HIERARCHICAL ANALYSIS OF 3D X-RAY CT IMAGES FOR GRANULAR MATERIALS

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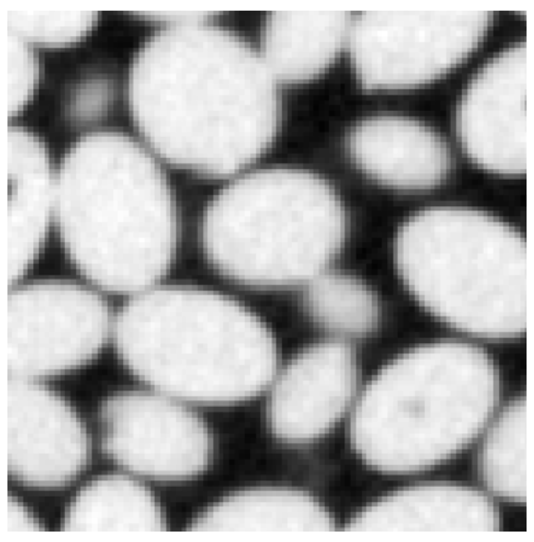
Motivations

Granular materials under CT scan

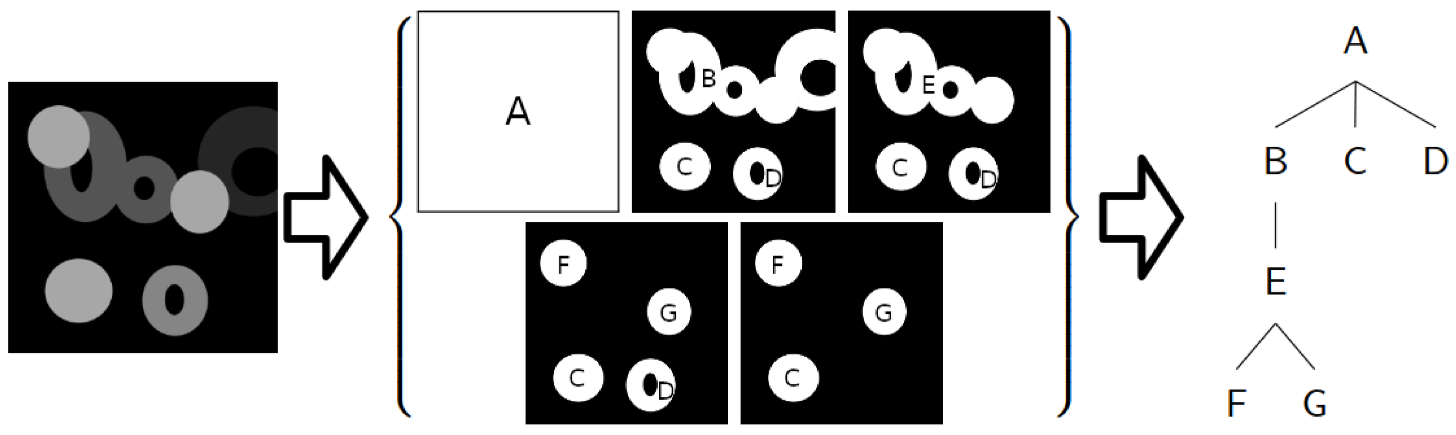
We work with 3D CT scans of grains with a resolution of (725×725×1420).



Question: Is it possible to segment each grain from the image using a tree structure?

Making use of the Max-tree and Min-tree

The **max-tree** [1] of a greyscale image I is the modelling of this image into a tree structure based on the inclusion of its connected components at each of its **threshold sets**.

