



Geodesic Tracking via Data-Driven Geometry for Vascular Tree Tracking

GEOMETRY AND MACHINE LEARNING 2024

Nicky J. van den Berg

Collaborators: Remco Duits (promoter),
Bart Smets (TU/e), Gautam Pai (TU/e), Jean-Marie Mirebeau (Paris-Saclay)

Motivation & Background

Data-driven frame for improved vessel tracking

Results

Conclusion

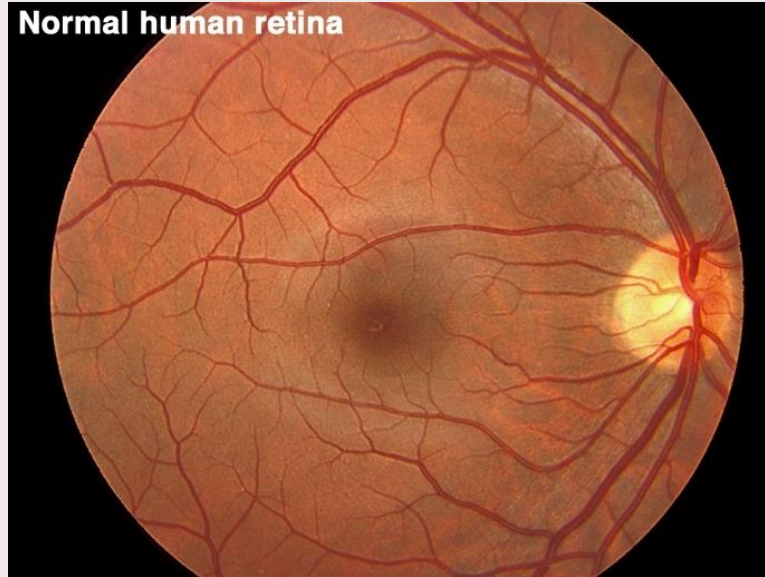
Retina Images

Retina of diabetic patient



Tortuous vessels
Hemorrhage and micro-aneurysms

Healthy retina

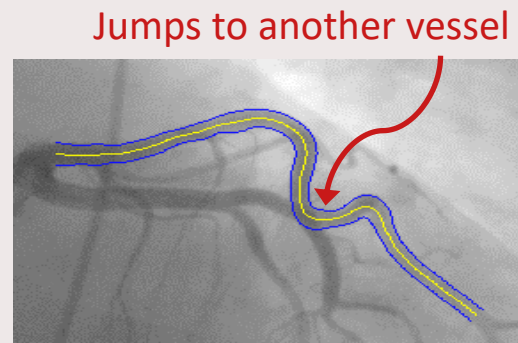


Normal human retina

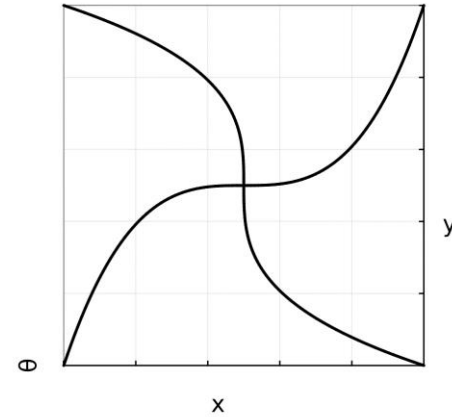
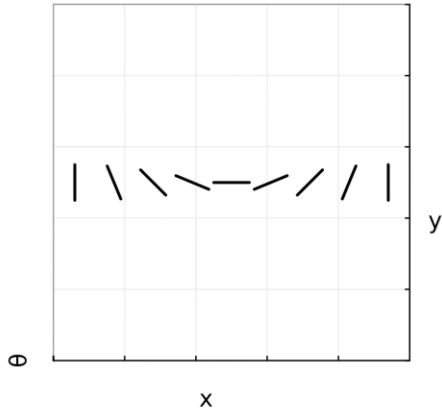
Tracking in Orientation Scores



Track vessel from one of the red arrows to the blue arrow



Tracking in Orientation Scores

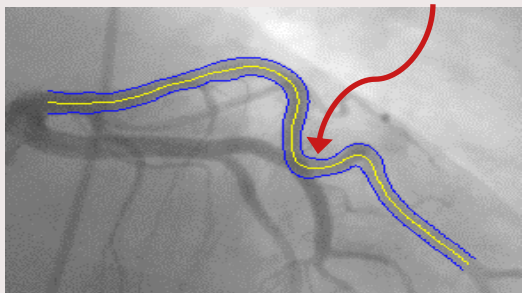


Tracking in Orientation Scores

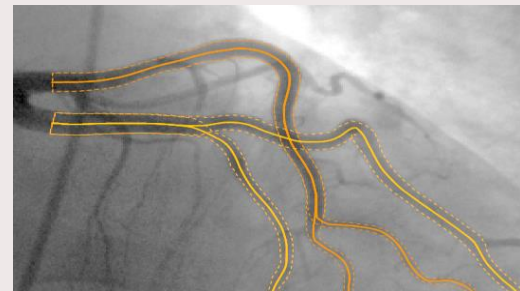
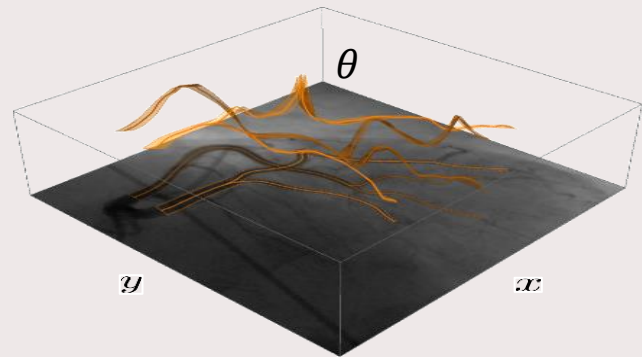


Track vessel from one of the red arrows to the blue arrow

Jumps to another vessel



1. Create a **3D image representation** based on the 2D image (in space of positions and orientations)
2. Perform **tracking** on 3D image (in orientation scores)
3. Project the tracking results onto the 2D image



Orientation Scores

Space of positions and orientations: $\mathbb{M}_2 := \mathbb{R}^2 \rtimes S^1$

where $S^1 \equiv \mathbb{R}/(2\pi\mathbb{Z})$

$(\mathbf{x}, \theta) \in \mathbb{M}_2$ where $\mathbf{x} \in \mathbb{R}^2$ and $\theta \in S^1$

Group product given by

$$(\mathbf{x}_1, R_{\theta_1}) \cdot (\mathbf{x}_2, R_{\theta_2}) = (\mathbf{x}_1 + R_{\theta_1} \mathbf{x}_2, R_{\theta_1} R_{\theta_2})$$

