

# Optimized Strict Multiscale Frangi Prefiltering for Segmentation

## Towards an automated PCSVN extraction

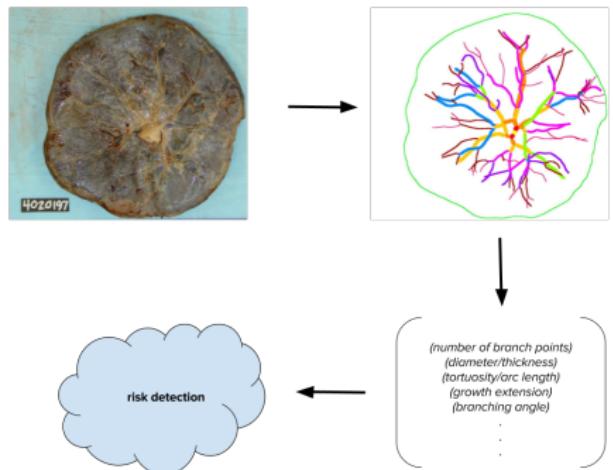
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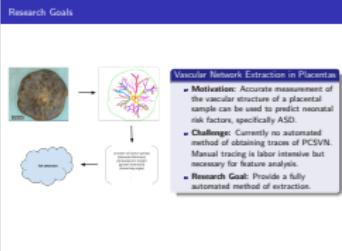
# Research Goals



## Vascular Network Extraction in Placentas

- **Motivation:** Accurate measurement of the vascular structure of a placental sample can be used to predict neonatal risk factors, specifically ASD.
- **Challenge:** Currently no automated method of obtaining traces of PCSVN. Manual tracing is labor intensive but necessary for feature analysis.
- **Research Goal:** Provide a fully automated method of extraction.

- Cake Defense
  - └ Introduction
    - └ Research Goals



1. In the figure, a manual trace of the placental chorionic vascular surface network (PCSVN) is performed. This trace is measured in multiple ways. Those measurements are turned into a feature vector, which can be used to predict a risk. Refer to Boruta paper.
2. Manual tracing requires like 5 hours or something and requires training. There is some guesswork that's done in it too and some limitations in the ground truth itself (will cover later)

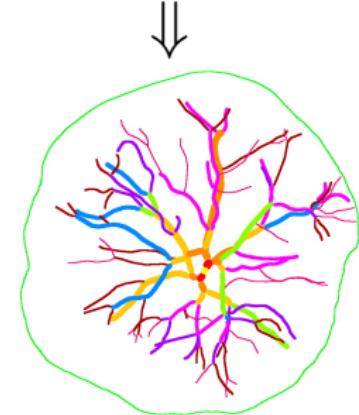
# The Image Processing Problem

## Our image domain

- The PCSVN is a connected network of veins and arteries on the surface of the placenta
- We have a ground truth for 201 samples from private NCS dataset
- Placentas have been formalin-fixed, so arteries are more prominent (there are issues)
- Pictures taken from top down, some glare, some inconsistencies.
- Placental images are comparatively noisy

## Strategy

Given the curvilinear nature of these vessels, we will appeal to differential geometry.



# Cake Defense

## └ Introduction

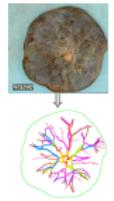
### └ The Image Processing Problem

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1. The surface of the placenta has a lot of changes in color/topology apart from the PCSVN so a lot of techniques that work elsewhere for vascular segmentation seem to fail here. Thus segmentation is more complicated than say, an eyeball MRI (like original Frangi paper)
2. Mention colors are simply vessel widths (3 to 19 odds) are part of the tracing protocol. that's really outside of the scope of this thesis, but kept anytime we show a ground truth because they're pretty

We want to find curvilinear structures in the images, so

- Idealize image as a 3D surface (a graph) with  $(x, y)$  spatial coordinates and

