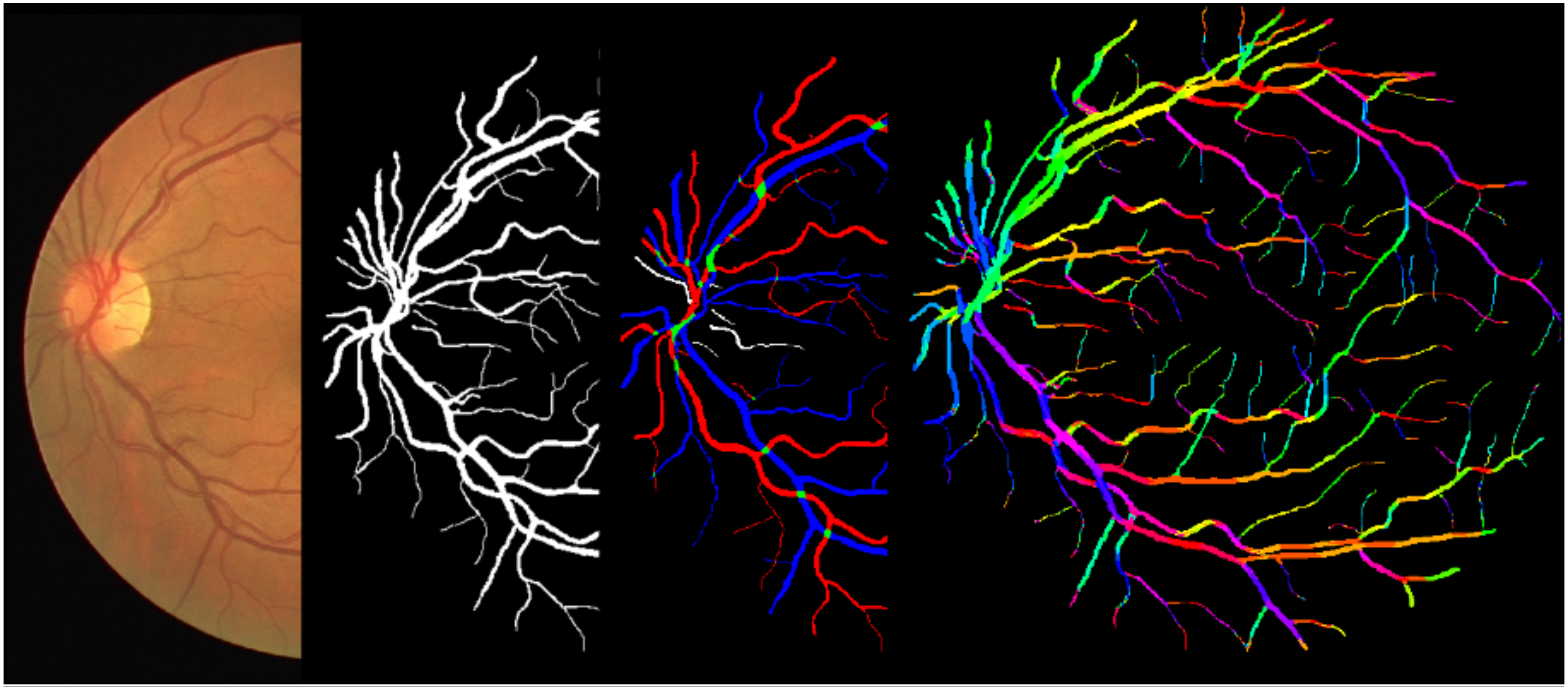


MAnET Meeting, Helsinki, 8-9 Dec. 2015

Automated Analysis of Retinal Images for Early Diabetes Detection with Sub-Riemannian Methods

Samaneh Abbasi-Sureshjani, Prof. Bart ter Haar Romeny

RetinaCheck-MAnET Project, Eindhoven University of Technology

TU/e Technische Universiteit Eindhoven University of Technology

Where innovation starts

RetinaCheck 眼科检查

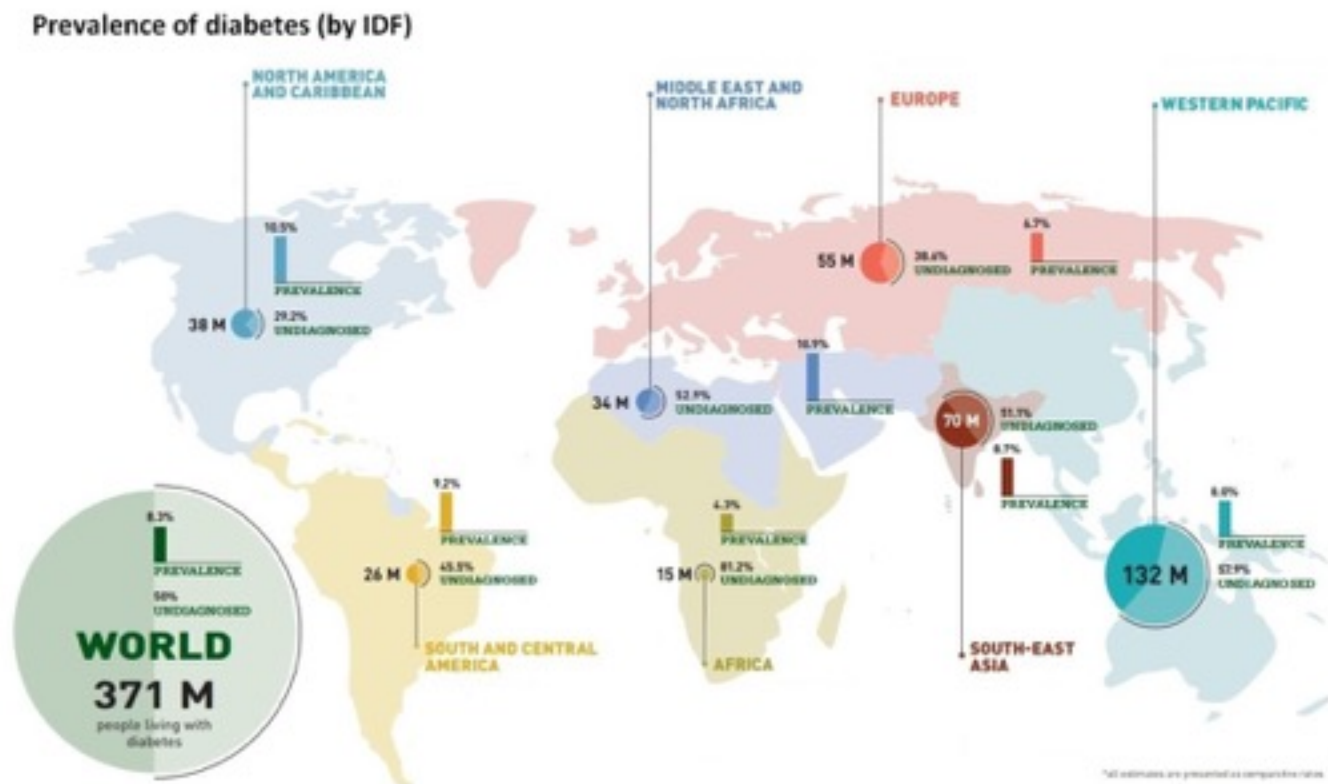
MAnET

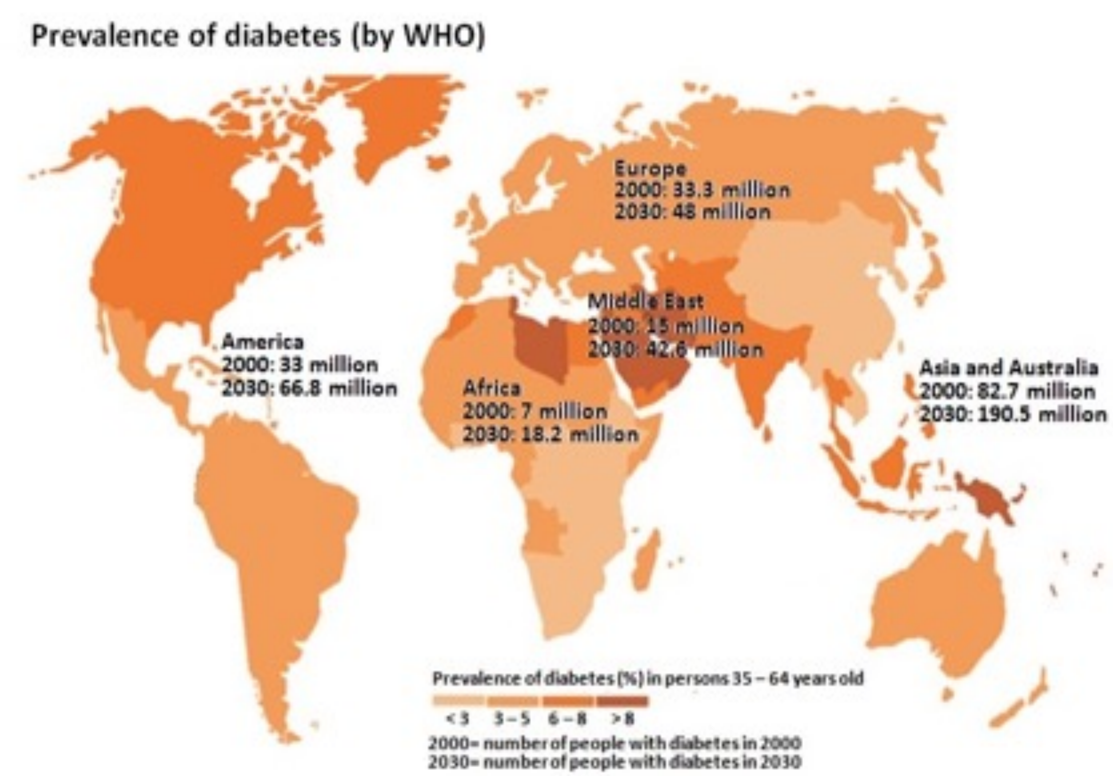
Outline

- Clinical background
- Difficulties in vessel delineation
- Orientation Score
- Vessel segmentation: BIMSO
- Junction detection: BICROS
- Connectivity kernels
- Junction resolution
- Conclusion
- Q & A

