Robust extraction of tumorous vascular networks in high resolution 3D images

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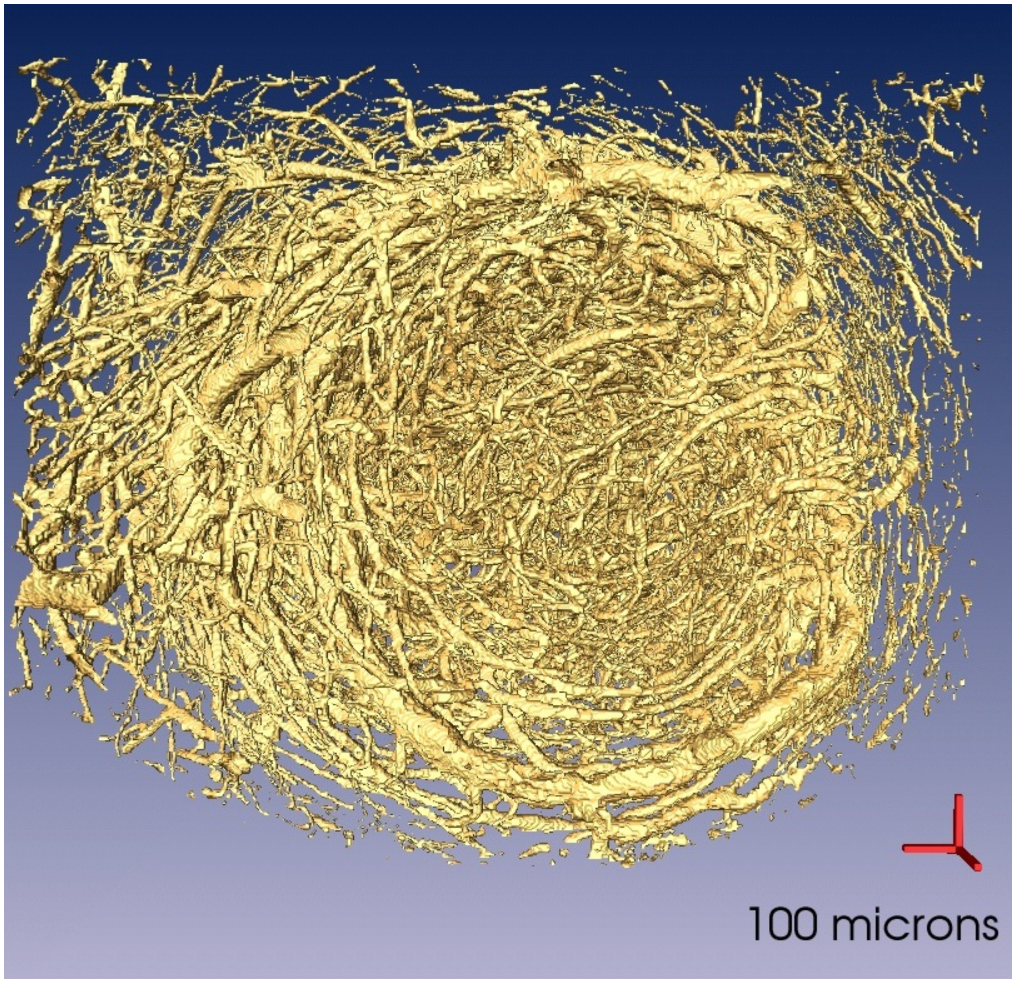
Joint work with:
- 2006 – 2008: F. Plouraboué (CNRS/IMFT), X. Descombes (INRIA Sophia Antipolis),
- 2015 - .: R. Bates (Univ. Oxford), J.A. Schnabel (Univ. Oxford / King's college London)

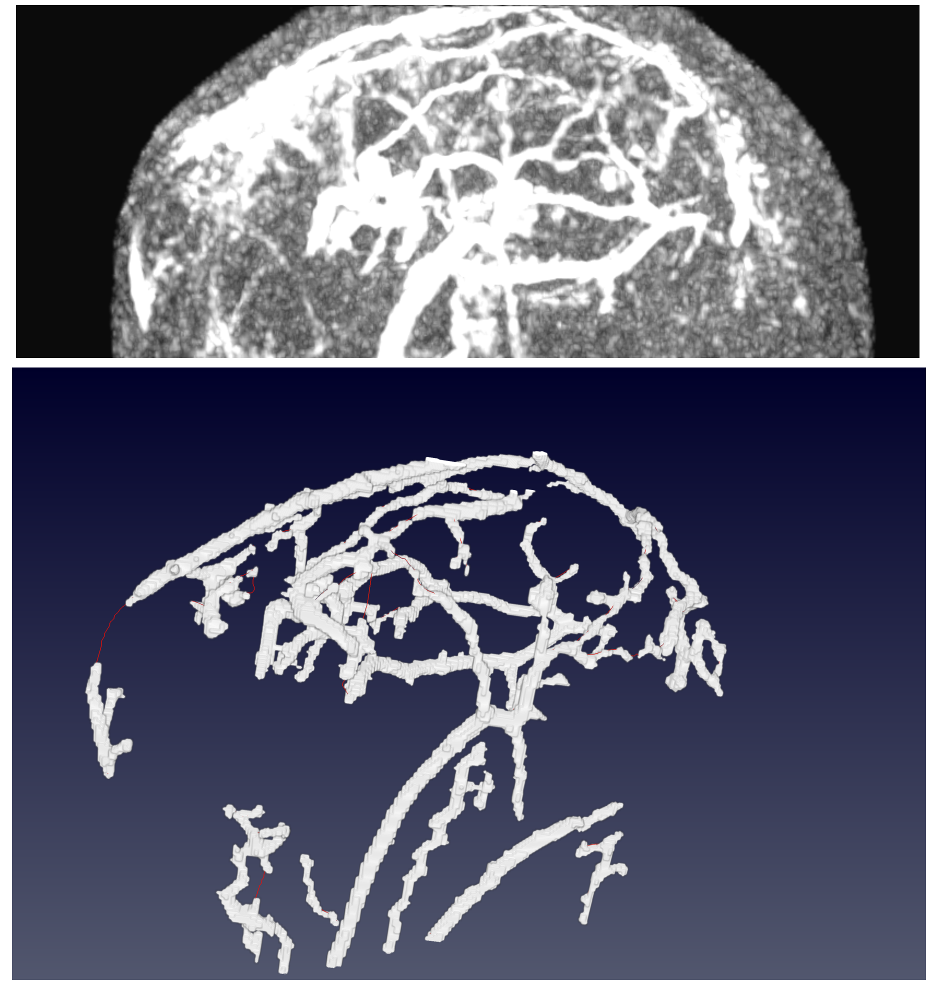
1: Context of this work

Driving motivations:

- Analysing the blood flow around tumours in pre-clinical models
- Extracting the vasculature topology around tumours out of high resolution 3D images



Synchrotron tomography images
ESRF Grenoble ➔ 8mm^3 / 1.4µm
[Risser et al., IEEE TMI 2007]

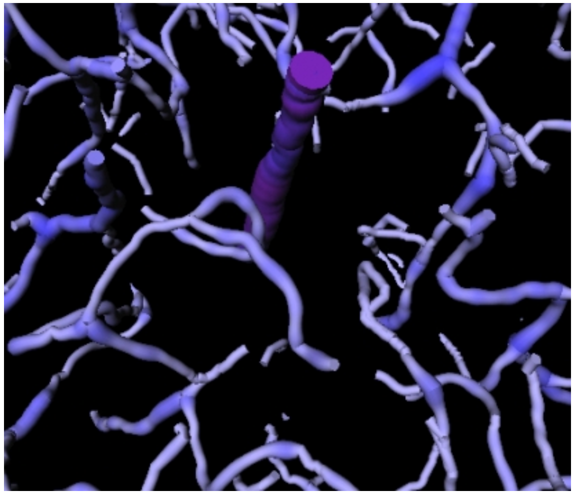


Contrast enhanced micro-CT
Siemens Inveon CT ➔ 250mm^3 / 32.7µm
[Bates et al., MICCAI 2015]

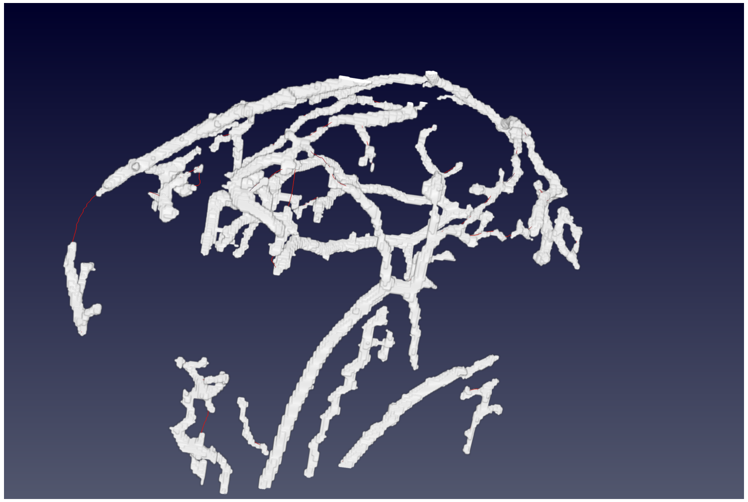
1: Context of this work

Standard pipeline:

1. Segmentation of the vessels enhanced by a contrast agent
2. Skeletonization of the extracted vessels
3. **If required: Gap filling**



Example of skeletonized network



Evidence for discontinuities (or gaps)

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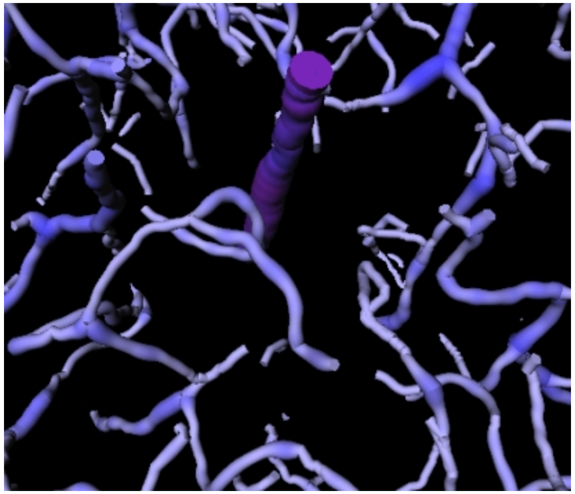

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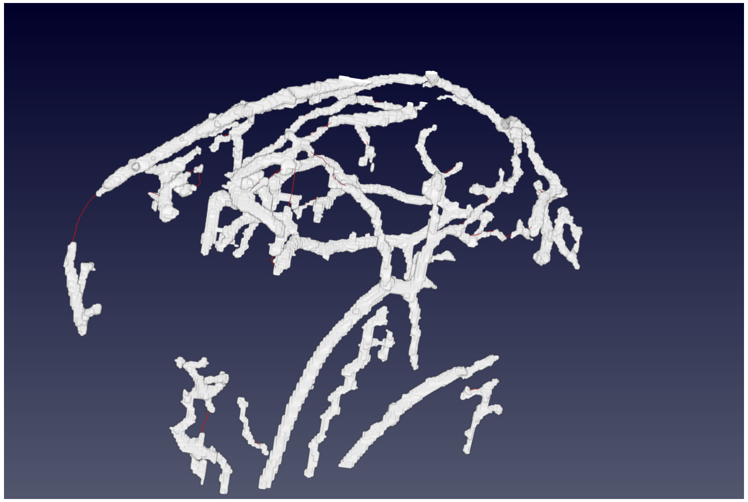


