Morphological methods for multispectral and hyperspectral remote sensing

Sébastien Lefèvre

Univ. Bretagne-Sud & CNRS – IRISA, OBELIX team
http://www.irisa.fr/obelix

Blåtand Program – November, 2014

INSTITUT DE RECHERCHE EN INFORMATIQUE ET SYSTEMES ALÉATOIRES

UBS Université de Bretagne-Sud

UMR IRISA

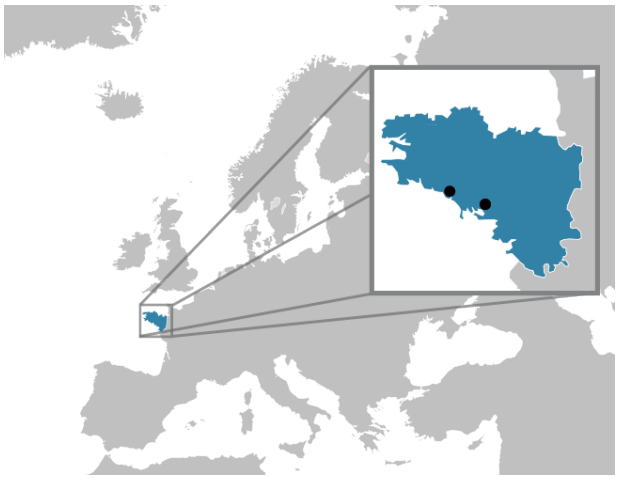
Outline

- My Research Environment: University, Institute, and Team
- Morphological Approaches
- Adaptation to multivariate data

Université de Bretagne-Sud – www.univ-ubs.fr

A recent and small university

- Officially created in 1995 in Vannes and Lorient (but faculties established in 70s)
- 8500+ students, 250+ faculty members (+150 lecturers)
- 4th French university for professional insertion



IRISA: Research Institute in Computer Science and Random Systems

The main research institute in computer science in Brittany

- Officially created in 1975 in Rennes (established in 1970)
- Joint research institute between:
  - CNRS
  - INRIA
  - Universities (Bretagne Sud, Rennes)
  - Graduate Schools (INSA, ENS, Telecom, Supelec)
- 700-800 members (including 250+ permanent researchers)
- staff in Vannes: 50+ members including 25 faculty members

Research at IRISA – www.irisa.fr

7 research departments

- Large-scale Systems;
- Networks, Telecommunications and Services;
- Architecture;
- Language and Software Engineering;
- Digital Signals and Images, Robotics;
- Media and Interactions;
- Data and Knowledge Management

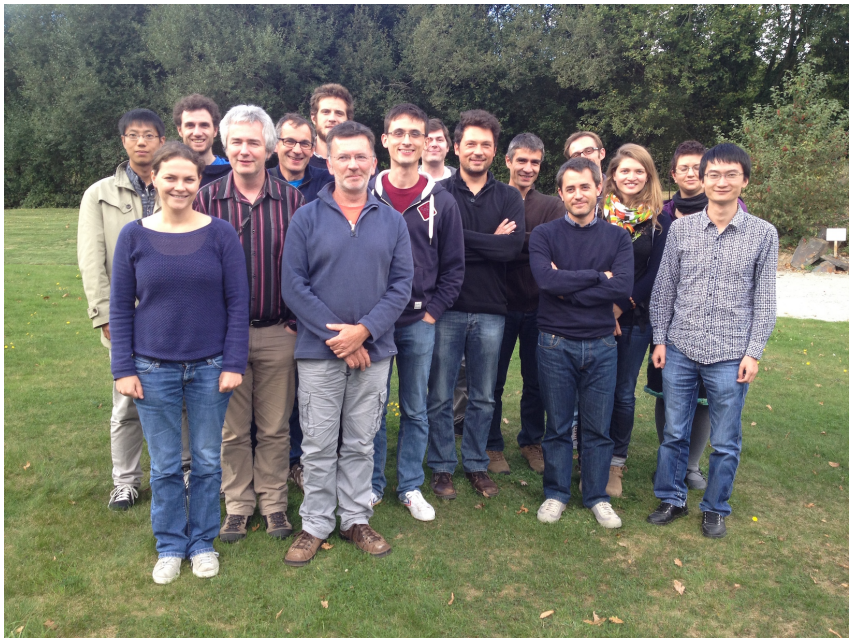
35-40 teams

4 (co)located in Vannes

- ARCHWARE
  software architectures;
- CASA
  mobile computing;
- EXPRESSION
  gesture/speech/text understanding
- and OBELIX.

The OBELIX team

- supported by UBS, UR2, CNRS
- closely related to OSUR & LETG Rennes
- located in Vannes & Rennes
- permanent staff (8): 1 Full Prof., 1 Research Director, 6 Ass.Prof.
- temporary staff (12): 6 PhD students (+ 3 defended 2014), 1 engineer + 2 postdocs
- **incoming open positions (Postdoc, PhD)**



Broceliande Forest, Oct. 13

Research at OBELIX – www.irisa.fr/obelix

Environment Observation through Complex Imagery

- image analysis and processing
- machine learning and data mining
- coupling physical models with observation data
- visual analytics
- in the context of remote sensing of environment

Challenges

- address complex data (multi*)
- exploit prior knowledge
- ensure scalability

Recent methodological achievements

- knowledge-driven features and models for description of multivariate data (MSc'14, WHISPERS'14, ICIP'14, ALCIP'13)
- efficient algorithms for hierarchical image representation and analysis (MSc'14, PRRS'14, ISMM'13, ICIAP'13, JVCIR'13)
- classification of time series (SAR, multispectral) (MSc'14, JARS'14)
- domain adaptation for classification of hyperspectral data (ECML'14, ICPR'14)
- manifold learning with few labeled samples (JSTARS'14)
- non-negative matrix factorization (ML'14), anomaly detection (ECML'14), manifold subsampling (GSI'13)

Active Projects & Grants

ASTERIX*	French National Research Agency ANR	275 k€
VEGIDAR*	French National Spatial Agency CNES	150 k€
RESIDUAL*	International Space Science Institute ISSI	38 k€
SENSE	Labex CominLabs	105 k€
Littoralg	Univ. Bretagne-Sud	48 k€

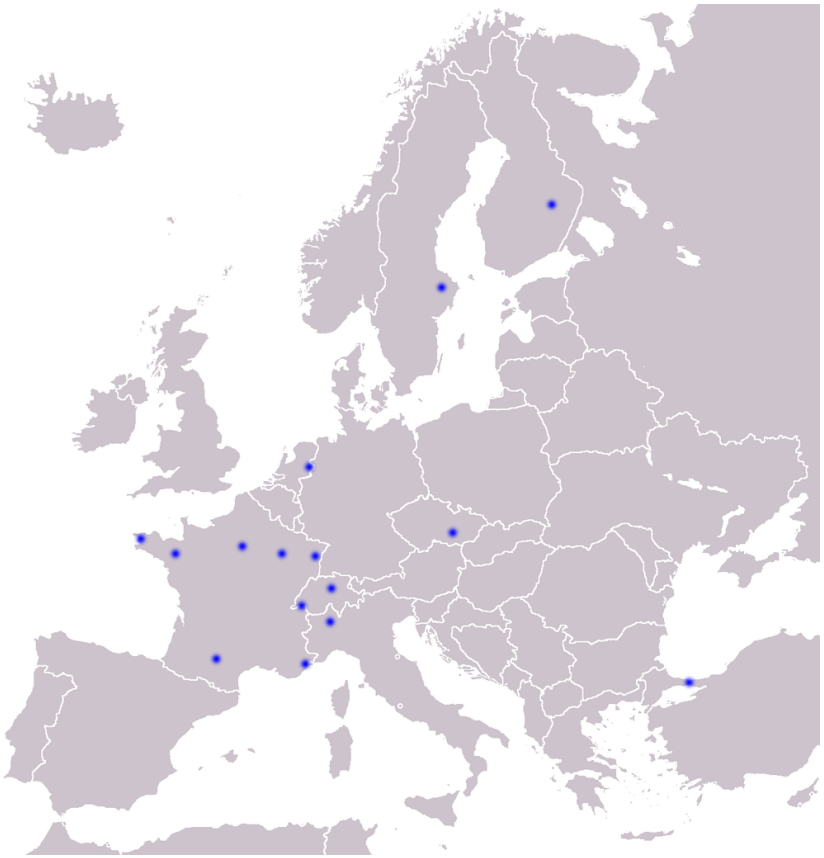
+ industrial contracts (MGDIS, WIPSEA, ACT-TER), ca. 60 k€

OBELIX acts as PI for starred projects

Publications (since 2012)

19 journal papers, 27 conference papers and 2 book chapters.
Available at `www.irisa.fr/obelix` and HAL repository

Collaborations



Researchers:

- Prof. Pasi Franti (UEF)
- Dr. Adam Herout (BUT)
- Dr. Erchan Aptoula (U Okan)
- Dr. Devis Tuia (EPFL / U Zurich)
- Dr. Cris Luengo (U Uppsala)
- Dr. Norman Kerle (ITC / U Twente)
- Prof. Baogang Hu (LIAMA Beijing)
- Prof. Tang Ping (CAS China)
- Prof. Daniel Racoceanu (IPAL / NUS Singapore)
- Dr. Suhaib Fahmy (NTU Singapore)

Visits & Stays: Uppsala, Joensuu, EPFL, LIAMA

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What is MM ?

Definition

- Theory introduced by Matheron and Serra in 1964
- Dedicated to analysis of spatial structures
- Basic operations: erosion, dilation by a structuring element (prehistoric morphology)

Famous toolbox of non-linear tools for image processing

- Filtering: opening, closing, ASF, reconstruction, attribute filters, connected filters, levelings
- Residue operators: gradients, top-hats
- Description: granulometry, covariance, DMP
- Template matching: hit-or-miss transform
- Segmentation: watershed, flat zones
- Hierarchical representations: inclusion trees and partition trees

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Binary case

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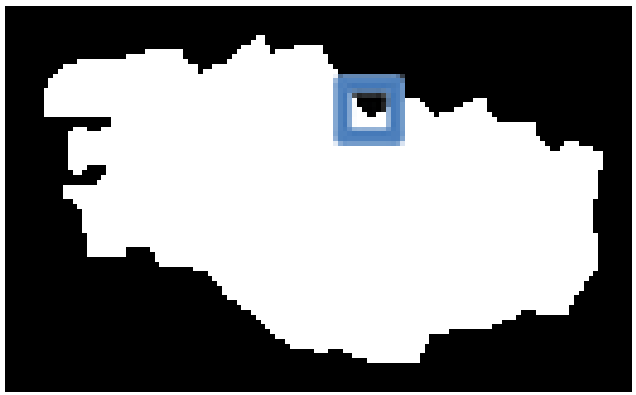

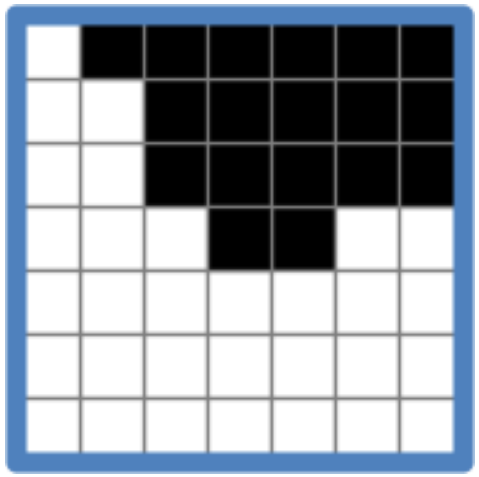

within a **structuring element** b

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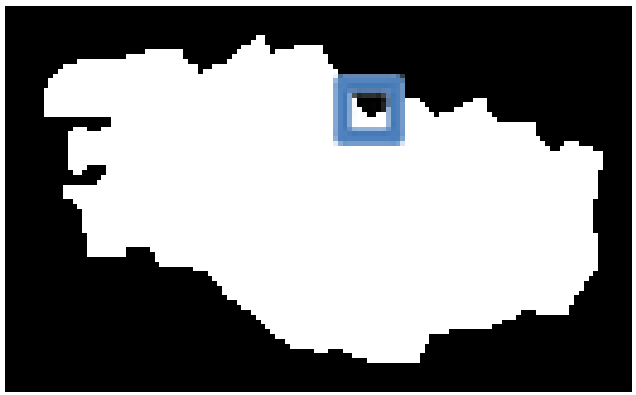

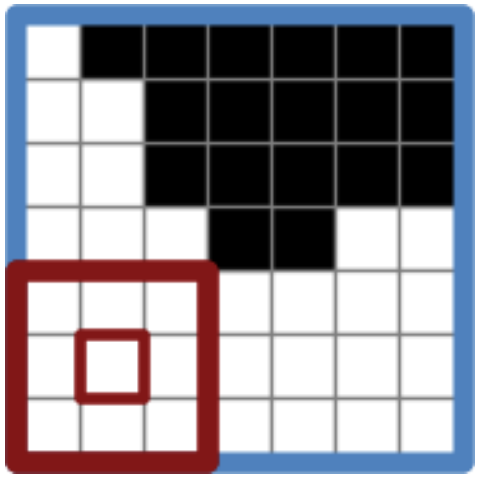

erosion ε shrinks objects

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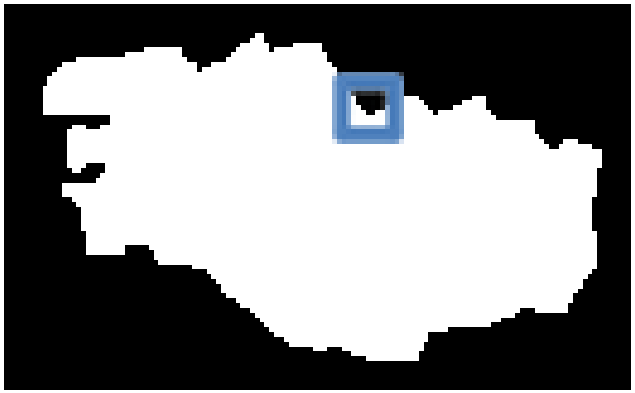

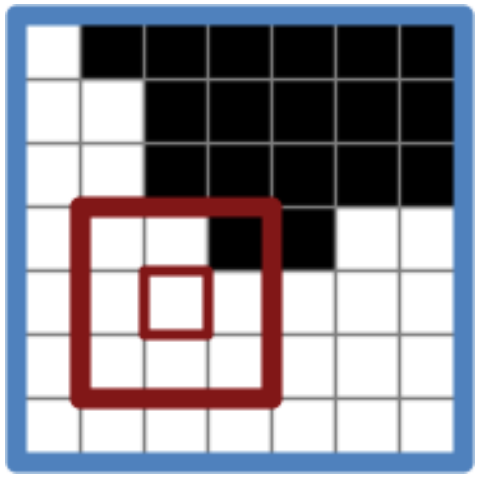

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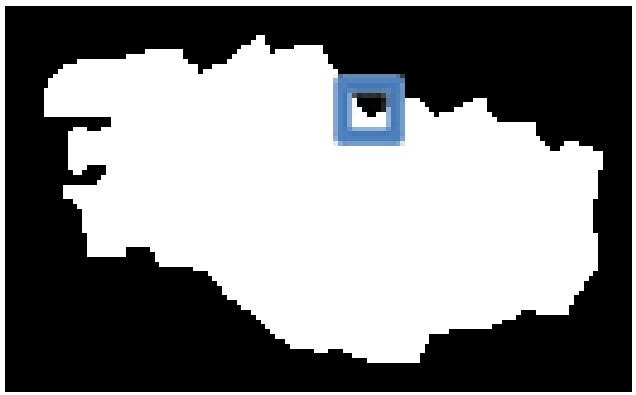

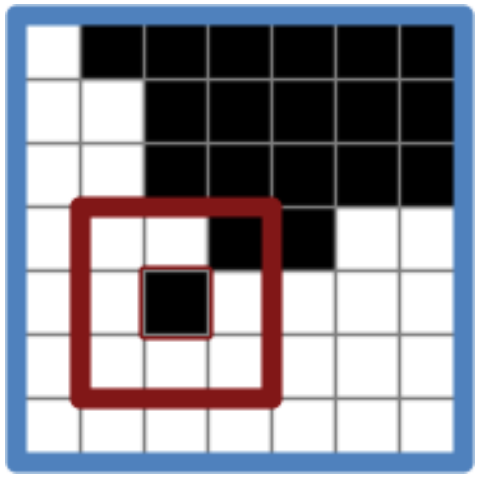

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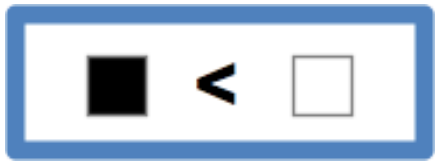

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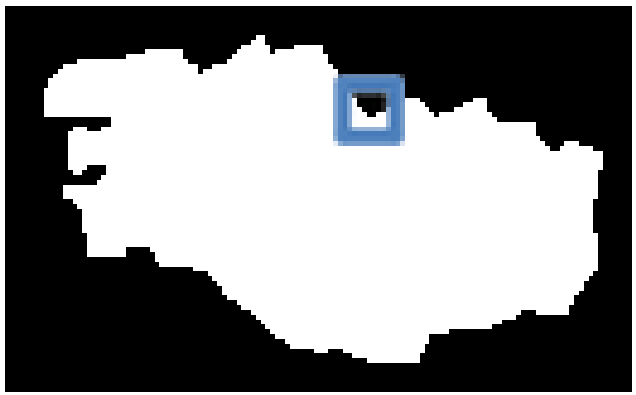

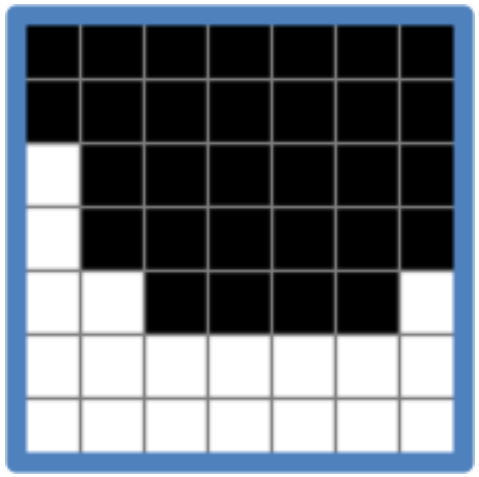

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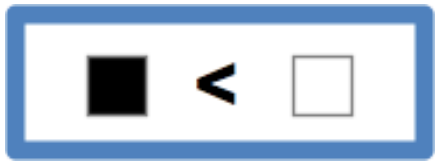

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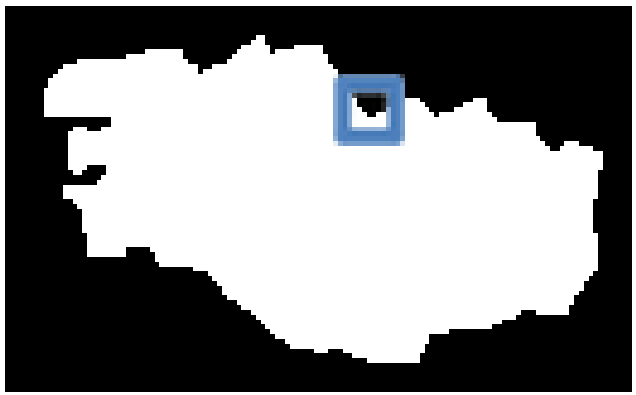

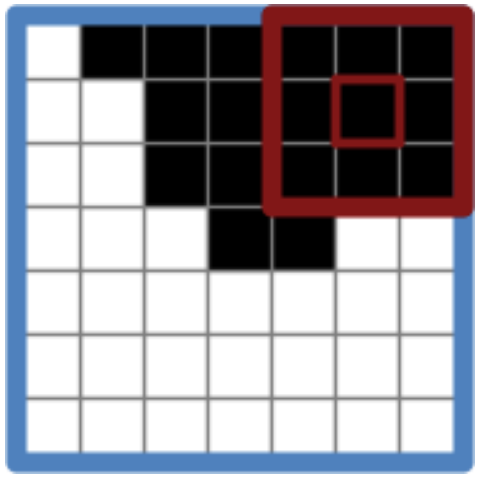

dilation δ enlarges objects

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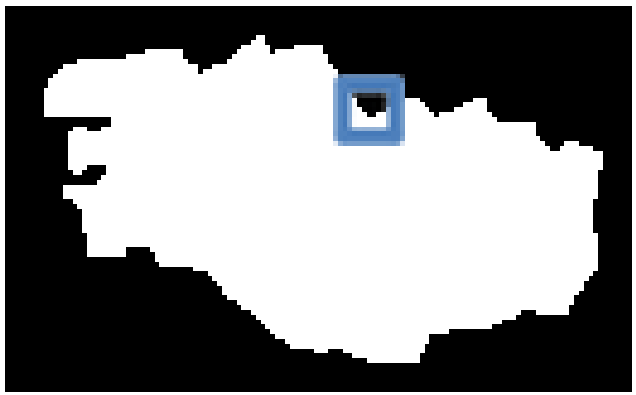

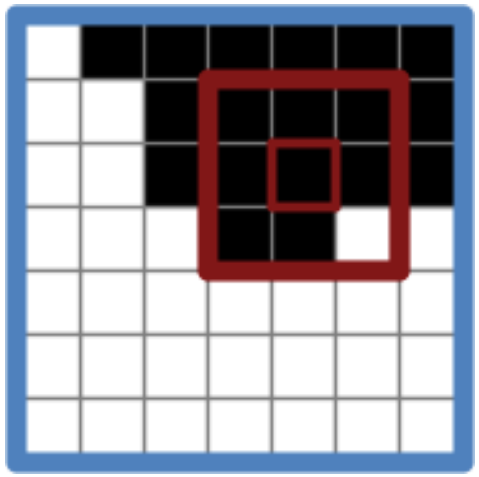

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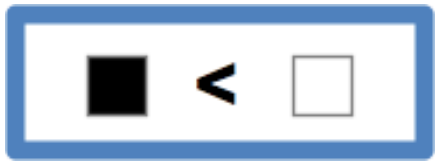

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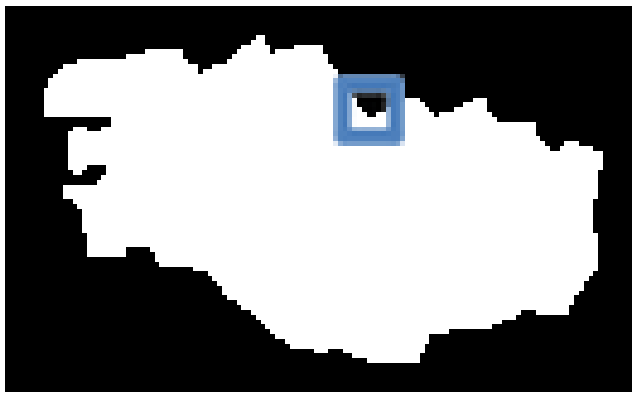

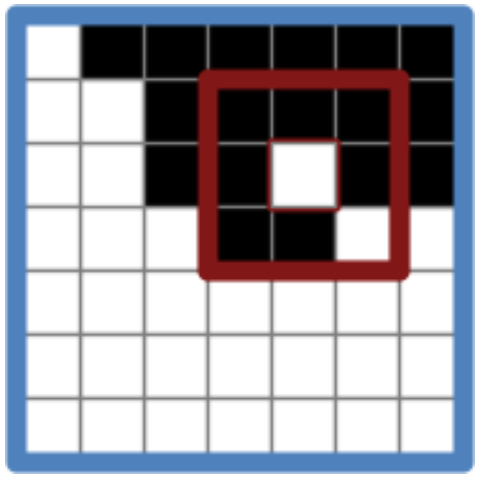

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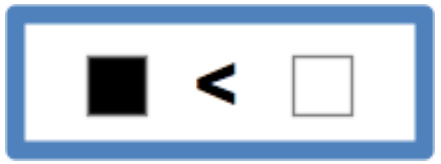

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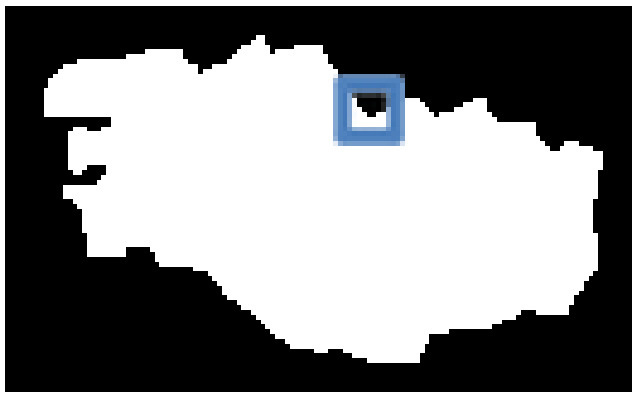

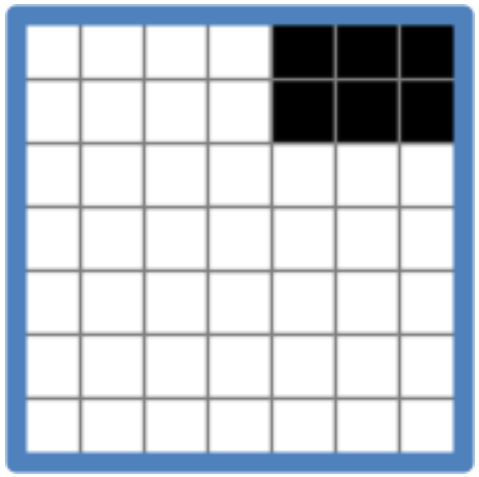

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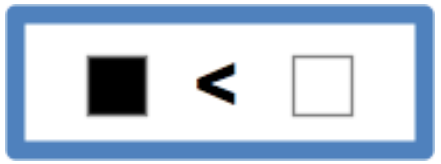
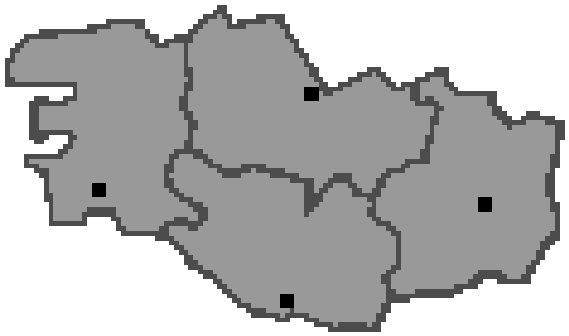


Grayscale case



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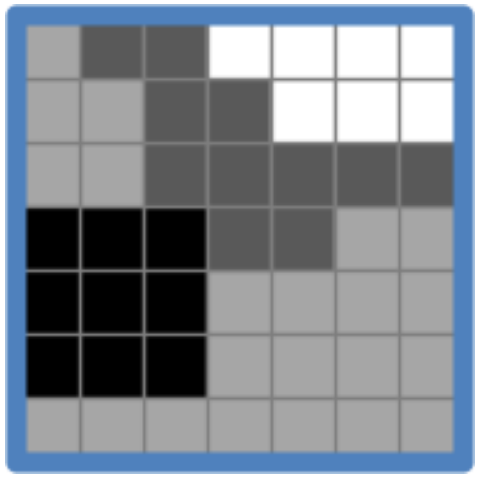
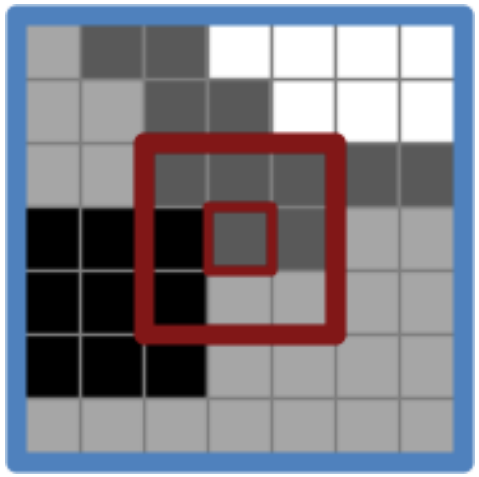


within a flat or functional
structuring element b

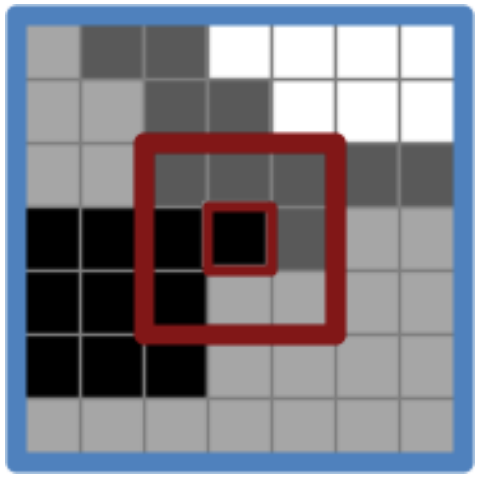
Grayscale case



erosion ε

shrinks maxima and enlarges minima

Grayscale case



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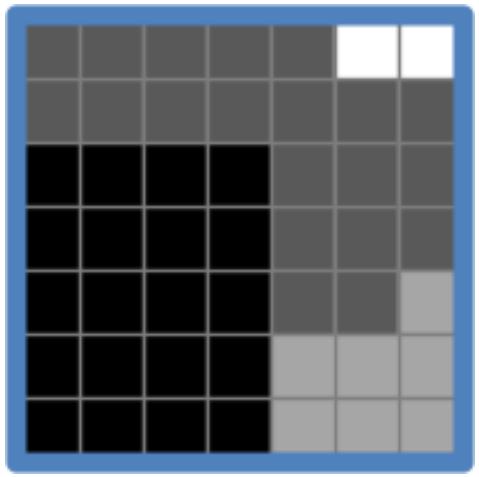

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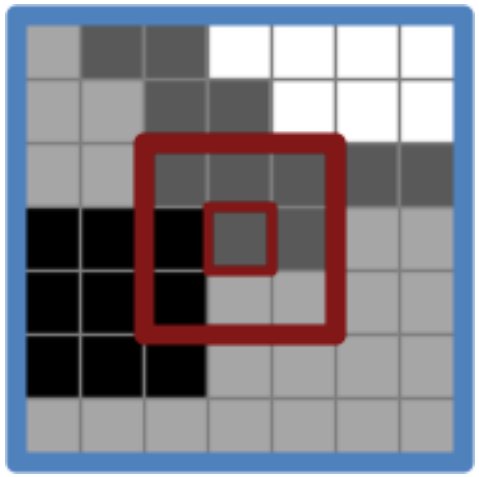

dilation δ

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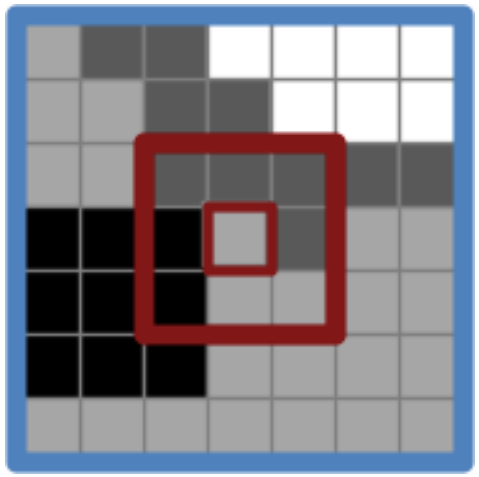

