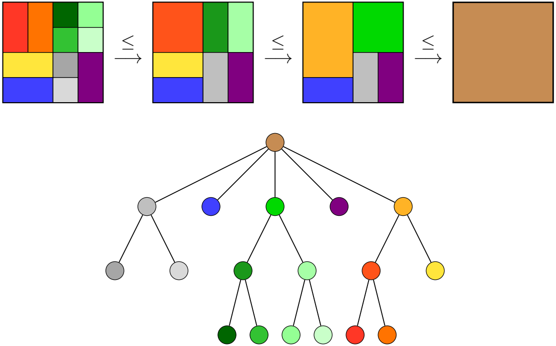
- → Collection of disjoint regions $\mathcal{R} \subseteq E$ whose union cover E.
  Π_E : set of all partitions of E.
- → Any two partitions may (or may not) be comparable with the refinement ordering $\leq$.
- → $(\Pi_E, \leq)$ is a lattice: any two partitions have a refinement *infimum* and refinement *supremum*.



A hierarchy of partitions H of E can be described as

- A sequence of partitions $H = \{\pi_i, i \in \{0, \ldots, n\}\}$ ordered by refinement: $0 \leq i \leq j \leq n \Rightarrow \pi_i \leq \pi_j$.
  π_0 is the *leaf* partition of H, and $\pi_n = \{E\}$ is the *root* of H.
- A collection of regions $H = \{\mathcal{R} \subseteq E\}$ such that $\emptyset \notin H$, $E \in H$, and for any two $\mathcal{R}_i, \mathcal{R}_j \in H$, $\mathcal{R}_i \cap \mathcal{R}_j \in \{\emptyset, \mathcal{R}_i, \mathcal{R}_j\}$.

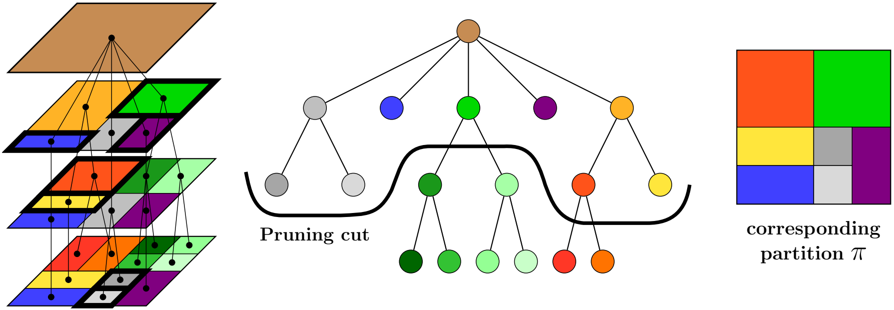




Cuts and partial partitions

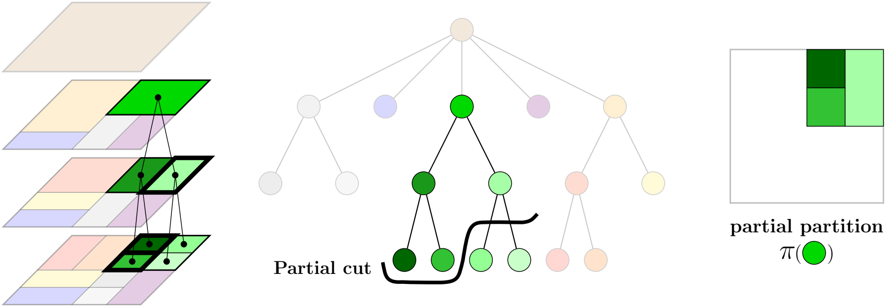
Cut

A cut of H is a partition π of E whose regions belong to H.
$\Pi_E(H)$ denotes the set of all cuts of a hierarchy of partitions H.



Partial partition

A partial partition $\pi(\mathcal{R})$ of a region $\mathcal{R} \in H$ is a cut of the sub-hierarchy $H(\mathcal{R})$ rooted at $\mathcal{R}$.