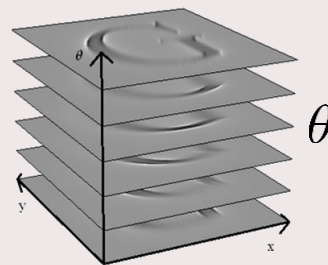


Invertible orientation score transform

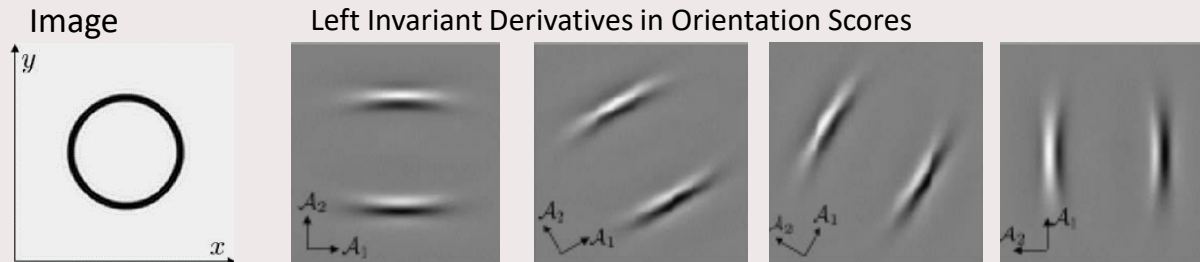
$$W_\psi f(\mathbf{x}, \theta) = \int_{\mathbb{R}^2} \overline{\psi(R_\theta^{-1}(\mathbf{y} - \mathbf{x}))} f(\mathbf{y}) d\mathbf{y}$$

Convolution with rotating and translating wavelet ψ

orientation score



Left Invariant Frame and Metric Tensor Field Model



Left invariant frame

$$\begin{cases} \mathcal{A}_1 = \cos \theta \partial_x + \sin \theta \partial_y \\ \mathcal{A}_2 = -\sin \theta \partial_x + \cos \theta \partial_y \\ \mathcal{A}_3 = \partial_\theta \end{cases}$$

Dual left invariant frame

$$\begin{cases} \omega^1 = \cos \theta dx + \sin \theta dy \\ \omega^2 = -\sin \theta dx + \cos \theta dy \\ \omega^3 = d\theta \end{cases}$$

Relation frame and its dual

$$\langle \omega^i, \mathcal{A}_j \rangle = \delta_j^i = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

Vessel Tracking

Objective: Find shortest path between point \mathbf{p}_S and \mathbf{p} in \mathbb{M}_2

Find minimizing curve γ with distance

$$d_{\mathcal{G}}(\mathbf{p}_S, \mathbf{p}) := \min_{\substack{\gamma \in \text{Lip}([0,1], \mathbb{M}_2) \\ \gamma(0) = \mathbf{p}_S \\ \gamma(1) = \mathbf{p}}} \int_0^1 \|\dot{\gamma}(t)\| dt$$

induced by metric tensor field \mathcal{G}

$$\|\dot{\gamma}(t)\|^2 = \mathcal{G}_{\gamma(t)}(\dot{\gamma}(t), \dot{\gamma}(t))$$

Vectors aligned to vessel structure have smaller norms compared to random other vectors

Computing shortest curves

1. Compute a viscosity solution U to the eikonal PDE

$$\begin{cases} \|\text{grad } U\| = 1 \\ U(\mathbf{p}_S) = 0 \end{cases}$$

U denotes the distance to the point \mathbf{p}_S

$$U(\cdot) = d_{\mathcal{G}}(\mathbf{p}_S, \cdot)$$

Computed U using Fast Marching approach

2. Compute the shortest path γ using steepest descent on U starting from end point \mathbf{p}

Wavefronts

Compute a viscosity solution U to the eikonal PDE

$$\begin{cases} \|\text{grad } U\| = 1 \\ U(\mathbf{p}_S) = 0 \end{cases}$$

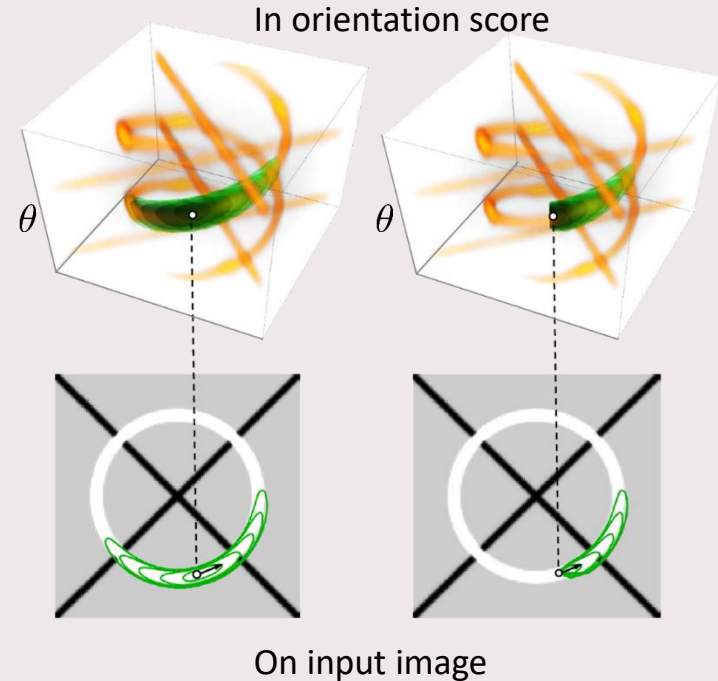
U denotes the distance to the point \mathbf{p}_S

$$U(\cdot) = d_G(\mathbf{p}_S, \cdot)$$

Interpretation: Level sets \leftrightarrow Wavefronts propagated by viscous fluid

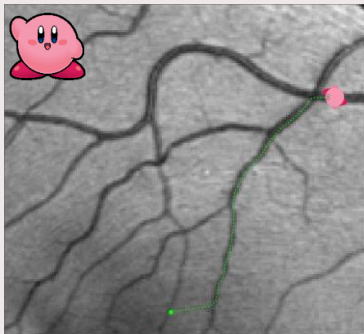
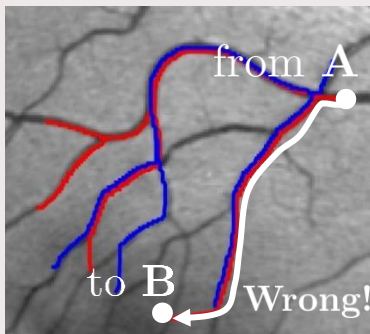
Important: wavefronts do not pass through each other!

