Multi-Image Segmentation: A Collaborative Approach Based on Binary Partition Trees

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28 May 2015

12th International Symposium on Mathematical Morphology

Plan

Plan

Image processing / analysis

Segmentation

- **Crucial task** for image analysis
- 2 definitions:
  1. Extraction of objects of interest from image background

     Examples: Deformable models, Graph-cuts
  2. Whole partition of the image support

     Examples: Connected operators [Salembier and Wilkinson, 2009] (Watersheds, . . .), Split-and-merge
- **Principal invariant: "one algorithm applied on one image"**

(a) Image (b) Partitioning

Image processing / analysis

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Ill-posed problem

Results from one image may not be completely satisfactory
⇒ Relevance of relaxing the "one image, one algorithm" paradigm

Segmentation fusion

Extension of the "one image, one algorithm" paradigm

- "*n* images, one algorithm" ⇒ enrich / improve the input information

  Examples: Pansharpened satellite image segmentation, Multi-source image segmentation

- "one image, *n* algorithms" ⇒ enrich / improve the output information

  Examples: Consensus approach between various methods, Mono-algorithmic stochastic approach

Main interest

- Obtaining **a more accurate segmentation from several segmentation maps**

Segmentation fusion

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Related works

- Geometrical problem of interpolation [Rohlfing and Maurer Jr., 2007, Vidal et al., 2007]
- Stochastic watersheds/minimum spanning forest [Angulo and Jeulin, 2007, Bernard et al., 2012]
- Segmentation fusion based on random walkers [Wattuya et al., 2008]
- Models of consensus and weak partitions [Topchy et al., 2005]
- Image segmentation fusion using general ensemble clustering methods [Franek et al., 2010]

Morphological hierarchies

Hierarchical segmentation

- Classical trees by fusion of flat zones
  - Component-trees [Salembier et al., 1998]
  - Trees of shapes [Monasse and Guichard, 2000]

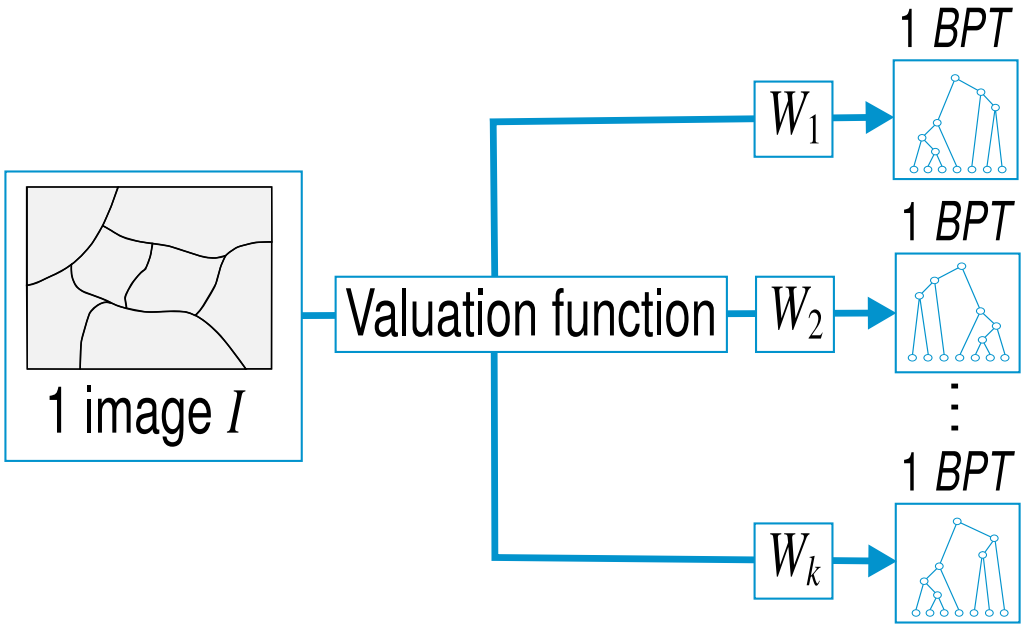
Drawbacks of classical morphological trees

- High dependency with the spectral information of the image
  - One image ⇒ one tree

Morphological hierarchies

Hierarchical segmentation

- Binary Partition Tree (BPT) [Salembier and Garrido, 2000]



Specificity of the Binary Partition Tree (BPT) [Salembier and Garrido, 2000]

- Intelligence based on a prior knowledge of the user
  - One image ⇒ various potential BPTs according to the metric used
  - Often used on remote sensing images segmentations [Vilaplana et al., 2008, Benediktsson et al., 2011]

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BPT tuning for *n* satellite images: related works

- Multi-resolution satellite images [Kurtz et al., 2012]
- Multiple morphological hierarchy [Akcay and Aksoy, 2008]
- Time series processing with BPT [Alonso-González et al., 2014]

Multi-image

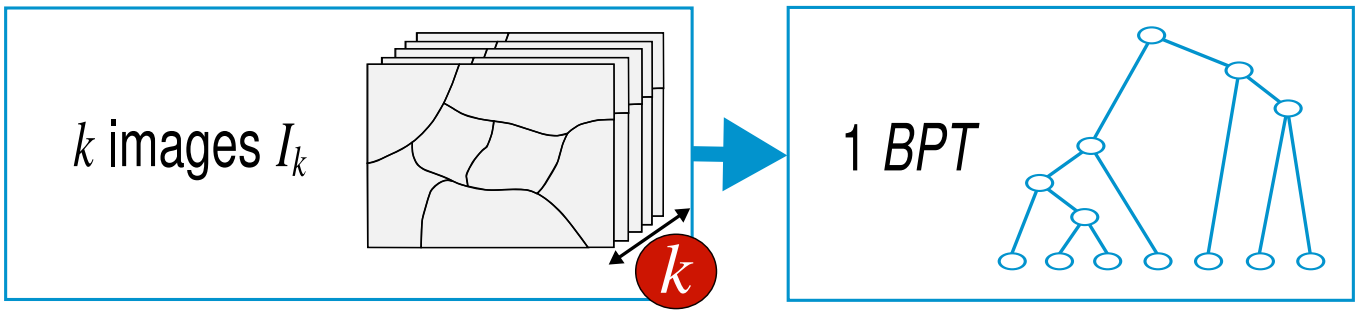
Interest of using multi-image

- Complementarity of available data (multi-resolution, multi-spectral, multi-temporal . . .)
- Improvement of hierarchical segmentation

Contributions

New approach for creating a unified hierarchical segmentation space

1. **“n images, one algorithm” paradigm**
2. **Extension** of existing hierarchical model (BPT)
   - Possibility to tune the creation process
   - Often used in remote sensing
3. **Use of consensus strategies** (derived from the machine learning field)



