# Automatic closed edge detection using level lines selection

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# Presentation Plan



1. Introduction
2. Probabilistic scheme
3. Maximality principle
4. Experimental results
5. Conclusion

## Motivation

→ Propose an automatic closed edge detection method
→ Illustrate the utility of closed level lines through pattern recognition and edge models with a medical imaging case study

## Open edge detection methods

| | |
|---|---|
| Filters | *Torre et al. 1986* |
| Masks | *Hueckel 1971* |
| Laplacian zero-crossings | *Marr & Hildreth 1980, Haralick 1984* |
| Analytic approaches | *Canny 1986, Deriche 1987* |

→Uses local concepts (opposed to Gestalt laws [*Kanizsa 1996*]),
→Needs open edge post processing

*Original image*

*Canny-Deriche detector with increasing threshold*

## Closed edge detection methods using deformable models

| | |
|---|---|
| Snakes | *Kass 1988* |
| Level-sets | *Osher 1988, Sethian et al. 1996* |
| geodesic models | *Casselles et al. 1997* |

→ Contour initialization
→ Deformation constraints and parameters



Ex: Snakes with GVF (gradient vector flow [*Xu and Prince 1997*])

## Mathematical morphology

Uses **morphological** **level sets** [*Serra 1987*] : $\chi_\lambda(u) = \{x \in \mathrm{R}^2, u(x) \geq \lambda\}$

**Property**: gray levels of one image can be fully reconstructed from its level sets collection.

**Definition**: **level lines** are morphological levels sets **boundaries** and the collection of level lines of one image is called **topographic map** [*Casselles et al. 1999*]

**Property 1:** object contours locally coincide with some level lines [*Serra 1987*]

**Property 2:** level lines inherit of an inclusion tree structure

**Property 3:** the topographic map also contain texture effects, noise etc…

Desolneux et al. proposed a level-lines selection method using a probabilistic scheme [*Desolneux et al. 2001*] .

**Our contributions :**
→ a general maximality principle reducing the redundancy of the resulting contours sets
→ a case study on medical images using curvature information to discriminate some specific objects

# Probabilistic scheme

**Goal:**

**→ find meaningful level lines among the topographic map**
**→ eliminate texture effect, and level lines due to noise**

***A contrario*** probabilistic scheme [*Desolneux et al. 2001*] based on the perceptual principle of Helmholtz applied to edge detection:

*« an observed geometric structure is perceptually meaningful*
*if its number of occurrences is very small in a random situation »*

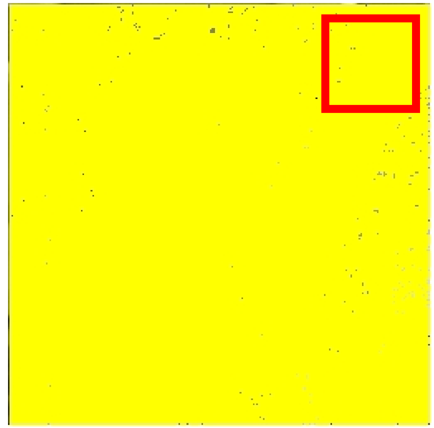
A level line is modeled as a **geometric event**, and it is said to be ***ε-meaningful*** if it occurs less than **ε times** in a **random** situation.

The **geometric event** is defined upon level line **minimal contrast** and **length**, and the probability is evaluated on the **contrast distribution** on image.

The only parameter happens to be **ε**, practical value is **ε**=1, robustness upon **ε** is logarithmic [*Desolneux et al. 2001*].