Visualization: projected level curves by **minimizing** over orientations

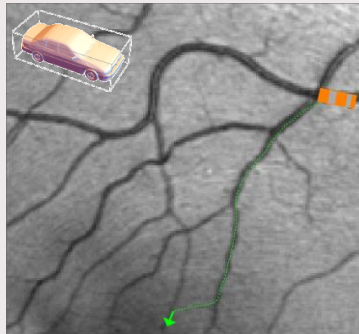
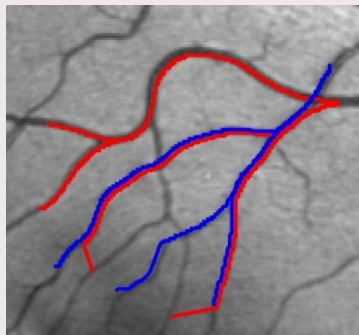


Left Invariant Metric Tensor Field Model

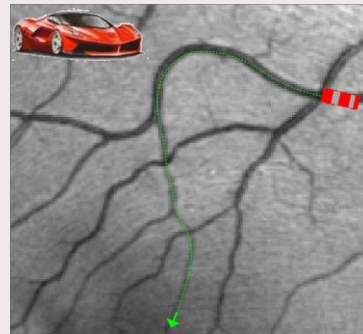
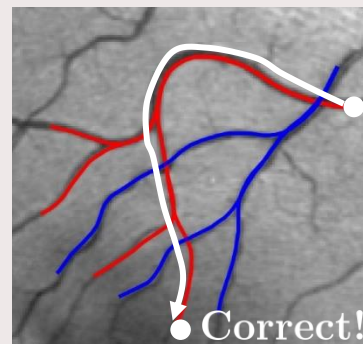
Standard Riemannian
shortest paths in \mathbb{R}^2



Riemannian (Isotropic)
shortest paths in $SE(2)$

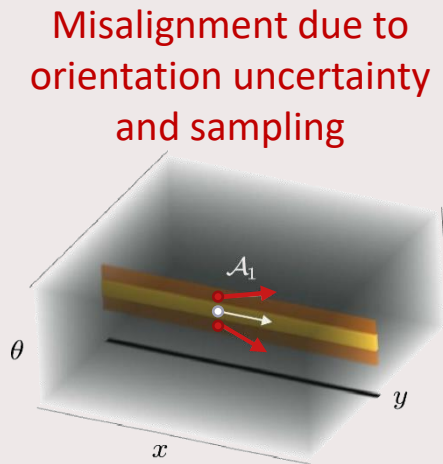


Sub-Riemannian shortest
paths in $SE(2)$



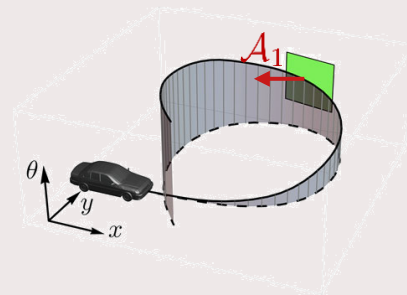
Orientation Scores and Left Invariant Frame

No perfect alignment of \mathcal{A}_1 and line structure



Possibly steering in wrong direction

Curvature

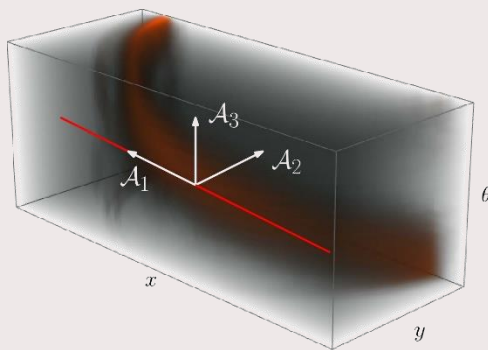


Only spatial alignment

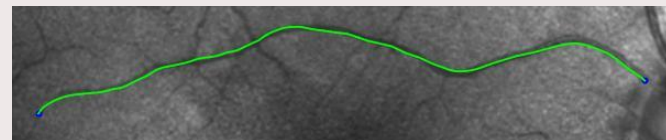
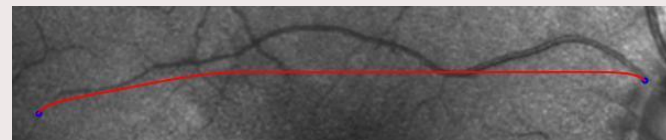
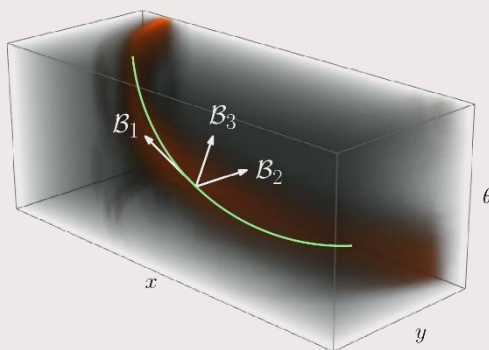
Solution to Short-Comings: New Geometrical Model

- Old model: diagonal with left invariant frame
- New model: **not** diagonal with left invariant frame
 - Metric tensor field locally aligned with lifted blood vessel
 - Also known as **Data-Driven Left Invariant Frame**
 - Fitted to image data

Left invariant frame



Data-driven left invariant frame



Motivation & Background

Data-driven frame for improved vessel tracking

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Equivariance

Metric tensor field is data-driven left invariant if

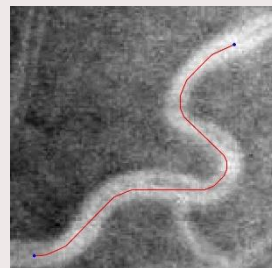
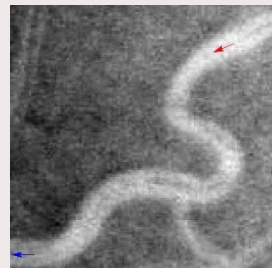
roto-translation of the input image

yields

geodesics that are rotated and translated accordingly.

