EDGE DETECTION BY SELECTION OF PIECES OF LEVEL LINES

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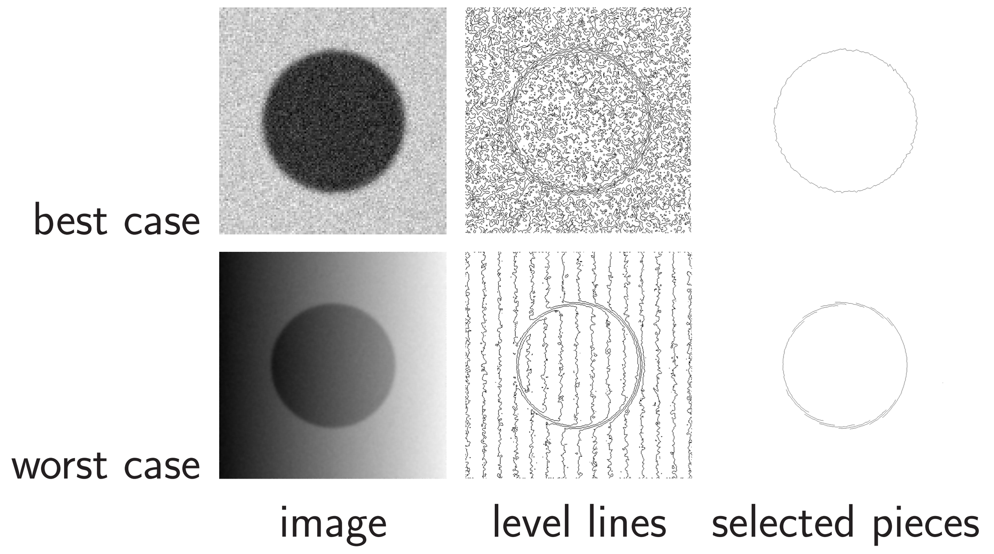
Summary

We propose a new method for detecting edges in digital images. It gives precise results while controlling the number of false detections. It can be applied to any digital image without parameter tuning. The method builds upon and combines the existing methods of Desolneux, Moisan and Morel, *Meaningful Edges*, and the well-known Canny edge detector.

Starting Point

In many digital images, edges are formed by large pieces of level lines. Let us find these pieces!
(or better, a representative subset of them).



Description of the Method

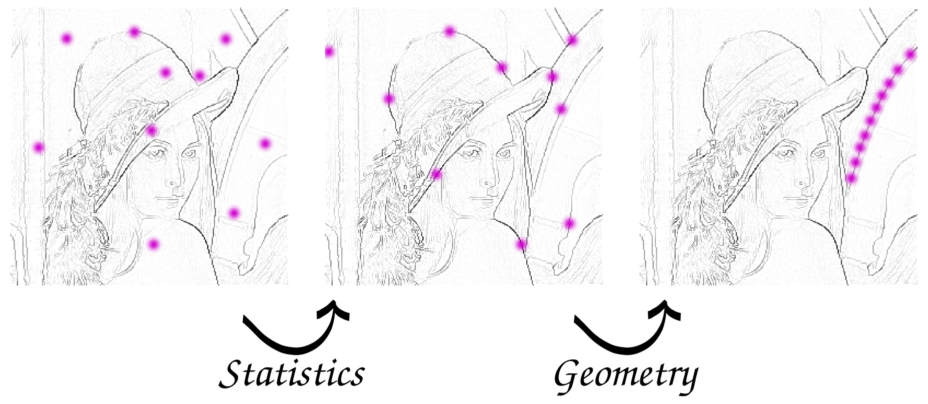
The detected curves are *defined* as follows:

1. Compute the result of Canny's filter with the parameters set to their extreme values (no initial filtering and no thresholdings).
2. Build a list of all the connected pieces of all the level lines of the original image.
3. For each of these curves use the Helmholtz Principle over Canny pixels to decide whether to keep it or to reject it.
4. Pick a representative subset of the non-rejected curves using the Exclusion Principle.

The curves are *computed* differently, taking advantage of the exclusion principle so that each pixel is processed only once.

Helmholtz Principle

A general principle of perception says: there is no perception in white noise. This gives a criterion for setting tresholds without any *a-priori* information. Objects are detected as outliers of a model of unstructured data.