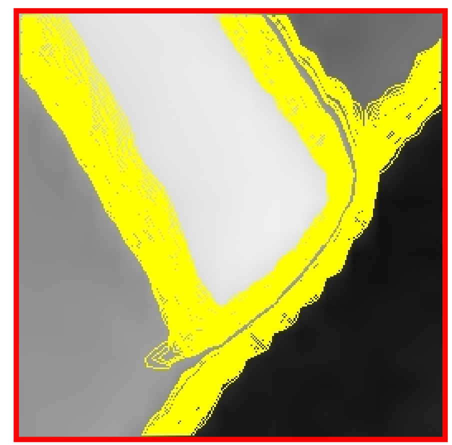
# Probabilistic scheme

*Topographic map, 47830 level lines*



*Zoom*

*3150 ε-meaningful levels lines*

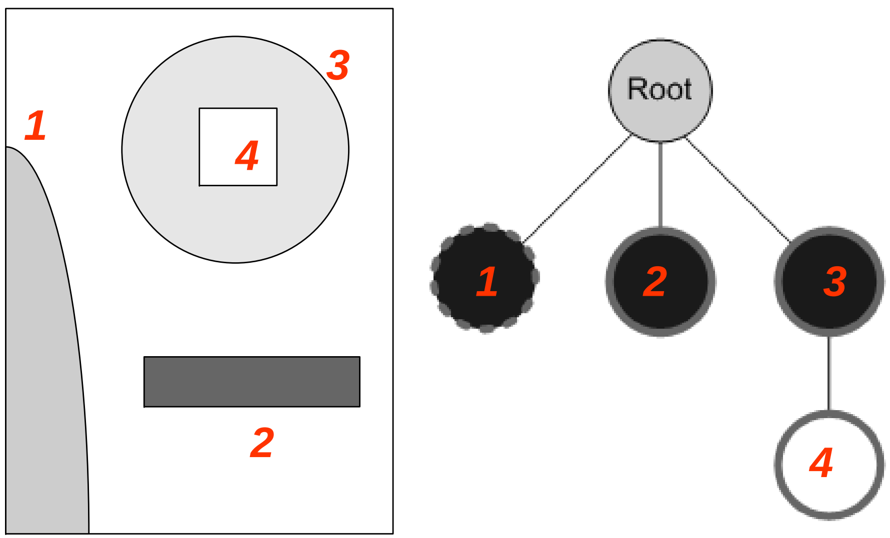


→ **Redundancies along contours:** due to image contours thickness, many lines pass along each object contour