Evidence for discontinuities (or gaps)

Existing strategies to tackle the *gap issue* in vascular networks:
1. Improving the robustness of the segmentation [Quek et al., TMI 2001] [Szymczak et al., SPIE 2005] [Pock et al., CVW 2005]
2. Learning heuristics to guide manual interactions [Kaufhold et al., MedIA 2012]
3. Simulating angiogenesis [Schneider et al. MICCAI 2014]
4. Tensor models to fill small gaps due to the noise [Cetin et al., TMI 2013]

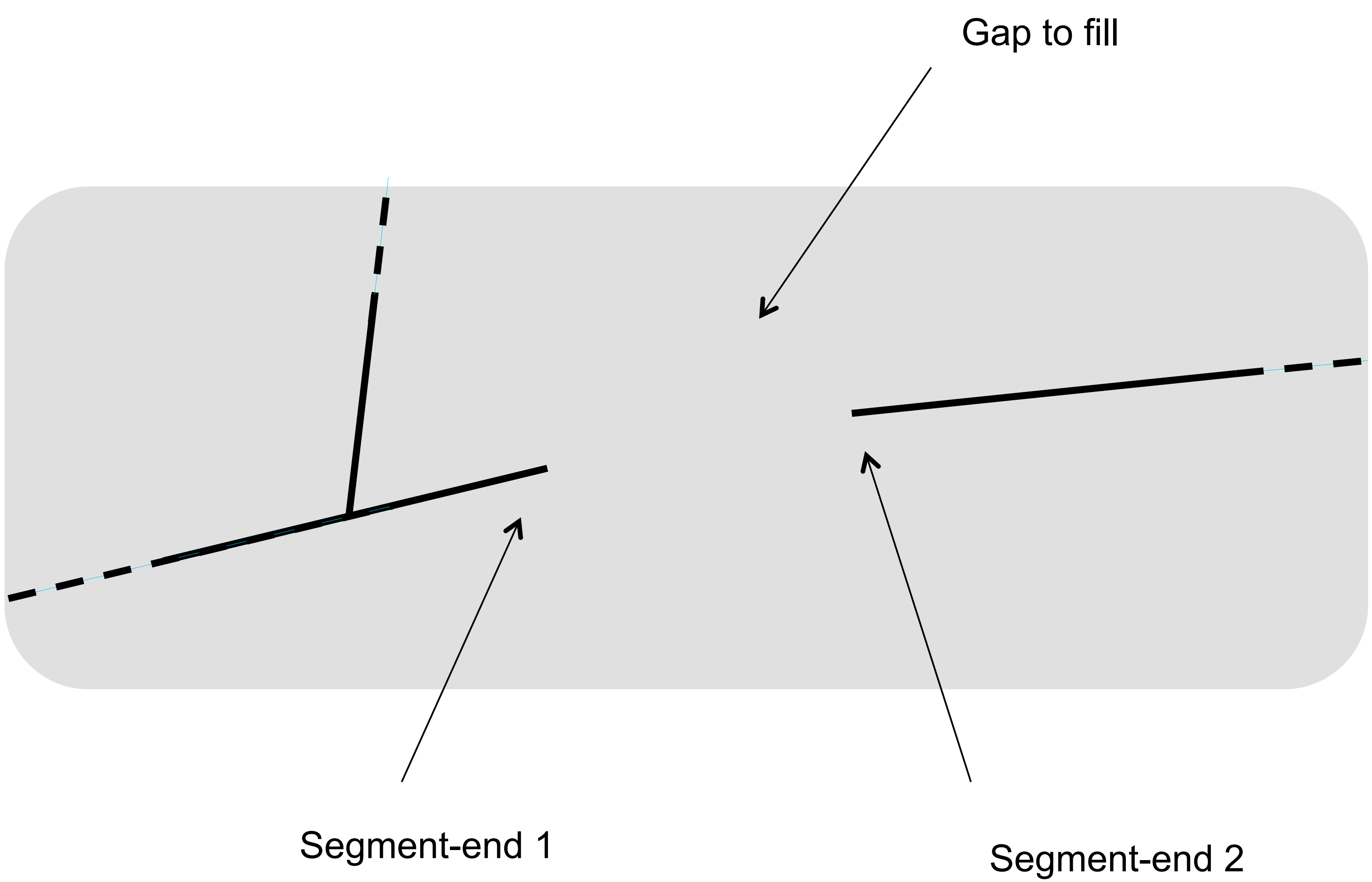
No method adapted to fill relatively large gaps with in irregular vascular networks

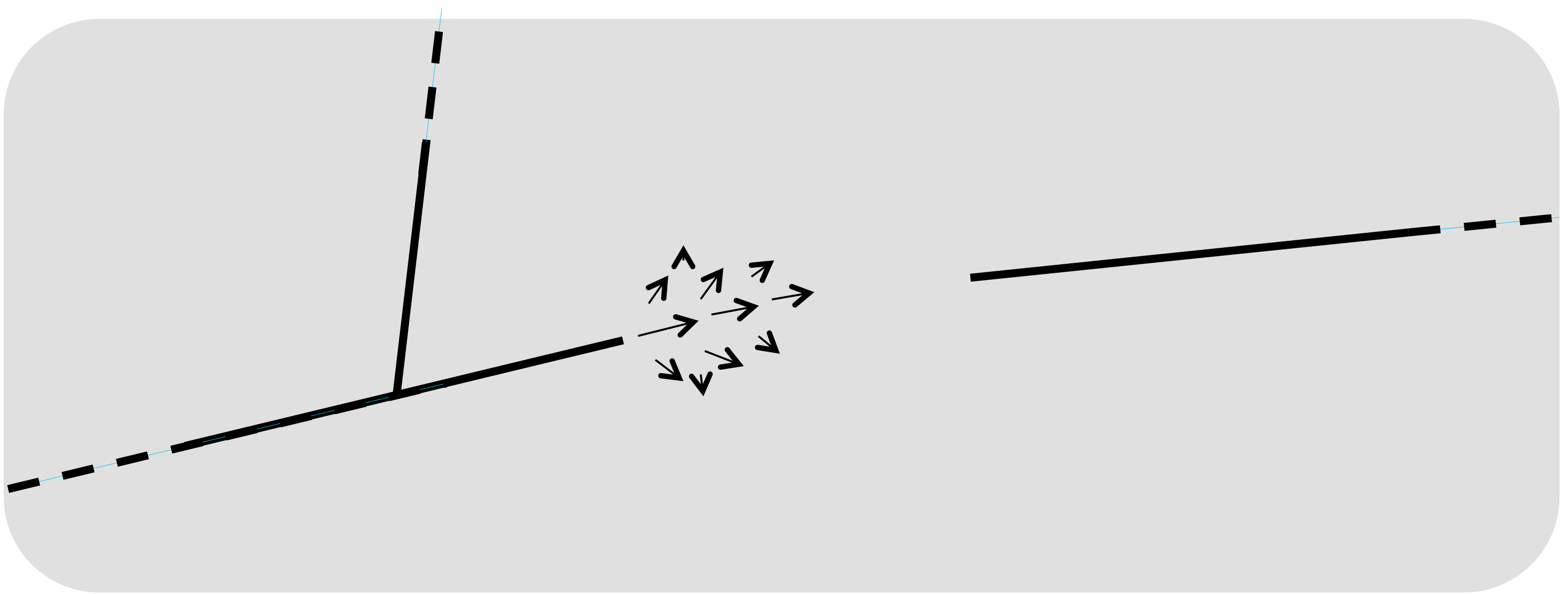
<u>Overview of this talk</u>:

- Using tensor fields to fill discontinuities
- Gap filling using skeleton-based information
- Gap filling using skeleton- and intensity-based information

2: Using tensor fields to fill discontinuities

Idea adapted from [Guy & Medioni, IEEE PAMI 1997] in [Risser et al., IEEE TMI 2007]