Segmentation by energy minimization

Energy of a partition

1. Define a regional energy: $\mathcal{E} : \mathcal{R} \subseteq E \mapsto \mathcal{E}(\mathcal{R}) \in \mathbb{R}^+$.
2. Compose the energy of the partition π w.r.t the energies of its regions:

$$\mathcal{E}(\pi = \{\mathcal{R}_i\}) = \underset{\mathcal{R}_i \in \pi}{\mathfrak{D}} \mathcal{E}(\mathcal{R}_i).$$

Optimal cut

The cut of H that is minimal (i.e., optimal) with respect to the energy $\mathcal{E}$ is defined as:

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Dynamic program and h-increasingness

Minimization of $\mathcal{E}$ on $\Pi_E(H)$ [Kiran & Serra, 2014]

Under assumptions of *singularity* and *h-increasingness* for $\mathcal{E}$, $\pi^\star$ is obtained by solving $\forall \mathcal{R} \in H$ the dynamic program:

$$\mathcal{E}^\star(\mathcal{R}) = \min\left\{\mathcal{E}(\mathcal{R}), \mathcal{E}\Big(\bigsqcup_{r \in \mathsf{S}(\mathcal{R})} \pi^\star(r)\Big)\right\}$$

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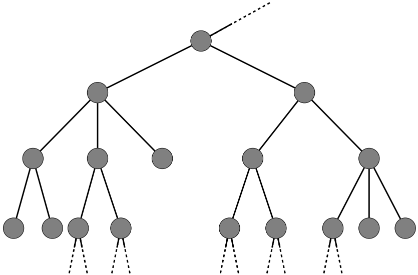

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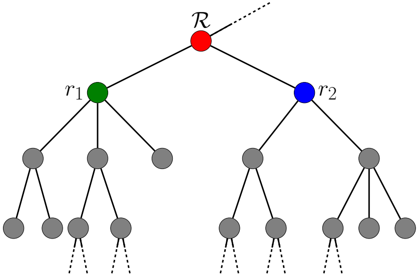

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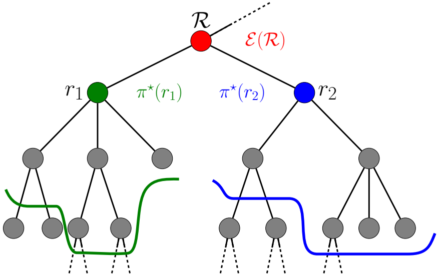

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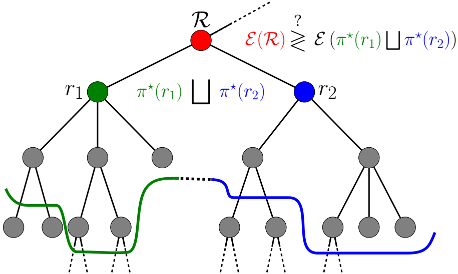

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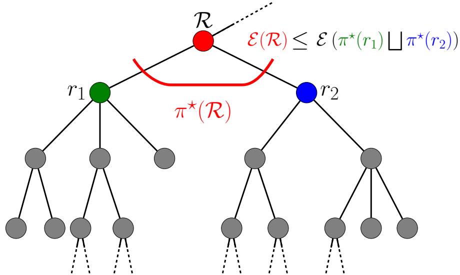

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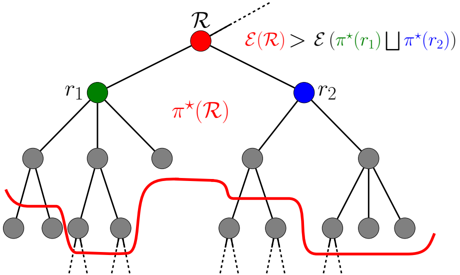

Persistence and scale-increasingness

Parametrized family of energies

Often in practice, the energy is parametrized by a positive real-valued parameter λ (e.g. Lagrange families $\mathcal{E}_\lambda(\pi) = \mathcal{E}_\phi(\pi) + \lambda\mathcal{E}_\rho(\pi)$).
$\{\mathcal{E}_\lambda\}_{\lambda\in\mathbb{R}+}$ therefore induces a family of optimal cuts $\{\pi^\star_\lambda\}_{\lambda\in\mathbb{R}+}$.

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Persistent hierarchy [Kiran & Serra, 2014]

Under the assumption of *scale-increasingness*, the optimal cuts can be ordered with λ, *i.e.*, $\lambda_1 \leq \lambda_2 \Rightarrow \pi^\star_{\lambda_1} \leq \pi^\star_{\lambda_2}$.
$H^\star$: **persistent** hierarchy of H, composed of all its optimal cuts with respect to $\mathcal{E}_\lambda$ when λ spans $\mathbb{R}^+$.