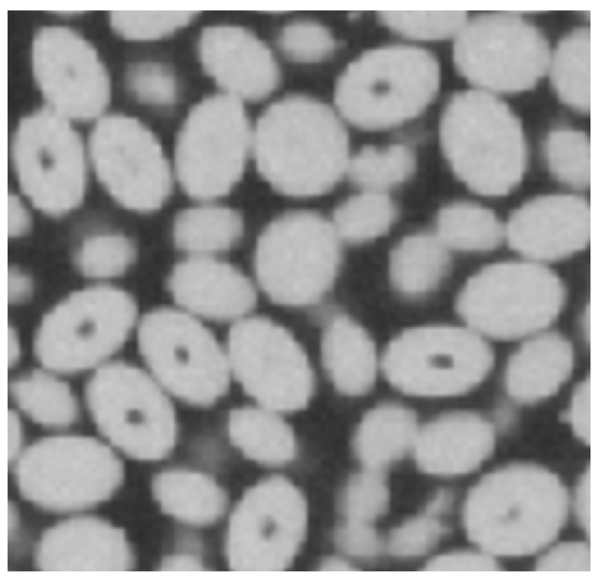


(a) I (b) Threshold sets (c) Max-tree

Core extraction with min-tree

Cores as segmentation markers

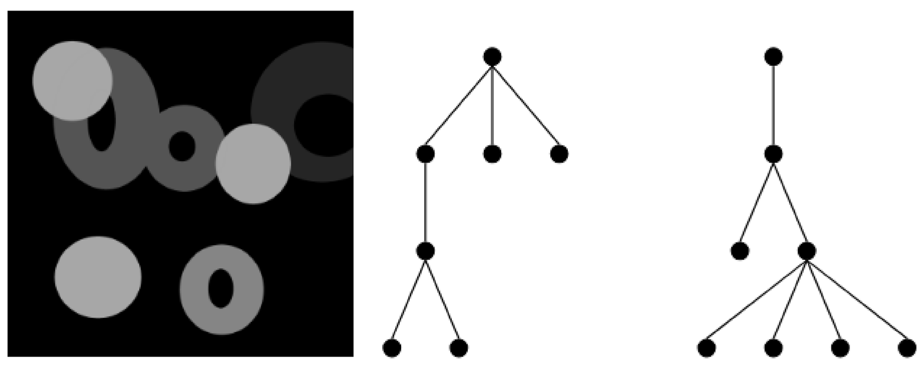
As the grains that we use is generated are a artificial way, we observe that each grain contains a single hollow core, represented with **small dark holes** in the images.



Our first goal is to extract those cores in order to use them as **markers** for our future segmentation.

Min-tree

With the same idea as the max-tree, we consider its dual called the min-tree. The min-tree of an image models the inclusion of its level lines, replacing the upper threshold with a **lower threshold**, allowing the identification of **dark components** in the image.

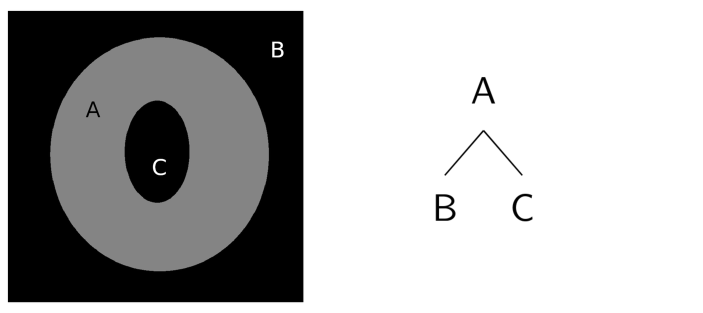


(a) Image (b) Max-tree (c) Min-tree

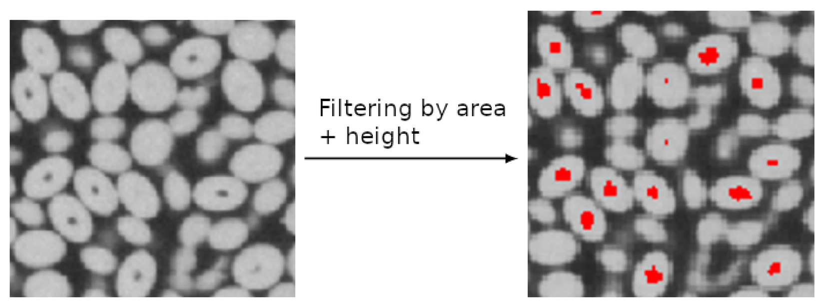
Hence, the black holes and the background of the image will become leaves.

Filtering core nodes

In the min-tree, cores correspond to **leaves with small area**. Then, extracting the cores from the image amounts to **simplifying** the tree by removing all non-leaf nodes with an area larger than a given size.



As the image contains noise, we add a **height** criteria to the simplification in order to remove components with low contrast. Extracted nodes are displayed in red.