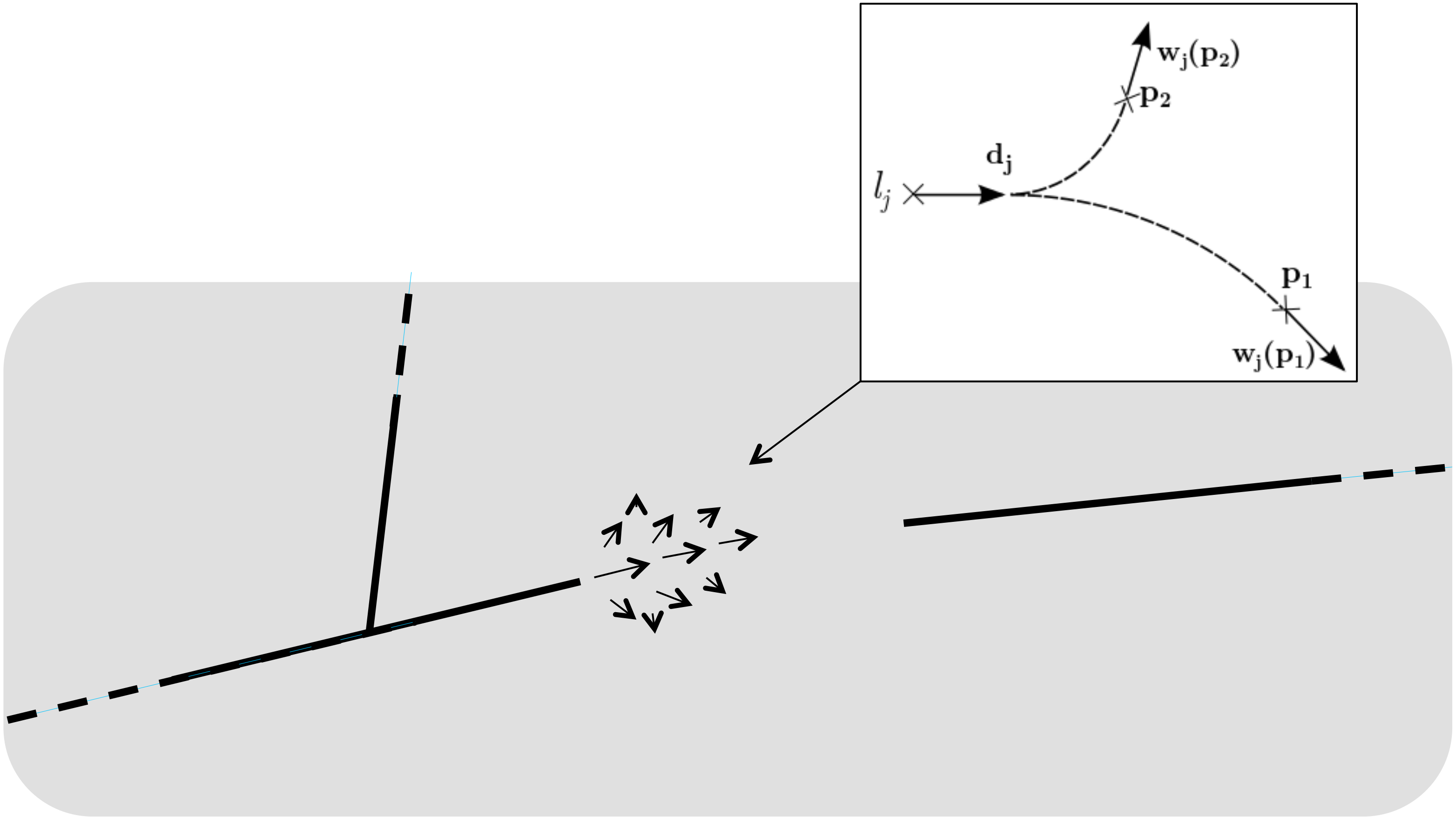


For segment-end 1: generate a vector field $\boldsymbol{P}_1$

➔ Represents how the vessel could be extended

➔ Here: $\boldsymbol{P}_1\,(i,j,k) = (x_1,y_1,z_1)$

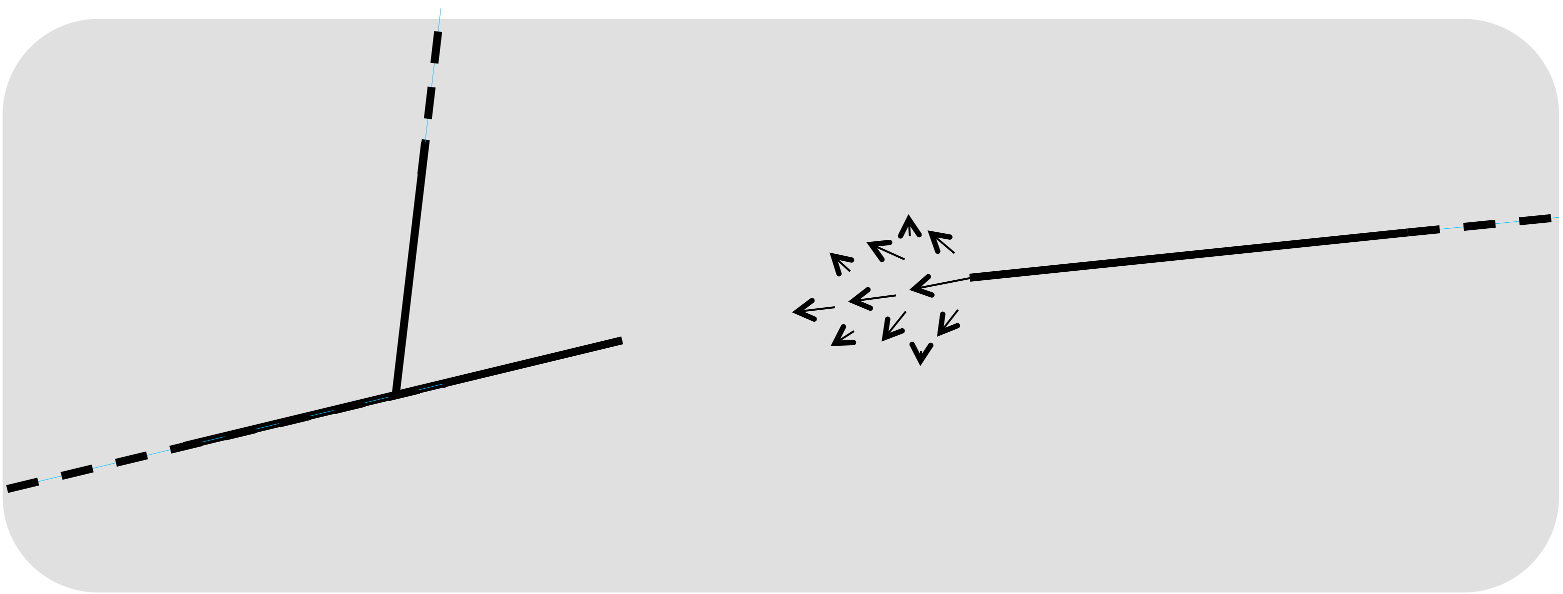
2: Using tensor fields to fill discontinuities



For segment-end 1: generate a <u>vector field</u> $\boldsymbol{P_1}$

- ➔ Represents how the vessel could be extended
- ➔ Here: $\boldsymbol{P_1}(i,j,k) = (x_1,y_1,z_1)$

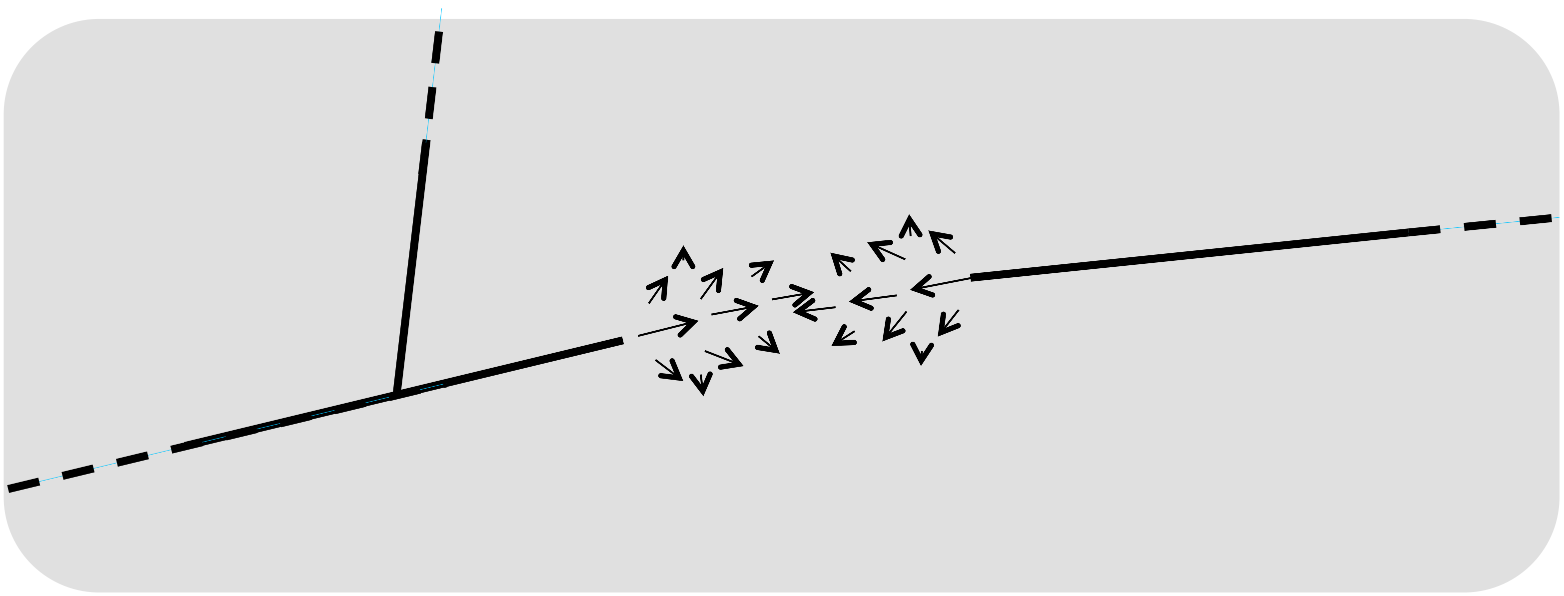
2: Using tensor fields to fill discontinuities



For segment-end 2: generate a <u>vector field</u> $\boldsymbol{P}_2$

➔ Represents how the vessel could be extended

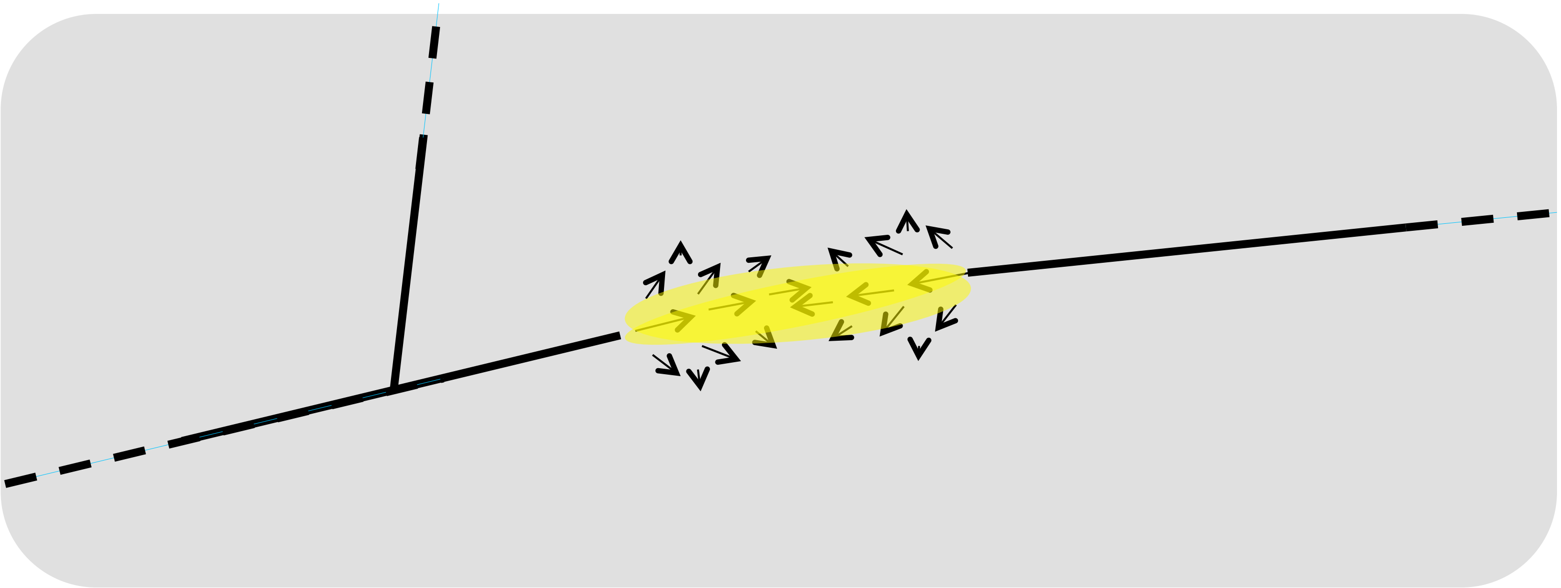
➔ Here: $\boldsymbol{P}_2\,(i,j,k) = (x_2,y_2,z_2)$



Communication at point (i,j,k) between segment-end 1 and segment-end 2 through a <u>tensor field:</u>

➔ $\boldsymbol{T}(i,j,k) = \boldsymbol{P}_1(i,j,k) \otimes \boldsymbol{P}_1(i,j,k) + \boldsymbol{P}_2(i,j,k) \otimes \boldsymbol{P}_2(i,j,k)$