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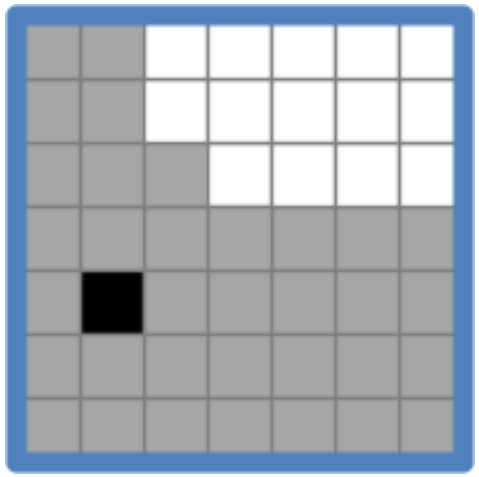

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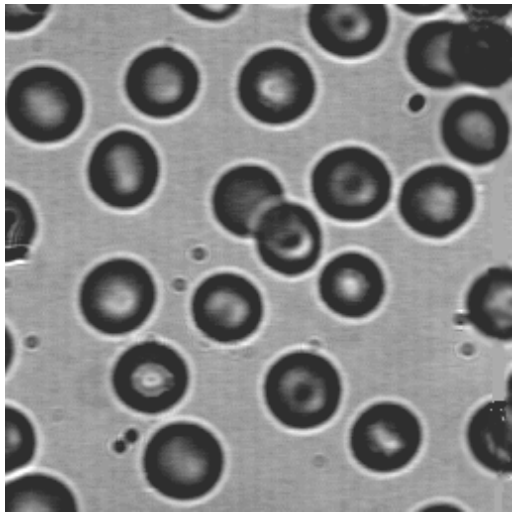
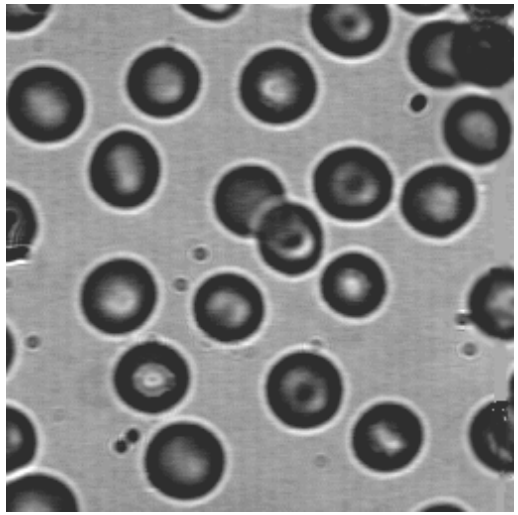
Filtering (and scale-spaces)

Multiscale representations

- morphological filters are parameterized
  - structuring element for structural filters
  - attribute in connected filters
- successive applications lead to morphological scale-spaces



Gaussian smoothings



Openings

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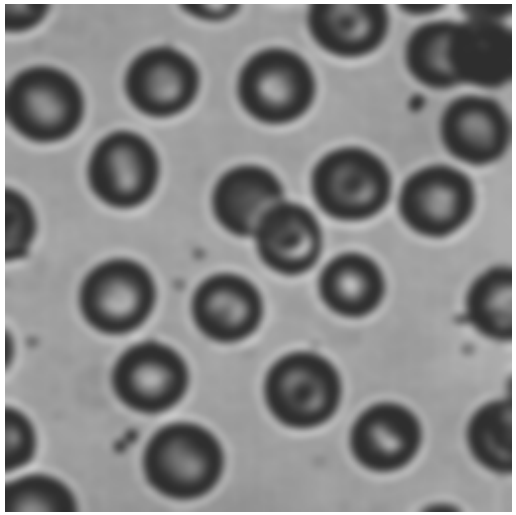

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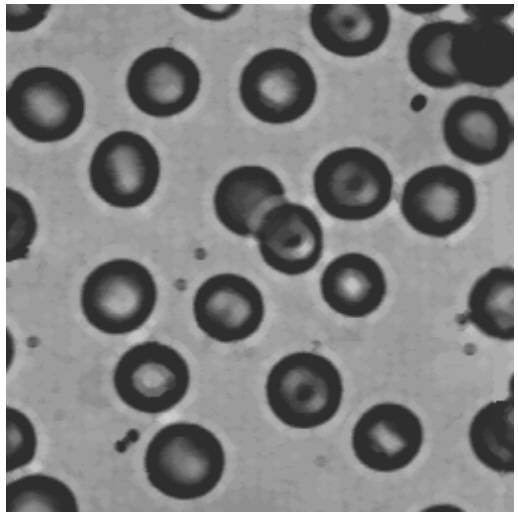

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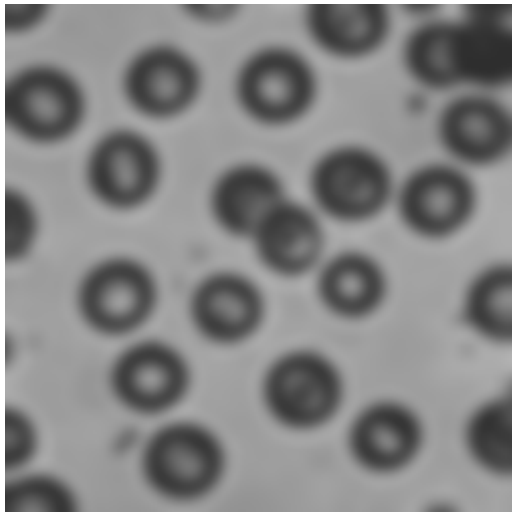

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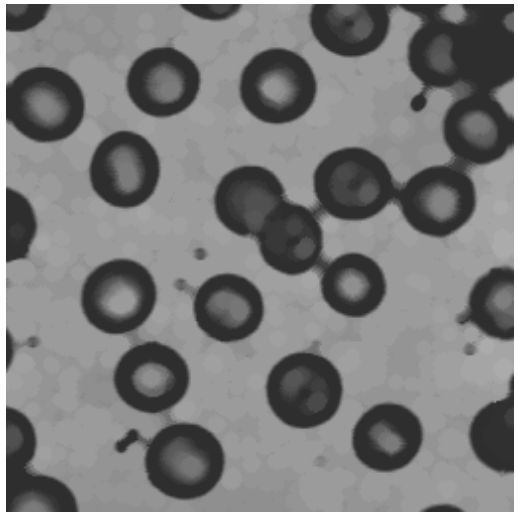

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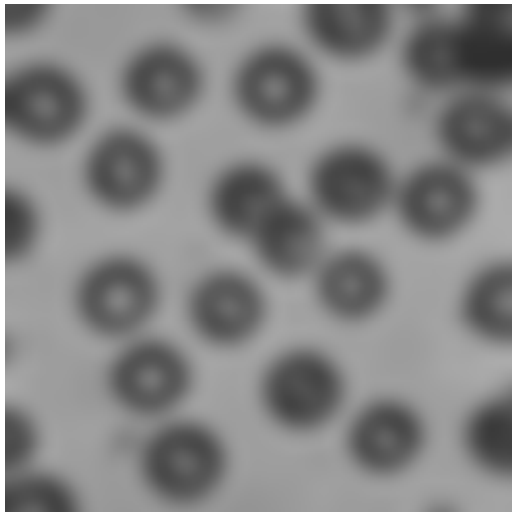

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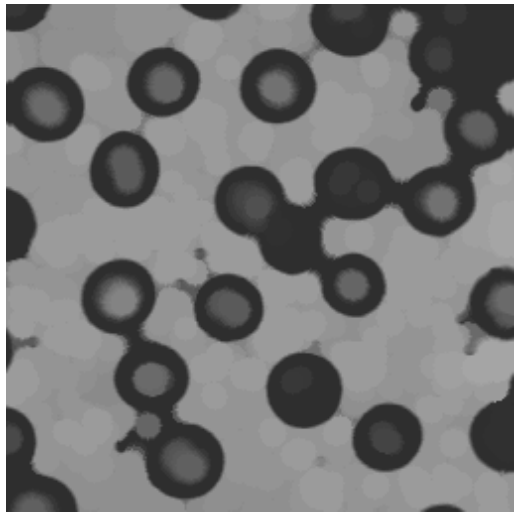

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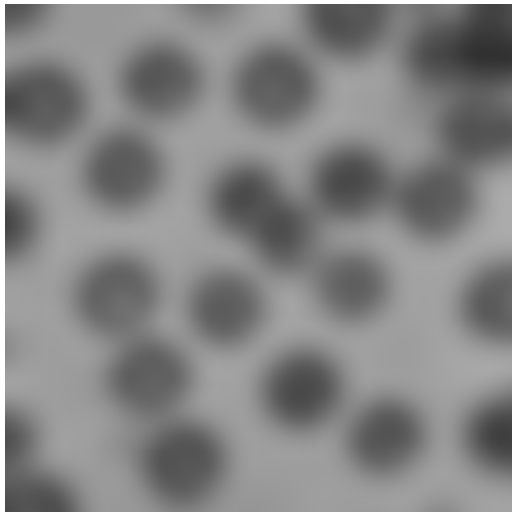
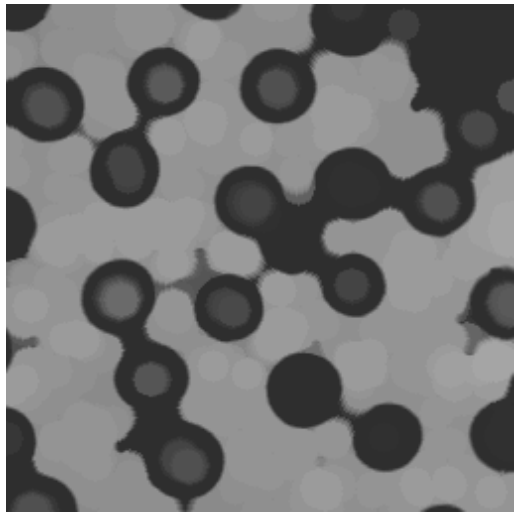


Gaussian smoothings



Openings

Filtering (and scale-spaces)

Multiscale representations

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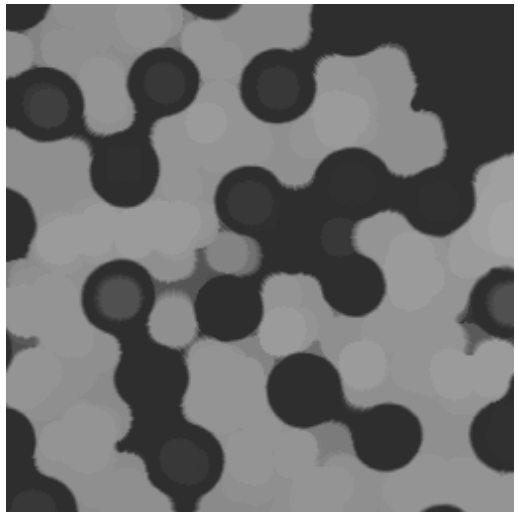

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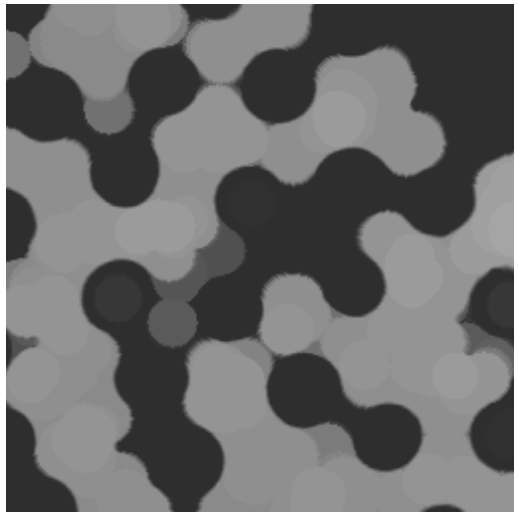

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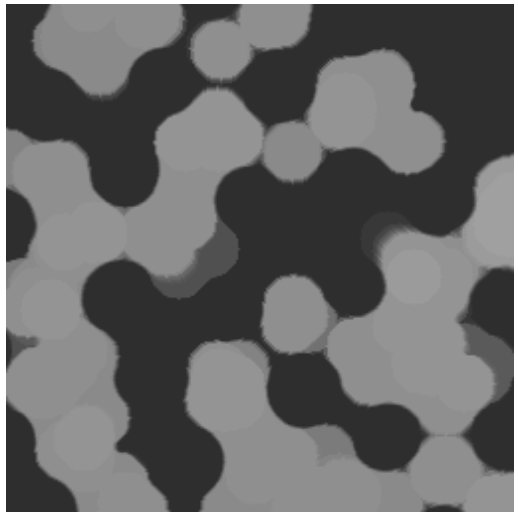

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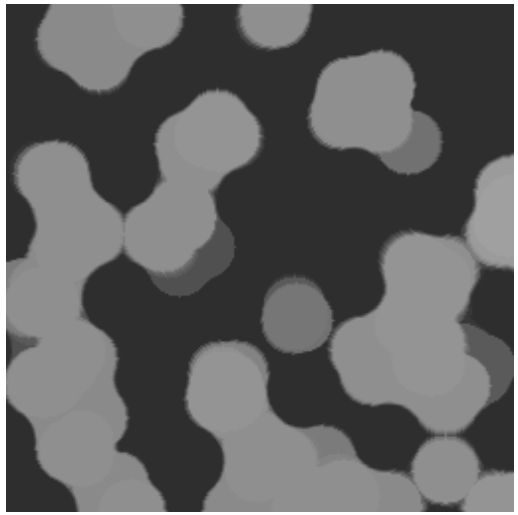

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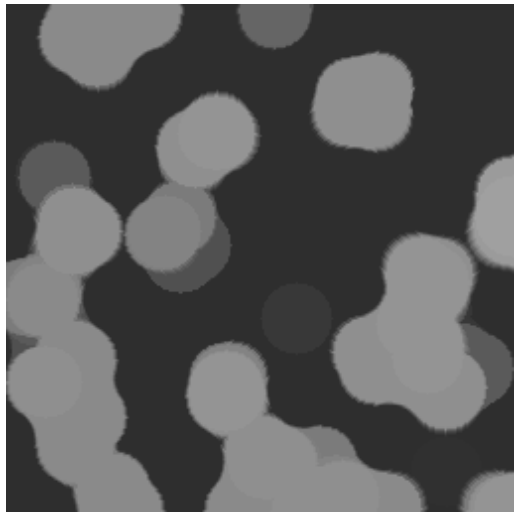

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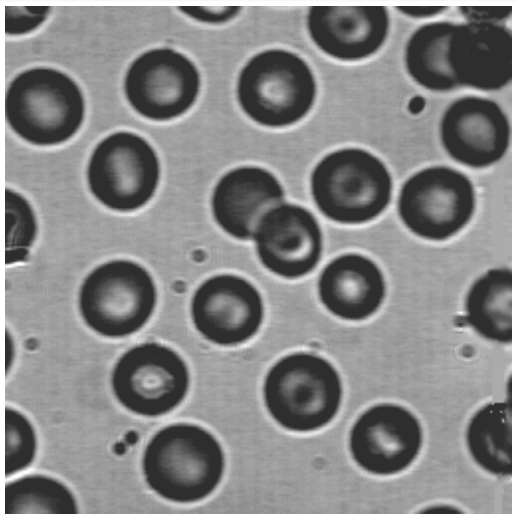

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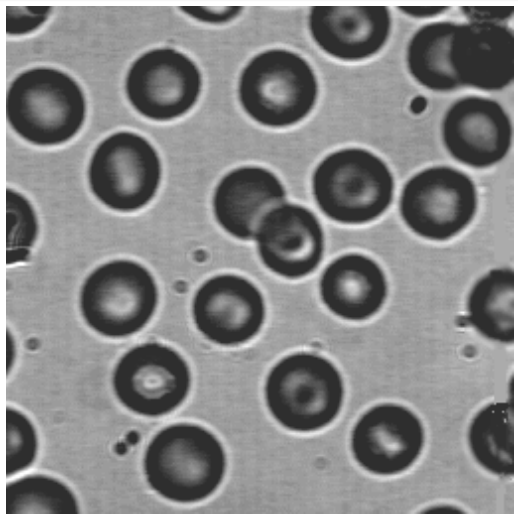

Openings by reconstruction

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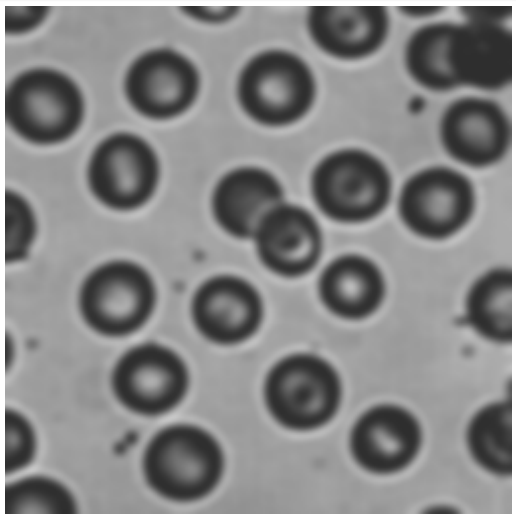

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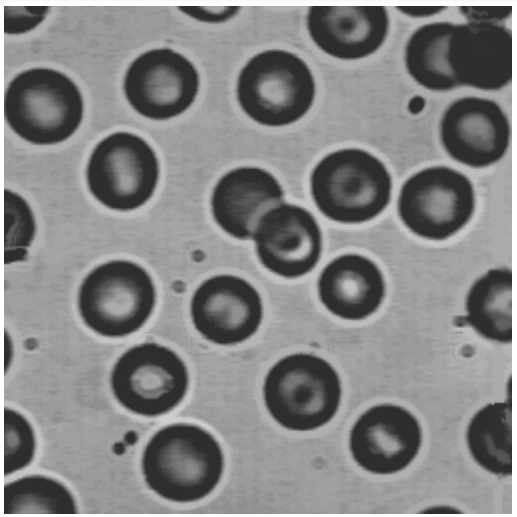

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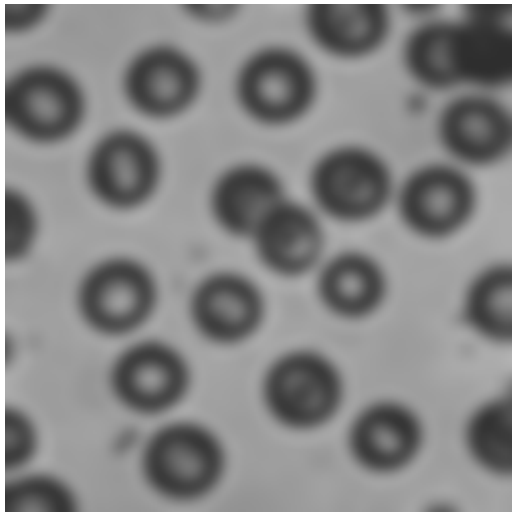

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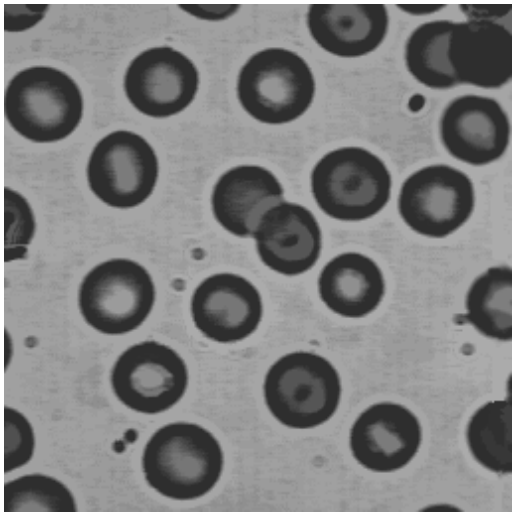

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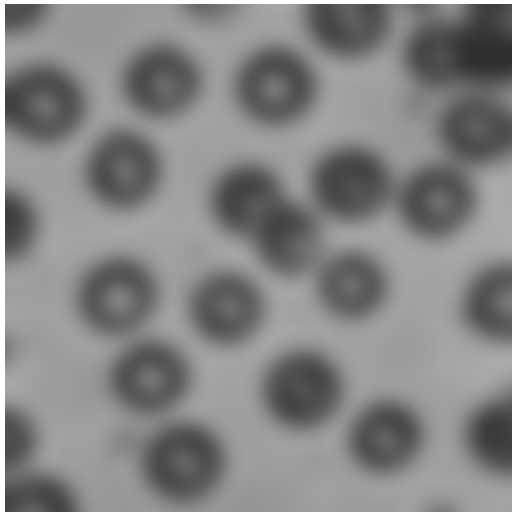

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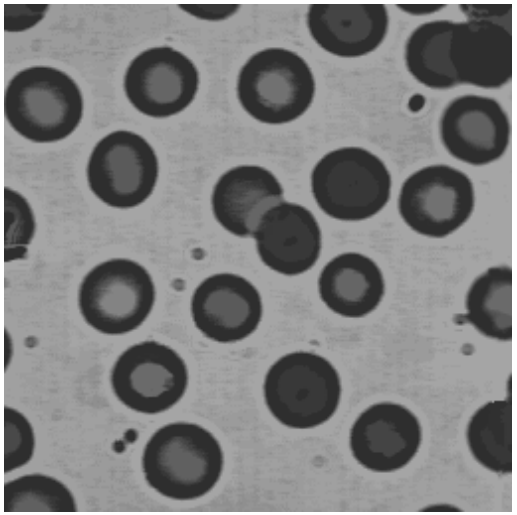

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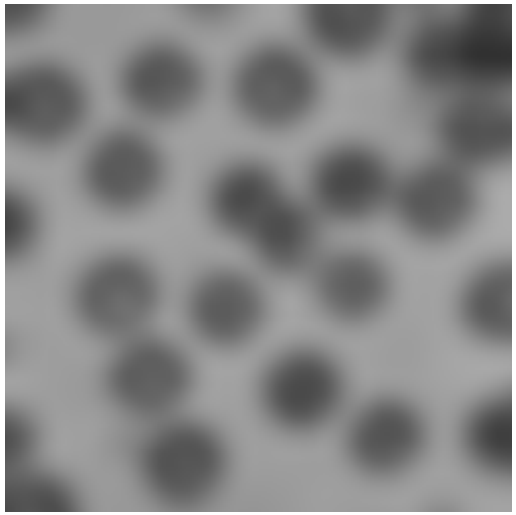

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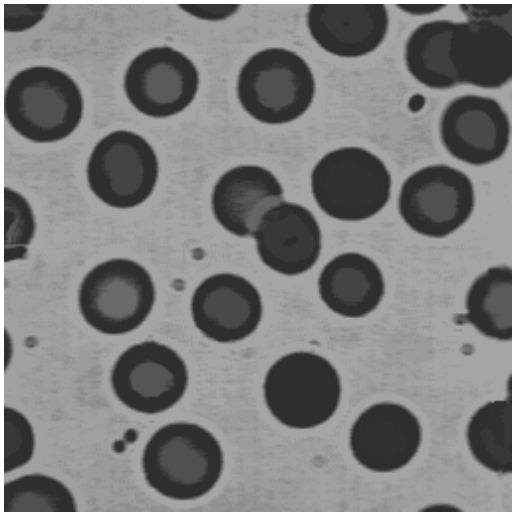

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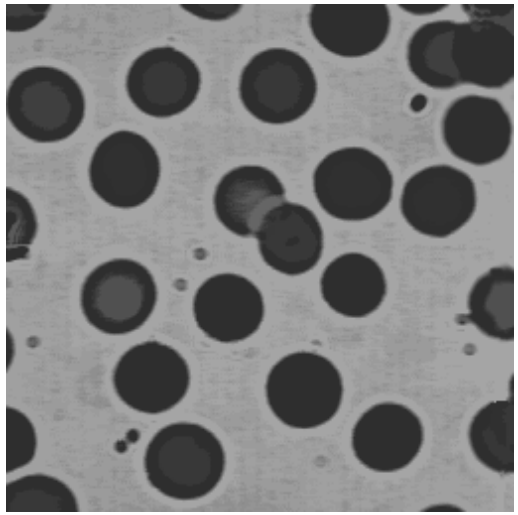

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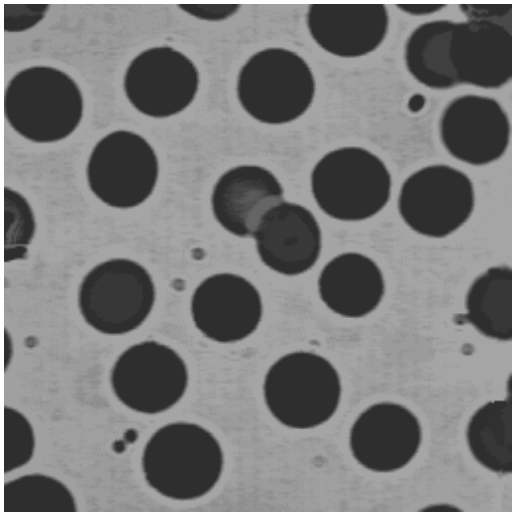

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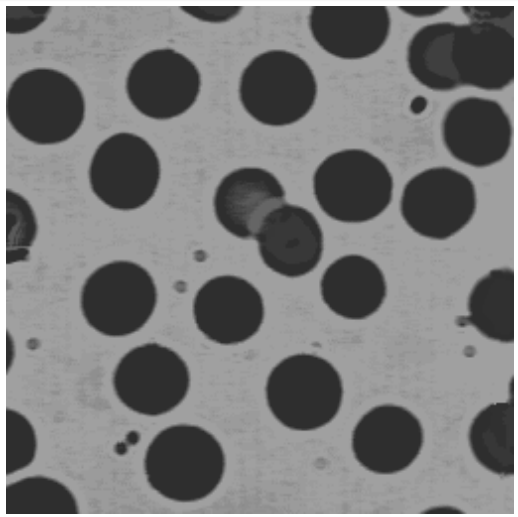

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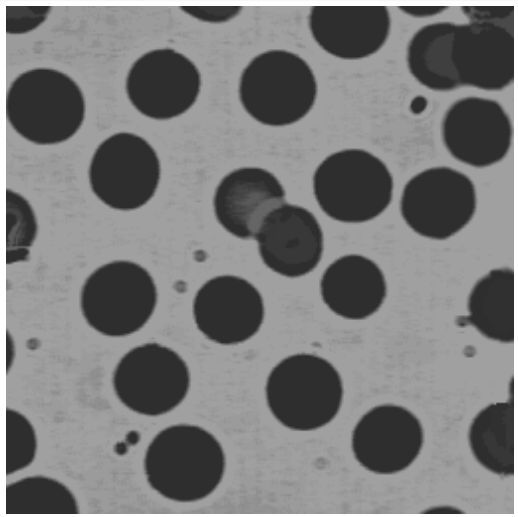

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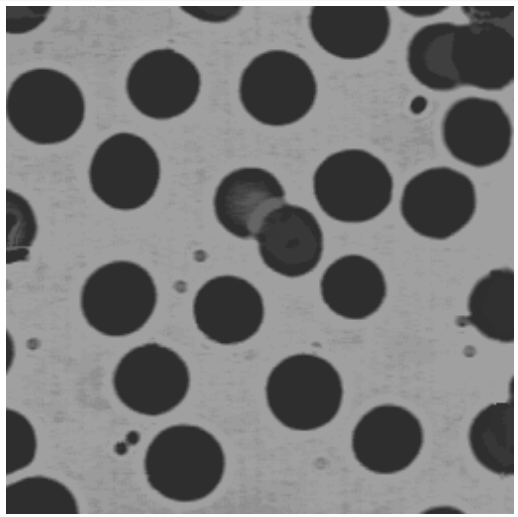

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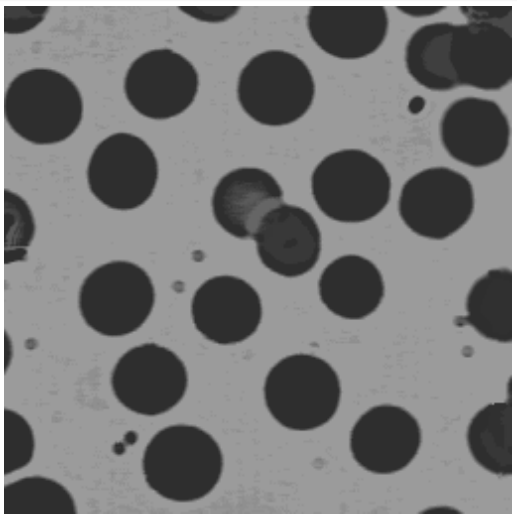

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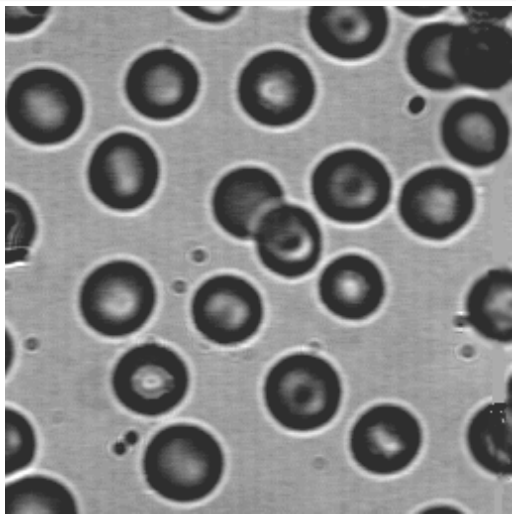

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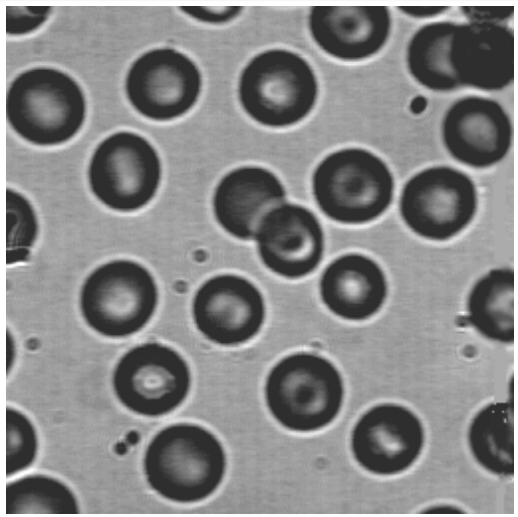

