Multivalued component-tree filtering

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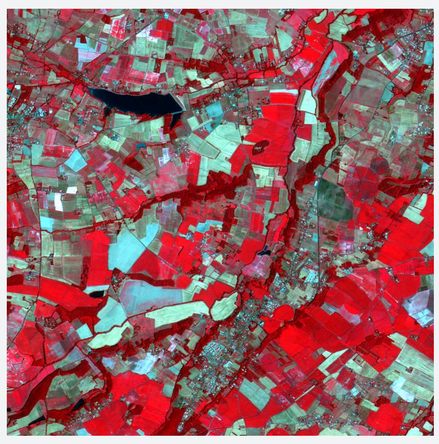
Motivations

Context: The component-tree is a hierarchical data structure that models a grey-level image via its binary level sets. It is well-suited for grey-level image filtering and segmentation methods, based on attribute-based or optimal cut strategies. The increasing need for applications involving multivalued images, has motivated its extension to the case of images with values in any – totally or partially – ordered sets. To deal with this issue, a notion of component-graph was recently introduced. By contrast with the component-tree, the component-graph is not a tree, in general, raising several algorithmic open issues.

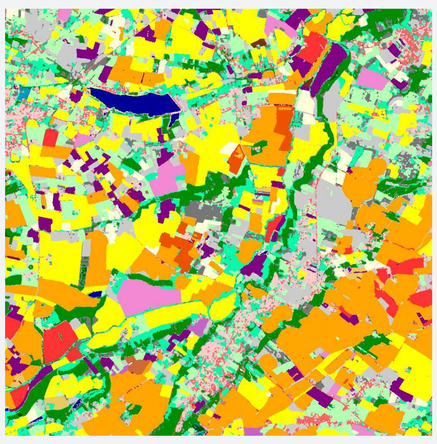
Purpose: We introduce intermediate data structures, called the multivalued component-trees (MCTs), namely a subfamily of component-graphs, that present a tree structure, and then extend the component-trees. We prove that MCTs can model images whose values are hierarchically organized. We also show that they can be built from standard component-tree construction algorithms, and involved in antiextensive filtering procedures.

Experiments and Results

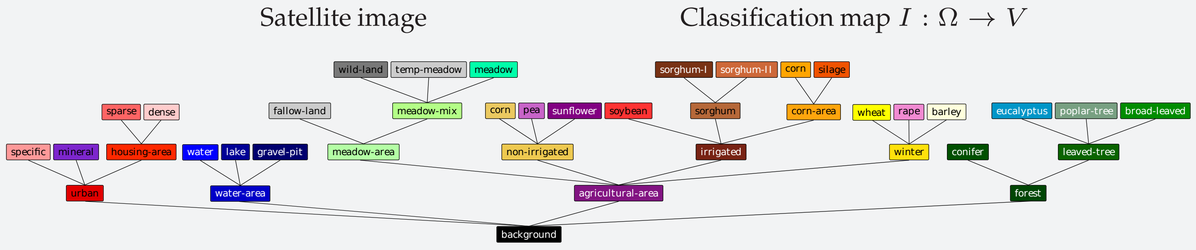
Task: We processed classification maps derived from satellite images. These maps involve images with values in hierarchical ordered sets V.



Satellite image



Classification map $I : \Omega \to V$



Hasse diagram of a hierarchically ordered set $(V, \leqslant)$ where V contains 40 semantic labels

Data: We used a set V of labels related to the **semantic elements of agricultural areas**. We considered an agricultural satellite image with a spatial resolution of 64 m^2 per pixel that has then been classified into 26 classes (leaves of V), thus leading to the map $I : \Omega \to V$.

Experiments: Two series of **antiextensive filterings** have been computed. The first has been performed with an increasing criterion, related to the minimal values of an **area attribute**. The second has been performed by considering a non-increasing criterion, related to intervals of values for the same area attribute.

Results: The simultaneous use of an area criterion, and a set of hierarchically structured labels, allows us to carry out a **spatial / semantic denoising** of the classification maps. Results depicted below show (1) three filtering results where only the largest semantic structures (*i.e.*, urban and agricultural areas, forest) are preserved and (2) three filtering results where only small structures (dense housing areas) are preserved.