Max-tree segmentation

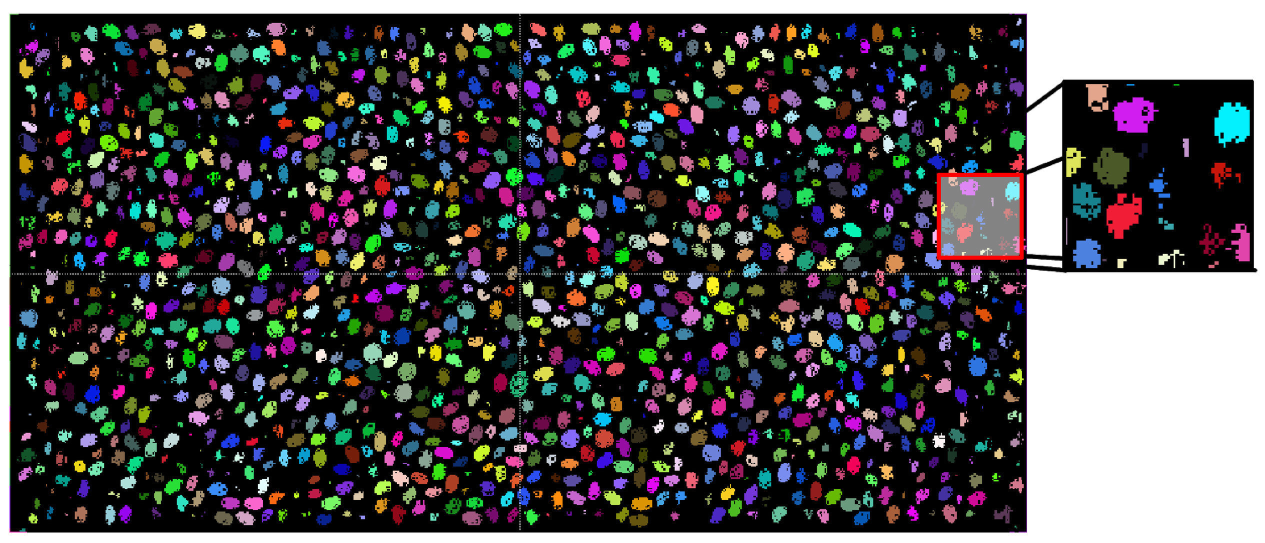
Algorithm

The idea is to extract the nodes of the max-tree corresponding to a **single grain**.
Hence, we define the previously extracted markers as maxima of the image, in order to have them as identifiable leaves in the max-tree. Then, we go from leaves corresponding to markers to the root of the tree, **propagating a unique label** for each marker. Finally, we remove nodes that have more than one label.

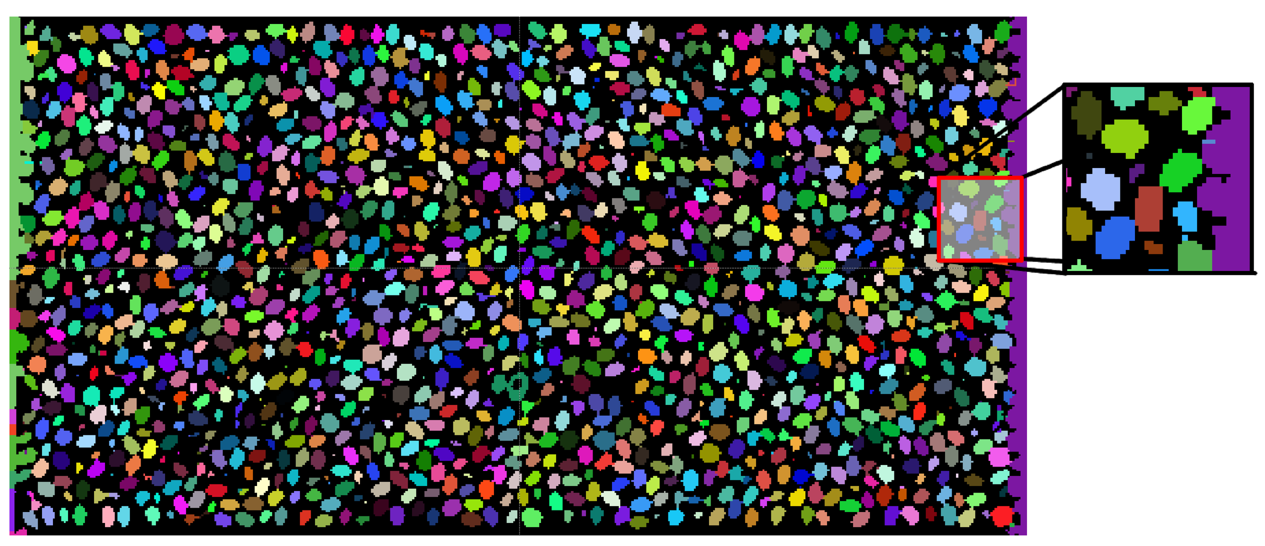
```
Data: Image I, set of markers M
Result: Image of segmented grains
core_val = I_max + 1;
forall m ∈ M do
    m.value = core_val;
end
I = overlap(I, M);
tree = maxtree(I);
i = 1;
forall l ∈ tree.leaves do
    if l.val = core_val then
        n = l;
        while n ≠ tree.root do
            n.count += 1;
            n.label = i;
            n = n.parent;
        end
        i += 1;
    end
end
forall n ∈ tree.nodes do
    if n.count > 1 then  n.label = 0 ;
end
return image_from_maxtree(tree)
```

This algorithms guarantees that the number of labels is equals to the number of markers, and that each component is **disconnected** from its neighbours.

Results



(a) Result of the max-tree segmentation on a raw image with size divided by two.



(b) Result of a seeded watershed on distance map with size divided by 3.

Gains: Contrary to the seeded watershed algorithm, we gain robustness with respect to to intensity variations caused by CT aquisition process. The proposed approach is also computationally faster, allowing to further work on larger and or higher resolution images.

References

[1] Philippe Salembier, Albert Oliveras et Luis Garrido. "Antiextensive connected operators for image and sequence processing". In : IEEE Transactions on Image Processing , p. 555-570 (1998)

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