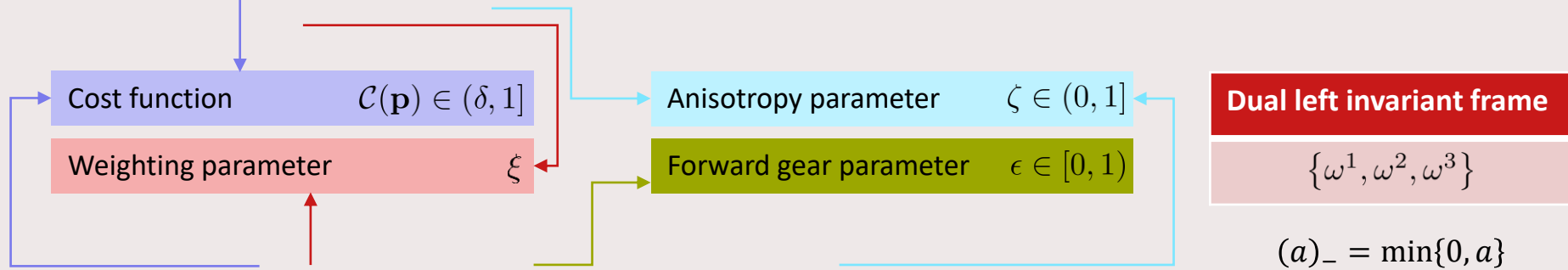
In other words:

$$\mathcal{G}_{\mathbf{p}}^U(\dot{\mathbf{p}}, \dot{\mathbf{p}}) = \mathcal{G}_{g\mathbf{p}}^{\mathcal{L}_g^U}((L_g)_*\dot{\mathbf{p}}, (L_g)_*\dot{\mathbf{p}})$$



Metric Tensor Fields

$$\mathcal{G}_{\mathbf{p}}(\dot{\mathbf{p}}, \dot{\mathbf{p}}) = \mathcal{C}^2 \left(\xi^2 (\omega^1 \otimes \omega^1 + \zeta^{-2} \omega^2 \otimes \omega^2) + \omega^3 \otimes \omega^3 \right) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$



$$\mathcal{F}(\mathbf{p}, \dot{\mathbf{p}})^2 = \mathcal{C}^2 \left(\xi^2 \left(\omega^1 \otimes \omega^1 + (\epsilon^{-2} - 1) (\omega^1 \otimes \omega^1)_- + \zeta^{-2} \omega^2 \otimes \omega^2 \right) + \omega^3 \otimes \omega^3 \right) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

$$(a)_- = \min\{0, a\}$$

Metric Tensor Fields

$$\mathcal{G}_{\mathbf{p}}(\dot{\mathbf{p}}, \dot{\mathbf{p}}) = \mathcal{C}^2 \left(\xi^2 (\omega^1 \otimes \omega^1 + \zeta^{-2} \omega^2 \otimes \omega^2) + \omega^3 \otimes \omega^3 \right) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

Dual left invariant frame

$$\{\omega^1, \omega^2, \omega^3\}$$

$$\mathcal{F}(\mathbf{p}, \dot{\mathbf{p}})^2 = \mathcal{C}^2 \left(\xi^2 (\omega^1 \otimes \omega^1 + (\epsilon^{-2} - 1) (\omega^1 \otimes \omega^1)_- + \zeta^{-2} \omega^2 \otimes \omega^2) + \omega^3 \otimes \omega^3 \right) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

$$(a)_- = \min\{0, a\}$$

$$\mathcal{G}_{\mathbf{p}}^U(\dot{\mathbf{p}}, \dot{\mathbf{p}}) = \mathcal{G}_{\mathbf{p}}(\dot{\mathbf{p}}, \dot{\mathbf{p}}) + \mathcal{C}^2 \lambda \frac{\|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{p}})\|_*^2}{\max_{\dot{\mathbf{q}}} \|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{q}})\|_*^2} = \mathcal{C}^2 (a_1 \omega_U^1 \otimes \omega_U^1 + a_2 \omega_U^2 \otimes \omega_U^2 + a_3 \omega_U^3 \otimes \omega_U^3) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

Cost function

$$\mathcal{C}(\mathbf{p}) \in (\delta, 1]$$

Curvature parameter

$$\lambda \in (0, \infty)$$

Dual data-driven frame

$$\{\omega_U^1, \omega_U^2, \omega_U^3\}$$

$$|\mathcal{F}^U(\mathbf{p}, \dot{\mathbf{p}})|^2 = |\mathcal{F}(\mathbf{p}, \dot{\mathbf{p}})|^2 + \mathcal{C}^2 \lambda \frac{\|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{p}})\|_*^2}{\max_{\dot{\mathbf{q}}} \|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{q}})\|_*^2}$$

Metric Tensor Fields

$$\mathcal{G}_{\mathbf{p}}(\dot{\mathbf{p}}, \dot{\mathbf{p}}) = \mathcal{C}^2 \left(\xi^2 (\omega^1 \otimes \omega^1 + \zeta^{-2} \omega^2 \otimes \omega^2) + \omega^3 \otimes \omega^3 \right) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

Dual left invariant frame

$$\{\omega^1, \omega^2, \omega^3\}$$

$$\mathcal{F}(\mathbf{p}, \dot{\mathbf{p}})^2 = \mathcal{C}^2 \left(\xi^2 (\omega^1 \otimes \omega^1 + (\epsilon^{-2} - 1) (\omega^1 \otimes \omega^1)_- + \zeta^{-2} \omega^2 \otimes \omega^2) + \omega^3 \otimes \omega^3 \right) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

$$(a)_- = \min\{0, a\}$$

$$\mathcal{G}_{\mathbf{p}}^U(\dot{\mathbf{p}}, \dot{\mathbf{p}}) = \mathcal{G}_{\mathbf{p}}(\dot{\mathbf{p}}, \dot{\mathbf{p}}) + \mathcal{C}^2 \lambda \frac{\|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{p}})\|_*^2}{\max_{\dot{\mathbf{q}}} \|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{q}})\|_*^2} = \mathcal{C}^2 (a_1 \omega_U^1 \otimes \omega_U^1 + a_2 \omega_U^2 \otimes \omega_U^2 + a_3 \omega_U^3 \otimes \omega_U^3) (\dot{\mathbf{p}}, \dot{\mathbf{p}})$$

Dual data-driven frame

$$\{\omega_U^1, \omega_U^2, \omega_U^3\}$$

$$|\mathcal{F}^U(\mathbf{p}, \dot{\mathbf{p}})|^2 = |\mathcal{F}(\mathbf{p}, \dot{\mathbf{p}})|^2 + \mathcal{C}^2 \lambda \frac{\|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{p}})\|_*^2}{\max_{\dot{\mathbf{q}}} \|HU|_{\mathbf{p}}(\cdot, \dot{\mathbf{q}})\|_*^2}$$

Straight vs. short curves for Left Invariant Framework

Left Invariant

Frame

$$\{\mathcal{A}_1, \mathcal{A}_2, \mathcal{A}_3\}$$

with dual

$$\{\omega^1, \omega^2, \omega^3\}$$

Connection:

$$\nabla^{[+]} = \sum_{i,k=1}^3 \left(\omega^i \otimes (\mathcal{A}_i \circ \omega^k) + \sum_{j=1}^3 (\omega^i \otimes \omega^j) c_{ij}^k \right) \mathcal{A}_k$$