# Maximality principle

**Goal: → eliminate line redundancies along contours**

**We make use of the tree inclusion structure:**

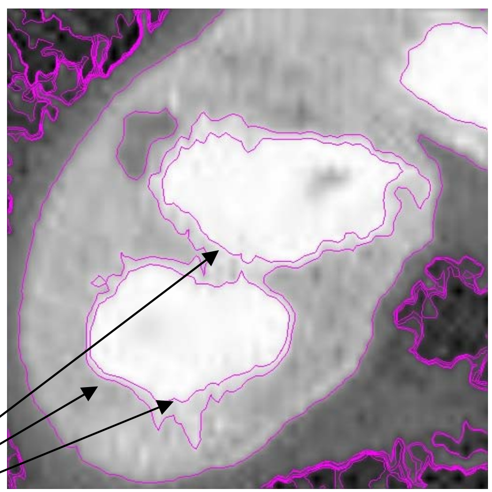



*A simple example*

# Desolneux's maximality principle

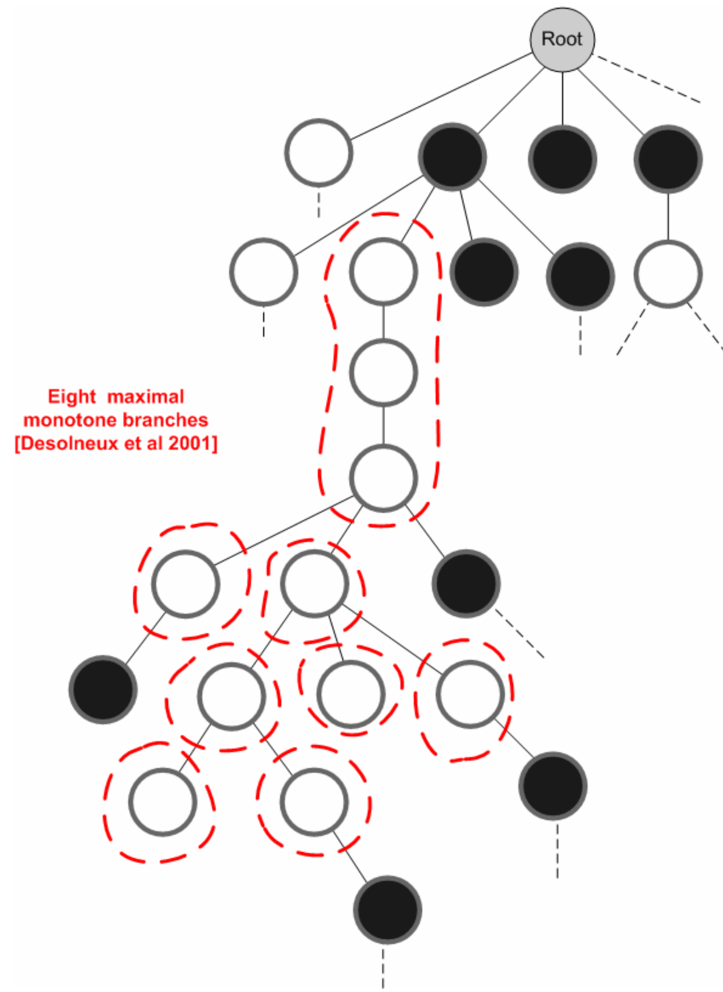
**Desolneux branch principle algorithm**:

"for each maximal monotone branch we select the most meaningful line"



*Ex: A redundancy with multiple children*

*Inclusion tree*



# Proposed maximality principle

**Proposed Maximal principle algorithm**:

Shortly said: “for each maximal monotone subtree we select most meaningful level lines which are not close from each other”

More precisely: using the asymmetrical Hausdorff distance $d_H$, and considering each **maximal monotone subtree**, we keep iteratively most meaningful lines if it is not included in a upward too much close line, or if it does not include a downard too much close line.

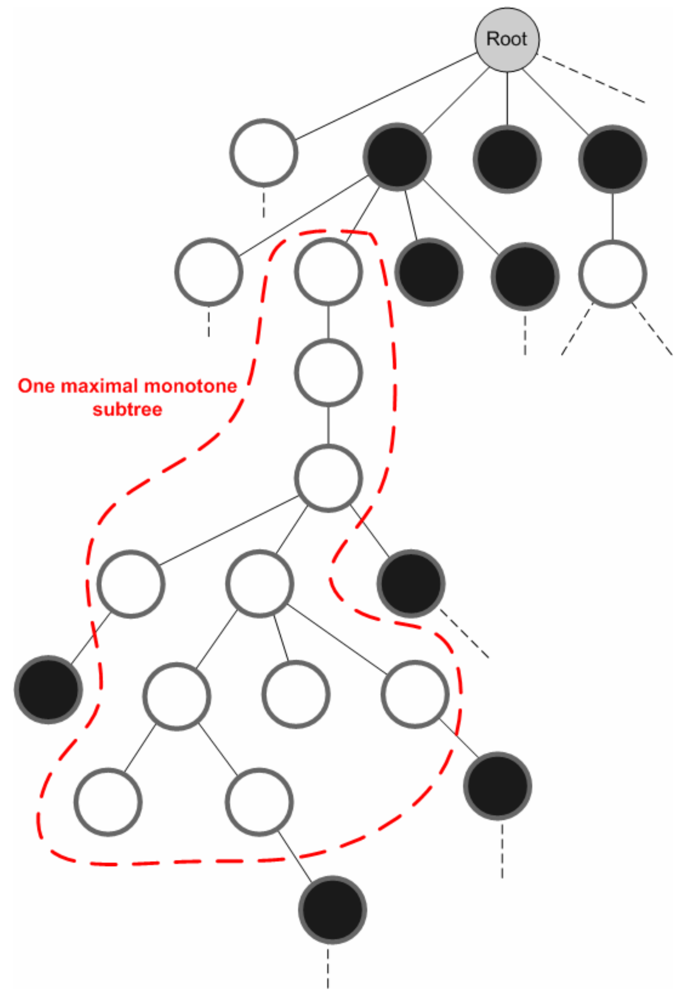
***Asymmetrical Hausdorff distance***:

$$d_H(C_c, C_p) = \max_{P_c \in C_c} \left( \min_{P_p \in C_p} d(P_c, P_p) \right)$$

***Where***:

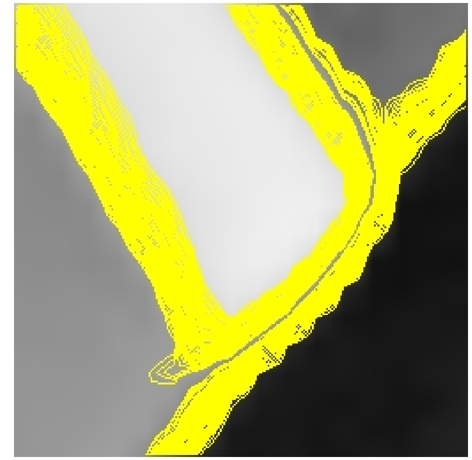
*$C_c$: children level line*
*$C_p$: parent level line*
*$P_c$: point on the children level line*
*$P_p$: point on the parent level line*

*Inclusion tree*

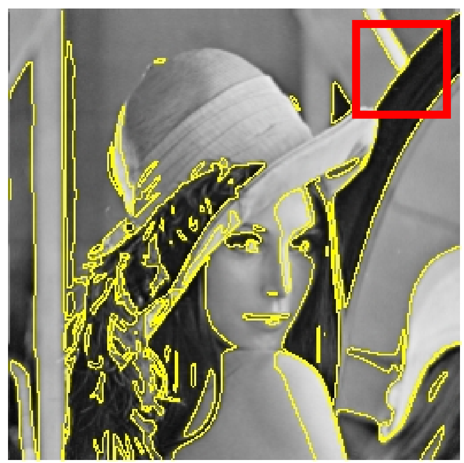


# Experimental results

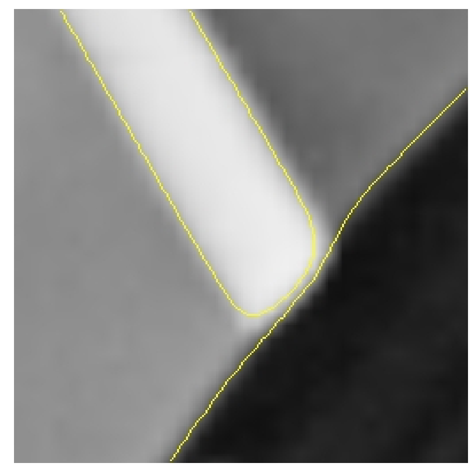
3150 *meaningful levels lines*



*239 branch-MAXIMAL*
*ε-meaningful levels lines*



*95 subtree-MAXIMAL*
*ε-meaningful levels lines*

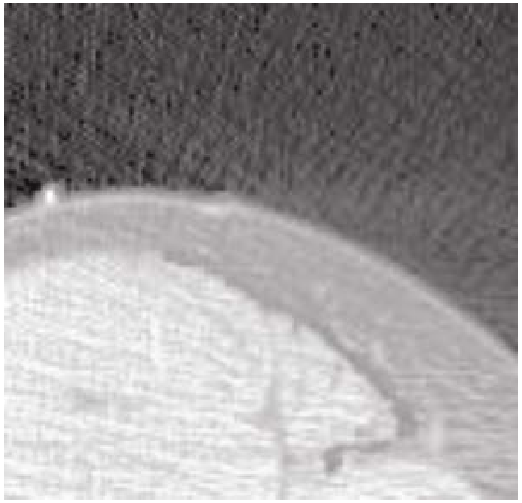


Threshold $h$ on distance $d_H$ is fixed with edge thickness. It depends on the digitization Sharpness. Practically $h$ value is several pixels.

