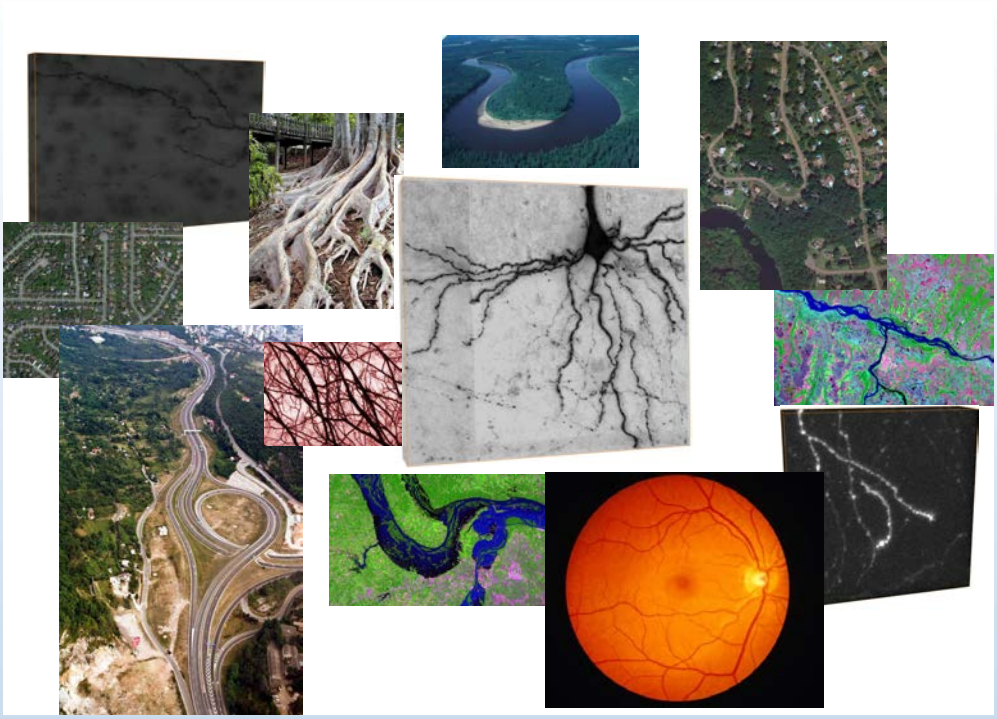
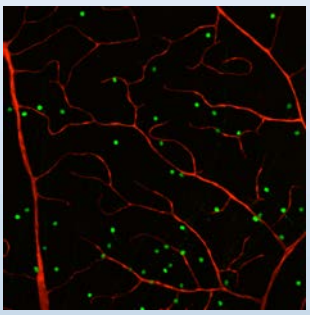
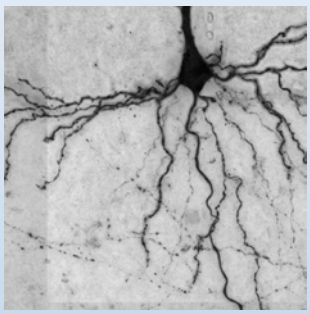
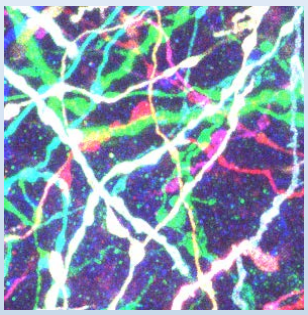


Using Machine Learning Techniques to Reconstruct Complex Curvilinear Structures

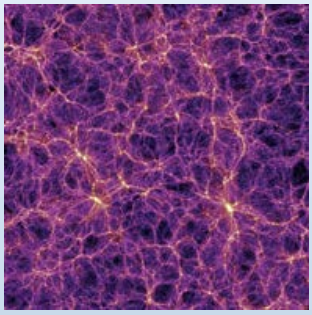
P. Fua
EPFL IC-CVLab

Complex Curvilinear Structures are Ubiquitous

~ 500 m	~ 1 cm	~ 1 mm	~ 200 microns	~ 25 microns
				
Road Networks (AERIAL)	Retinal Vasculature (FUNDUS CAMERA)	Vessels and Neurons (CONFOCAL)	Neurons (BRIGHTFIELD)	Dendrites and Axons (BRAINBOW)

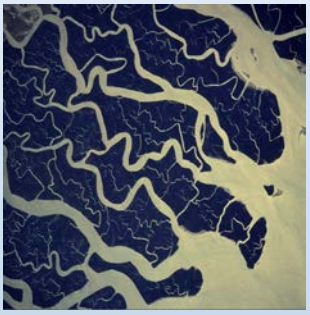
Complex Curvilinear Structures are Ubiquitous

~ 1e22 km !



Cosmic Web
(SIMULATION)

~ 25 km



Delta and Rivers
(AERIAL)

. . .

~ 500 m

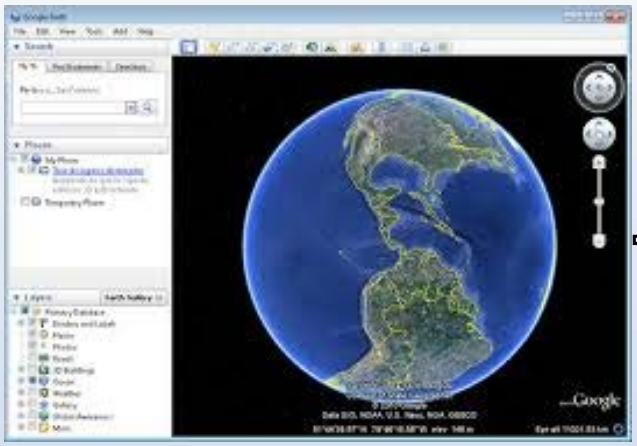
Road Networks
(AERIAL)

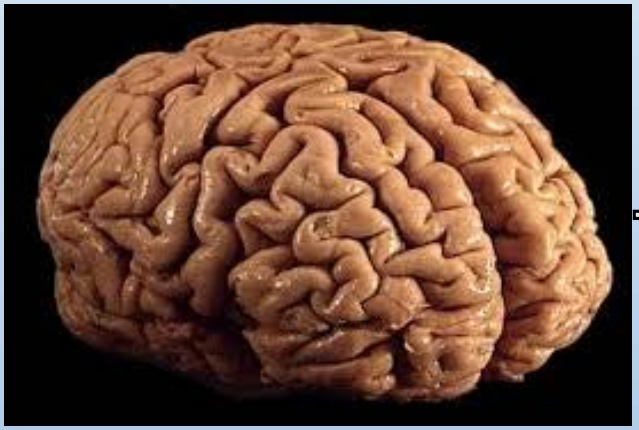
~ 1 cm

Retinal Vasculature
(FUNDUS CAMERA)

… and often contain loops.

Google Earth ..

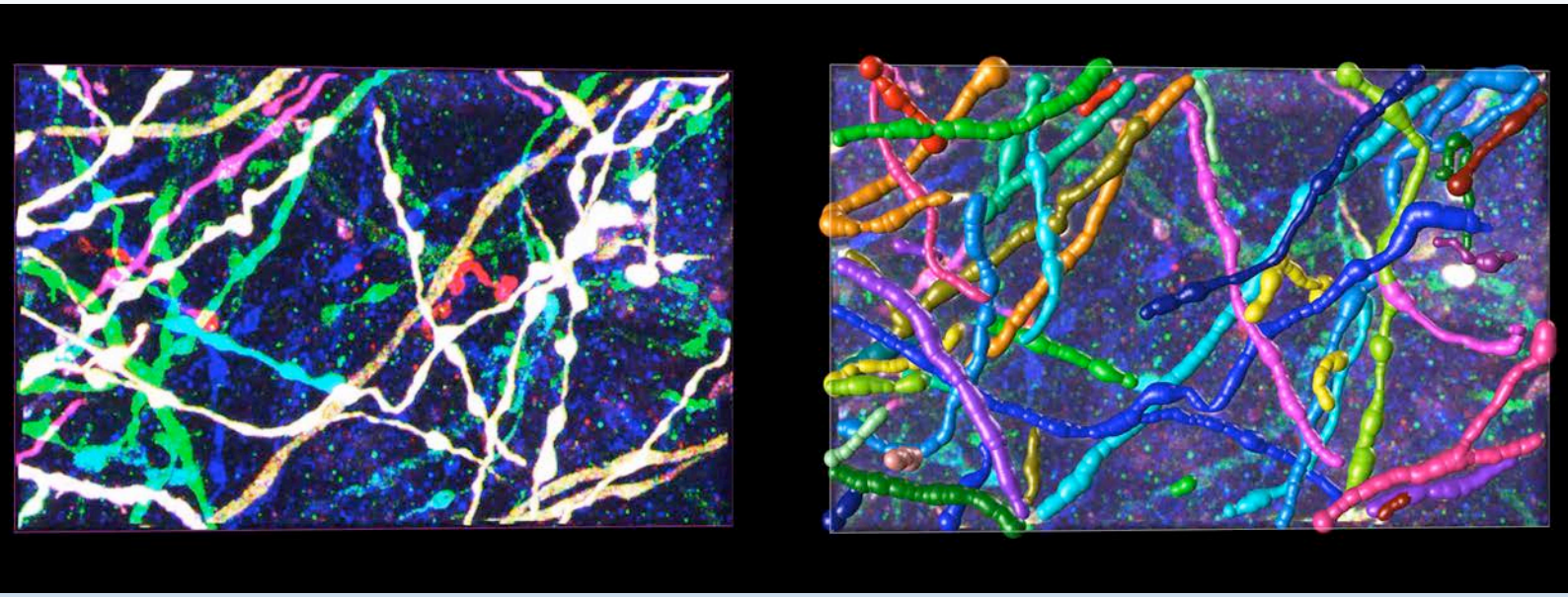




???

.. and Brain

Curse of Dimensionality



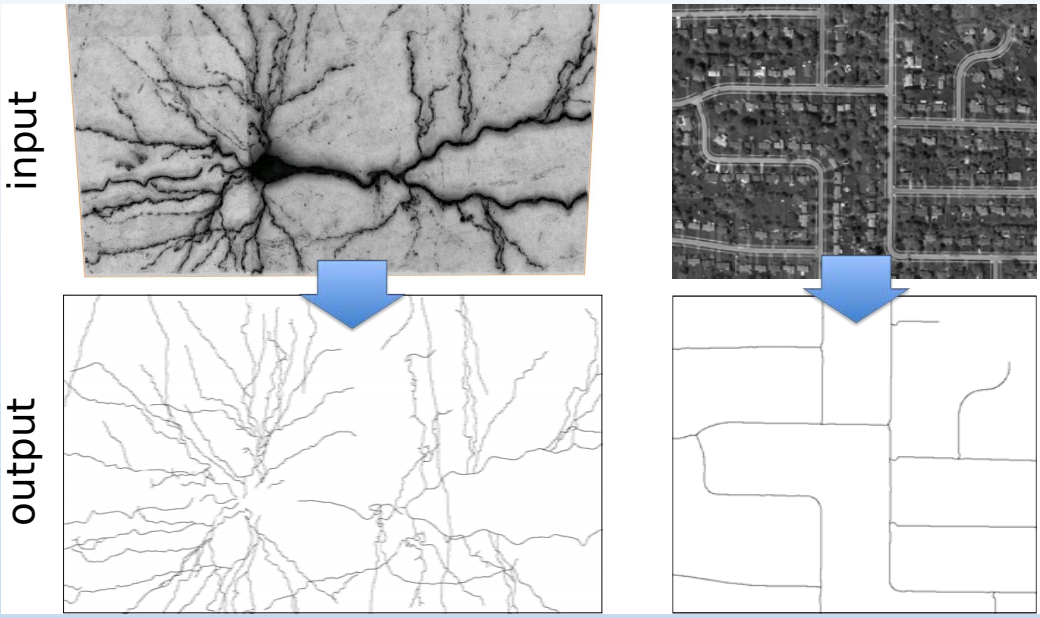
Brainbow 500x300x50 stack
(Courtesy J. Lichtman)

Automated Reconstruction

- A 10 cm^3 cube or brain matter would produce a 100000x100000x100000 image at this resolution.
- Some hand tracing is possible but takes weeks and months.

