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Content Adaptive Morphological Filtering: Thin Objects

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Vessel reconnection

Vessel connectivity

- Connectivity is crucial for vessel identification and classification (i.e. vein, artery). We need this information for instance for pre-op planning.
- However noise causes disconnections and denoising typically is not enough to reconnect.
- So we need to be more "forceful".

Spatially-variant morphology (SVMM)

Reconnection must be spatially variant

- A natural idea for a morphologist might be to use openings or closings for reconnecting disconnected vessels.
- However, using standard morphology with a spatially invariant structuring element will not work

(a) Noisy vessels (b) SI closing (c) SV closing

SVMM definition

SV and adjunction

- Defining a SV erosion or dilation is *easy*
- Defining their SV adjunct dilation or erosion (resp.) is *not so easy*

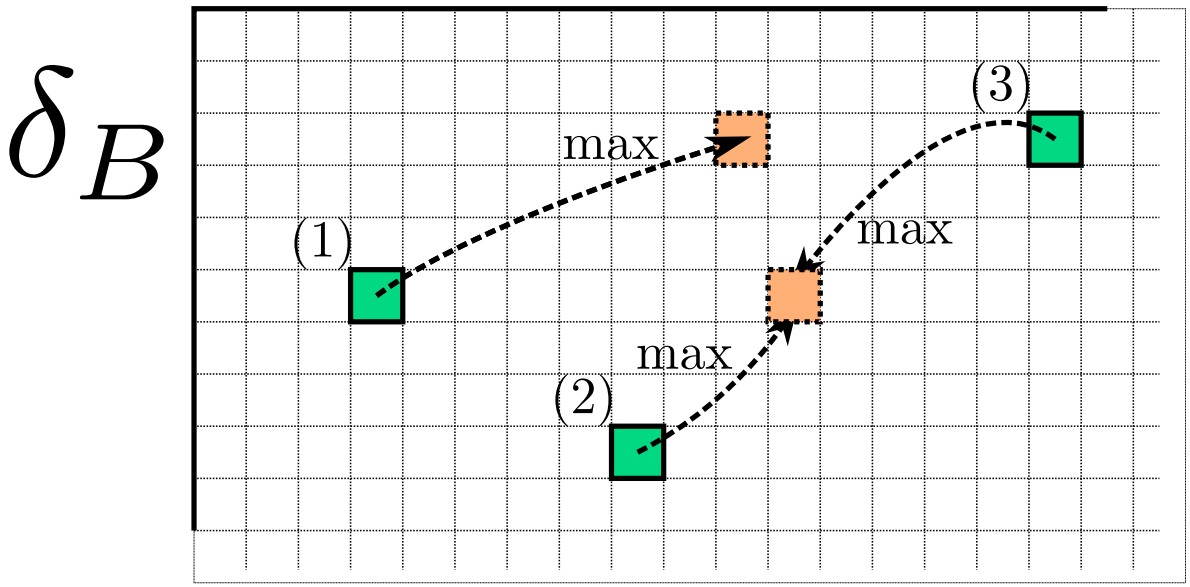
$$\forall x \in \mathcal{L}, \forall y \in \mathcal{M}, \delta(x) \leq y \Longleftrightarrow x \leq \varepsilon(y)$$

- We still have $\delta_B(I) = \bigvee_{p \in B} I_p$ adjunct to $\varepsilon_B(I) = \bigwedge_{p \in \check{B}} I_p$
- However, we need to consider the full definition of the transpose of a SE

$$\check{B}(x) = \{y \mid x \in B(y)\}, \tag{1}$$

- In the SI case, $\check{B}(x) = -B(x)$, but not in the SV case.
- It is possible to *compute it* but inefficient in the SVMM case.
- Fortunately we have an alternative.

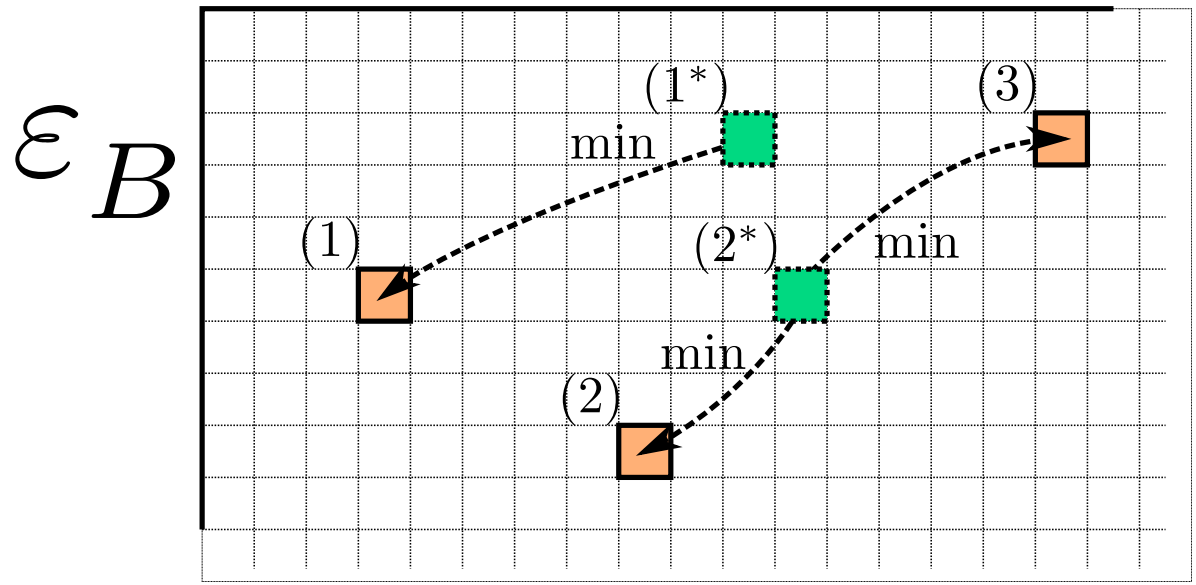
Adjunct erosion computation



Spatially variant dilation

This is easy to compute.

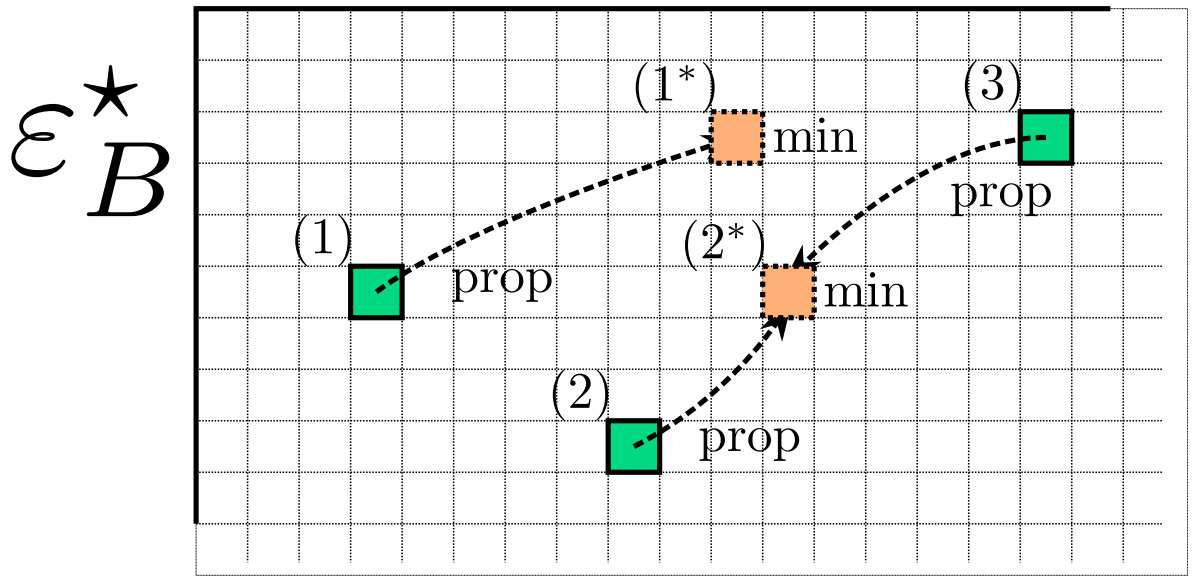
Adjunct erosion computation



Spatially variant adjunct erosion with computed SE

This can be expensive to compute.

Adjunct erosion computation



Spatially variant adjunct erosion alternative definition

This operator is equivalent to the adjunct erosion, and is as efficient to compute as the initial dilation.

More formally: morphology on graphs

- Let (E, Γ) be a graph with vertices E and oriented edges Γ (a.k.a arcs). if x is a vertex, we denote $\Gamma(x)$ its successors in the graph.
- Let $S \in E$ be a subset of E, then

$$\varepsilon_\Gamma(S) = \{\Gamma(x), x \in S\} \tag{2}$$

- Let ψ be an operator on (E, Γ), then we define the dual of ψ for any subset S of E, as $\psi^\star(S) = \overline{\psi(\overline{S})}$, where $\overline{S}$ is the set complement of S.
- Then, the adjunct of ε_Γ is:

$$\delta_\Gamma = \varepsilon^\star_{\Gamma^{-1}}, \tag{3}$$

where (E, Γ^{-1}) is the symmetric graph of (E, Γ), i.e. where all the edge orientations have been reversed.

End of formalities

- This extends the standard erosions and dilations, which correspond to Γ being a regular, reflexive, symmetric graph.
- E.g, with E arranged in a regular square grid, Γ the 4-connected reflexive connectivity, this defines the standard erosion / dilation pair with the 4-connected neighborhood.
- Arbitrary structuring elements are defined by the equivalent graph connectivity.
- Openings and closings are defined as usual:

$$\gamma_\Gamma = \delta_\Gamma \circ \varepsilon_\Gamma \quad \text{(opening)} \tag{4}$$

$$\phi_\Gamma = \varepsilon_\Gamma \circ \delta_\Gamma \quad \text{(closing)} \tag{5}$$

- Grey-level operators are formally defined by threshold decomposition, but implemented efficiently with a max or min operator.

A tubular objects filtering procedure

Filtering pipeline

- Filter the image to eliminate noise with an efficient NLM implementation (MPI + GPU , 5s for a $200 \times 200 \times 200$ image).
- Detect tubular objects using Frangi's vesselness
- Reconnect vessels with a spatially variant closing.

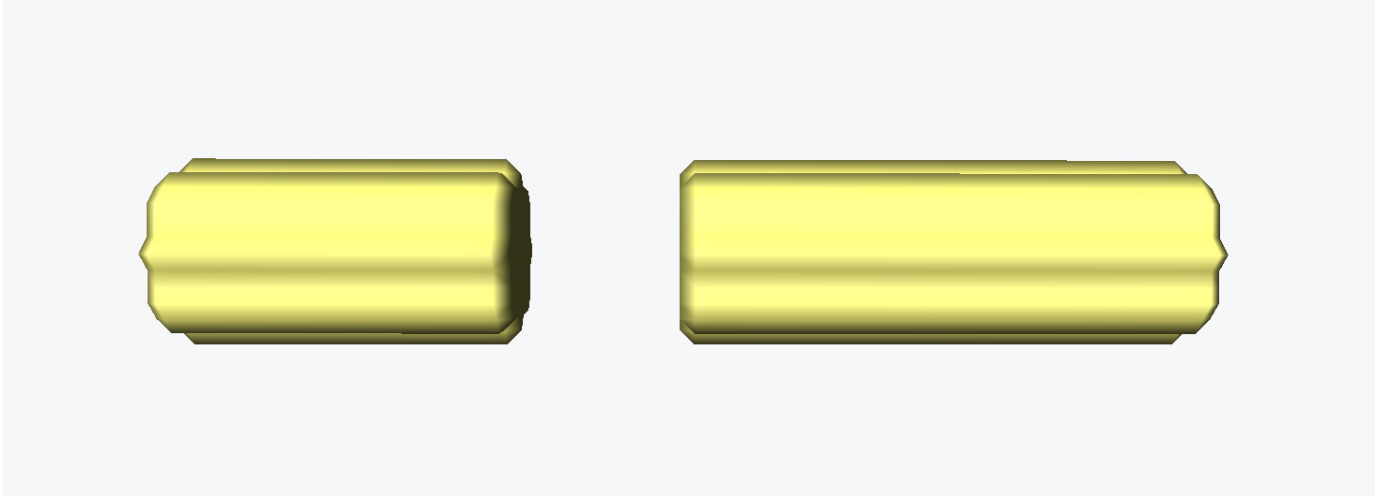
No problem in theory, however to reconnect vessels we require a dense direction field.

Direction field

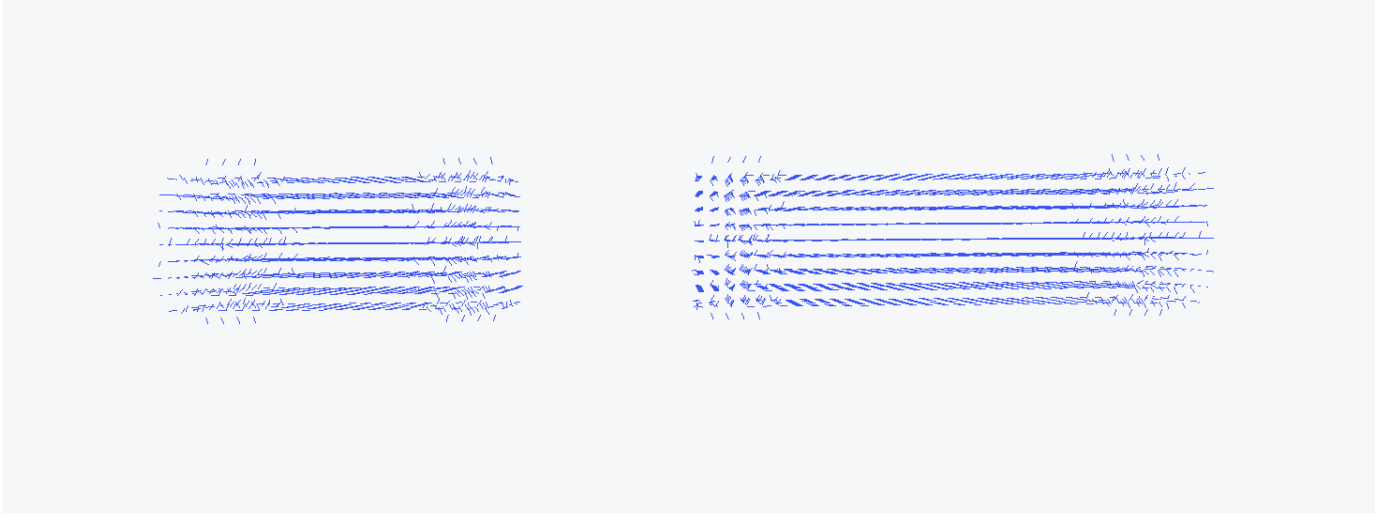
Dense direction field We need to:

- Estimate vessel directions from the Hessian eigenvectors
- Robustify these directions by sampling them near the center of the vessels
- Dilate the direction field
- Perform the SV closing with a segment oriented along these directions