2: Using tensor fields to fill discontinuities



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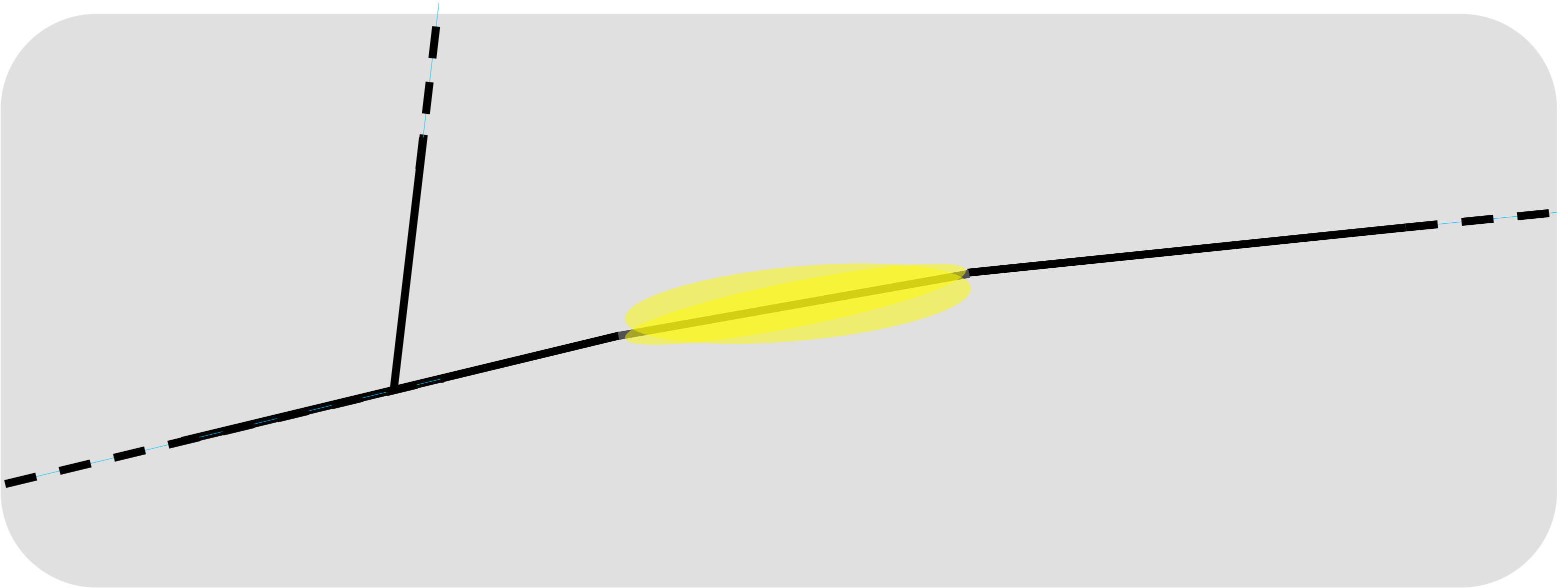
Saliency to a curve computed as the difference between the two first eigenvalues of $\boldsymbol{T}(i,j,k)$:

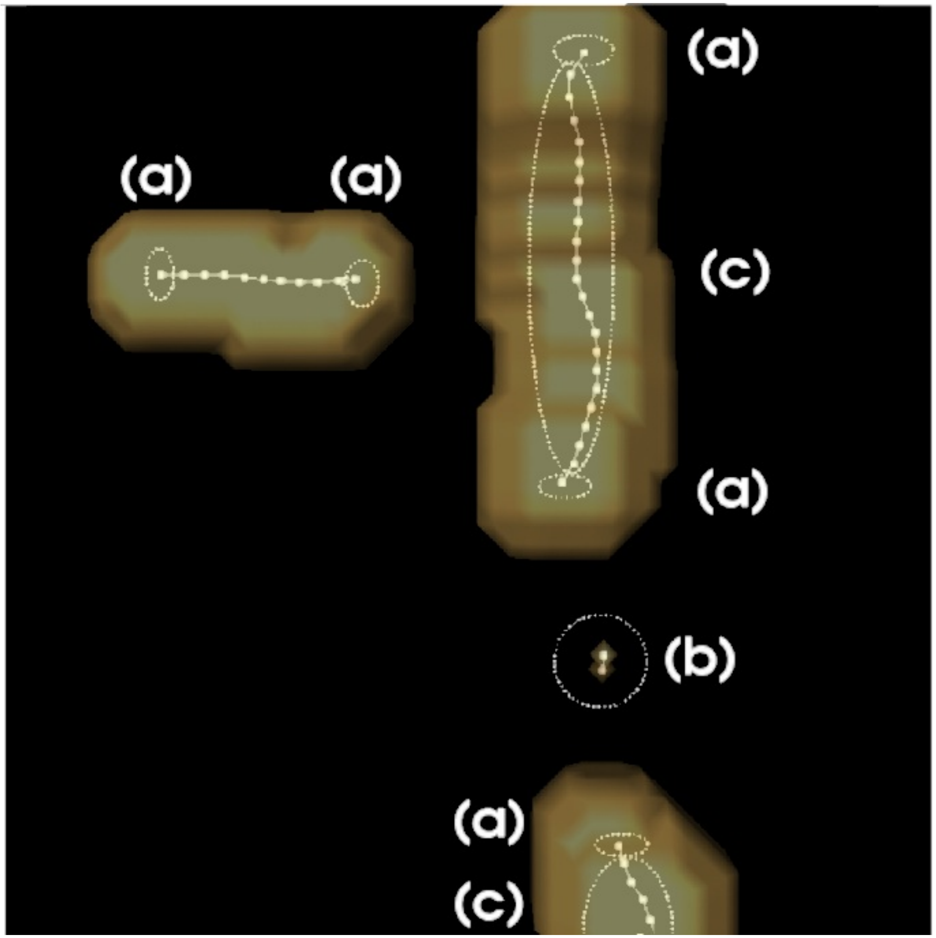
➔ $S(i,j,k) = \lambda_1(i,j,k) - \lambda_2(i,j,k)$



Path search:

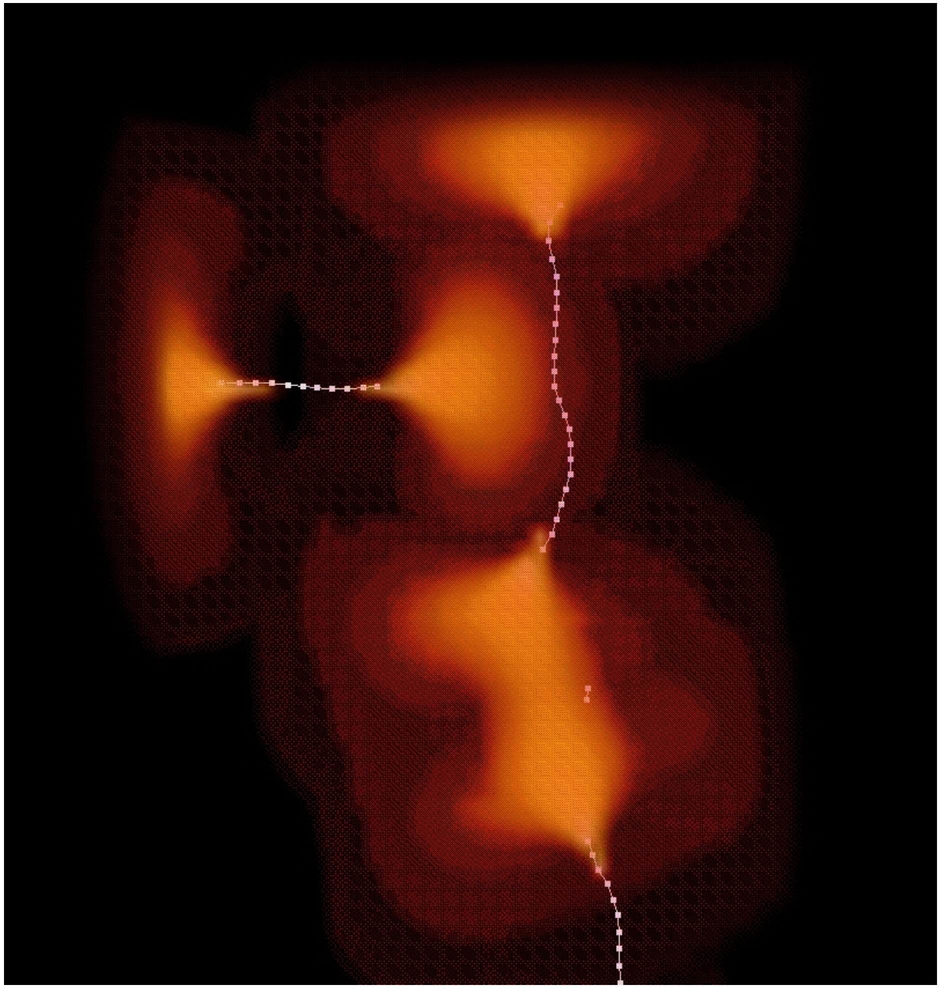
- Start from a segment end
- Follow the local maxima of the saliency to a curve

Three types of tokens
[Risser et al., IEEE TMI 2007]



- Segment-end tokens (a)
- Island tokens (b)
- Segment tokens (c)

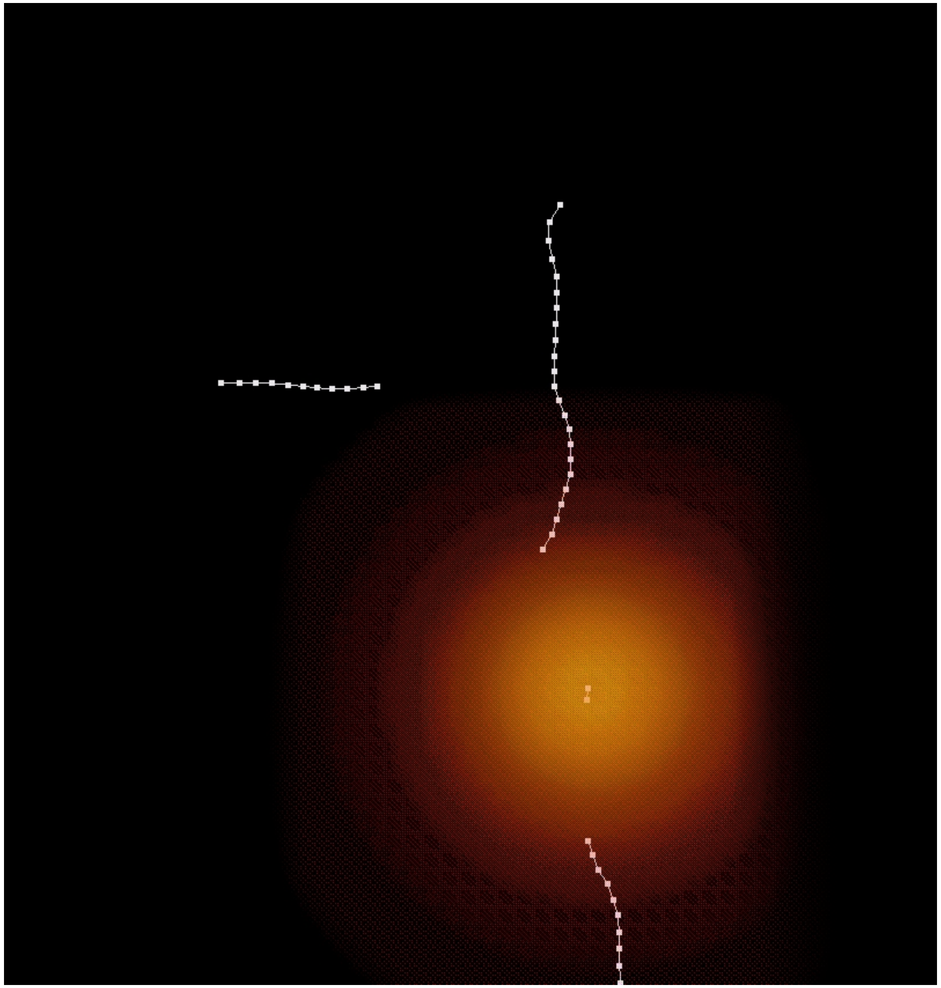
Communication



- Segment-end tokens
- Island tokens
- Segment tokens

$$\mathbf{T}(i,j,k) = \sum_{n=1}^{N} \mathbf{TE}_n(i,j,k) + \sum_{m=1}^{M} \mathbf{TI}_m(i,j,k) + \sum_{q=1}^{Q} \mathbf{TS}_q(i,j,k)$$