# Experimental results – case study

**Level lines** are sampled closed contours (except at image borders), which can be directly manipulated into pattern analysis problems.

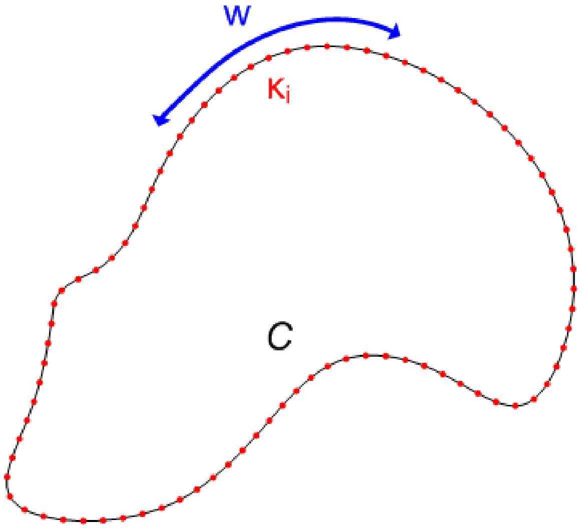
**Medical MRI and CT scans** have a specific important noise (quantum noise) occurring at a fixed scaled granularity. Using the level lines sets and curvature analysis we can select level lines more precisely.



*Ex: Quantum noise*

**For each level line *C of length L*:**
standard deviation **σ** of the curvature **κ** distribution is calculated over two window sizes **w=L and w=L/10** :

$$\sigma_w = \max_w \left( \sqrt{\sum_{i \in w} \frac{(\kappa_i - \overline{\kappa})^2}{|w|}} \right)$$