—> Automation is required.

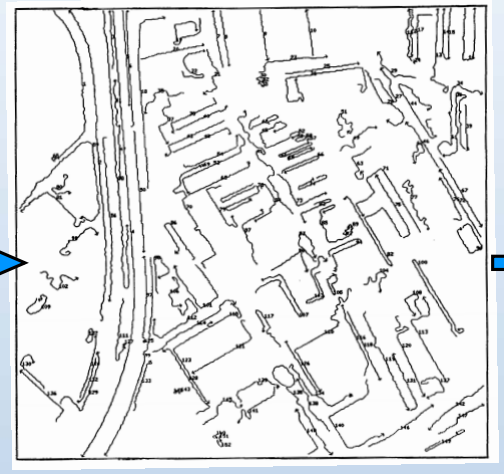
Delineation in 2D and 3D



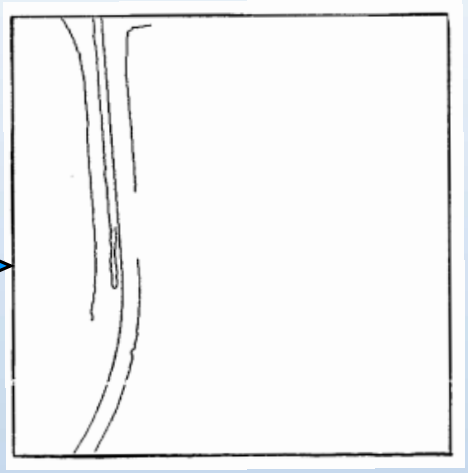
A very old topic in Computer Vision but full automation remains elusive:

- Images are very noisy.
- The structures are often complex.

A Few Years ago at INRIA



All Edge Chains



Longest Edge Chains

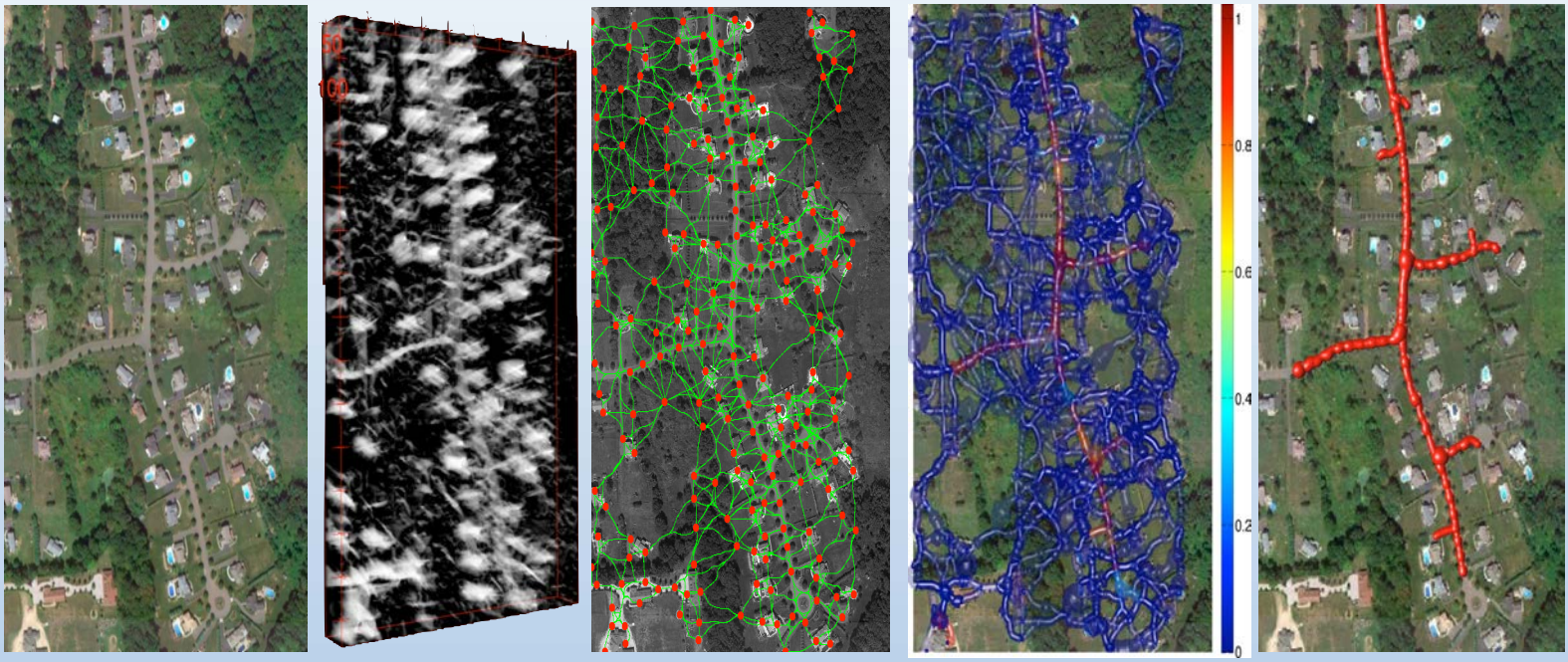
Garnesson, Giraudon, Monesinos, 1989

Meanwhile at SRI

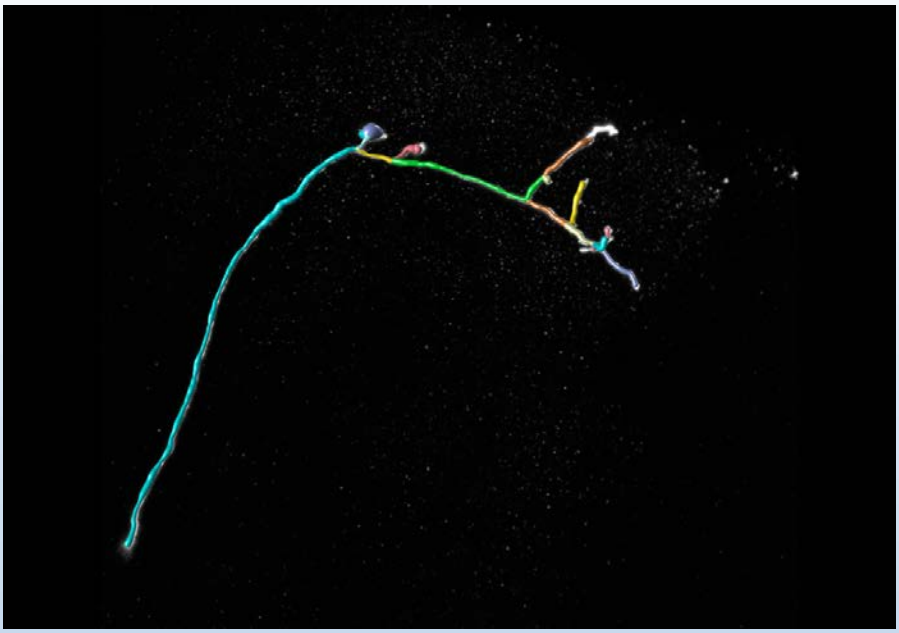
- Find centerlines.
- Build spanning tree.
- Retain road-like branches.
- Compute width.

Graph-Based Approach (2D)

Image | Tubularity Volume | Graph | Weighted Graph | Reconstruction



Graph-Based Approach (3D)



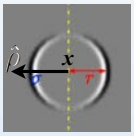
Processing steps:

1. Compute the tubularity of individual voxels.
2. Select voxels that locally maximize this measure.
3. Build a *tubular* graph by linking these voxels.
4. Find an optimal subgraph within the graph.

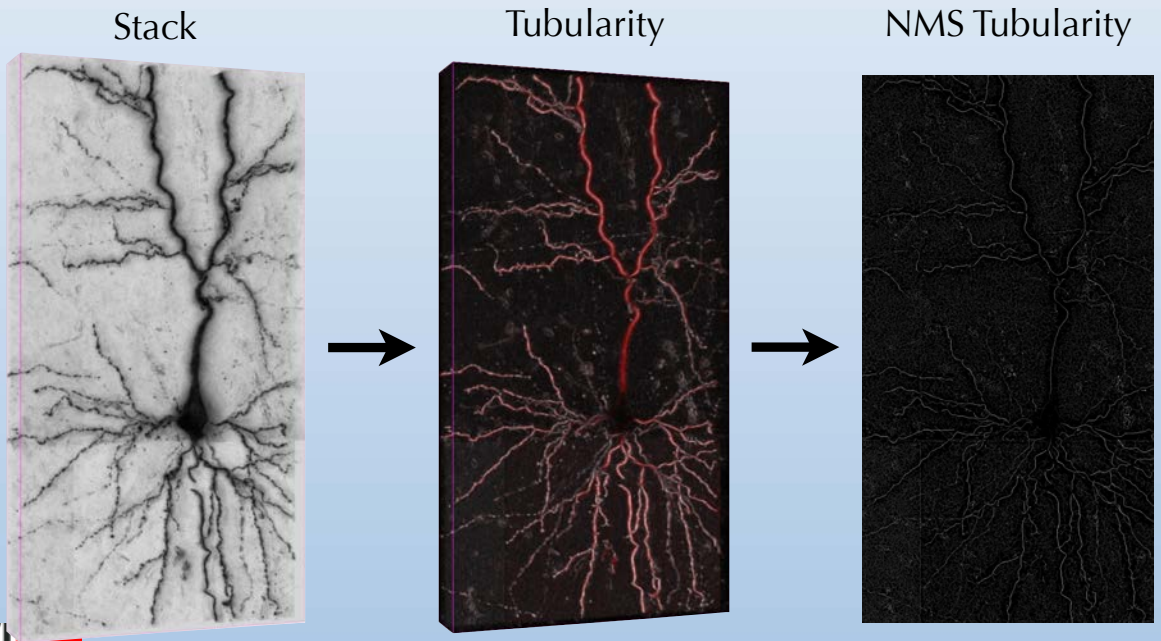
Building the Tubular Graph

- Compute tubularity in scale space.

$$f(\boldsymbol{x};r,\hat{\rho}) = \frac{1}{4\pi r^2}\int_{\partial B_r}\Big((\boldsymbol{v}(\boldsymbol{x}-\boldsymbol{A})\cdot\hat{\rho})\hat{\rho}\Big)\cdot\hat{n}dA \quad s(\boldsymbol{x};r,\hat{\rho}) = \frac{1}{4\pi r^2}\int_{\partial B_r}\Big(\boldsymbol{v}(\boldsymbol{x}+\boldsymbol{A})\cdot\hat{\rho}\Big)dA$$



- Canny like Non maximum suppression.