# The Frangi Filter

## Implementation Detail: Calculating Discrete Hessian

# Differential Geometry in Image Processing and the Frangi Filter

## Principal Curvatures and Principal Directions

$$L \in \mathbb{R}^{m \times n} \iff L \in C^2([0, m] \times [0, n])$$

$$H(x, y) = \begin{bmatrix} L_{xx} & L_{xy} \\ L_{yx} & L_{yy} \end{bmatrix}$$

$$\kappa_i, u_i \text{ for } i = 1, 2$$

such that

$$Hu_i = \kappa_i u_i, |\kappa_1| < |\kappa_2|$$

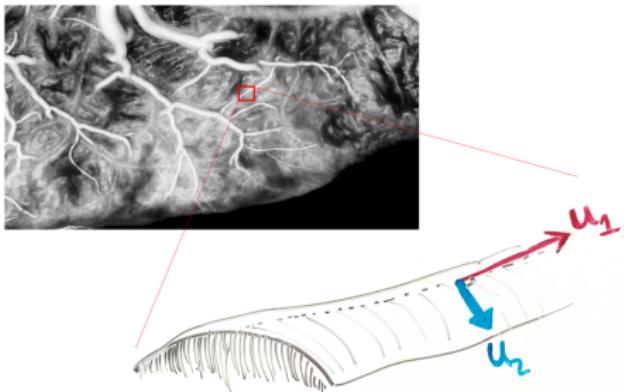
## Frangi Filter Measure

$$F\{\cdot\} = \begin{cases} 0 & \text{if } \kappa_2 < 0, \\ \exp\left(\frac{-A^2}{2\beta^2}\right) \left(1 - \exp\left(\frac{-S^2}{2c^2}\right)\right) & \text{else} \end{cases} \quad (1)$$

$$S = \sqrt{\kappa_1^2 + \kappa_2^2} \quad (\text{structureness}) \quad (2)$$

$$A = \left| \frac{\kappa_1}{\kappa_2} \right| \quad (\text{anisotropy}) \quad (3)$$

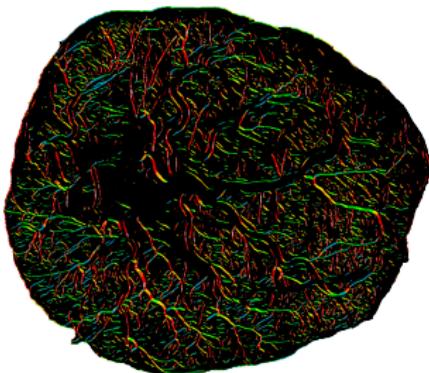
with  $\beta, c$ , parameters



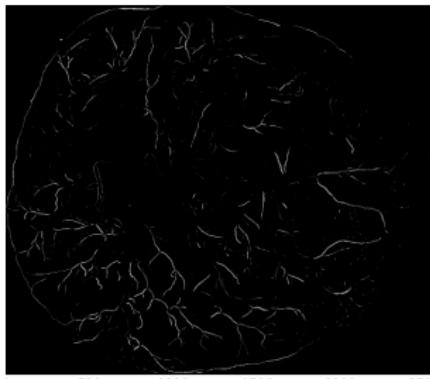
**Figure:** The principal curvatures (eigenvectors of the Hessian matrix) point in the direction of greatest and least curvature at each pixel

The Frangi filter [2] finds tubular structures on the surface. Corresponds to areas where  $\kappa_2$  is large and  $\kappa_1$  is small.

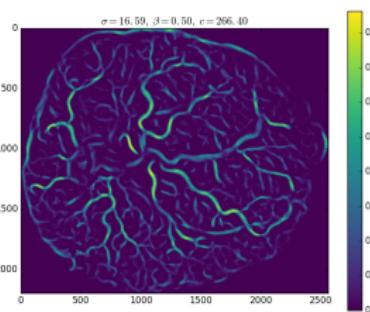
# Improved Parameters for Frangi Filter



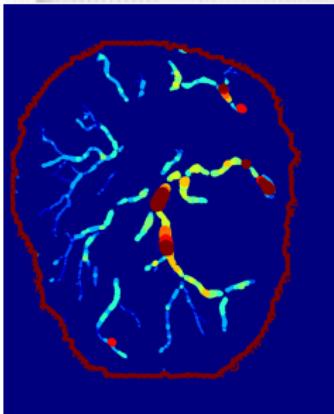
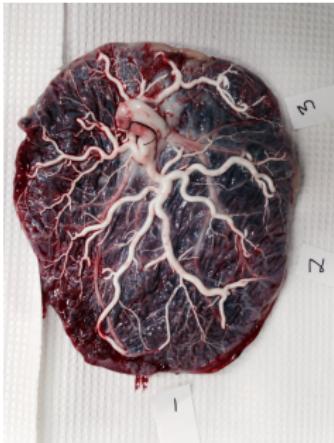
(a) Placental sample (bad parameters)