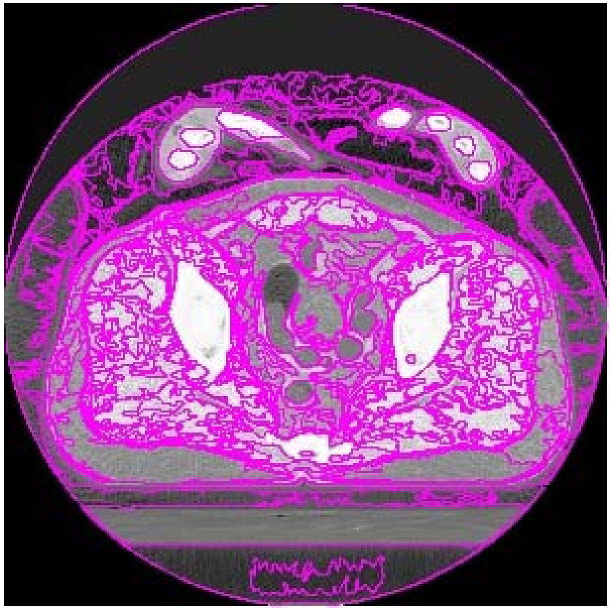



**Using a ~900 boundaries training set we fixed the following thresholds:**

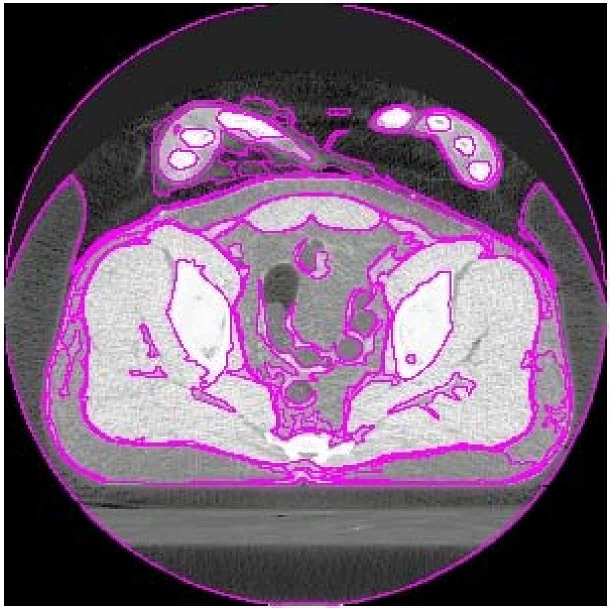
$$\sigma_{w=L} < 0.35 \qquad \sigma_{w=L/10} < 0.45$$