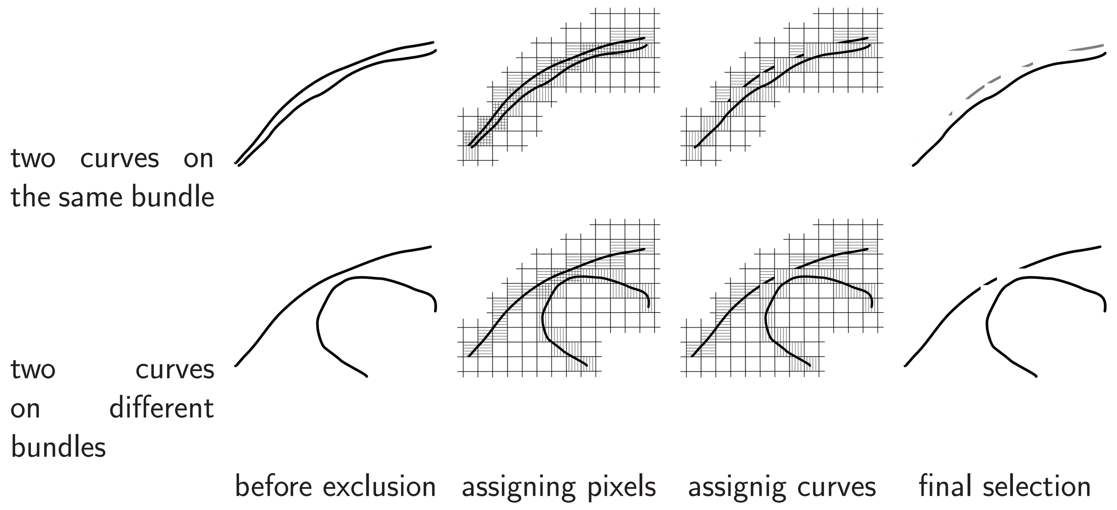


In our case, the model of unstructured data is defined as random subsets of the image, where the Canny filter is evaluated. Since this filter takes very low values everywhere except at edges, the minimum value of a random subset is very low. Deviations from this expected behaviour are detected, or *perceived*.

Exclusion Principle

Helmholtz Principle detects a highly redundant set of curves: every edge is represented by a bundle of pieces of curve.

To select representative curves out of a set of bundles, we impose an Exclusion Principle, which states that each pixel can be part of only one detection, the more meaningful one.



Formulae

Original image $I : \Omega \to \mathbb{R}$ and its Canny filtering $c : \Omega \to \mathbb{R}$.

Level lines of I, $L := \{I^{-1}(\lambda) \mid \lambda \in \mathbb{Z}\}$ and pieces of level lines $P :=$ {connected subsets of L}.

Distribution of Canny pixel values: $H(\mu) := \dfrac{\#\{x \in \Omega \mid c(x) \leq \mu\}}{\#\Omega}$.

Number of False Alarms: $\mathrm{NFA} : 2^{\Omega} \to \mathbb{R}$; $\mathrm{NFA}(s) := \#P \cdot H\left(\min_{x \in s} c(x)\right)^{\#s}$