Communication



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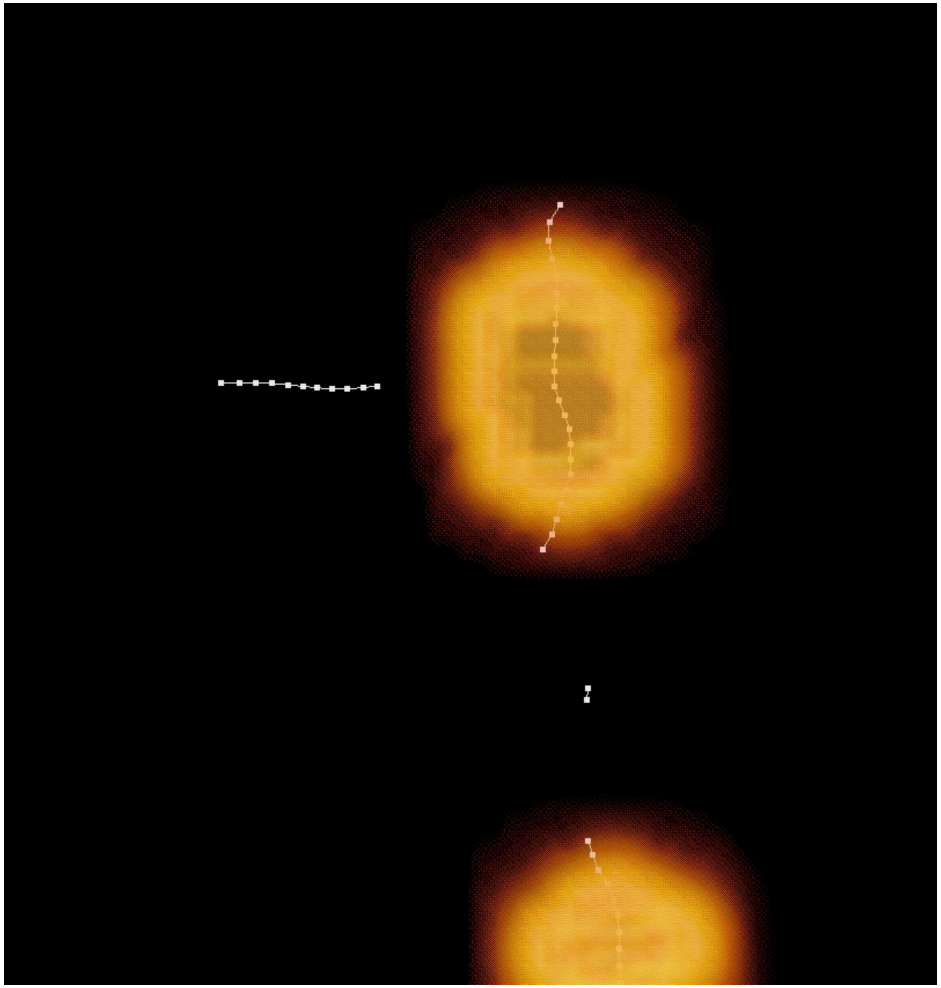

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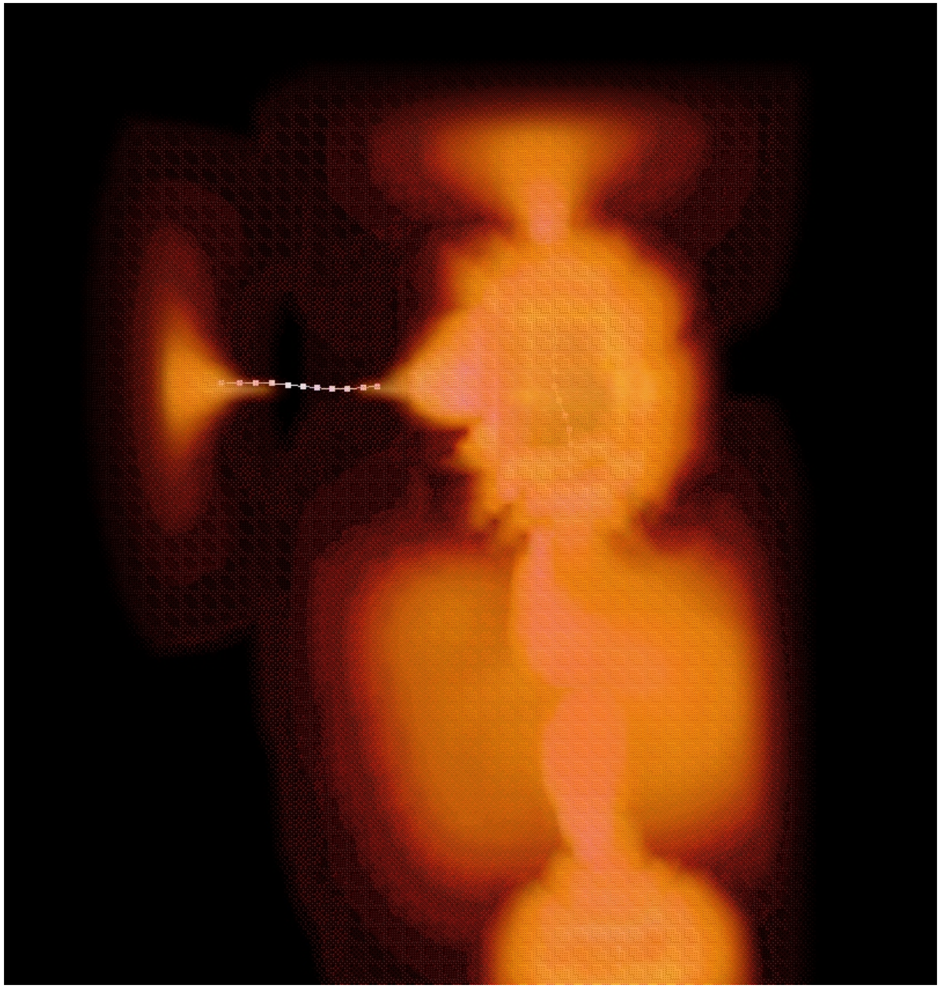

- Segment-end tokens
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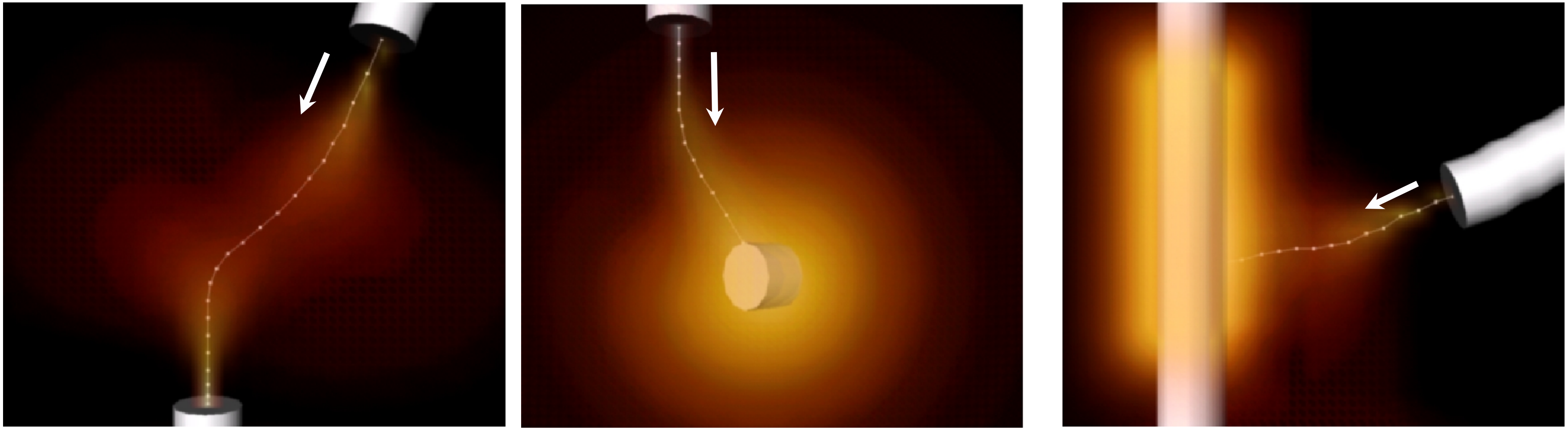
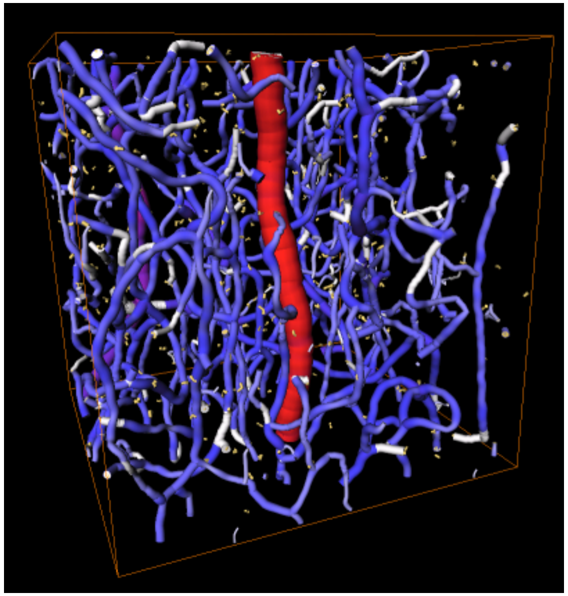
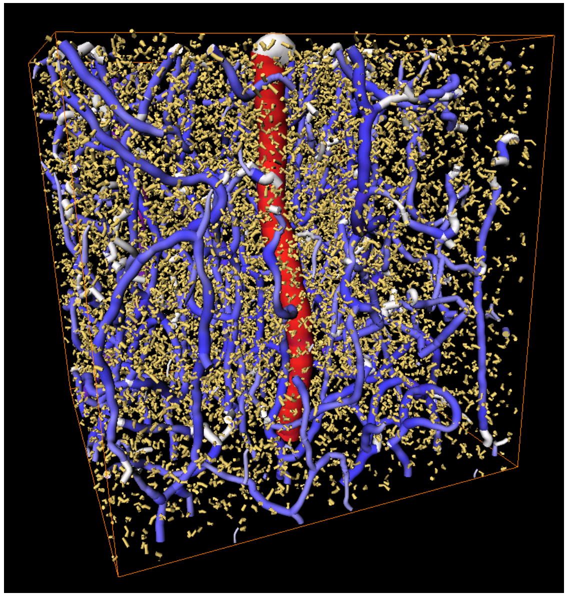
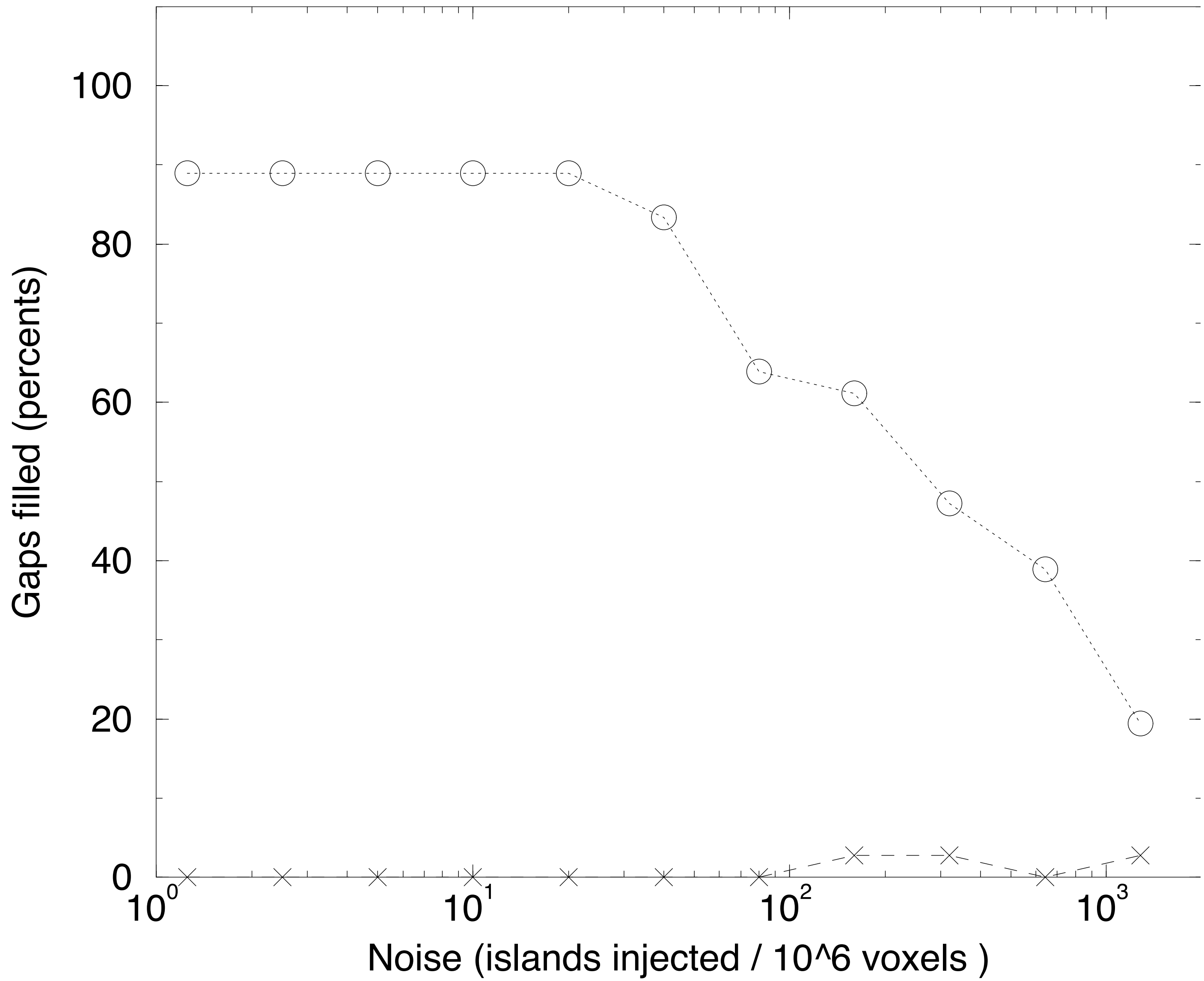
Path search: from segment-ends to other tokens



