HIERARCHIES AND SHAPE-SPACE FOR PET IMAGE SEGMENTATION

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Introduction/Context

Positron Emission Tomography (PET) using 18-fluorine fluorodeoxyglucose (^{18}F-FDG) is recognized as the **modality of choice** for **lymphoma imaging**. PET imaging is now routinely used, not only to **detect tumor lesions**, but also to **assess their metabolic activity**, allowing **diagnosis**, **staging** and **treatment response evaluation**. Thus, efficient PET image analysis is essential in clinical practice. Our contribution is twofold. First, we present the **component-tree** as a relevant data-structure for developing **interactive, real-time, intensity-based segmentation of PET images**. Second, we prove that thanks to the recent concept of **shapings**, we can efficiently involve **a priori knowledge** for lesion segmentation.

Hierarchical Representation

Definition: The component-tree $\mathcal{T}$ associates discrete grey-level image I with a hierarchical data-structure induced by the inclusion relation (represented by *graph edges*). This relation is between the binary connected components (i.e, the maximally connected regions) obtained at successive level sets of I (represented by a set of *graph nodes* Θ).

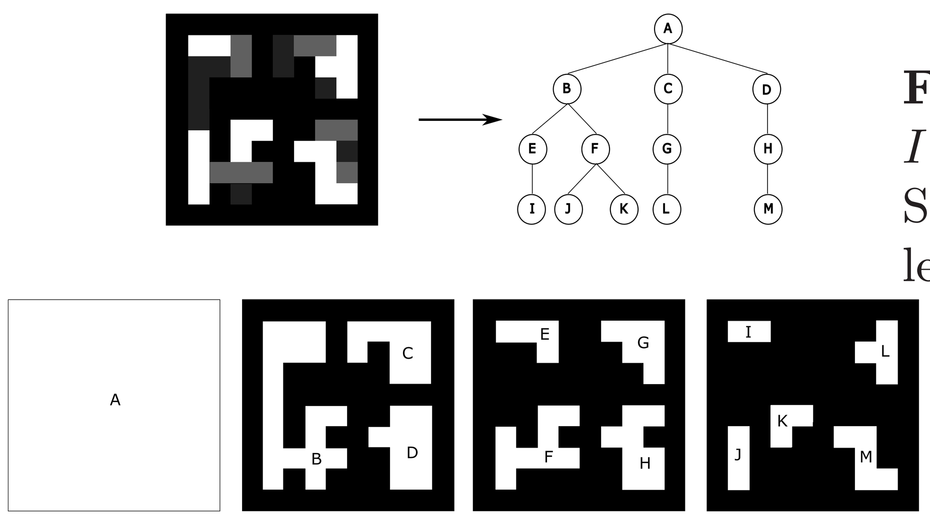


Figure 1: First row : Original image I and its associated component-tree $\mathcal{T}$. Second row : Successive thresholded level-sets of I.

$\mathcal{T}$: a relevant model for intensity-based segmentation of PET images

- Processing I via $\mathcal{T}$ is a **low-cost** operation : a quasi-linear time for $\mathcal{T}$ building and a linear time to retrieve an image from its component-tree.
- $\mathcal{T}$ is a **lossless** image representation.
- $\mathcal{T}$ is well-fitted for
  - Handling 3D images when the structures of interest correspond to extremal intensity values (as oncological lesions).
  - Developing interactive and real-time segmentation method.
- $\mathcal{T}$ handles **monotonic attribute filtering frameworks** (see *black path* in Fig. 3): it is possible to filter I by discarding some of the nodes of $\mathcal{T}$, and then reconstructing a resulting image I' from the preserved nodes.
- Compliant with all principal strategies as it intrinsically models the space of ***all* the potential thresholding operations**.