Straight curves – parallel velocity

$$\nabla_{\dot{\gamma}} \dot{\gamma} = 0$$

Short curves – parallel momentum

$$\begin{cases} (\nabla)_{\dot{\gamma}}^* \lambda = 0 \\ \mathcal{G} \dot{\gamma} = \lambda \end{cases}$$

Straight vs. short curves for Data-Driven Left Invariant Framework

Left Invariant

Frame

$$\{\mathcal{A}_1, \mathcal{A}_2, \mathcal{A}_3\}$$

with dual

$$\{\omega^1, \omega^2, \omega^3\}$$

Connection:

$$\nabla^{[+]} = \sum_{i,k=1}^3 \left(\omega^i \otimes (\mathcal{A}_i \circ \omega^k) + \sum_{j=1}^3 (\omega^i \otimes \omega^j) c_{ij}^k \right) \mathcal{A}_k$$

Straight curves – parallel velocity

$$\nabla_{\dot{\gamma}} \dot{\gamma} = 0$$

Data-Driven Left Invariant

Frame

$$\{\mathcal{A}_1^U, \mathcal{A}_2^U, \mathcal{A}_3^U\}$$

with dual

$$\{\omega_U^1, \omega_U^2, \omega_U^3\}$$

Connection:

$$[\mathcal{A}_i^U, \mathcal{A}_j^U] = \tilde{c}_{ij}^k(\cdot) \mathcal{A}_k^U$$

$$\nabla^U = \sum_{i,k=1}^3 \left(\omega_U^i \otimes (\mathcal{A}_i^U \circ \omega_U^k) + \sum_{j=1}^3 (\omega_U^i \otimes \omega_U^j) \tilde{c}_{ij}^k \right) \mathcal{A}_k^U$$

Short curves – parallel momentum

$$\begin{cases} (\nabla)_{\dot{\gamma}}^* \lambda = 0 \\ \mathcal{G} \dot{\gamma} = \lambda \end{cases}$$

New theorem

Calculating Geodesics via Steepest Descent on the Distance Map

Theorem 1 *The shortest curve $\gamma : [0, 1] \rightarrow \mathbb{M}_2$ with $\gamma(0) = \mathbf{p}$ and $\gamma(1) = \mathbf{p}_0$ can be computed by steepest descent tracking on distance map $W(\mathbf{p}) = d_{\mathcal{F}^U}(\mathbf{p}, \mathbf{p}_0)$*

$$\gamma(t) := \gamma_{\mathbf{p}, \mathbf{p}_0}^U(t) = \text{Exp}_{\mathbf{p}}(t v(W)), \quad t \in [0, 1], \quad (1)$$

where Exp integrates the following vector field on \mathbb{M}_2 : $v(W) := -W(\mathbf{p}) \nabla_{\mathcal{F}^U} W$ and where W is the viscosity solution of the eikonal PDE system

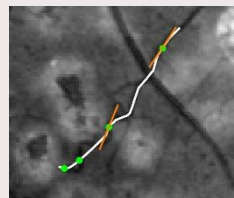
$$\begin{cases} \mathcal{F}_U^*(\mathbf{p}, dW(\mathbf{p})) = 1 & \mathbf{p} \in \mathbb{M}_2, \\ W(\mathbf{p}_0) = 0, \end{cases} \quad (2)$$

assuming \mathbf{p} is neither a 1st Maxwell-point nor a conjugate point, with dual Finsler function $\mathcal{F}_U^*(\mathbf{p}, \hat{\mathbf{p}}) := \max\{\langle \hat{\mathbf{p}}, \dot{\mathbf{p}} \rangle \mid \dot{\mathbf{p}} \in T_{\mathbf{p}}(\mathbb{M}_2) \text{ with } \mathcal{F}^U(\mathbf{p}, \dot{\mathbf{p}}) \leq 1\}$. As $v(W)$ is data-driven left invariant, the geodesics carry the symmetry

$$\gamma_{g \cdot \mathbf{p}, g \cdot \mathbf{p}_0}^{\mathcal{L}_g U}(t) = g \gamma_{\mathbf{p}, \mathbf{p}_0}^U(t) \text{ for all } g \in SE(2), \mathbf{p}, \mathbf{p}_0 \in \mathbb{M}_2, t \in [0, 1]. \quad (3)$$

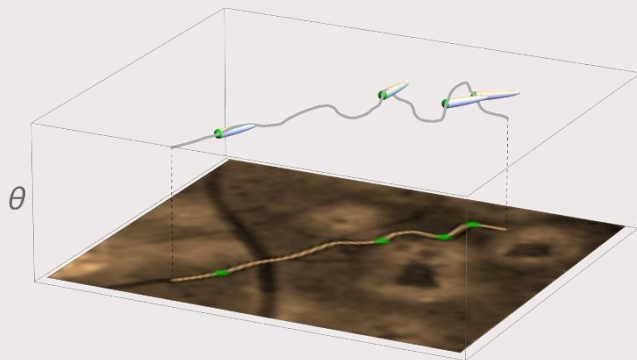
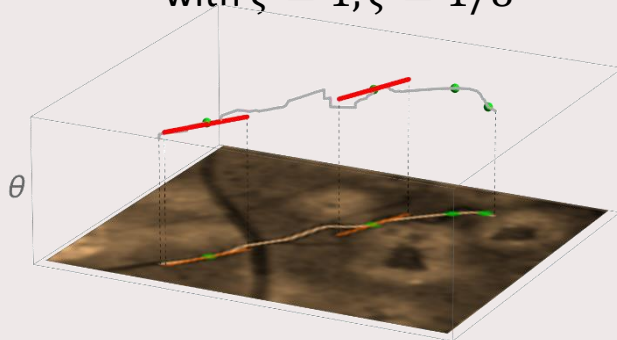
New theorem

Straight vs. short curves



Exponential curves
– Straight lines

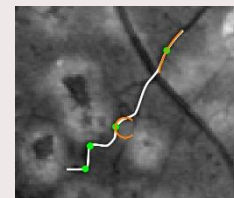
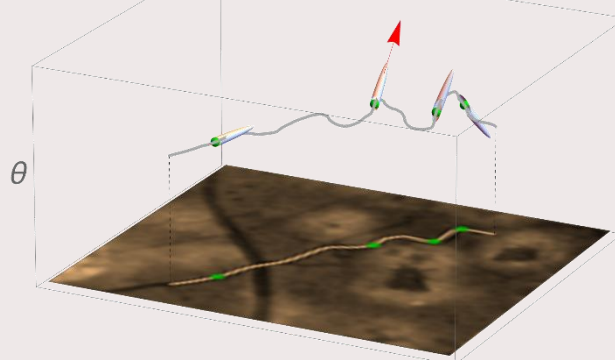
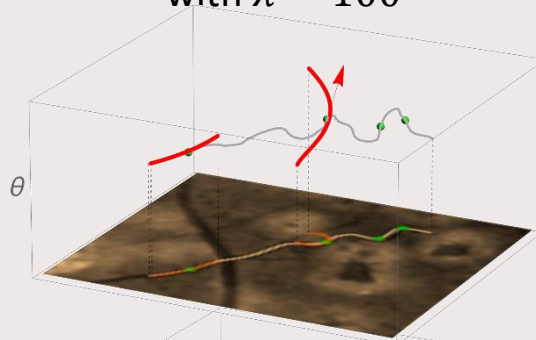
Left invariant frame
with $\xi = 1, \zeta = 1/8$