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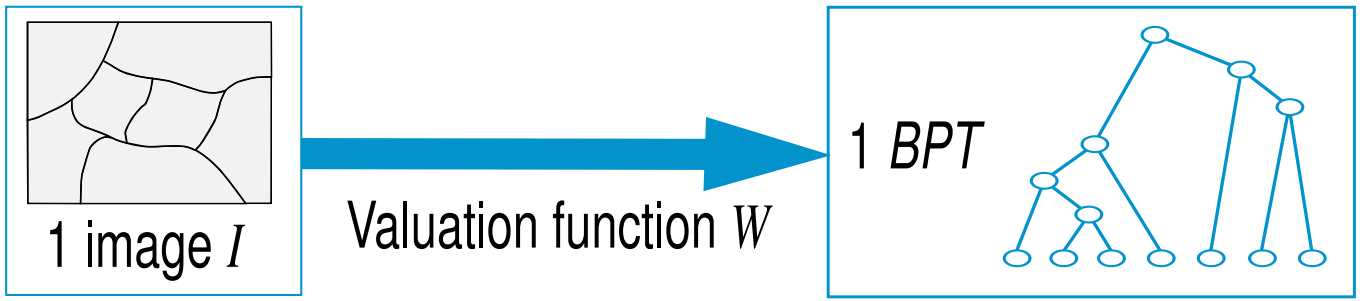
Mono-image Binary Partition Tree

General structure

A hierarchical representation of the regions contained in an image

- Leaves: elementary regions
- Nodes: fusion of two neighbouring regions
- Root: node representing the image support

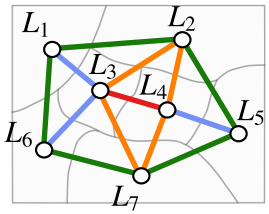
Creation based on a bottom-up algorithm



Mono-image BPT creation

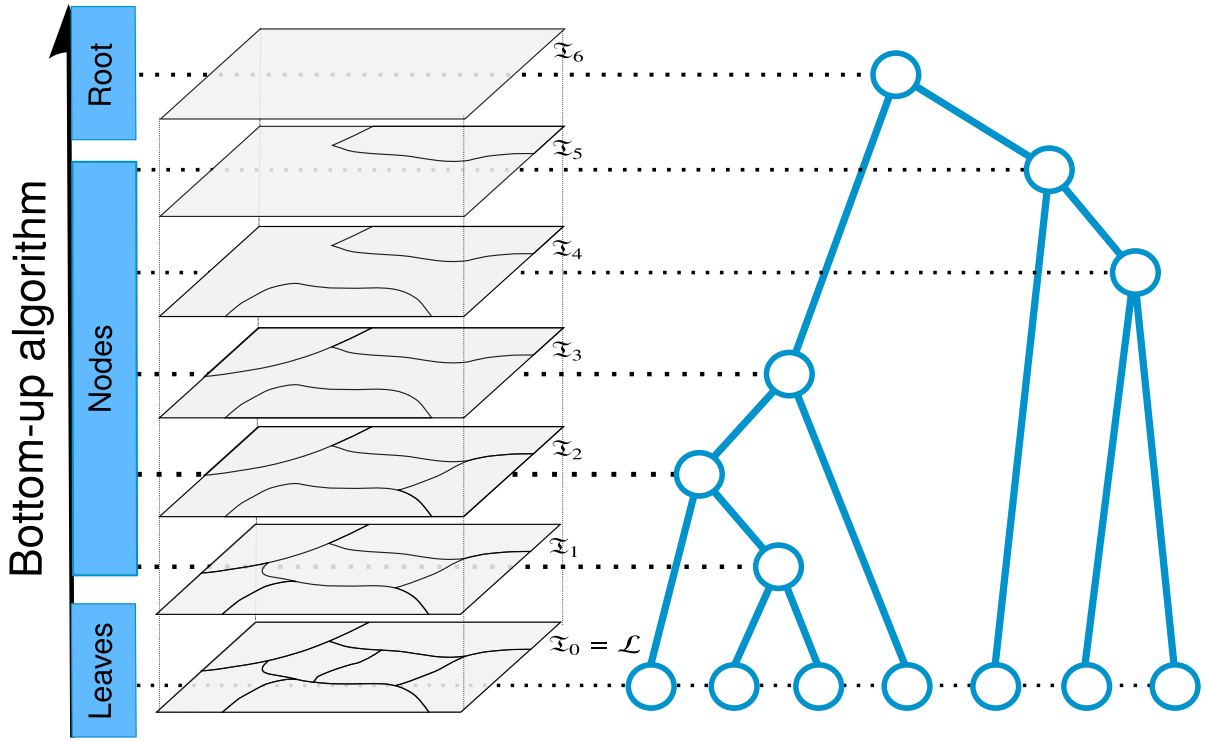
Input

One graph $\mathfrak{G}_{\mathcal{L}} = (\mathcal{L}, A_{\mathcal{L}})$



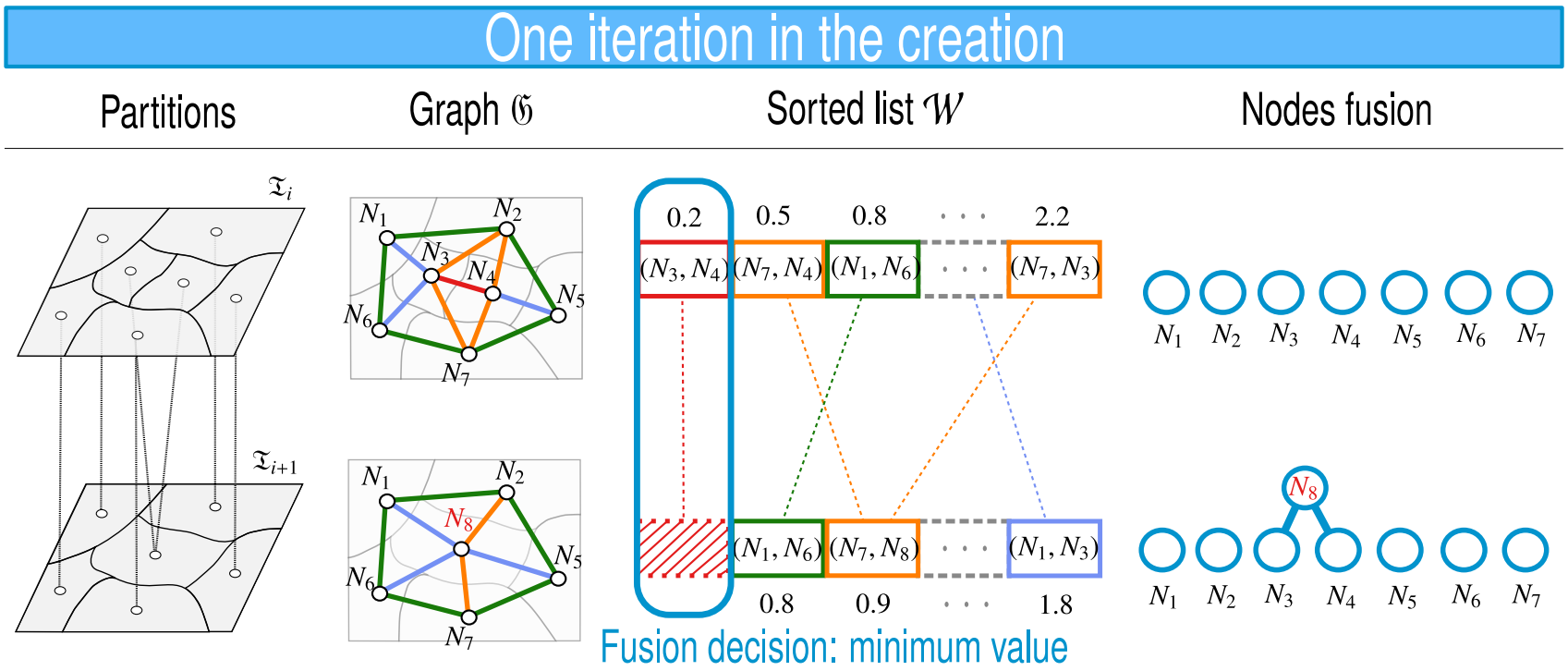
$\mathcal{L}$: initial partition of the image I
Each node $L \subseteq \mathcal{L}$ is connected with respect to $A_{\mathcal{L}}$ 1