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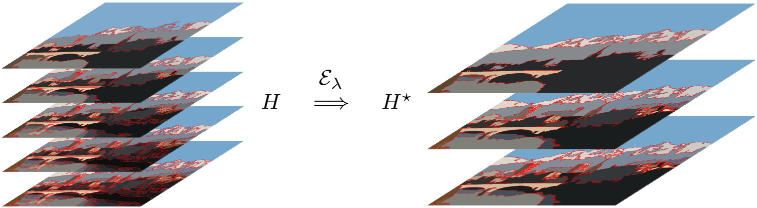
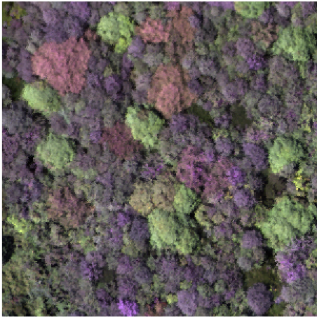
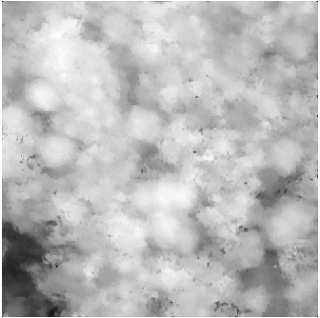
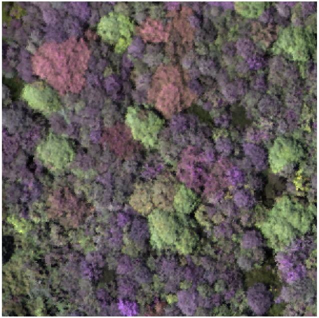
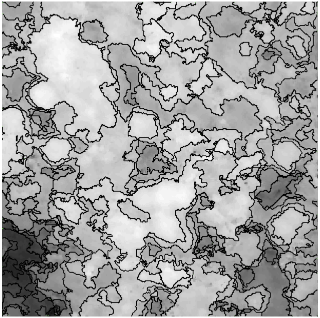
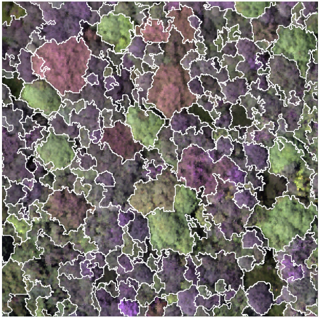


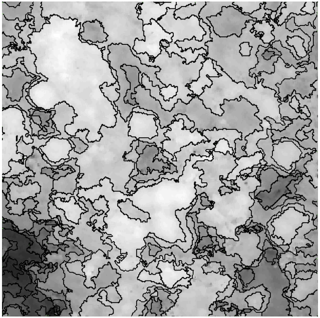






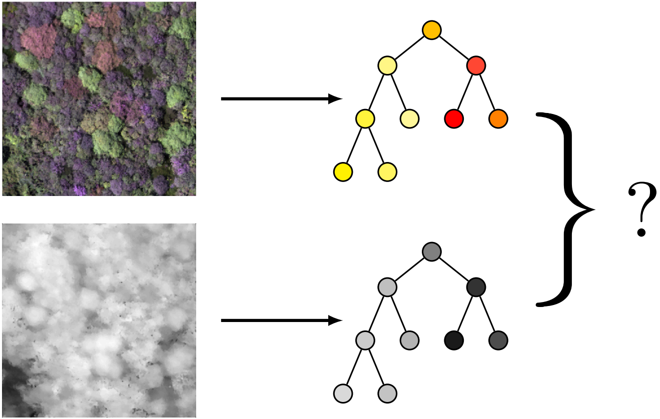






Sensorial multimodality

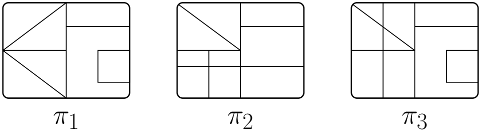
Multisource images

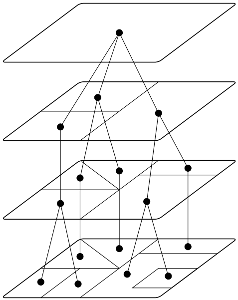


Braid [Kiran & Serra, 2015]