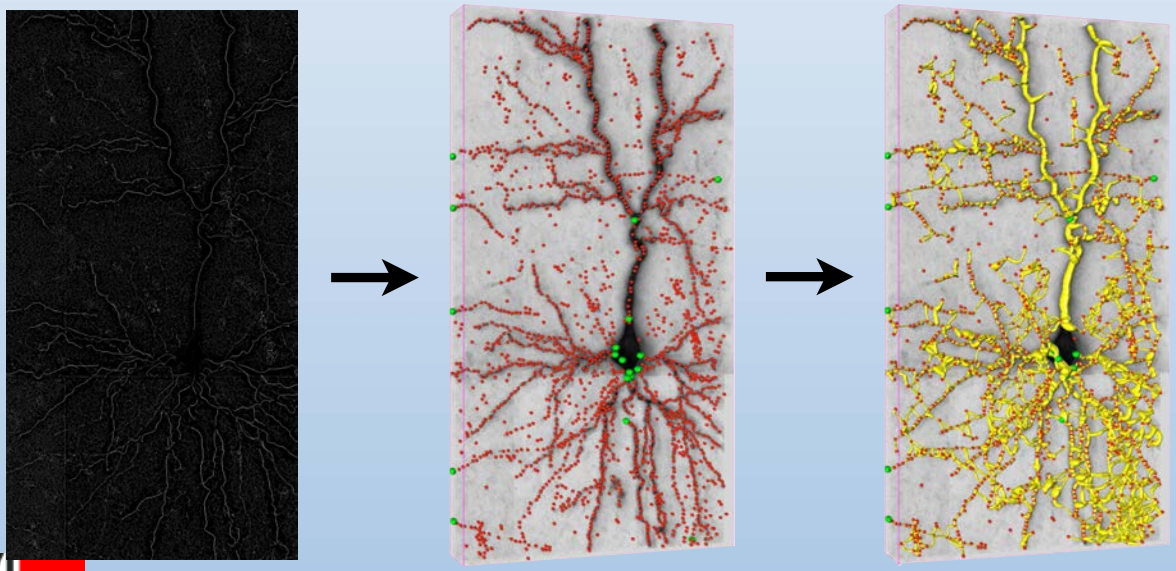


Building the Tubular Graph

- Vertices: Local-maxima sampled iteratively at regular intervals.
- Edges: Tubular paths linking pairs of samples through high-tubularity voxels.

$$\gamma^*(v_i, v_j) = \underset{\gamma}{\operatorname{argmin}} \int_0^1 \mathcal{P}(\gamma(s))\, d(s)$$

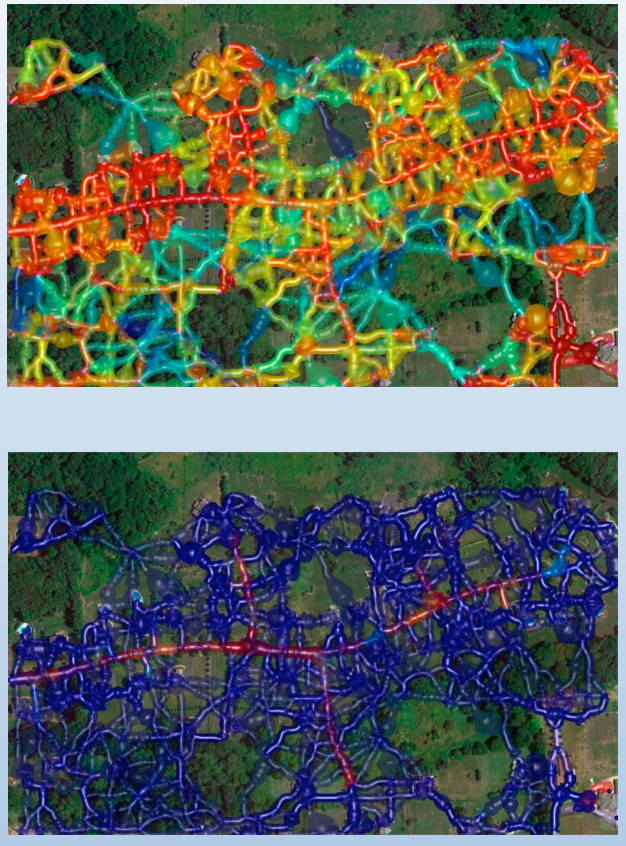
NMS Tubularity | Samples | Graph



Giving Weights to the Edges

- Standard Approach: Integrate tubularity values along paths.

$$\mathcal{E}(\gamma) = \int_{\gamma} \mathcal{P}(\gamma) \mathrm{d}\gamma$$

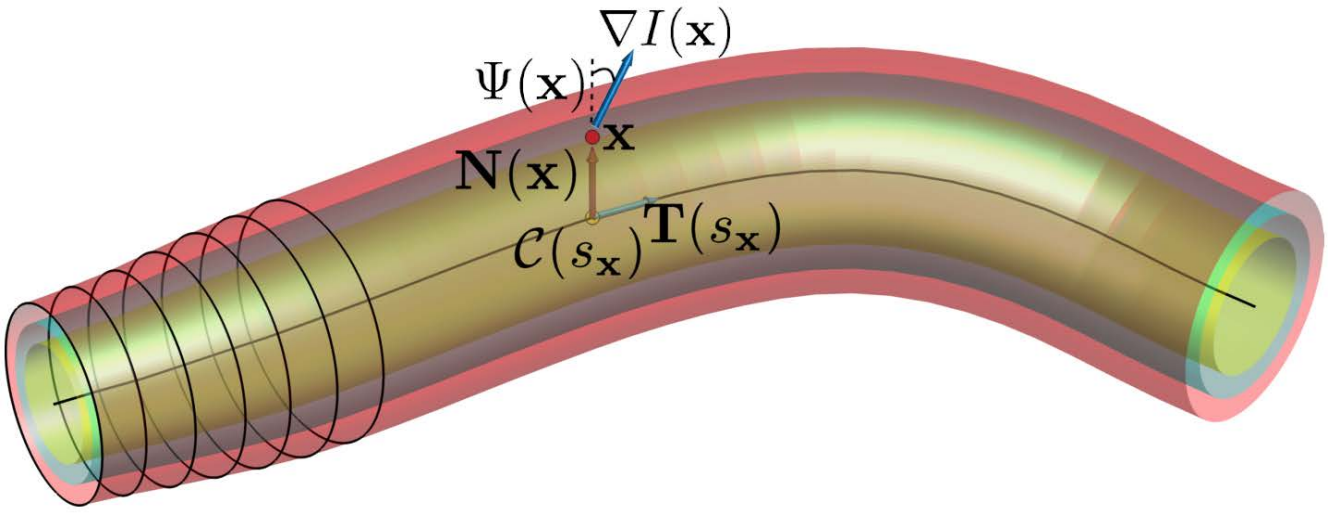


Uninformative for paths that partially right and partially wrong.

- Better Approach: Learn a quality function based on global appearance and geometry.

Provides much more informative scores!

Histograms of Gradient Deviations

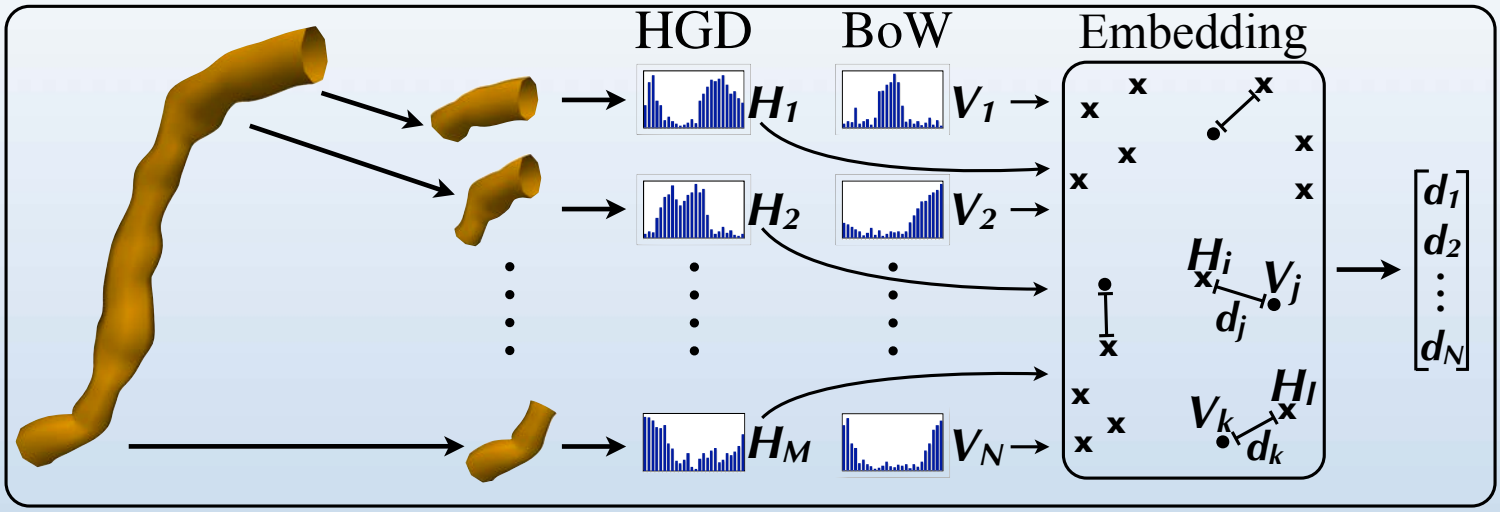


radius intervals

$$\Psi(\mathbf{x}) = \begin{cases} \text{angle}(\nabla I(\mathbf{x}), \mathbf{N}(\mathbf{x})) \text{ , if } \|\mathbf{x} - \mathcal{C}(s_\mathbf{x})\| > \varepsilon \\ \text{angle}(\nabla I(\mathbf{x}), \mathbf{\Pi}(\mathbf{x})) \text{ , otherwise,} \end{cases}$$

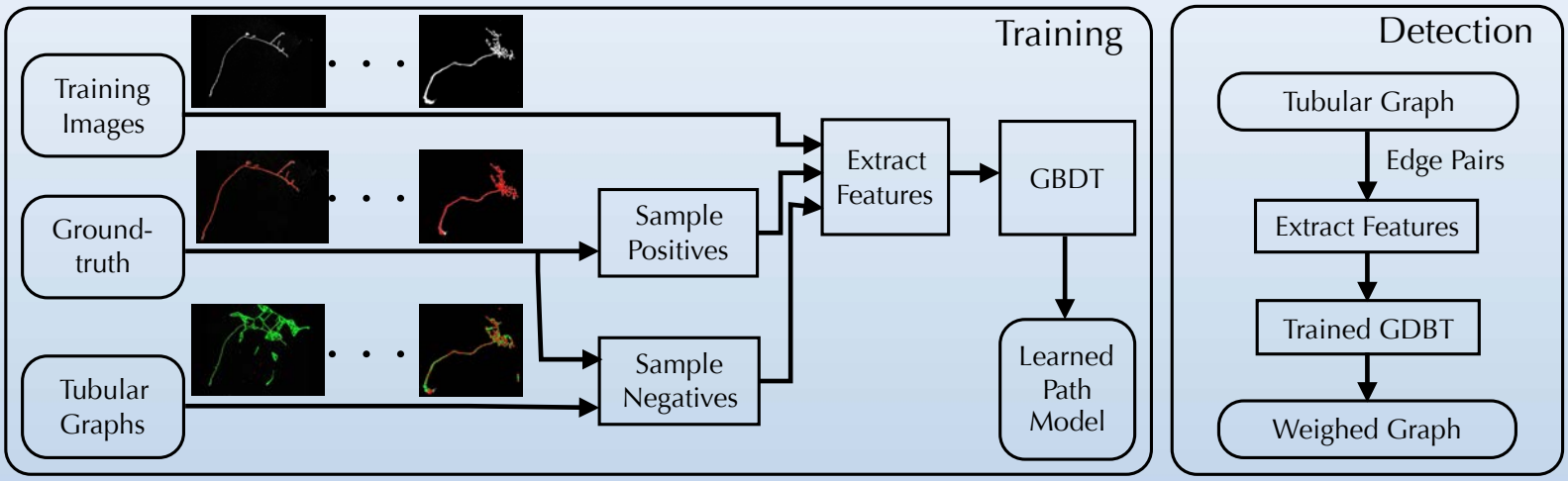
—> One histogram per radius interval plus four geometry features (curvature, tortuosity, ….)