One valuation function W
Computation of distances between neighbouring nodes 2



Mono-image BPT: one iteration in the creation

One iteration in the creation

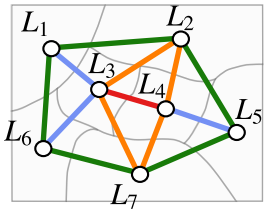


Removed edge | Merged edges | Updated edges | Non affected edges

Multi-images BPT creation

Input

One graph $\mathfrak{G}_{\mathcal{L}} = (\mathcal{L}, A_{\mathcal{L}})$



1

Valuation function W_j 2

Computation of distances between neighbouring nodes

k

Consensus strategy 3

Calculator

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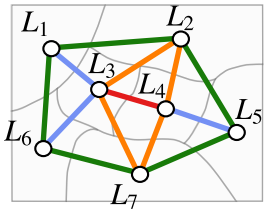
Construction process of the tree

Multi-images BPT creation

Input

One graph $\mathfrak{G}_{\mathcal{L}} = (\mathcal{L}, A_{\mathcal{L}})$



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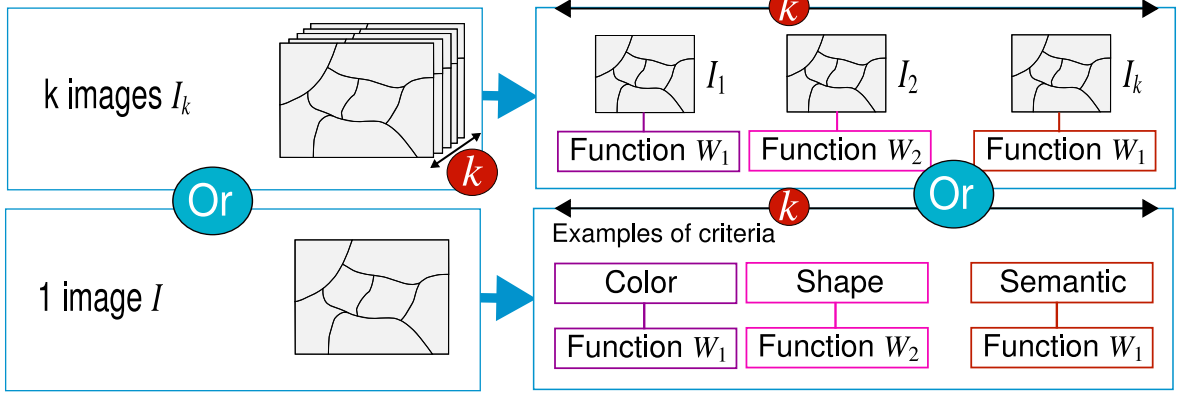
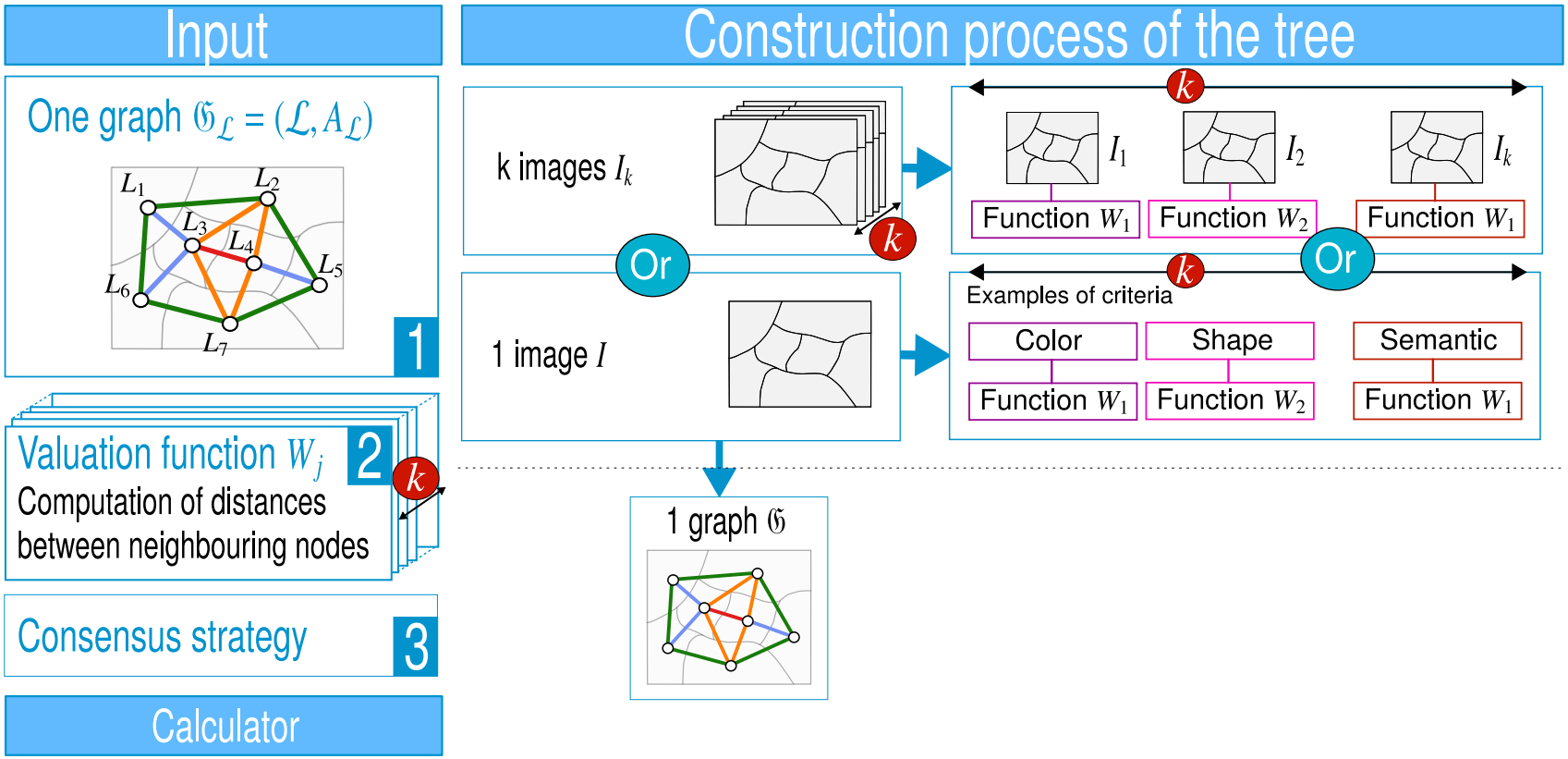