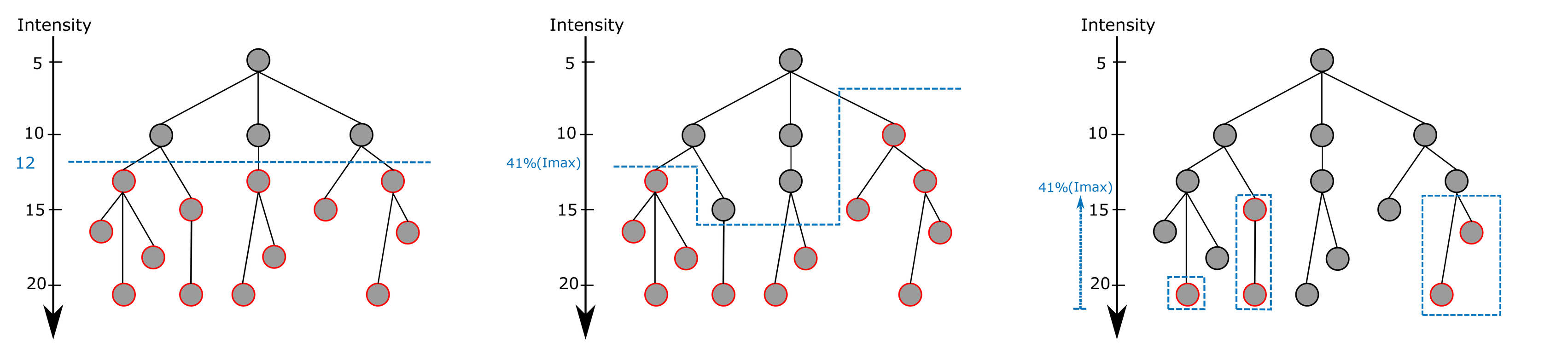


Figure 2: Major Thresholding Strategies : Left : Fixed Threshold - Middle : Adaptive Threshold - Right : Bouding-box Threshold. Selected subsets of nodes (in red)

Shape-based image analysis

We consider the paradigm of **shapings**, proposed by Xu et al [1], to extend the filtering capabilities of tree-based representation to **non-monotonic** attributes.

- **Shapings** are a two-layer component-tree, a *tree of tree*, that transforms any non-monotonic attribute into a monotonic one. With this we embed additional information to enable user interaction.

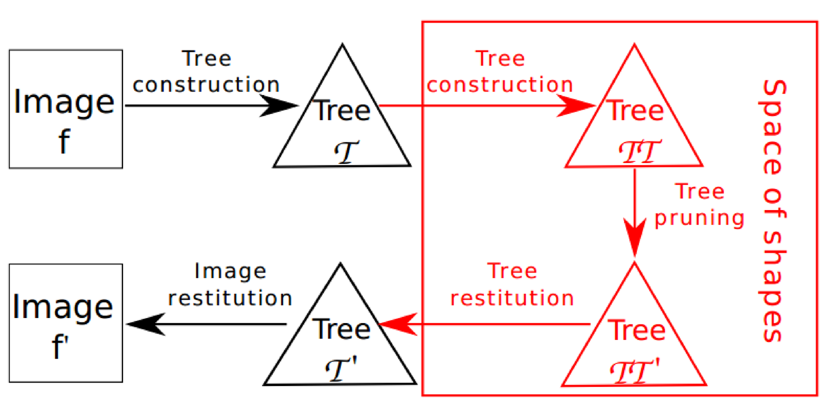


Figure 3: Classical connected operators (black path) and shape-based morphology schema (black + red path) by Xu et al.

- For example, as lesions appear roughly spherical (especially in the thorax), we propose to define a numerical value describing the compacity of a component, i.e., the similarity to a sphere.
$$\mathcal{E}(K) = \lambda_3/\lambda_1$$
This attribute is defined as the ratio between the lowest and highest eigenvalues associated to the eigenvectors of the 3×3 matrix of inertia of the (binary) shape $K \in \Theta$, ordered such that $\lambda_1 \geq \lambda_2 \geq \lambda_3$. Lying in $[0, 1]$, if $\mathcal{E}(K)$ is close to 1, then K then has a compact shape.
- With this, higher-level knowledge (various geometrical or anatomical priors,...) can be handled with a smart thresholding strategy.