Let $B = \{\pi_i \in \Pi_E\}$ be some family of partitions. B is a braid iff there exists some hierarchy H_m, called monitor hierarchy, such that

$$\forall \pi_i, \pi_j \in B, \pi_i \vee \pi_{j \neq i} \in \Pi_E(H_m) \backslash \{E\}$$





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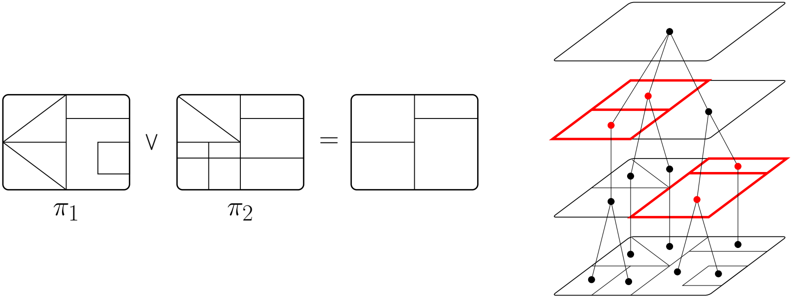

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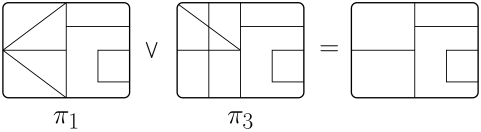

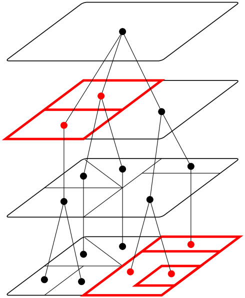

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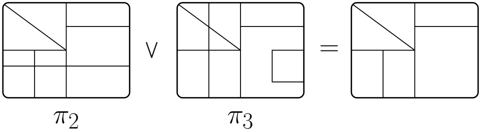

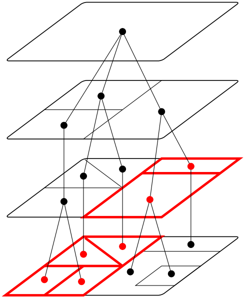

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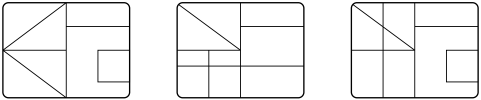
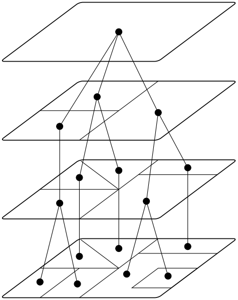


π_1 π_2 π_3

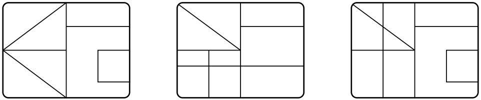


Provided that π_1, π_2 and π_3 are extracted from different modalities:

→ H_m encodes the redundant part of multimodal information.

→ B expresses the complementarity between modalities.

⇒ $B/H_m \Leftrightarrow$ hierarchical representation of multimodal image.



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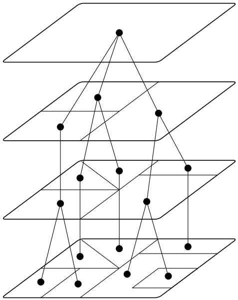
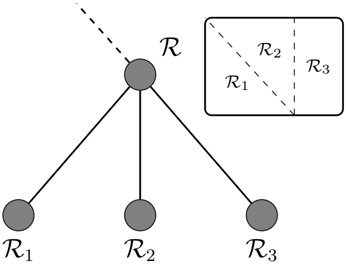


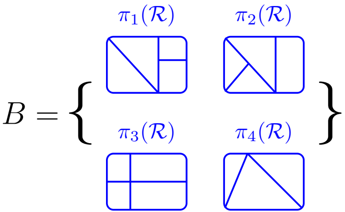
Braid of partitions
Optimal cut

Optimal cut [Kiran & Serra, 2015]

The optimal cut of a braid B is reached by solving $\forall \mathcal{R} \in H_m$:

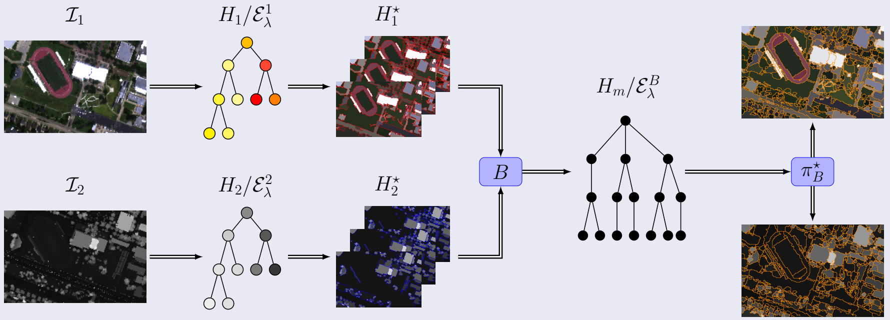
$$\mathcal{E}^\star(\mathcal{R}) = \min \left\{ \mathcal{E}(\mathcal{R}), \mathcal{E}\left(\bigsqcup_{r \in \mathsf{S}(\mathcal{R})} \pi^\star(r) \right), \bigwedge_{\pi_i(\mathcal{R}) \in B} \mathcal{E}(\pi_i(\mathcal{R})) \right\}$$





Construction of the braid

The ideal workflow



G. Tochon, "Hierarchical analysis of multimodal images," PhD Thesis.
https://www.archives-ouvertes.fr/tel-01242836v2/document

Consequence: for $B = \{H_1 = \{\pi_1^1 \geq \pi_1^2\}, H_2 = \{\pi_2^1 \geq \pi_2^2\}\}$ to be a braid, it is necessary (but not sufficient!) that $\pi_1^1 \overset{h}{\simeq} \pi_2^1$.

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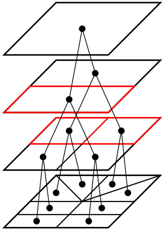
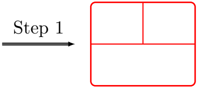
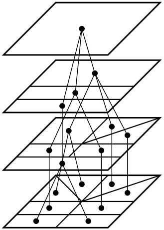
Procedure for the construction of the braid:



H_1



$\pi_1^1 \in \Pi_E(H_1)$



H_2

Construction of the braid

Composing the braid from two hierarchies

Consequence: for $B = \{H_1 = \{\pi_1^1 \geq \pi_1^2\}, H_2 = \{\pi_2^1 \geq \pi_2^2\}\}$ to be a braid, it is necessary (but not sufficient!) that $\pi_1^1 \overset{h}{\simeq} \pi_2^1$.

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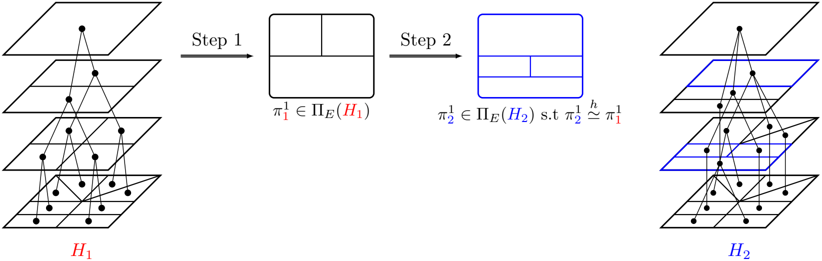

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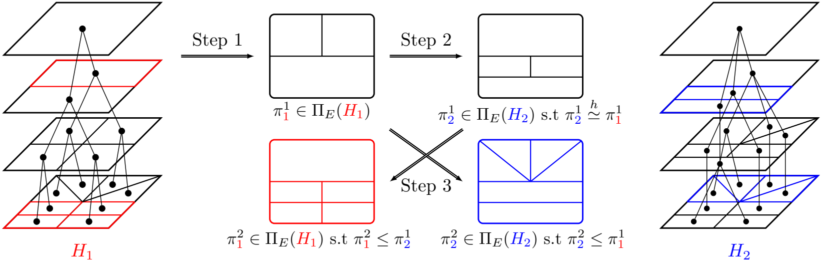