Multi-images BPT creation



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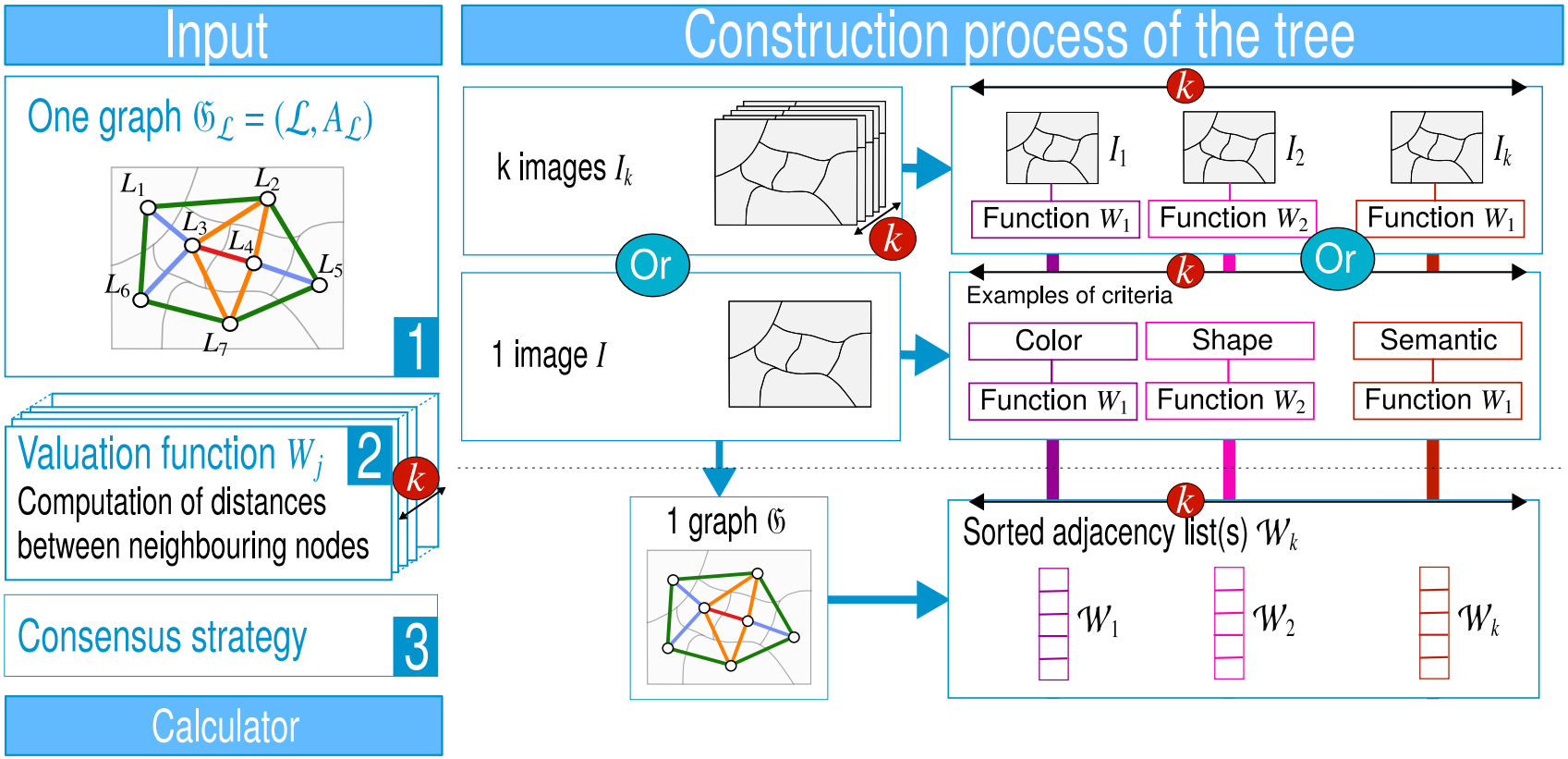

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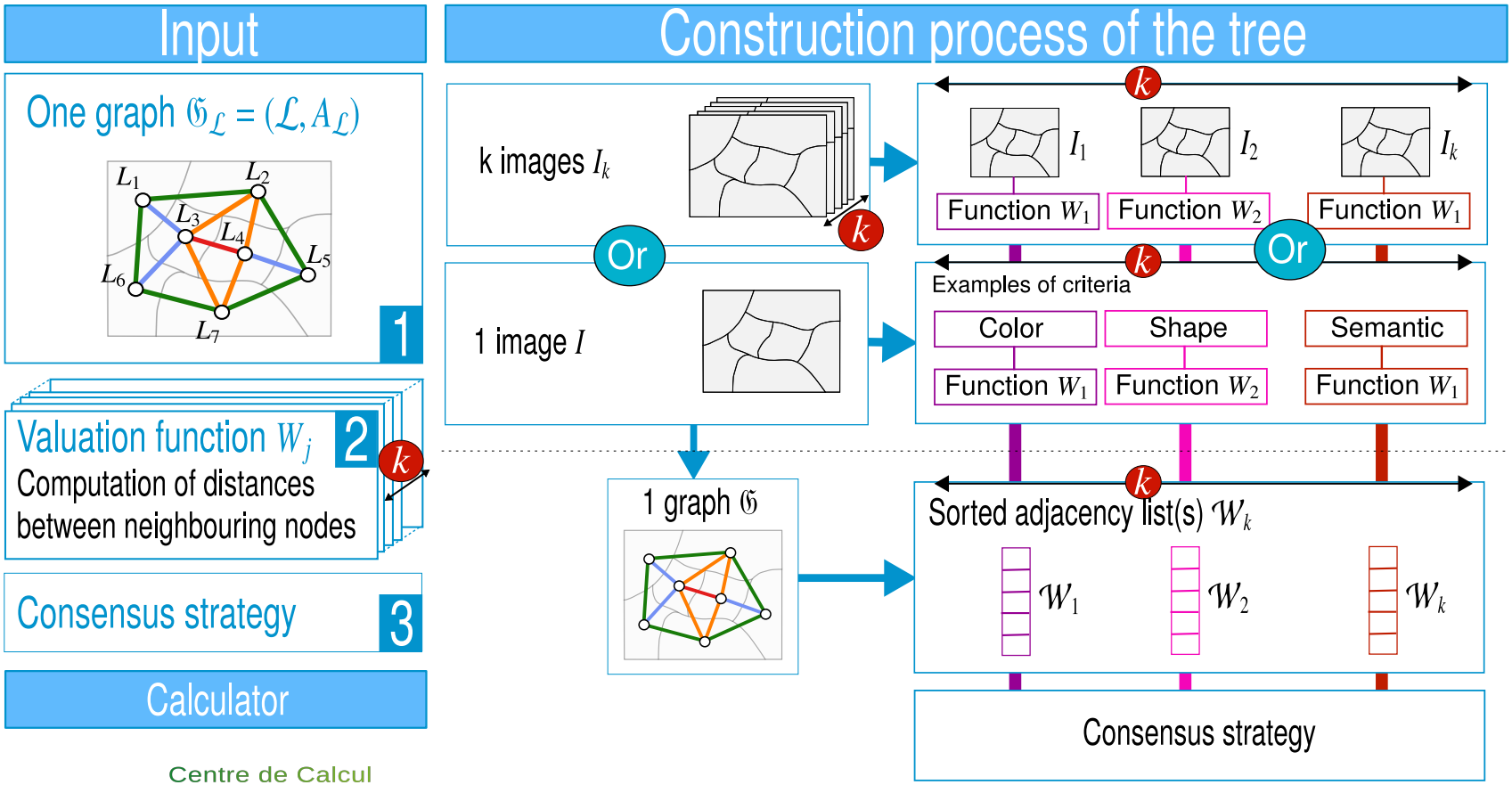