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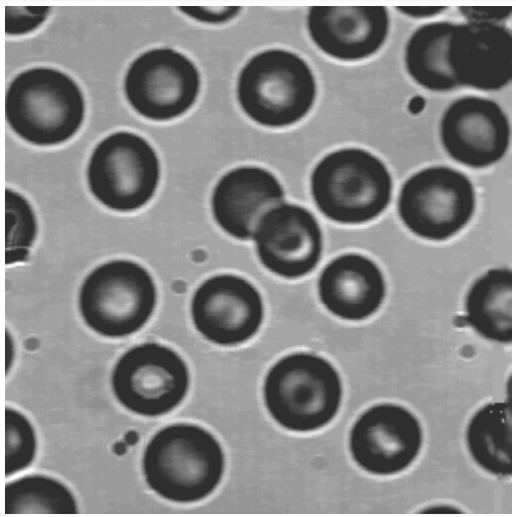

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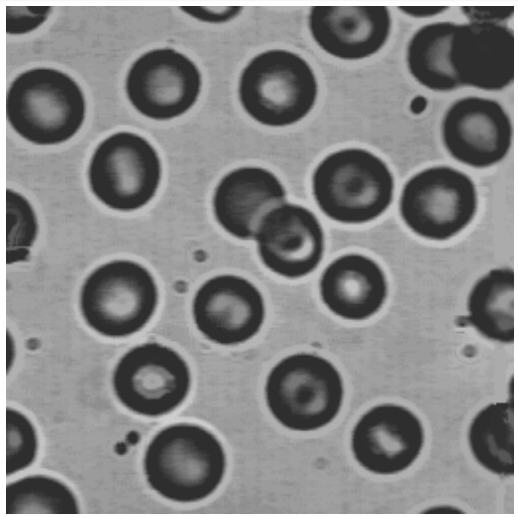

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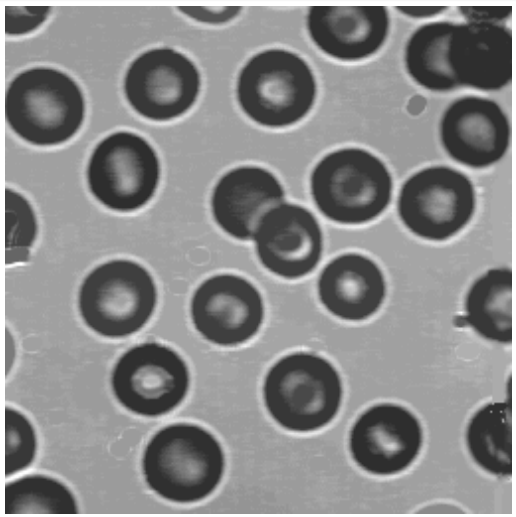

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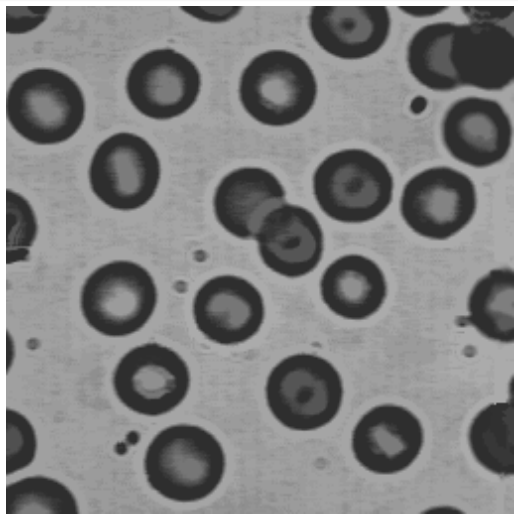

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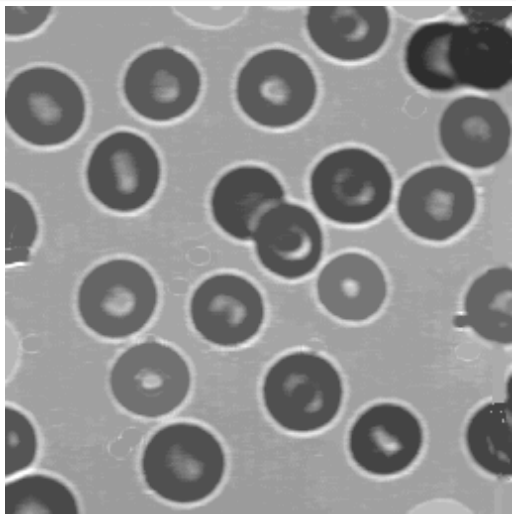

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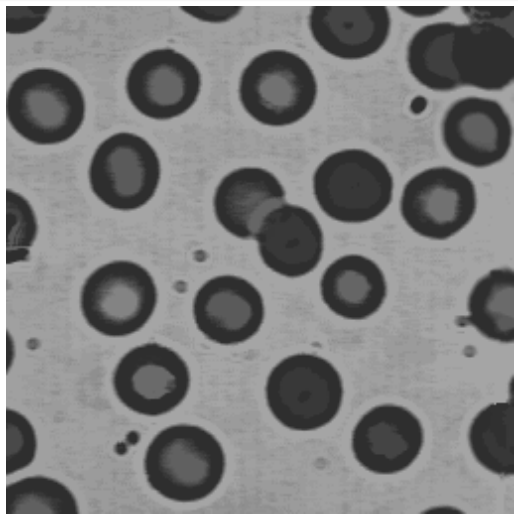

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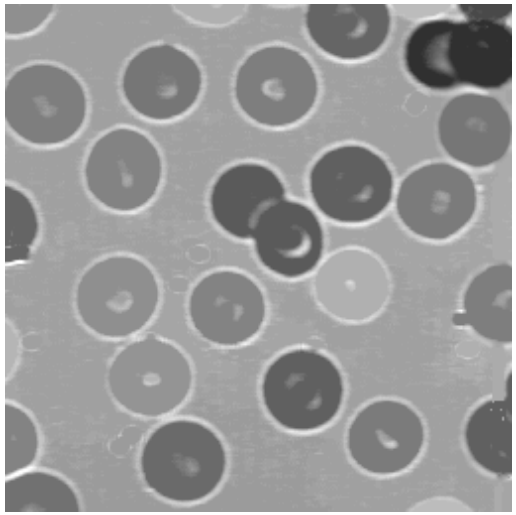

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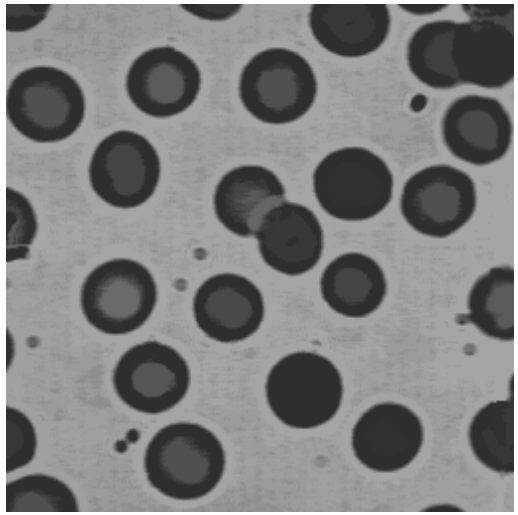

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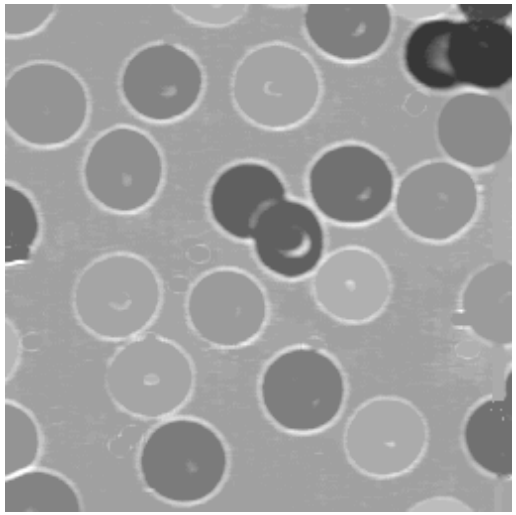

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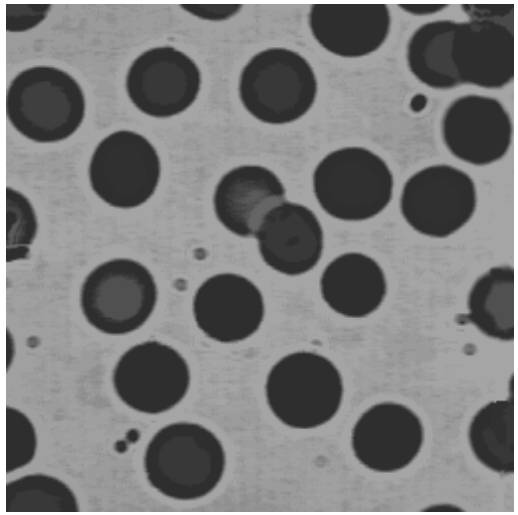

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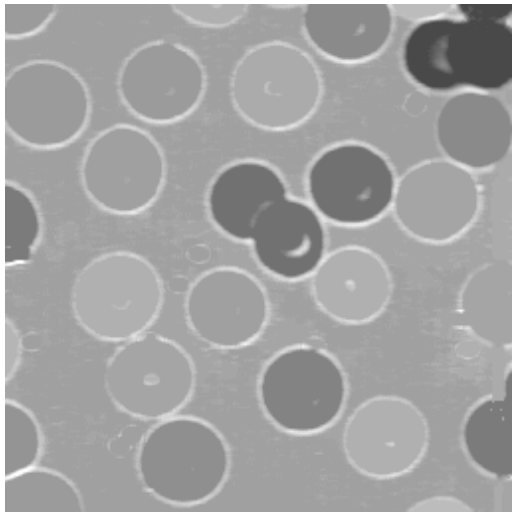

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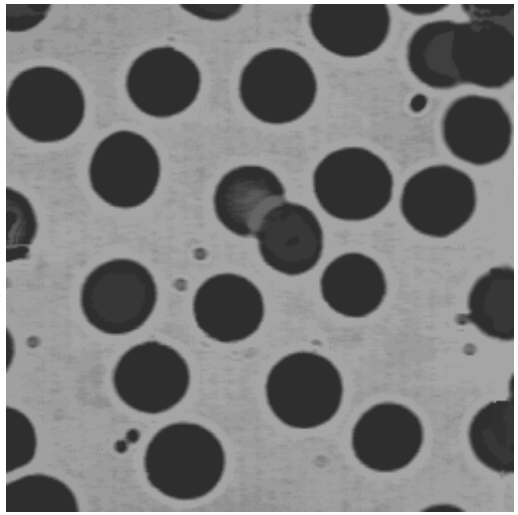

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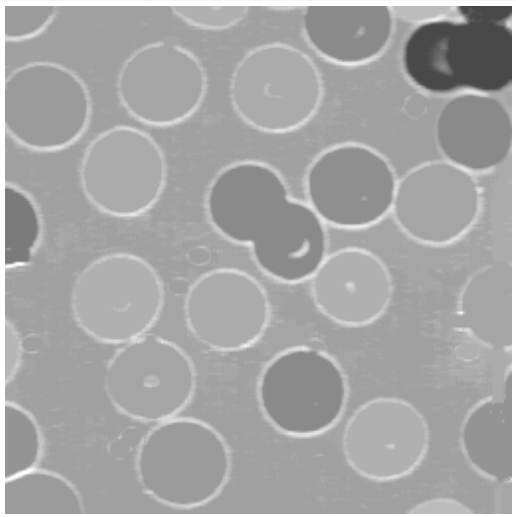

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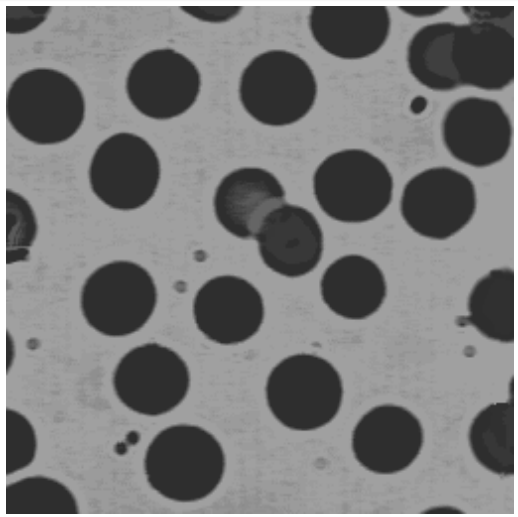

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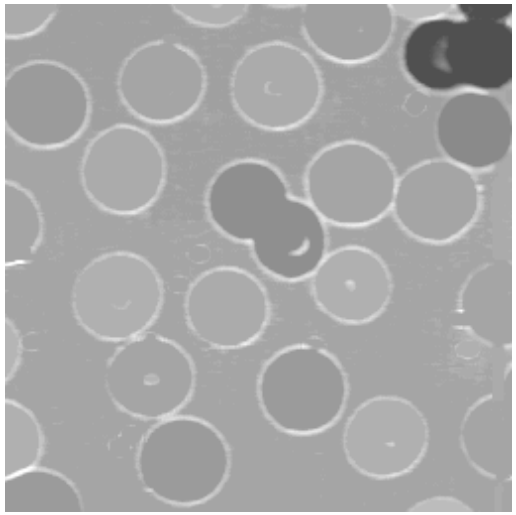

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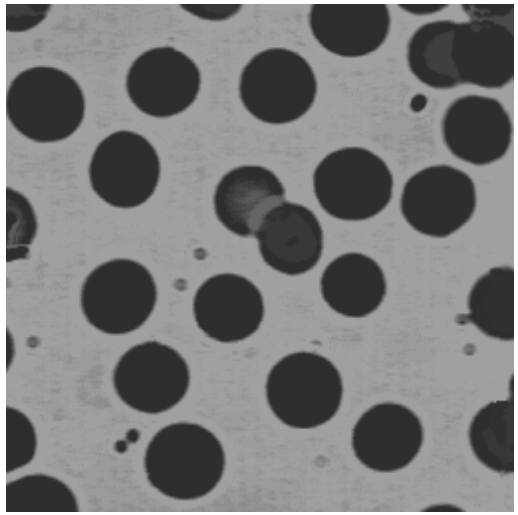

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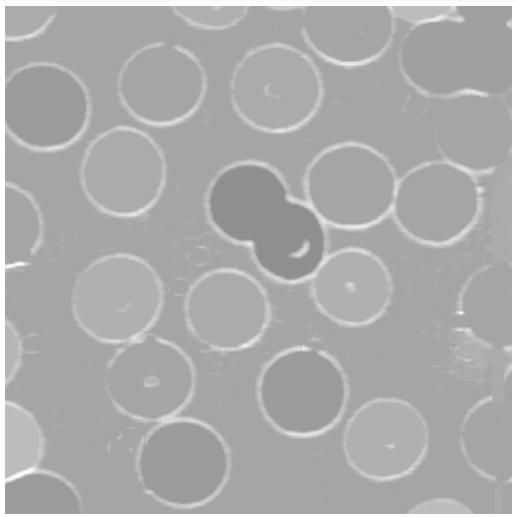

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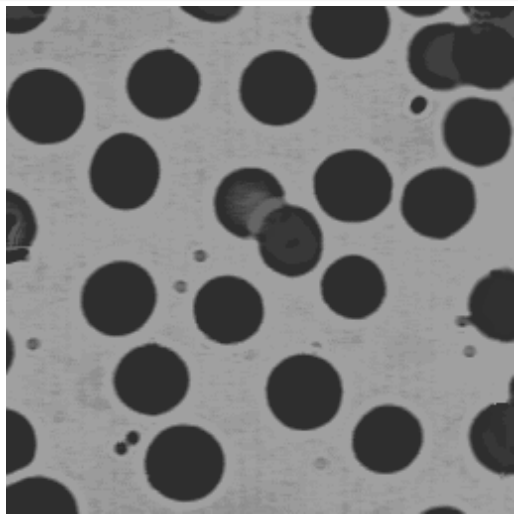

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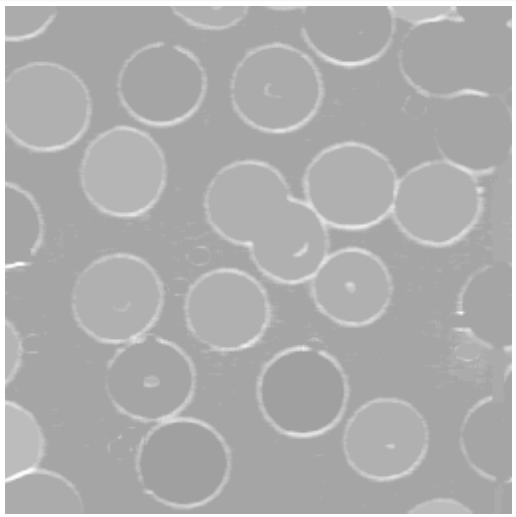

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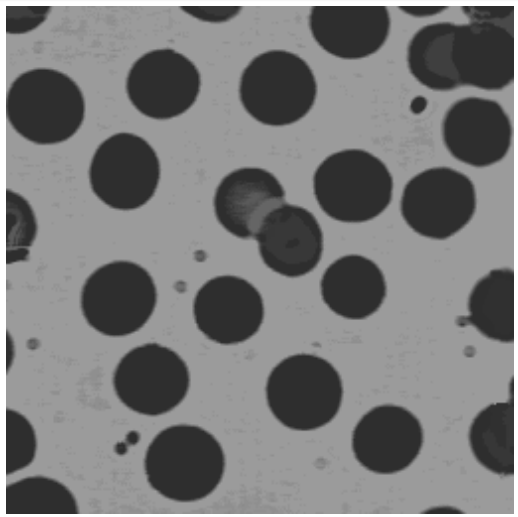


Openings by reconstruction

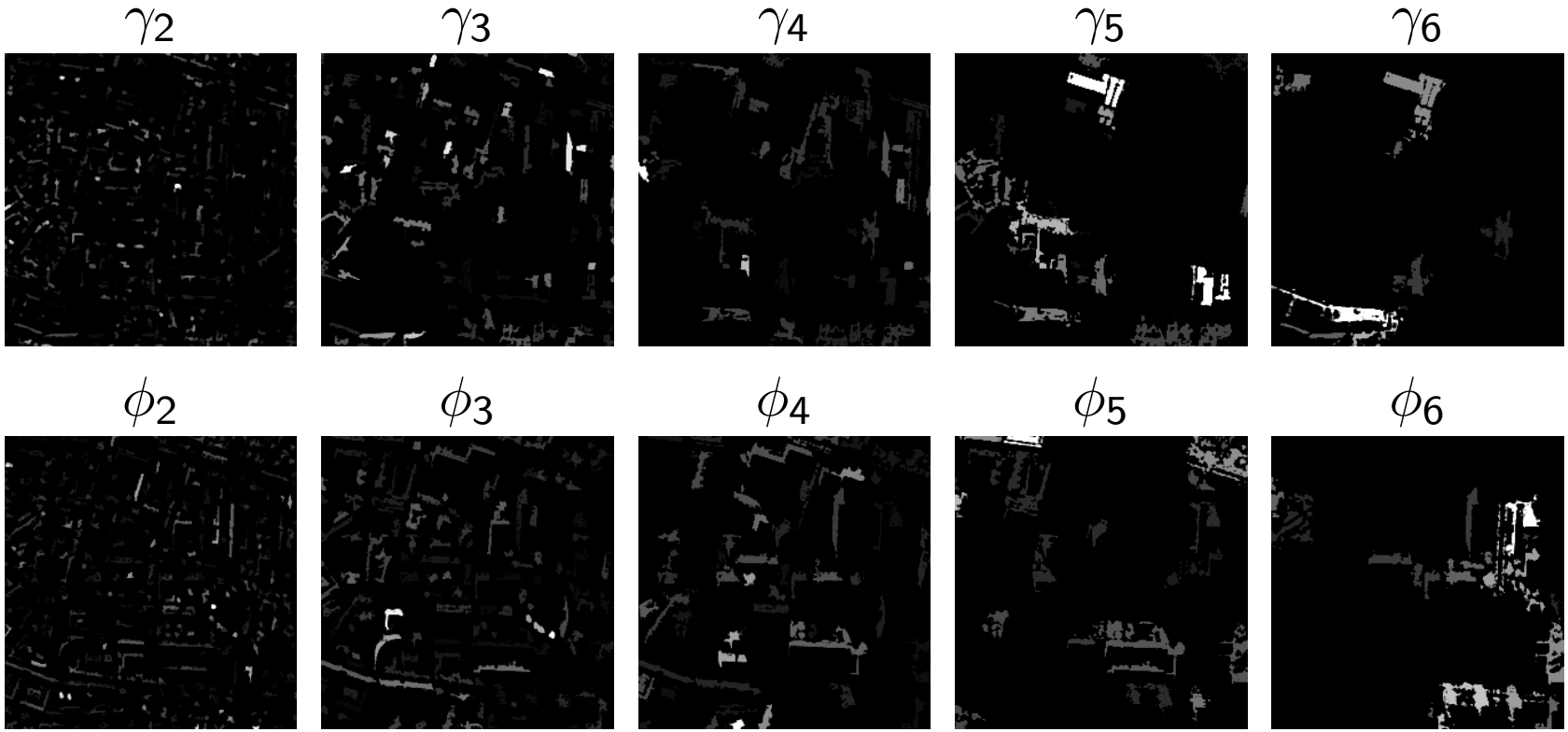
Residue operators

Difference between input and filtered images, or between two filtered images.

Illustration with openings/closings by reconstruction

Residue operators

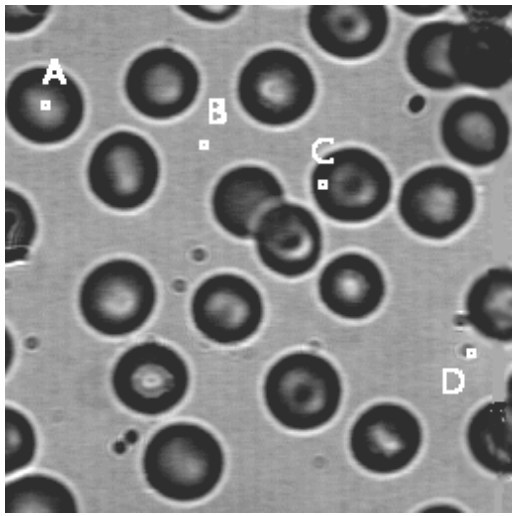
Difference between input and filtered images, or between two filtered images.

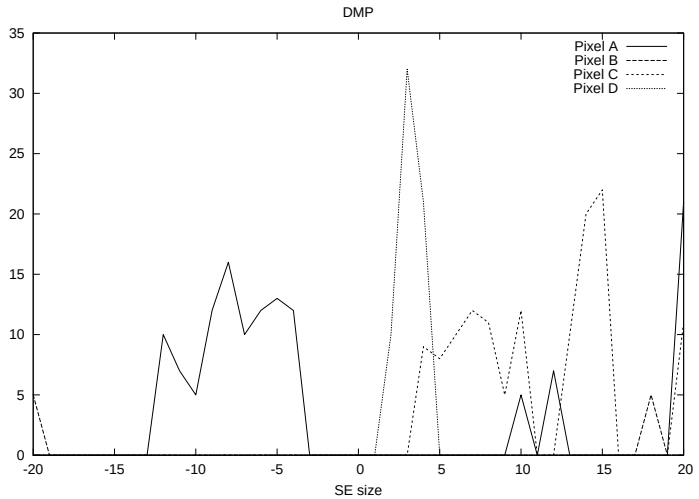


Morphological Description

- global features (image): granulometry, attribute distribution
- local features (pixel): texture, structure
- built from morphological scale-spaces

Differential Morphological Profile (DMP) = series of first-order derivatives considering filters by reconstruction.





E. Aptoula and S. Lefèvre. "Morphological texture description of grayscale and color images". In: Advances in Imaging and Electron Physics. Ed. by Peter Hawkes. Vol. 169. Elsevier, 2011, pp. 1–74

Template matching: Hit-or-Miss Transform

Definition

Consider simultaneously two SE A and B.

A must fit the foreground f and B the background f^c.

$$\eta_{A,B}(f)(p) = \varepsilon_A(f)(p) \wedge \varepsilon_B(f^c)(p)$$

Recall: main morphological operators

Erosion: $\varepsilon_B(f)(x,y) = \bigwedge_{(r,s)\in B} f(x+r, y+s), \quad (x,y) \in E$

Dilation: $\delta_B(f)(x,y) = \bigvee_{(r,s)\in \check{B}} f(x+r, y+s), \quad (x,y) \in E$

Opening: $\gamma_{\check{B}}(f)(p) = \delta_B(\varepsilon_B(f)(p))$

Closing: $\phi_B\check{B}(f)(p) = \varepsilon_B(\delta_B(f)(p))$

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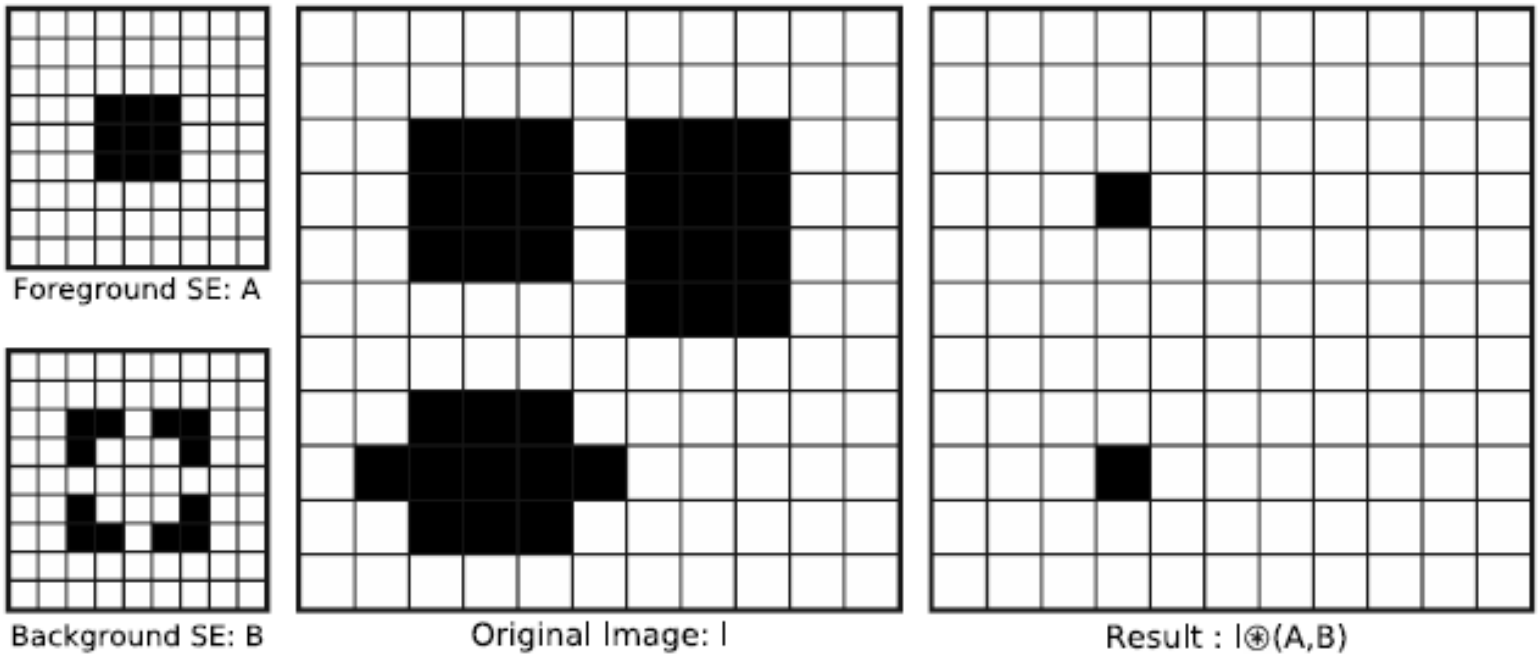
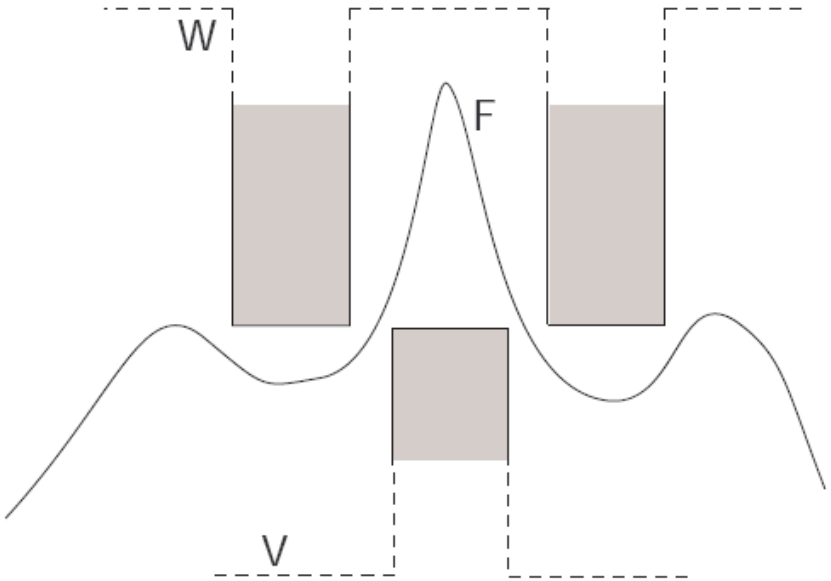


Grayscale Hit-or-Miss: several definitions !

$$\eta_{g,h}^{\text{Soille}}(f)(p) = max\{\varepsilon_g(f)(p) - \delta_{\check{h}}(f)(p), 0\}$$

$$\eta_{g,h}^{\text{Ronse}}(f)(p) = \begin{cases} \varepsilon_g(f)(p) & \text{if } \varepsilon_g(f)(p) \geq \delta_{h^*}(f)(p) \\ 0 & \text{otherwise} \end{cases}$$



B. Perret, S. Lefèvre, and C. Collet. "A Robust Hit-or-Miss Transform for Template Matching in Very Noisy Astronomical Images". In: Pattern Recognition 42.11 (Nov. 2009), pp. 2470–2480