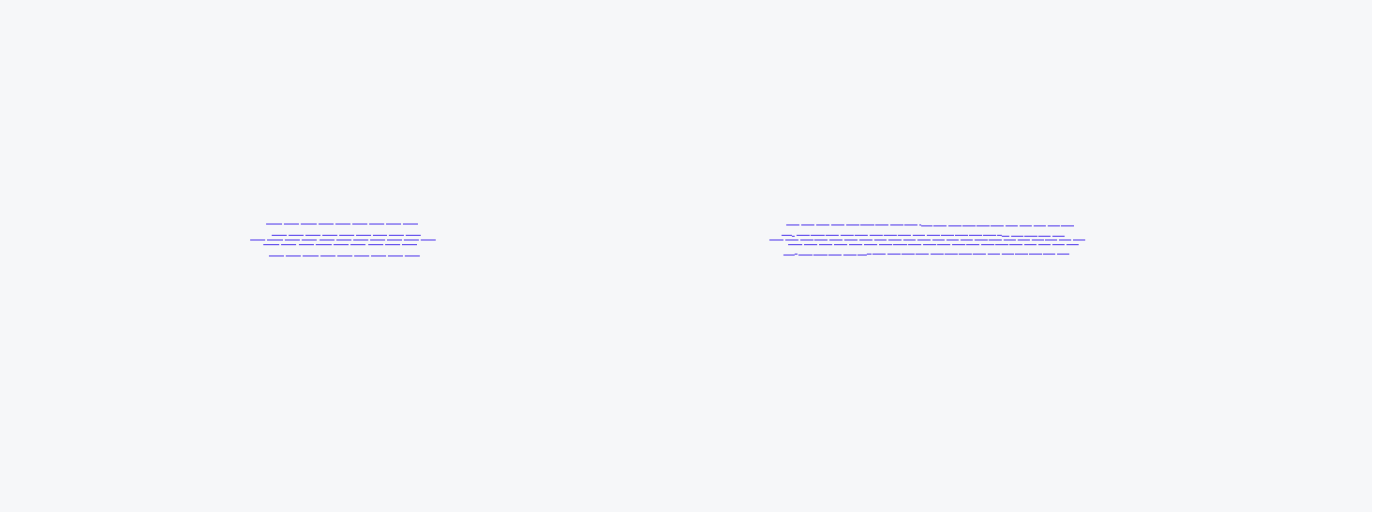
SV closing illustration



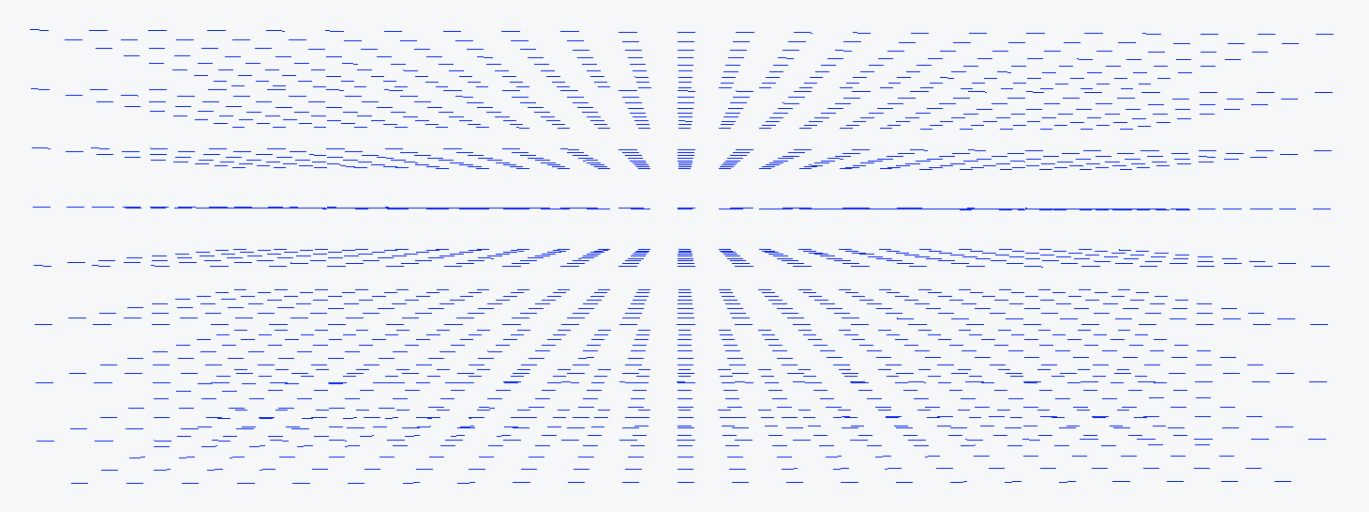
SV closing illustration



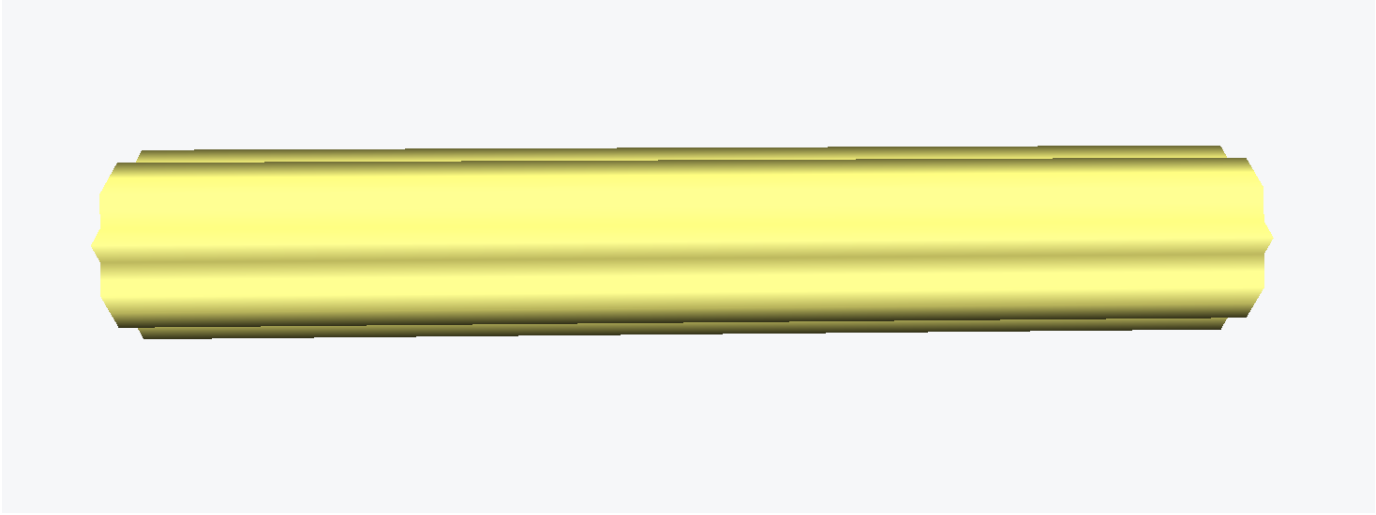
SV closing illustration



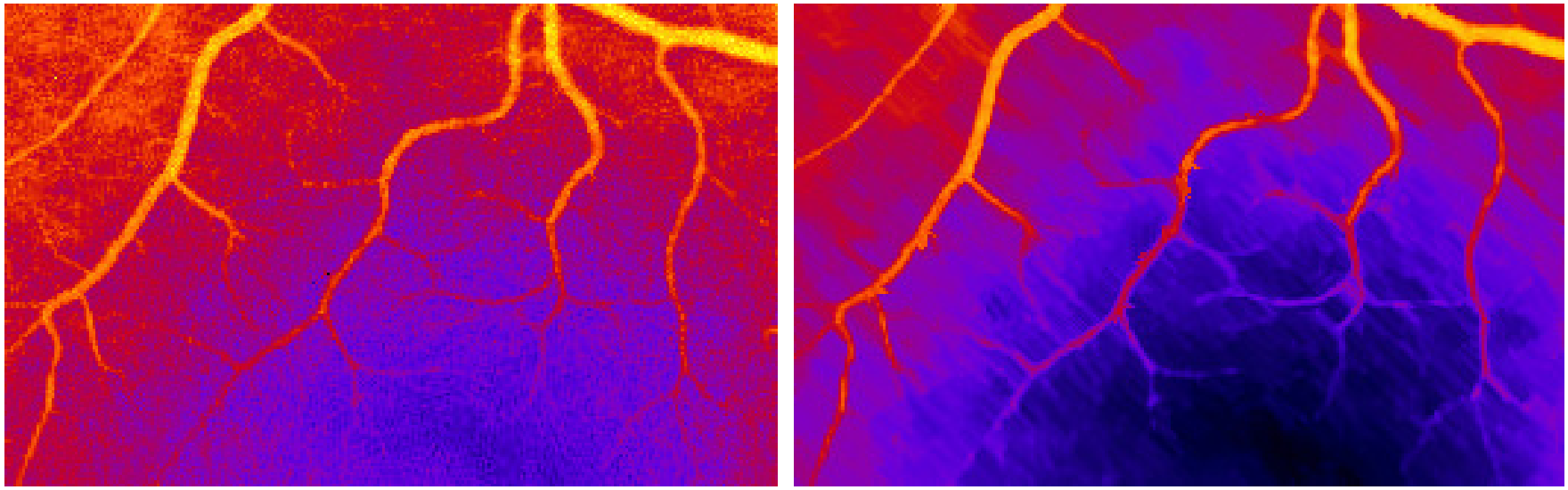
SV closing illustration



SV closing illustration

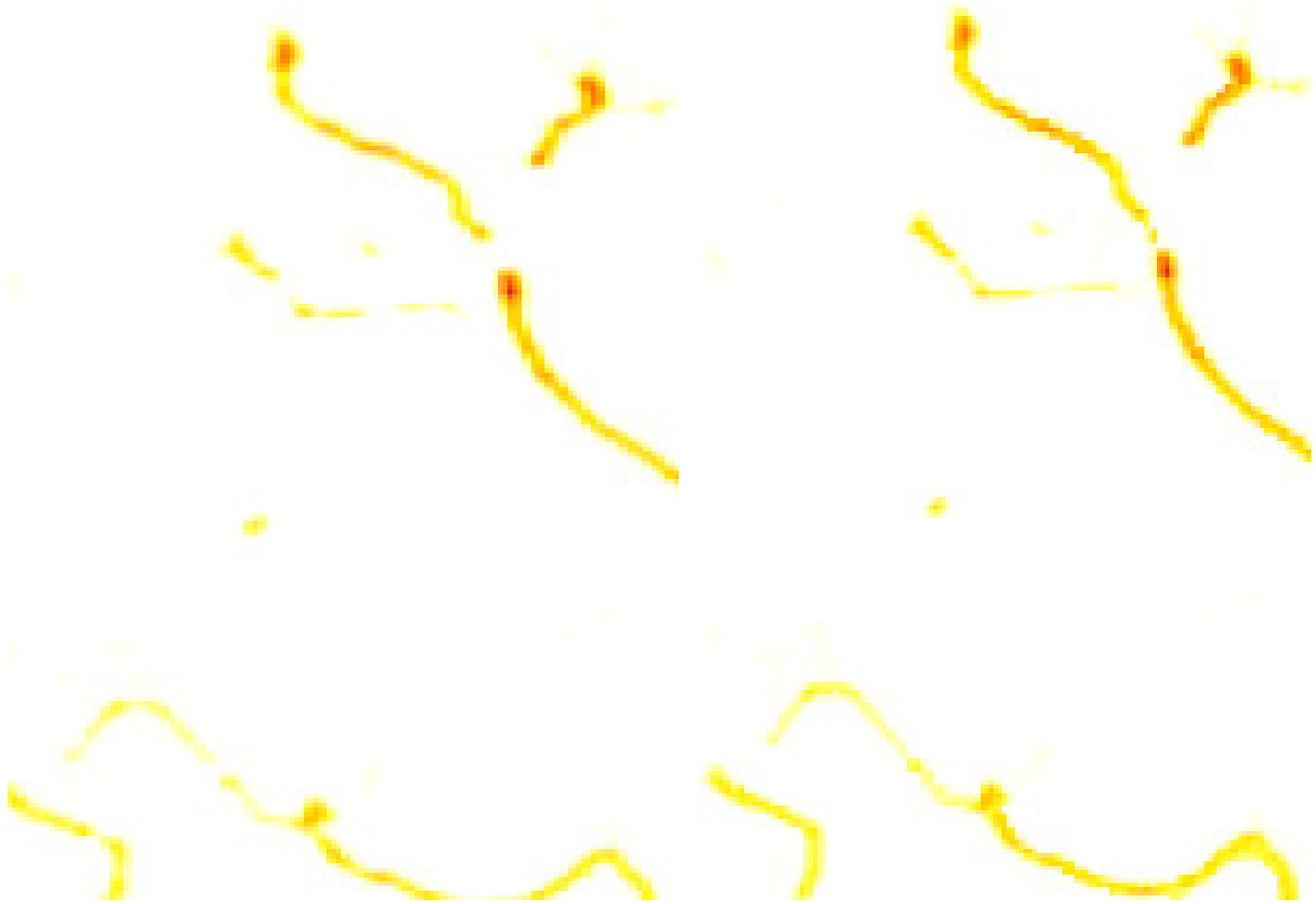


Visual results



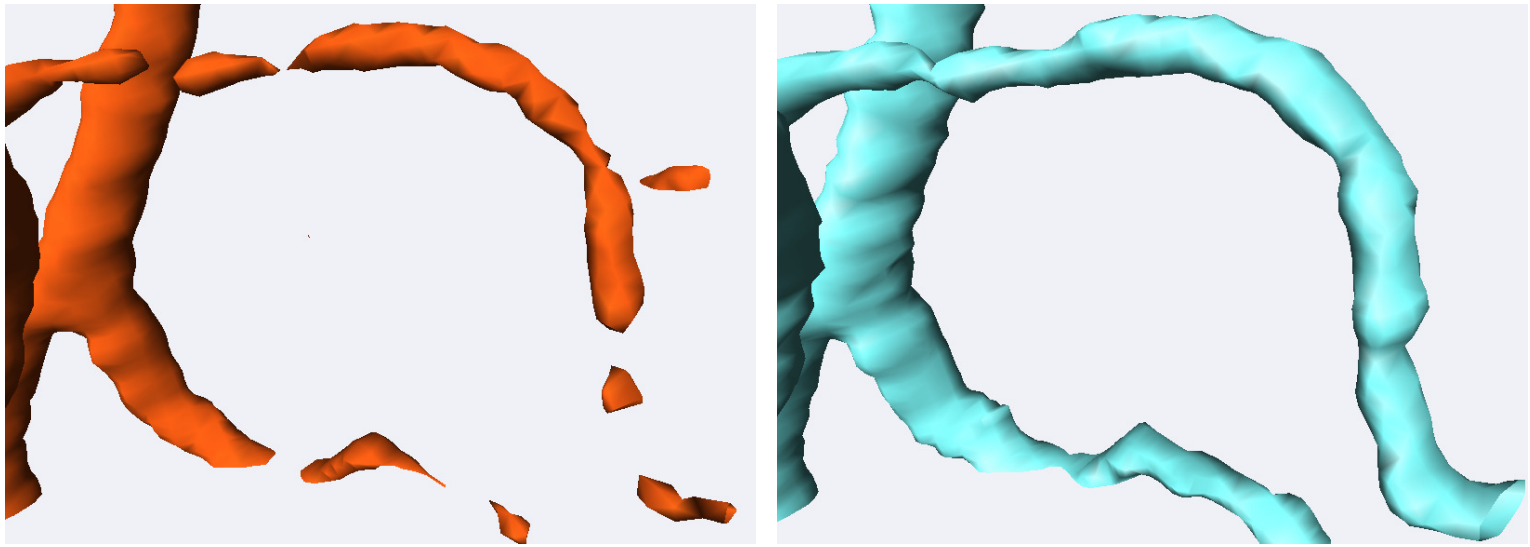
Eye fundus filtering

Visual results



Neurite filtering

Visual results

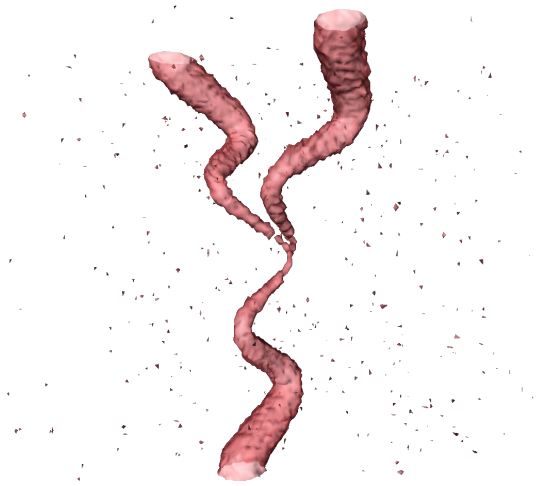


3D image of vessels in the brain

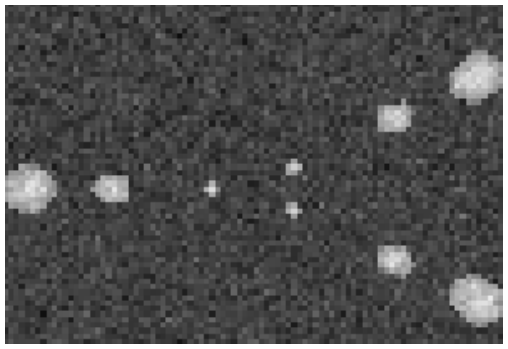
Phantom for validation

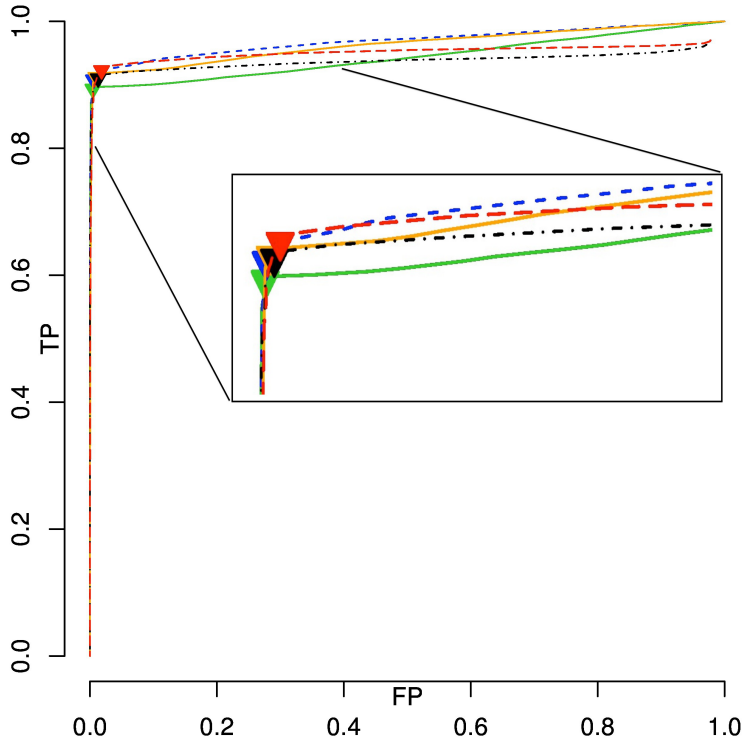
Description and origin

- We use a phantom from [8], which is a $100 \times 100 \times 100$ image used in a MICCAI workshop.
- It is tortuous and vessel-like
- grey-level with a parabolic intensity from 200 at the center to 150 at the edges. The background is 100, consistent e.g. with TOF MRA.
- In the following ROC analyses, the triangle indicates best fully-connected result.