Control sets

$$B_G(\mathbf{p}) \\ = \{ \dot{\mathbf{p}} \in T_{\mathbf{p}}(\mathbb{M}_2) \mid \\ \mathcal{G}_{\mathbf{p}}(\dot{\mathbf{p}}, \dot{\mathbf{p}}) \leq 1 \}$$

Data-driven left invariant frame
with $\lambda = 100$

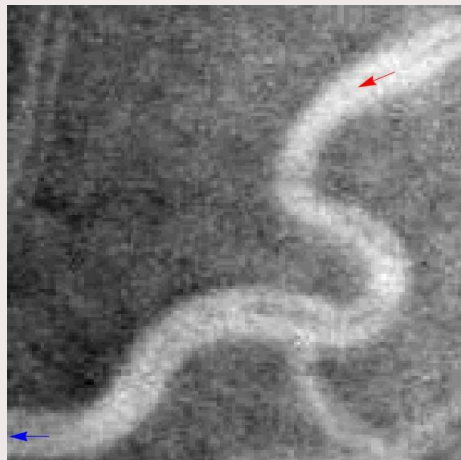


Motivation & Background

Data-driven frame for improved vessel tracking

Results

Conclusion

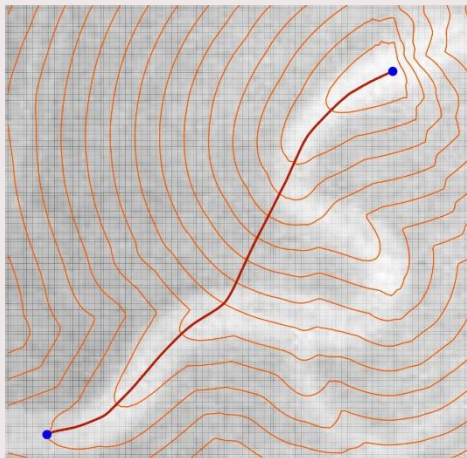


Experimental Setting:
Track from red to blue arrow

Influence Data-Driven Left Invariant Frame

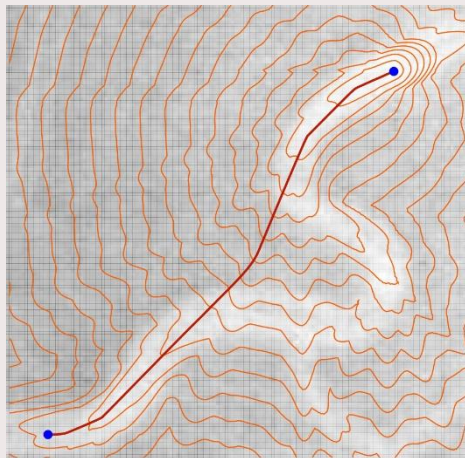
$N_\theta = 16$

Isotropic left invariant
frame, $\zeta = 1$



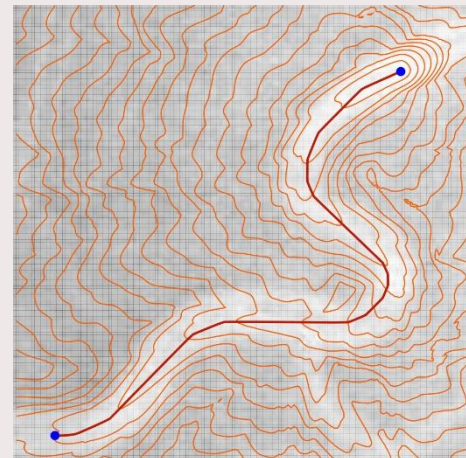
Wavefronts do not follow
vessel structure

Anisotropic left invariant
frame, $\zeta = 0.125$



Wavefronts do not follow
vessel structure

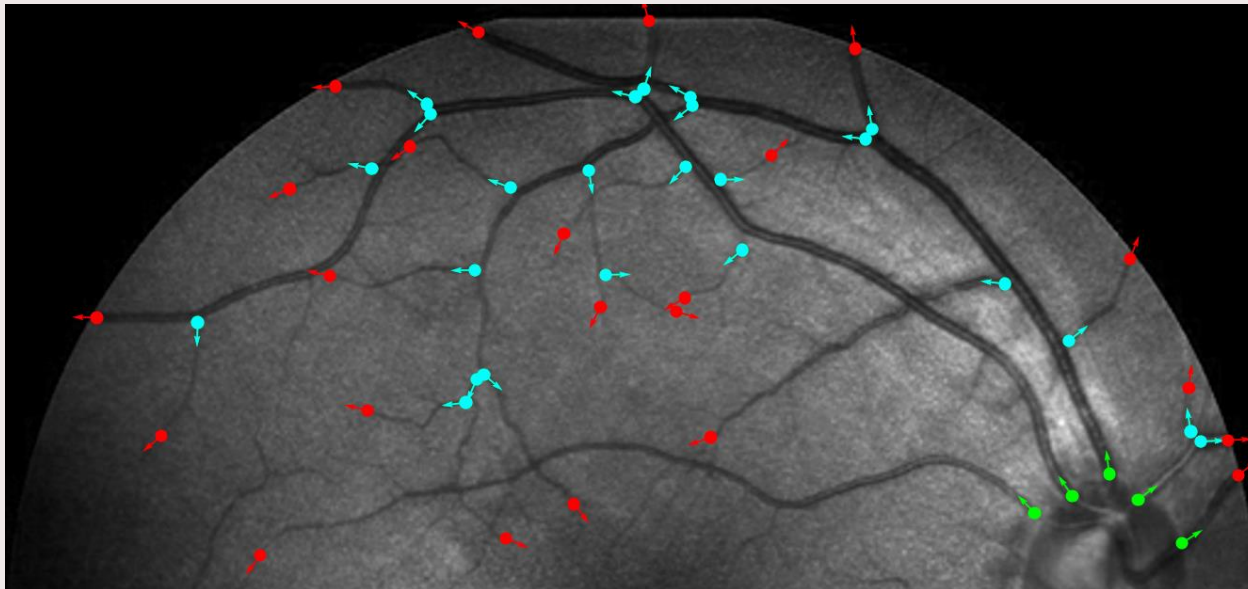
Data-driven left invariant
frame, $\zeta = 0.125, \lambda = 100$