Diabetes worldwide

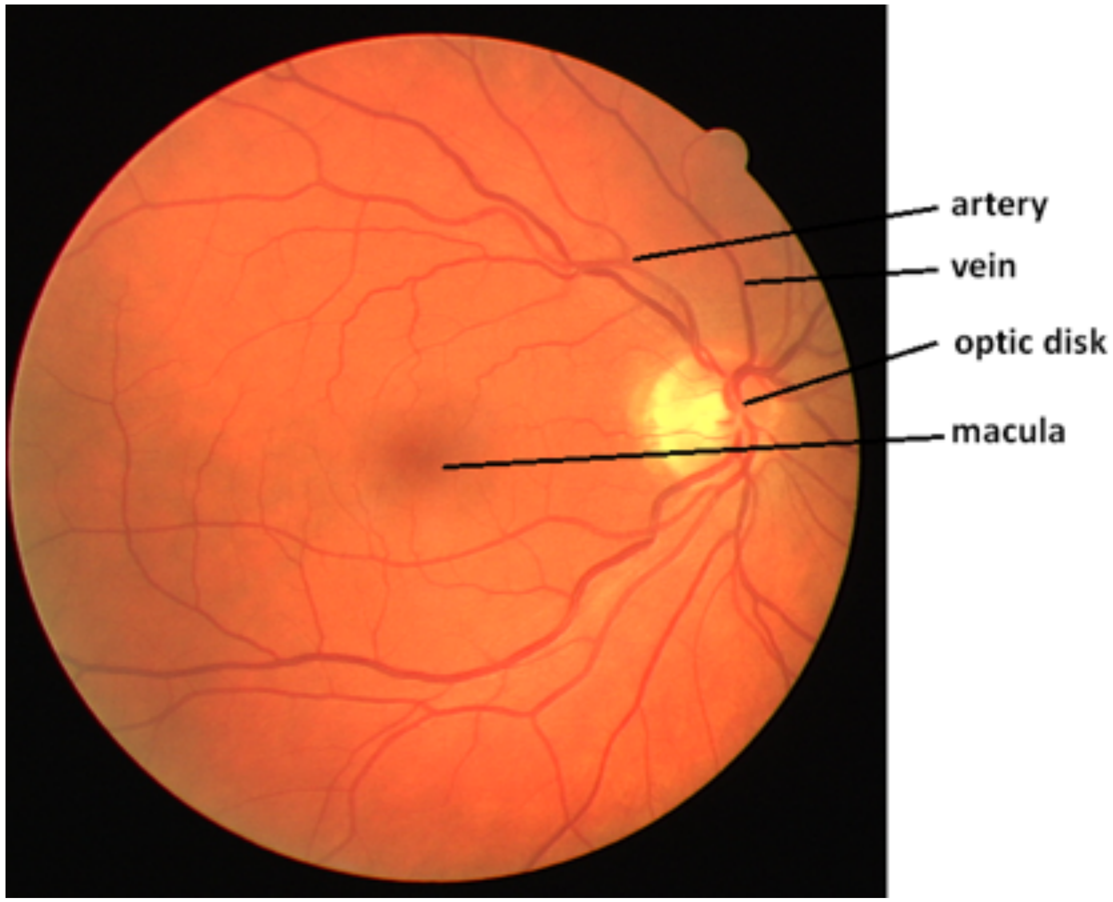
- In 2004, WHO predicted that the number of patients would grow from 171 (2000) to 366 million (2030)
- The IDF annual report shows that the population was already 371 million!
- China has the largest absolute disease burden of diabetes in the world.
- 113.9 million Chinese adults with diabetes and 493.4 million with pre-diabetes in 2010
    - about 10% of total population
- The majority of diabetes cases undiagnosed and untreated
- Estimated medical costs for diabetes and its complications accounted for 18.2 percent of China's total health expenditure in 2007.

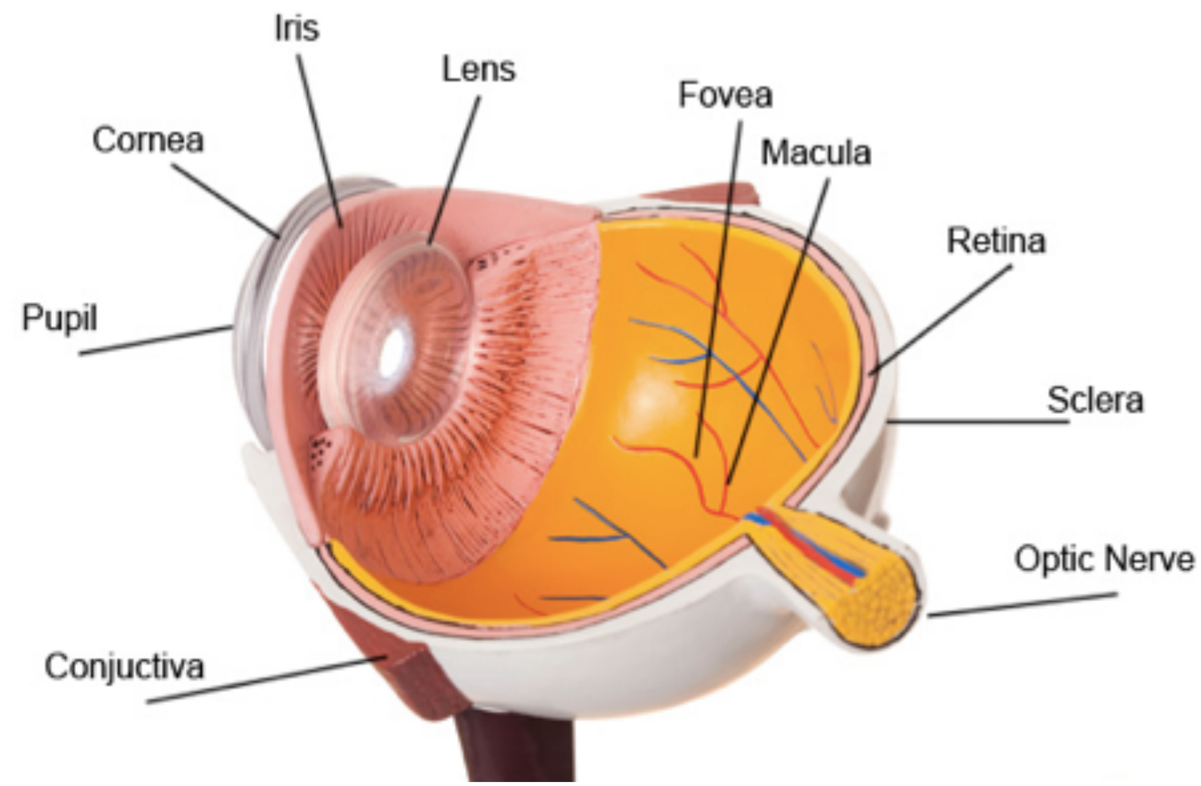




Y. Xu, L. Wang, J. He, Y. Bi, M. Li, T. Wang, L. Wang, Y. Jiang, M. Dai, J. Lu, et al., “Prevalence and control of diabetes in chinese adults,” JAmA, vol. 310, no. 9, pp. 948–959, 2013.

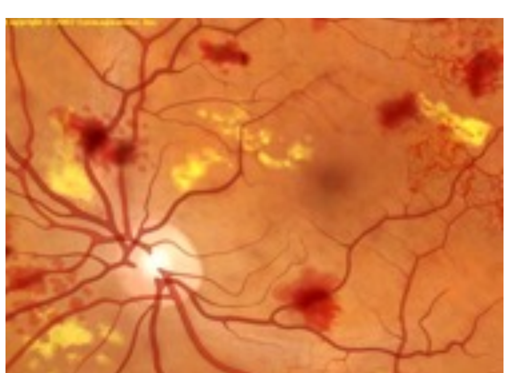
The retinal vasculature





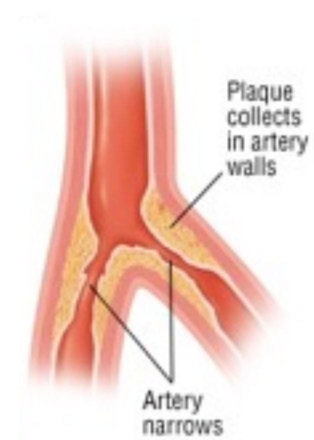
The retinal vasculature reflects the health of the microvasculature of the brain, heart, and other organs.