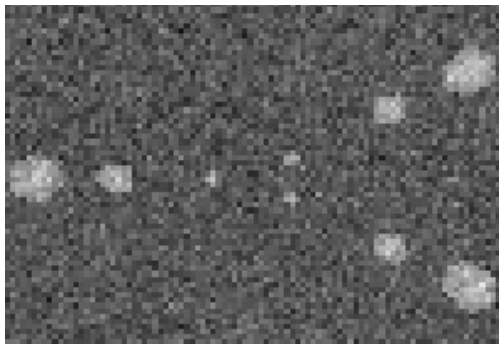
Validation

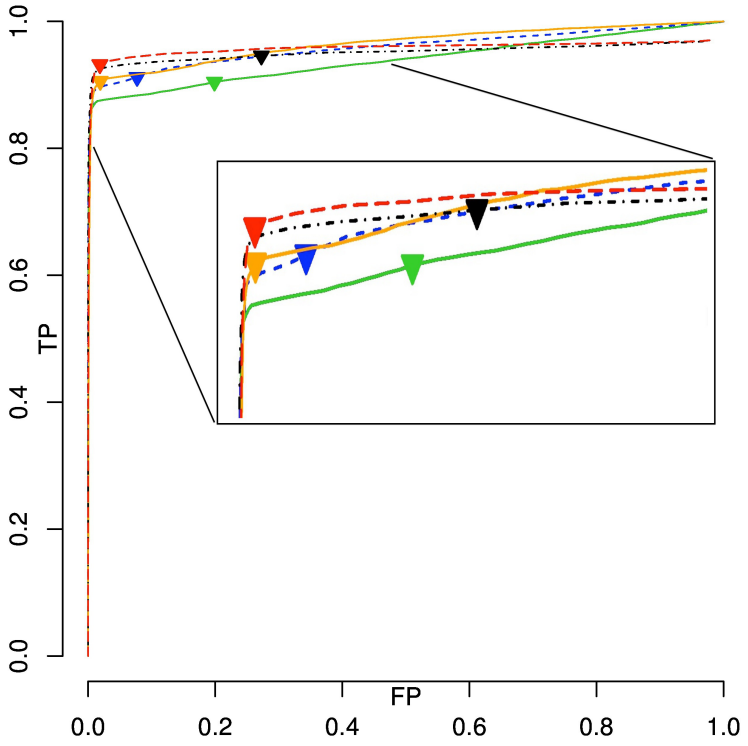




Level of noise standard deviation $\sigma = 10$

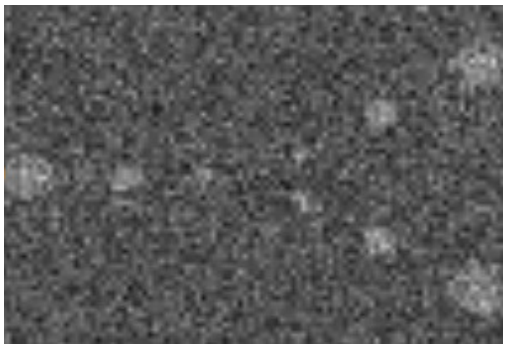
Validation

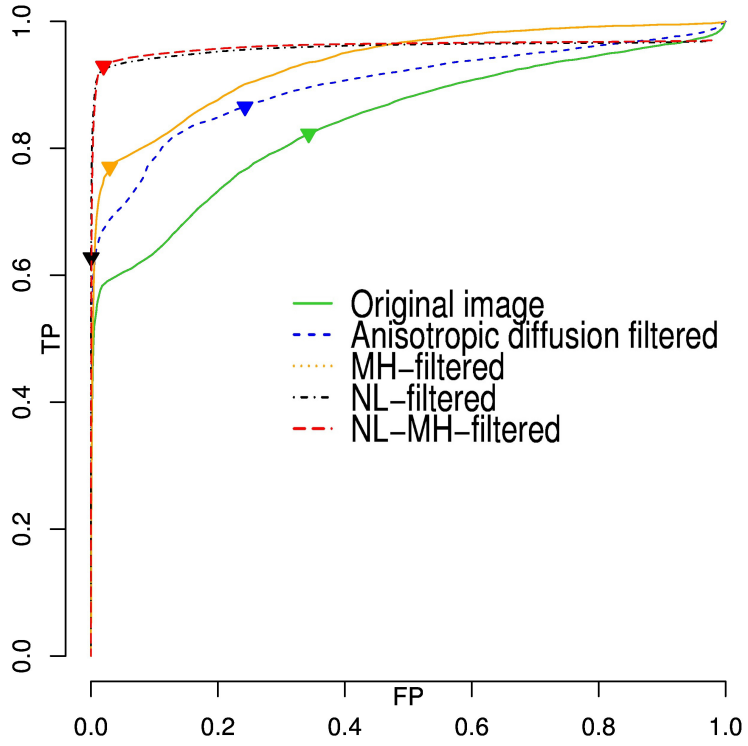




Level of noise standard deviation $\sigma = 20$

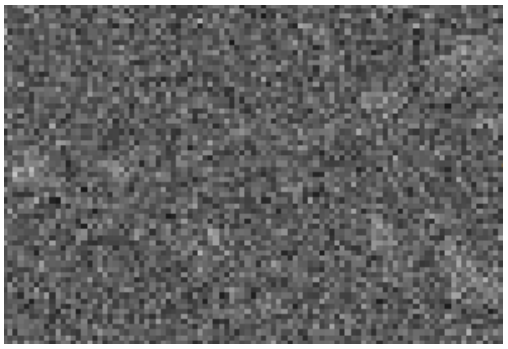
Validation

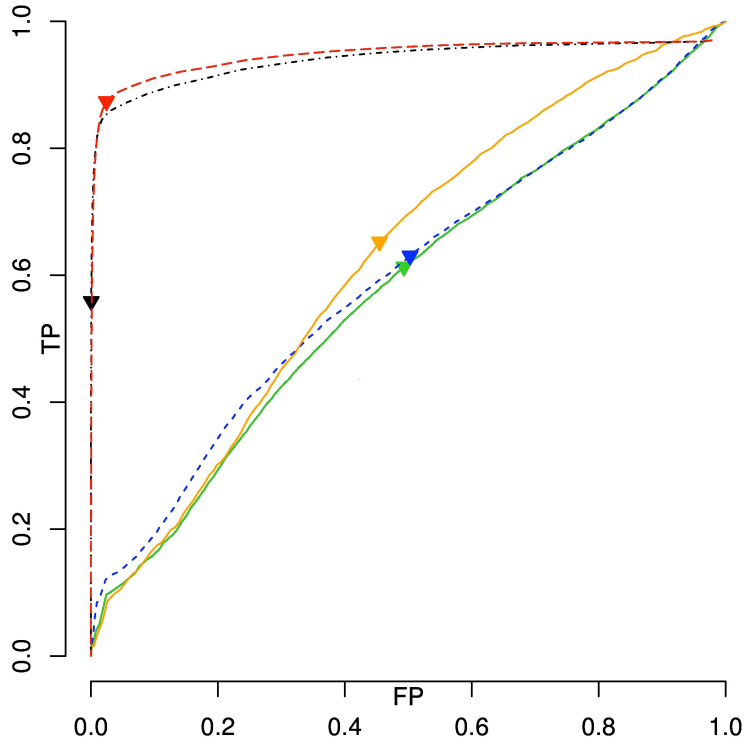




Level of noise standard deviation $\sigma = 40$

Validation





Level of noise standard deviation $\sigma = 80$

Notice that the filtered phantom remains connected even at very high noise levels.

Discussion

Remarks

- Noise reduction achieved with non-local approaches, orientation measured by vesselness, reconnection achieved by Spatially Variant morphology.
- Combining noise reduction techniques with morphology allows us to achieve extremely robust results for thin object detection

Publications This work is described in greater detail in [25], as well as [26, 22, 23, 24, 6, 7, 17].

Discussion and challenges

- This pipeline is effective but requires the tuning of a number of parameters ;
- It requires significant hardware to be sufficiently fast
- Vessel detection is limited by the vesselness measure, which is not very effective
- It still needs to be evaluated on larger dataset, e.g. full brain vascular network, but annotated data is difficult to obtain.

Step 1: Extracting the vascular network from brain MRA data

- **Filtering**
  Improve images (Denoising, contrast enhancement)
- **Segmentation**
  Detecting the vascular network
- **Post-processing**
  Reconnexion, quantitative data analysis: directions, diameter, vessel density ...)

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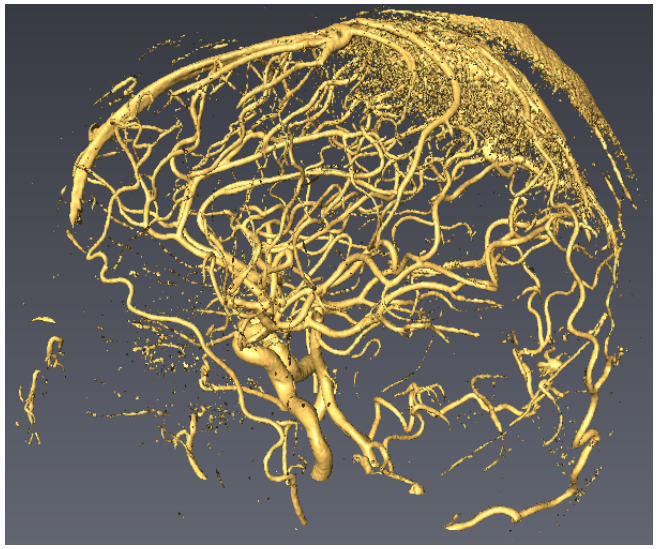
In this talk

A new filtering method to improve existing segmentation pipeline

2 complementary axes :

- Noise reduction
- Vascular network contrast enhance-ment



3D MRA data surface rendering

Maximum intensity projection

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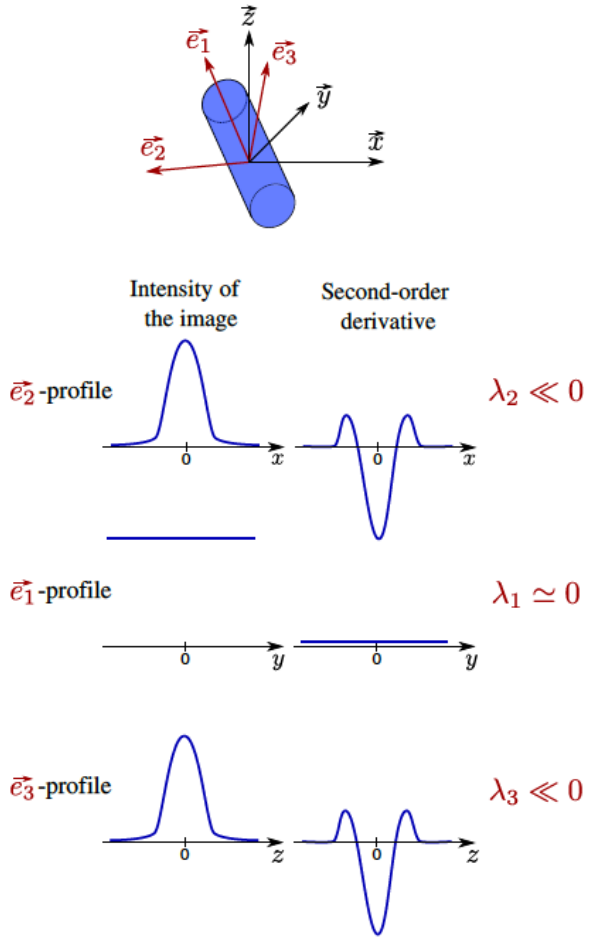
Classical tubular segmentation



Classical approach using the Hessian

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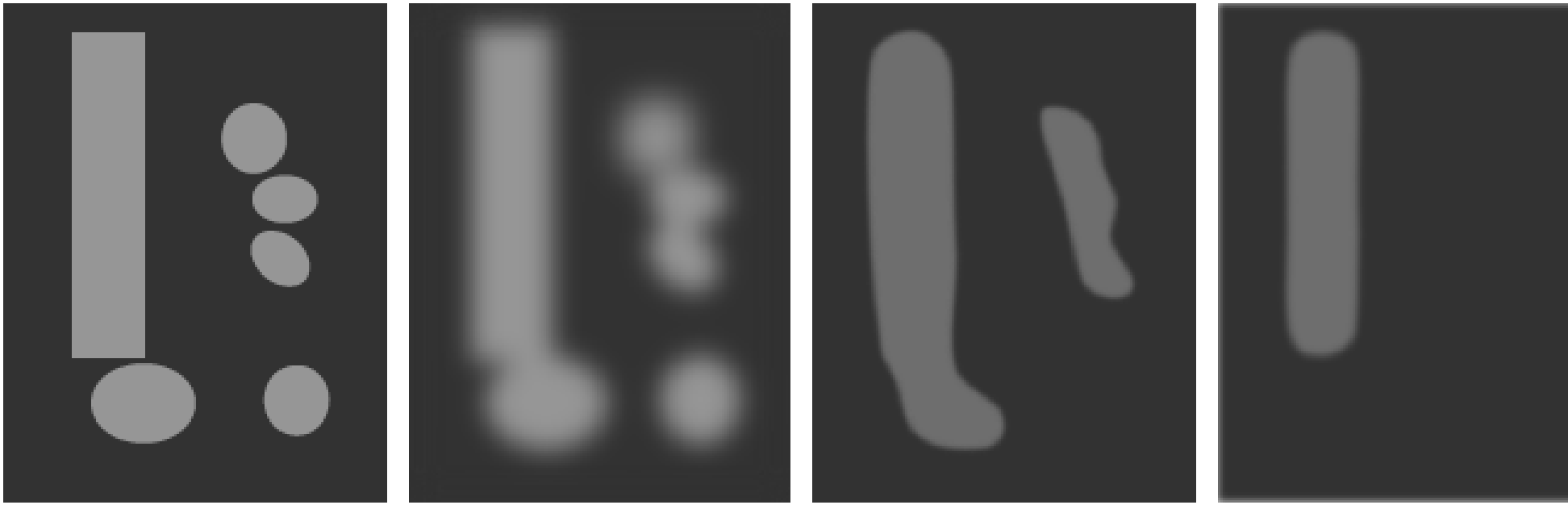
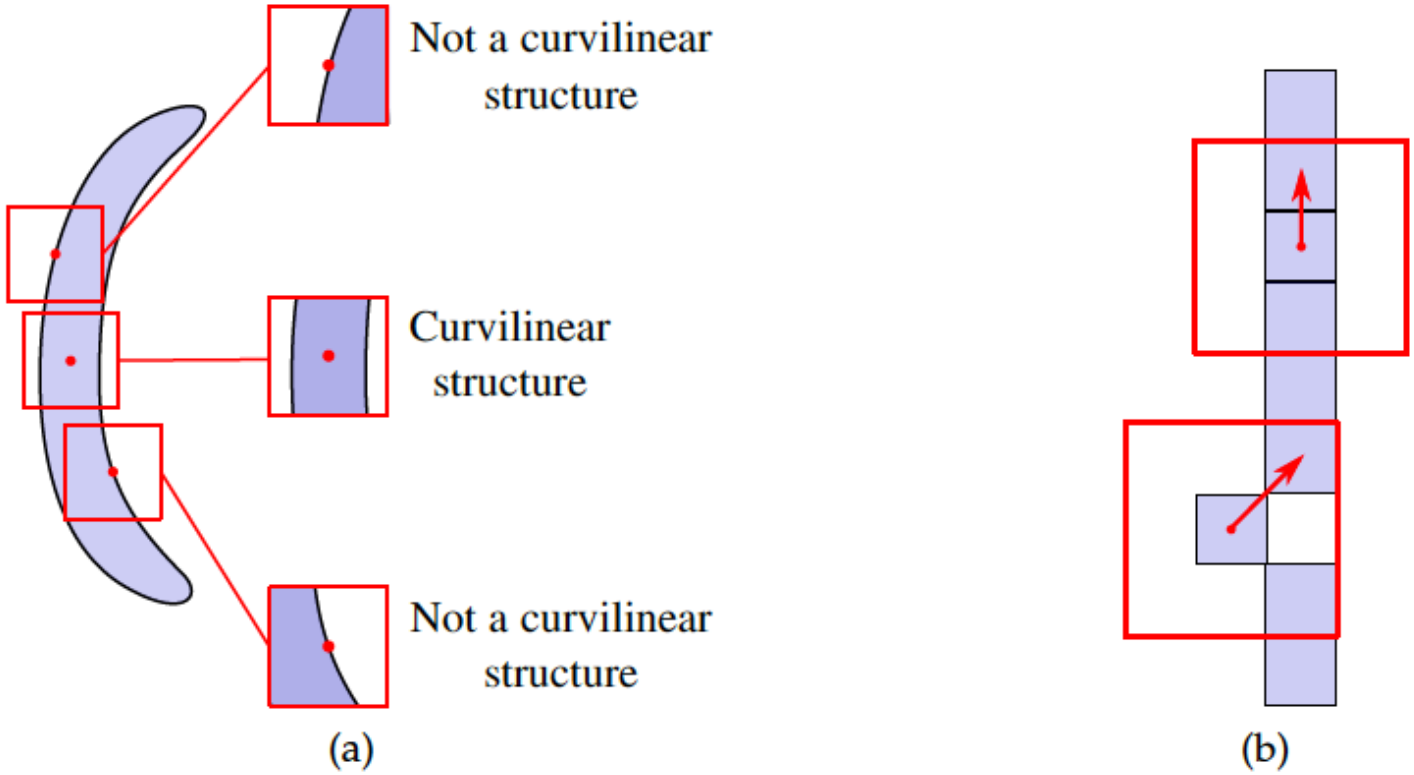
Errors due to scale-space



(a) Initial image (b) Gaussian filter result (c) Hessian-based filter result (d) Expected result

Scale-space filtering problem

Errors due to locality



Scale space methods use local neighborhoods and are susceptible to misinterpretation at some scales.

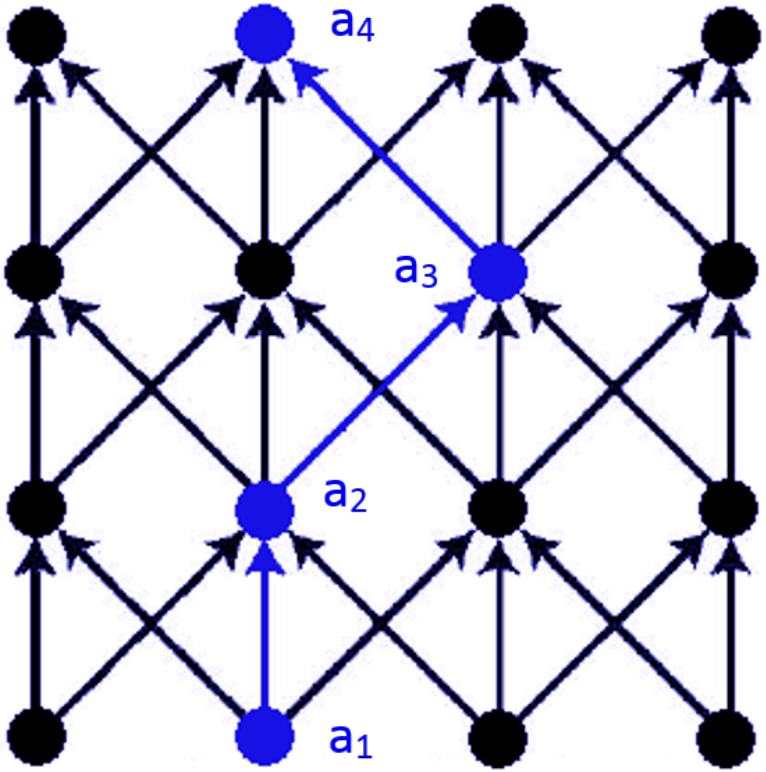
Proposed solution

- Scale selection and combination is a challenging problem in traditional scale-space methods.
- One solution is to use semi-local neighborhoods, i.e. that gather information over long distances at all scales.
- We propose the use of paths.