Wavefronts follow vessel
structure

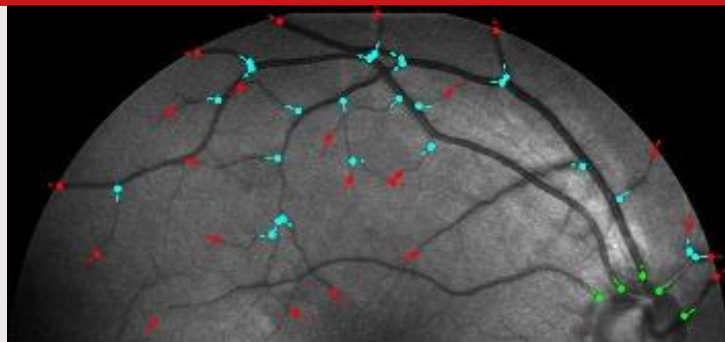


Tracking Vessels in Vessel Tree



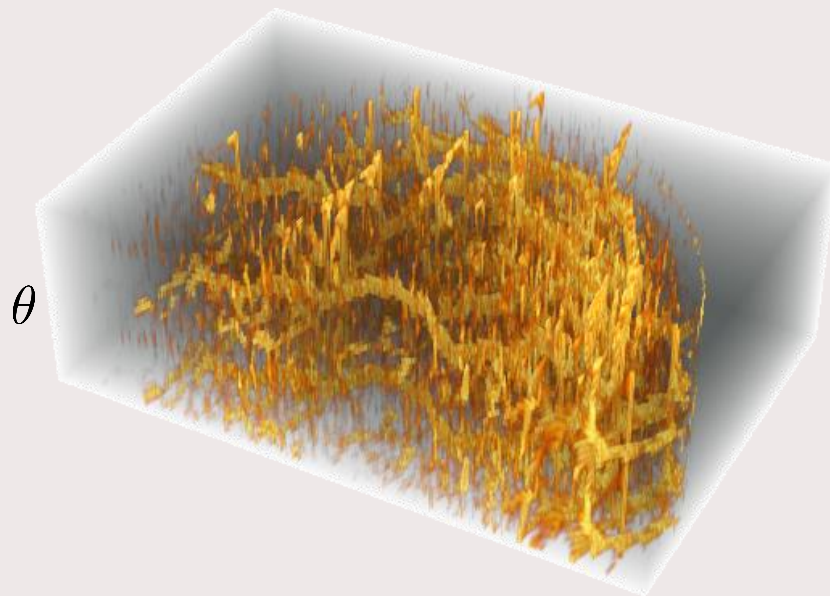
Experimental setting

Tracking Vessels in Vessel Tree in Two Steps

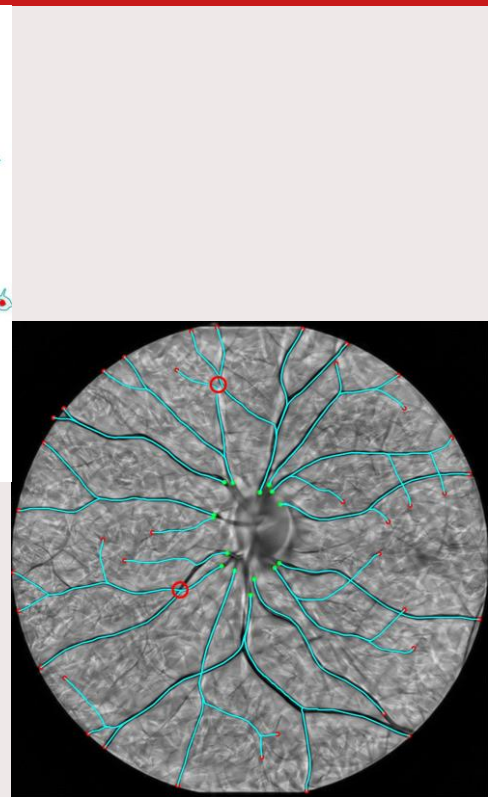
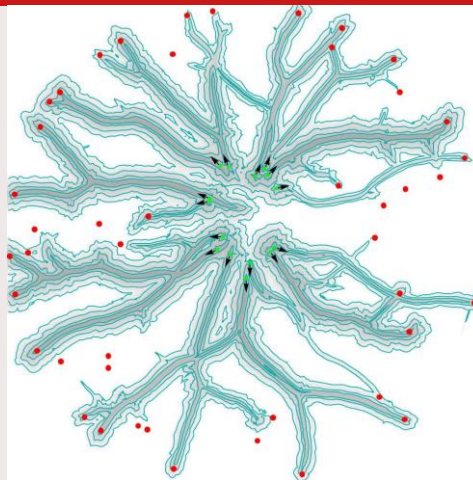
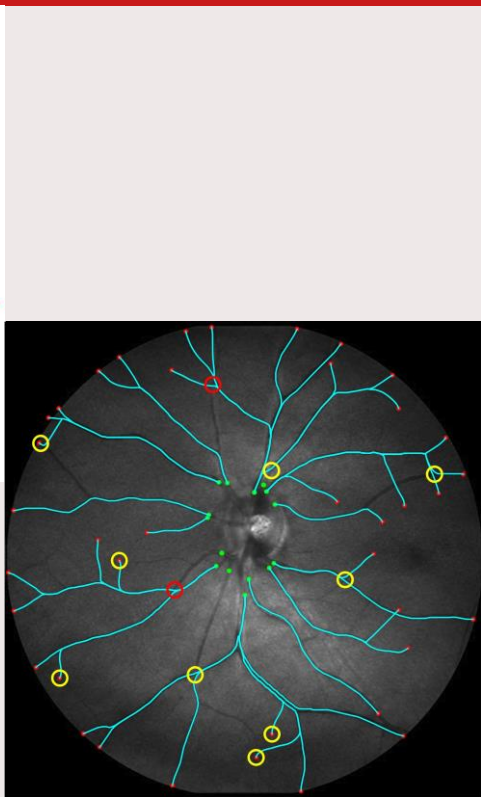
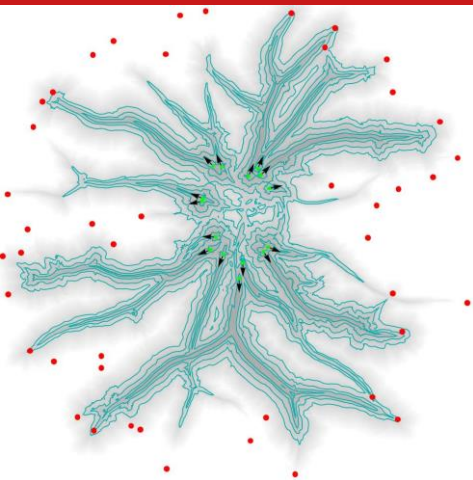