Diabetic Retinopathy



Stroke

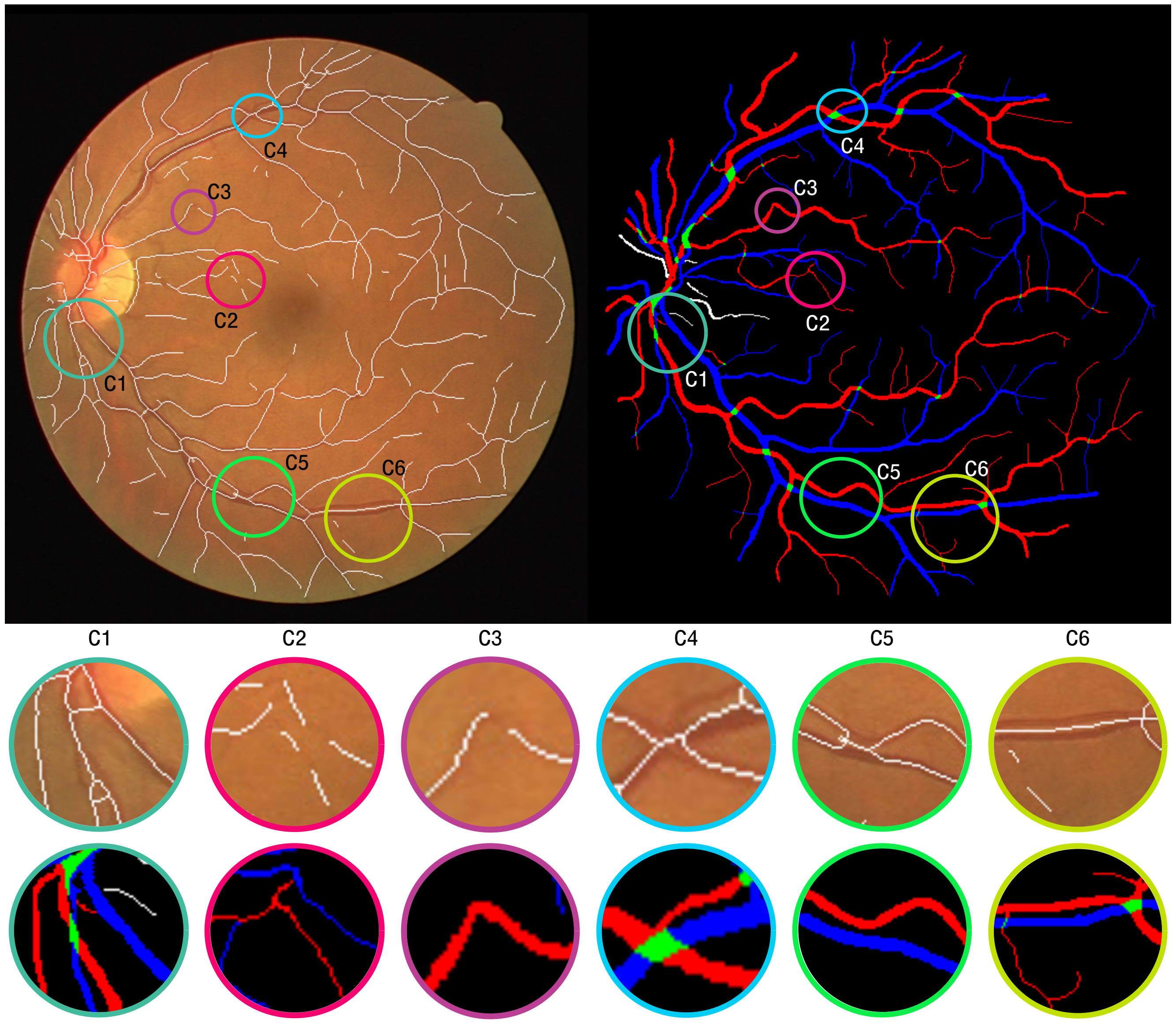
Arteriosclerosis

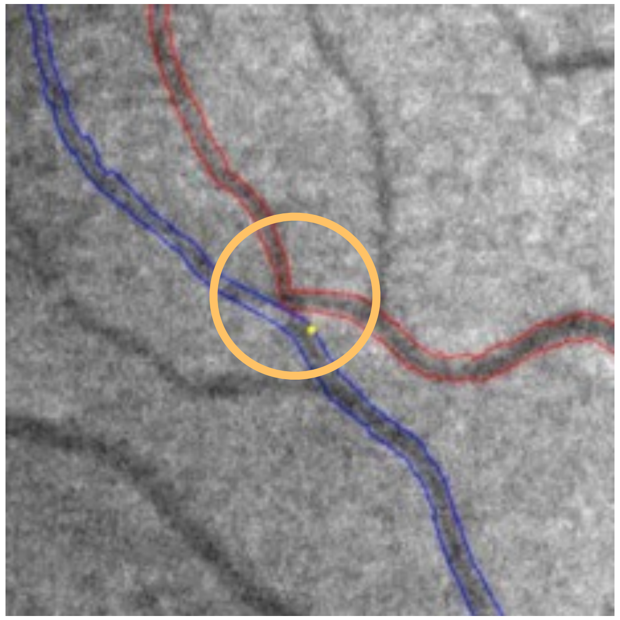


Hypertension

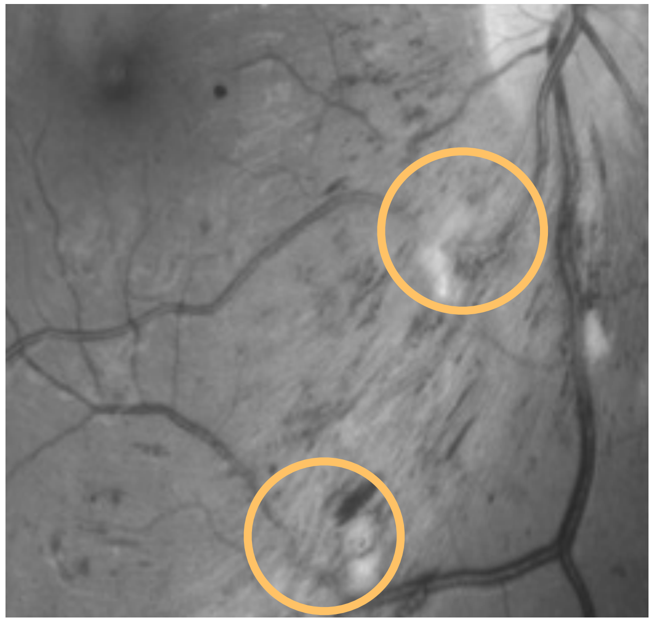
Difficulties in vessel delineation

- Presence of noise
- Broken up vessel segments
- Missing small vessels
- Wrongly merged parallel vessels
- Presence of spur branches in thinning
- Narrow crossing angles
- Complex junctions
- High curvature structures
- …