Adjacency graph

A path, **a**, is a set of neighboring pixels on a graph defining an adjacency relation $x \rightarrow y$:

$$\mathbf{a} = (a_1, a_2, ..., a_L) \quad si \; a_k \rightarrow a_{k+1}$$

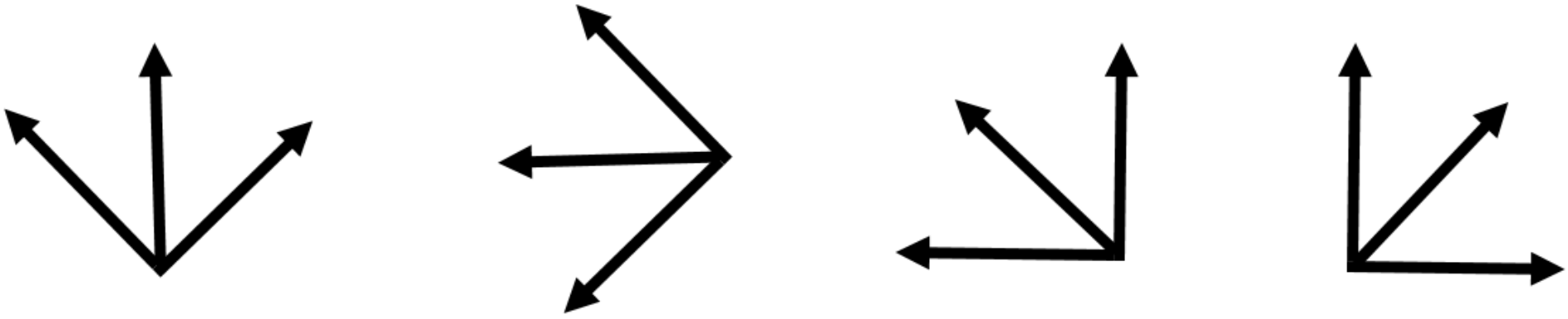


*Adjacency graph (black) and vertical path **a** of length 4 (blue).*

Multiple orientations

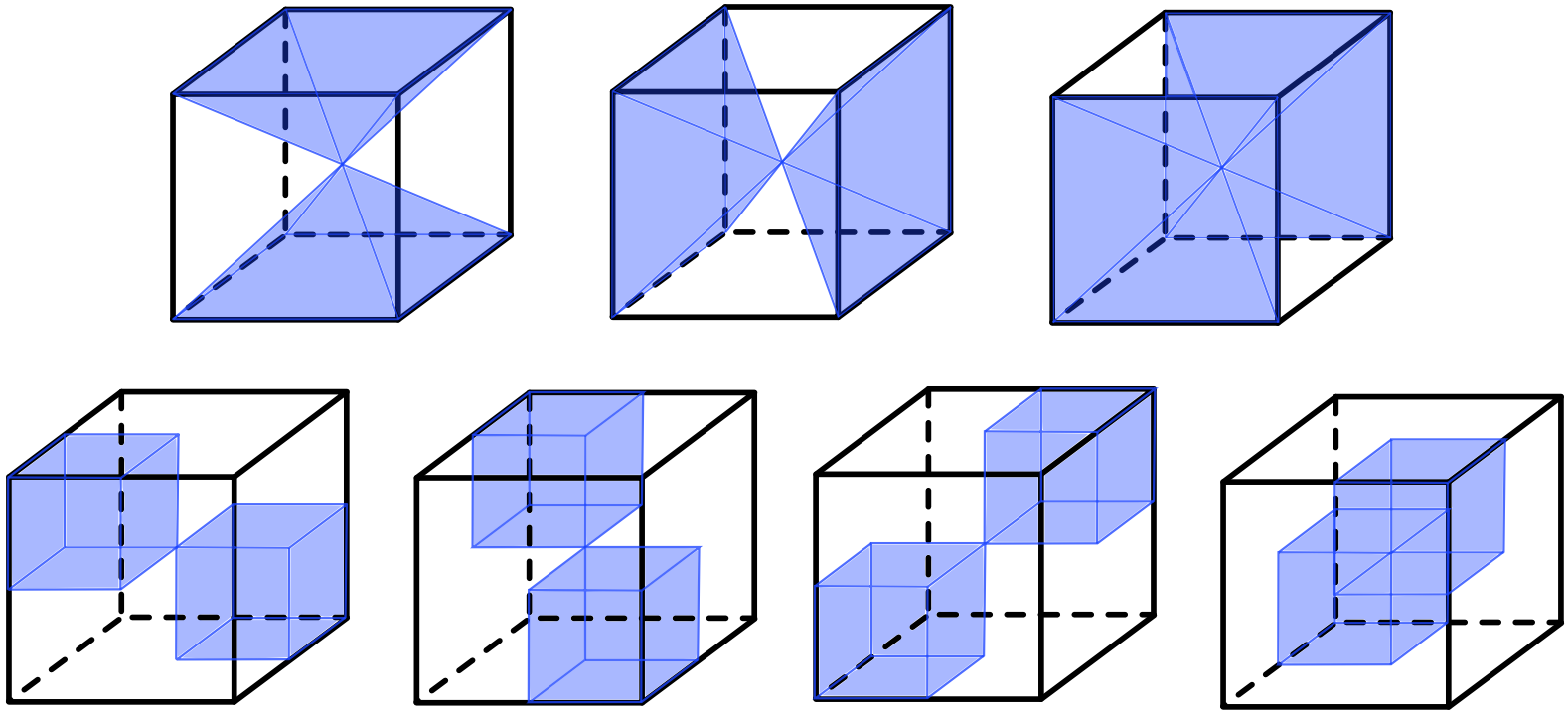
Filtering of an image by a path opening Preserving thin structures in arbitrary orientations imposes to filter the image by several paths each using a particular adjacency graph.

The 2D space is discretized in 4 different orientations :



Multiple orientations in 3D

In 3D, the discrete space is discretized in 7 different orientations :

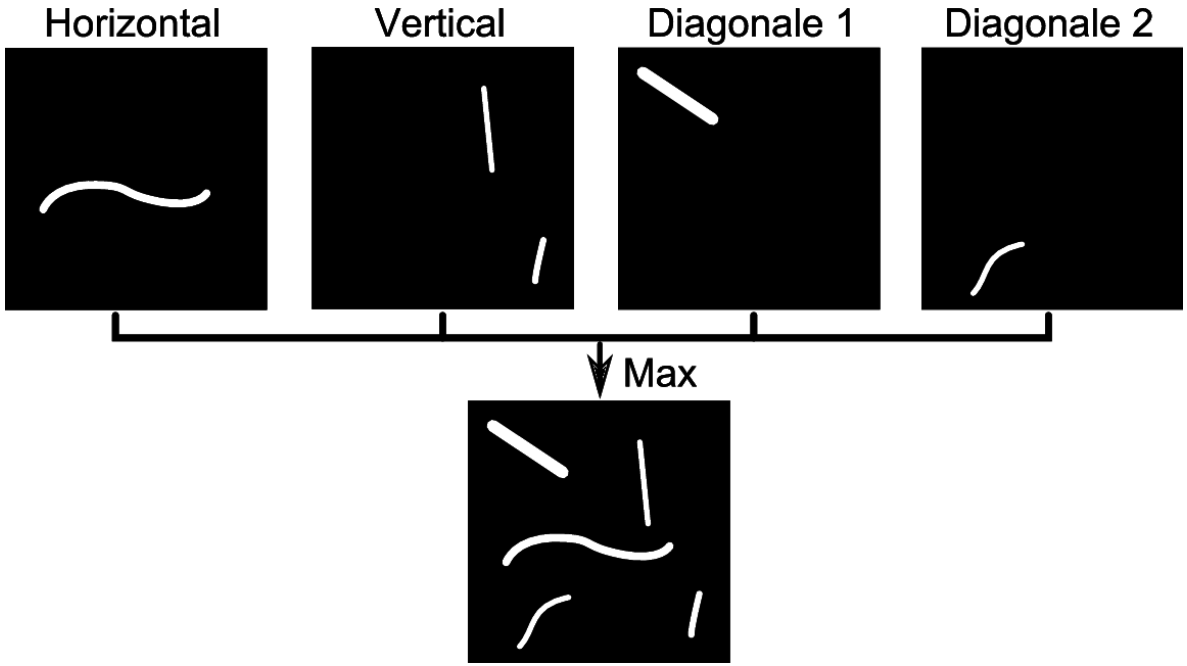


Path filtering

Example binary path opening

$$\alpha_L = \bigvee\{\sigma(\mathbf{a}), \mathbf{a} \in \Pi_L(X)\}$$

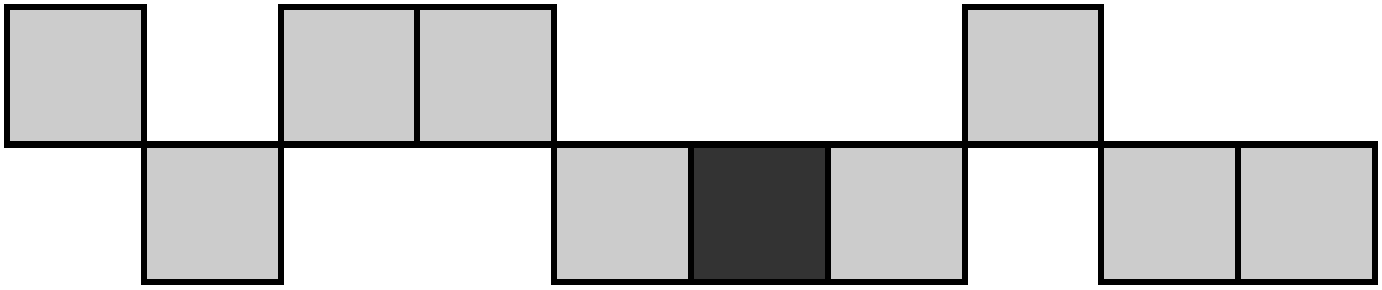
σ_L : Set of all pixels belonging to path **a**.
$\Pi_L(X)$: Set of all paths of length L.



Principle

Path definition relaxation A path can now admit K consecutive noise pixels between path pixels

This makes it possible to preserve partially disconnected thin/tubular structures :

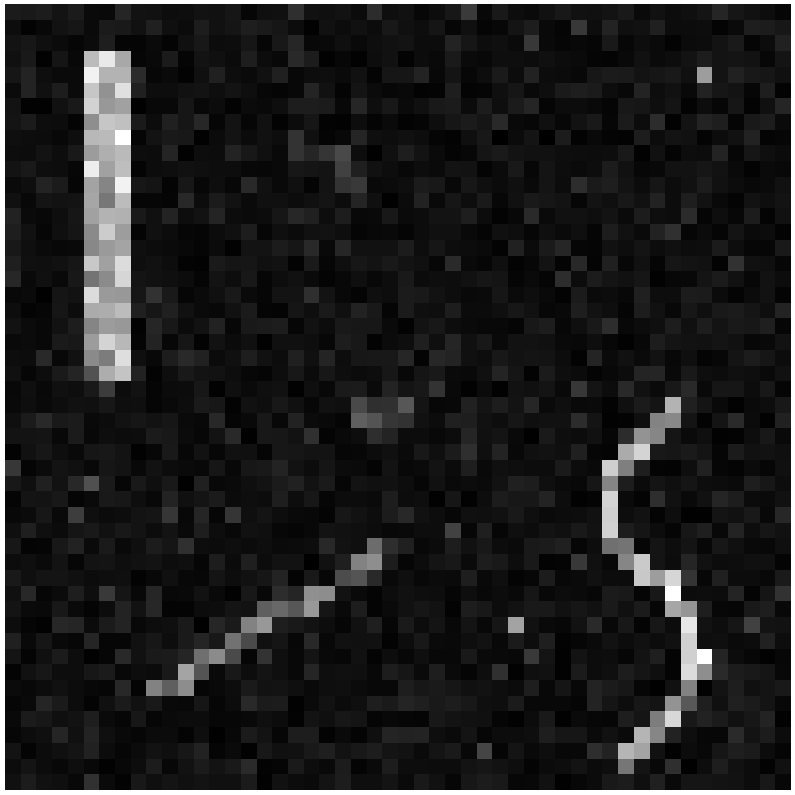


Path with $L = 10$ and $K = 1$ noise pixel

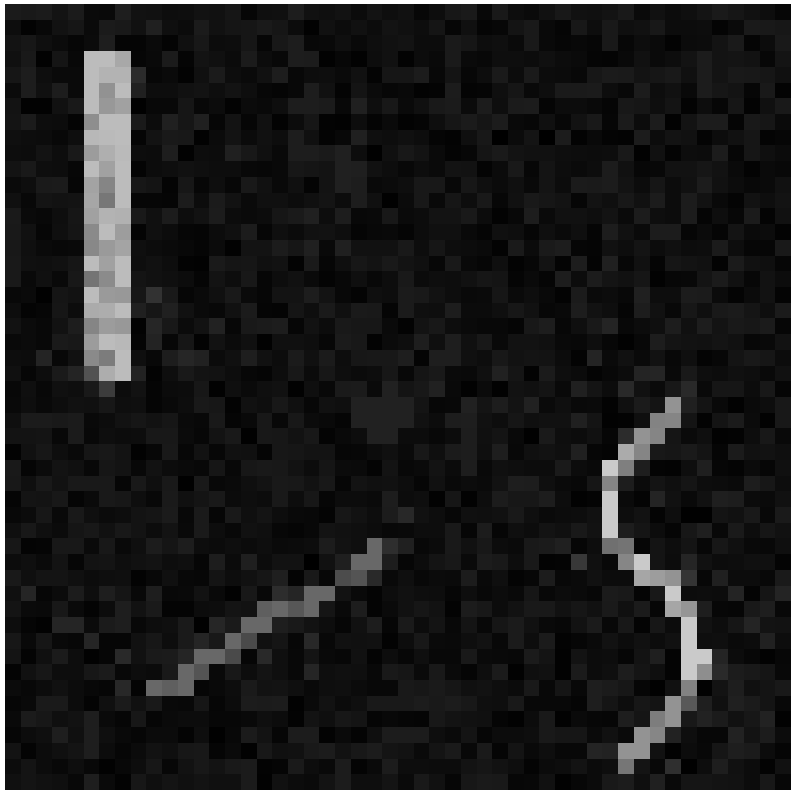
This notion is different from that of *path incompleteness* by Heijman et al, it was proposed by F. Cokelaer [5] and is simpler to implement.

Example

RPO Example on a synthetic, noisy 2D image (AWGN mean $= 0, \sigma = 20$:



Initial image 50x50px

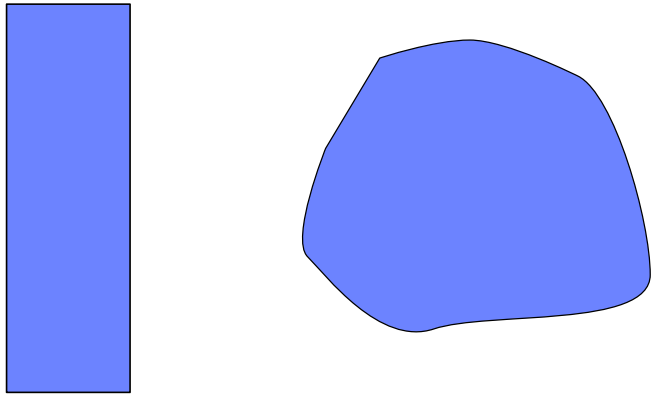


RPO L=10, K=1

The 3D case is more complicated than 2D

2D Case 2 Types of structures :

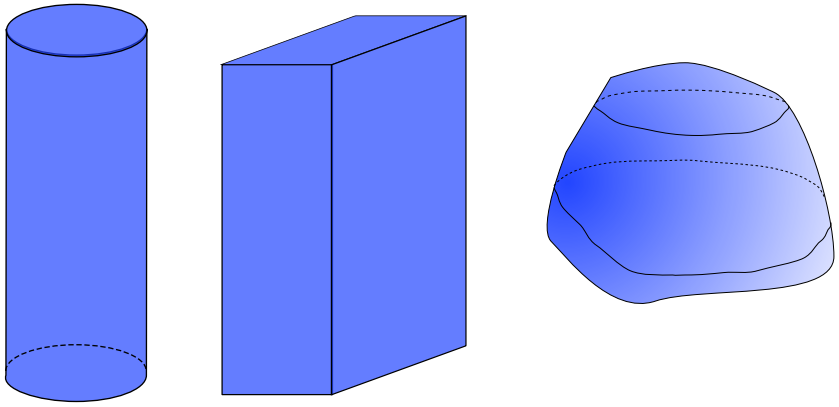
Fibres and Blobs



RPO preserves only fibres if blobs are not too big.

3D Case 3 Types of structures :

Tubes, Planes and Blobs



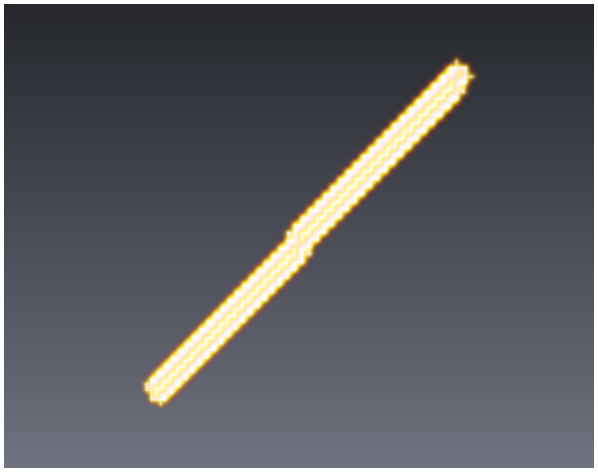
RPO preserves both tubes and planes.