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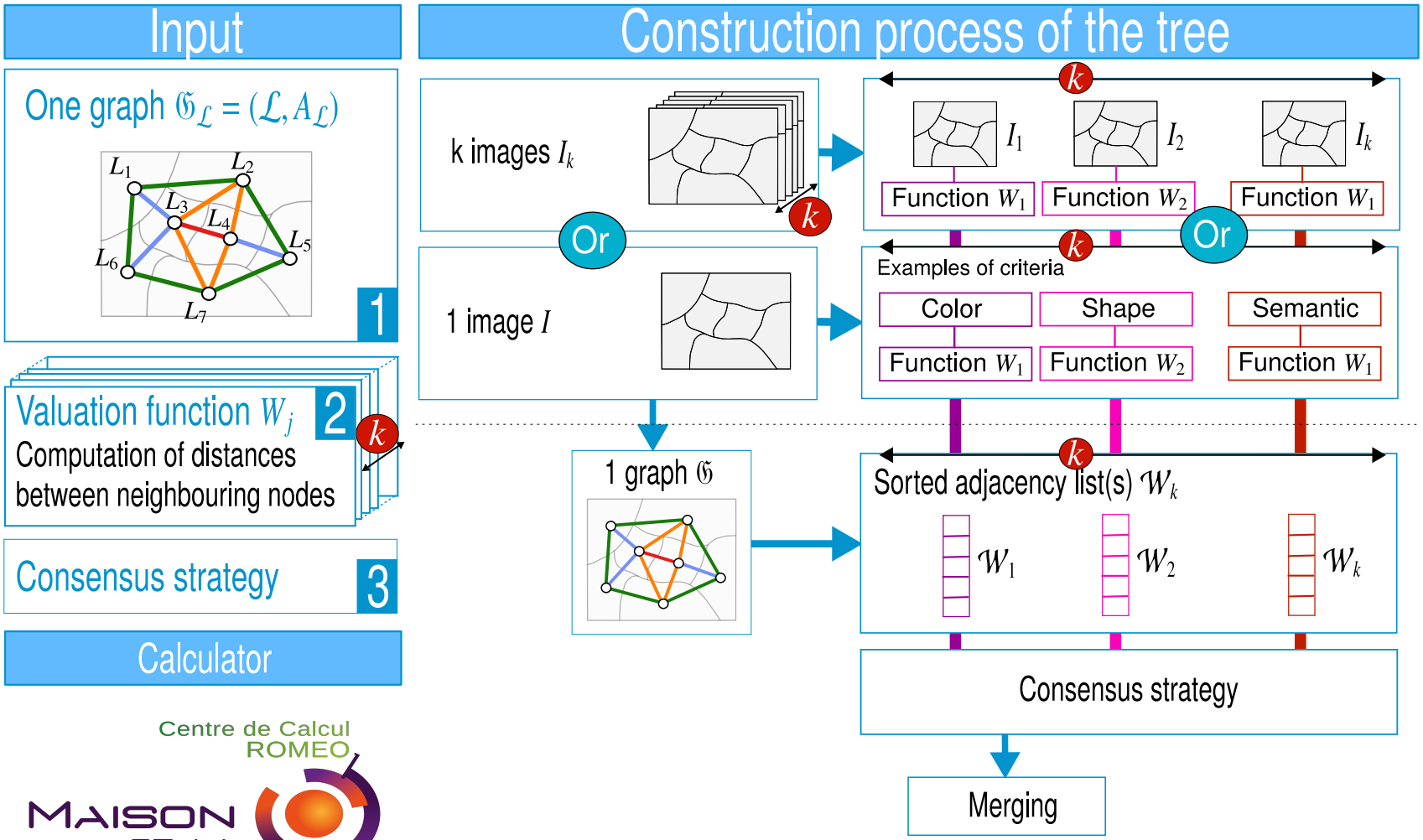

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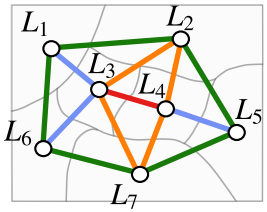

1

Valuation function W_j 2

Computation of distances between neighbouring nodes

Consensus strategy 3

Calculator

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Construction process of the tree

k images I_k

Or

1 image I

1 graph $\mathfrak{G}$

Update the graph $\mathfrak{G}$

- Remove the adjacency between the merged nodes and their neighbours
- Create adjacencies between the new node and its neighbours