# Experimental results – case study

*Original image*

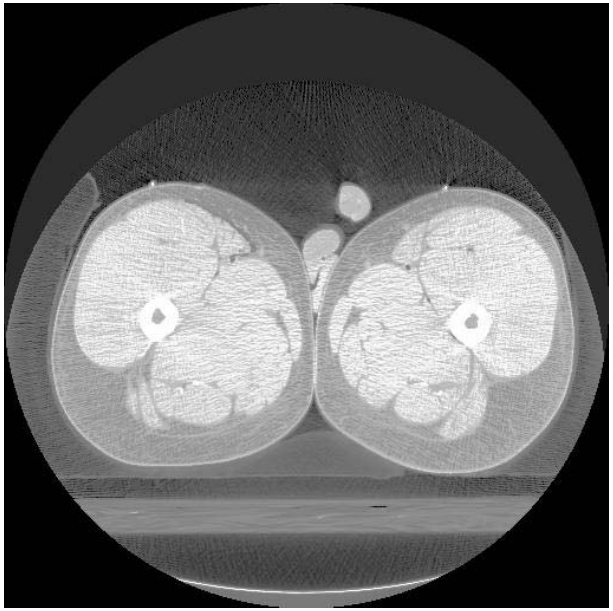


*MAXIMAL meaningful levels lines*



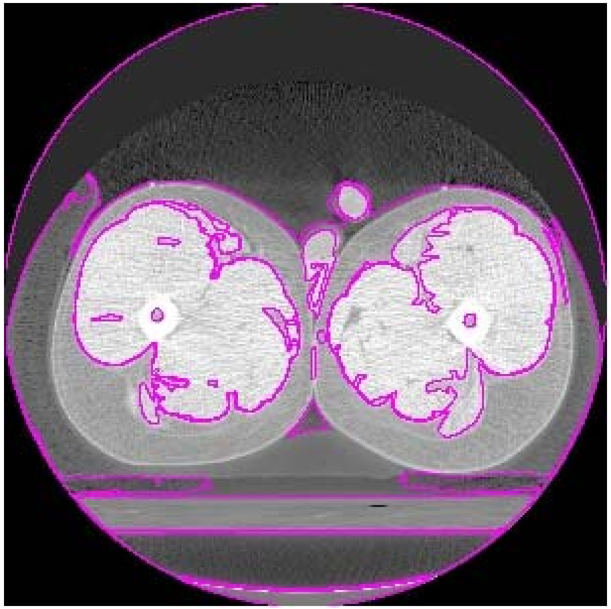
*After curvature analysis*

# Experimental results – case study



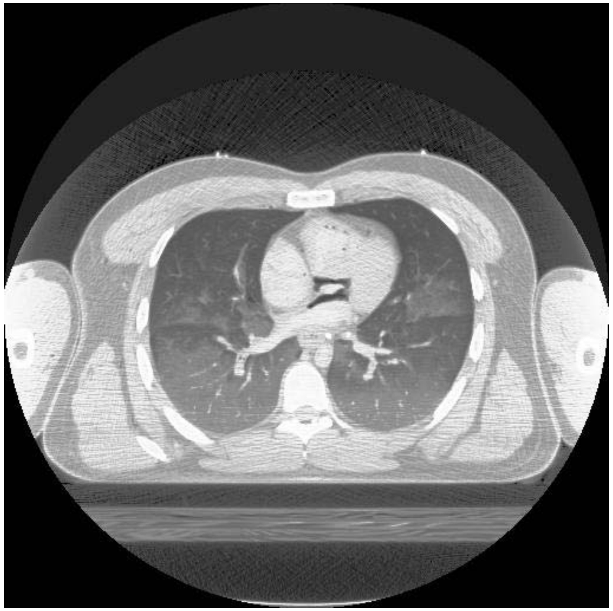
*Original image*

*MAXIMAL meaningful levels lines*

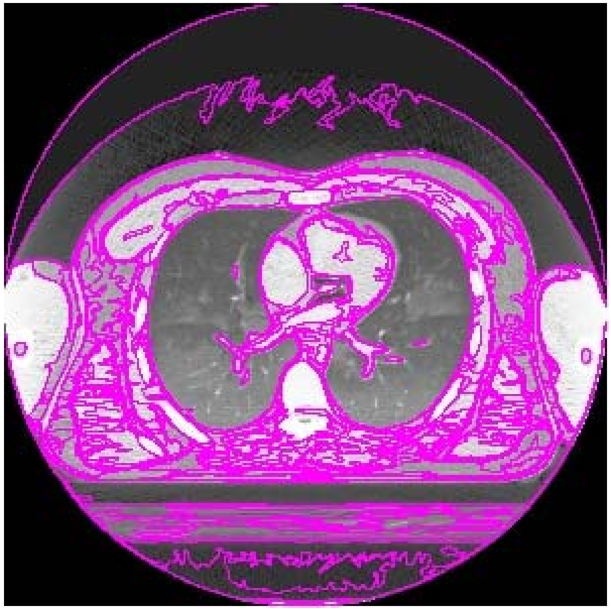


*After curvature analysis*

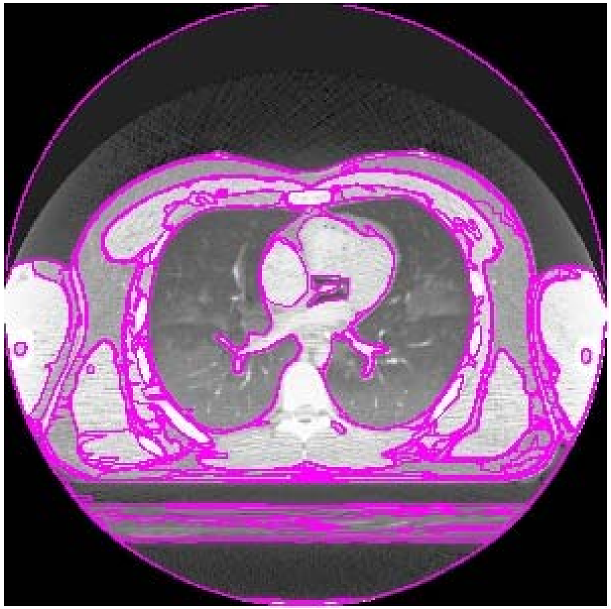
# Experimental results – case study



*Original image*



*MAXIMAL meaningful levels lines*



*After curvature analysis*

# Conclusion

Our main contribution is the **maximal monotone subtree principle**. On **CT scans imaging**, this selection principle allows a 67% lossless reduction rate of the meaningful level lines set compared the Desolneux et al. method maximal selection principle.

Our goal was also to illustrate that level lines can be easily manipulated. They inherit of several interesting properties:

- embedded in an inclusion tree
- require no edge reconstruction method
- the probabilistic scheme is robust
- contrast invariant

We illustrate the high flexibility of this kind of approach for medical imaging. We addressed an important CT scans image segmentation problem, by using simple and intuitive criteria on level lines such as a two thresholds curvature analysis.