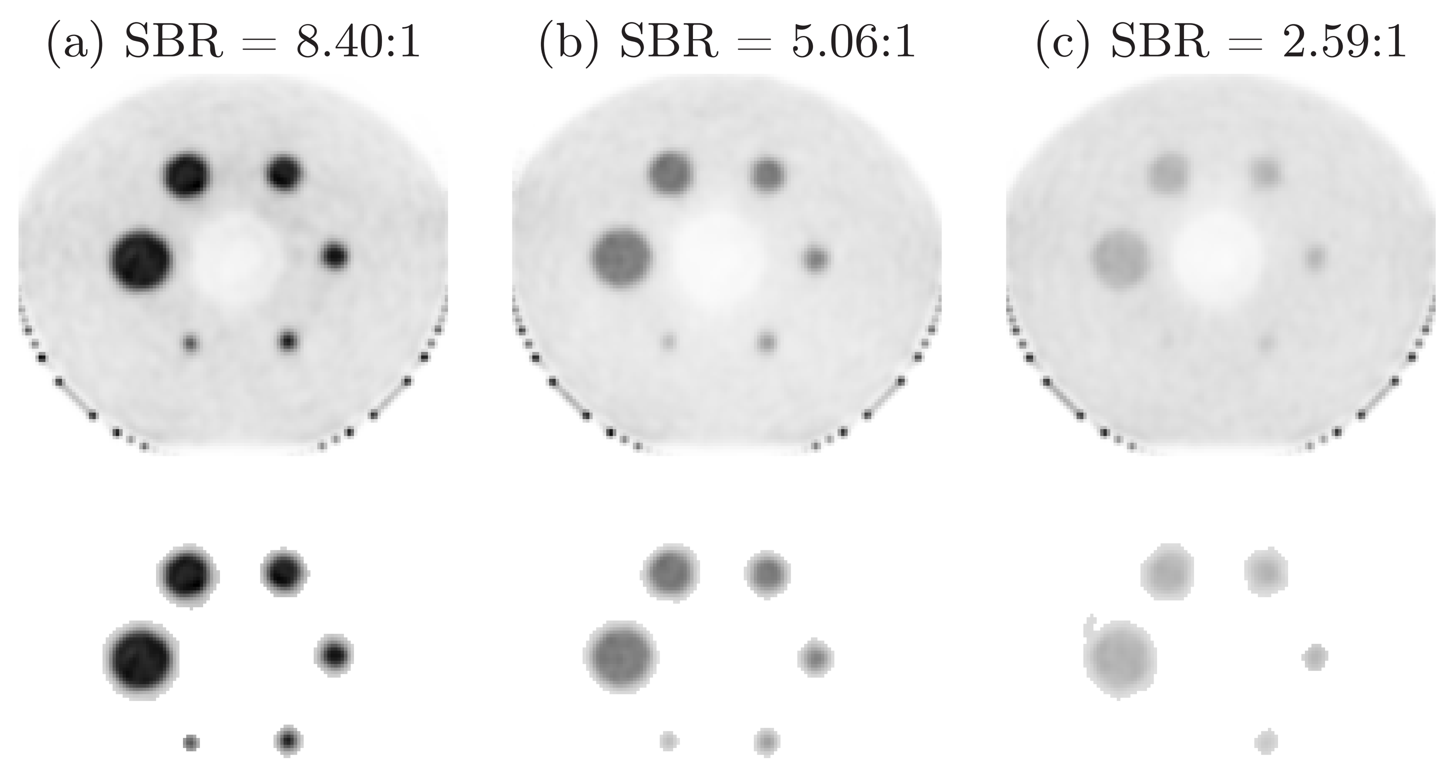
[1] Xu, Y. and Géraud, Th. and Najman, L., *Morphological filtering in shape spaces: Applications using tree-based image representations*, in ICPR, Proc., 2012, pp. 485-488

PET image segmentation

We use **shapings** to develop an interactive attribute-based procedure for discriminating active lesions from hyperfixating organs in PET images, in the context of lymphoma.

- We **validate** the method on the **NEMA 2007 IEC image phantom**, with three different signal to background ratios (SBRs).
  - Reference segmentation : closest interactive thresholding to the known geometry on the highest contrast image.
  - Fig. 5 illustrates the impact of the signal loss on the segmentation results. Excellent results for the highest contrast image, and even for more realistic SBRs, the results remain satisfactory.

Figure 4: First row: phantom PET images, with three different SBRs. Second row: segmentation results (3D Maximum Intensity Projection).