Embedding

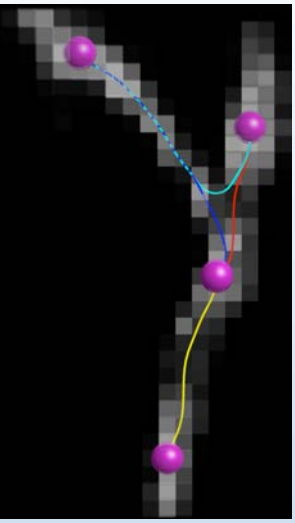


—> Same length feature vectors whatever the actual length of the path.

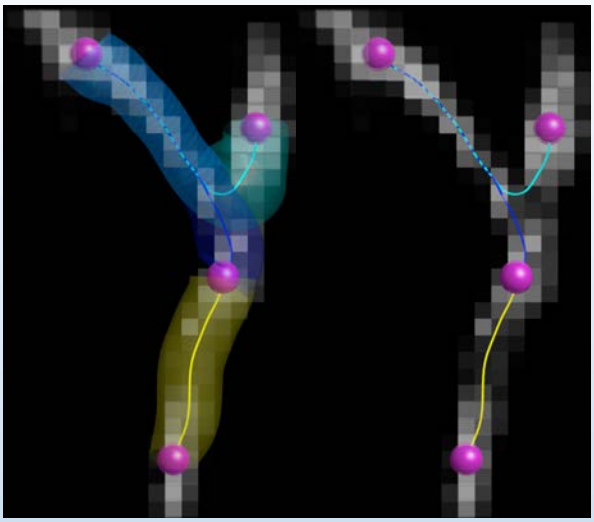
Path Classification



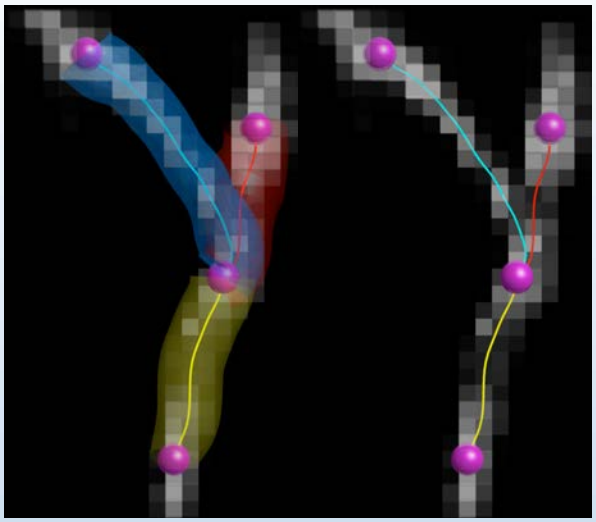
Finding the Best Tree



Tubularity graph



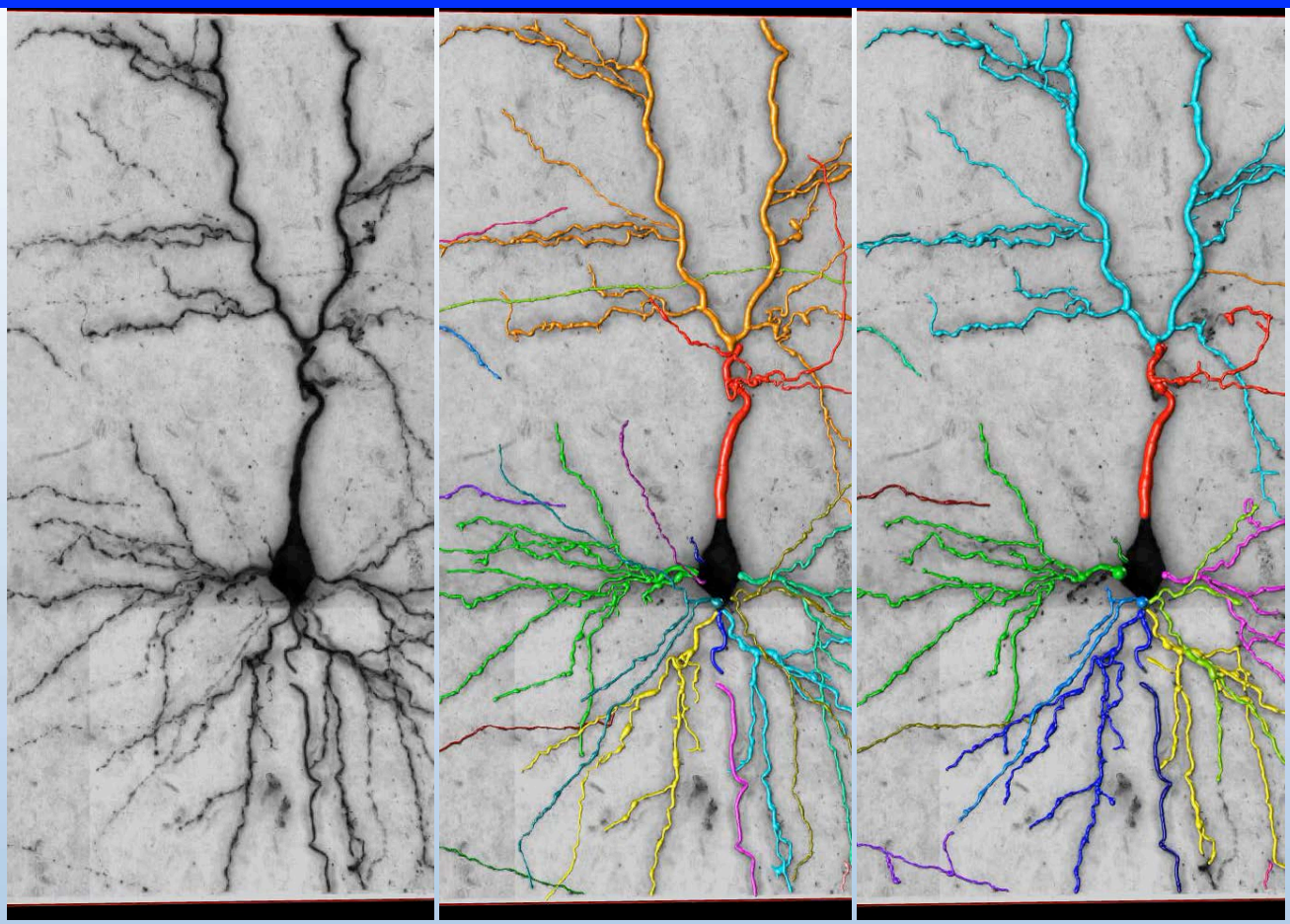
Without edge pair term



With edge pair term

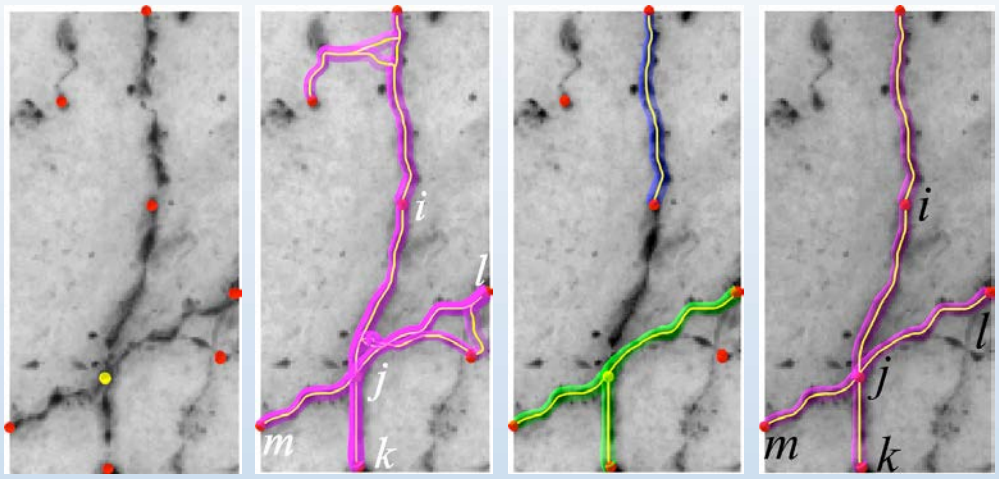
$$
\begin{aligned}
\mathbf{t}^* &= \underset{\mathbf{t}\in\mathcal{T}(G)}{\operatorname{argmax}} P(\mathbf{T}=\mathbf{t}|I) \ , \\
&= \underset{\mathbf{t}\in\mathcal{T}(G)}{\operatorname{argmax}} P(I|\mathbf{T}=\mathbf{t})P(\mathbf{T}=\mathbf{t}) \ , \\
&= \underset{\mathbf{t}\in\mathcal{T}(G)}{\operatorname{argmin}} \sum_{e_{ij}\in G} c_{ij}^d t_{ij}
\end{aligned}
$$

Brightfield



Brightfield Stack | Ground Truth | QMIP reconstruction

From Trees to Subgraphs

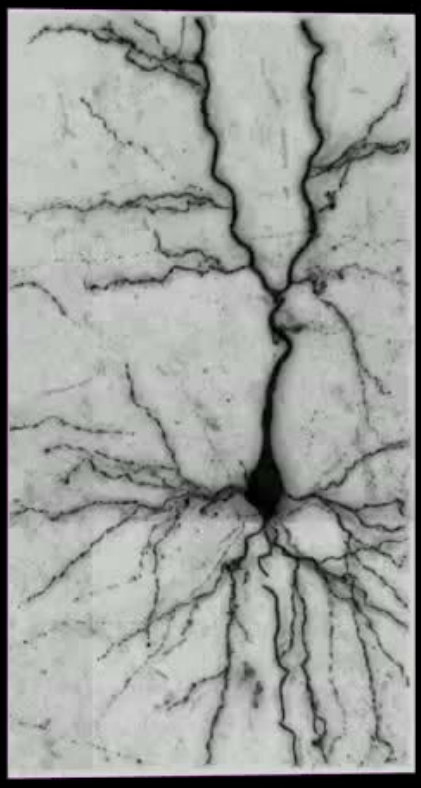


Even in true tree structures, some vertices might have to be shared to avoid topological errors:

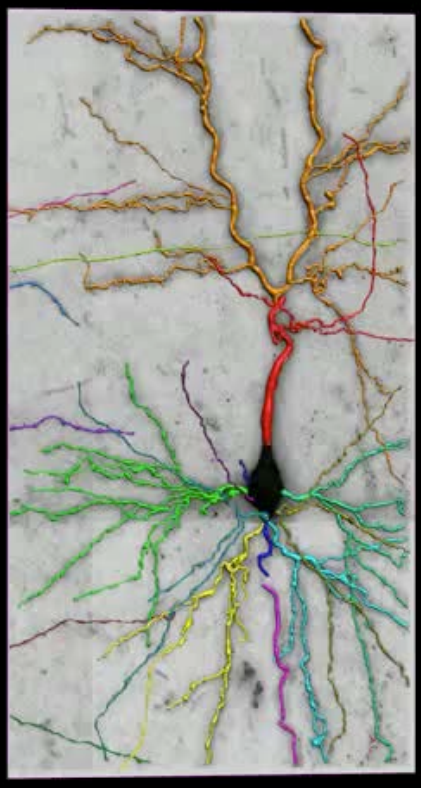
- Allow loops
- Penalize hanging branches.