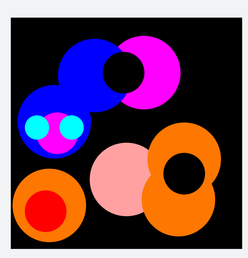
Antiextensive filtering scheme

We extend the original antiextensive filtering scheme proposed for component-trees (for grey-level images) to multivalued component-trees. It consists of the following three successive steps:

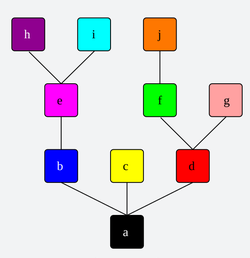
1. **construction of the MCT** $\mathfrak{G}$ associated to $I : \Omega \to V$; The problem can be interpreted as the problem of building a component-tree on a grey-level image I, where each pixel encodes the depth of its label in the hierarchy induced by V. To do so, pre- and post-processing steps are required. The pre-processing consists of creating interpixel points that take virtual values between each pair of non-comparable points. These virtual values are defined as the infimum of the two values. The enriched image can then be interpreted as a grey-level one. The post-processing consists of removing from the computed tree, these virtual points and the potentially induced nodes. Three variants of MCTs ($\mathfrak{G}$, $\dot{\mathfrak{G}}$ and $\ddot{\mathfrak{G}}$) can be defined, see below.

2. **reduction of** $\mathfrak{G}$, leading to a reduced MCT $\widehat{\mathfrak{G}}$; The choice of nodes relies on: (1) a selection criterion $\rho : \Theta \to \mathbb{B}$ that indicates if the nodes satisfy a required property; and (2) a reduction policy which is combined with ρ to determine which parts of the component-graph should be preserved or discarded. Various reduction policies can be considered ($\min$, direct, and $\max$).

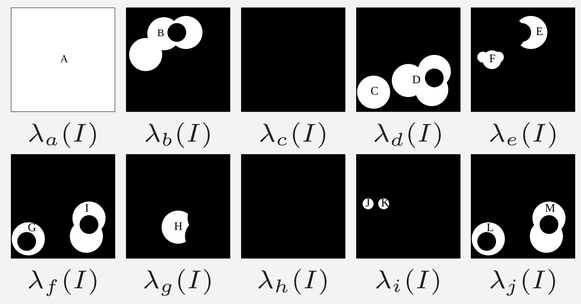
3. **reconstruction of a filtered image** $\widehat{I} \leq I$ induced by $\widehat{\mathfrak{G}}$.