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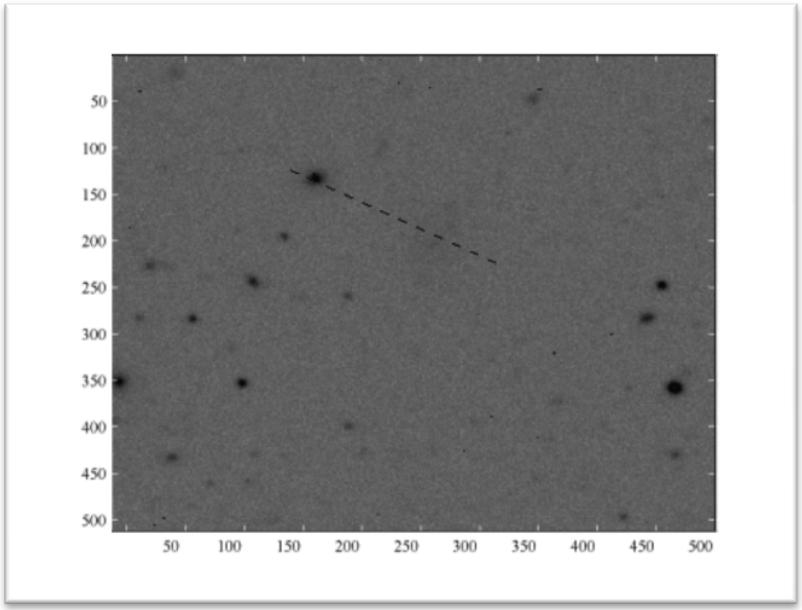

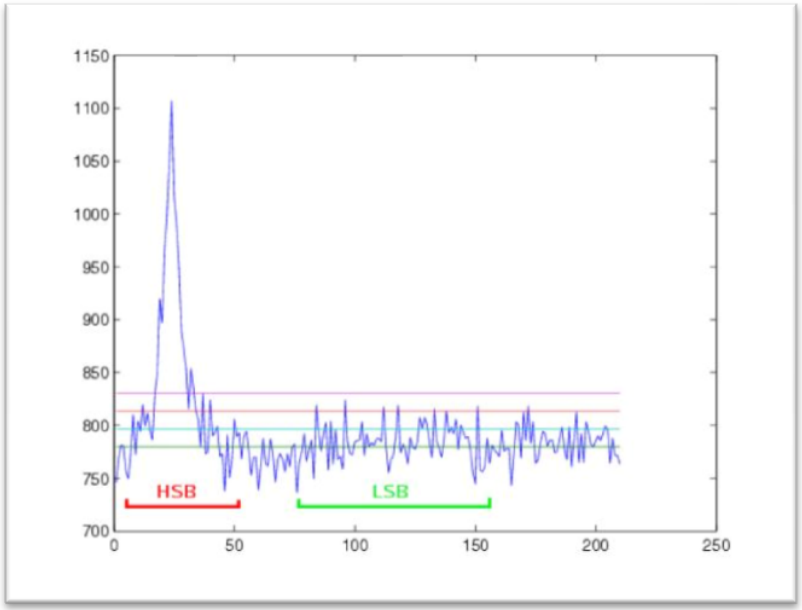

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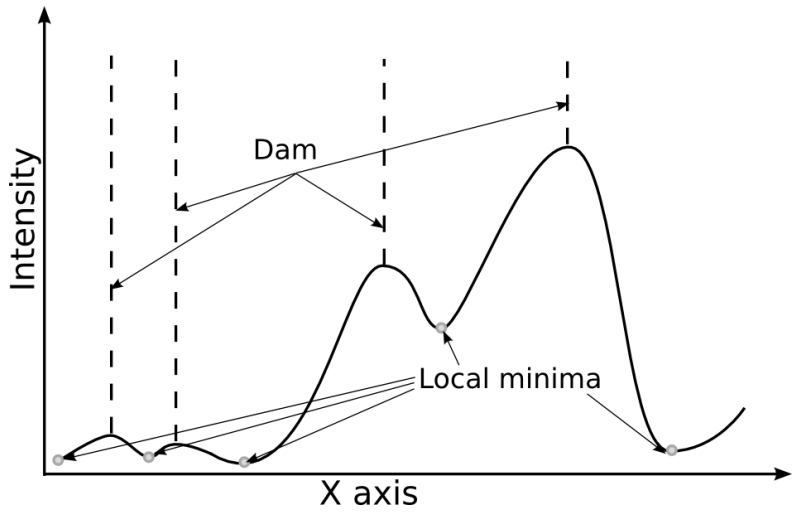
Morphological Segmentation: Watershed Transform

Immersion paradigm

1. the input image is considered as a topographic surface
2. surface is flooded from its local minima (catchment basins)
3. dams are built to avoid water merging
4. after flooding the whole surface, dams are watershed lines



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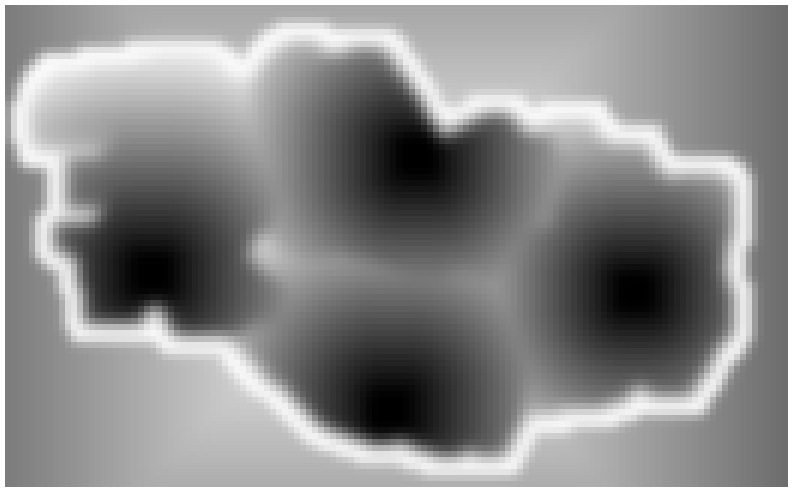

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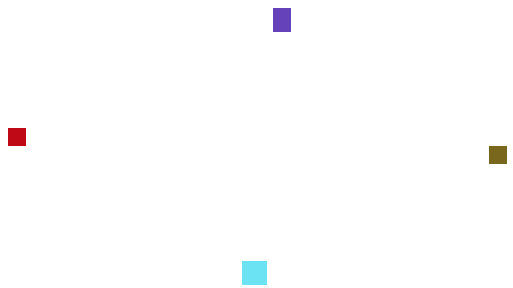

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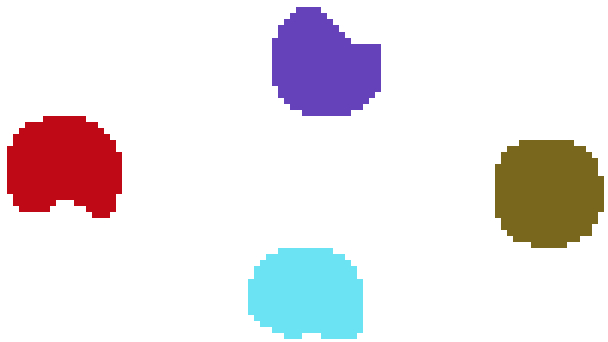

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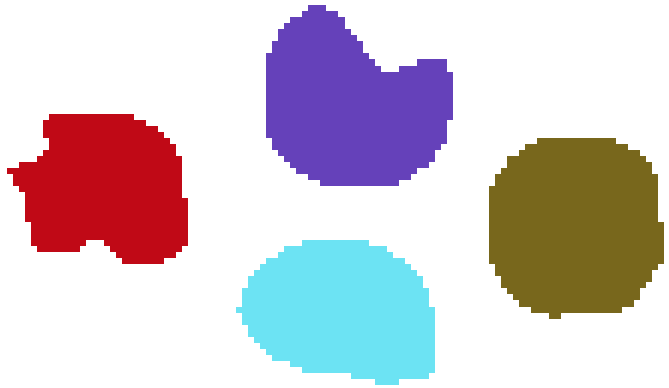

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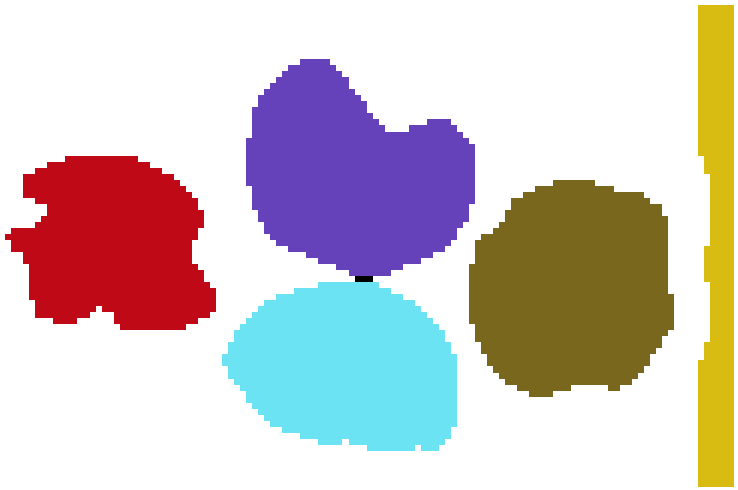

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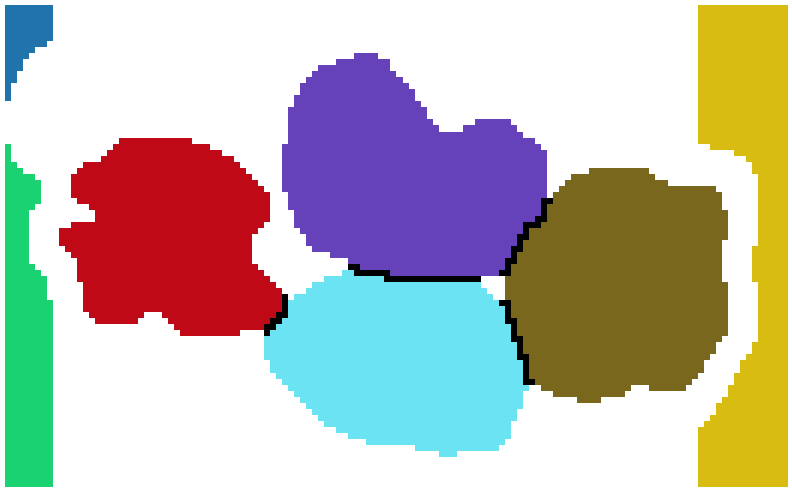

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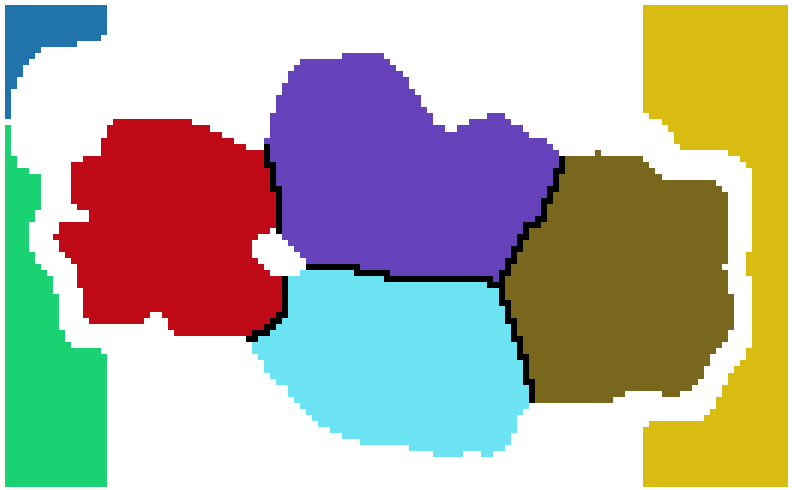

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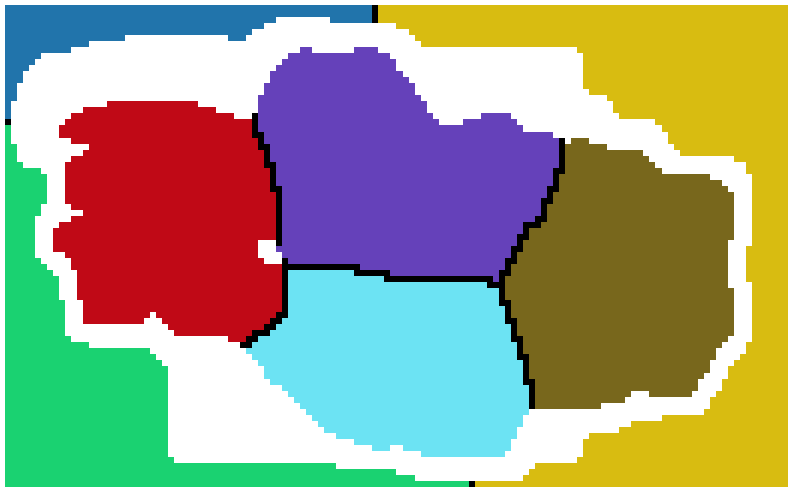

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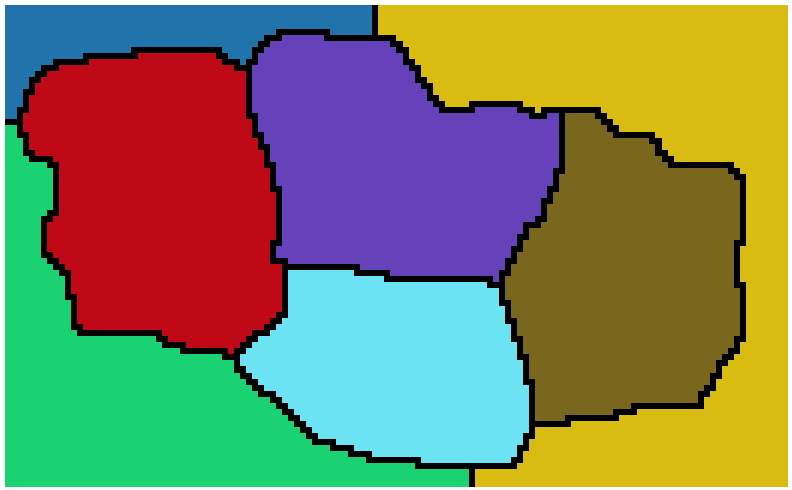

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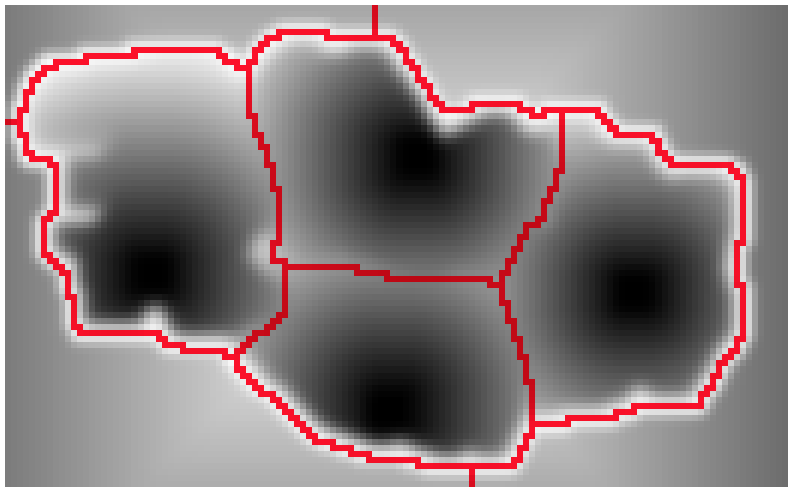
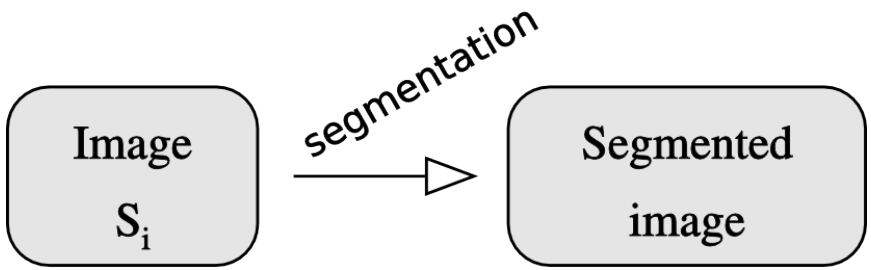


Supervised watershed: (1) non-spatial samples



How the samples may be used

- preprocessing: learning set to modify the input space for watershed segmentation
- postprocessing: test set to optimize oversegmentation reduction parameters

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

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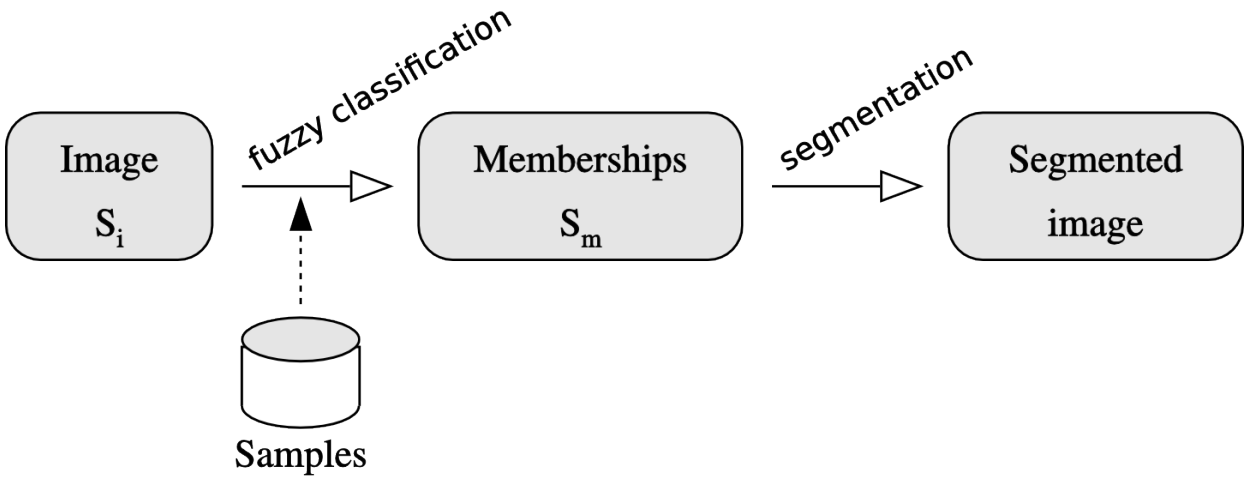

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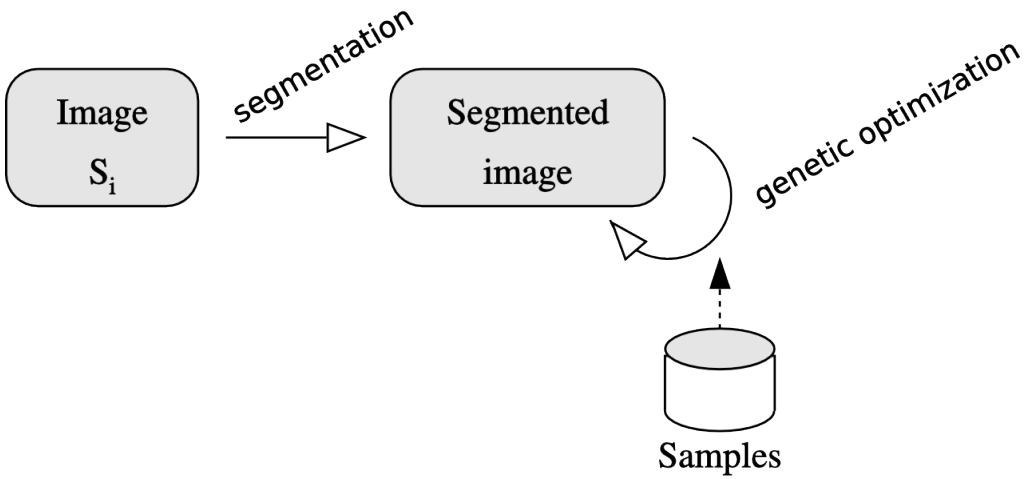

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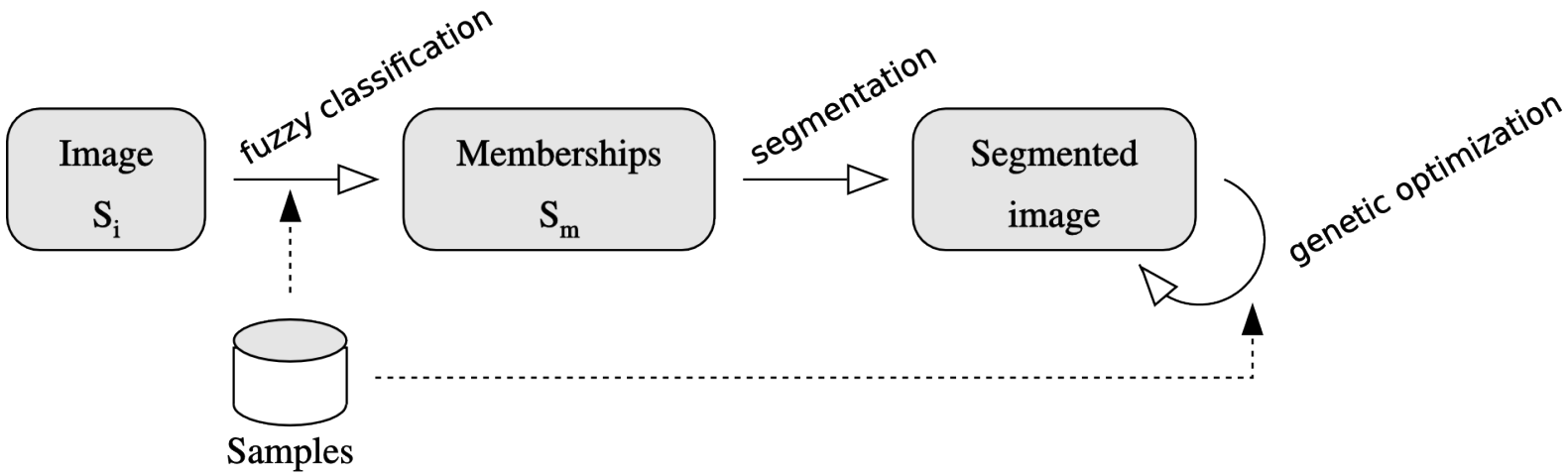

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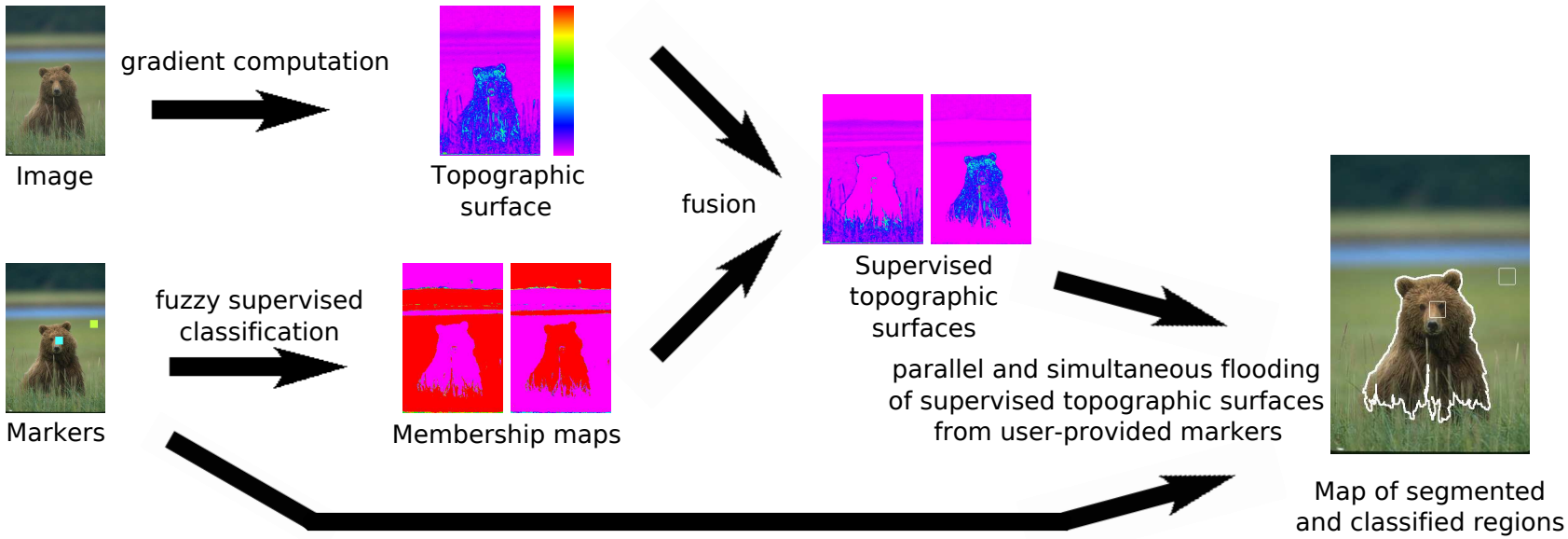
Supervised watershed: (2) spatial samples

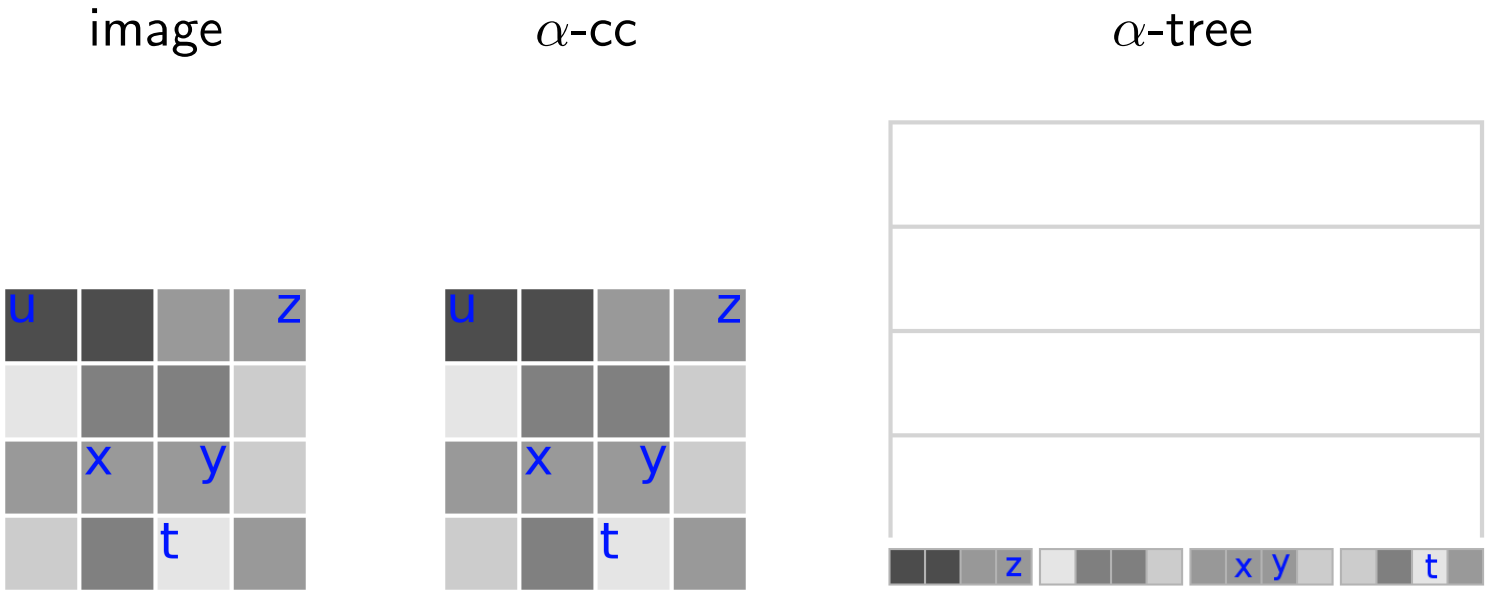
Principle

- learning sets are markers in watershed segmentation
- multiple surface are flooded simultaneously



S. Lefèvre. "Knowledge from markers in watershed segmentation". In: International Conference on Computer Analysis of Image and Patterns (CAIP). vol. 4673. Lecture Notes in Computer Science. Vienna, Austria: Springer-Verlag, Aug. 2007, pp. 579–586

Hierarchies: The α-tree model



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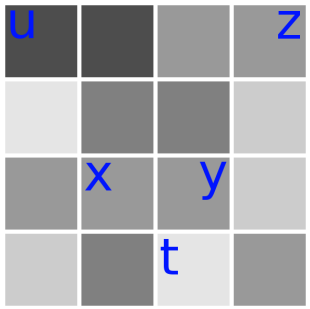
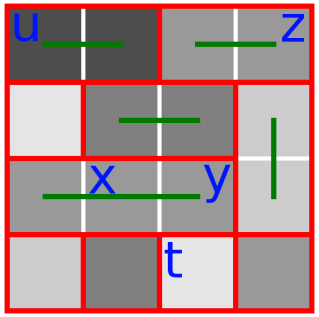
Hierarchies: The α-tree model

image



α-cc



$d(p, q) \leq 0$
p and q neighbors

α-tree

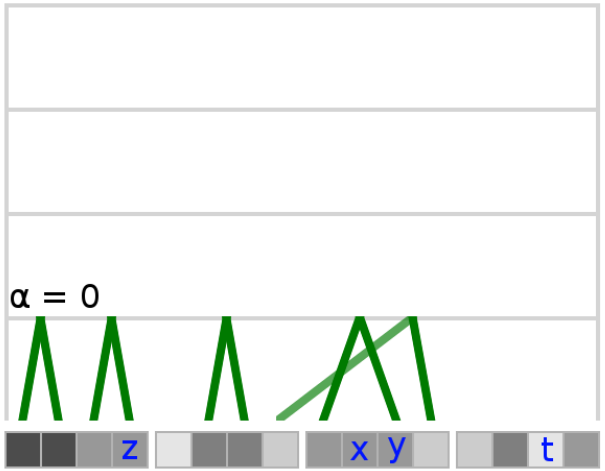


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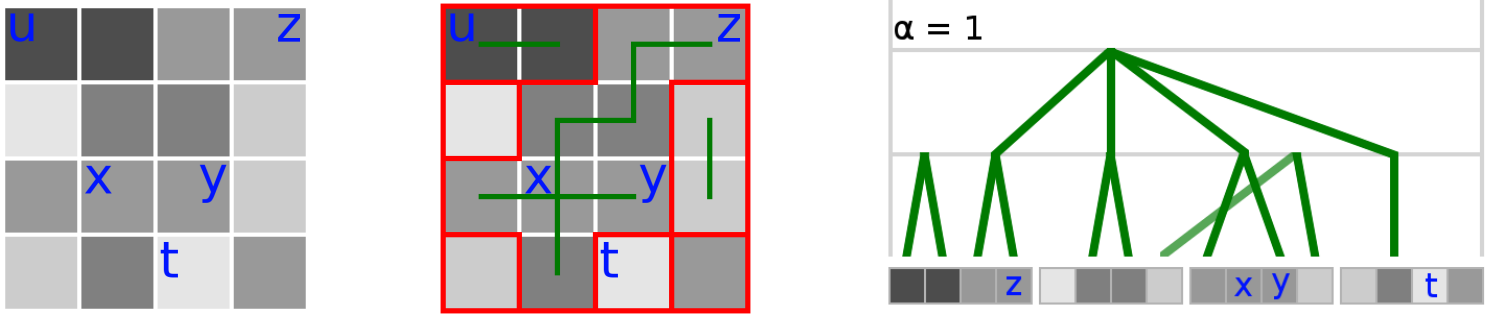
image α-cc α-tree