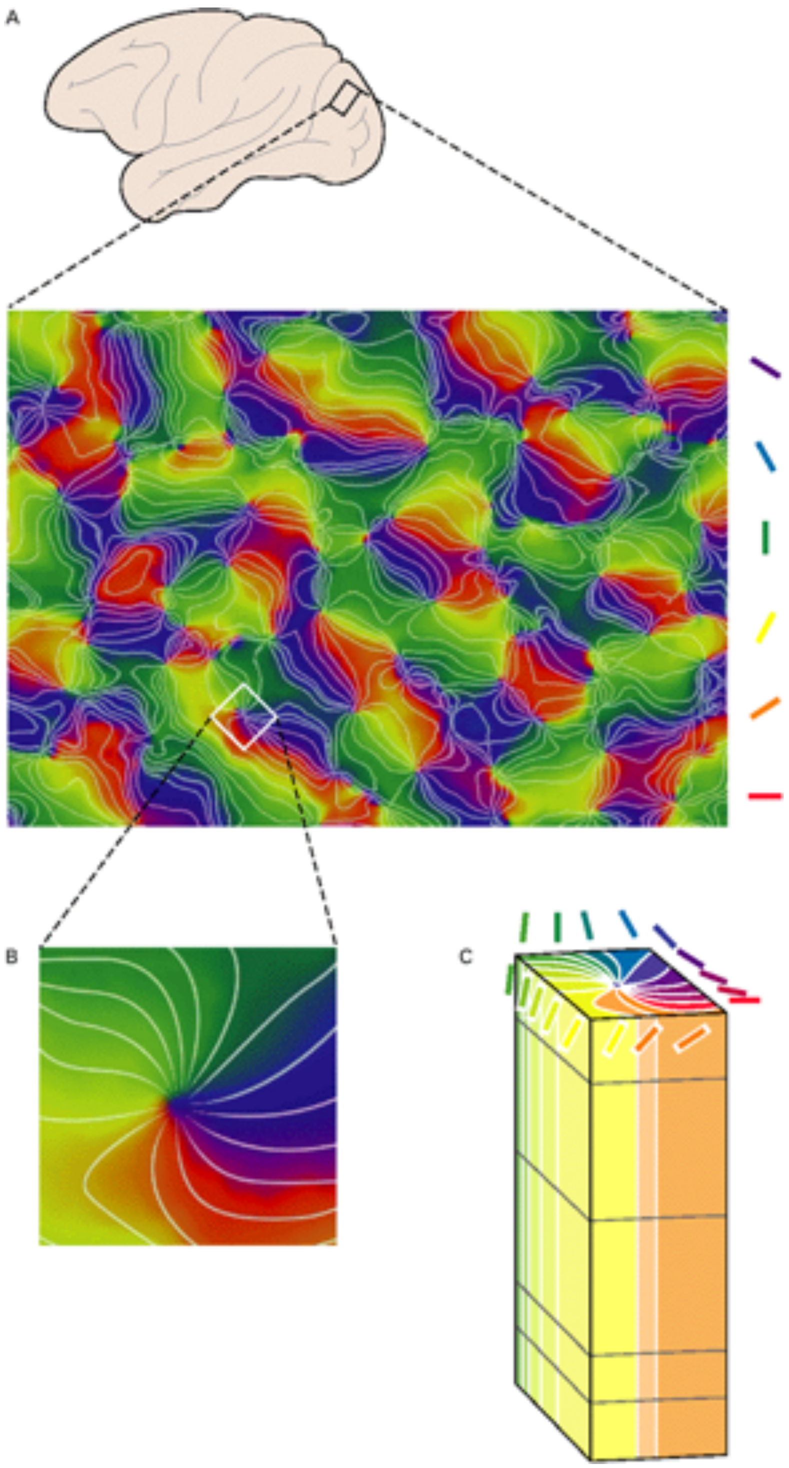


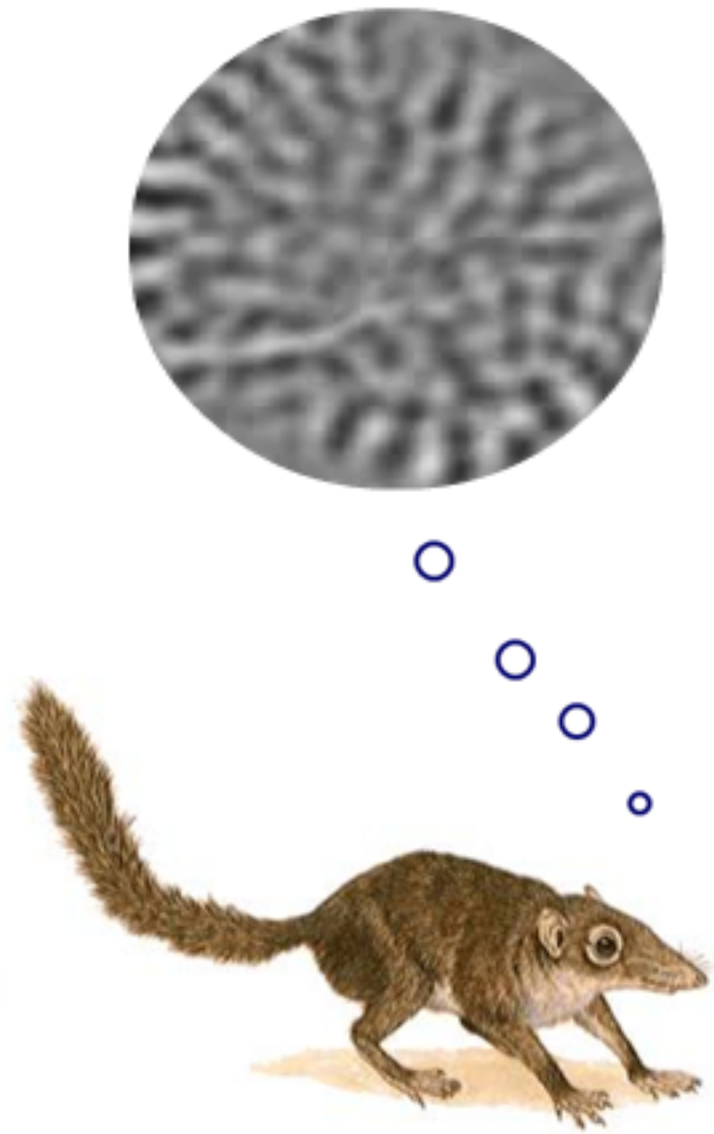
Low contrast and noisy image



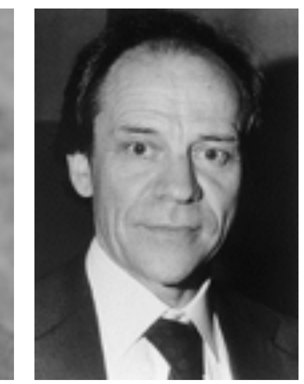
Very small vessels with missing parts

Brain inspired modeling

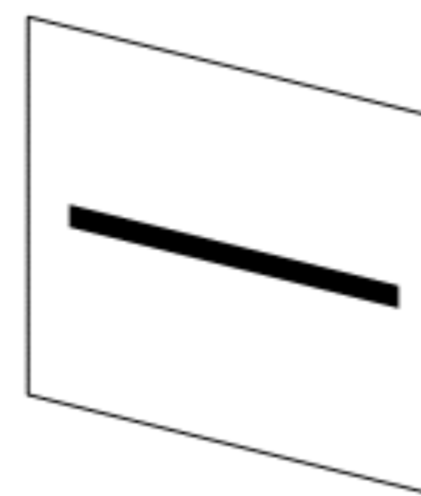




David
Hubel

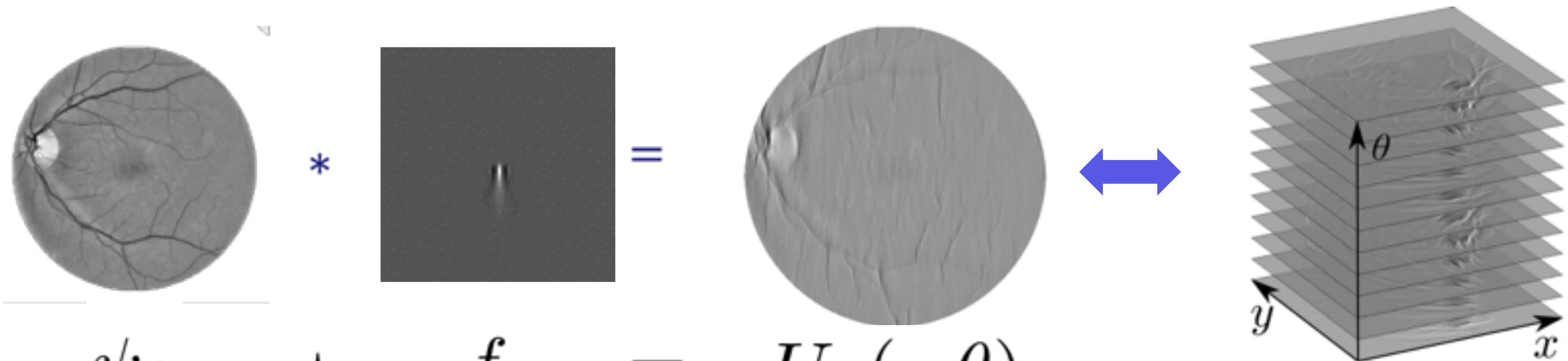


Torsten
Wiesel



Hubel et. al., Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. J. Physiol. 160(1), 106 (1962)

Invertible orientation scores

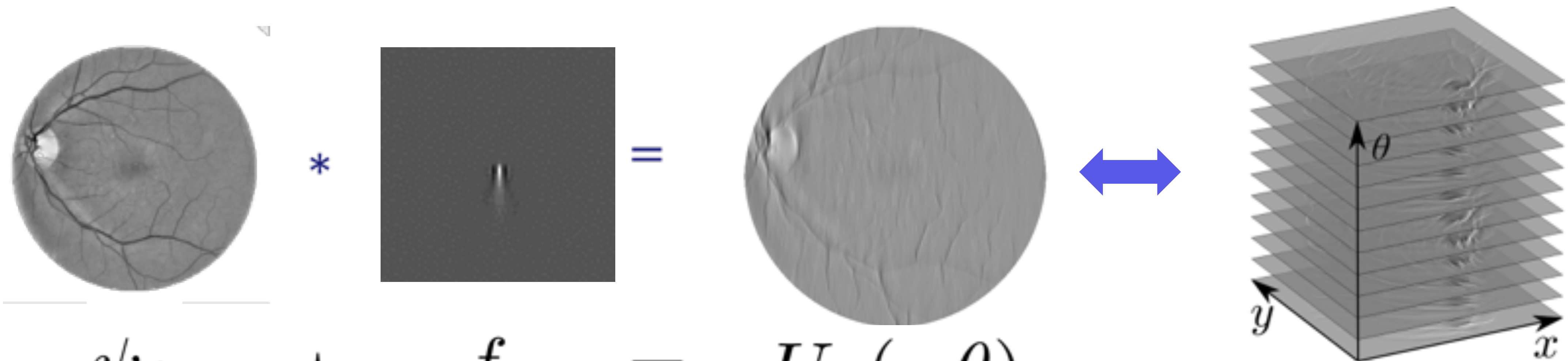


$$\psi_\theta \quad \star \quad f \quad = \quad U_f(\cdot,\theta)$$

$$U_f(\mathbf{x},\theta)$$

Duits et. al., "Invertible orientation scores as an application of generalized wavelet theory," Pattern Recognition and …, vol. 17, no. 1, pp. 42–75, Mar. 2007.