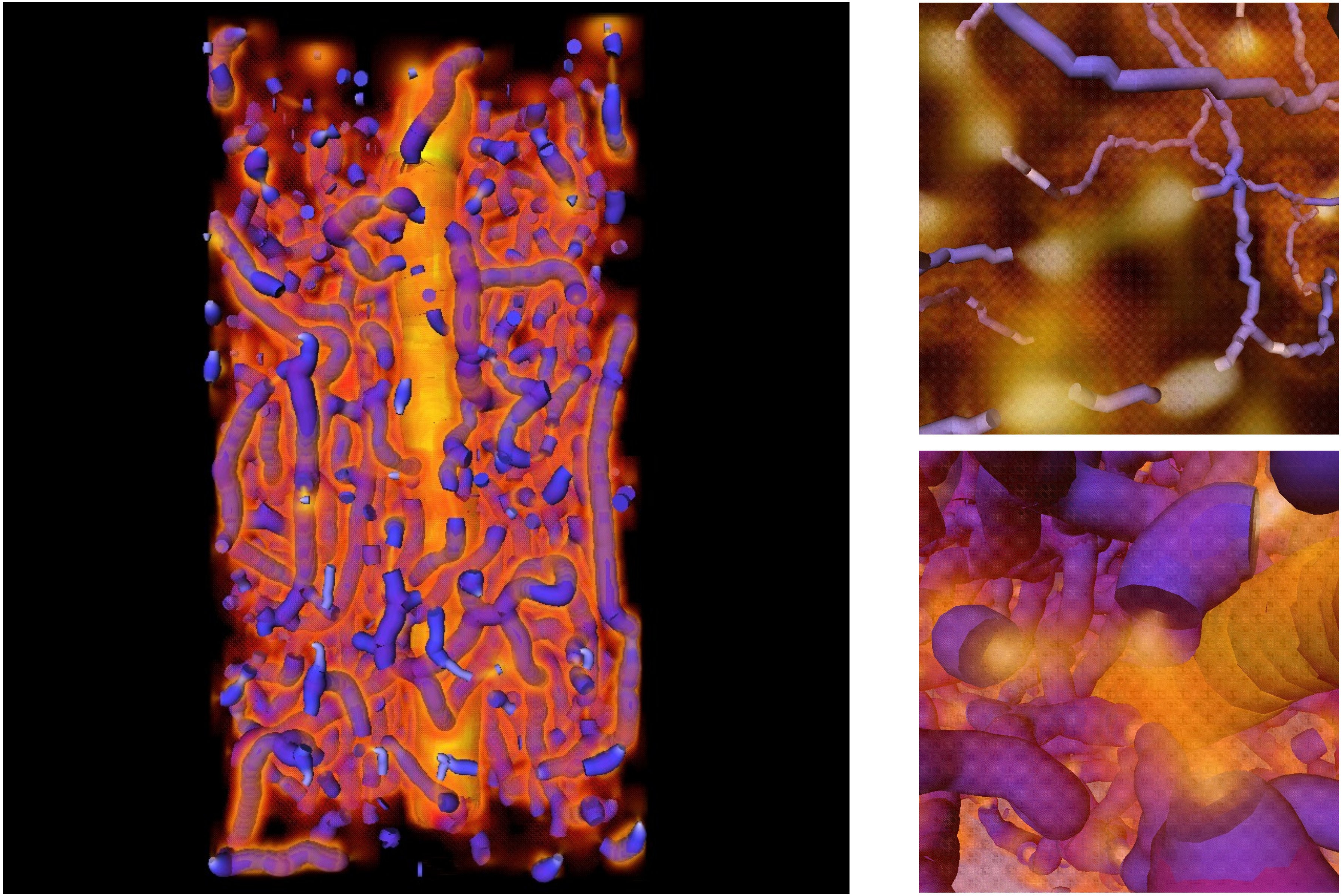
Results on phantom data



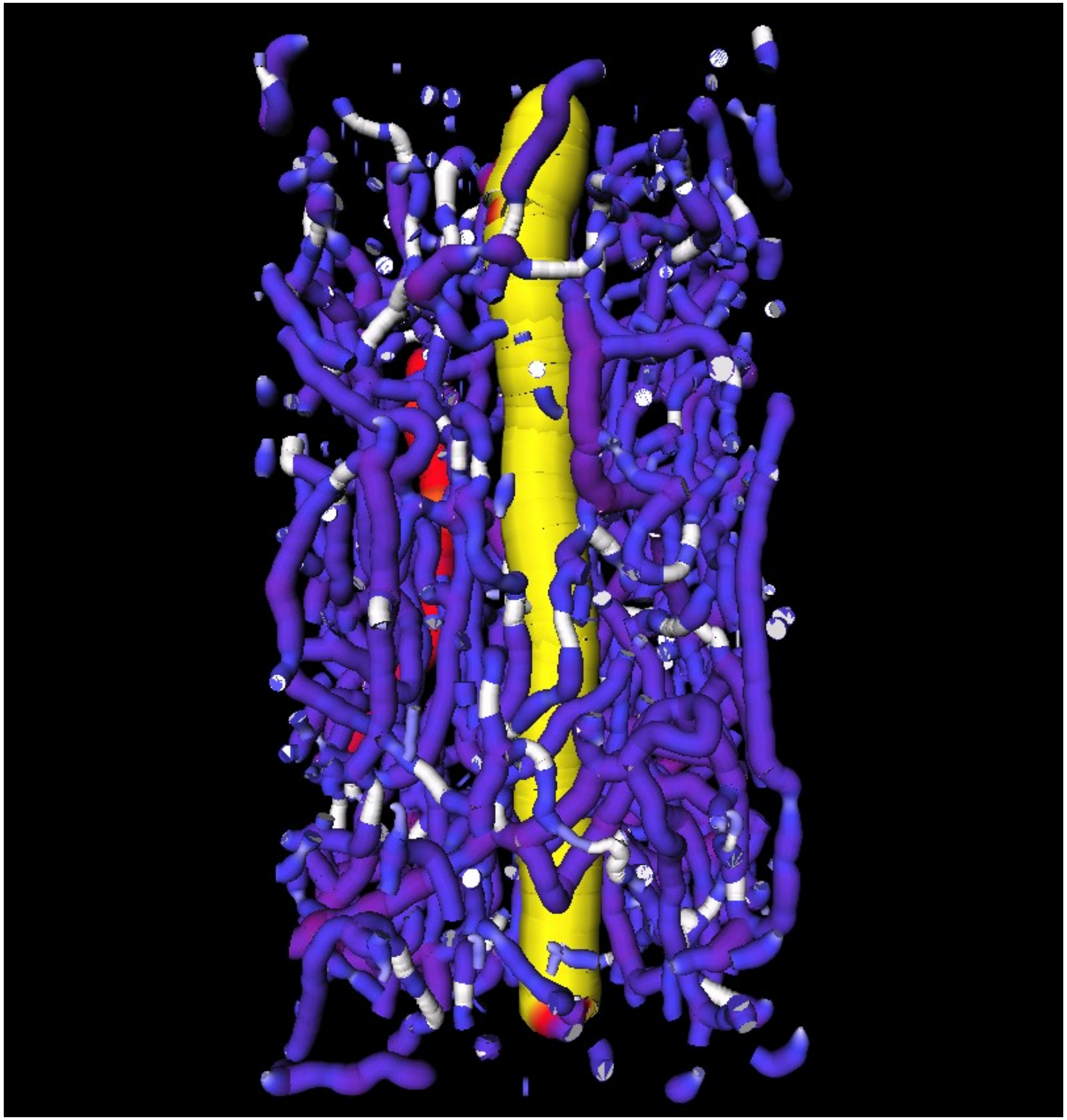


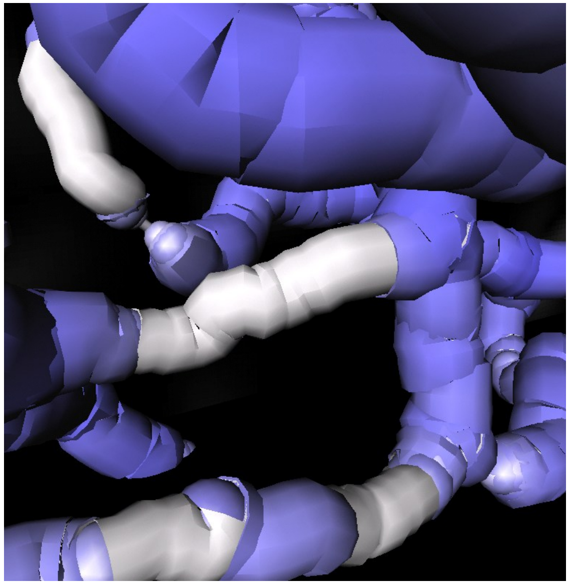


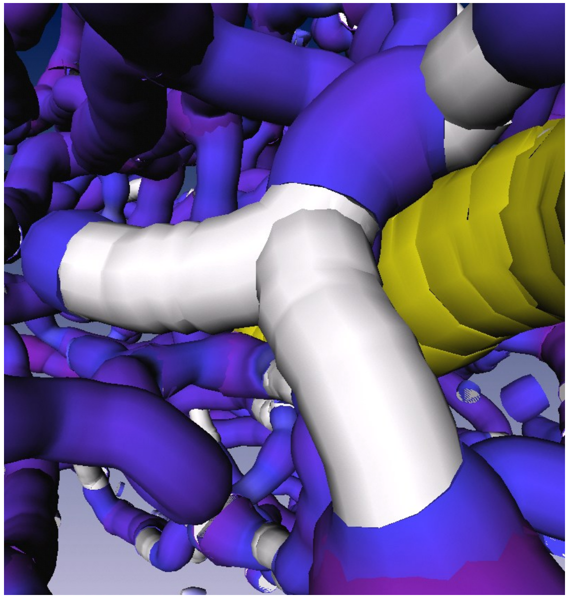
Results on real data



Results on real data ➔ About 90% of gaps filled

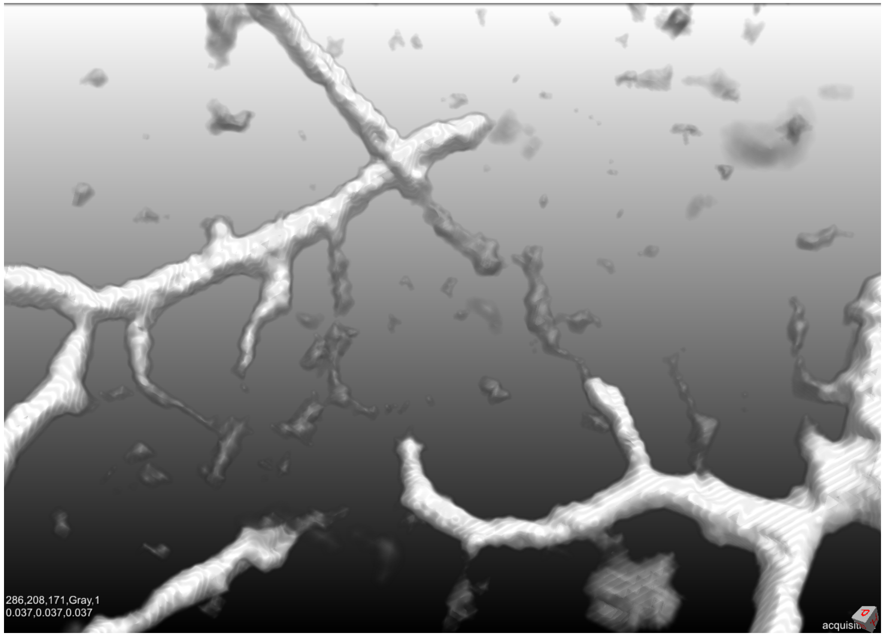




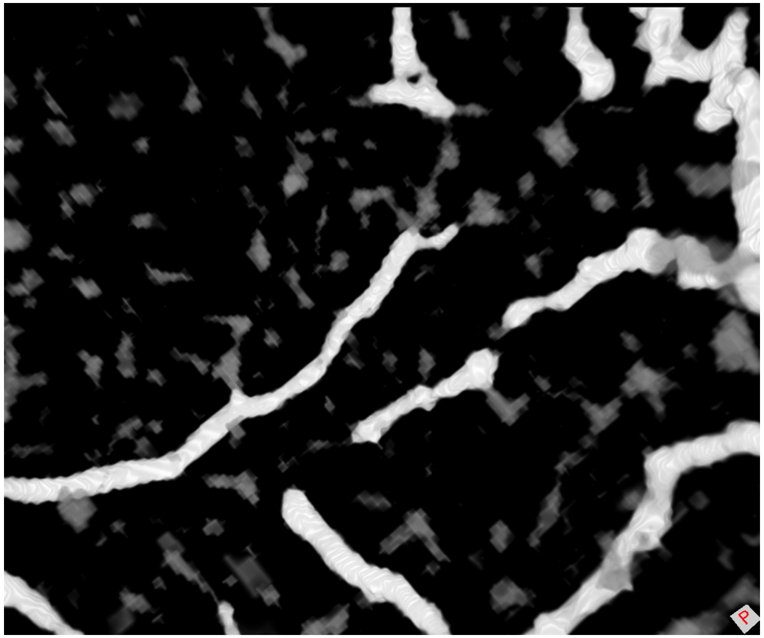


Good results obtained using skeleton-based information, but…

… *intensity-based* information would be helpful for *robust long distance* gap filling