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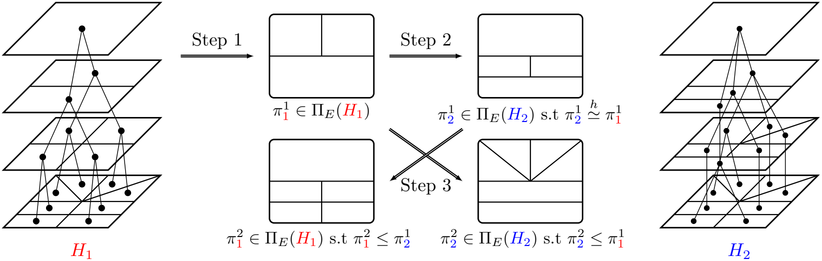
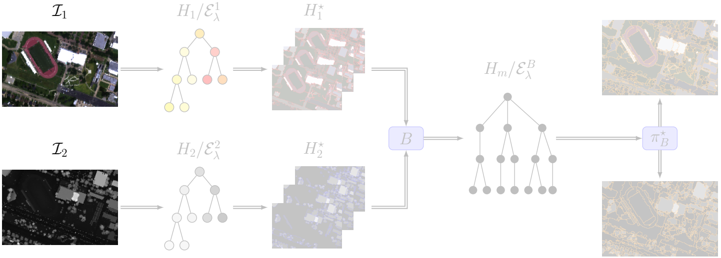


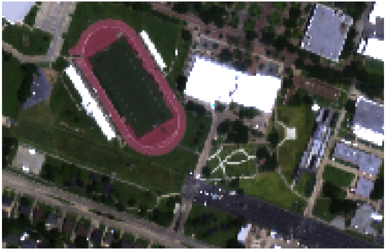
$\Longrightarrow B = \{\pi_1^1, \pi_1^2, \pi_2^1, \pi_2^2\}$ has a braid structure.

Braid-based multimodal segmentation

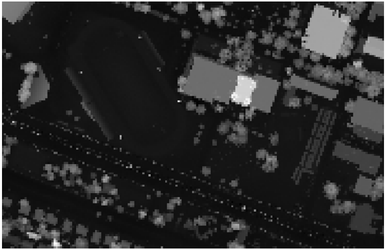
Experimental setup

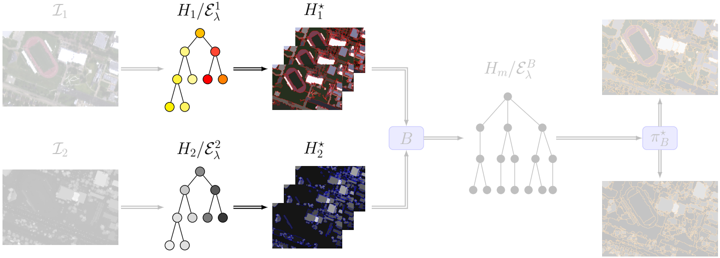


$\mathcal{I}_1$: 144 bands hyperspectral image



$\mathcal{I}_2$: LiDAR-derived digital surface model



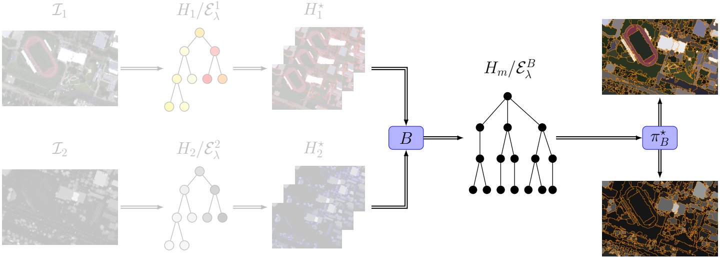


↪ H_i: binary partition tree built on $\mathcal{I}_i$, with standard parameters.

↪ $\mathcal{E}^i_\lambda$: Piecewise constant Mumford-Shah model:

$$\mathcal{E}^i_\lambda(\pi) = \sum_{R\in\pi} \left(\Xi_i(\mathcal{R}) + \frac{\lambda}{2}|\partial\mathcal{R}| \right) \text{ with } \Xi_i(\mathcal{R}) = \sum_{\mathbf{x}\in\mathcal{R}} \|\mathcal{I}_i(\mathbf{x}) - \boldsymbol{\mu}_i(\mathcal{R})\|_2^2$$

↪ $H^\star_i$: persistent hierarchy of H_i w.r.t $\mathcal{E}^i_\lambda$.