Invertible orientation scores



$$\psi_\theta \quad \star \quad f \quad = \quad U_f(\cdot, \theta)$$

$$U_f(\mathbf{x}, \theta)$$

Re *Im* *Fourier* *Fourier*

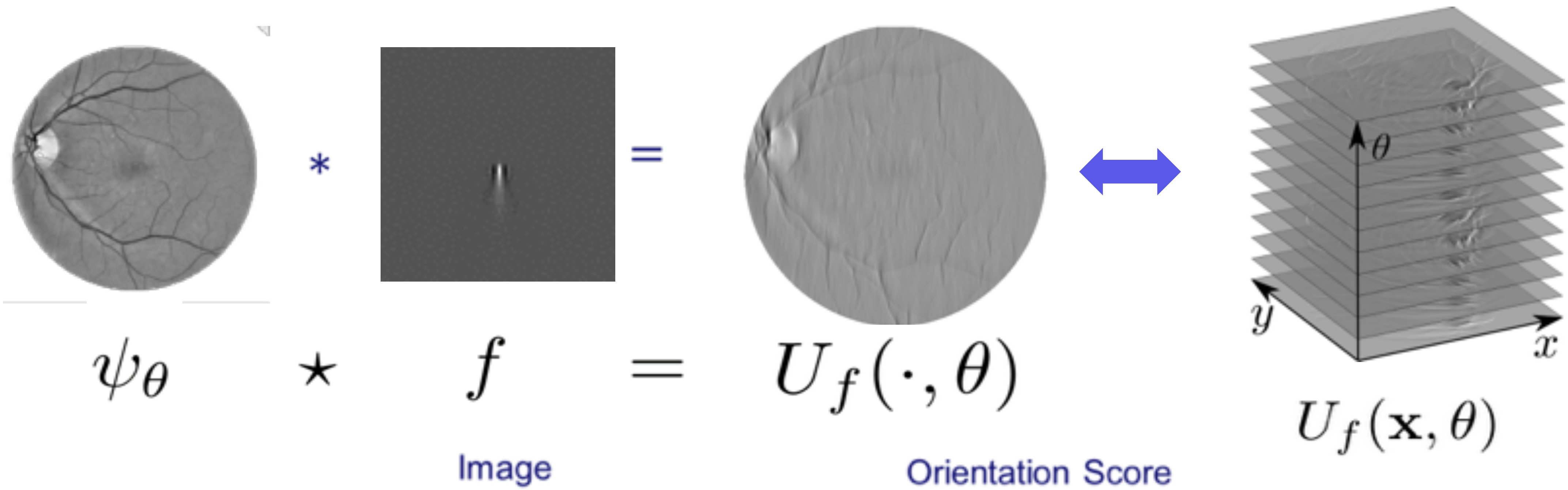
Cake wavelets:
- Scale independent
- Invertible
- Quadrature property

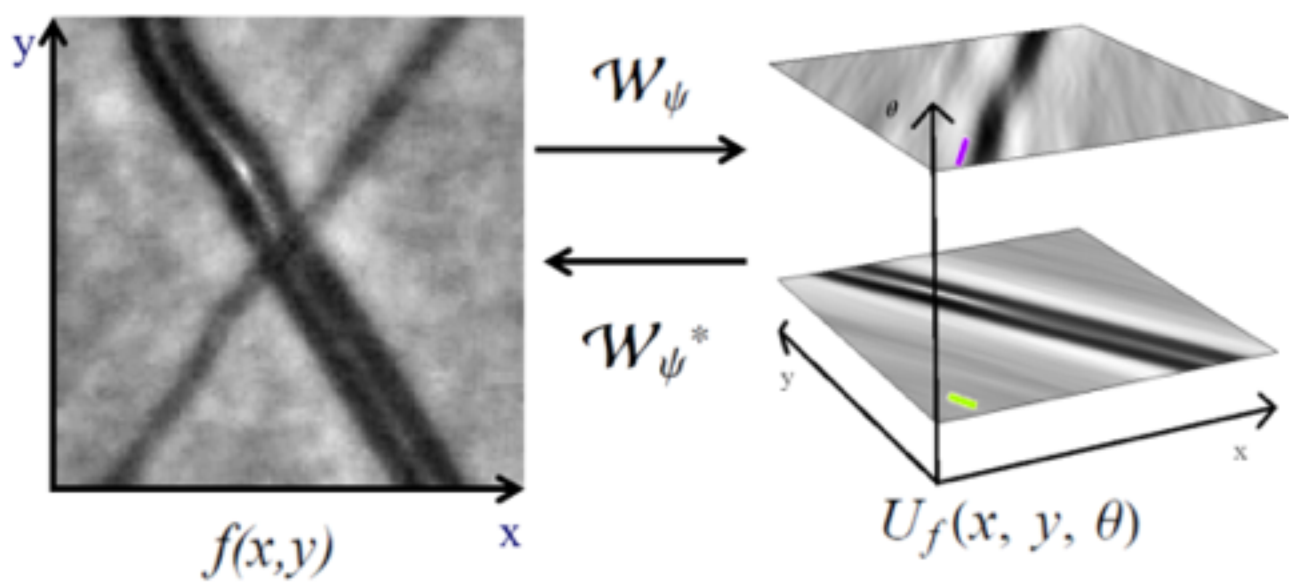
Re *Im* *Fourier* *Fourier*

Gabor wavelets:
- Scale specific wavelet
- Non-invertible
- Quadrature property
-

Duits et. al., “Invertible orientation scores as an application of generalized wavelet theory,” Pattern Recognition and …, vol. 17, no. 1, pp. 42–75, Mar. 2007.

Invertible orientation scores



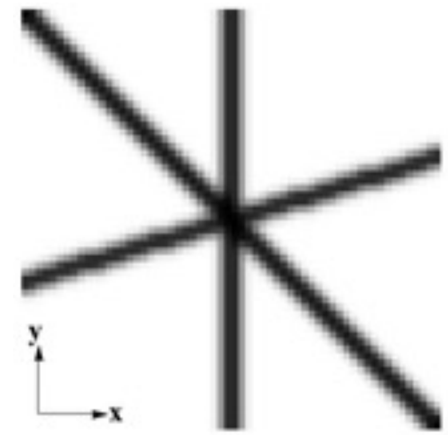


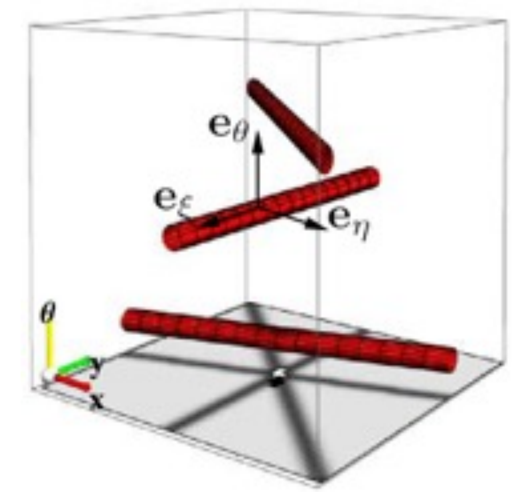
In the score, vessels are disentangled because of their difference in orientation

Duits et. al., "Invertible orientation scores as an application of generalized wavelet theory," Pattern Recognition and …, vol. 17, no. 1, pp. 42–75, Mar. 2007.

Vasculature segmentation in SLO retinal fundus images

BIMSO: "Biologically-inspired multi-scale and multi-orientation"





- Preprocessing
  - Luminosity and contrast normalization
  - Non-linear enhancement in SE(2),

$$\check{U}_{\tilde{f}} = \alpha |U_{\tilde{f}}|^\gamma, \;\; \alpha = sign(Re(U_{\tilde{f}})), \gamma \approx 1.8$$

- Feature Extraction:
  - Contextual information
    - OS transform
    - 1st and 2nd order left-invariant Gaussian derivatives in OS space
    - Multiple scales to cover all vessel widths
  - Intensity-based features
- Neural Network Classifier

$$\check{f}(x) = \sum_{j=0}^{N_o - 1} \check{U}_{\tilde{f}(x, j s_\theta)}$$

$$\partial_\xi := \cos\theta \partial_x + \sin\theta \partial_y$$

$$\partial_\eta := -\sin\theta \partial_x + \cos\theta \partial_y$$

$$\partial_\theta := \partial_\theta$$

$$[\partial_\theta, \partial_\xi] = \partial_\eta, \;\; [\partial_\theta, \partial_\eta] = -\partial_\xi$$

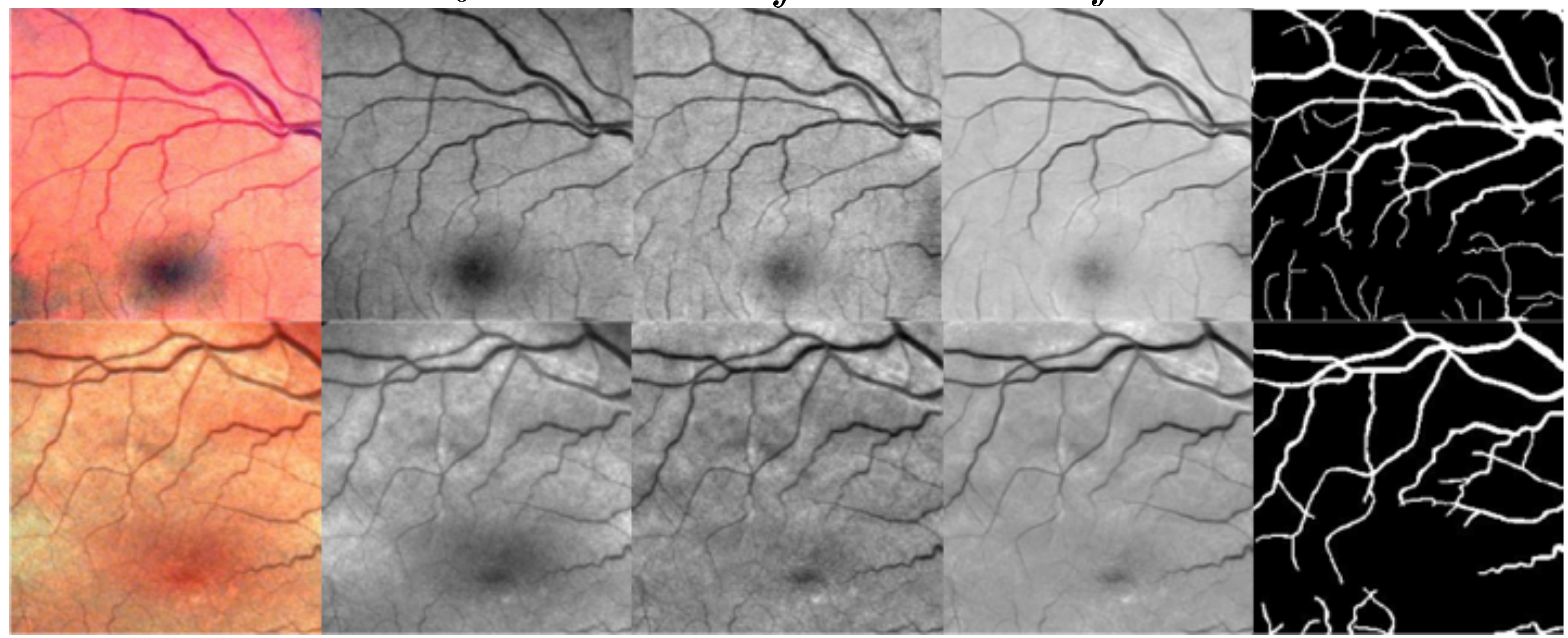
Abbasi-Sureshjani et al.: Biologically-inspired supervised vasculature segmentation in SLO retinal fundus images. In: Image Analysis and Recognition, vol. 9164, pp. 325–334. Springer (2015)