Example 1

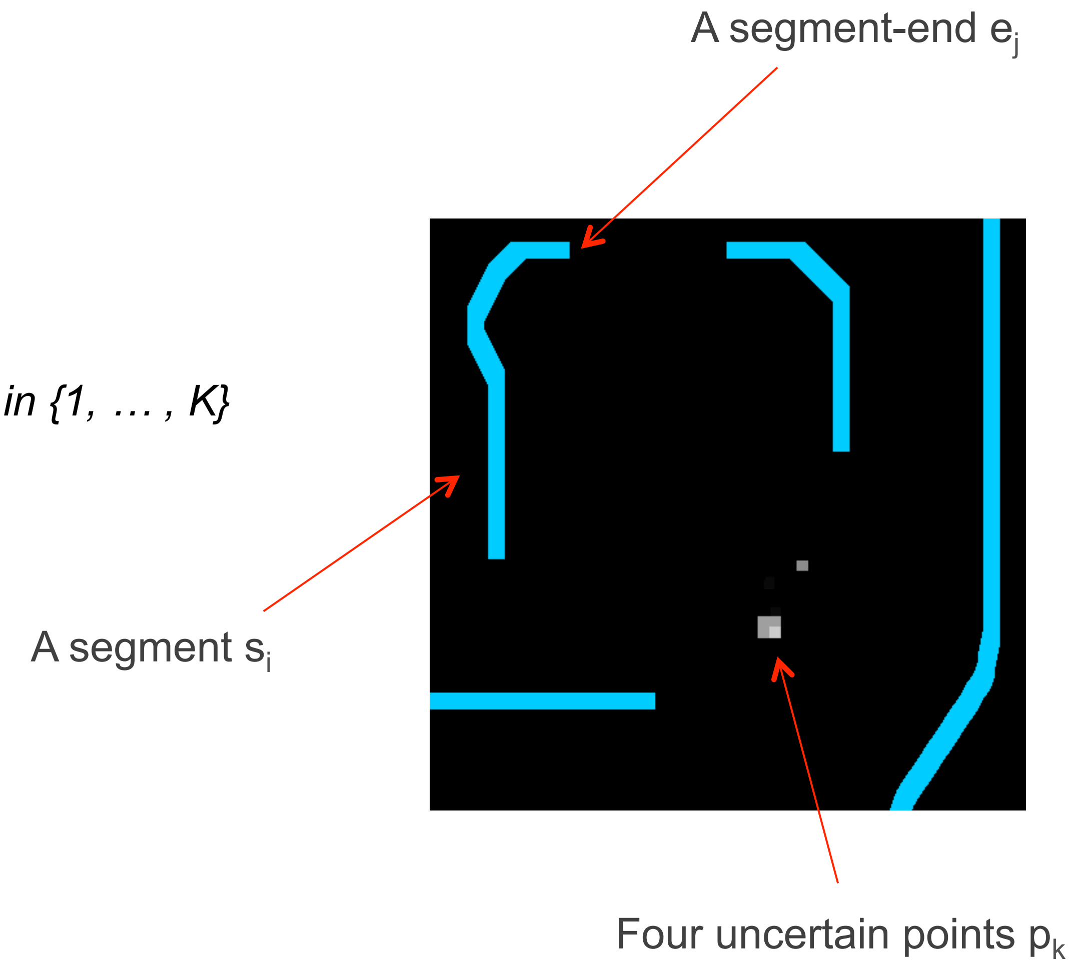


Example 2

Proposed strategy

Consider:

- A set of segments s_i , *i in {1, … , I}*
- A set of segment-ends e_j , *j in {1, … , J}*
- A set of uncertain points p_k with weights ω_k , *k in {1, … , K}*



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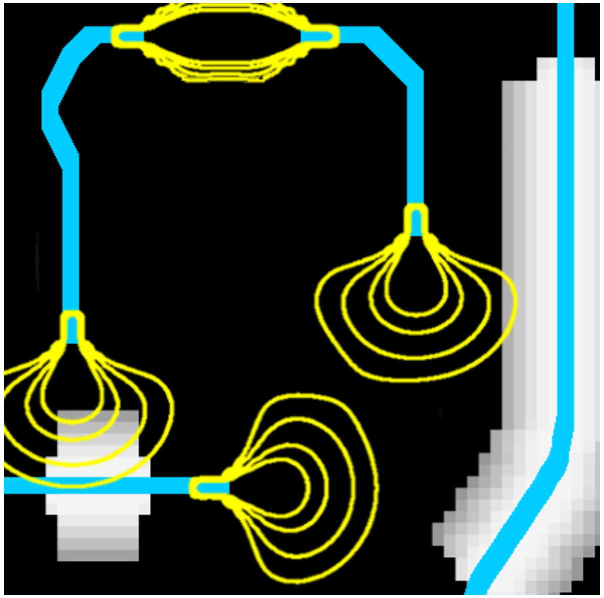
Generate a tensor field ***T*** using the e_j and s_i



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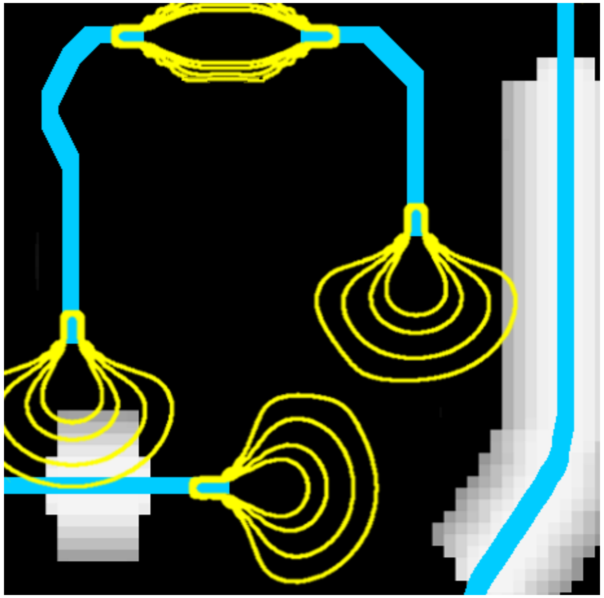