➡Still a QMIP problem.

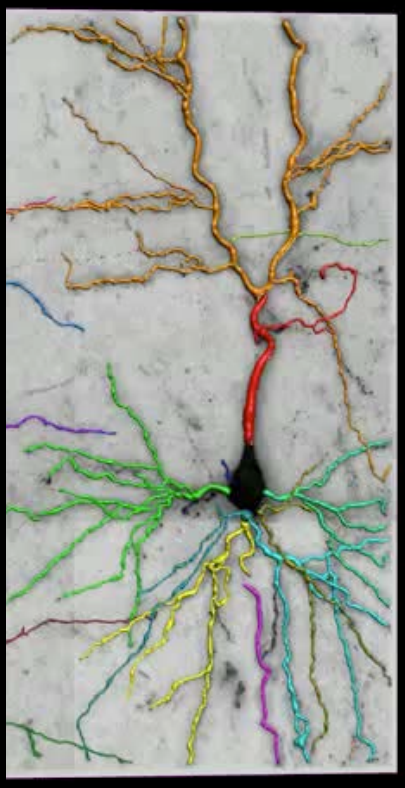
Loopy Brightfield



Brightfield Stack



Ground Truth

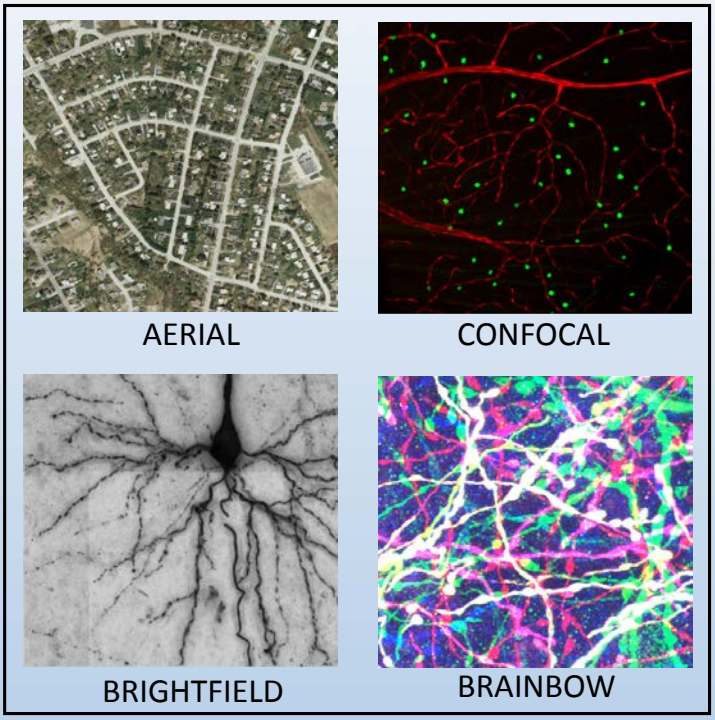


QMIP reconstruction

Turetken, CVPR'13

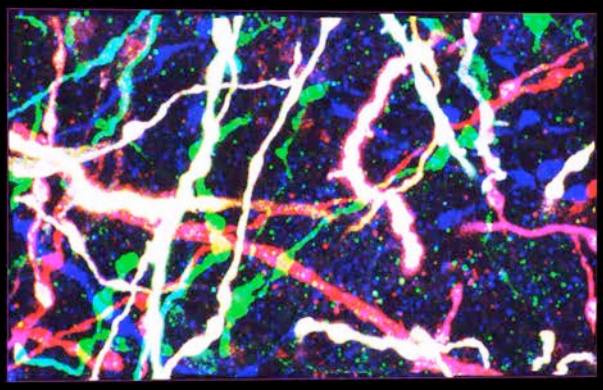
Test Datasets

- **Aerial** Roads: 21 training and 8 test images.
- **Confocal** Blood Vessels: 1 partially traced image stack for training and 2 for testing. (Maximilian Joesch, Markus Meister - Harvard)
- **Brightfield** Neurons: 1 training and 3 test image stacks. (Felix Schürmann, Henry Markram - EPFL)
- **Brainbow** Neurites**:** 3 training and 3 test image stacks. (Luke Bogart, Takao Hensch, Jeff Lichtman - Harvard)
- 80000 positive and negative samples for each dataset.
- Same path classifier parameters for all four datasets.



Results: Brainbow

Stack

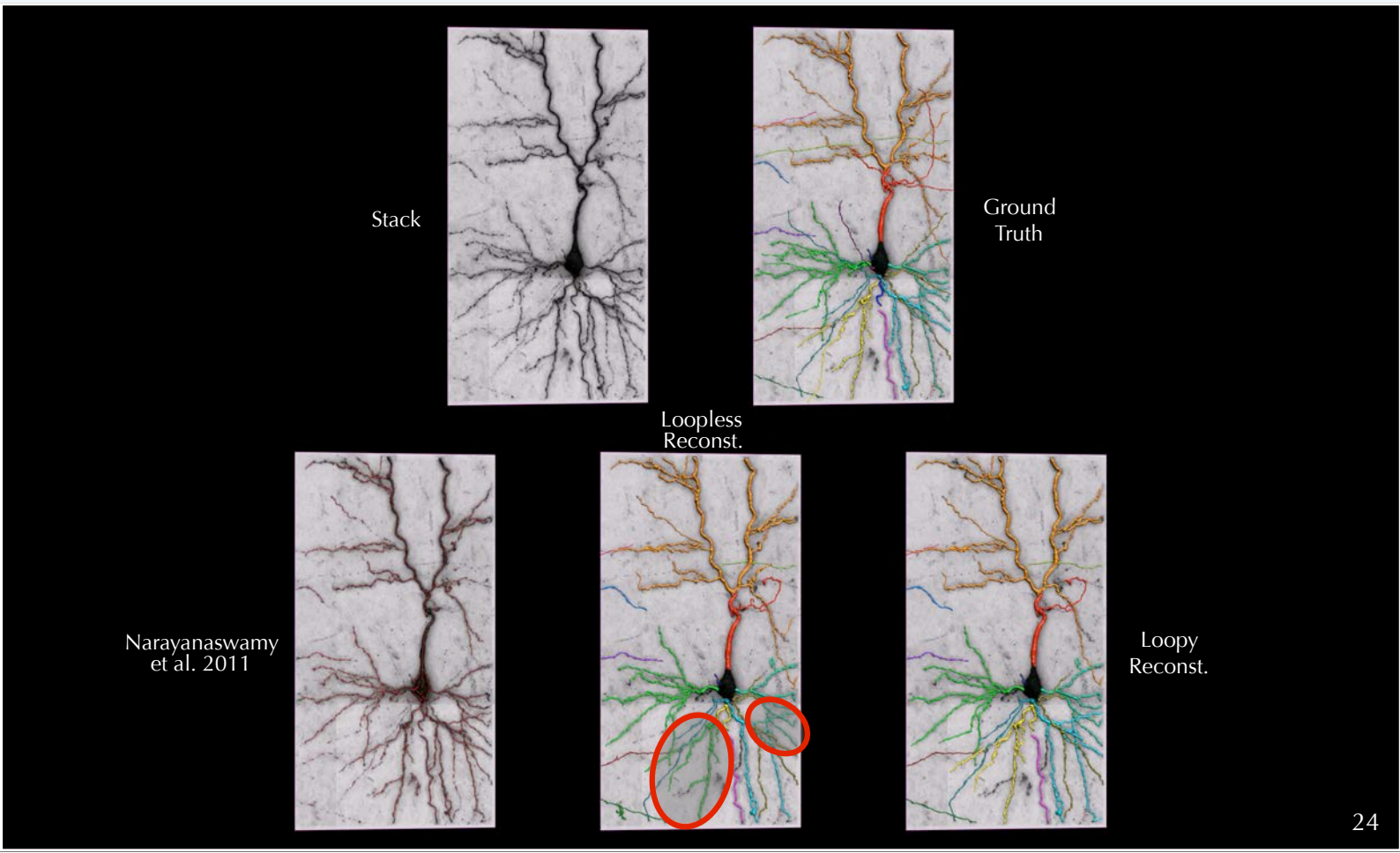


Quantitative Quality Measures For Trees

- DIADEM Measure (Topological Quality):

	BRBW1	BRBW2	BRBW3
Loopless Reconst.	0.3692	0.5118	0.4016
Loopy Reconst.	**0.8327**	**0.6897**	**0.7848**

Results: Brighfield



Quantitative Quality Measures For Trees

- DIADEM Measure (Topological):

	BRF1	BRF2	BRF3
Loopless Reconst.	0.6114	0.4263	0.6551
Loopy Reconst.	**0.7282**	**0.5122**	**0.7391**

- NETMETS Measure (Geometric & Connectivity):

	BRF1				BRF2				BRF3			
Loopy-IP	**0.05**	**0.29**	**0.71**	**0.65**	**0.11**	**0.29**	**0.81**	**0.78**	**0.07**	**0.28**	0.77	**0.70**
k-MST	0.10	0.44	0.79	0.88	**0.11**	0.53	0.84	0.91	0.13	0.35	0.81	0.92
Focus	0.39	0.54	0.75	1.00	0.49	0.53	0.90	1.00	0.38	0.46	**0.74**	1.00
OSnake	0.66	0.63	0.98	0.99	0.66	0.59	0.99	1.00	0.69	0.38	0.95	0.99
APP2	0.68	0.64	1.00	1.00	0.63	0.54	1.00	1.00	0.65	0.49	1.00	1.00