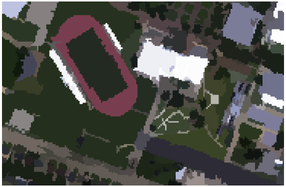
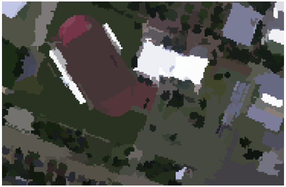
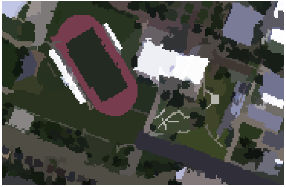
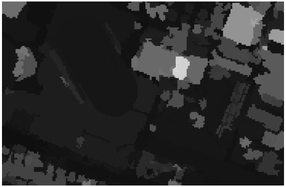
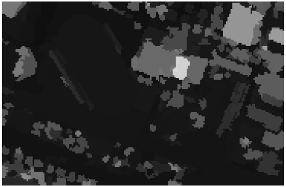


↪ B: constructed as previously described.

↪ $\mathcal{E}^B_\lambda$: proposed multimodal piecewise constant Mumford-Shah energy:

$$\mathcal{E}^B_\lambda(\pi) = \sum_{\mathcal{R}\in\pi}\left(\max\left(\frac{\Xi_1(\mathcal{R})}{\Xi_1(\mathcal{I}_1)}, \frac{\Xi_2(\mathcal{R})}{\Xi_2(\mathcal{I}_2)}\right) + \frac{\lambda}{2}|\partial\mathcal{R}|\right)$$

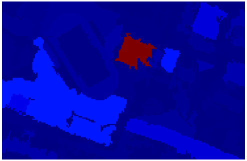
↪ $\pi^\star_B$ extracted from H_m by setting λ empirically/to achieve a constrained number of regions.

Hyperspectral optimal cut	LiDAR optimal cut	Braid optimal cut
		
$\pi_1^\star$ (325 regions)	$\pi_2^\star$ (325 regions)	$\pi_B^\star$ (325 regions)
		

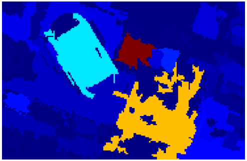
Braid-based multimodal segmentation

Results

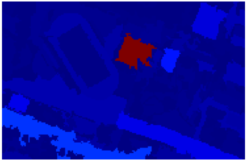
average GOF value: $\epsilon(\pi|\mathcal{I}_i) = \frac{1}{|E|}\sum_{\mathcal{R}\in\pi} |\mathcal{R}| \times \Xi_i(\mathcal{R})$



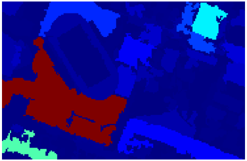
$\epsilon(\pi_1^\star|\mathcal{I}_1) = 52.5$



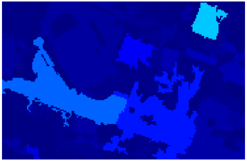
$\epsilon(\pi_2^\star|\mathcal{I}_1) = 145.4$



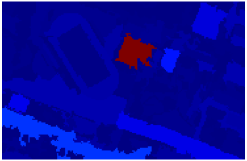
$\epsilon(\pi_B^\star|\mathcal{I}_1) = \mathbf{48.5}$



$\epsilon(\pi_1^\star|\mathcal{I}_2) = 3884.5$



$\epsilon(\pi_2^\star|\mathcal{I}_2) = 1224.8$



$\epsilon(\pi_B^\star|\mathcal{I}_2) = \mathbf{994.9}$

Conclusion and perspectives

- Hierarchical Segmentation, proved to be effective for phase identification in S.E.M. images
- The supervised classification approach proposed based on hierarchical segmentation and user's interaction is currently in use at LafargeHolcim R&D center
- The proposed technique of hierarchical segmentation of multimodal images led promising results on EO images
- ... test it on S.E.M. images

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Conclusion and perspectives

- Hierarchical Segmentation, proved to be effective for phase identification in S.E.M. images
- The supervised classification approach proposed based on hierarchical segmentation and user's interaction is currently in use at LafargeHolcim R&D center
- The proposed technique of hierarchical segmentation of multimodal images led promising results on EO images
- ... test it on S.E.M. images

Hierarchical segmentation of multimodal images

from Earth observation to the analysis of building geo-materials

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