I_1 I_2 I_k

Function W_1 Function W_2 Function W_1

Or

Examples of criteria

Color Shape Semantic

Function W_1 Function W_2 Function W_1

Sorted adjacency list(s) $\mathcal{W}_k$

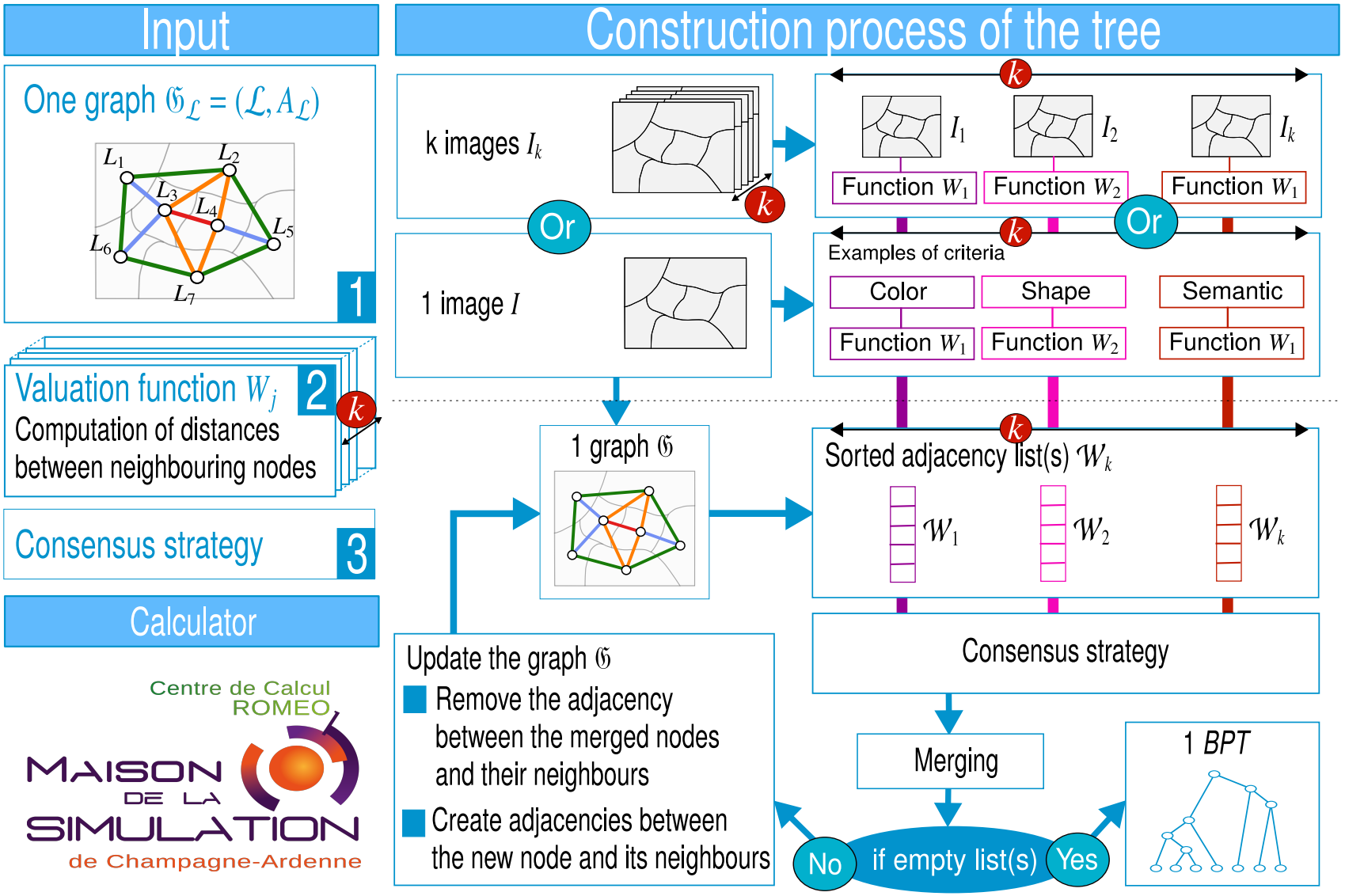
$\mathcal{W}_1$ $\mathcal{W}_2$ $\mathcal{W}_k$

Consensus strategy

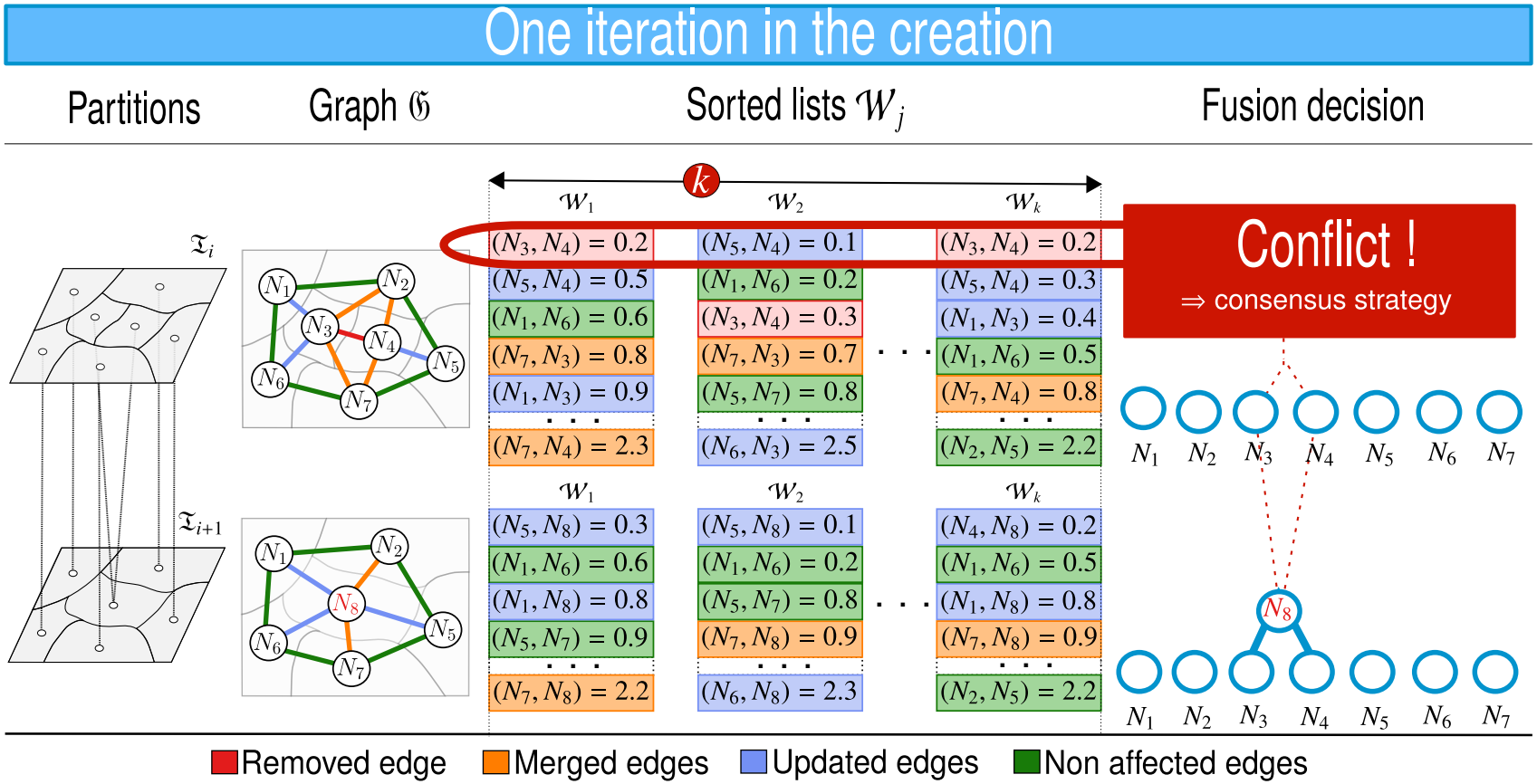
Merging

No if empty list(s)