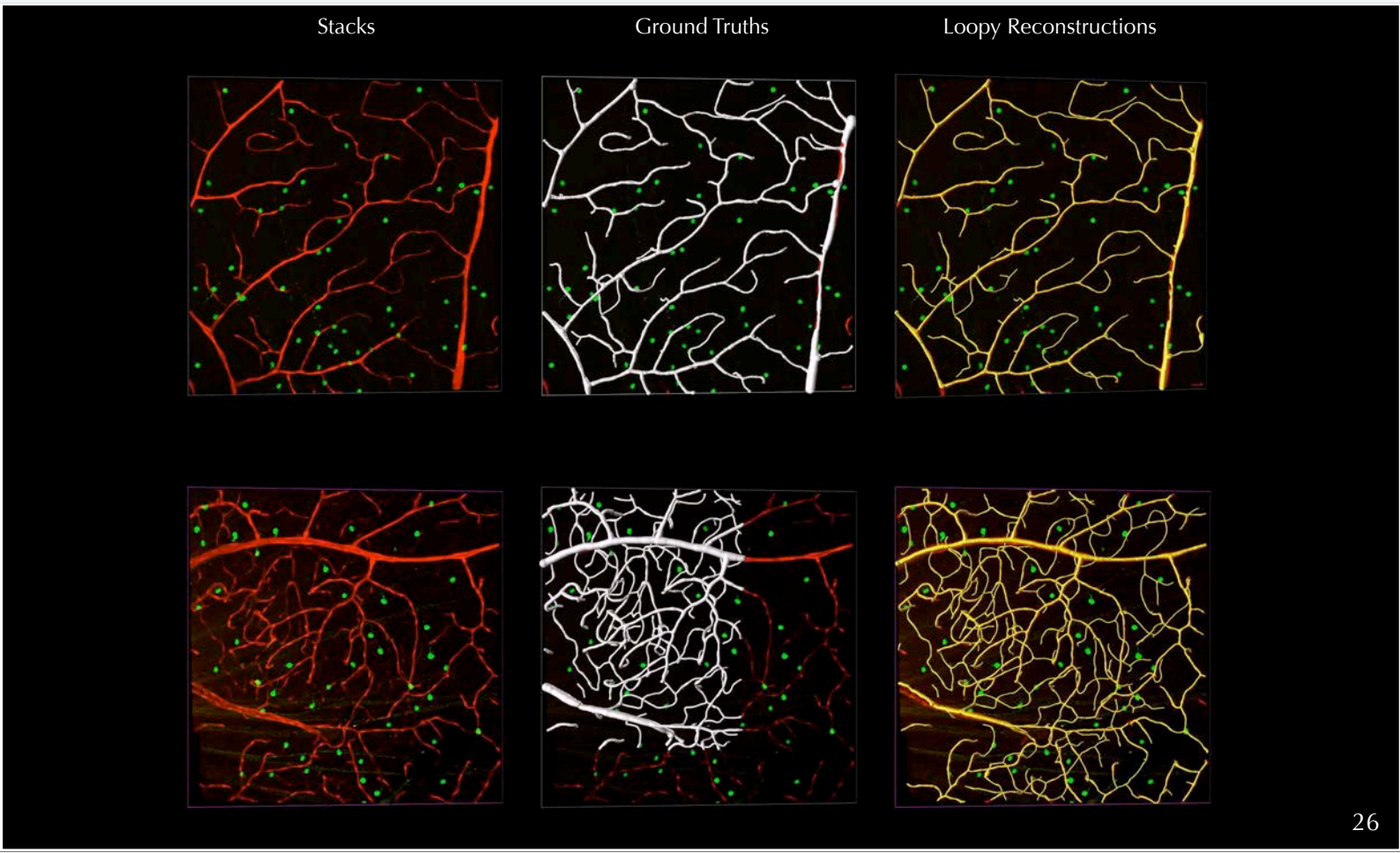
Geometric FPR

Geometric FNR

Connectivity FPR

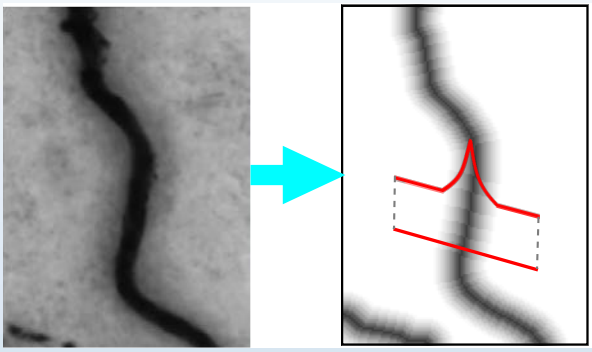
Connectivity FNR

Results: Confocal



Results: Roads

Finding Better Centerlines

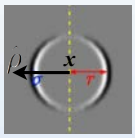


An ideal tubularity measures should:

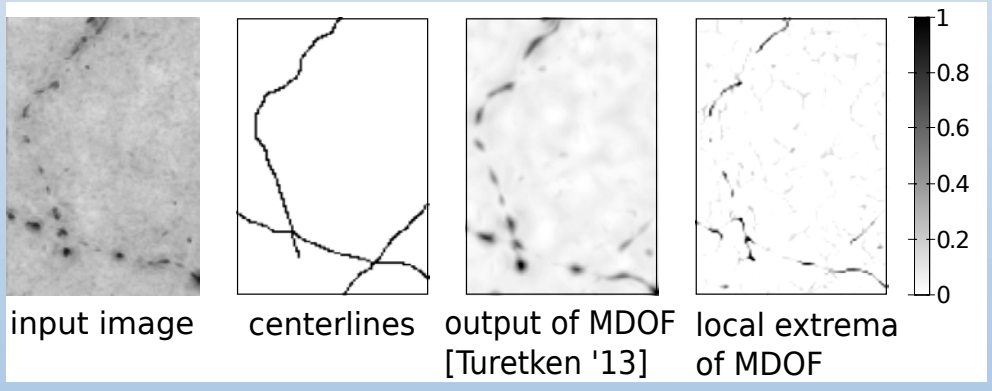
- Have a strong response at the centre of the ribbons or tubes.
- This response should be maximal at the centre and decrease away from it so that non-maximum suppression works well.
- There should ***no*** response at the tube boundaries to avoid confusing the algorithm further down the processing chain.

Oriented Flux

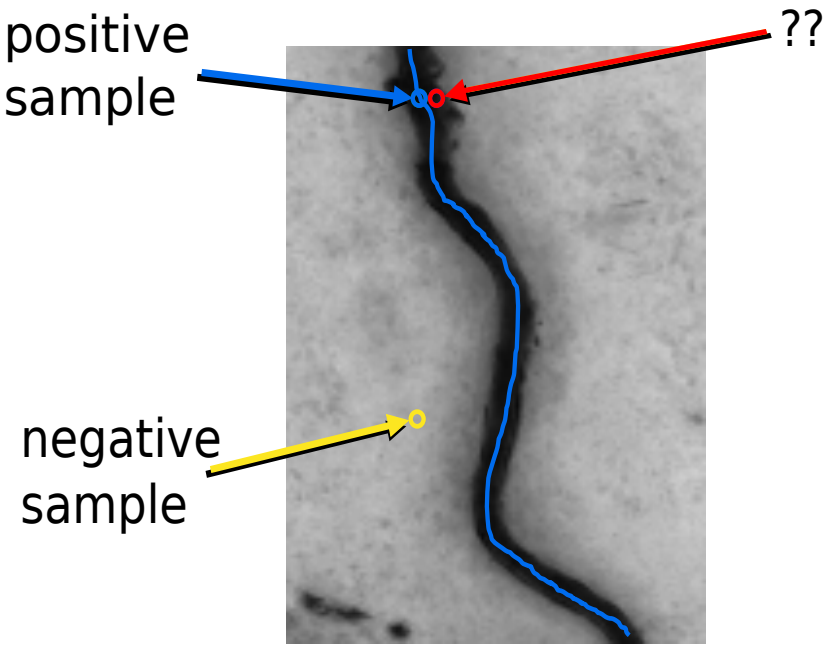
$$f(\boldsymbol{x};r,\hat{\rho}) = \frac{1}{4\pi r^2}\int_{\partial B_r}\Big((\boldsymbol{v}(\boldsymbol{x}+\boldsymbol{A})\cdot\hat{\rho})\hat{\rho}\Big)\cdot\hat{n}\,dA \qquad s(\boldsymbol{x};r,\hat{\rho}) = \frac{1}{4\pi r^2}\int_{\partial B_r}\Big(\boldsymbol{v}(\boldsymbol{x}+\boldsymbol{A})\cdot\hat{\rho}\Big)\,dA$$



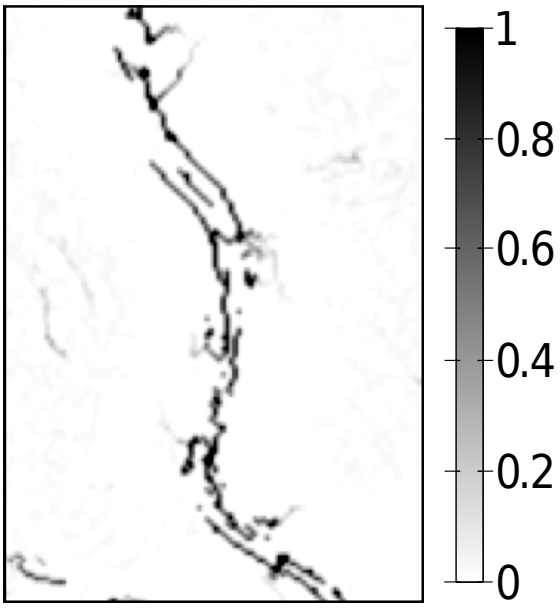
- Can be computed by convolving the images with appropriately designed filters.
- Works very well when the tubes are relatively regular but performance decreases as the irregularity increases.



Centerline Detection as a Classification Problem



Input image

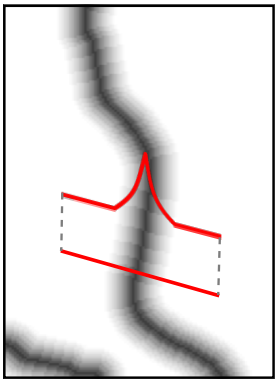


Non-maxima suppression

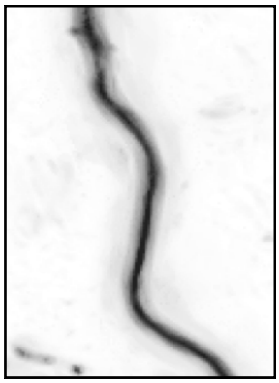
- Classification is not the right approach to deal with pixels near the centerline, i.e. hard negatives.
- What other formalism could we use?

Centerline Detection as a **Regression** Problem

Input image



Desired regressor output



Actual output

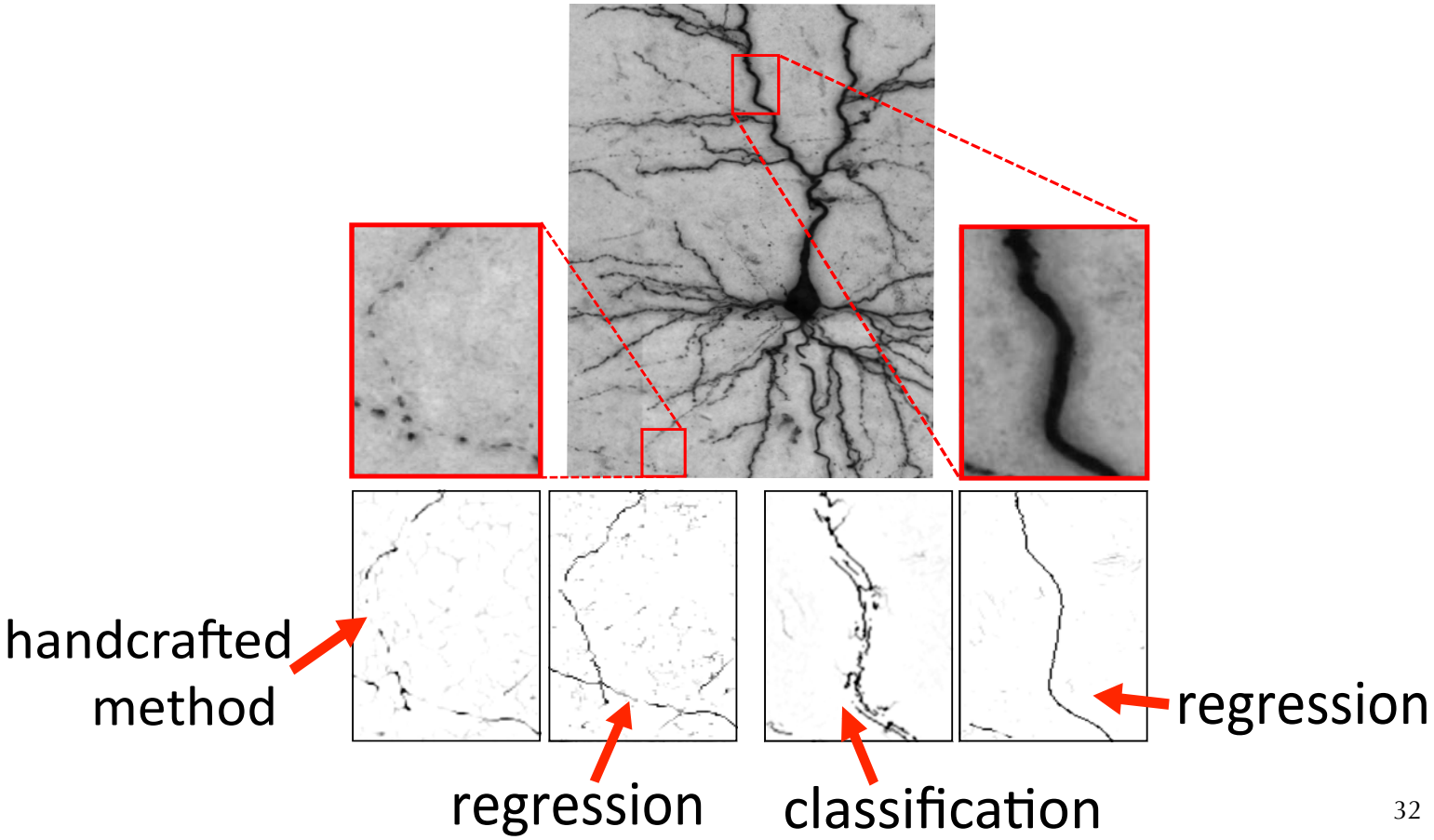
After non-maxima suppression

- Regression guarantees that non-maximum suppression will do the right thing.