(b) improved parameters



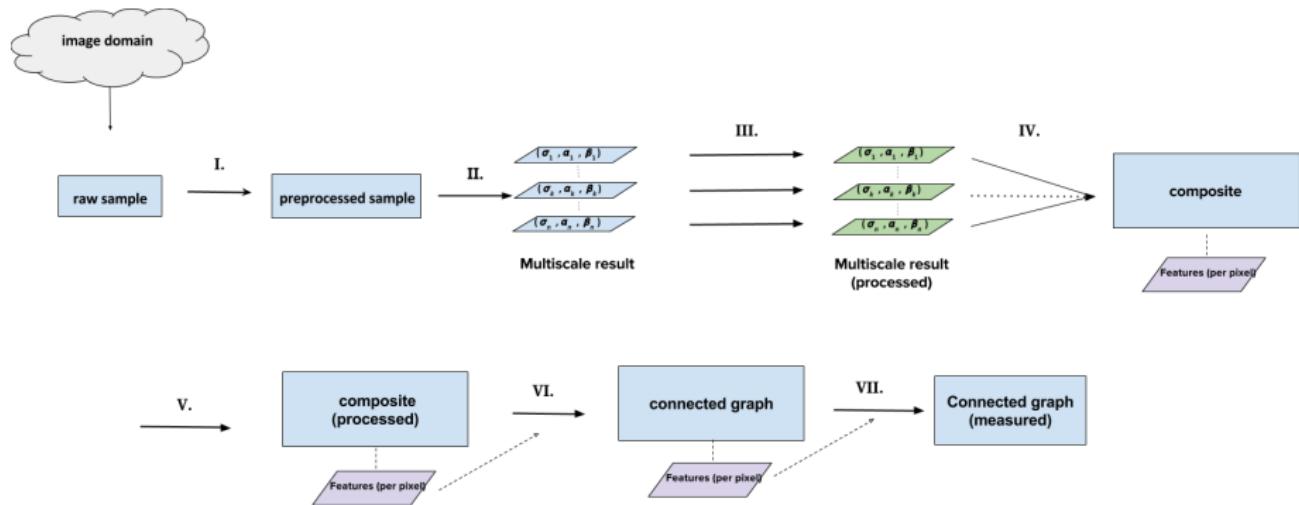
(c) improved parameters (larger scale space)



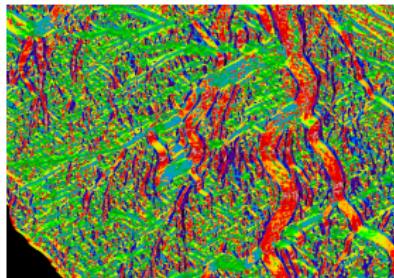
## Additional Work Required

- Extend to other samples and image domains.
  - new barium samples
  - other placental samples (NCS, EARLI)
  - STARE, DRIVE retinal database
  - other curvilinear image sets?
- Adapt previous morphological filtering to improved frangi targets
- Speedups with FFT (completed!)
- Find good way to quantify results
- Graph connection problem, etc.

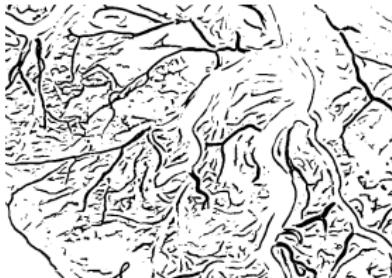
# Appendix: Main Extraction Process



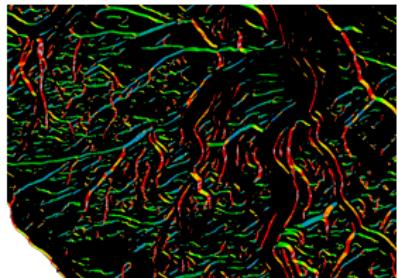
# Principal Directions with Frangi Filter (Example with $\sigma = 2$ )



(a) all  $\theta(u_2, e_1)$



(b) Frangi targets



(c) frangi targets with  $\theta$



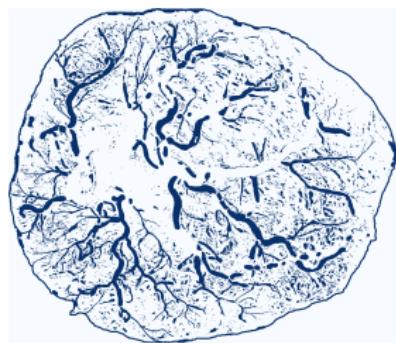
## Morphological Filter

- Rectangular filter rotated by  $\theta(u_1, e_1)$
- Rectangle size dependent on  $\sigma$  (scale size)
- Binary closing  $\rightarrow$  binary opening with disk

# Skeletonization & Sieving

## Morphological Filtering Algorithm

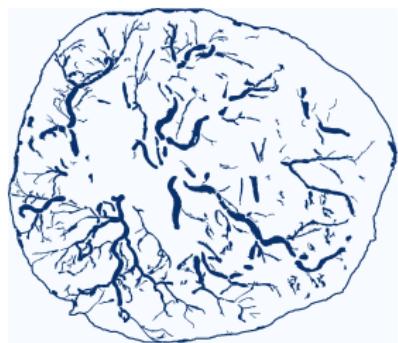
- (a) Join all scales.
- (b) Skeletonize.
- (c) Iterate over each scale extraction and keep content only if it is connected to the skeleton.



(a) Union of all scales



(b) Skeletonization of (a)



(c) Sieving (a) through (b)

Figure: Morphological Filtering (smaller scales only)