$d(p, q) \leq 1$
p and q neighbors

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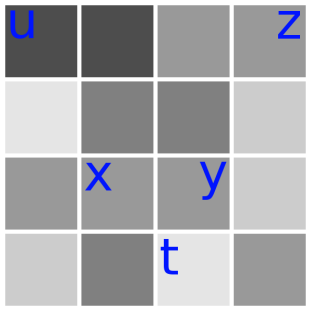
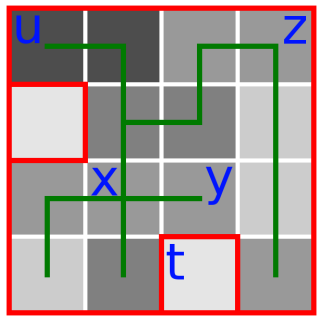
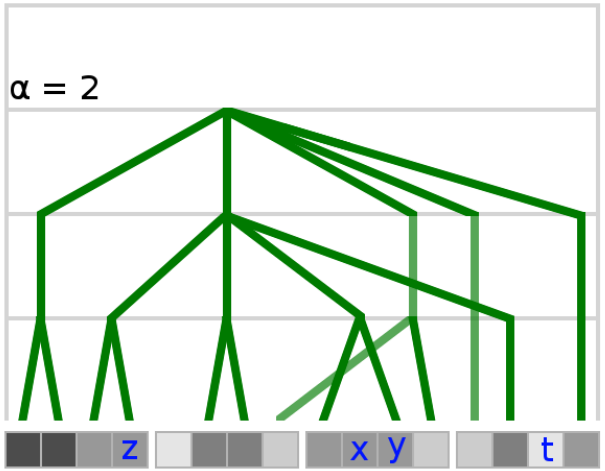
Hierarchies: The α-tree model

image α-cc α-tree





$d(p, q) \leq 2$
p and q neighbors



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Hierarchies: The α-tree model

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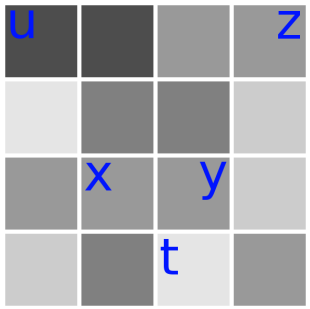
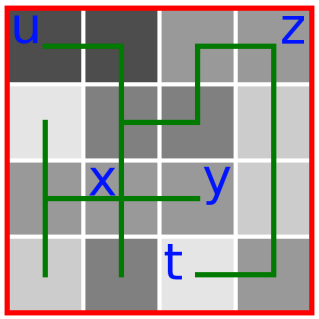
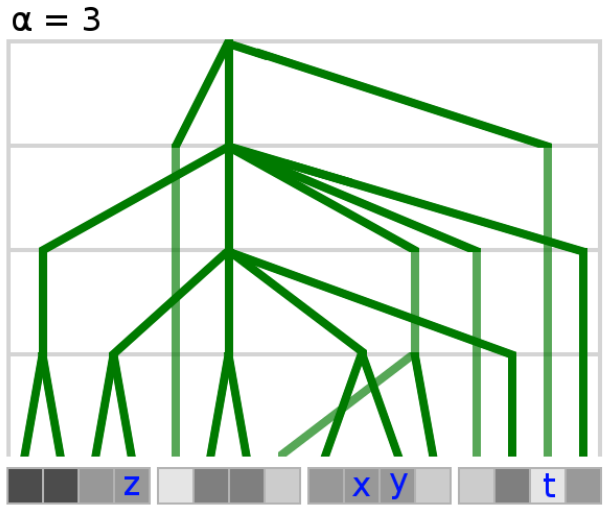


α-cc



$d(p, q) \leq 3$
p and q neighbors

α-tree



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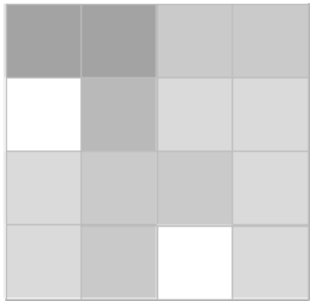
The chaining effect

image



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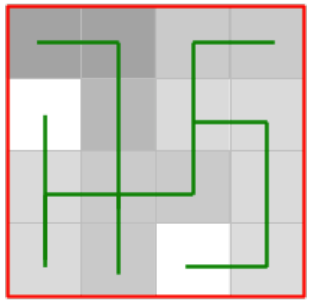

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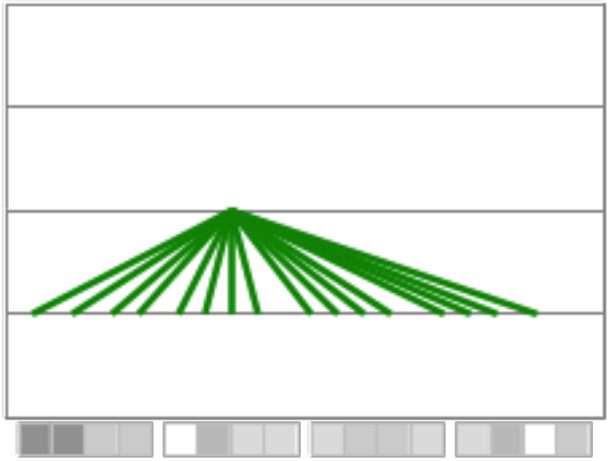
α-tree



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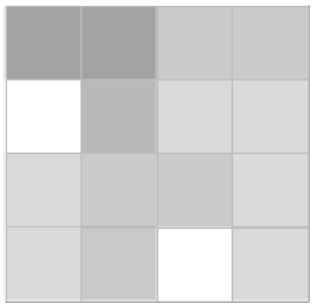

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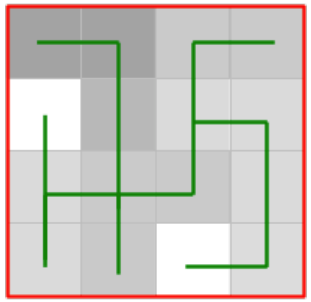

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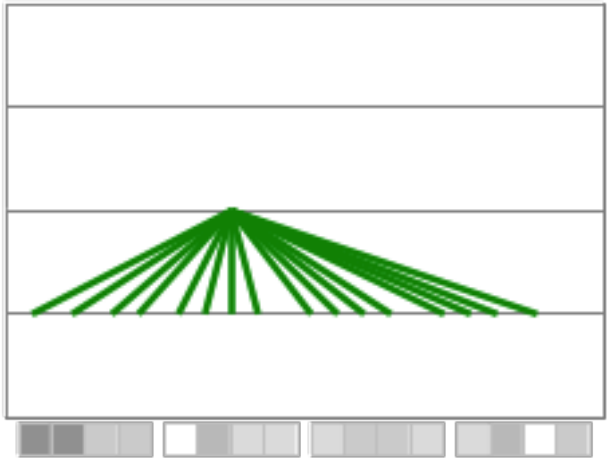
p and q neighbors

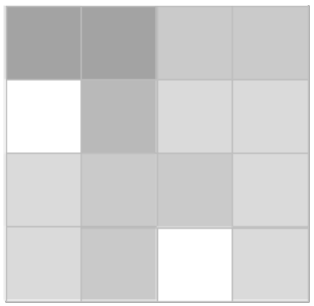
α-tree

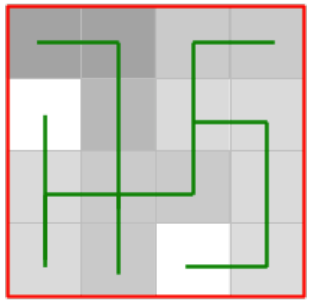


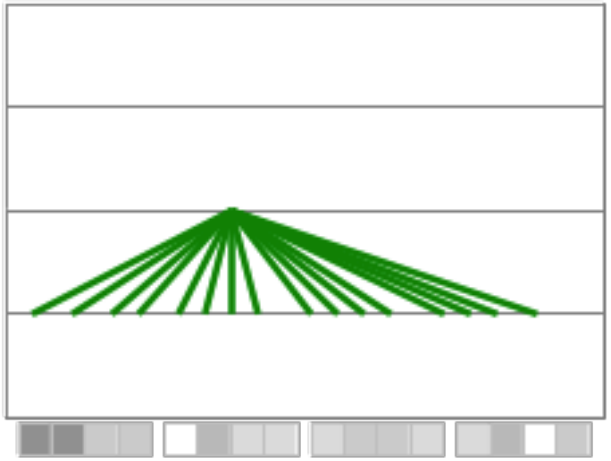
$\rightarrow$ pixels with very distinct values are gathered in a unique α-CC assumed to be of low complexity

The chaining effect

image α-cc α-tree







$d(p, q) \leq 1$
p and q neighbors

(α, ω) connected components with threshold ω on the α-CC global range

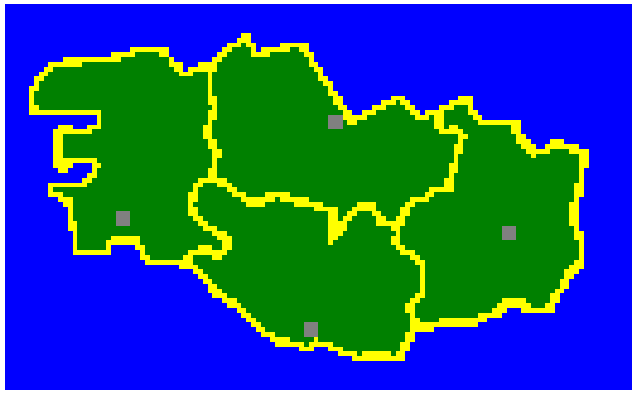
$d(p, q) \leq \alpha$, $\forall p, q$ neighbors

$d(u, v) \leq \omega$, $\forall u, v \in \alpha$-CC

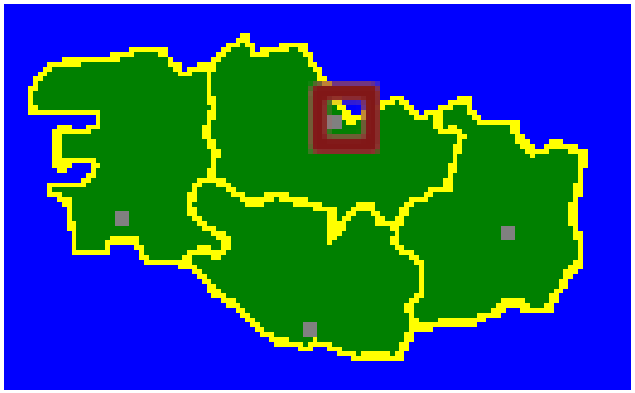
Outline

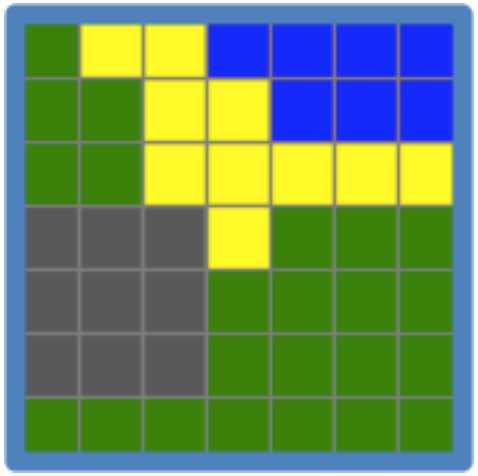
- My Research Environment: University, Institute, and Team
- Morphological Approaches
- Adaptation to multivariate data
  - Orderings
  - Filtering
  - HMT
  - Watershed
  - Hierarchies

Multivariate case

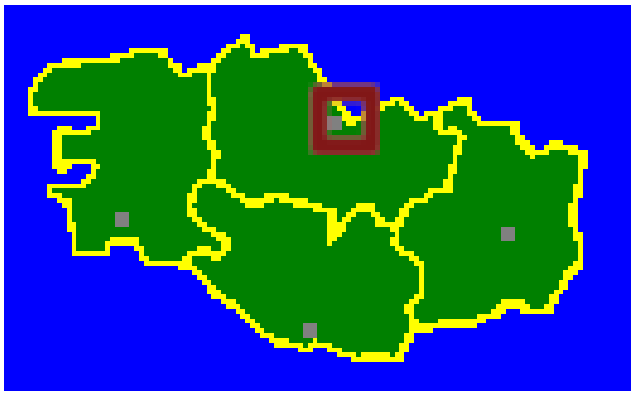


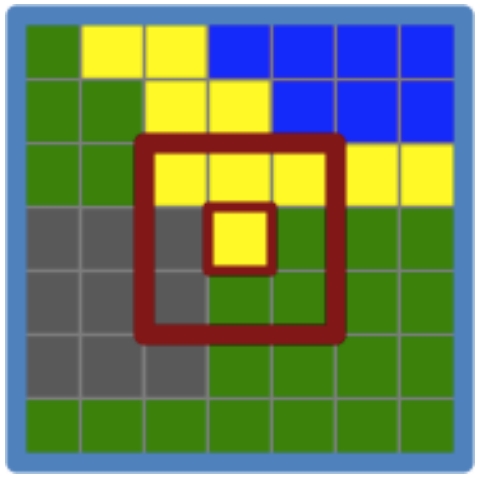
Multivariate case



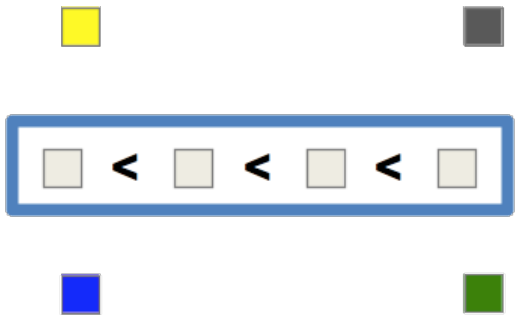


Multivariate case

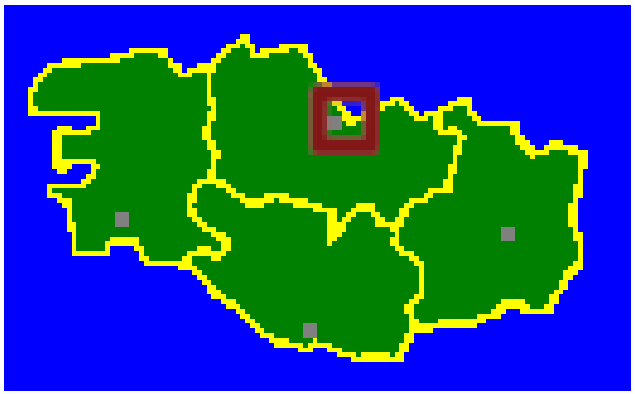


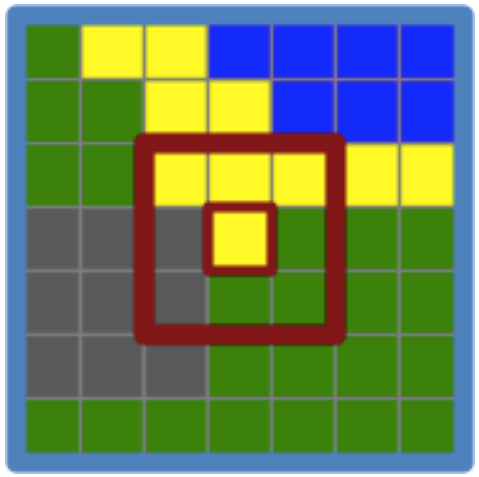


color / multivariate ordering is required

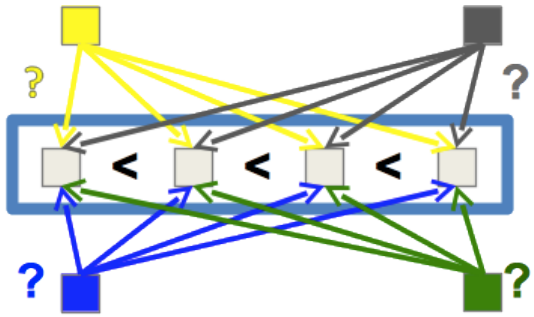


Multivariate case





but there is no such natural ordering !



Multivariate morphology

- marginal processing: each spectral band is a grayscale image
- vectorial processing: pixel values are vectors

Vectorial strategies

- partial ordering e.g. marginal strategy (but lack of correlation)
- pre-ordering e.g. reduced ordering (but no unique extrema)
- total ordering e.g. lexicographical ordering (but unbalanced)

E. Aptoula and S. Lefèvre. "A comparative study on multivariate mathematical morphology". In: Pattern Recognition 40.11 (Nov. 2007), pp. 2914–2929

E. Aptoula and S. Lefèvre. "alpha-trimmed lexicographical extrema for pseudo-morphological image analysis". In: Journal of Visual Communication and Image Representation 19.3 (Apr. 2008), pp. 165–174

E. Aptoula and S. Lefèvre. "On lexicographical ordering in multivariate mathematical morphology". In: Pattern Recognition Letters 29.2 (Jan. 2008), pp. 109–118

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Ordering with color references

Morphology in the luminance – saturation – hue space

- choice of the improved (bi-conic) HLS space
- reliability/independence of saturation and luminance
- hue is an angular value!

$$L_{LSH} = \frac{1}{3}(\max + \text{med} + \min)$$

$$S_{LSH} = \begin{cases} \frac{3}{2}(\max - L_{LSH}) & \text{if } L_{LSH} \geq \text{med} \\ \frac{3}{2}(L_{LSH} - \min) & \text{if } L_{LSH} \leq \text{med} \end{cases}$$

$$H_{LSH} = \frac{\pi}{3}\left[\lambda + \frac{1}{2} - (-1)^{\lambda}\left(\frac{\max+\min-2\text{med}}{2S_{LSH}}\right)\right]$$

$$\lambda = \begin{array}{lll} 0 \text{ if } r > g \geq b & 1 \text{ if } g \geq r > b & 2 \text{ if } g > b \geq r \\ 3 \text{ if } b \geq g > r & 4 \text{ if } b > r \geq g & 5 \text{ if } r \geq b > g \end{array}$$

Ordering with color references

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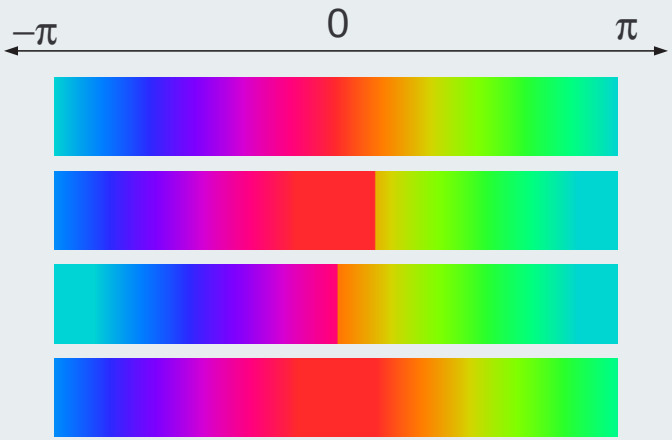
Various hue orderings



input image (red reference hue)

dilation (scalar)

dilation (Peters)

dilation (Hanbury and Serra)

Ordering with color references

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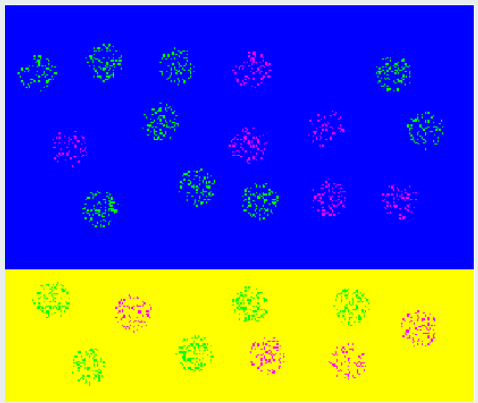
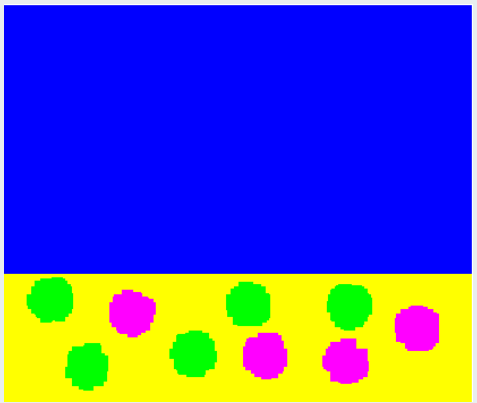
- reliability/independence of saturation and luminance
- hue is an angular value!

One or more reference hues ?



input image



dilation with a single reference

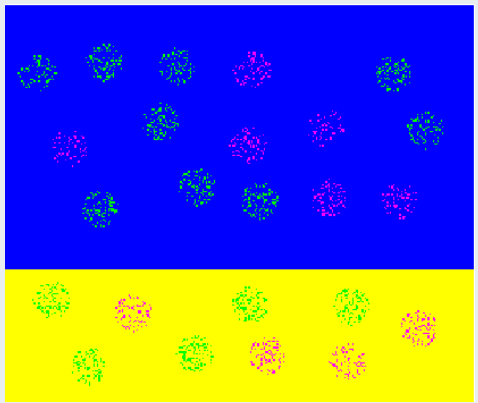
dilation with several references

Ordering with color references

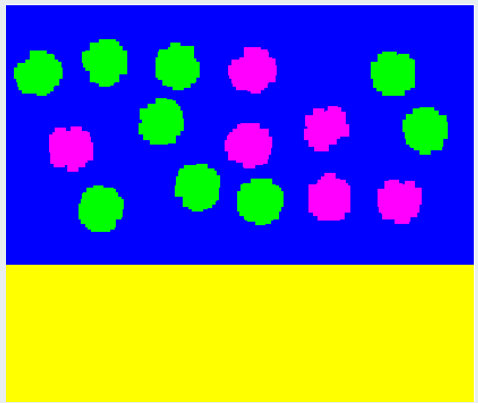
Morphology in the luminance – saturation – hue space

- choice of the improved (bi-conic) HLS space
- reliability/independence of saturation and luminance
- hue is an angular value!

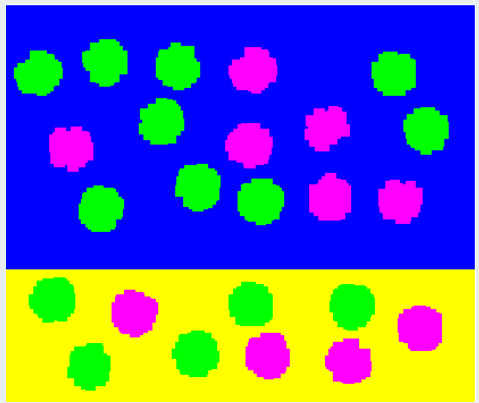
One or more reference hues ?



input image



erosion with a single reference



erosion with several references

Ordering with color references

Morphology in the luminance – saturation – hue space

- choice of the improved (bi-conic) HLS space
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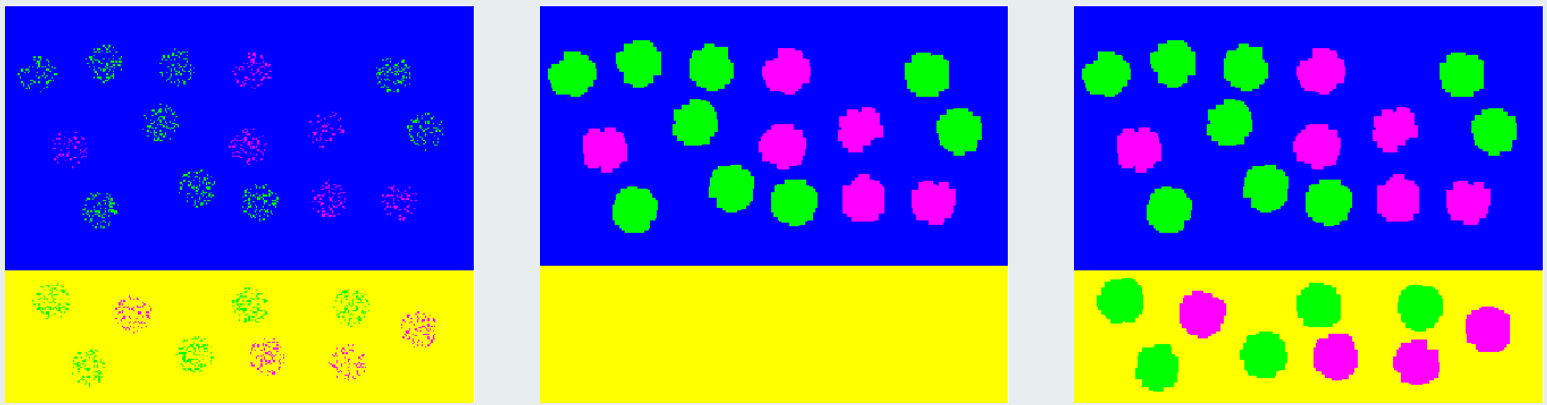
- hue is an angular value!

One or more reference hues ?



E. Aptoula and S. Lefèvre. "On the morphological processing of hue". In: Image and Vision Computing 27.9 (Aug. 2009), pp. 1394–1401

Ordering with spectral references (end-members)

- Each pixel in an hyperspectral image is assigned a vector of reflectances sampled over different wavelengths
- Spatial resolution and scattering effect lead to mixed pixels, with values that are actually combination of spectra, each of them describing the reflectance of a pure material
- These pure material are called end-members, and can be identified by several algorithms e.g., N-FINDR
- While the end-members are usually employed for spectral unmixing, they can also be used for devising a supervised ordering with physical foundations

---

E. Aptoula, N. Courty, and S. Lefèvre. "An end-member based ordering relation for the morphological description of hyperspectral images". In: IEEE International Conference on Image Processing (ICIP). Paris, France, Oct. 2014

Ordering with spectral references (end-members)

1. Extraction of end-members m_i, used as reference spectra
2. Distance between each pixel p and end-member m_i is computed
3. Ordering of the pixels based on their distance to the closest end-member (inspired from ordering hues)
   $\min_i \{d(f(p), m_i)\} < \min_j \{d(f(q), m_j)\} \Rightarrow \mathbf{f}(q) <_M f(p)$
4. a lexicographical cascade is added to avoid ties (not in practice)

Ordering with spectral references (end-members)

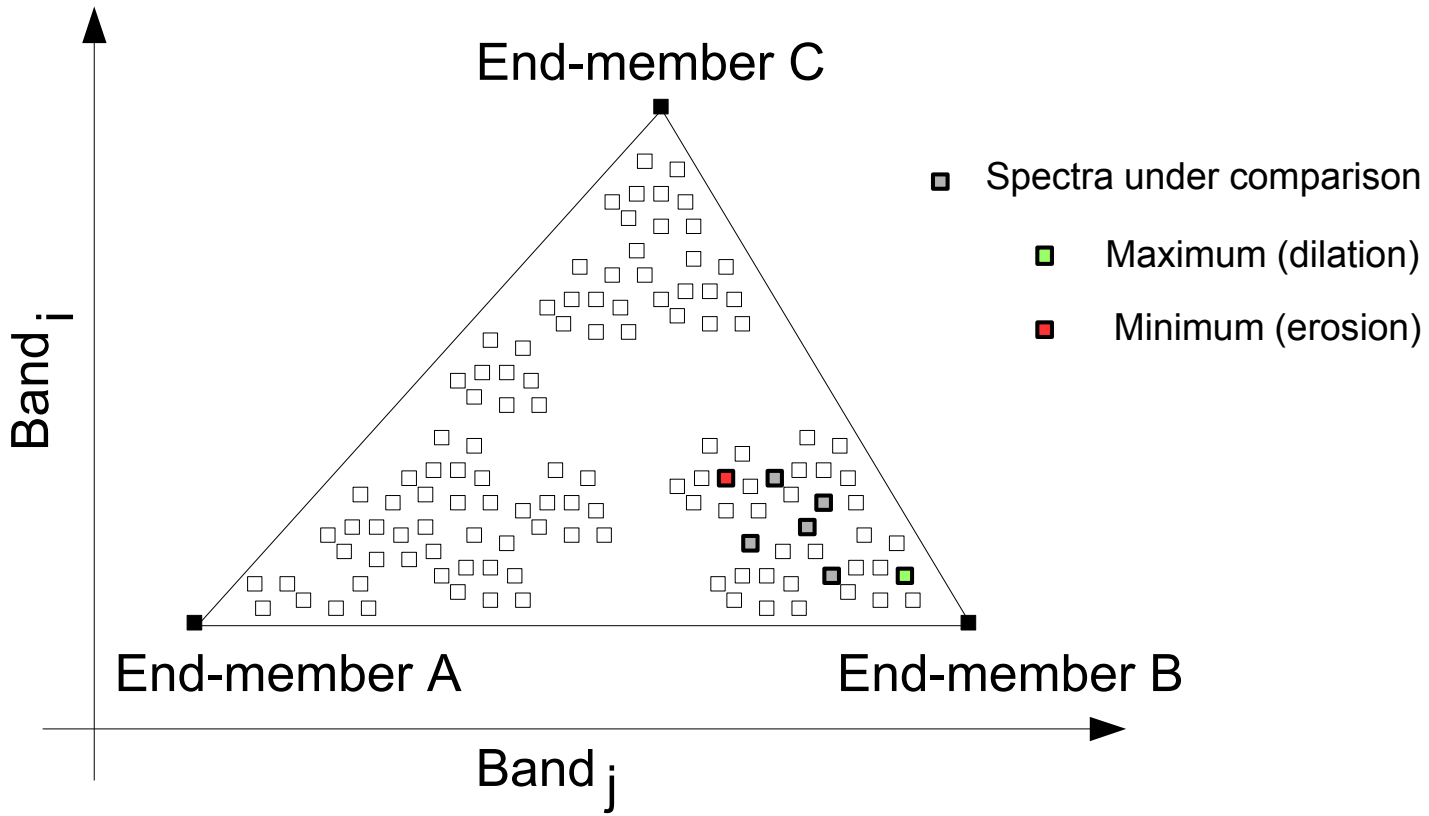
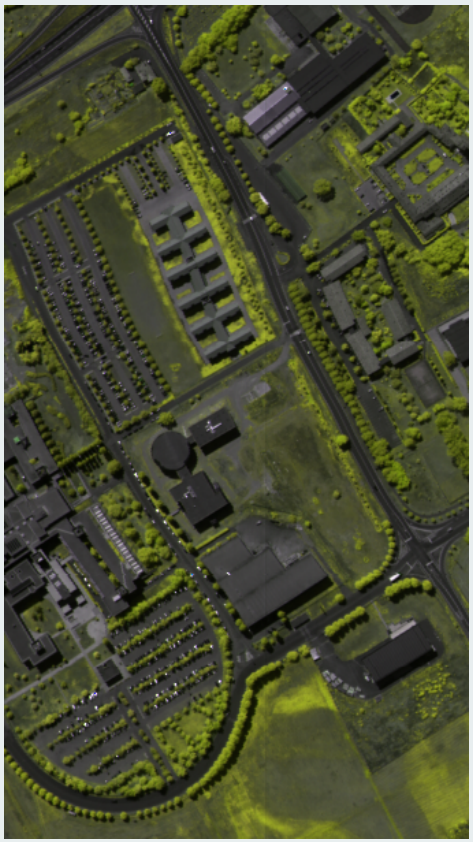