$I : \Omega \to V$

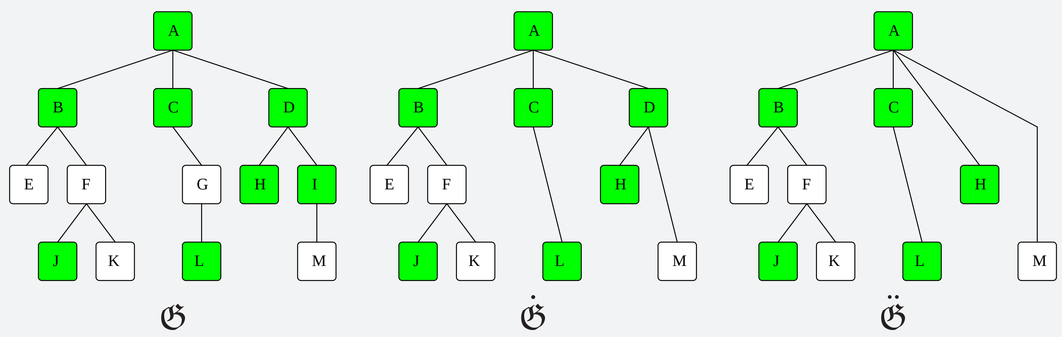


$(V, \prec)$

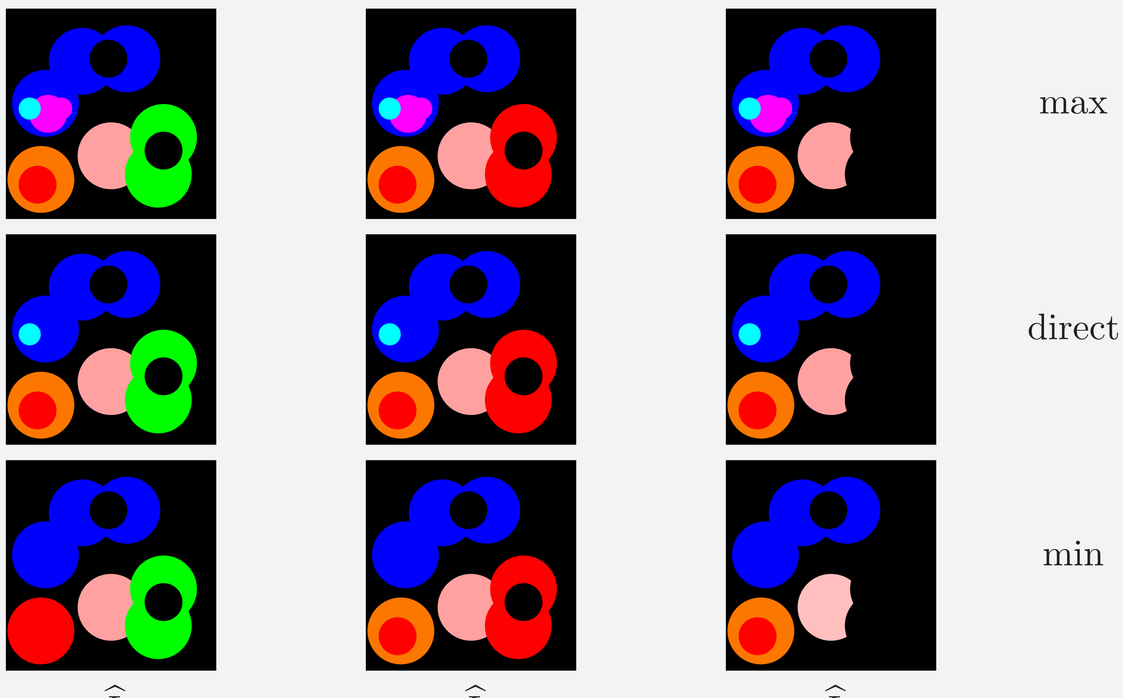


$\lambda_a(I)$ $\lambda_b(I)$ $\lambda_c(I)$ $\lambda_d(I)$ $\lambda_e(I)$

$\lambda_f(I)$ $\lambda_g(I)$ $\lambda_h(I)$ $\lambda_i(I)$ $\lambda_j(I)$



$\mathfrak{G}$ $\dot{\mathfrak{G}}$ $\ddot{\mathfrak{G}}$



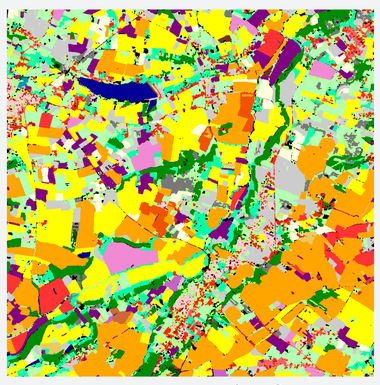
max

direct

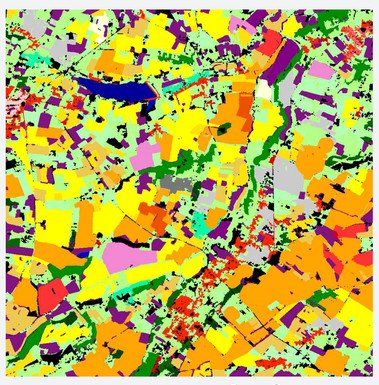
min

$\widehat{I}$ $\widehat{I}$ $\widehat{I}$

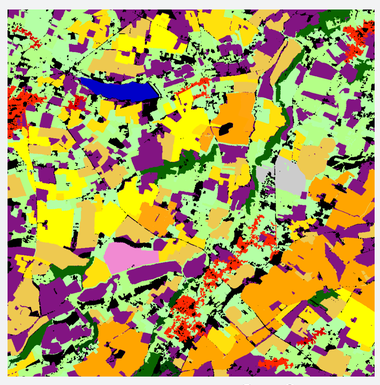
Hierarchically classified image filtering



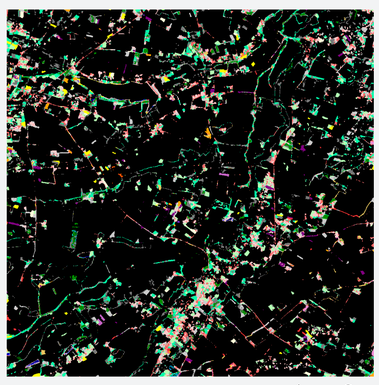
$\tau_{min} = 10^4$ m^2



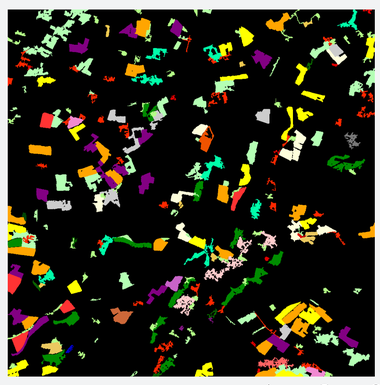
$\tau_{min} = 10^5$ m^2



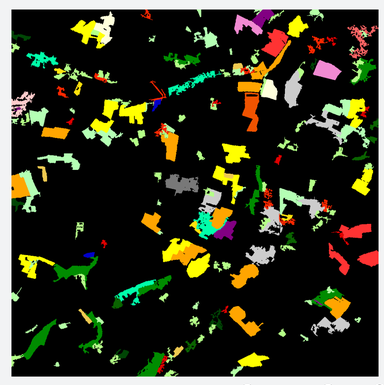
$\tau_{min} = 5.10^5$ m^2



$[\tau_{min}, \tau_{max}] = [0, 10^4]$ m^2



$[\tau_{min}, \tau_{max}] = [5.10^4, 10^5]$ m^2



$[\tau_{min}, \tau_{max}] = [10^5, 2.10^5]$ m^2

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