An RPO by itself preserves more than just tubes in 3D images.
Another filter is thus necessary to eliminate planar structures.

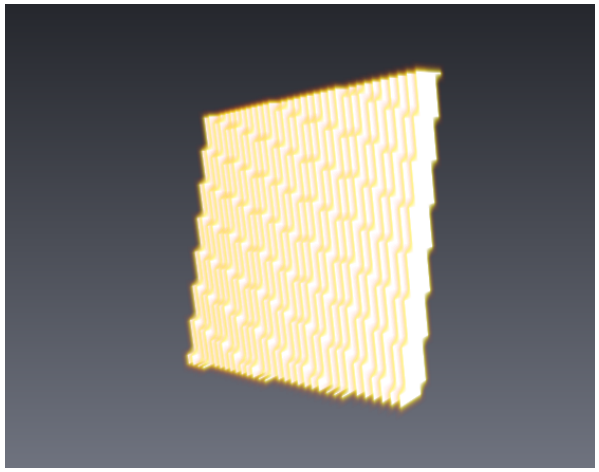
Principle

Hypothesis Planar structures should be detected in at least one more orientation than tubular structures

Test of this hypothesis on 3 synthetic structures :



Tube



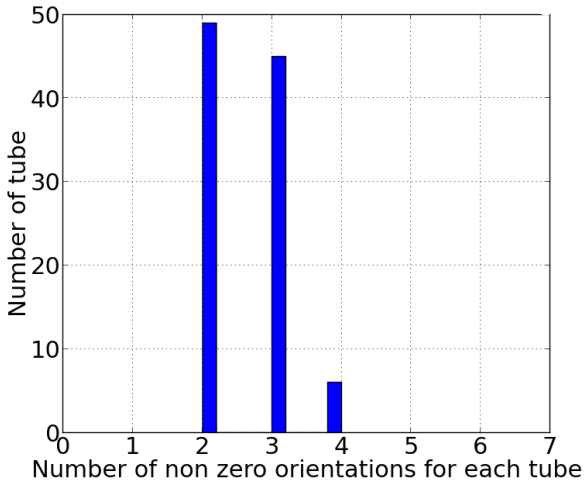
Plane

Half-ellipsoid surface

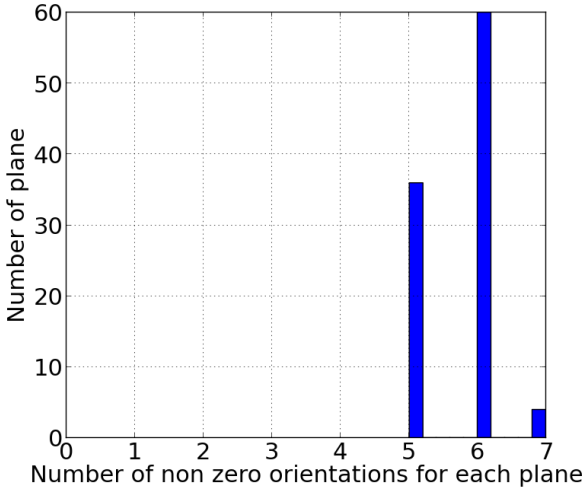
Hypothesis testing

Test : Filtering 100 3D images of each structure and measuring the number of RPO orientations still containing the structure after filtering

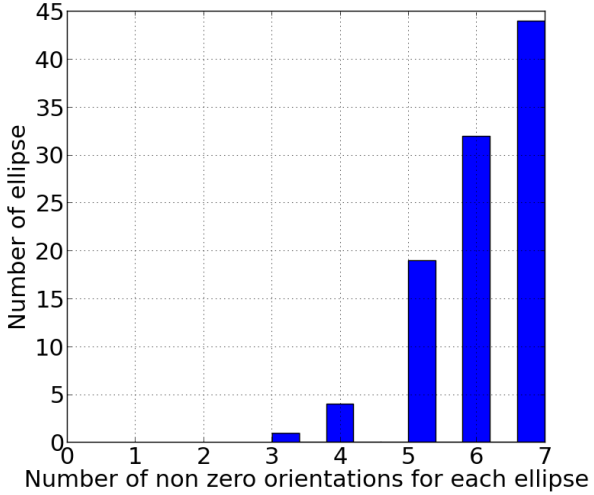
Histogram of the number of orientations preserving the synthetic structure:



Tubes



Planes



Half-ellipsoids

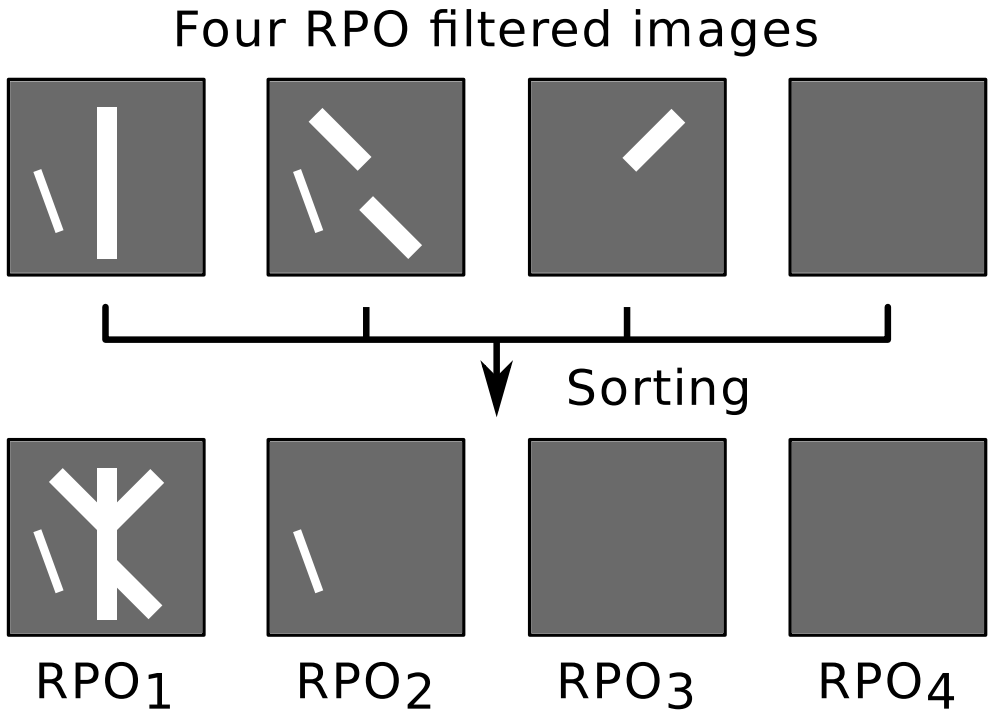
Methodology

New operator

We order the result of each RPO orientation pixelwise and compute

$$\mathrm{RORPO} = RPO_1 - RPO_i$$

RPO_1 : Result of standard RPO (max of all RPOs)
RPO_i : The $i-th$ rank of the RPO.



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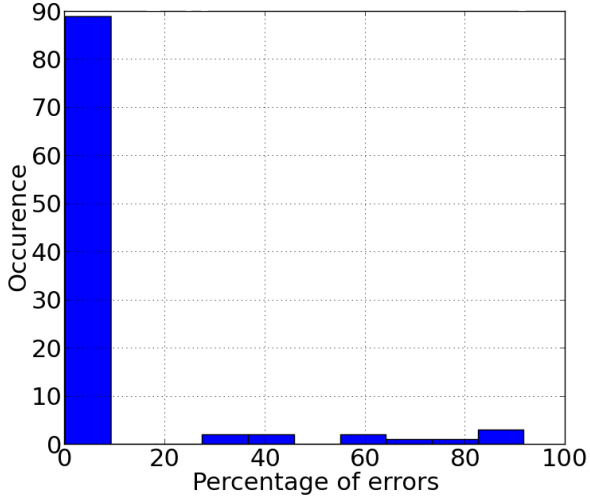
Robustness test

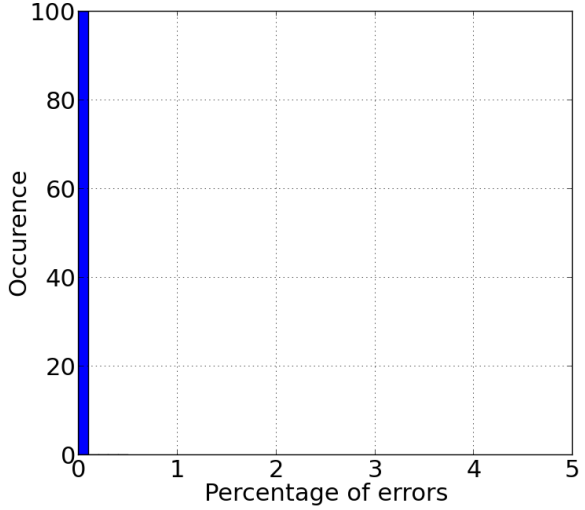
We compute the RORPO error rate on 100 random synthetic structure of each type.

$$\%error = \frac{nb_{error}}{nb_{pixels}} \times 100$$

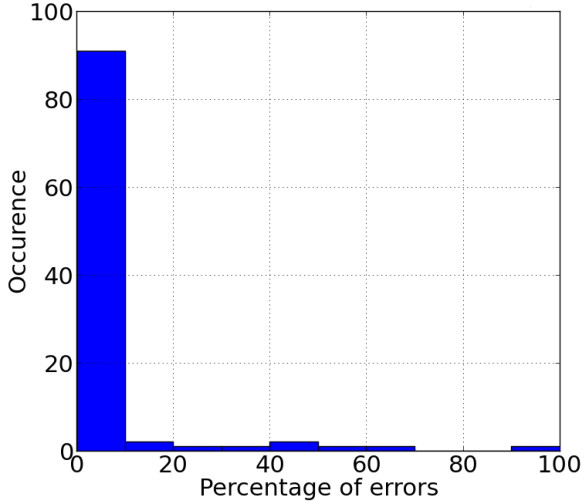
nb_{error}: number of false negative pixels for the tubes and of false positifs for the planes and half-ellipsoids.



Tubes ($m = 4\%$)



Planes ($m = 0\%$)



Half ellipsoids ($m = 4\%$)

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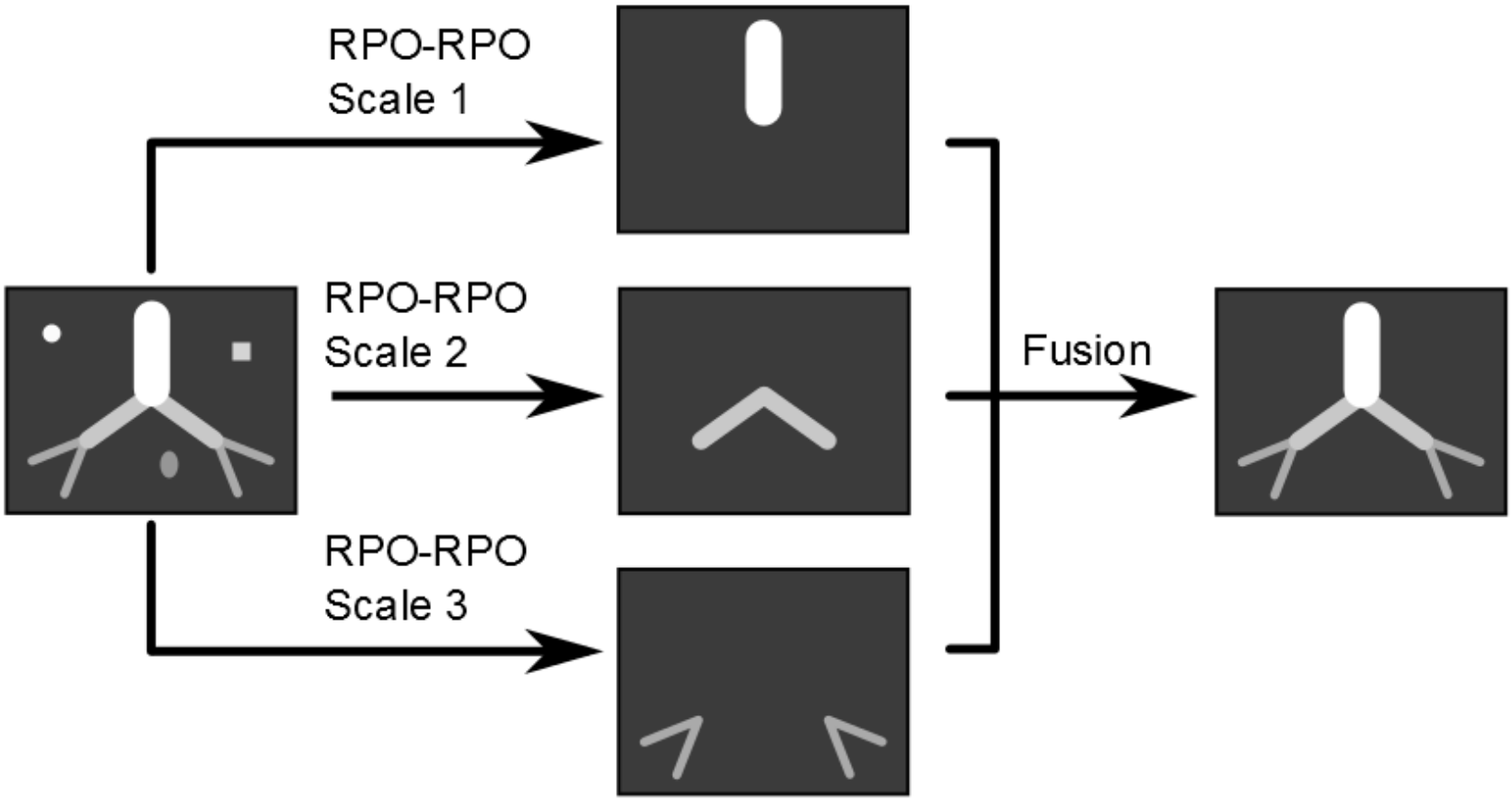
What is a multi-scale approach ?



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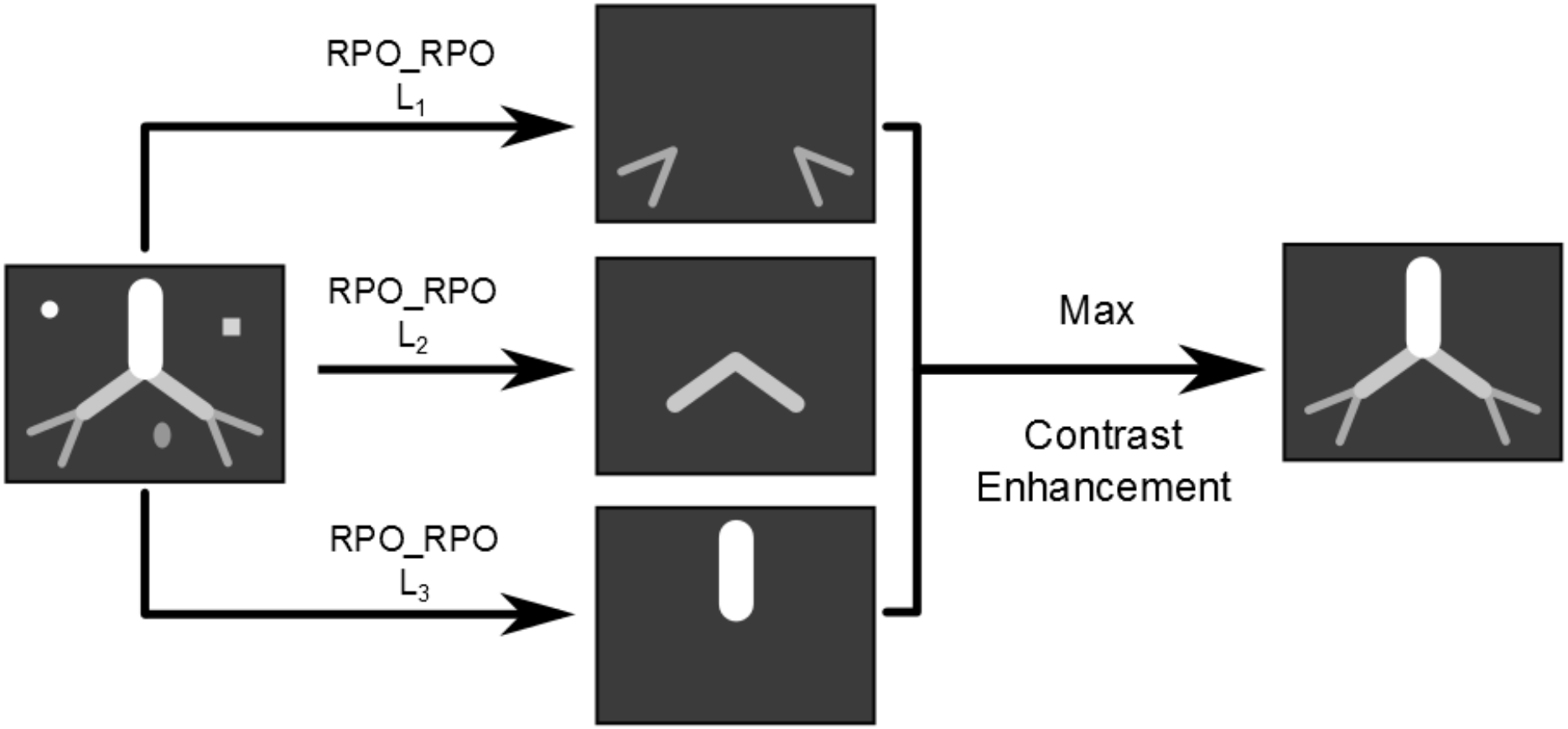
Multiscale Principle