Illustration on Pavia University image (9 classes)



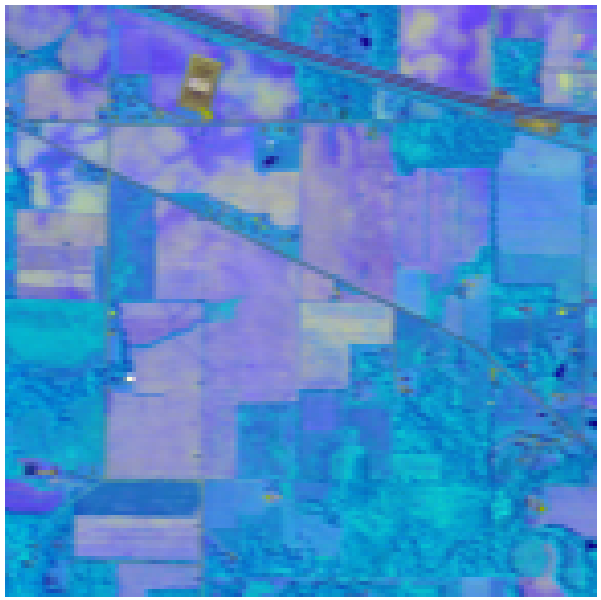
Original image
(80,90,70)

Dilation
3×3 square SE

Erosion
3×3 square SE

Dataset: Indian Pines

- image: 145×145 pixels, 200 spectral bands
- learning set: 16 classes, $10,249$ labeled pixels



Setup

- N-FINDR with 16 end-members (i.e. number of classes)
- Euclidean distance between pixels and end-members
- Morphological operators are used to compute DMP of size 3, 5, 7 and 9, leading to a profile of length 9 for each band
- We limit the number of spectral bands to 16 (regular sampling) to limit the feature vector to $9 \times 16 = 144$
- We perform classification using random forest (100 trees), 10 pixel/class for training (the rest for testing), results averaged over 30 runs

Classification results

Class	Set Size	MARG (s.dev)	NORM (s.dev)	SAD (s.dev)	ENDM (s.dev)
Alfalfa	46	94.99 (1.74)	91 (1.71)	97.87 (1.74)	**97.21** (1.91)
Corn-notill	1,428	**60.71** (1.85)	56.69 (1.49)	39.68 (1.87)	59.5 (1.69)
Corn-mintill	830	**76.48** (1.63)	70.13 (1.23)	43.05 (1.63)	73.54 (1.54)
Corn	237	90.95 (1.96)	91.69 (1.53)	76.92 (1.42)	**93.99** (1.62)
Grass-pasture	483	86.51 (1.85)	83.86 (1.86)	61.73 (1.41)	**87.04** (1.87)
Grass-trees	730	89.8 (1.84)	85.34 (1.67)	78.08 (1.31)	**91.88** (1.65)
Grass-pasture-mowed	28	99.77 (1.45)	**100** (0.14)	**100** (0.11)	**100** (0.4)
Hay-windrowed	478	97.65 (1.85)	99.16 (1.12)	97.34 (1.63)	**99.89** (1.9)
Oats	20	**100** (0.2)	96.4 (0.34)	94.8 (1.62)	**100** (0.44)
Soybean-notill	972	70.53 (1.01)	66.19 (1.45)	53.8 (1.41)	**72.57** (1.83)
Soybean-mintill	2,455	67.49 (1.84)	57.52 (1.57)	41.49 (1.73)	**70.71** (1.95)
Soybean-clean	593	**76.77** (1.9)	72.55 (1.15)	47.23 (1.92)	76.01 (1.84)
Wheat	205	97.99 (1.85)	97.59 (1.46)	96.66 (1.28)	**98.4** (1.8)
Woods	1,265	**93.11** (1.96)	88.86 (1.27)	75.59 (1.73)	92.51 (1.5)
Build.-Grass-Trees-Drives	386	94.95 (1.84)	84.15 (1.83)	80.5 (1.84)	**95.43** (1.41)
Stone-Steel-Towers	93	**99.04** (0.98)	97.31 (0.84)	94.70 (1.85)	98.94 (1.62)
Average Accuracy		87.3 (1.65)	83.65 (1.29)	73.72 (1.53)	**87.98** (1.56)
Overall Accuracy		77.76 (1.95)	72.27 (1.55)	57.36 (1.74)	**78.58** (1.81)

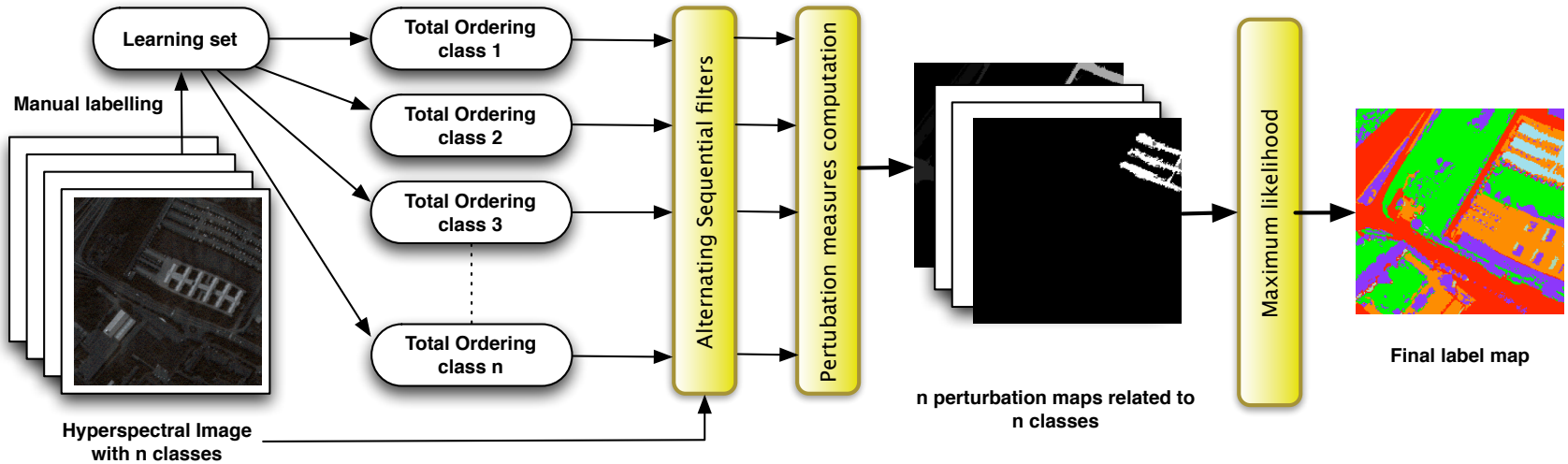
Ordering based on machine learning

Rely on a recent manifold learning technique based on manifold perturbation.

A perturbo-based ordering: $\mathbf{x_a} >_\ell \mathbf{x_b} \Rightarrow \tau_\ell(\mathbf{x_a}) > \tau_\ell(\mathbf{x_b})$

where $\tau_\ell(\cdot) = \tau(\cdot, \mathcal{M}_\ell)$

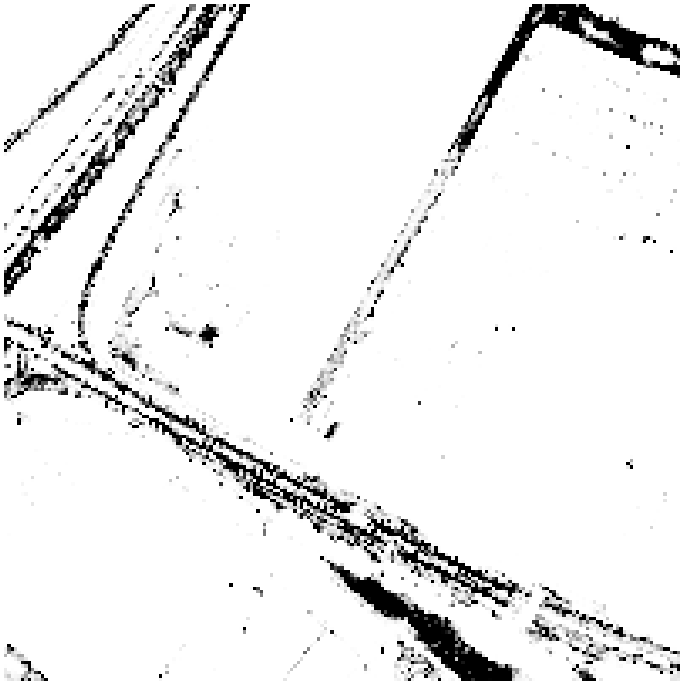
(+ lexicographical comparison of $\mathbf{x_a}$ and $\mathbf{x_b}$ to ensure totality).

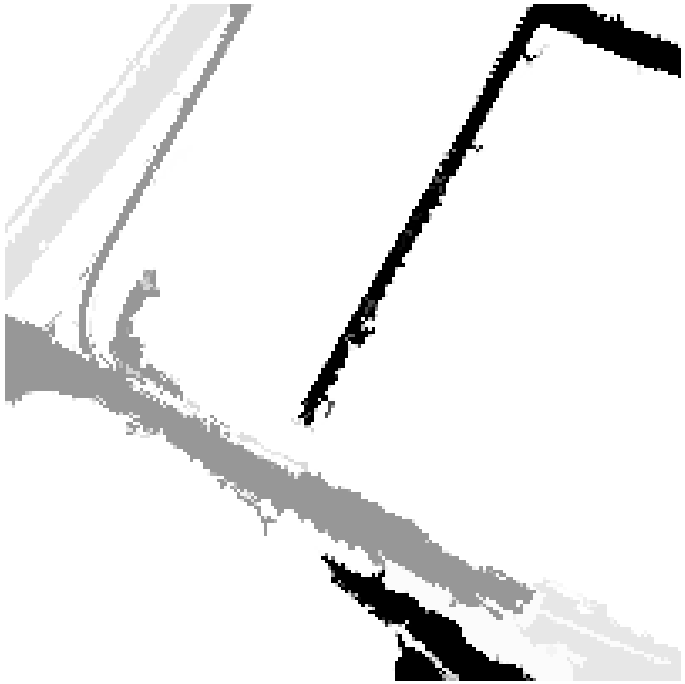


N. Courty, E. Aptoula, and S. Lefèvre. "A Classwise Supervised Ordering Approach for Morphology Based Hyperspectral Image Classification". In: IAPR International Conference on Pattern Recognition (ICPR). Tsukuba, Japan, Nov. 2012

Ordering based on machine learning

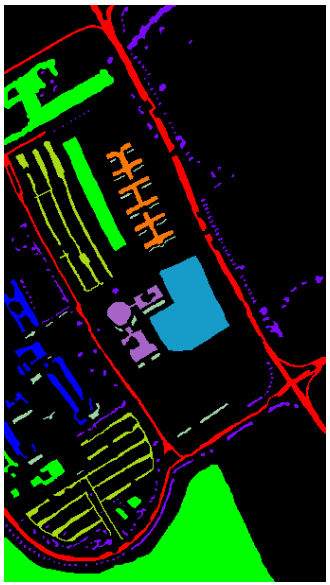
We replace here the DMP by a simple alternate sequential filter that aims to smooth the image. Example is given for the Asphalt class.

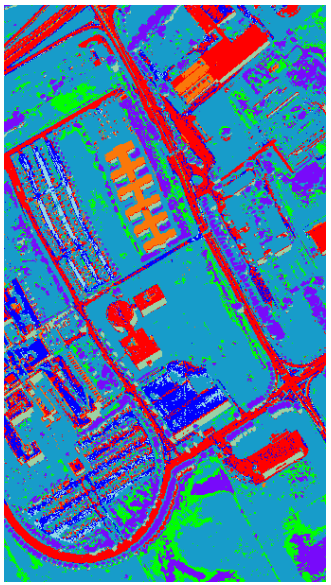


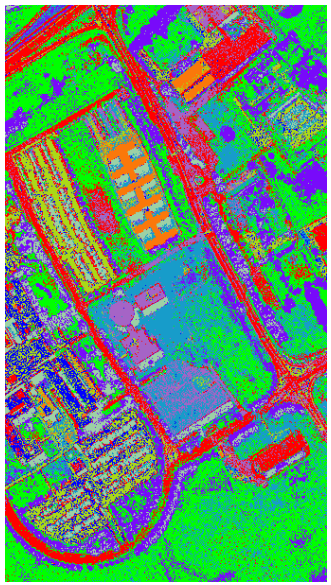


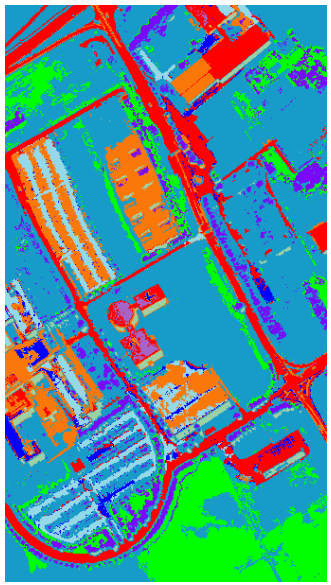
Ordering based on machine learning

input

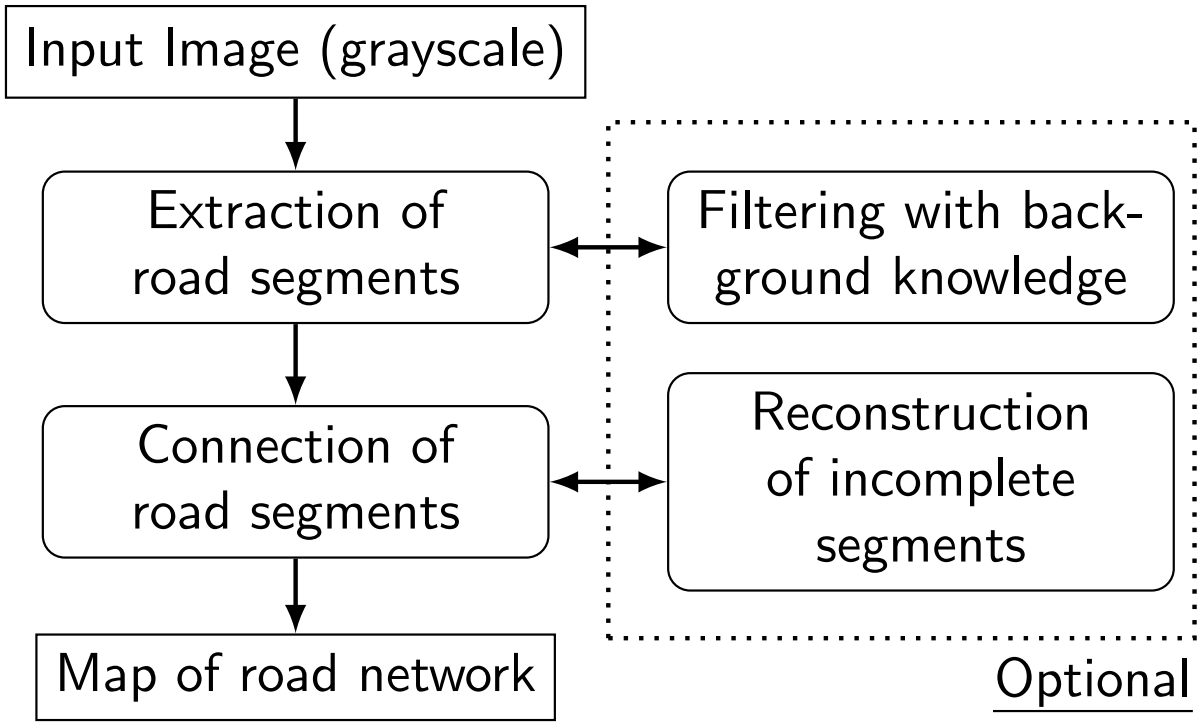

ground truth


Perturbo


EMP


Proposed

Filtering for extraction of road network



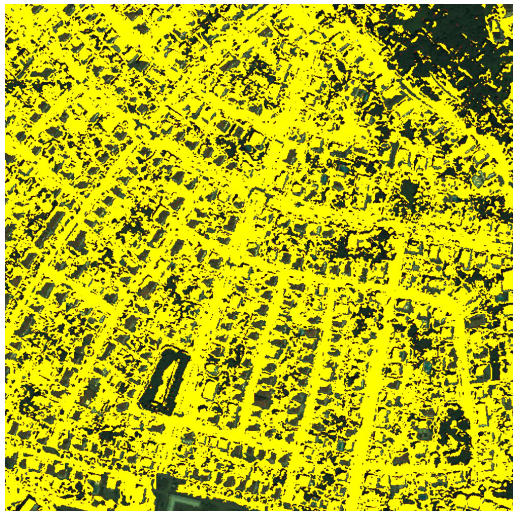
L. Courtrai and S. Lefèvre. "Road Network Extraction from Remote Sensing using Region-based Mathematical Morphology". In: IAPR International Workshop on Pattern Recognition in Remote Sensing (PRRS). Stockholm, Sweden, Aug. 2014. DOI: 10.1109/PRRS.2014.6914283

Path filtering at a region level

Original image
(RGB composition)

Path filtering at a region level

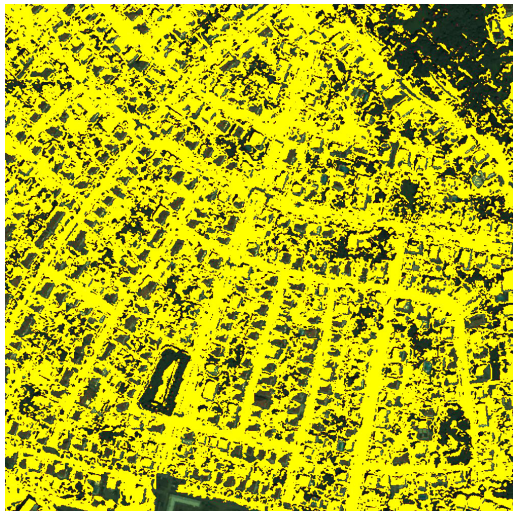
Original image
(RGB composition)



Pixelwise
path closing

Path filtering at a region level

Original image
(RGB composition)



Pixelwise
path closing

Region-based
path closing

Template matching

- impose a vectorial ordering on the data
- combine spectral properties with spatial ones
- other strategies available

E. Aptoula, S. Lefèvre, and C. Ronse. "A Hit-or-Miss Transform for Multivariate Images". In: Pattern Recognition Letters 30.8 (June 2009), pp. 760–764

J. Weber and S. Lefèvre. "Spatial & Spectral Morphological Template Matching". In: Image and Vision Computing 30.12 (2012), pp. 934–945

S. Lefèvre et al. "Morphological Template Matching in Color Images". In: Advances in Low-Level Color Image Processing. Ed. by E. Celbi and B. Smolka. Vol. 11. Lecture Notes in Computational Vision and Biomechanics. Springer-Verlag, 2014, pp. 241–277. DOI: 10.1007/978-94-007-7584-8_8

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J. Weber and S. Lefèvre. "Spatial & Spectral Morphological Template Matching". In: Image and Vision Computing 30.12 (2012), pp. 934–945

S. Lefèvre et al. "Morphological Template Matching in Color Images". In: Advances in Low-Level Color Image Processing. Ed. by E. Celbi and B. Smolka. Vol. 11. Lecture Notes in Computational Vision and Biomechanics. Springer-Verlag, 2014, pp. 241–277. DOI: 10.1007/978-94-007-7584-8_8

Template matching

- impose a vectorial ordering on the data
- combine spectral properties with spatial ones
- other strategies available

E. Aptoula, S. Lefèvre, and C. Ronse. "A Hit-or-Miss Transform for Multivariate Images". In: Pattern Recognition Letters 30.8 (June 2009), pp. 760–764

J. Weber and S. Lefèvre. "Spatial & Spectral Morphological Template Matching". In: Image and Vision Computing 30.12 (2012), pp. 934–945

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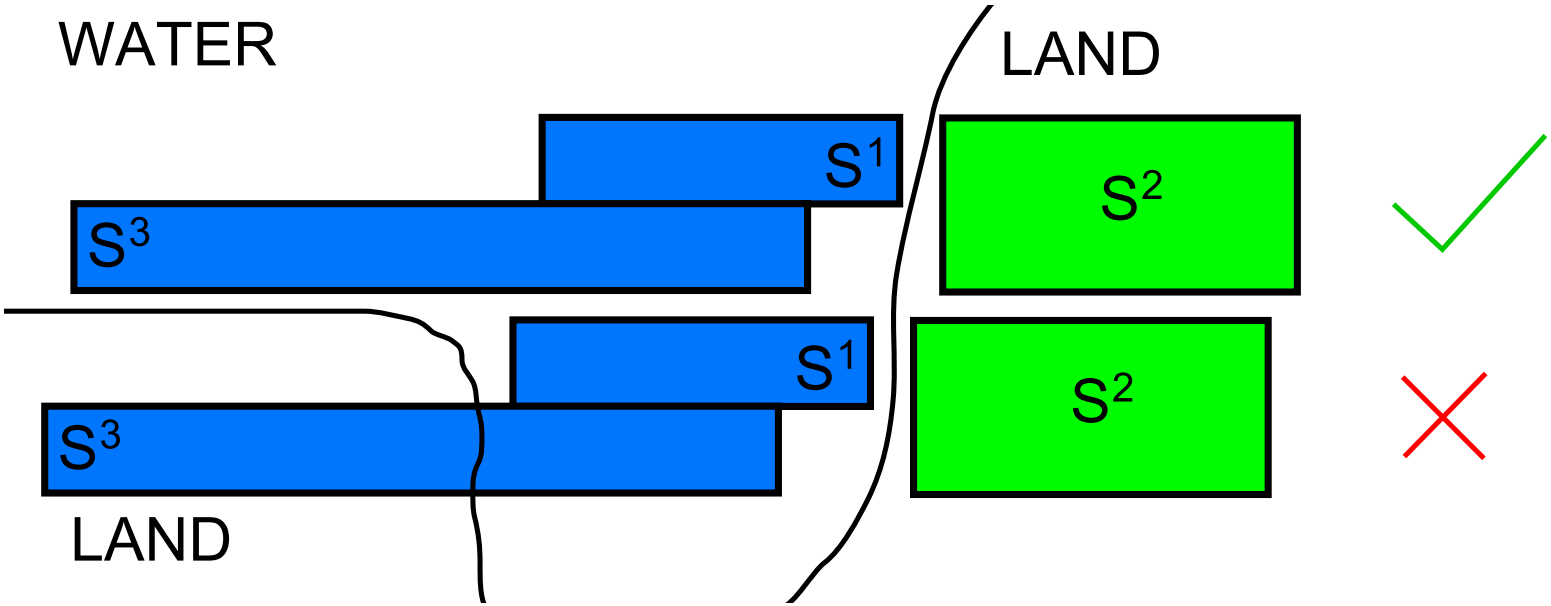
Template matching (coastline)



$$\{s^1_{\text{shape}} = 180 \quad +0, \quad s^1_{\text{band}} = \text{NDVI}, \quad s^1_{\text{thr}} = 0.5, \quad s^1_{\text{type}} = G\}$$
$$\{s^2_{\text{shape}} = -180 \quad +0, \quad s^2_{\text{band}} = \text{NDVI}, \quad s^2_{\text{thr}} = 0.5, \quad s^2_{\text{type}} = L\}$$
$$\{s^3_{\text{shape}} = 360 \quad +12, \quad s^3_{\text{band}} = \text{R}, \quad s^3_{\text{thr}} = 0.05, \quad s^3_{\text{type}} = L\}$$

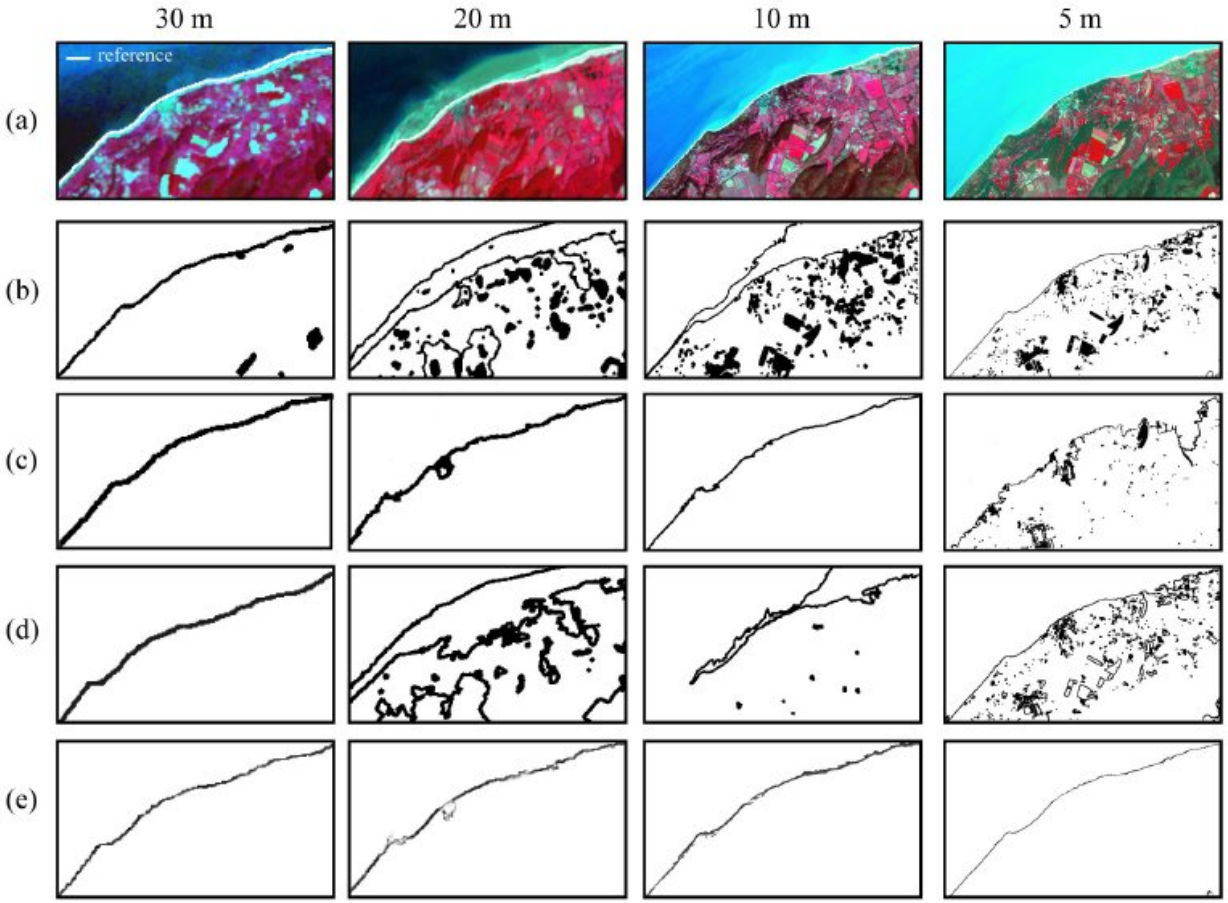
J. Weber and S. Lefèvre. "Spatial & Spectral Morphological Template Matching". In: Image and Vision Computing 30.12 (2012), pp. 934–945

Template matching (coastline)

Synopsis

1. Apply the MHMT in all orientations (and take the max)
2. Connect the detected points through a double threshold procedure

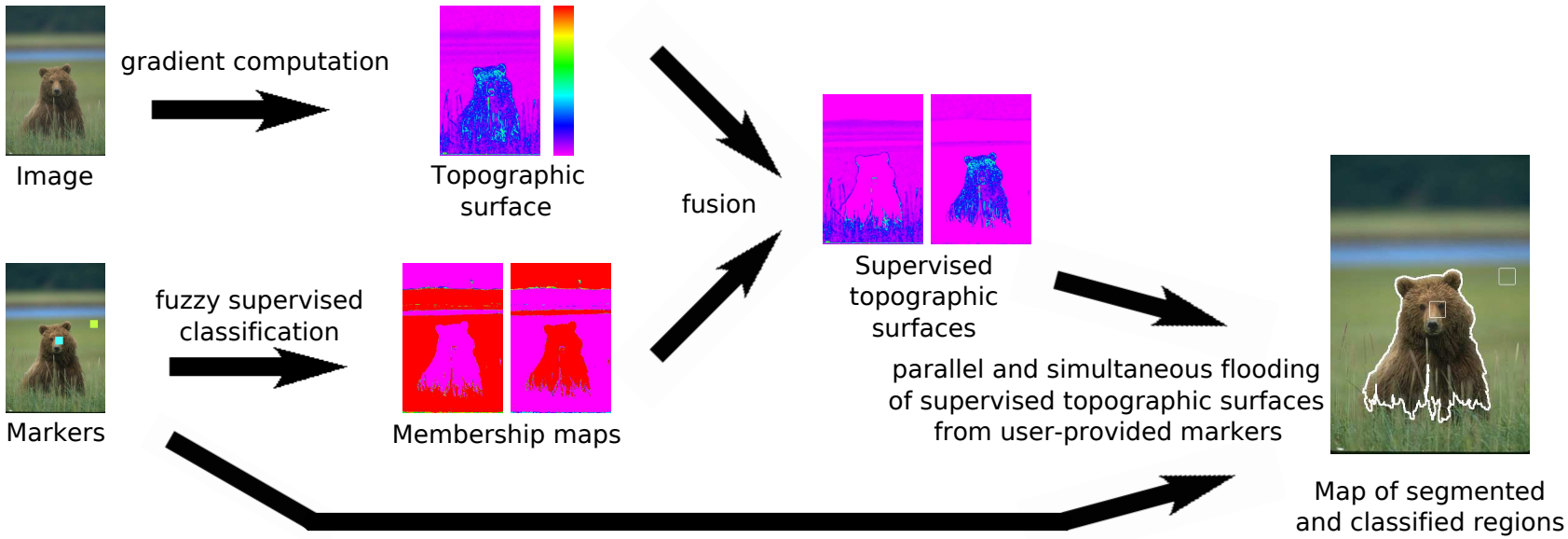
Template matching (coastline)