Sironi, CVPR'14

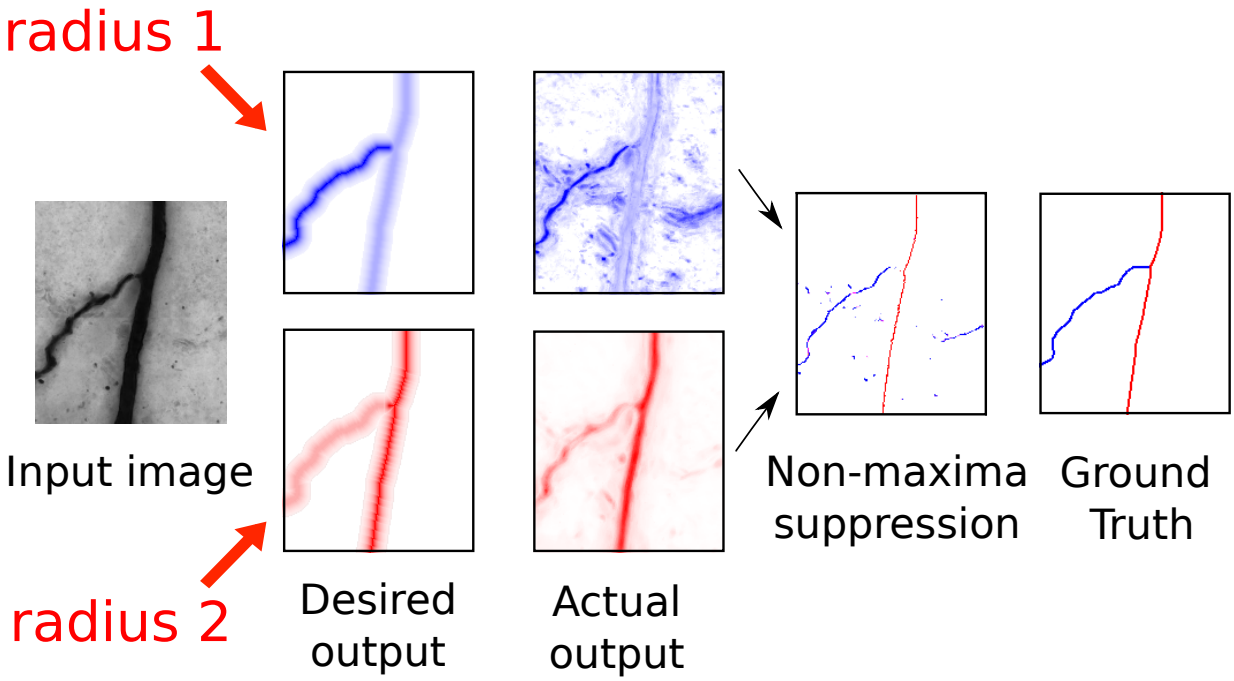
Single Scale Results

- More accurate than classification methods

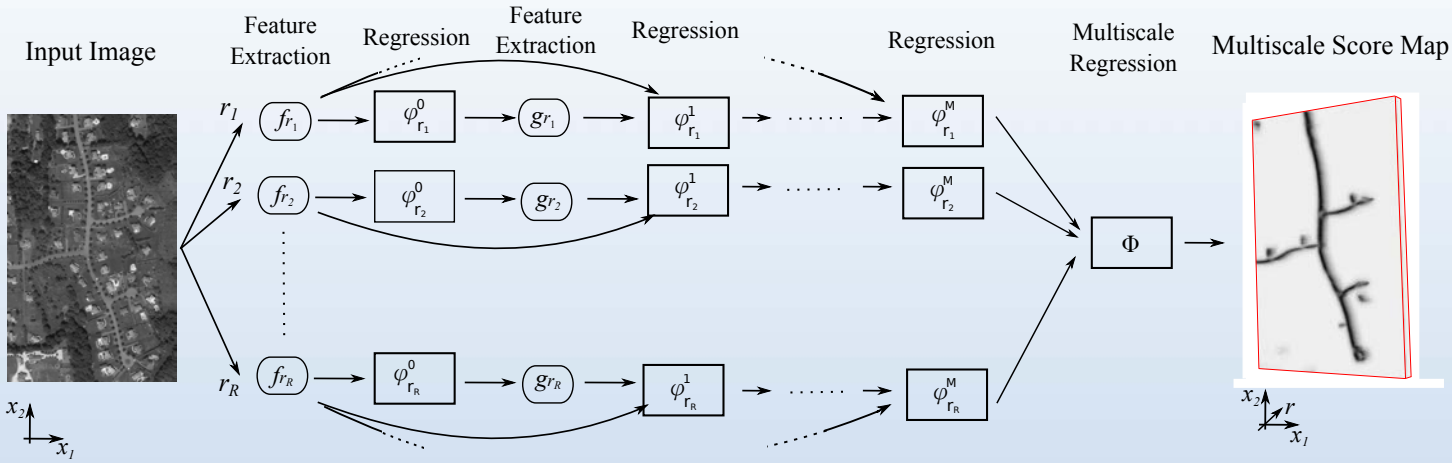


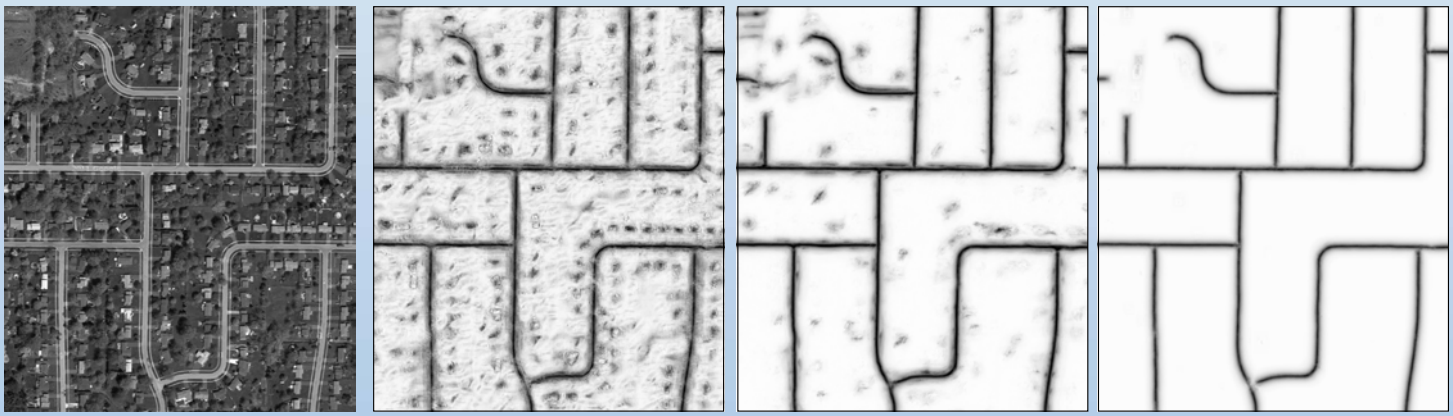
Multi Scale Results

- Multiscale detection
  $\Rightarrow$ We also estimate tubular structures radius



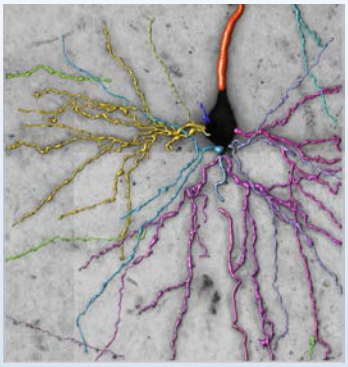
Recursive Approach



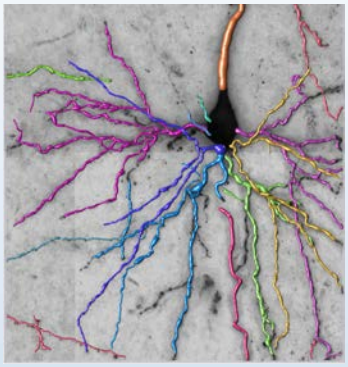


(a) Input Image I (b) Score map $\varphi^{(0)}$ (c) Score map $\varphi^{(M)}$ (d) Final approximation Φ