Multi-images BPT creation



Multi-images BPT: one iteration in the creation

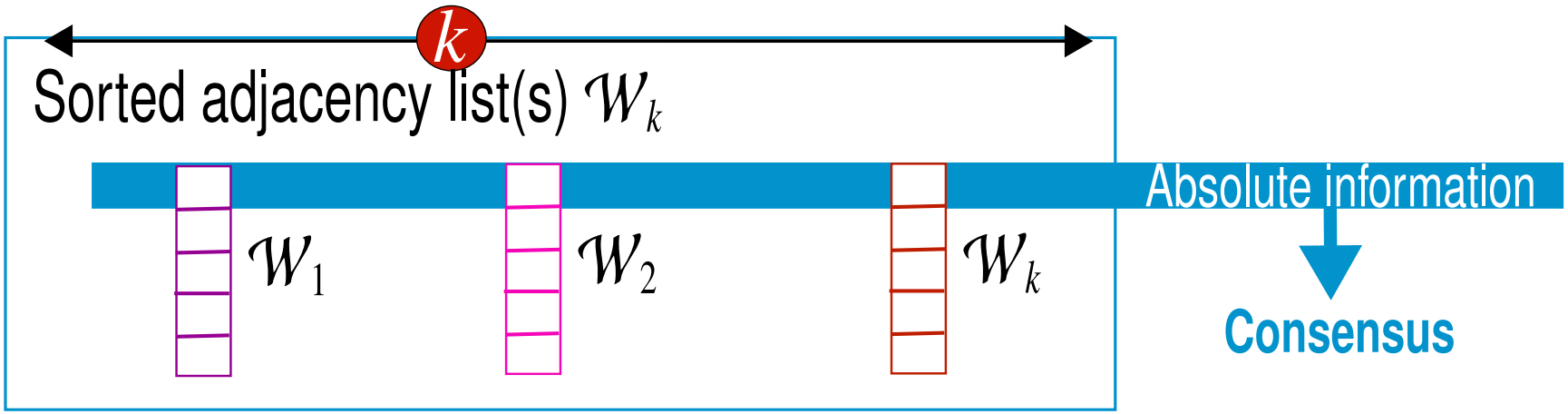


Consensus strategies

Absolute information consensus

The decision is made by considering the absolute information carried by the first edges of each list.

- *min of mean*
- *min of min*

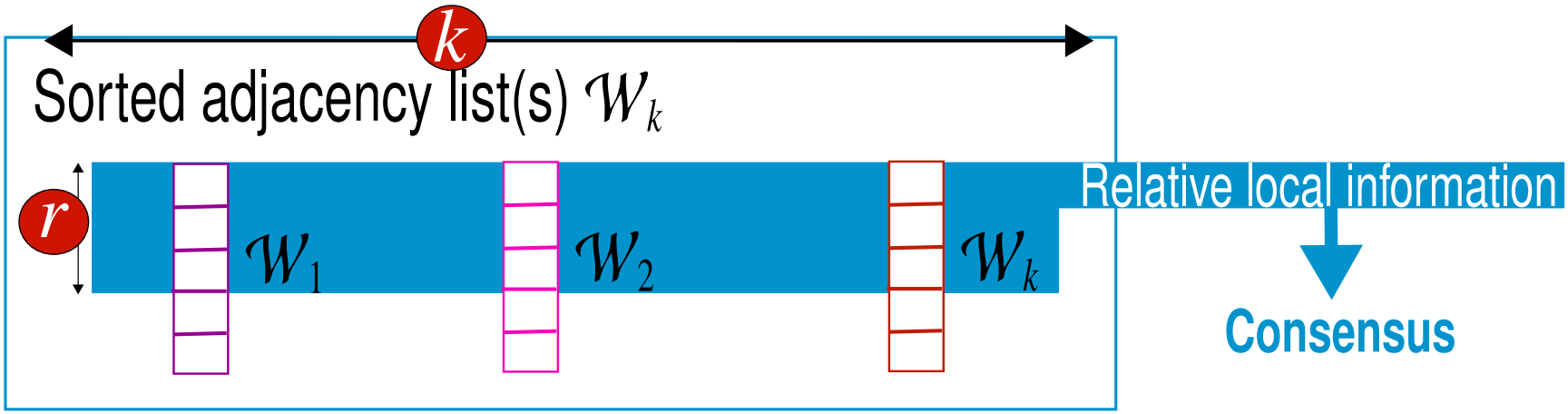


Consensus strategies

Relative local information consensus

For a restricted set of elements of each list, the decision is made by considering the relative position of the edges in the sorted lists.

- *majority vote*
- *most frequent (potentially weighted)*

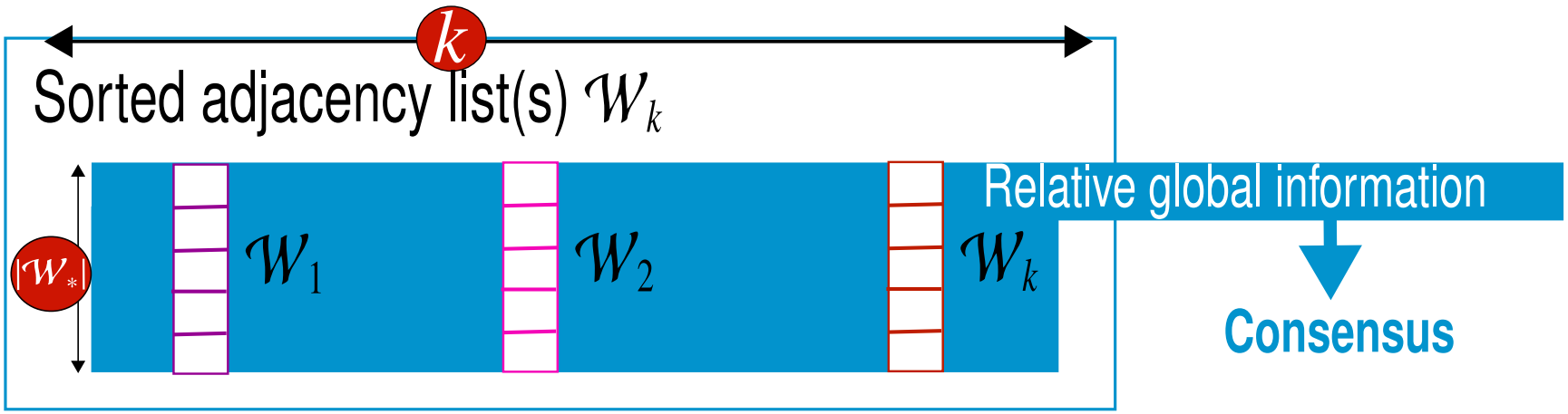


Consensus strategies

Relative global information consensus

The decision is made by considering the relative position of the edges in the whole content of all sorted lists.

- *best average*
- *best median ranking*



Plan

Experimental illustration

Context

Analysis of remote sensing satellite images

Applications

- One-time, one-sensor, several (noisy) images
  $\Rightarrow$ information retrieval despite image degradation
- Multi-time, one-sensor, one image per date
  $\Rightarrow$ redundant information

At this stage

- Basic choice of the BPT construction and segmentation approaches
  $\Rightarrow$ focus on the actual structural effects of multi-image BPT versus standard BPT
- Experiments considered as only toy-examples
  - No quantitative validation done (yet)
  - No fine parameter tuning carried out

Purpose

Giving the intuition of potential uses of the approach in the field of remote sensing

Urban noisy images


(c) Original


(d) Noised example

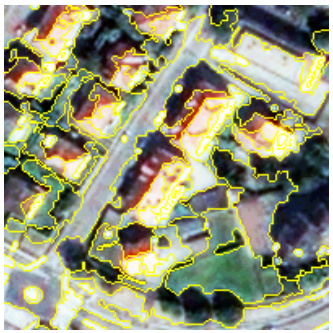
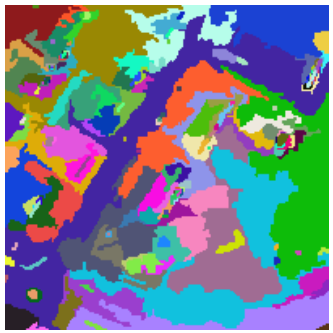
- **Data:** 7 noisy images generated with Gaussian ($\sigma = 10\%$) and speckle noise (5%)
- **Method:**
  - BPT creation from an initial partition $\mathcal{L}$ (one pixel per region)
  - Valuation function W_* used: increase of the ranges of the intensity values (for each radiometric band)
  - Consensus strategy: most-frequent (weighted) applied for the first 10% of the lists $\mathcal{W}_*$
  - Segmentation by a cut on the BPT (leading to 200 regions)

Figure: Experiment on zoomed samples (200×200 pixels) of noised Pléiades images (Gaussian noise ($\sigma = 10\%$) and speckle noise (5%)) of Strasbourg in 2012.