Supervised segmentation (recall)

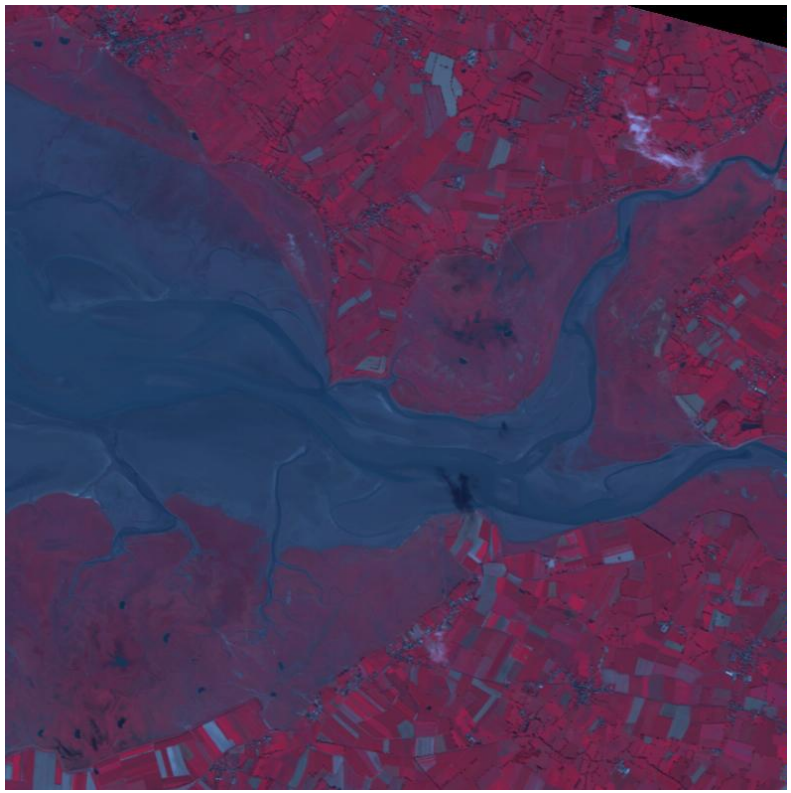
Principle

- learning sets are markers in watershed segmentation
- multiple surface are flooded simultaneously

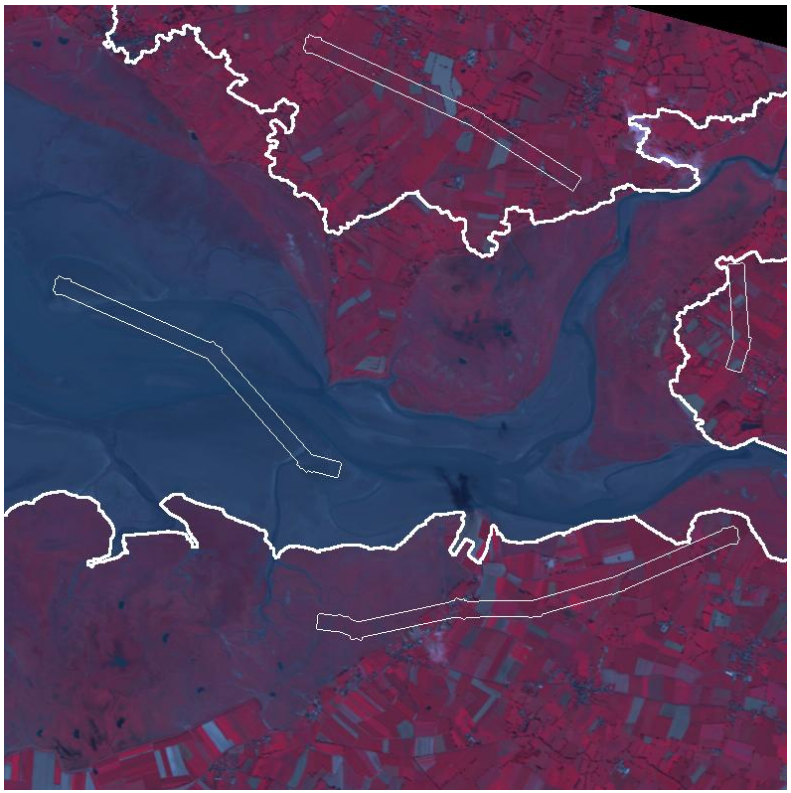


S. Lefèvre. "Knowledge from markers in watershed segmentation". In: International Conference on Computer Analysis of Image and Patterns (CAIP). vol. 4673. Lecture Notes in Computer Science. Vienna, Austria: Springer-Verlag, Aug. 2007, pp. 579–586

Segmentation (coastline)

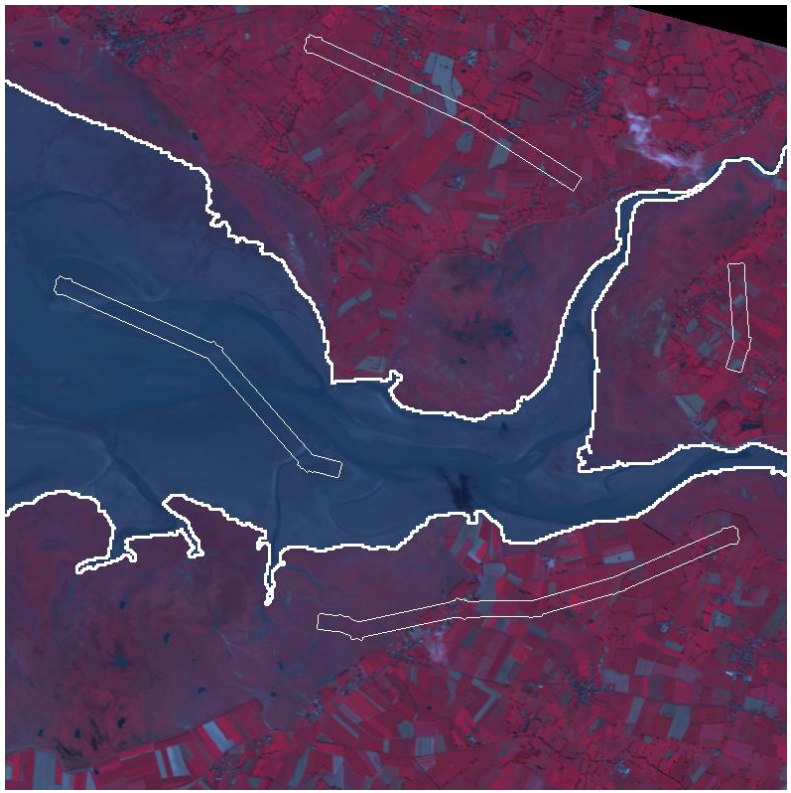


input image

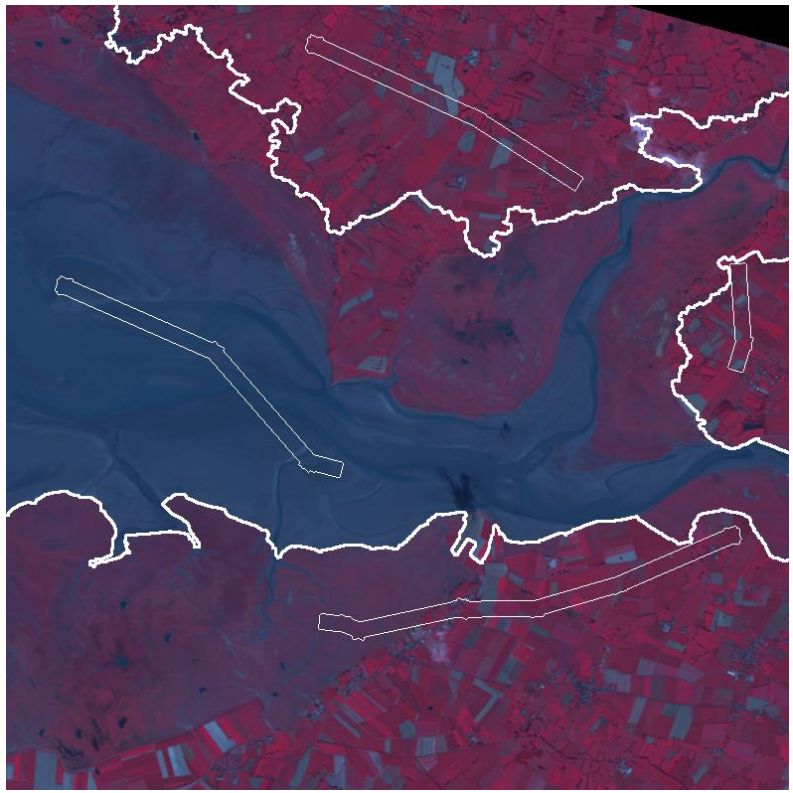


marker-based watershed

Segmentation (coastline)

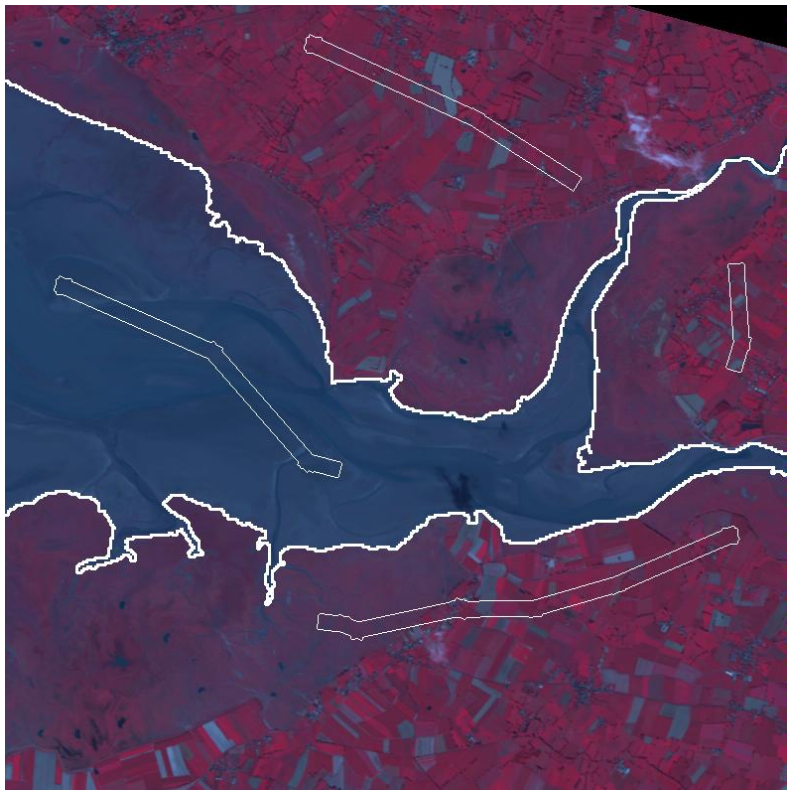


using spectral markers



marker-based watershed

Segmentation (coastline)



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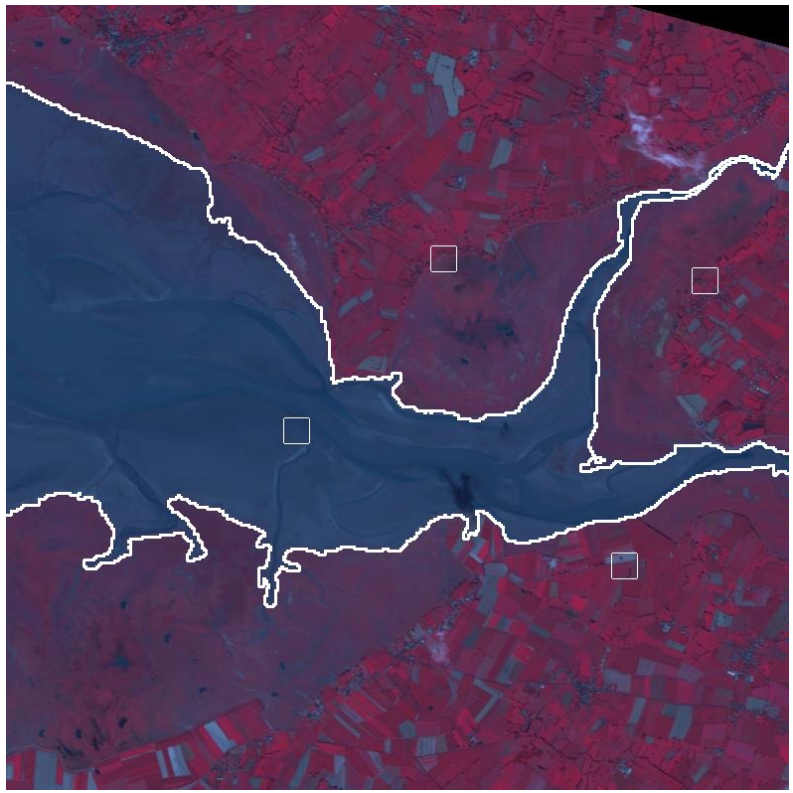
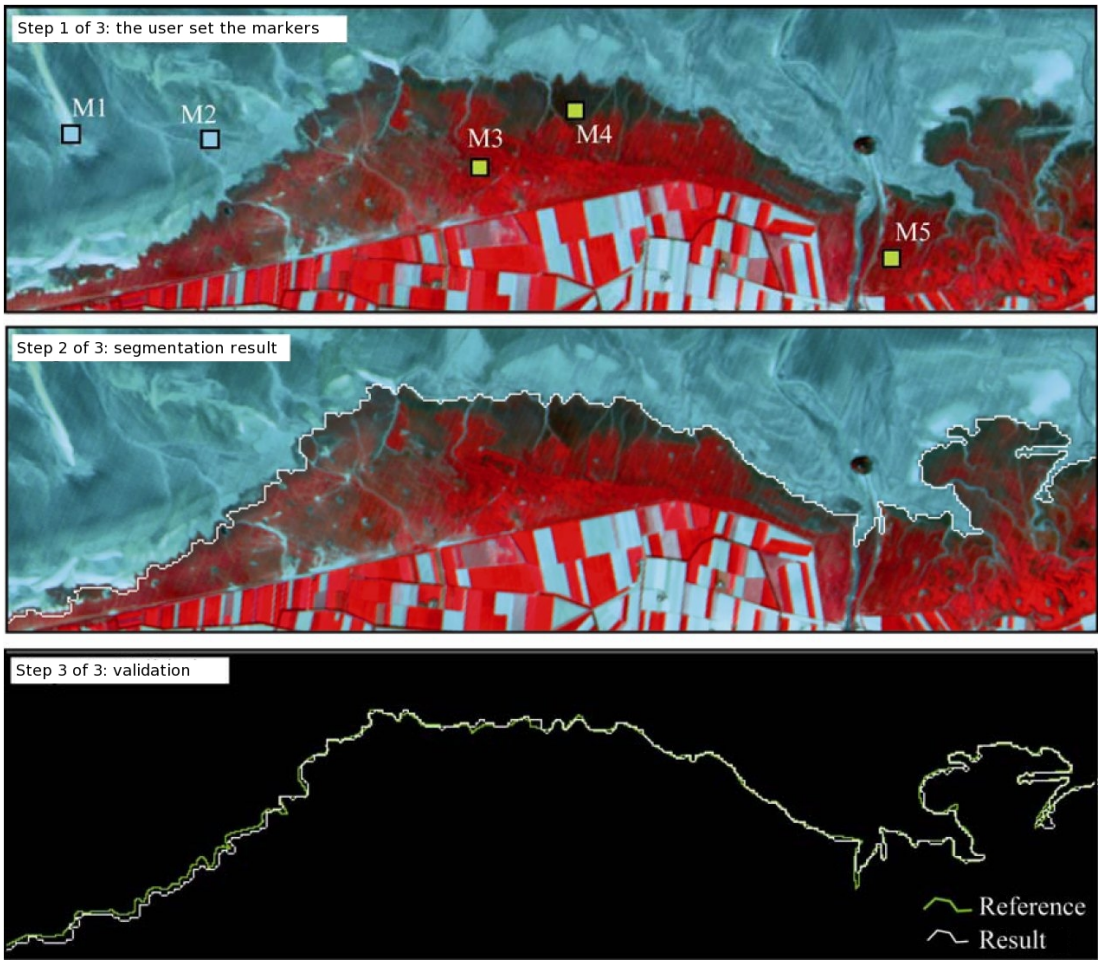
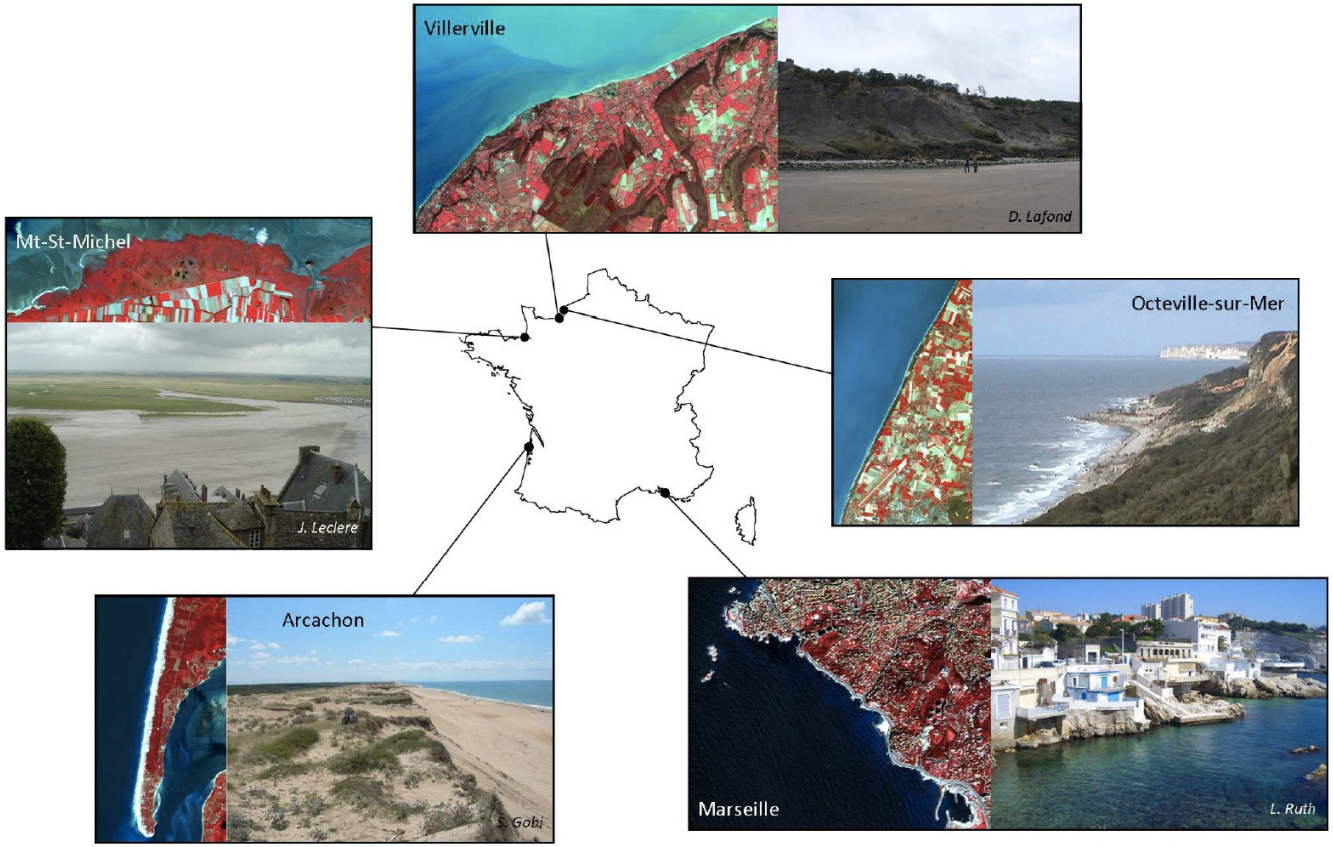


even with smaller markers

Segmentation (coastline)



Segmentation (coastline)

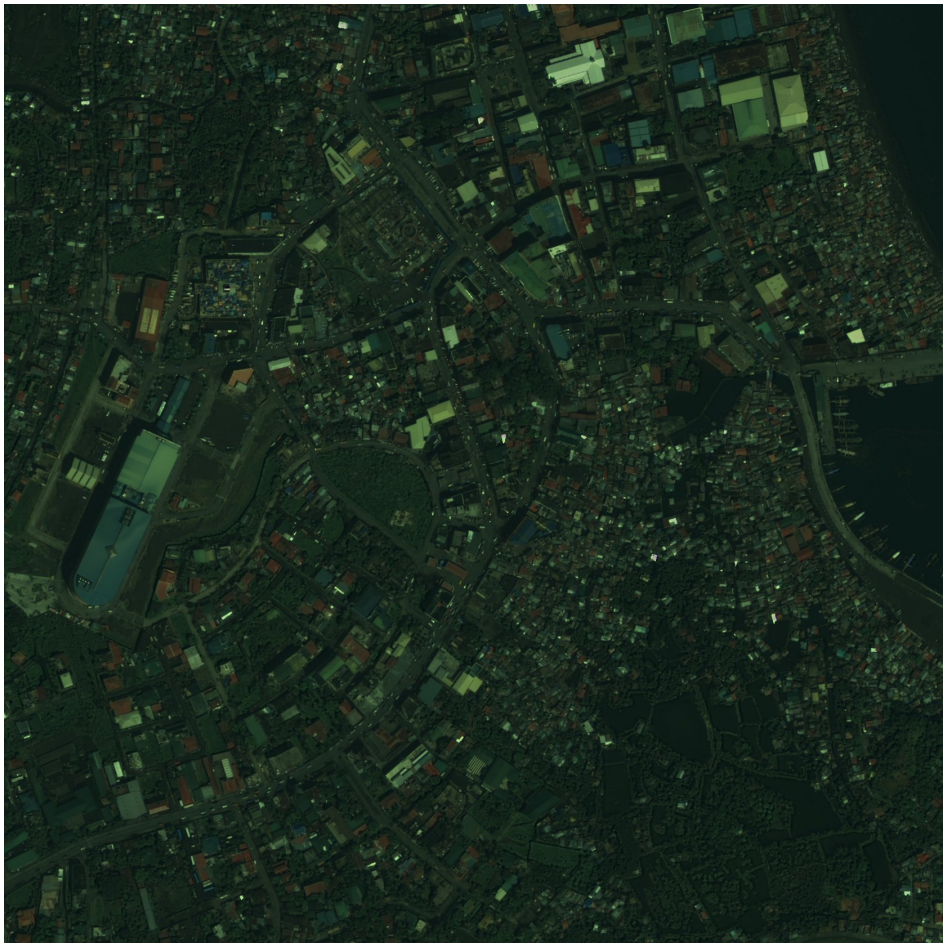


A. Puissant et al. "Automated Mapping of Coastline From High Resolution Satellite Images Using Supervised Segmentation". In: International Conference on Geographic Object-Based Image Analysis (GEOBIA). Rio de Janeiro, Brazil, May 2012, pp. 515–517

Segmentation (building contest)

Context

- objective: relevance of general user-driven morphological tools ?
- attempt #1: fully supervised strategy (3000 buildings / 90 minutes of mouse clicking)
- attempt #2: weakly-supervised strategy (14 markers)



S. Aksoy et al. "Performance evaluation of building detection and digital surface model extraction algorithms: Outcomes of the PRRS 2008 Algorithm Performance Contest". In: IAPR International Workshop on Pattern Recognition in Remote Sensing (PRRS). Tampa, USA, Dec. 2008

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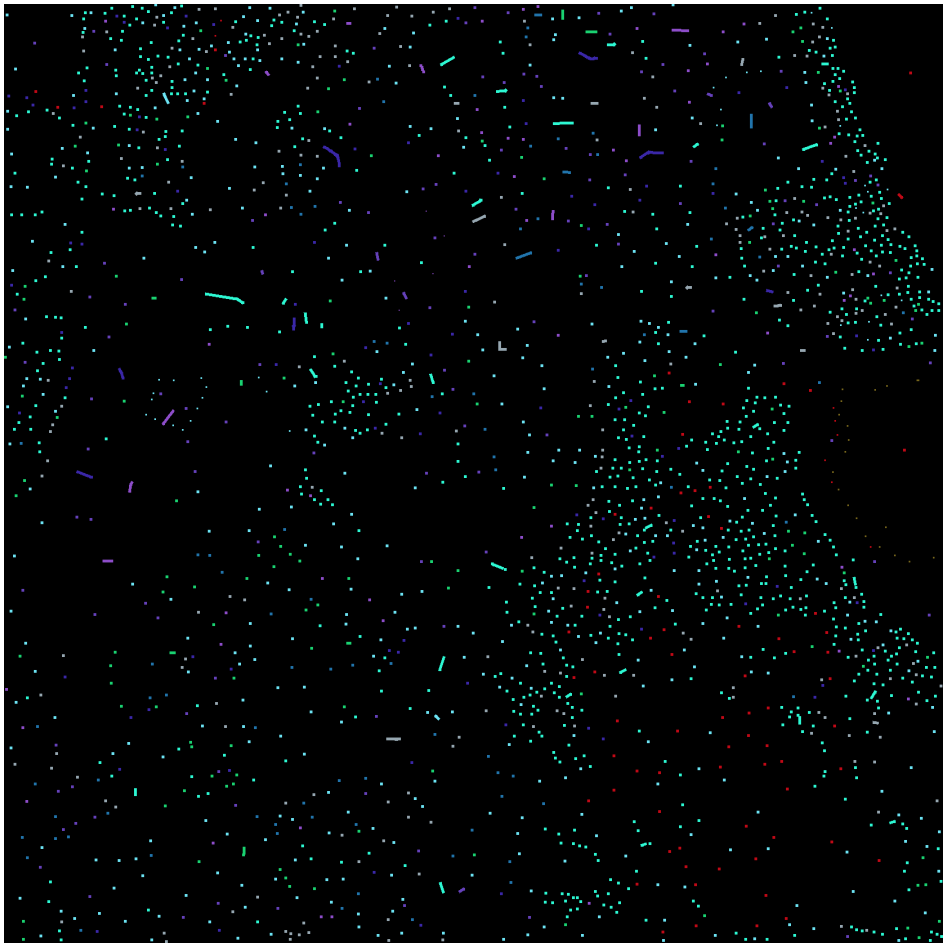

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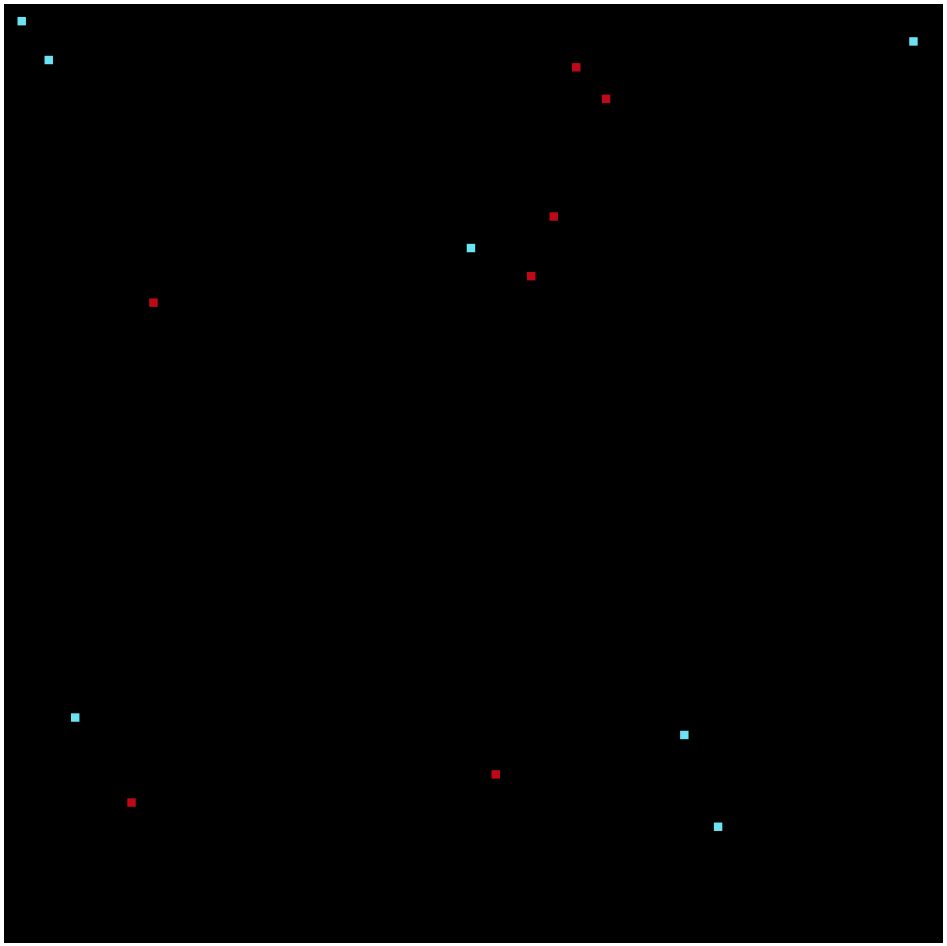

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Segmentation (building contest)

Results

- precision/recall using multiple evaluation criteria
- very good performance with no tuning

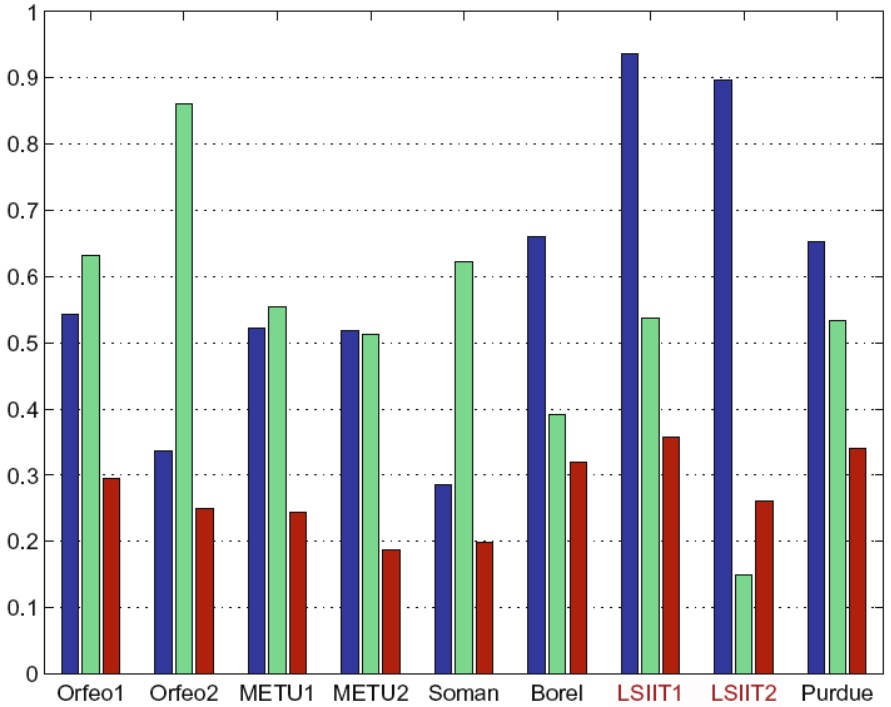

Fig. 5. Precision (blue), recall (green), and detection accuracy (red) scores obtained using the bipartite graph matching algorithm for the results in Fig. 4. (For interpretation of the references in color in this figure legend, the reader is referred to the web version of this article.)