Preprocessing

DRIVE:
RGB

IOSTAR:
SLO

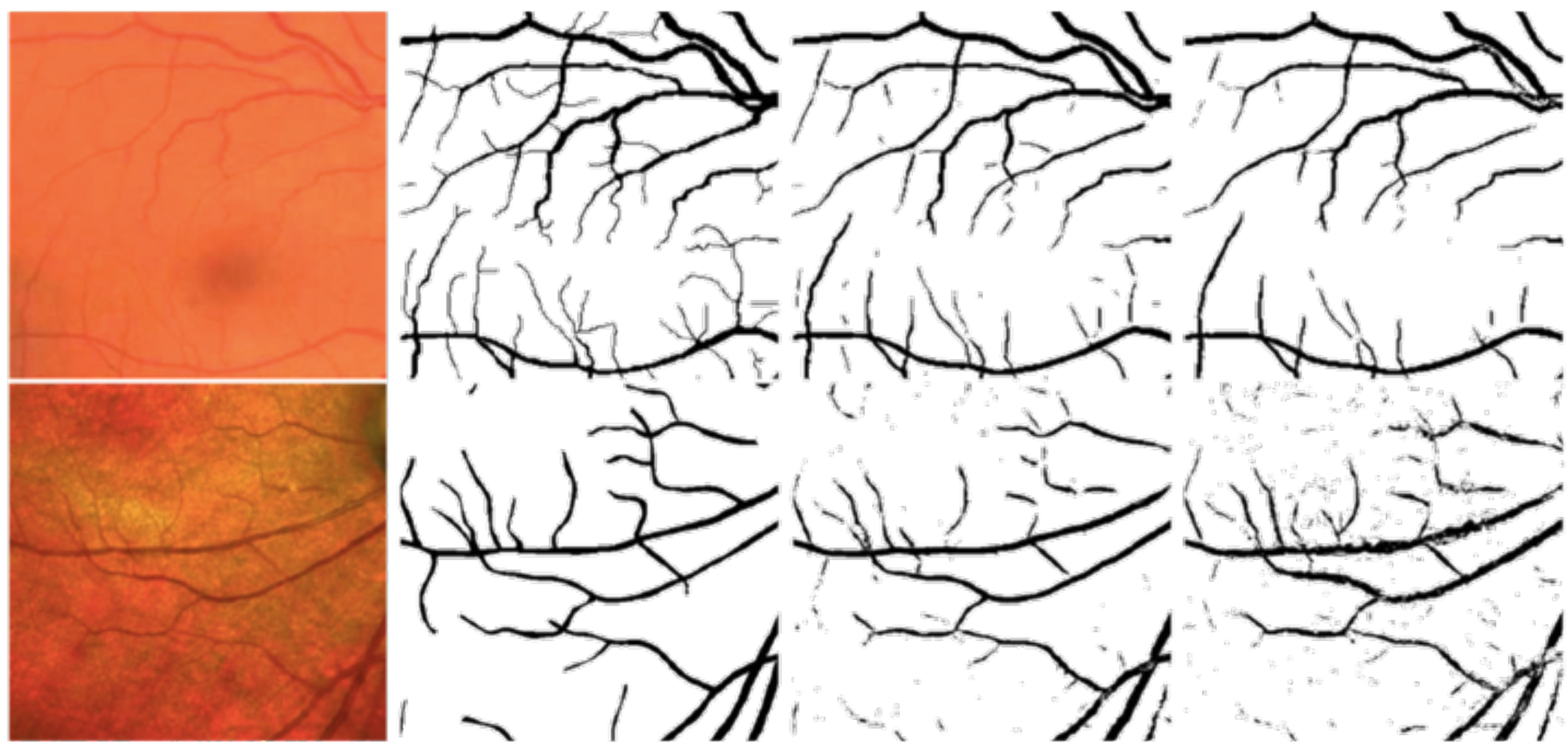
Original Image | f | $\tilde{f}$ | $\check{f}$ | Ground Truth



Segmentation

DRIVE:
AUC=**0.9525**
Sensitivity=**0.7695**

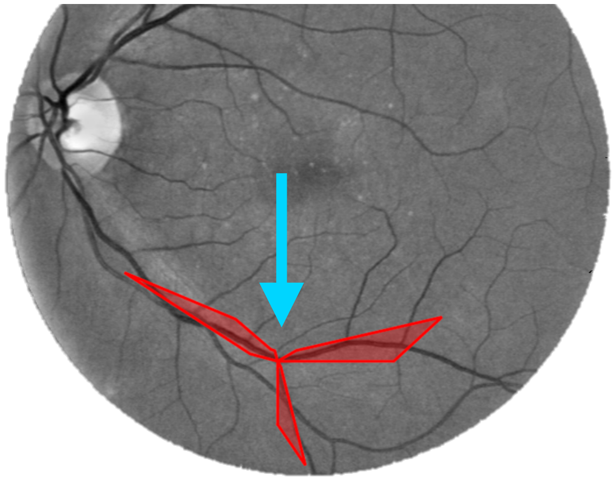
IOSTAR:
AUC=**0.9614**
Sensitivity=**0.7863**

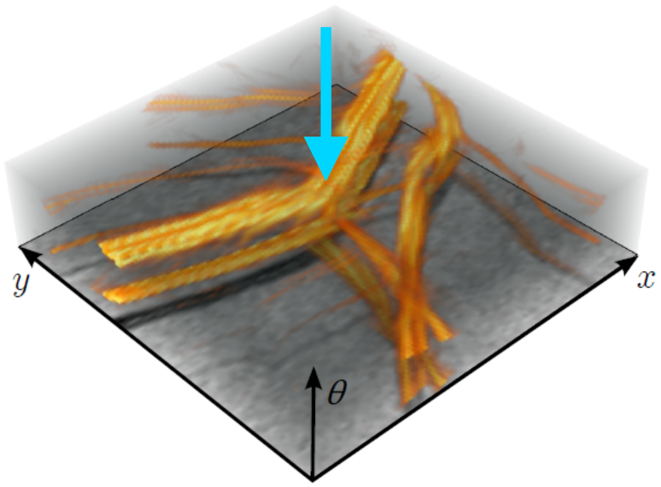


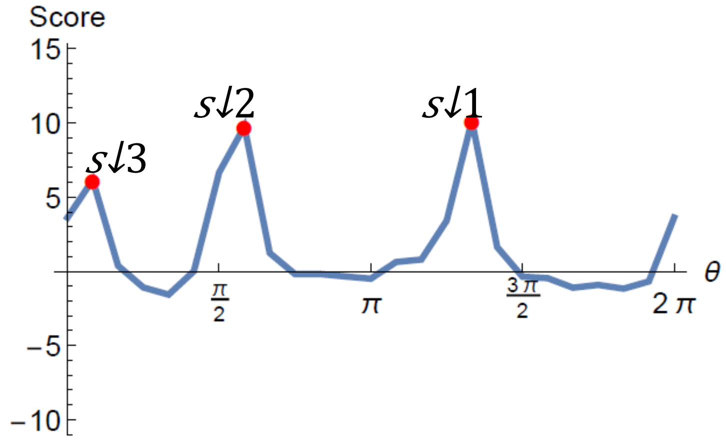
Original image | Ground truth | BIMSO | Soares et al.