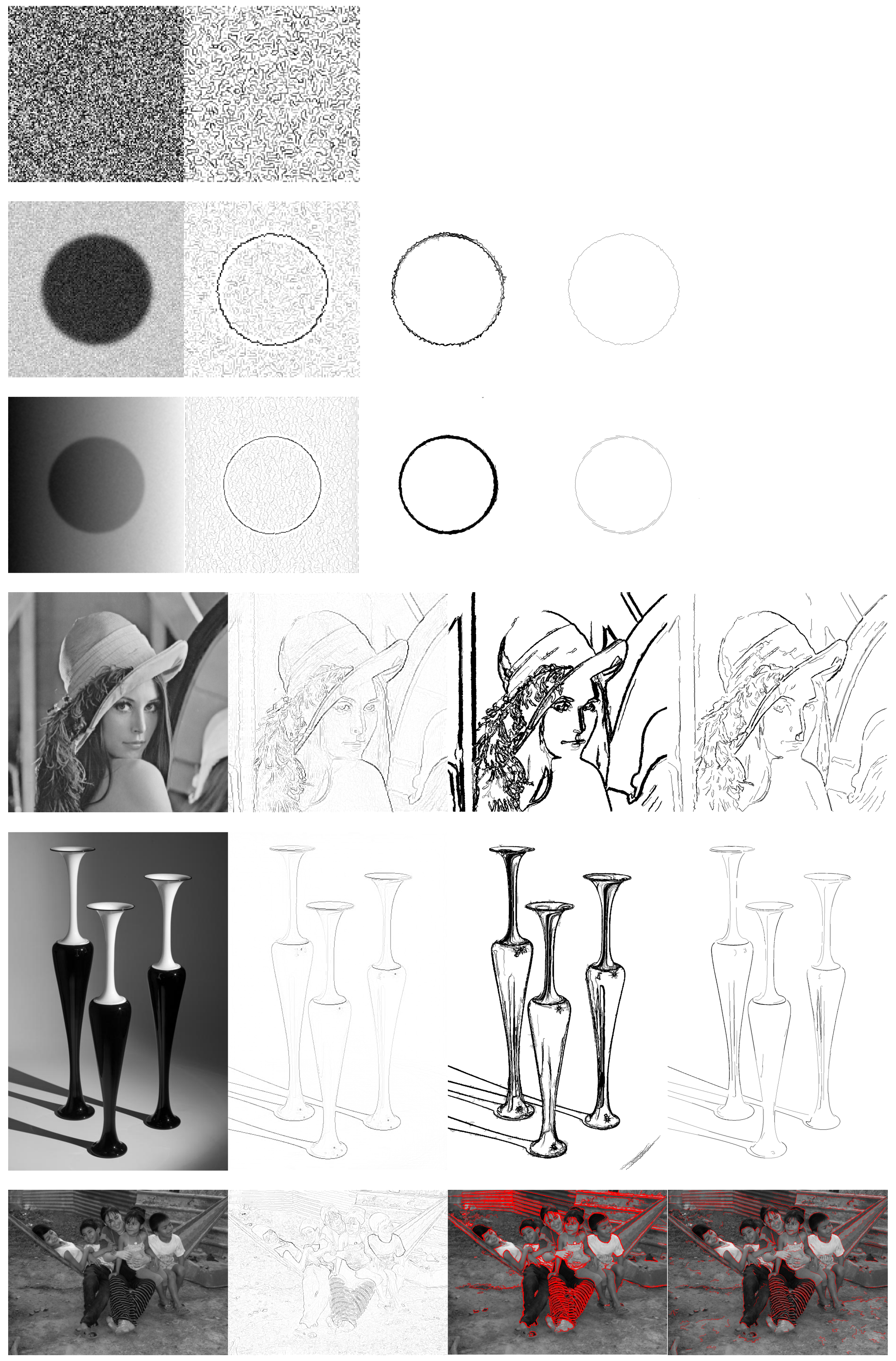
Proposition: for random subsets $s \subset \Omega$, we have $\mathrm{NFA}(s) > \epsilon$

Helmholtz Principle: piece $p \in P$ is selected when $\mathrm{NFA}(p) < \epsilon$

Implementation detail: $\epsilon = 1$

Experiments

We show for each input image, the output of Canny filter, Meaningful Edges, and the proposed method.



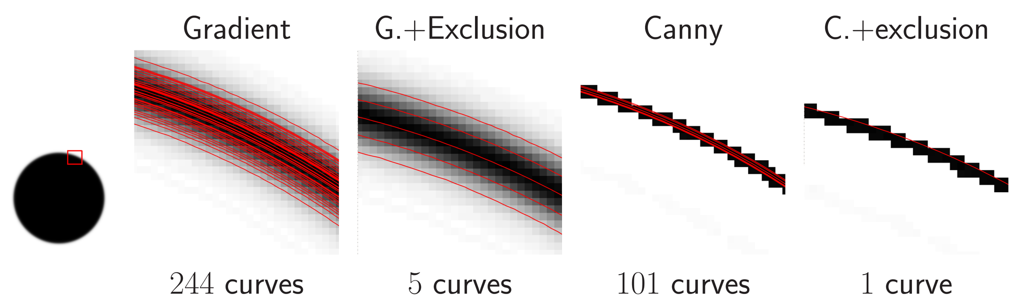
Evaluation

Advantages over Canny

- No need of parameter tuning
- Empty response to noise
- Output given as curves, not pixels