Generate a tensor field ***T*** using the e_j and s_i

After performing a SVD at each point, derivate from ***T*** :

- Saliency map to a curve $S = \lambda_1 - \lambda_2$
- Preferential directions $\boldsymbol{D} = \boldsymbol{v_1}$

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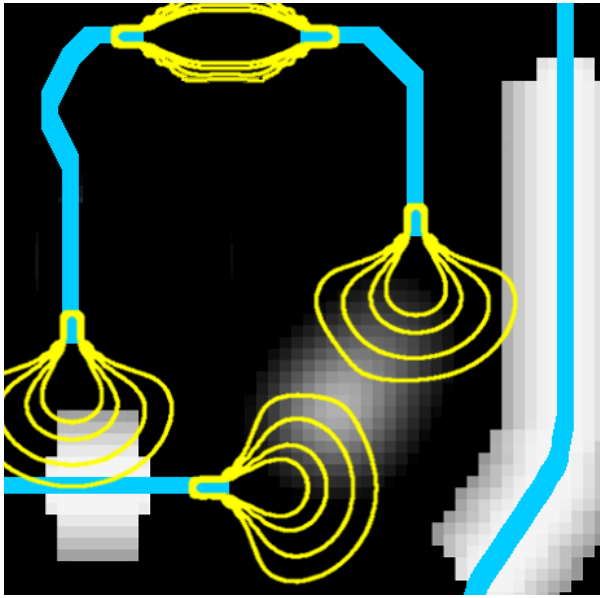

Generate a tensor field $\boldsymbol{T}$ using the e_j and s_i

After performing a SVD at each point, derivate from $\boldsymbol{T}$:

- Saliency map to a curve $S = \lambda_1 - \lambda_2$
- Preferential directions $\boldsymbol{D} = \boldsymbol{v_1}$

After constructing and image P using the (p_k, ω_k) compute an enhancement map E:

$$E = \frac{K_\sigma \otimes P}{K_{2\sigma} \otimes I(P) + \varepsilon}$$

Inspired from the normalized convolution strategy of [Knutsson and Westin CVPR 1993]

Proposed strategy

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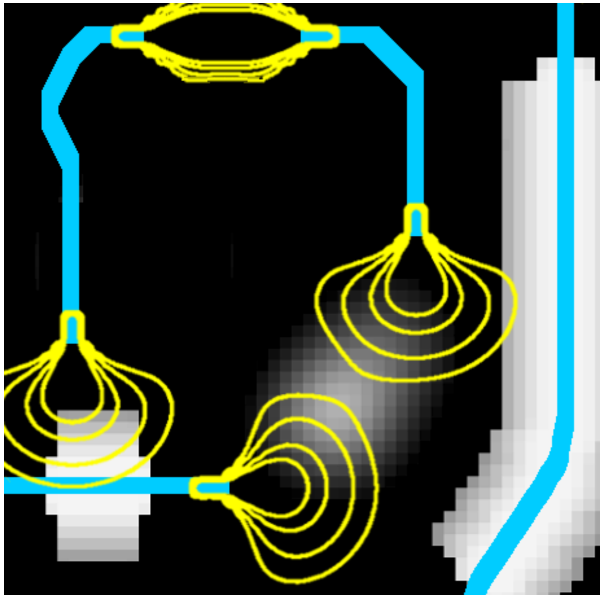

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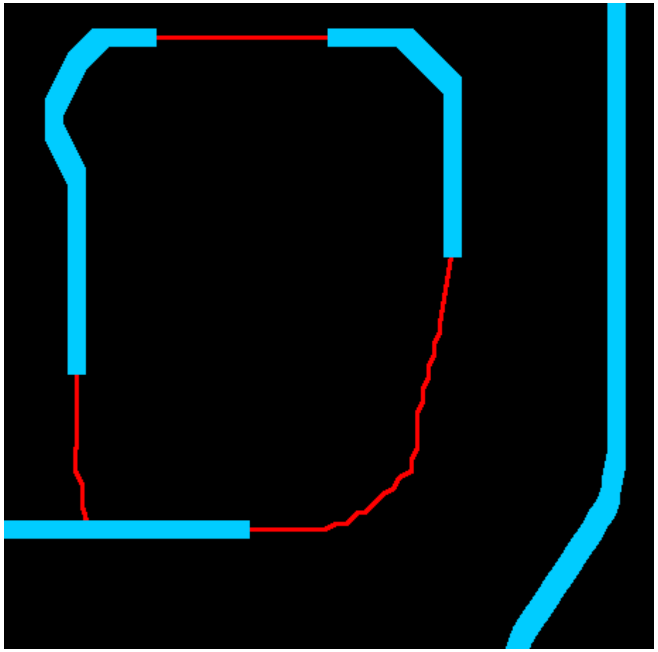
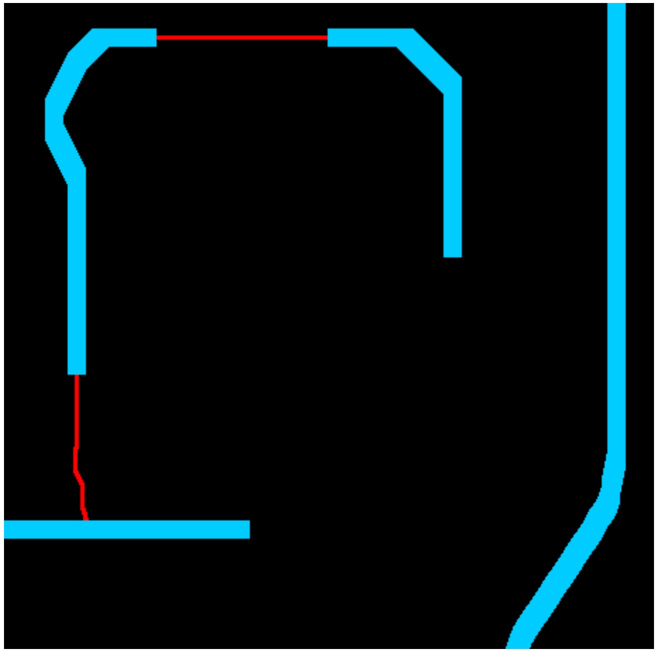
… then path search

Results in the 2D synthetic example:



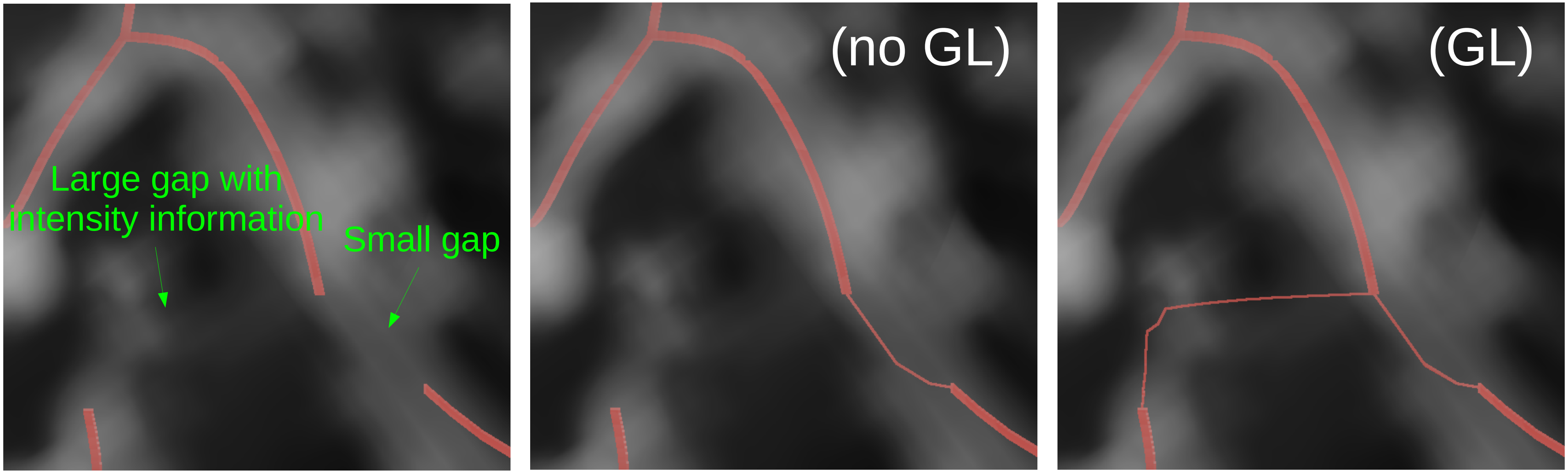
Using intensity information



No intensity information

Results on 3D real data:

- Ten volumes of preclinical tumour model
- Female CBA mouse with murine adenocarcinoma NT (CaNT) implanted subcutaneously on the right flank.
- Contrast enhanced micro-CT scanning using an Inveon system (Siemens Healthcare)
- Isotropic voxel size of 32.7µm / 300×200×170 voxels



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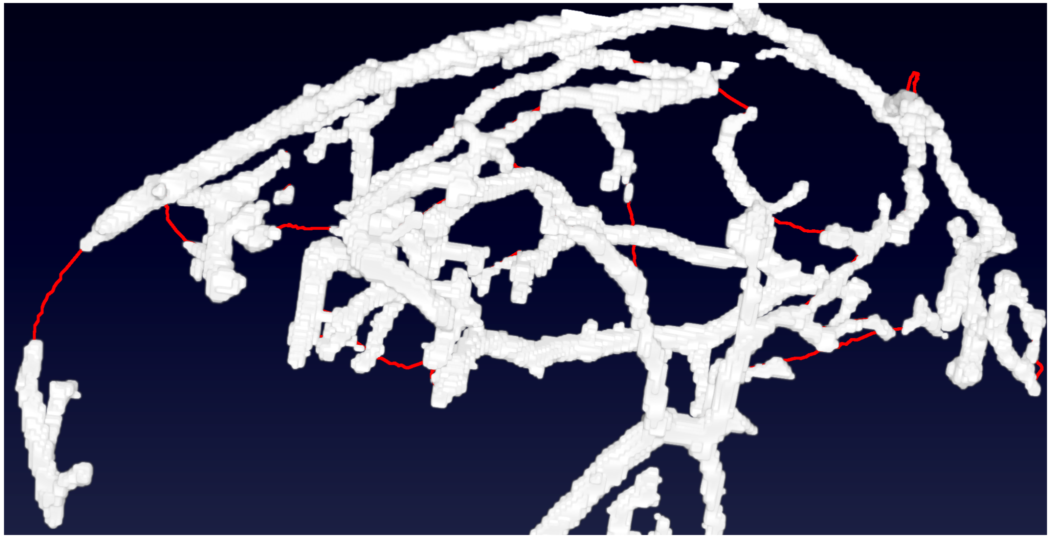

- 75 gaps filled using no intensity information
- 95 gaps filled using intensity information
- No obvious false positive

4: Gap filling using skeleton- and intensity-based information

Results on 3D real data:

- Ten volumes of preclinical tumour model
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Conclusion:
- Model adapted to the vasculature in tumours
- Encouraging results

Current work:
- Stochastic path search strategy

References

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