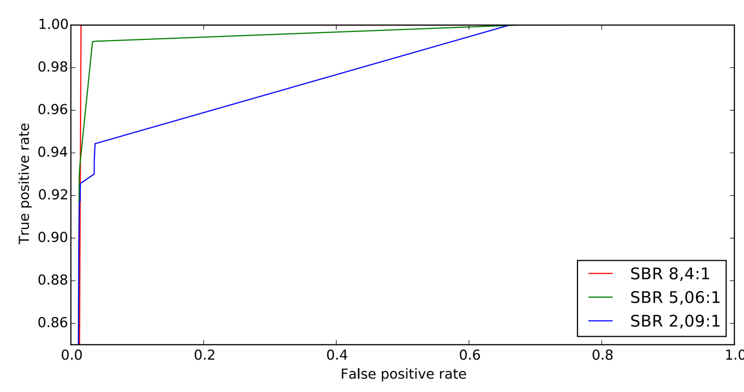


Figure 5: ROC curves for the attribute-based shapings approach, for various SBRs (see Fig. 4).

- **Qualitative evaluation** of the approach on a serie of 13 **PET images of lymphoma patients**.
  - Comparison with global thrsholding
  - Our method improves the robustness to signal heterogeneity due to intrinsic adaptivity. The shapings paradigm improves in particular the robustness to texture effects, for instance here in the right lung (see Fig. 6).

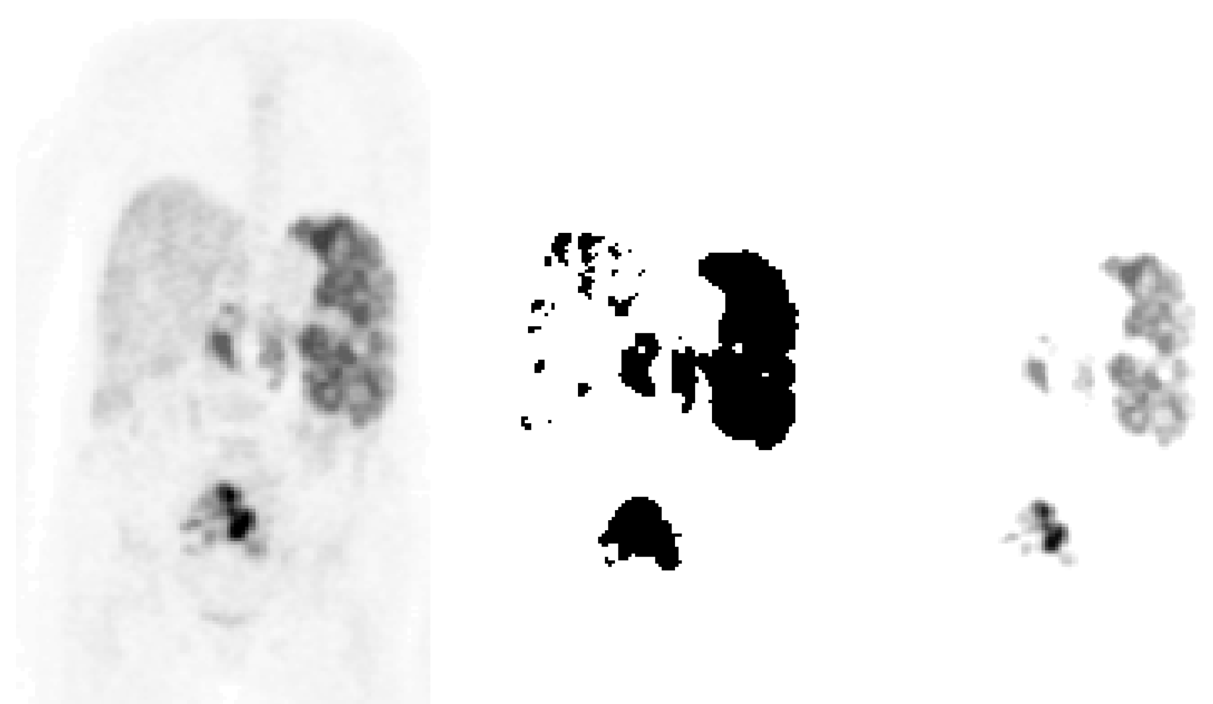


Figure 6: Left: PET image. Middle: optimal global thresholding. Right: Shapings segmentation (3D Maximum Intensity Projection).

Conclusion and Perspectives

Component-trees are shown to be relevant for the segmentation of PET images. We proposed a solution based on the shapings paradigm to embed additionnal anatomical priors, preserving real-time computation and user-friendly interaction. For future work, we plan to combine the concept of shapings with the use of PET/CT data, through the notion of component-graphs to retrieve more anatomically accurate information.