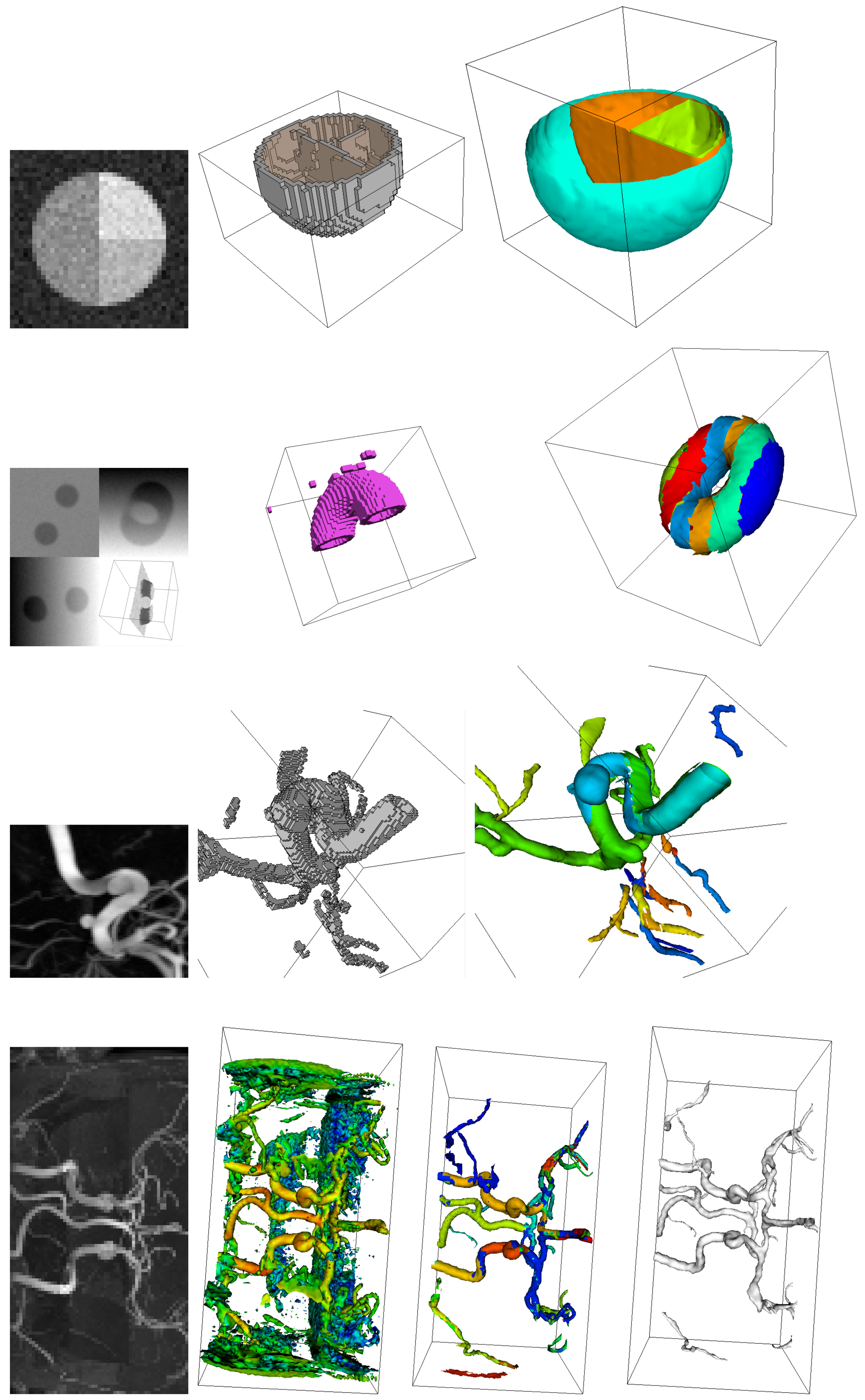
Advantages over "Meaningful Edges"

- No edge replication (tanks to Exclusion Principle)
- Better edge localisation (tanks to usage of Canny's filter)
- Much smaller output (thousands vs. dozens of curves)



Experiments in 3D

The method is generalizable to 3D, where it produces surface patches.



References

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