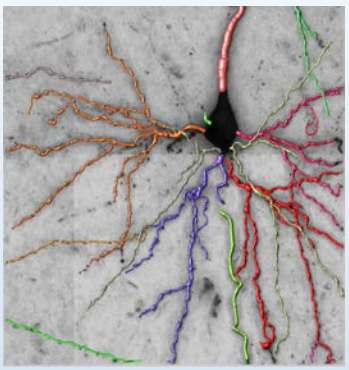
Improved Delineation



Ground Truth



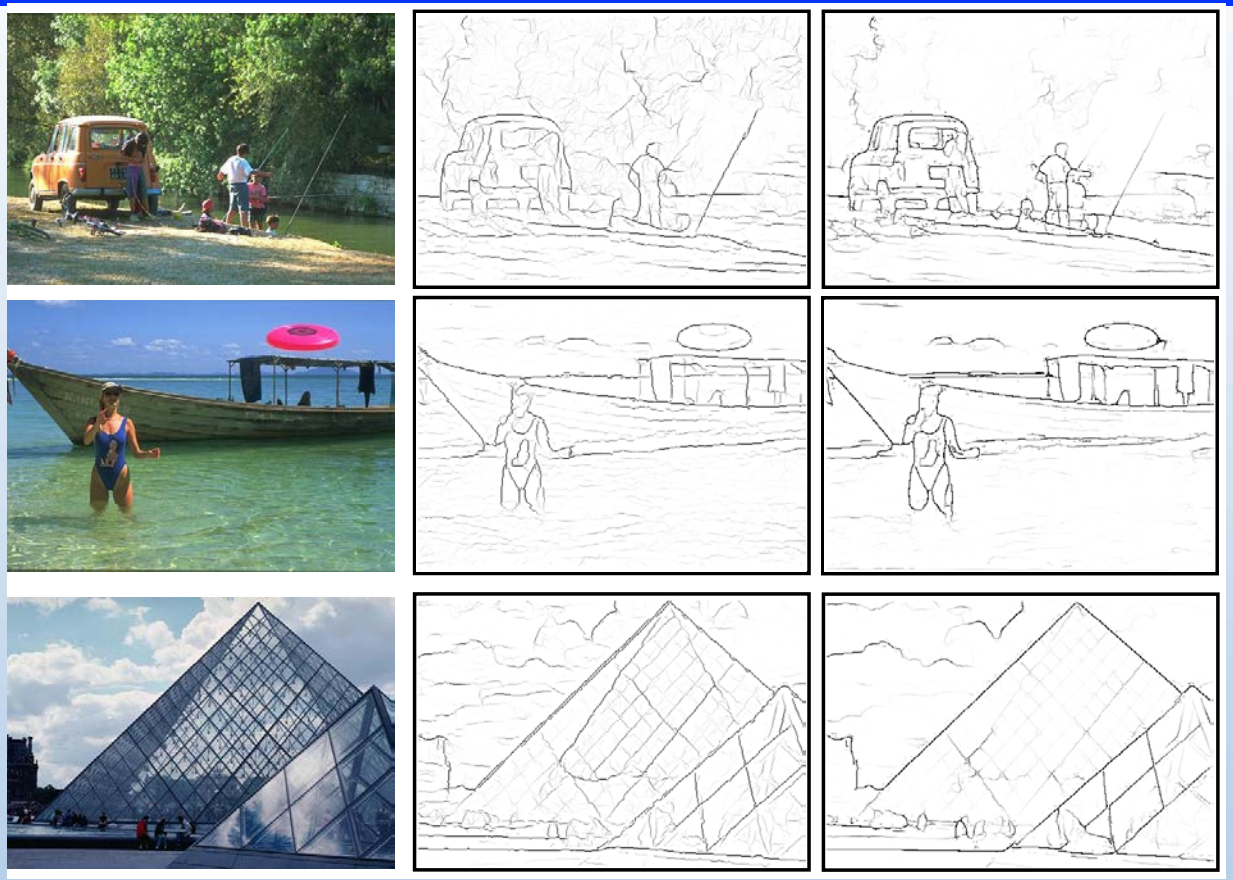
OOF



Regression

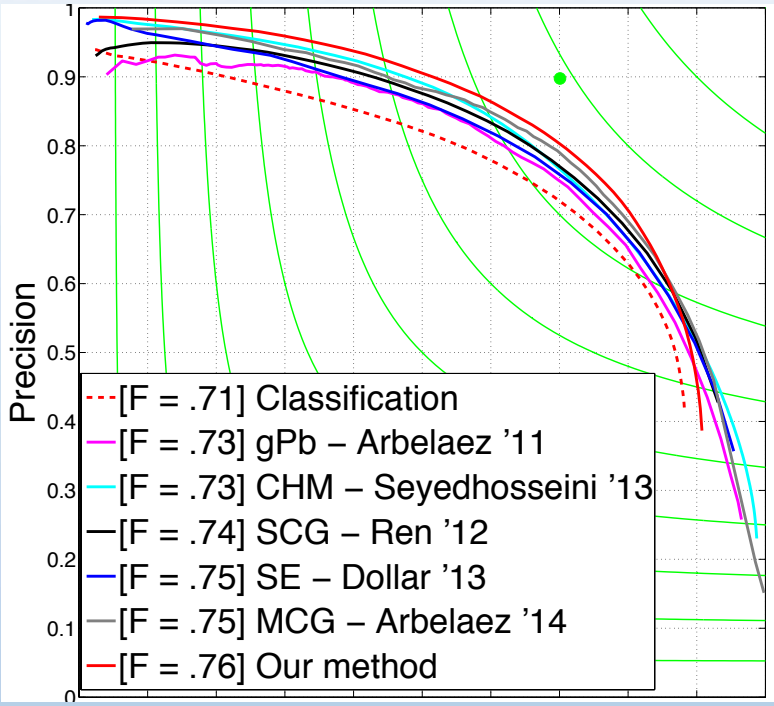
Method	Aerial	Brightfield
Loopy IP + Regression	**0.84**	**0.60**
Loopy IP + OOF	0.75	0.56

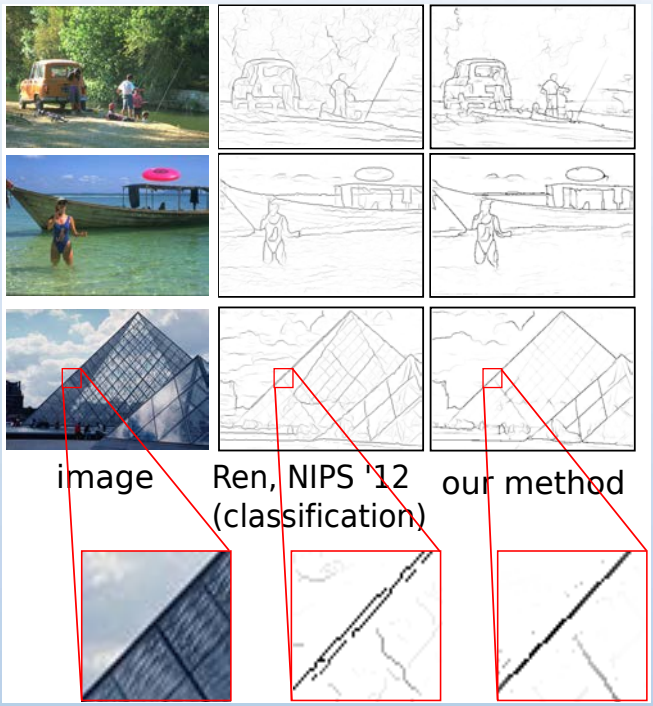
Regression for Contour Detection



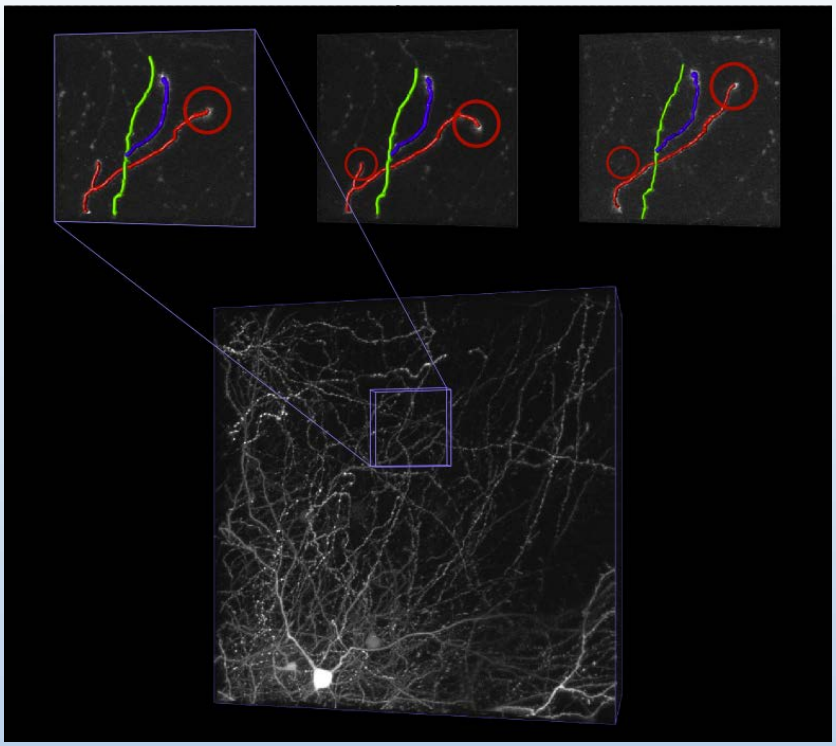
BSDS500 Dataset | Ren, NIPS'12 Classification | Our approach Regression

Regression for Contour Detection





Evolving Structures

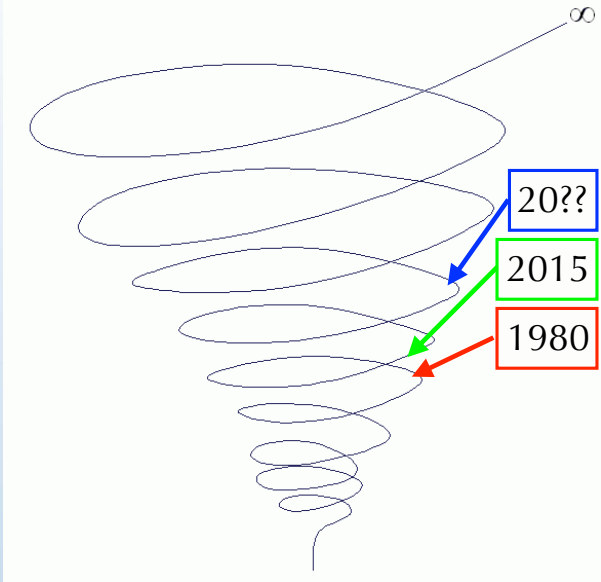


Courtesy of A. Holtmaat

- Three Two-photon image stacks taken a week apart in-vivo.
- Simultaneous reconstruction in all three stacks.

—> Automated change detection + More robust delineation.

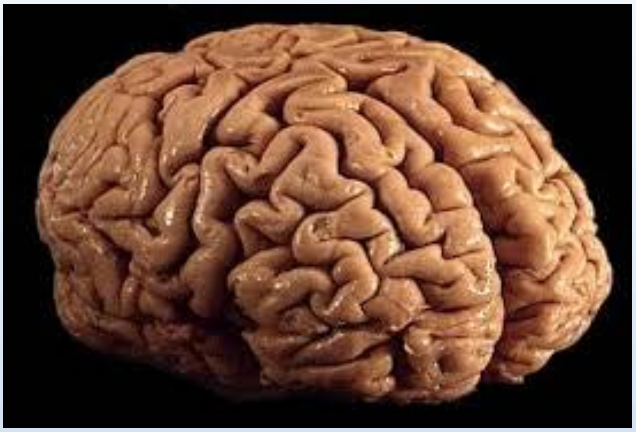
Conclusion



An automated reconstruction algorithm that

- reliably detects centerlines,
- relies on informative path classification scores,
- allows for loops and penalizes early branch terminations,
- can be optimized exactly.

Future Work



A human brain contains approximately:

- 100 billion neurons.
- 100 trillion synapses.
- Some neurons extend over several cms.

- Develop optimisation algorithms that can handle these kinds of scales.
- Incorporate much more global connectivity constraints.
- Reduce the amount of training data required using Transfer Learning.

References

Centerline and Contour Detection.

- A. Sironi, V. Lepetit and P. Fua. Multiscale Centerline Detection by Learning a Scale-Space Distance Transform. Conference on Computer Vision and Pattern Recognition (CVPR), Columbus, Ohio, USA, 2014.

- A. Sironi, E. Turetken, V. Lepetit and P. Fua. Multiscale Centerline Detection, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2015, in press.

Delineating Curvilinear Structures

- E. Turetken, F. Benmansour and P. Fua, Reconstructing Loopy Curvilinear Structures Using Integer Programming, Conference on Computer Vision and Pattern Recognition, June 2013.

- E. Türetken, F. Benmansour, B. Andres, H. Pfister and P. Fua. Reconstructing Curvilinear Networks using Path Classifiers and Integer Programming, submitted to IEEE Transactions on Pattern Analysis and Machine Intelligence, 2014.