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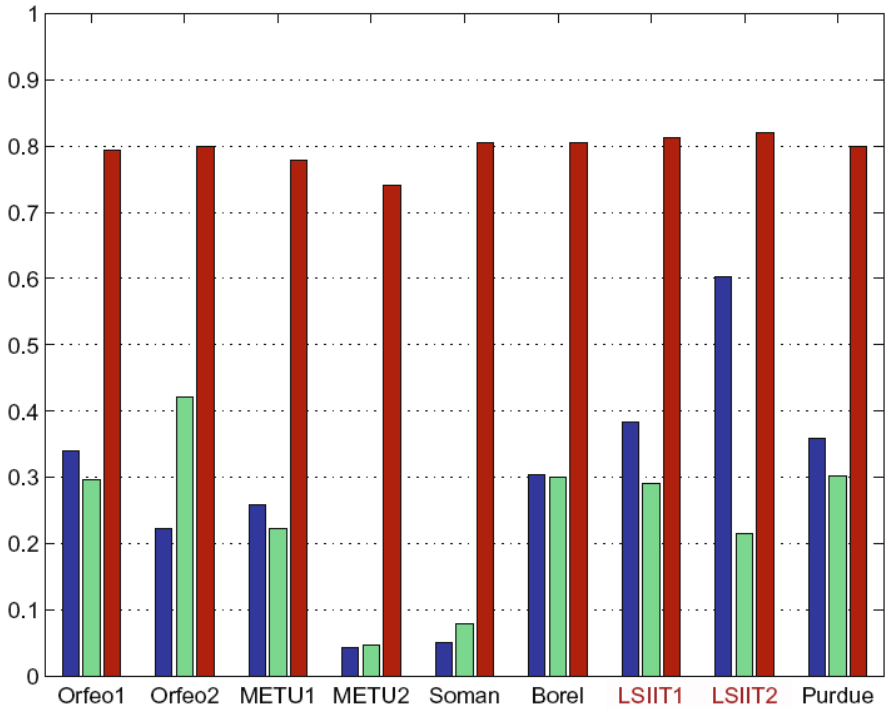

Fig. 6. Precision (blue), recall (green), and detection accuracy (red) scores obtained using the Hoover algorithm for the results in Fig. 4. (For interpretation of the references in color in this figure legend, the reader is referred to the web version of this article.)

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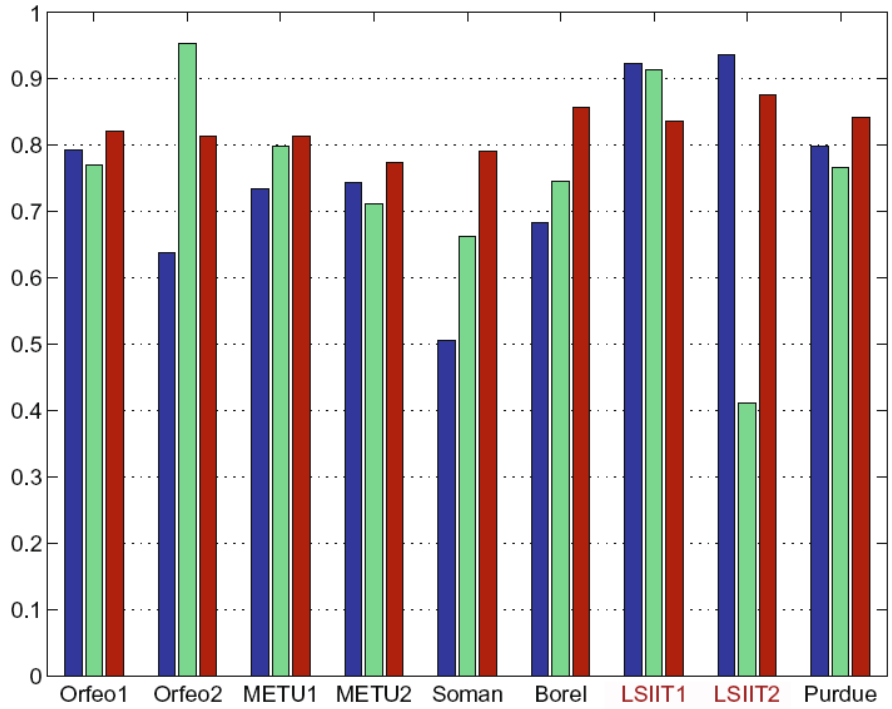

Fig. 7. Precision (blue), recall (green), and detection accuracy (red) scores obtained using the proposed multi-object maximum overlap matching algorithm and the Mallows measure for the results in Fig. 4. (For interpretation of the references in color in this figure legend, the reader is referred to the web version of this article.)

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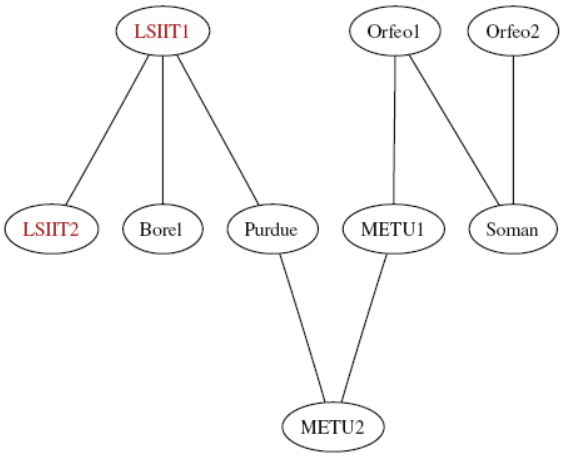

Rank 1: LSIIT1
Rank 2: Orfeo1
Rank 3: Orfeo2
Rank 4: Purdue
Rank 5: Borel
LSIIT2
METU1
Rank 8: Soman
Rank 9: METU2

Fig. 8. The Hasse diagram and the corresponding ranking for the scores in Fig. 5 obtained using the bipartite graph matching algorithm.

S. Aksoy et al. "Performance evaluation of building detection and digital surface model extraction algorithms: Outcomes of the PRRS 2008 Algorithm Performance Contest". In: IAPR International Workshop on Pattern Recognition in Remote Sensing (PRRS). Tampa, USA, Dec. 2008

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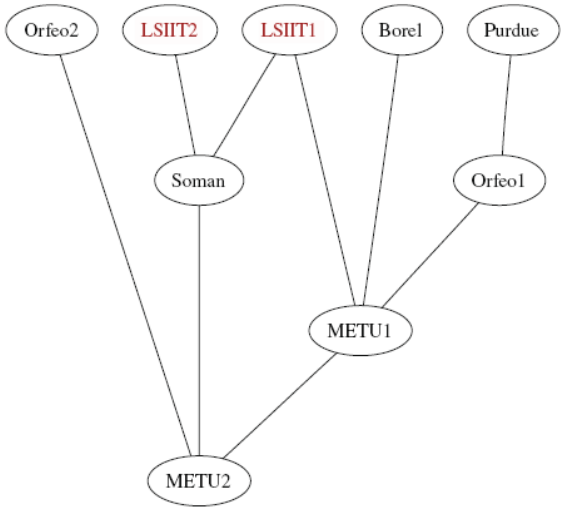

Fig. 9. The Hasse diagram and the corresponding ranking for the scores in Fig. 6 obtained using the Hoover algorithm.

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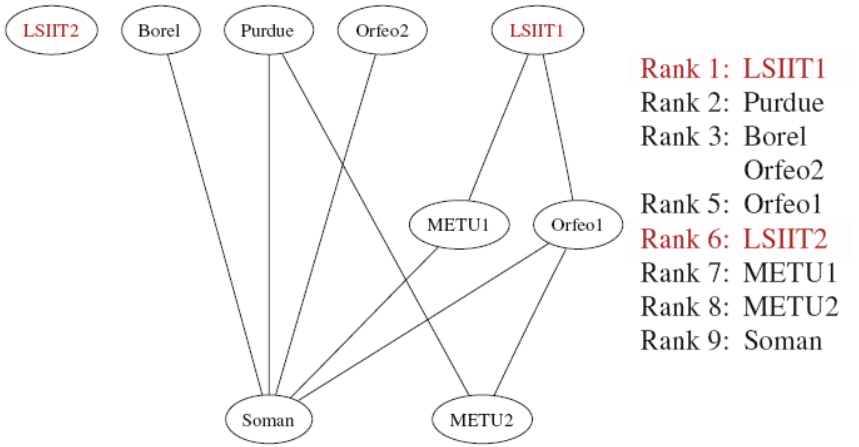

Fig. 10. The Hasse diagram and the corresponding ranking for the scores in Fig. 7 obtained using the proposed multi-object maximum overlap matching algorithm and the Mallows measure.

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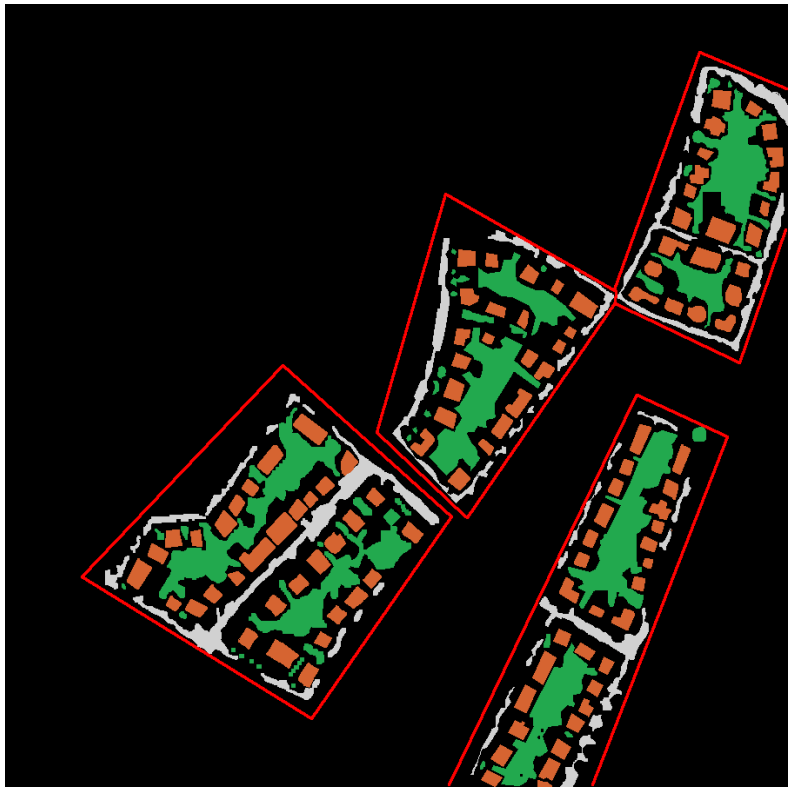
Markerless supervised segmentation of urban scenes

Input image

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes



Learning sets

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes

Unsupervised watershed

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes

(Pre-)Supervised watershed

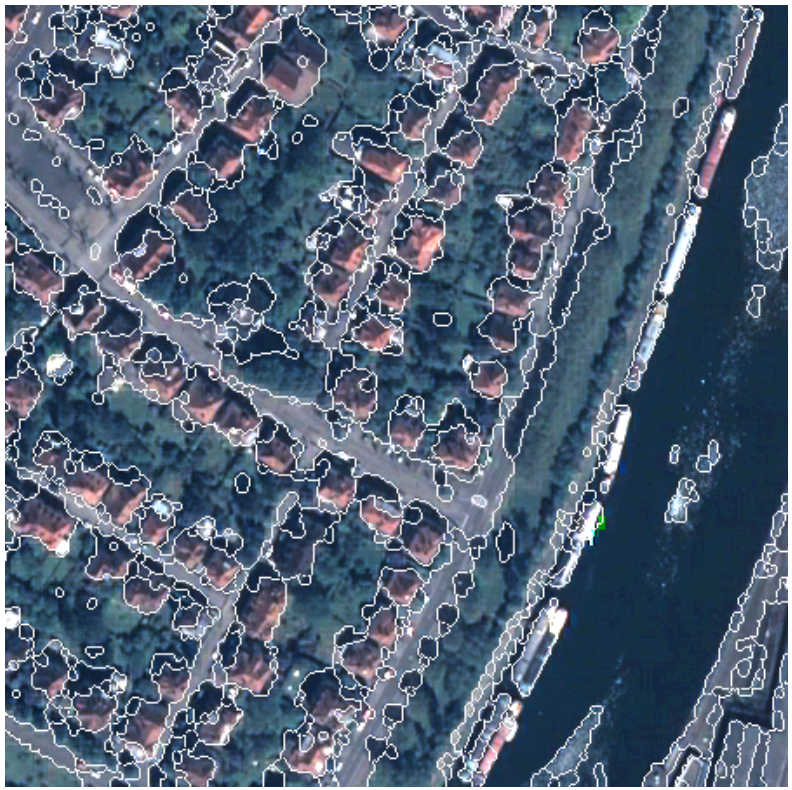
S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes

(Post-)Supervised watershed

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes



(Pre+Post-)Supervised watershed

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes

ENVI segmentation

S. Derivaux et al. "Supervised Segmentation Using Machine Learning and Evolutionnary Computation". In: Pattern Recognition Letters 31.15 (Nov. 2010), pp. 2364–2374

Markerless supervised segmentation of urban scenes

E-cognition segmentation

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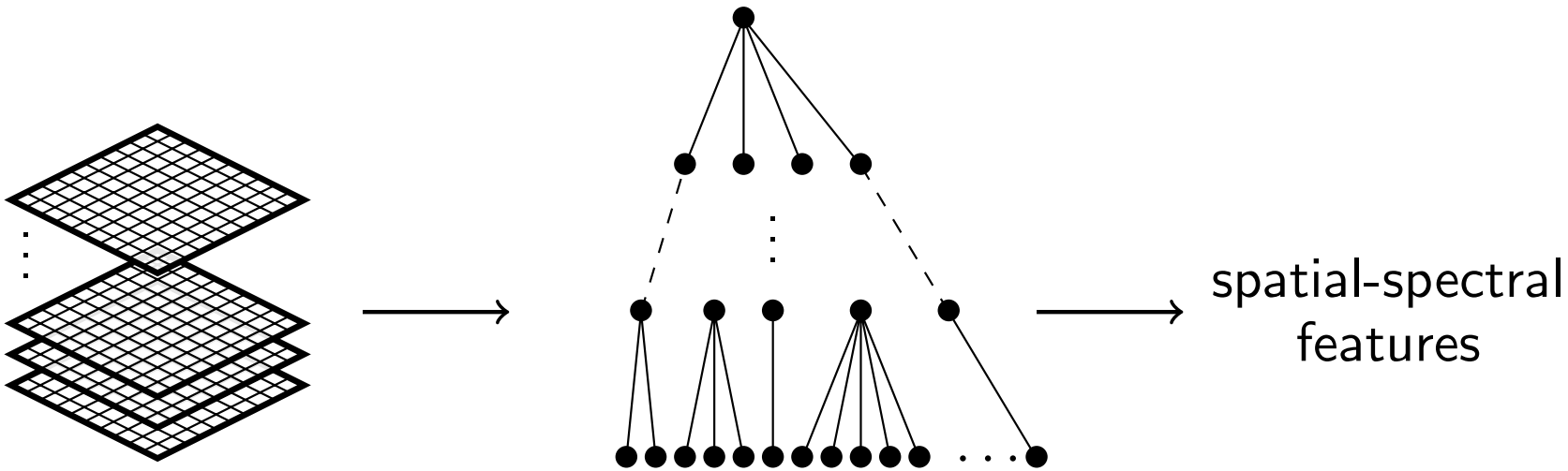
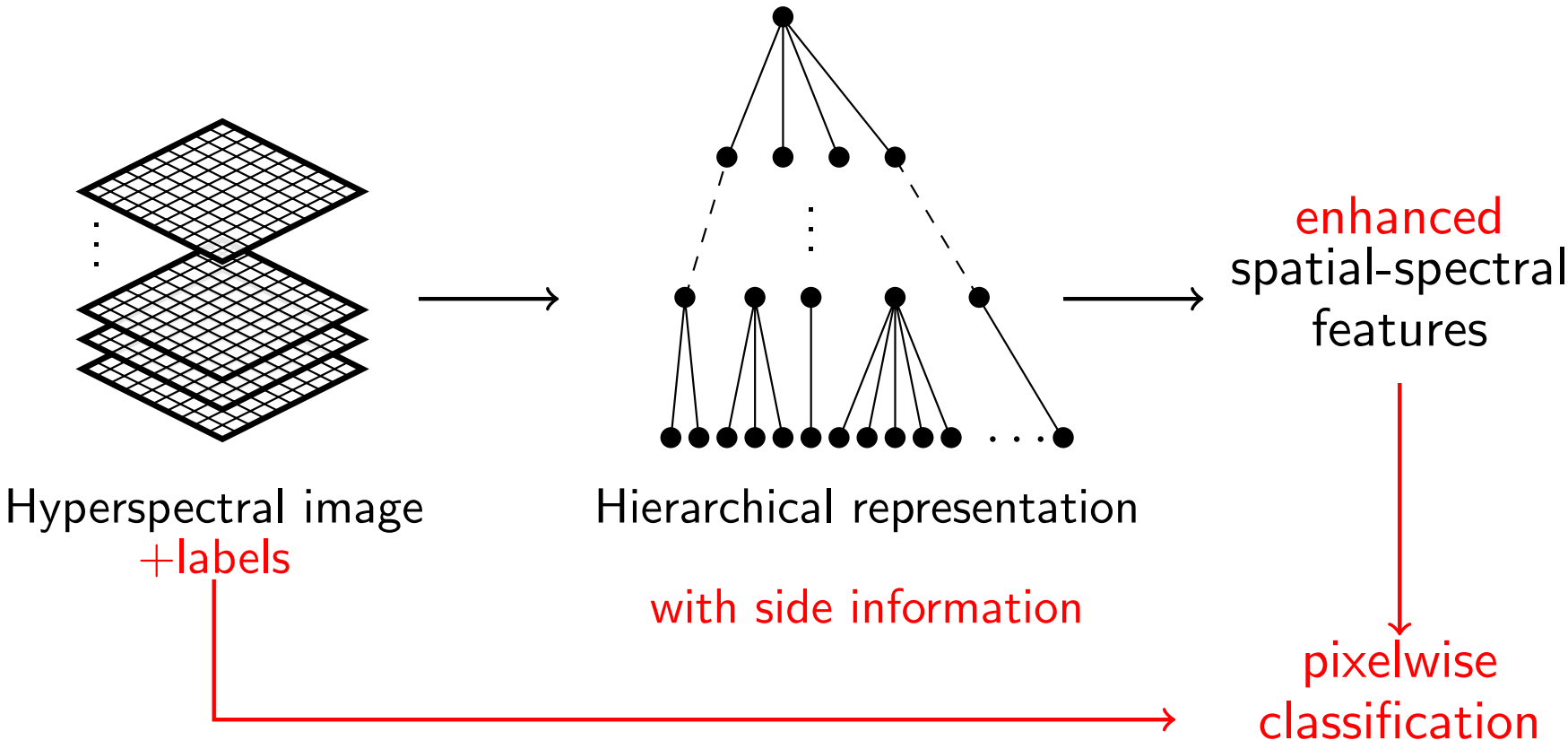
Multiscale description



Multiscale description driven by domain knowledge



Hyperspectral distances

- $L_1 = \sum_{i=1}^{p} \left| a^i - b^i \right|$
- $L_2 = \sqrt{\sum_{i=1}^{p} (a^i - b^i)^2}$
- $L_\infty = \max_i(|a^i - b^i|)$
- SAM $= \arccos\left(\frac{\mathbf{a}\cdot\mathbf{b}}{\|\mathbf{a}\|\,\|\mathbf{b}\|}\right)$ (Spectral Angle Mapper)

Knowledge-driven distance

- Mahalanobis distance $d(\mathbf{a},\mathbf{b}) = \sqrt{(\mathbf{a}-\mathbf{b})^t M(\mathbf{a}-\mathbf{b})}$ with $M = \mathrm{cov}(\mathbf{a},\mathbf{b})^{-1}$ gives "classical" Mahalanobis distance
- Additional knowledge
  - must-link $\mathcal{S} = \{(\mathbf{a},\mathbf{b}) | \mathbf{a},\mathbf{b}$ belong to the same class$\}$
  - cannot-link $\mathcal{D} = \{(\mathbf{a},\mathbf{b}) | \mathbf{a},\mathbf{b}$ are in different classes$\}$
- The optimal matrix M can be learnt from those pairs
  - $\sum_{\mathbf{a},\mathbf{b}\in\mathcal{S}} d(\mathbf{a},\mathbf{b})$ is minimum
  - $\sum_{\mathbf{a},\mathbf{b}\in\mathcal{D}} d(\mathbf{a},\mathbf{b})$ is maximum

F. Merciol, L. Chapel, and S. Lefèvre. "Hyperspectral image representation through α-trees". In: ESA Conference on Image Information Mining: Geospatial Intelligence from Earth Observation (IIM). Bucharest, Romania, Mar. 2014, pp. 37–40. DOI: 10.2788/25852

(α, ω) connected components

- Threshold ω on the global range of the α-CC

$$d(p, q) \leq \alpha, \forall p, q \text{ neighbors}$$

$$d(u, v) \leq \omega, \forall u, v \in \alpha\text{-CC}$$

- Storing the minimum and maximum values of each α-CC in grayscale image
- Extension to hyperspectral images? Complexity $O(n^3)$
  1. can not be computed from the maximum and minimum
  2. no universal ordering for vectorial data

Efficient overestimation for hyperspectral images

- Solution 1: α and ω criteria shall be fulfilled in all spectral bands
- Solution 2: total ordering on pixel values
- Here, overestimation of the global range
  1. compute the diagonal of the set (bounding box)
  2. diameter of a bounding sphere: only need to store the gravity centers and the (α, ω)-CC size

J. Weber, E. Aptoula, and S. Lefèvre. "Vectorial quasi-flat zones for color image simplification". In: International Symposium on Mathematical Morphology (ISMM). Uppsala, Sweden, May 2013, pp. 231–242

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Efficient overestimation for hyperspectral images

- Solution 1: α and ω criteria shall be fulfilled in all spectral bands
- Solution 2: total ordering on pixel values
- Here, overestimation of the global range
  1. compute the diagonal of the set (bounding box) but dimensionality curse!
  2. diameter of a bounding sphere: only need to store the gravity centers and the (α, ω)-CC size (not optimal!)

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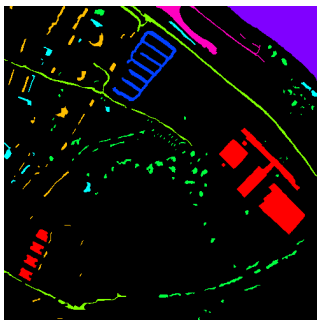
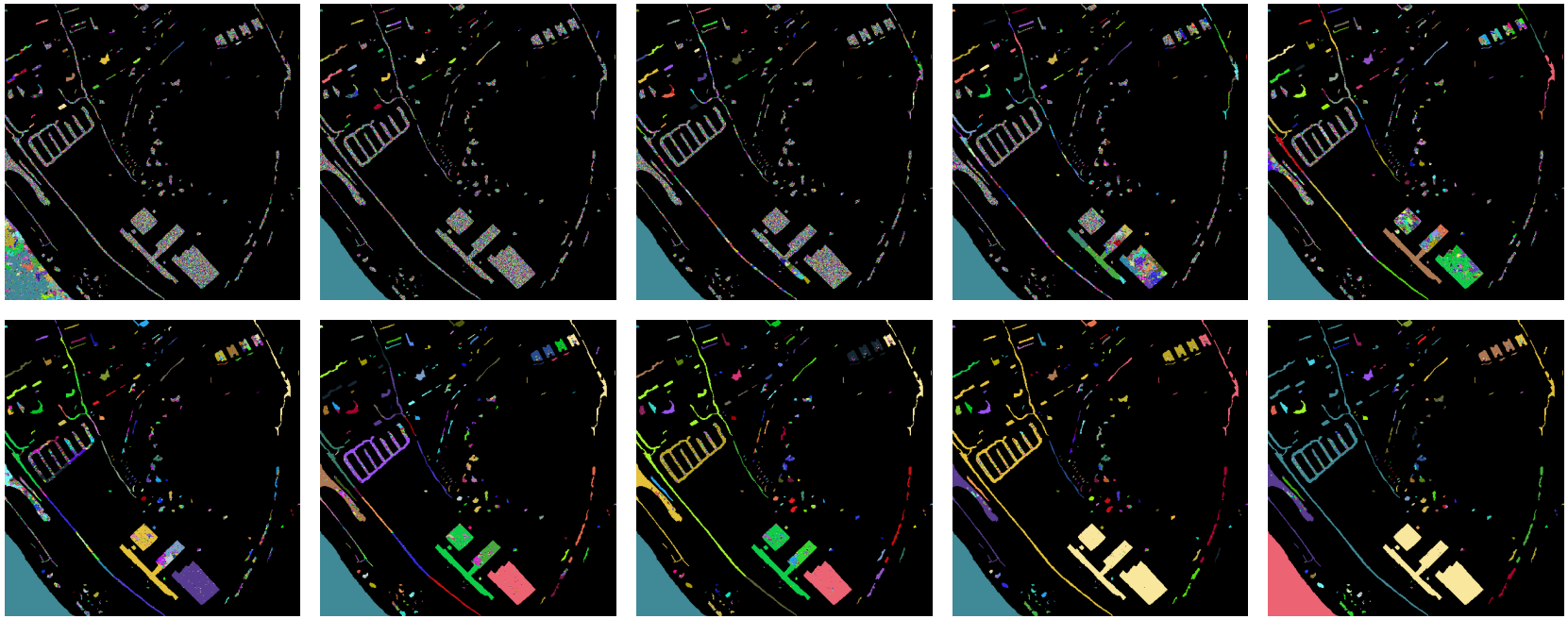
Experimental setup: Pavia Center (sample)

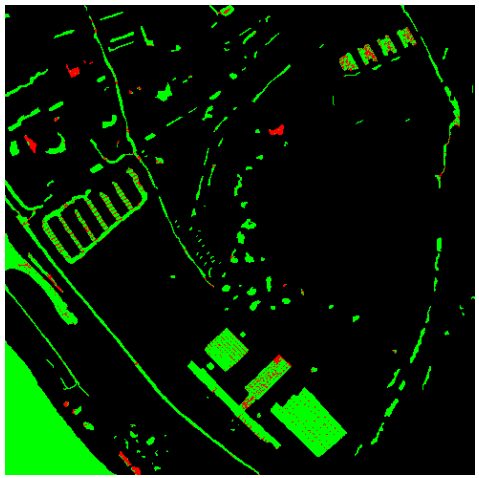


- Features = Spectral bands
- Tree-based features
  - extract (α, ω)-CCs using a regular sample of ω values
  - stack the size, within cluster variance, averaged spectral signature for all the bands of all the CCs
- 1% of the points for learning, SVMs

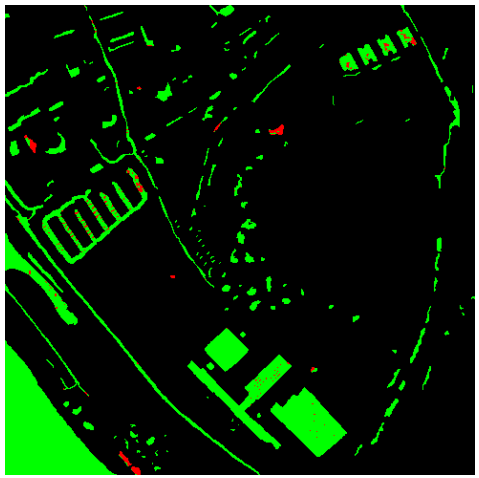
Extracted (α, ω) zones



Results



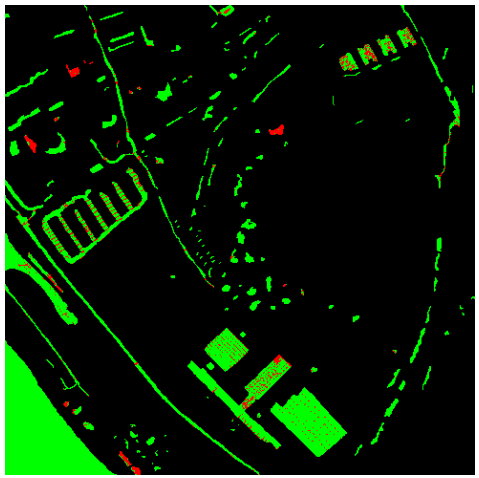
raw features



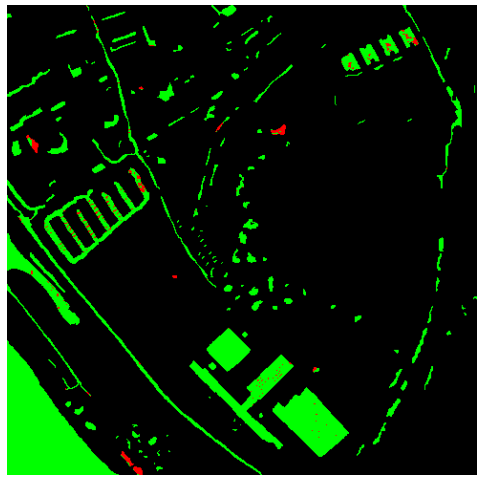
spatial-spectral features

Method	Pavia University OA (%)	Pavia Center OA (%)
Spectral bands features	93.19 ± 0.19	93.37 ± 0.90
Tree-derived features	98.14 ± 0.25	97.00 ± 0.62

Results



raw features



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Mathematical morphology offer a wide range of efficient and powerful tools, with increasing impact in remote sensing.

Dealing with multivariate data is far from being trivial. Supervised strategies appear as a relevant way to derive morphological solutions.

Any questions?