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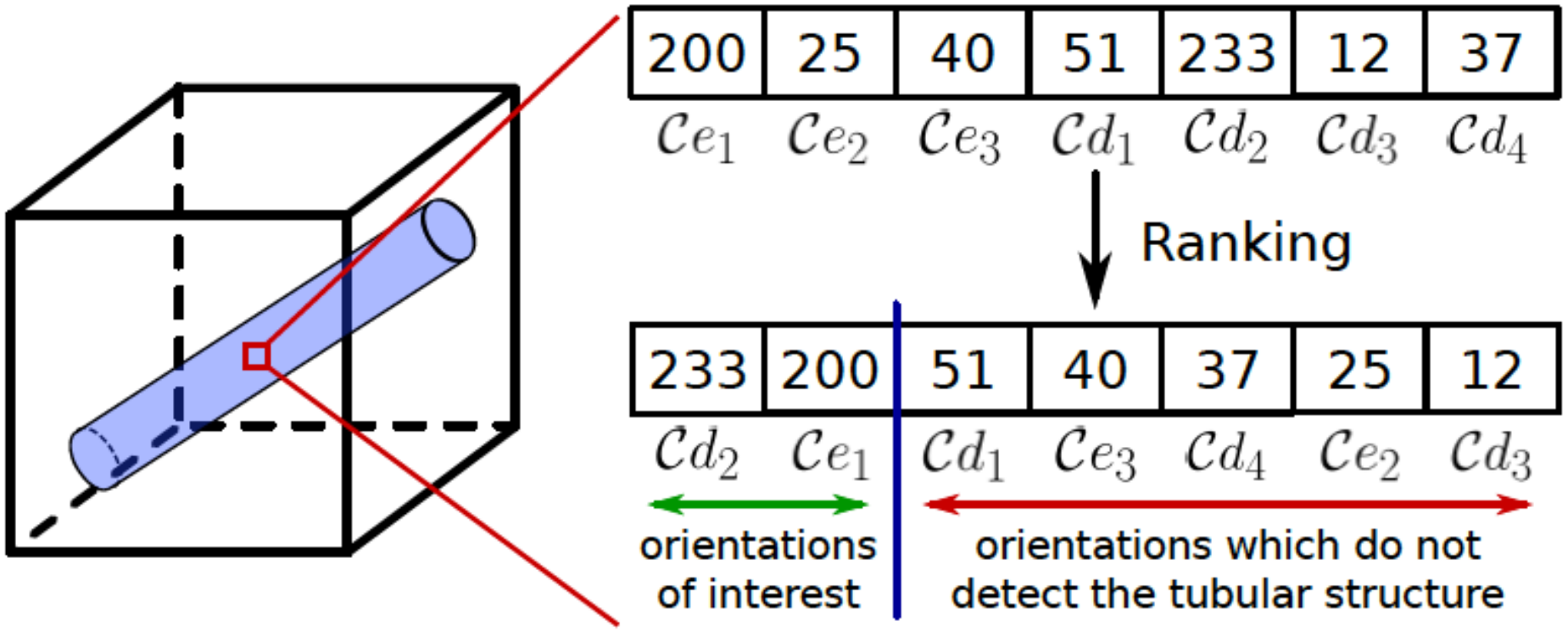
Comparisons

We performed qualitative comparisons of various methods according to four criteria on a full cerebral MRA

- Capacity to reduce background noise
- Capacity to detect large blood vessels
- Capacity to detect small blood vessels
- Presence of artifacts

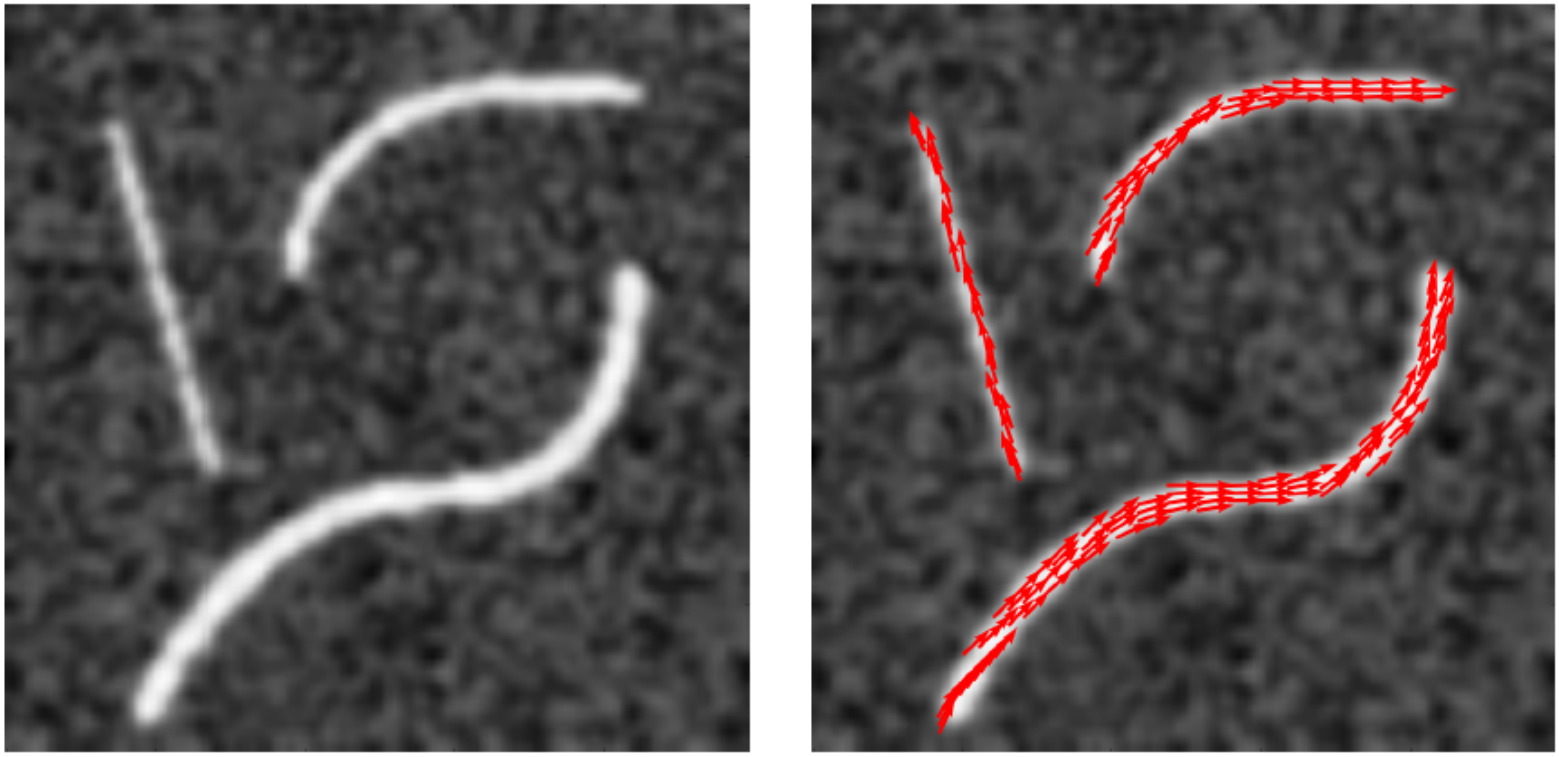
RORPO with classical adjacencies and a multiscale approach based on path lengths seems to provide the best compromise.

Computing directions from RORPO



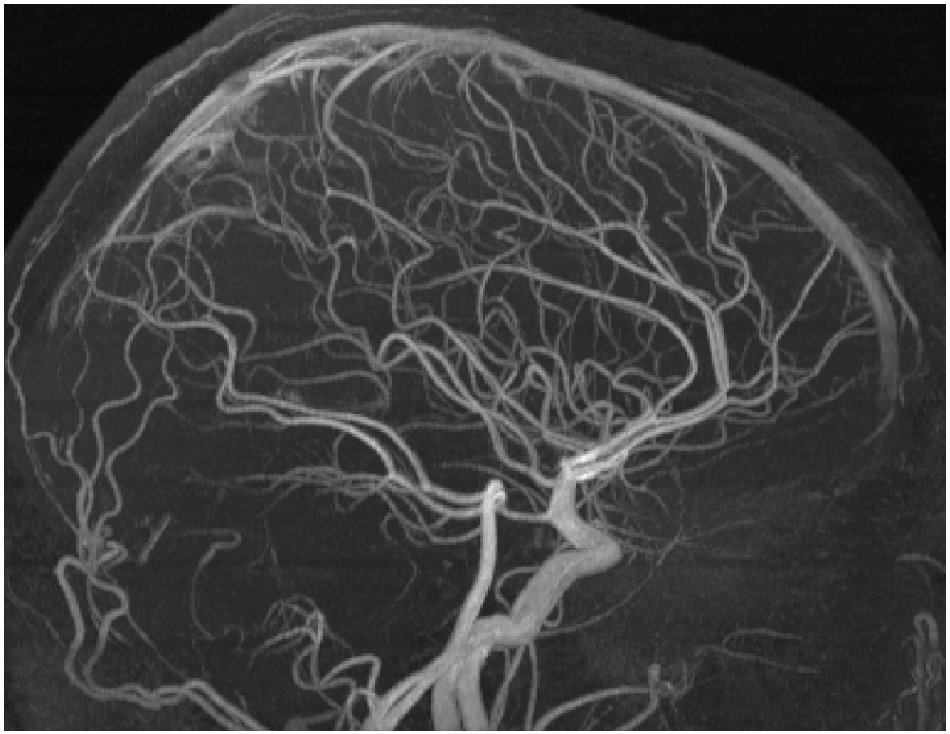
Computing directions from RORPO can be done by averaging the directions of high response.

Orientation results (in 2D)

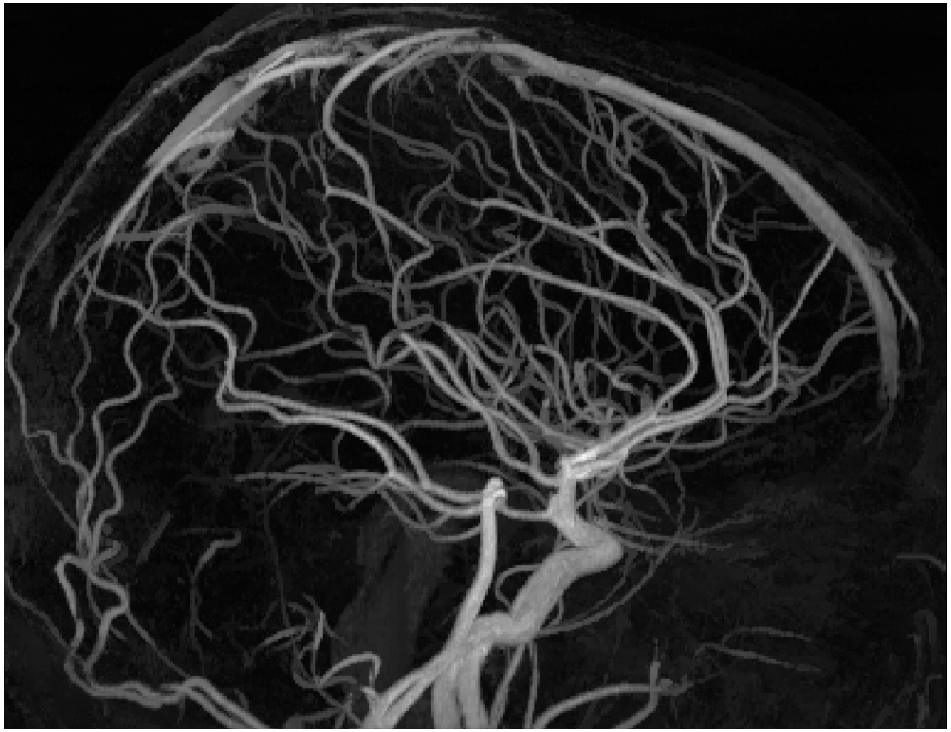


Orientation feature in 2D

Brain MRA result



Initial image MIP



Length-based multiscale RORPO

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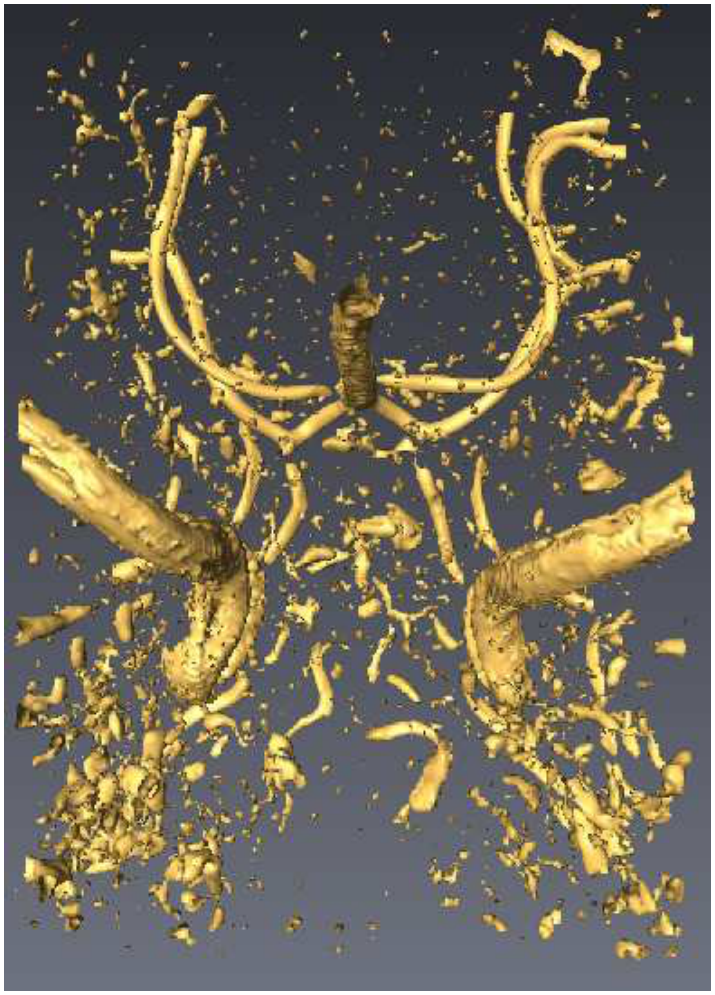
Comparison with Frangi vesselness

Proposed method



Optimized Frangi vesselness

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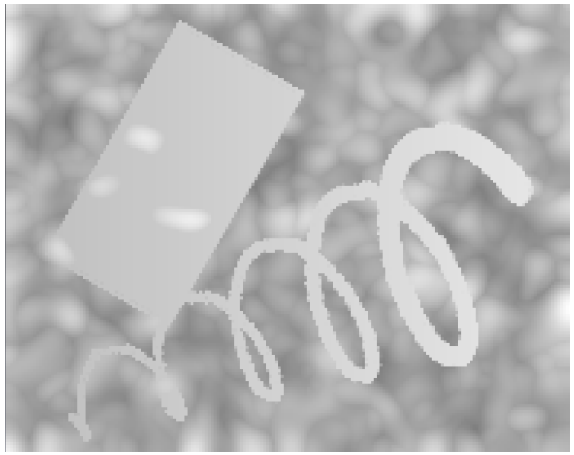
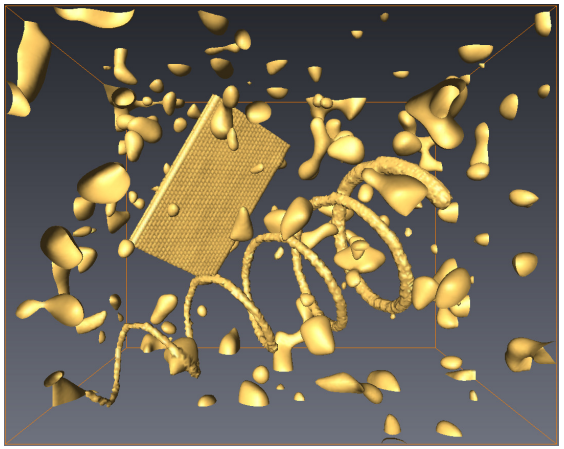
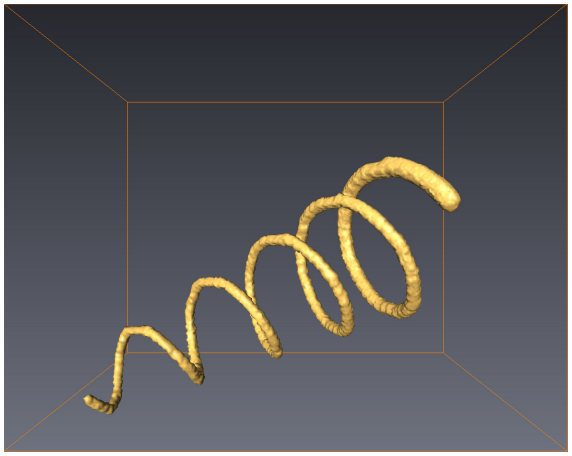
Quantitative comparison



(a) CCM=0.605, Dice=0.634



(b)

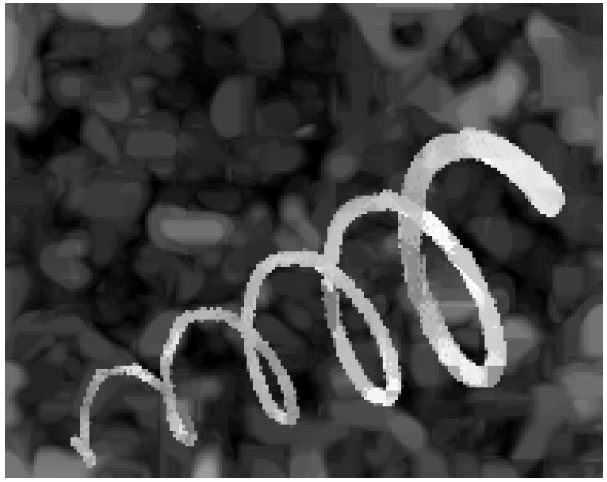


(c)

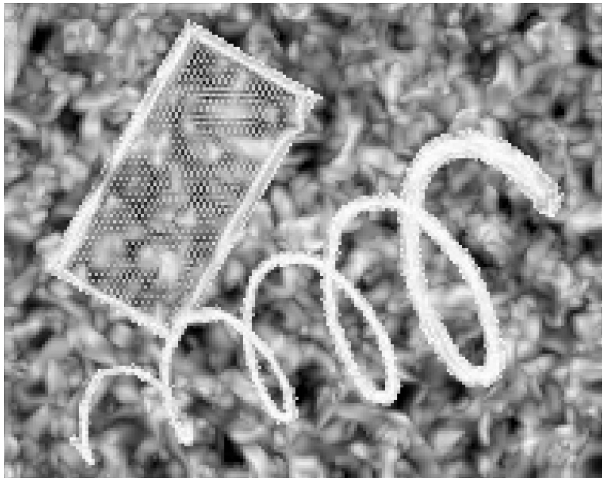
Synthetic image: (a) maximum intensity projection and (b) isosurface. (c) Ground truth.