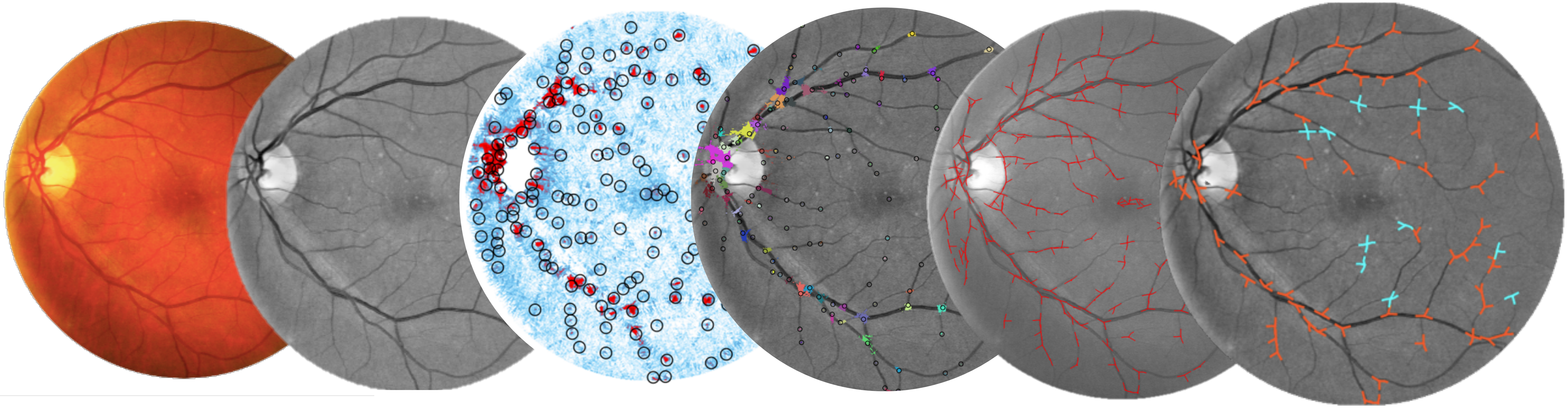
Automatic Detection of Vascular Bifurcations and Crossings

BICROS: *"BIfurcation and CRossing detection method using Orientations Scores"*





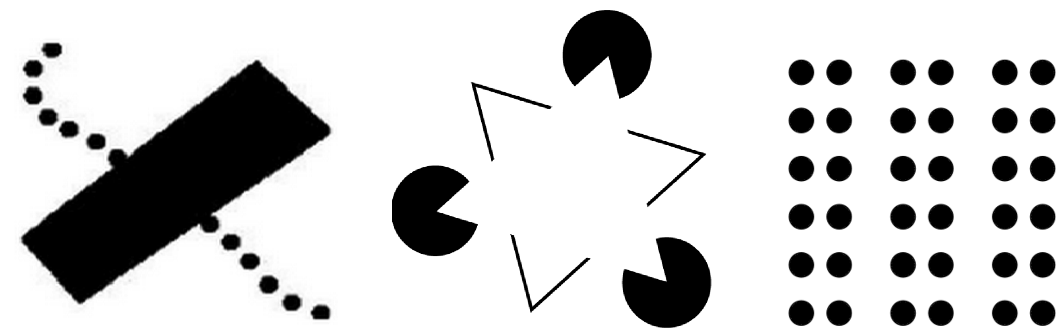




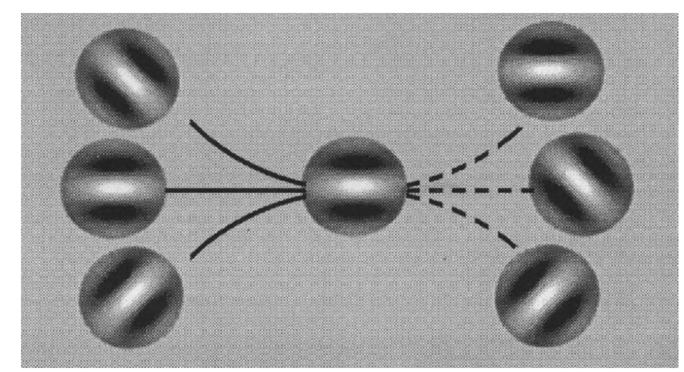
Abbasi-Sureshjani et. al. : Automatic Detection of Vascular Bifurcations and Crossings in Retinal Images Using Orientation Scores, submitted to ISBI 2016.

Geometry of visual cortex

- Gestalt laws of grouping:
  - individuation of perceptual units in the visual space
- Association field:
  - Introduced by Field, Hayes and Hess
  - co-linearity and co-circularity
- Bosking: the rules of association fields are implemented in the primary visual cortex (V1).



Good continuation Closure proximity



The association fields

- Wagemans et. al.: A century of Gestalt psychology in visual perception: I. perceptual grouping and figure–ground organization. Psychol. Bull. 138(6), 1172 (2012)
- Field et. al.: Contour integration by the human visual system: Evidence for a local “association field”. Vision Res. 33(2), 173–193 (1993)
- Bosking et. al. : Orientation selectivity and the arrangement of horizontal connections in tree shrew striate cortex. J. Neurosci. 17(6), 2112–2127 (1997)

Cortical connectivity

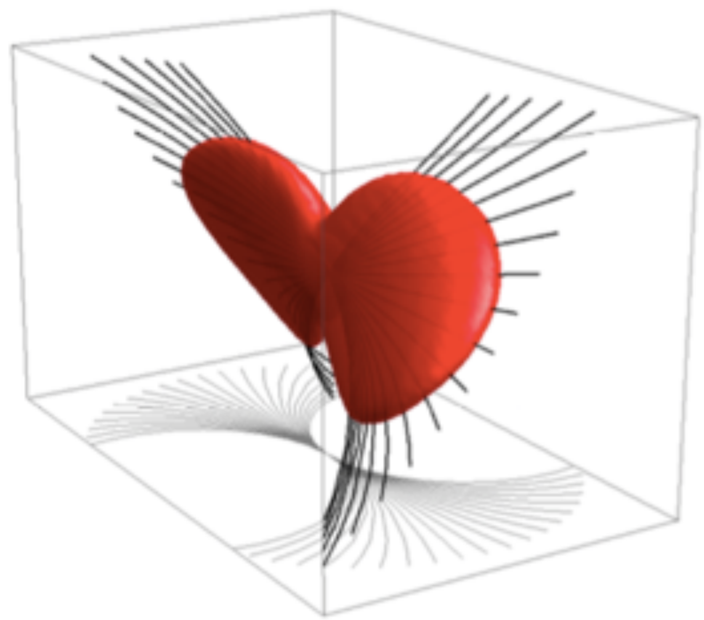
- The lifted curves are connected by integral curves ($X_1 + kX_2$) of the two vector fields
  - a good model of association fields
- Cortical connectivity modeled as the fundamental solution of the Fokker-Planck equation
- The sum of two Fokker-Planck Green functions:
  - forward & backward directions

$$(x, y) \to (x, y, \theta)$$

$$X_1 = (\cos\theta, \sin\theta, 0), X_2 = (0, 0, 1)$$

$$-X_1 p(x,y,\theta) + \frac{\sigma^2}{2} X_{22} p(x,y,\theta) = \frac{1}{2}\delta(x,y,\theta)$$

$$X_1 p(x,y,\theta) + \frac{\sigma^2}{2} X_{22} p(x,y,\theta) = \frac{1}{2}\delta(x,y,\theta)$$



sub-Riemanninan Fokker-Planck kernel

- Sarti, A., Citti, G.: The constitution of visual per- ceptual units in the functional architecture of V1. J. Comput. Neurosci. 38(2), 285–300 (2015)
- Sanguinetti et. al.: A model of natural image edge co-occurrence in the rototranslation group. J. Vision 10(14), 37 (2010)

Analysis of vessel connectivities

- Extended 4D feature space

- Connectivity kernel

$$\omega_1((x,y,\theta),(x',y',\theta')) = \frac{1}{2}\Big(\Gamma_1((x,y,\theta),(x',y',\theta')) + \Gamma_1((x',y',\theta'),(x,y,\theta))\Big)$$

- The Euclidean distance between intensities

$$\omega_2(f,f') = e^{-\frac{1}{2}(\frac{f-f'}{\sigma})^2}$$

- Affinity matrix:
  - connectivity information between lifted points

$$\omega_f((x,y,\theta,f),(x',y',\theta',f')) = \omega_1((x,y,\theta),(x',y',\theta'))\omega_2(f,f')$$

- Spectral Clustering:

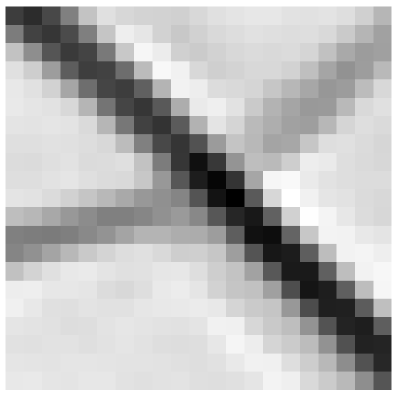
$$A_{i,j} = \omega_f((x_i,y_i,\theta_i,f_i),(x_j,y_j,\theta_j,f_j))$$

  - Clustering the groups according to their similarities

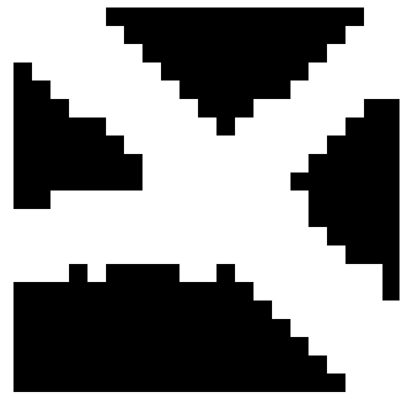
- Salient objects: eigenvectors with highest eigenvalues

- M. Favali, S. Abbasi-Sureshjani et. al.: Analysis of Vessel Connectivities in Retinal Images by Cortically Inspired Spectral Clustering, submitted to JMIV, Oct. 2015
- Gucci et. al.: Cortical spatiotemporal dimensionality reduction for visual grouping. Neural. Comput. (2015)