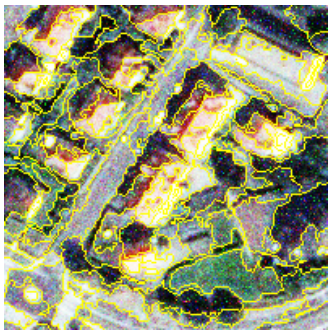
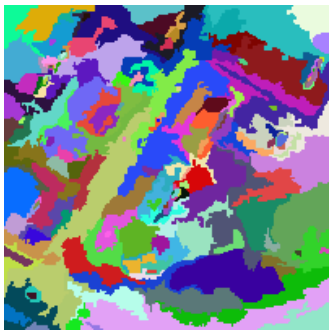
Urban noisy images


(a) Original


(b) Noised example

(c) Segmentation of (a)

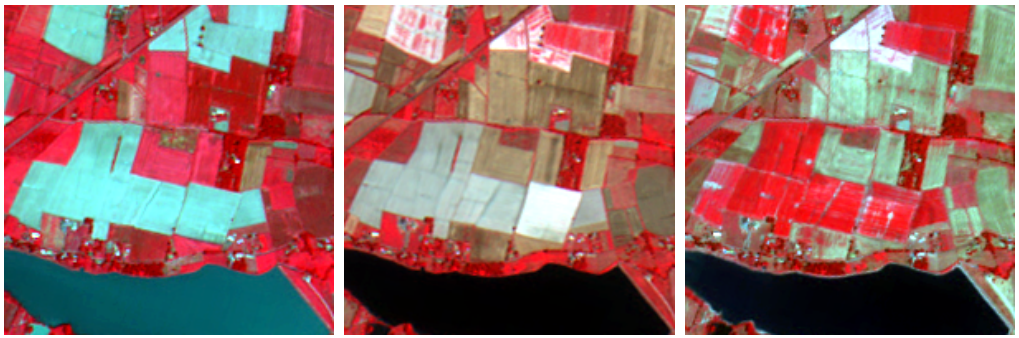



(d) Segmentation of (b + 6 noisy images)

- **Result:** slight degradation of the segmentation obtained from the 7 noisy images, but of comparable quality $\Rightarrow$ ability of the multi-image BPT-based segmentation to generate accurate results

Figure: Experiment on zoomed samples (200×200 pixels) of noised Pléiades images (Gaussian noise ($\sigma = 10\%$) and speckle noise (5%)) of Strasbourg in 2012.

Agricultural Image Time Series



(a) May (b) July (c) August

- **Data:** 3 agricultural images images of a time series
- **Method:**
  - BPT creation from an initial partition $\mathcal{L}$ (one pixel per region)
  - Valuation function W_* used: increase of the ranges of the intensity values (for each radiometric band)
  - Consensus strategy: most-frequent (weighted) applied for the first 10% of the lists $\mathcal{W}_*$
  - Segmentation by a cut on the BPT (leading to 105 regions)

Figure: Experiment on zoomed samples (200×200 pixels) of FORMOSAT-2 agricultural image time series of Toulouse in 2007.

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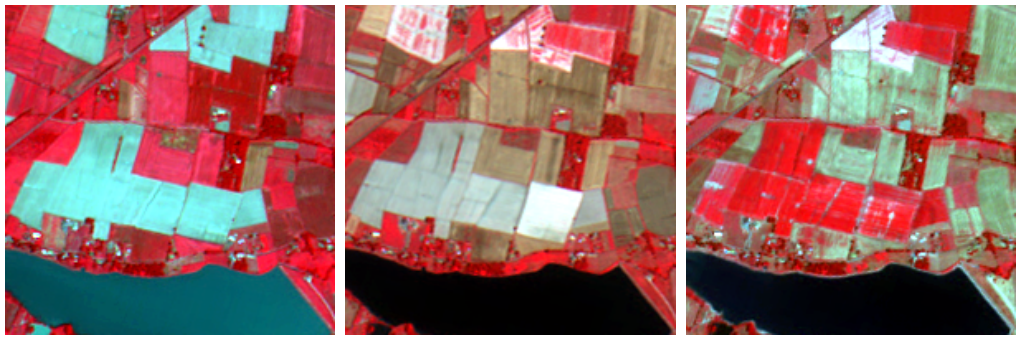

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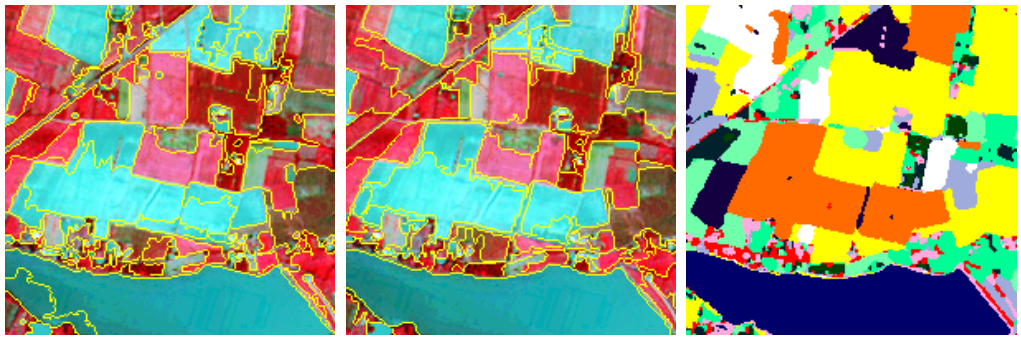

(d) Mono-image seg. (e) Multi-image seg. (f) Ground truth

- **Result:** Correction of some segmentation effects deriving from semantic noise in mono-image segmentation $\Rightarrow$ potential useful tool for such data

Figure: Experiment on zoomed samples (200×200 pixels) of FORMOSAT-2 agricultural image time series of Toulouse in 2007.

Plan

Conclusion

Contributions

- Presentation of an approach for building a unique BPT from several images
  - Proposition of a data-structure / algorithmic framework
  - Study of various consensus strategies
- Development of a prototype
- Experiments on multi-image satellite datasets
  - Quality of the morphological hierarchies ⇒ improving segmentation

Perspectives

- Integration of a higher-level consensus ⇒ improve the quality of the hierarchies
- Proposition of a consensual way of creating a BPT from several valuation functions
- Handling the multi-temporal aspect by using hyper-trees

Thanks for you attention!

Any questions?

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Paper reference: http://dx.doi.org/10.1007/978-3-319-18720-4_22