Quantitative comparison

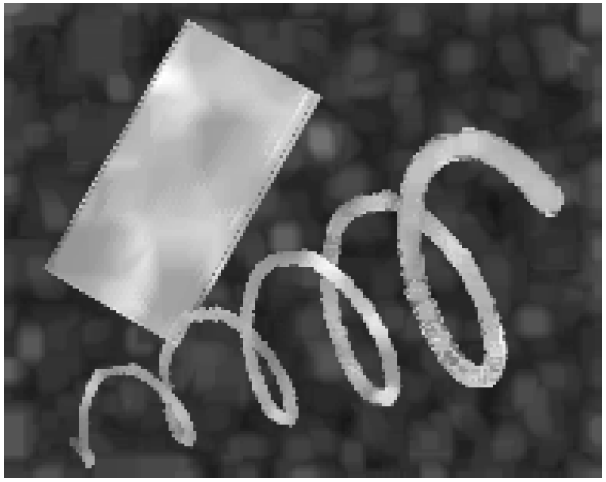
Filtering response



(a) CCM=0.884, Dice=0.893



(b) CCM=0.706, Dice=0.730



(c) CCM=0.655, Dice=0.654

Filtered synthetic image: maximum intensity projection. (a) RORPO. *(b) Frangi's vesselness. (c) and RPO-top-hat.*

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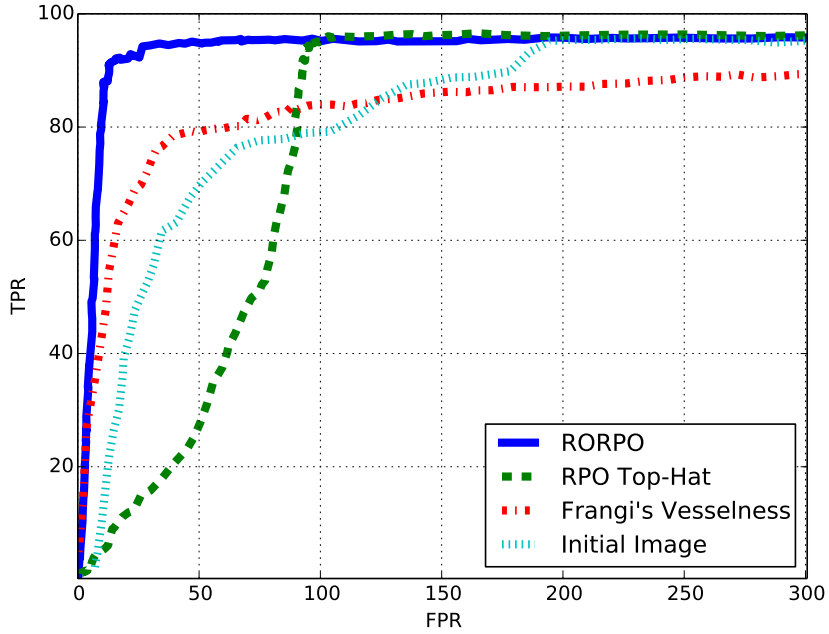
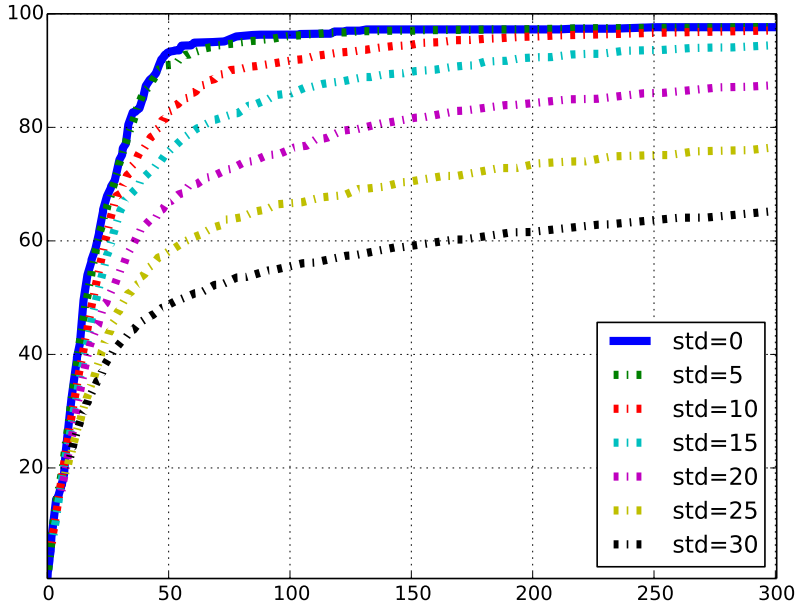
Quantitative comparison - ROC analysis



(d)

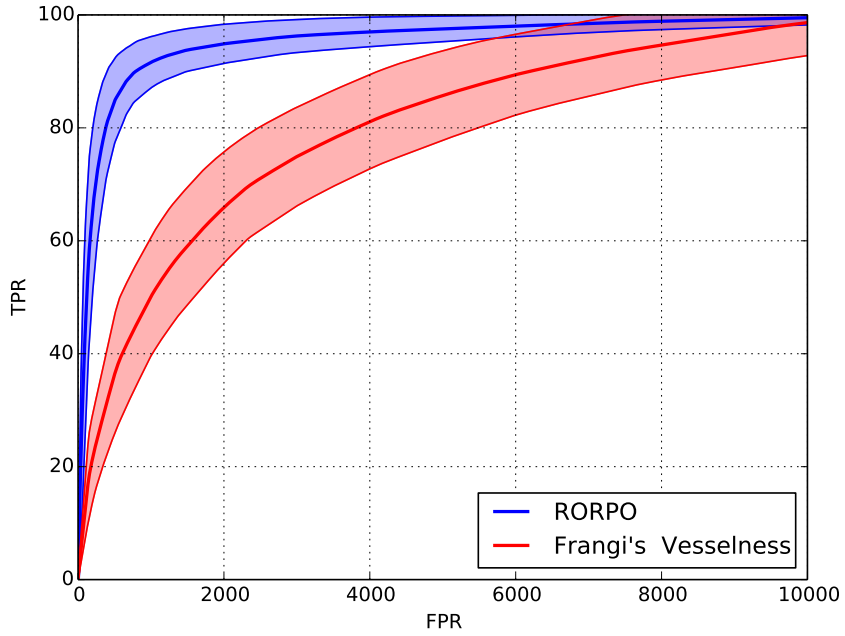


(e)

ROC curves on synthetic data. (a) Comparison of the three filters, plus the native image. (b) Noise robustness of the RORPO *filter.*

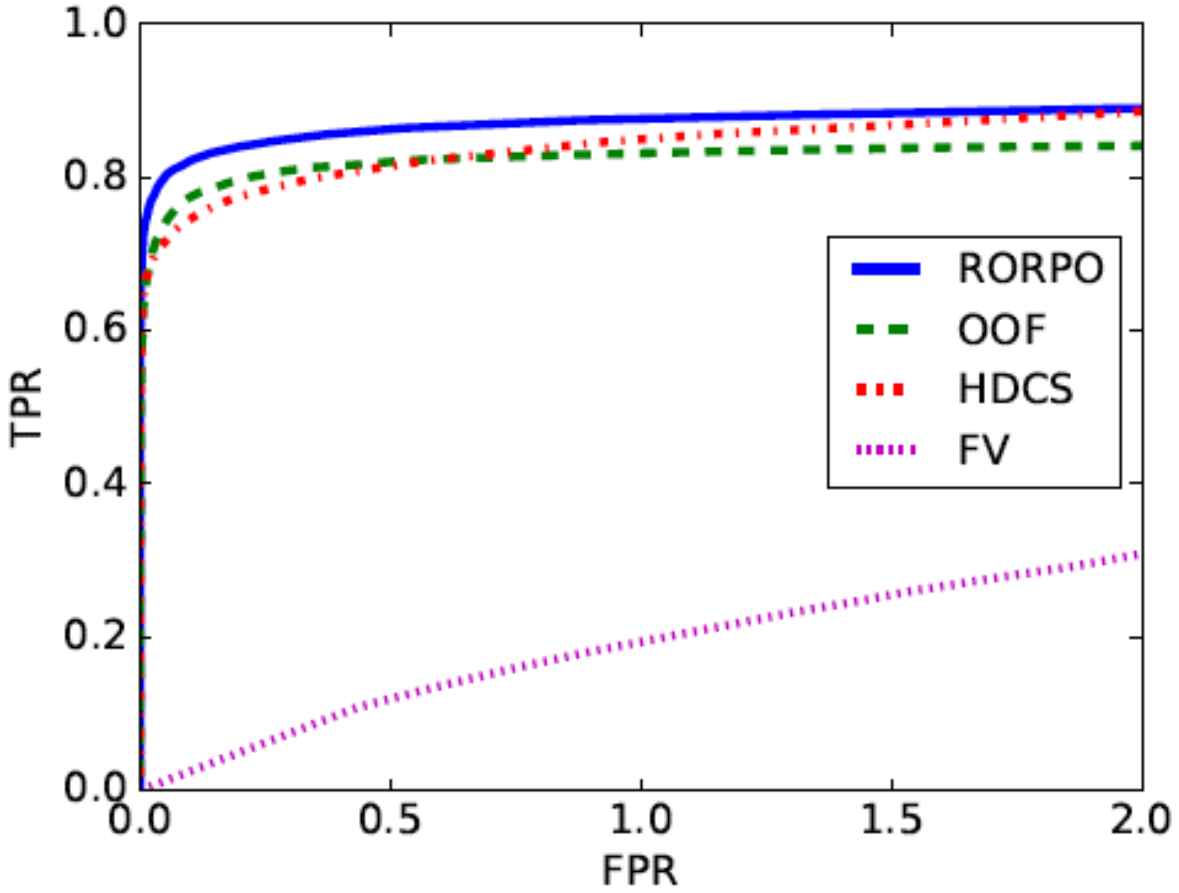
Quantitative Comparison

MICCAI Rotterdam Coronaries Database



ROC curves of RORPO and Frangi's Vesselness on the Rotterdam repository. For both filtering the central curve is the mean ROC curve and the two others are the mean plus or minus one standard deviation ROC curve.

Quantitative comparison, synthetic data



Three-way ROC analysis RORPO vs. OOF [11], HDCS [13] and Frangi Vesselness (FV)

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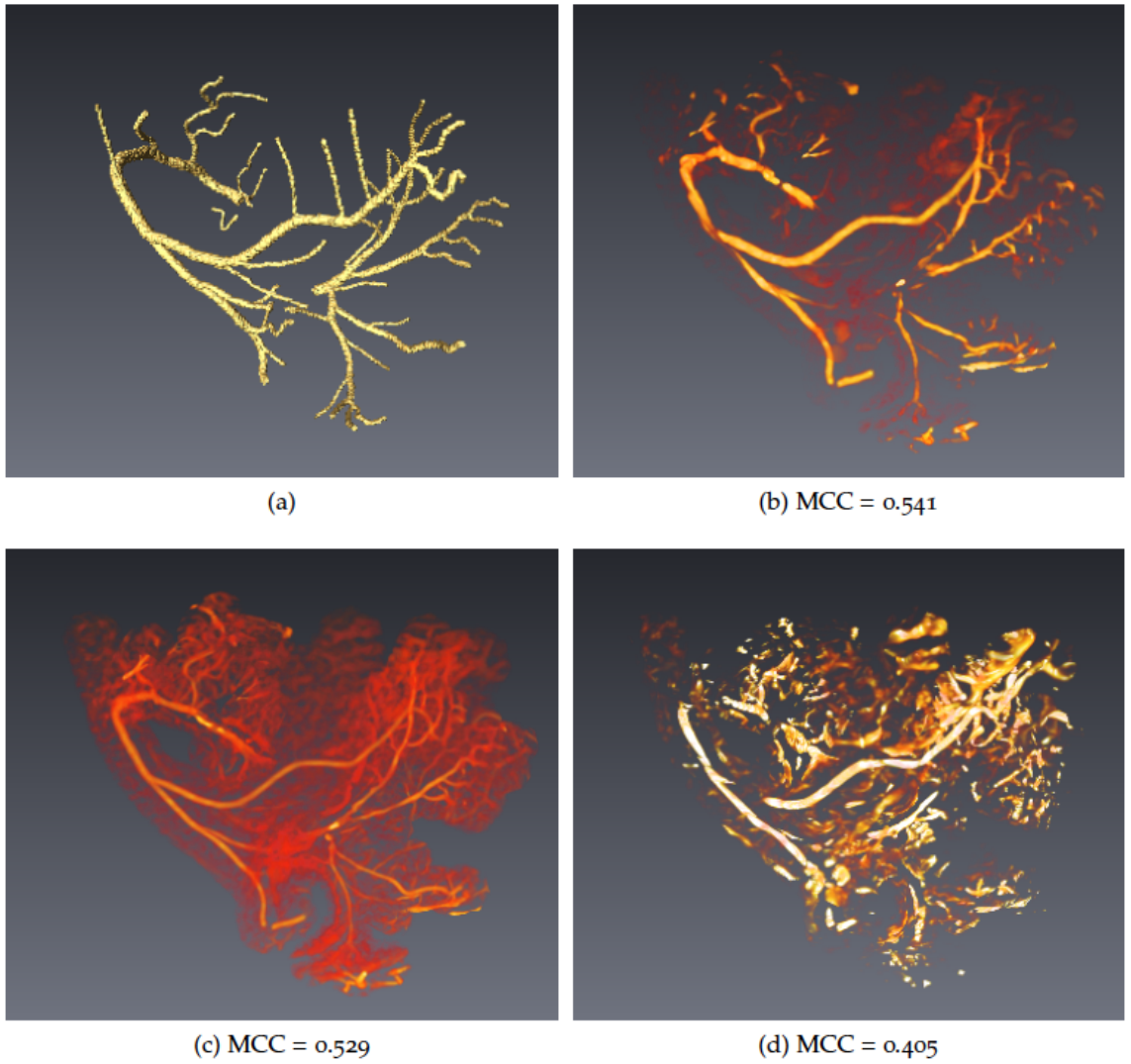
Quantitative comp., Heart Coronaries



Ground truth (a) : RORPO (b), OOF [11] (c), Frangi (d)

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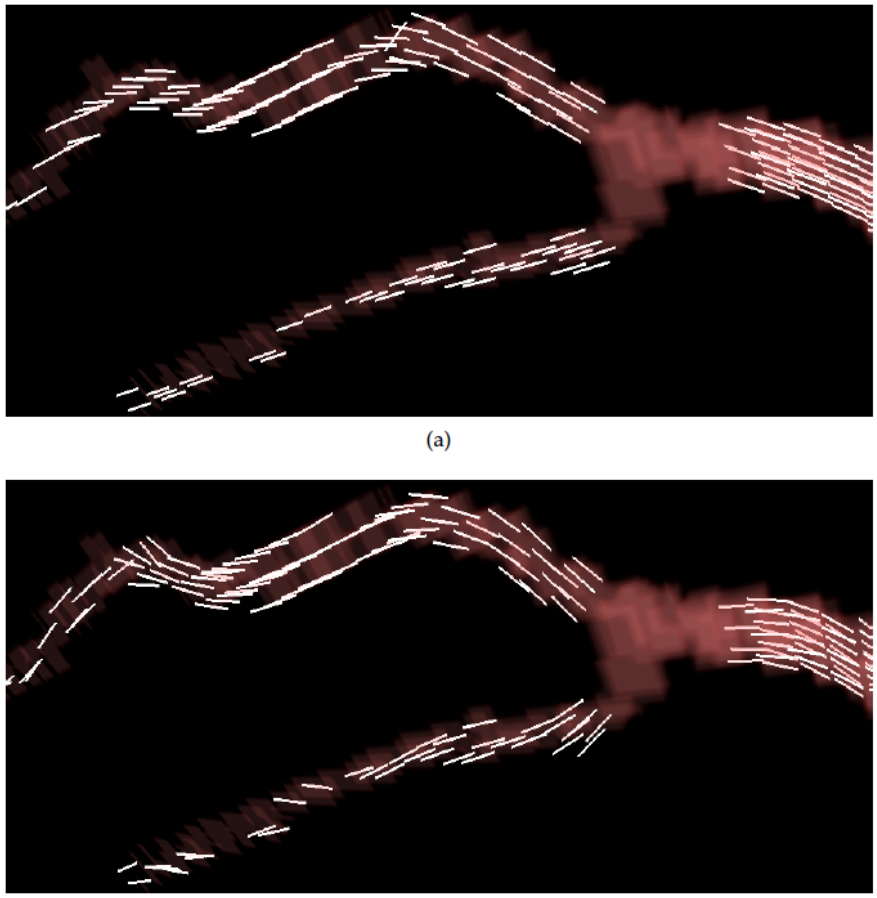
MRA Result

Initial image

Multiscale RORPO

Orientation feature 3D



Orientation feature in 3D, Heart data: RORPO (a) vs Frangi Vesselness (b)

Tubular structures segmentation

- So far we have proposed a solution for curvilinear structure filtering.
- Segmentation of more complex structures that include tubes/cylinders can be built from this.
- We propose to use a variational framework by improving Total Variation (TV) to include a directional component.