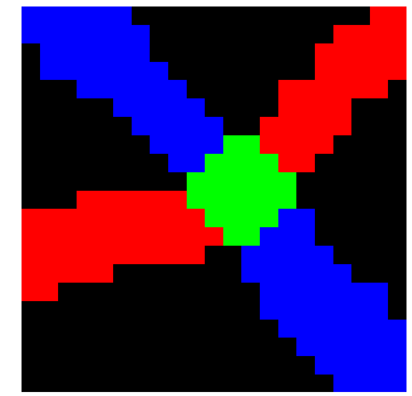
Analysis of vessel connectivities



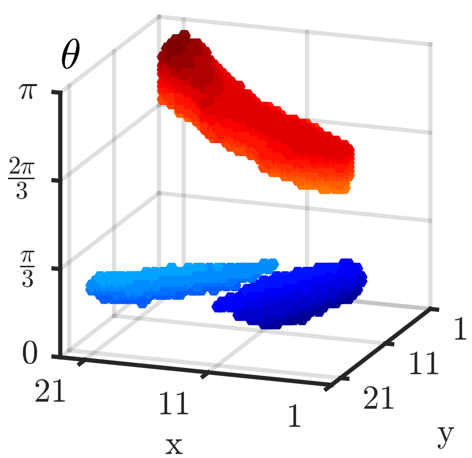
gray scale image



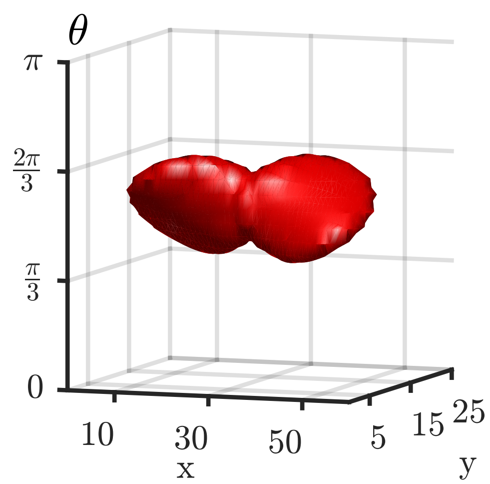
hard segmentation



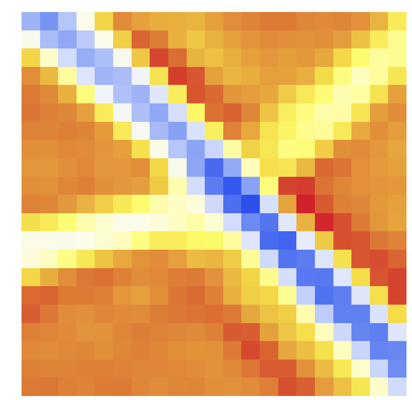
artery / vein labels



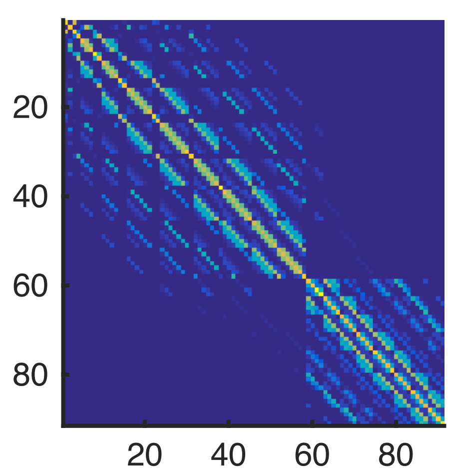
lifted image



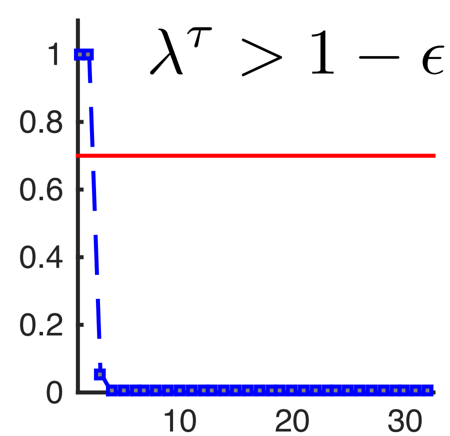
connectivity kernel



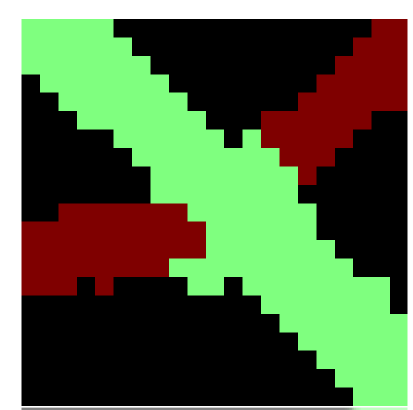
intensity



affinity

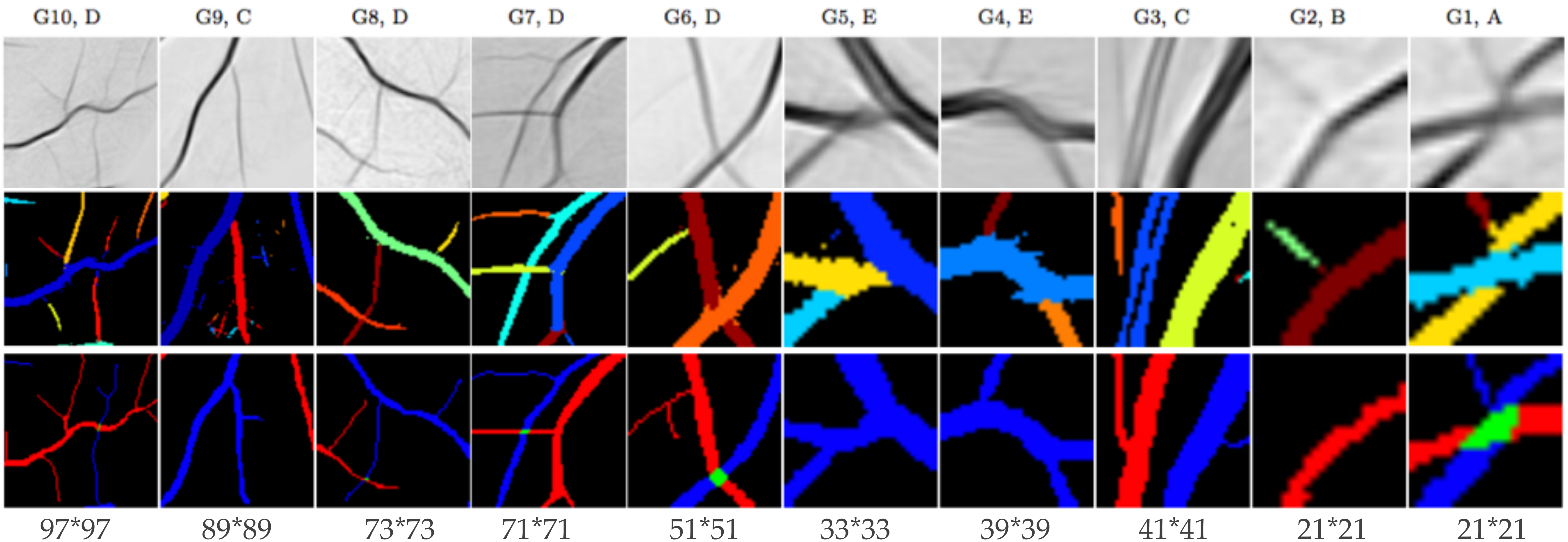


exp. eigenvalues

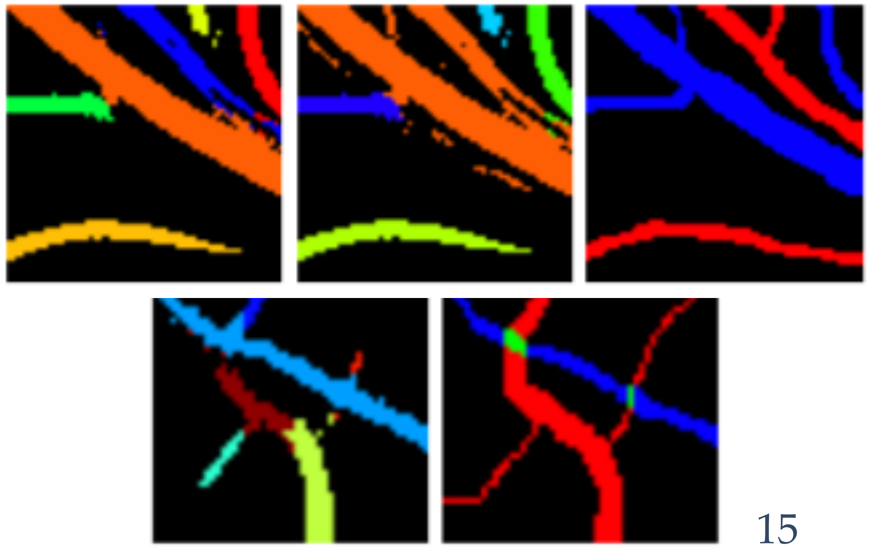


clustering result

Results



- DRIVE dataset, with 5 different types of complexity at junctions
- Including the intensity term is very effective.
- The parameters are almost constant, despite different patch sizes
- limitation: high curvature vessels



Conclusion

- Localization of vessels and junctions is the first step in measuring and finding the biomarkers.
- Mathematical model inspired by the geometry of the primary visual cortex is used in retinal image analysis
- Dealing with most of the challenging cases in retinal images:
  - Detection of bifurcations & crossings, parallel vessels, interrupted segments, noisy backgrounds
- Future work: considering data adaptivity & using other kernels

Thanks for your attention.