Projection
cost function

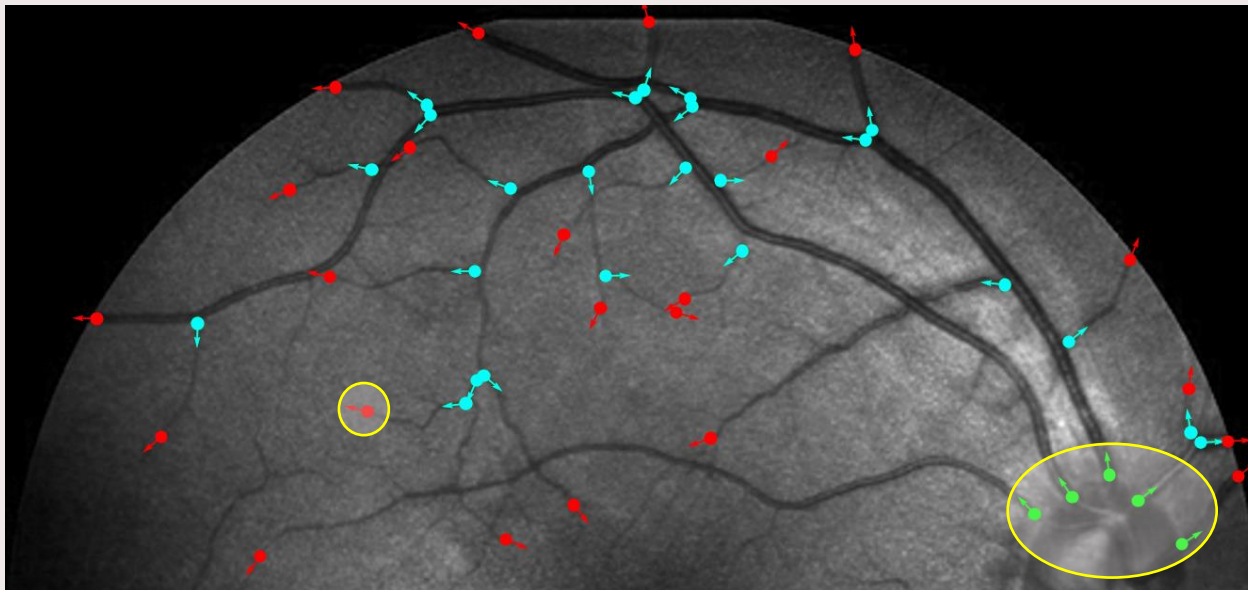
3D visualization
cost function



Geodesics Tracking of Vascular Trees

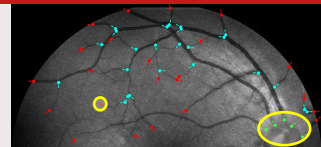


Tracking Vessels in Vessel Tree

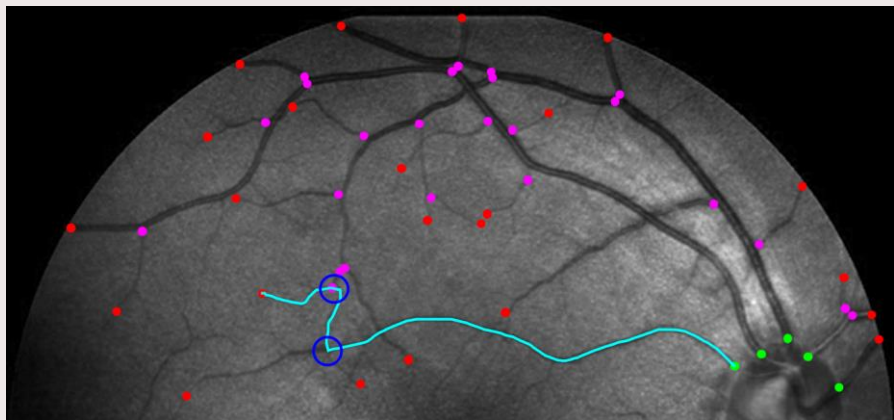


Experimental setting

Tracking Vessels in Vessel Tree

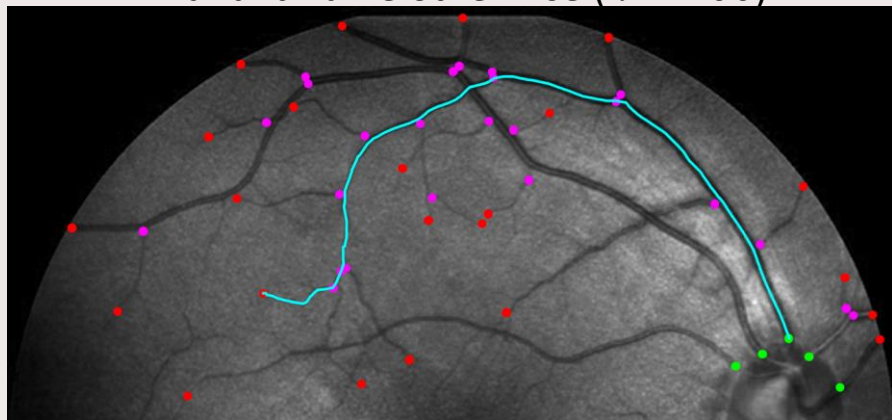


Data-driven left invariant frame
 $\lambda = 100$



Occasionally runs into trouble at crossings

Solution: Mixed data-driven left invariant frame:
Left invariant frame at crossings, data-driven left
invariant frame otherwise ($\lambda = 100$)



Shows correct behavior at crossings

Motivation & Background

Data-driven frame for improved vessel tracking

Results

Conclusion

Conclusion

- Model corresponding with the data-driven frame, relying on data-driven Cartan connection
 1. Better adaptation for curvature
- Theorem:
 1. Geodesics (parallel momentum w.r.t data-driven Cartan-connection) can still be found with steepest descent
 2. Geodesics have appropriate equivariant behavior
- Tracking of complete vascular tree from a single distance map gives good results

A contour plot with a grid background. The plot features several nested, irregular orange contour lines. A thick green line, representing a geodesic path, starts from the bottom left, moves horizontally to the right, and then curves upwards and to the right, ending near the top right corner of the plot area.

Geodesic Tracking via Data-Driven Geometry for Vascular Tree Tracking

GEOMETRY AND MACHINE LEARNING 2024

Nicky J. van den Berg

Collaborators: Remco Duits (promoter),
Bart Smets (TU/e), Gautam Pai (TU/e), Jean-Marie Mirebeau (Paris-Saclay)