Variational framework

We consider a convex variational framework

$$\min_{u \in X} F(u, f) + \lambda G(u). \tag{6}$$

- Here F is a data fidelity term and G a regularization.
- f is the input data and u the desired result.
- Typically F is associated to a noise model and G to an image model.
- A common image model is the Total Variation (TV)

Standard TV

This is isotropic standard TV regularization term (in 2D):

$$\mathrm{TV}(u) = \|\nabla u\|_{2,1} = \sum_{0 \leq i,j < N} \sqrt{((\nabla u)^x_{i,j})^2 + ((\nabla u)^y_{i,j})^2} \tag{7}$$

where $\nabla u = \left((\nabla u)^x, (\nabla u)^y\right)$ is the 2D gradient.

It is classical in mathematics, and was proposed for image regularization in [18] (ROF model).

Directional TV

We define a directional gradient, $\nabla_D \in X^p$:

- We first define a *span* $(\mathsf{v}_1, \ldots, \mathsf{v}_p)$ of p unitary vectors.
- This span contains all the discrete undirected orientations in a $k \times k$ neighborhood
- then:

$$\nabla_D u = \left(D^1 \circ (\nabla_d u)^1, \cdots, D^p \circ (\nabla_d u)^1 \right) \tag{8}$$

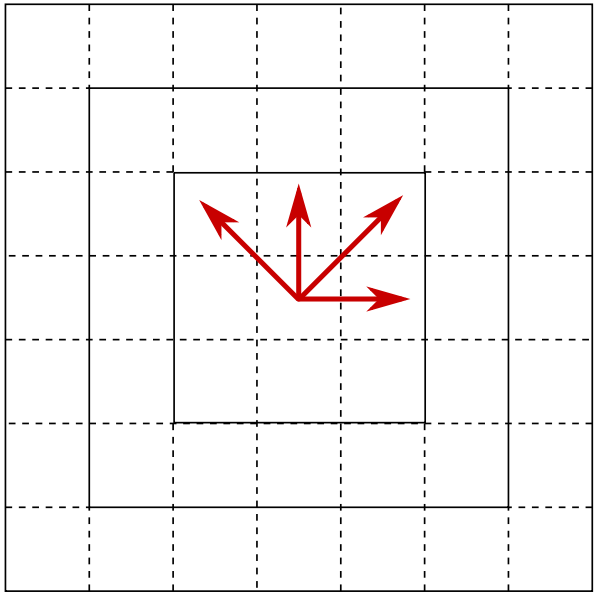
$$(\nabla_D u)_{i,j} = D^1_{i,j} (\nabla_d u)^1_{i,j} \mathsf{v}_1 + \cdots + D^p_{i,j} (\nabla_d u)^p_{i,j} \mathsf{v}_p \tag{9}$$

- with $D^q \in X,\ 1 \leq q \leq p$ a weight image such that:

$$D^q_{i,j} = d^q_{i,j} \Phi_{i,j} + (1 - \Phi_{i,j}) \tag{10}$$

Link with RORPO

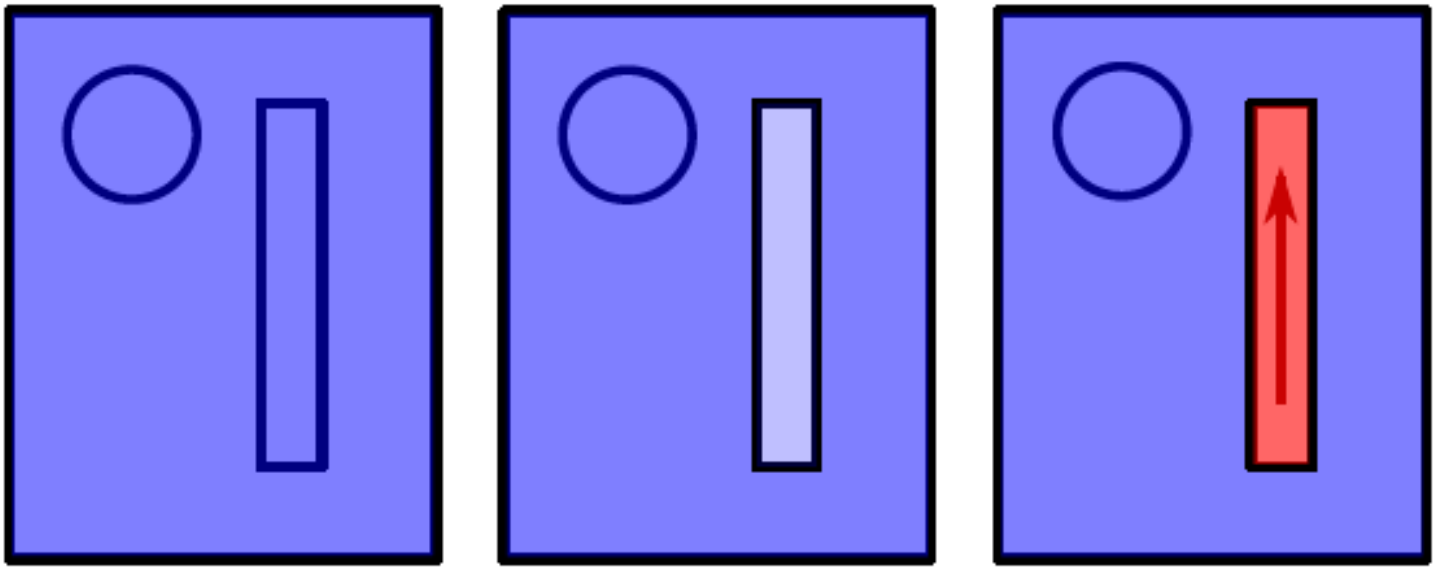
- $\Phi \in X$ is a vesselness-like intensity feature normalized to the interval $[0, 1]$
- $(d^i)_{i \in [\![1,p]\!]}$, are computed from an orientation field



Span of vectors in a 3×3 neighborhood.

We used the RORPO response as the vesselness feature and the orientation field computed from RORPO.

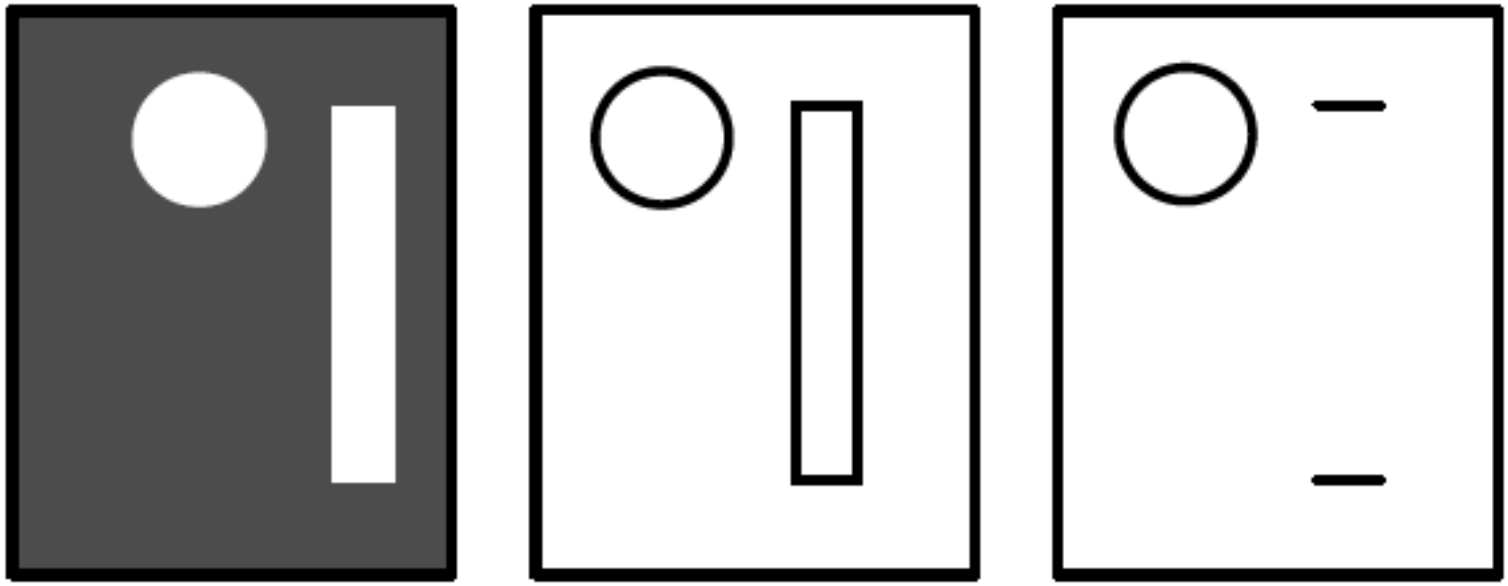
Directional TV idea



Directional TV idea

- Standard TV will penalize all edges identically; weighted TV may attempt to penalize edges less in a curvilinear object.
- A directional feature will not penalize edges inside a curvilinear object

Directional TV edges



Theoretical edge weights

- Thin, curvilinear object are all edges, and so are easily filtered out in standard/weighted TV.
- A directional TV will filter only along the direction of the curvilinear object, preserving it.

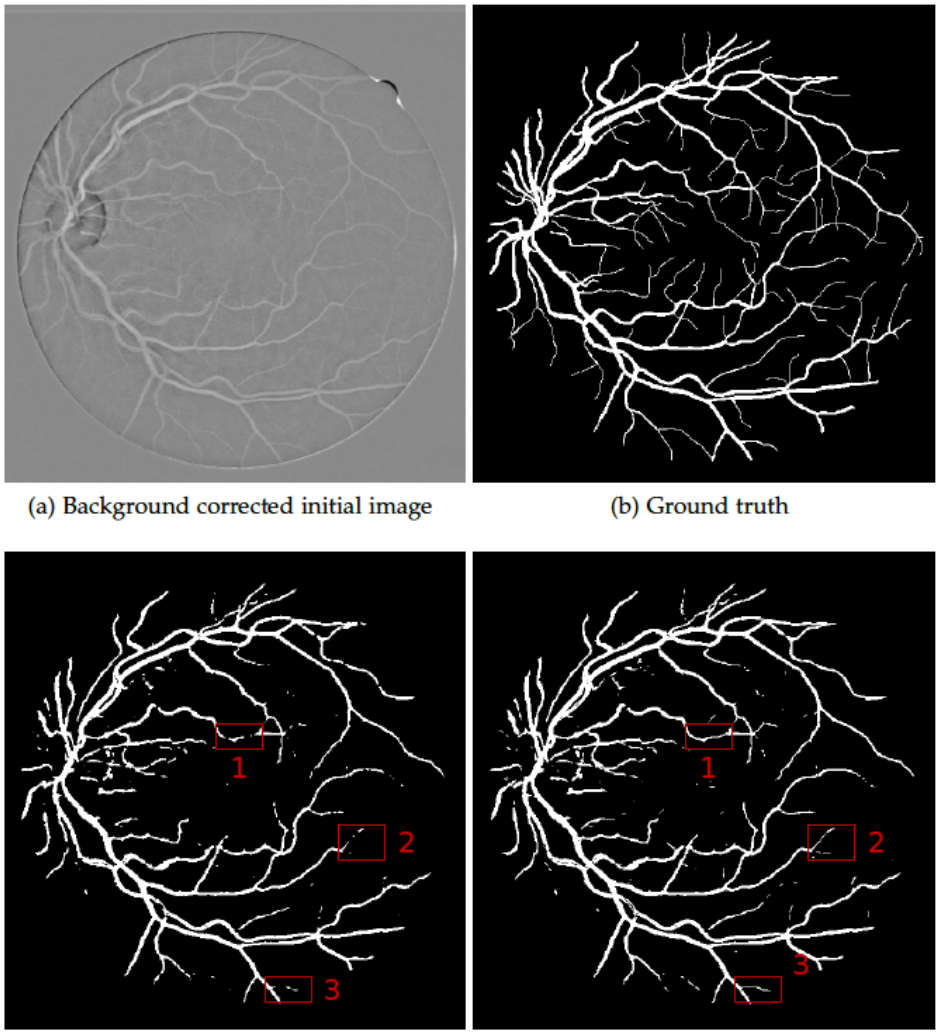
Segmentation model

Our model is base on TV_D, as follows:

$$\underset{u\in[0,1]^{N\times N}}{\text{minimize}} \quad \langle c_f, u\rangle_F + \lambda\|\nabla_D u\|_{2,1} \tag{11}$$

- $\|\nabla_D u\|_{2,1}$ is the directional Total Variation
- $\langle c_f, u\rangle_F$ is the Chan et al. data fidelity term [3] where $(c_f)_{i,j} = (c_1 - f_{i,j})^2 - (c_2 - f_{i,j})^2$ and $\langle u, v\rangle_F$ is the Frobenius product.
- The scalars c_1 and c_2 are respectively the foreground and background constant and f is the initial image.

DRIVE segmentation result

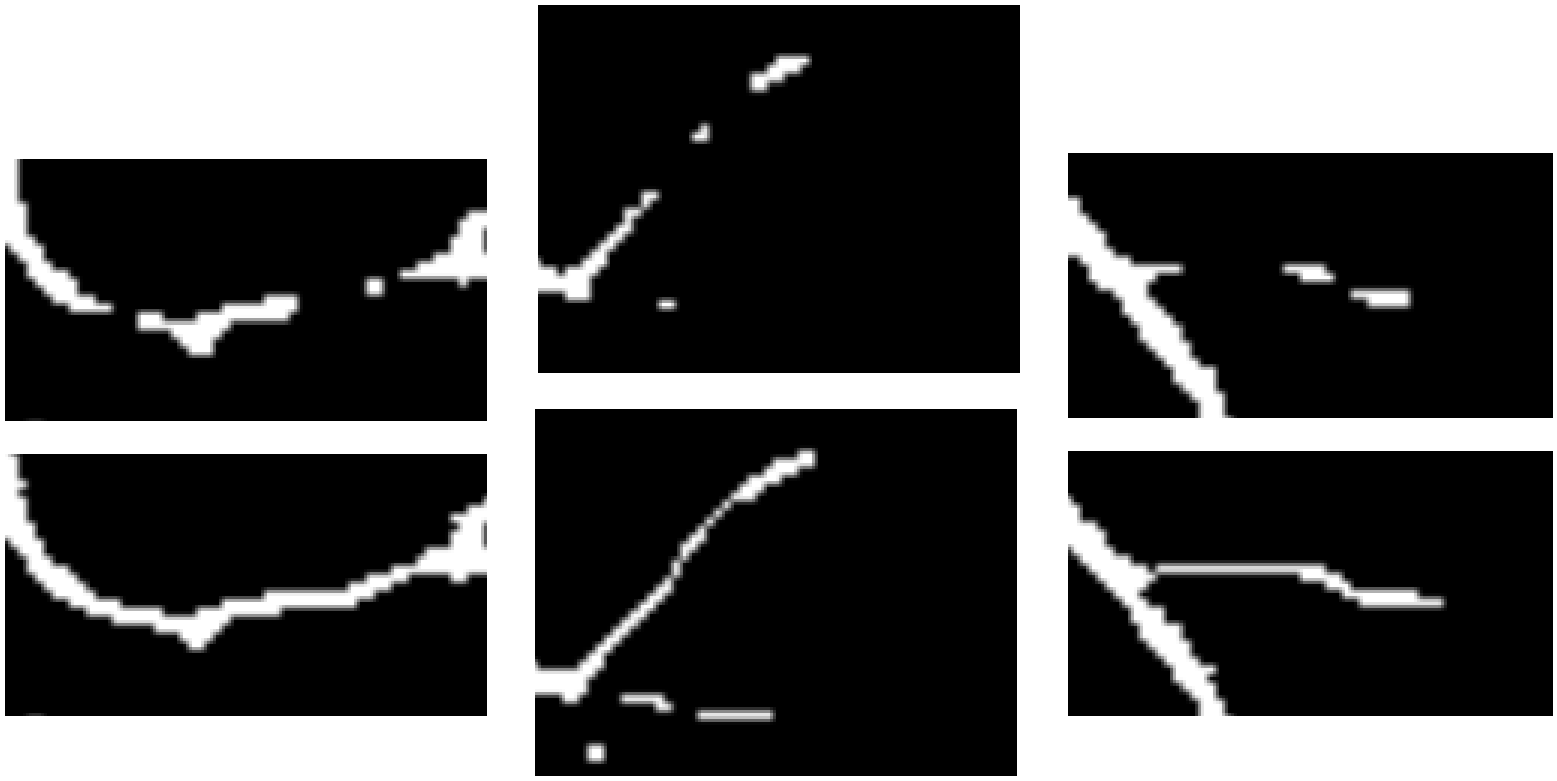


(a) Background corrected initial image (b) Ground truth

(c) Chan model (d) Proposed model

2D Results on DRIVE

DRIVE result details



(e) box 1 (f) box 2 (g) box 3

2D Result on DRIVE (details) top: standard TV ; bottom: directional TV

DRIVE numerical results

Our segmentation result compare favourably with the state of the art. Note that some learning-based approaches can still outperform these results.

	TP	TN	Acc
Standard TV	0.656	0.985	0.9421
Directional TV	0.690	0.981	0.9434
Staal [20]	-	-	0.9442
Human observer	-	-	0.9470

Quantitative segmentation results on the DRIVE database.

Conclusion

We have studied a thin object filtering methods called RORPO

Associated with a multiscale approaches based on path length

Our method is effective at significantly reducing background noise while simultaneously suppressing non-tubular structures.

Perspectives

Quantitative evaluation of our results :

- Use phantoms produced by VascuSynth
- Use ground truth from heart MRA data.

Perspectives

- Produce images of scales

- Adapt the path operator framework to the max-tree/min-tree framework
  - This would allow discriminating objects on more complex measures than mere length
  - Think about incorporating robustness to max-trees / min-trees

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Literature on path operators

- Definitions and early algorithms [2, 9, 10]
- Faster algorithms [1, 21]
- Extension to 3D and regularisation [12]
- RPO and 3D [5], [4]
- Applications [27, 28, 29, 19]
- RORPO [15, 16, 14]

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