Vessel Enhancement With Multiscale And Curvilinear Filter Matching For Placenta Images

Jen-Mei Chang* Nen Huynh Marilyn Vazquez Carolyn Salafia

*Department of Mathematics and Statistics
California State University, Long Beach
jen-mei.chang@csulb.edu

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Outline

Research Motivation

- Recent medical research indicates that the placenta may be the crystal ball for the health of the baby.
- An analysis of the placenta may help to predict risks for certain diseases that develop in the womb such as diabetes, autism, and heart disease.

Q: *Can you tell which placenta is more likely to have supported a healthy baby and which one is less likely so?*

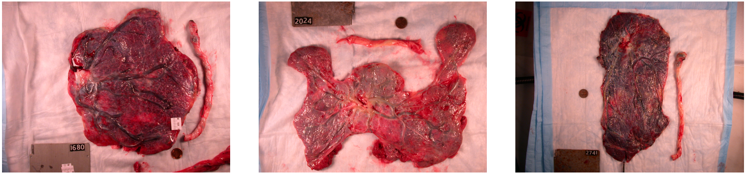


Figure: Sample digital placenta images in the UNC data set provided by Placental Analytics.

Research Aim

- In particular, the structure of the blood vessel network of the human placenta may contain important medical clues.
- This project aims to develop an **automated** program that **detects and enhances vessels in placenta images.**

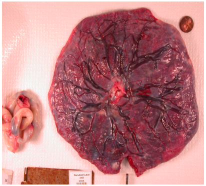
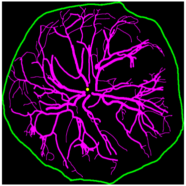


image captured

→ automatically



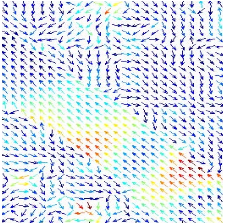
desired output

- Currently, this is done through a laborious process that is very time consuming, hence making large-scale studies intractable.

Research Method

- A **multiscale** filtering process that is based on images' 2nd-order feature is used to highlight **locally curvilinear** structures and minimize surrounding non-vessel noise.

a vessel



$\mathbf{v}_1$ of $\mathbf{H}$

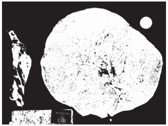
- The enhancement results are reported in Matthews Correlation Coefficient (MCC) value.
- The proposed method performs superior than all existing competitor's work.

Image Registration

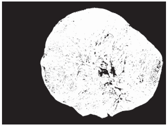
Preprocessing in this context entails a preparation of useable images by removing irrelevant objects, reducing glare, & enhancing contrast to get images that are ready for vessel extraction.

1. original

2. stretched



3. thresholded

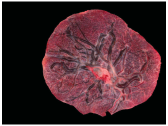


4. object removal

5. filled

6. smoothing

7. masking



8. glare removal

Multiscale Vessel Enhancement

- Let the 2D Gaussian filter be defined as follows

$$G(x,y) = e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_1^2}+\frac{y^2}{\sigma_2^2}\right)}.$$

- Let $I(x,y)$ denote a 2D digital (grayscale) image and G a Gaussian filter function, its (continuous version) **Hessian matrix** is given by

$$\mathbf{H} = G \star \begin{pmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{pmatrix}.$$

Multiscale Vessel Enhancement

- Let $\mathbf{u}_1$ and $\mathbf{u}_2$ denote eigenvectors of $\mathbf{H}$ corresponding to **eigenvalues** λ_1 and λ_2 satisfying $|\lambda_1| < |\lambda_2|$, respectively.
- These eigenvalues can then be used to define two **vesselness** measures suited for medical images:
  $A = \frac{|\lambda_1|}{|\lambda_2|}$ (anisotropy) & $S = \sqrt{\lambda_1^2 + \lambda_2^2}$ (structureness)
- With A & S, the probability that a pixel is a vessel is given by

$$F\{\cdot\} = \begin{cases} 0 & \text{if } \lambda_2 < 0, \\ \exp\left(\frac{-A^2}{2\beta^2}\right)\left(1 - \exp\left(\frac{-S^2}{2c^2}\right)\right) & \text{otherwise} \end{cases}$$

where β and c are scaling parameters that control the sensitivity of the vesselness measures.

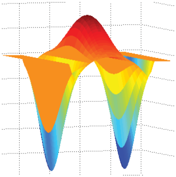
Curvilinear Filter Matching

- Enlarge each image with a bi-cubic interpolation by a factor of s to obtain I_s.
- For each image pixel (X, Y), determine whether it is a vessel pixel using a binary response function

$$B(X,Y) = \begin{cases} 1 & \text{if} \quad F\{I_s(X,Y)\} > \alpha \\ 0 & \text{otherwise} \end{cases}$$

- A **curvilinear filter function** is proposed here

$$\Psi(x,y) = \begin{cases} \frac{1-w^2x^2}{4-w^2x^2}\, e^{-\frac{1}{2}\left(\frac{3}{4-w^2x^2}+\ell^2y^2\right)} & \text{if} \quad |x| \le 2w \\ 0 & \text{if} \quad |x| > 2w \end{cases}$$



to highlight locally linear structure by controlling the width (w) and length (ℓ) parameters, while penalizing neighborhood pixels that present non-cohesive structure.

Curvilinear Filter Matching

- To account for direction information, specify a collection of the curvilinear templates $W_k(x,y) = \Psi \circ T_k(x,y)$, where

$$T_k(x,y) = \begin{bmatrix} \cos\theta_k & -\sin\theta_k \\ \sin\theta_k & \cos\theta_k \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

  and $\theta_k = \frac{k\pi}{n}$ for some fixed n.

- With this, a **curvilinear filter (CLF) response** is computed by considering $V_k(x,y) := (W_k * B)(x,y)$ for various k, where $*$ denotes the usual convolution.

- Finally, from the collections of CLF responses, a point (x,y) is assigned the maximum CLF response

$$V(x,y) = \max_{1 \le k \le n} V_k(x,y),$$

  which represents the amount of curvilinear structure the pixel possesses.

Vessel Enhancement with MVE & CLF

The curvilinear filter identifies the linear regions from the multiscale filtered results. To take advantage of both methods, we propose the following enhancement procedure.

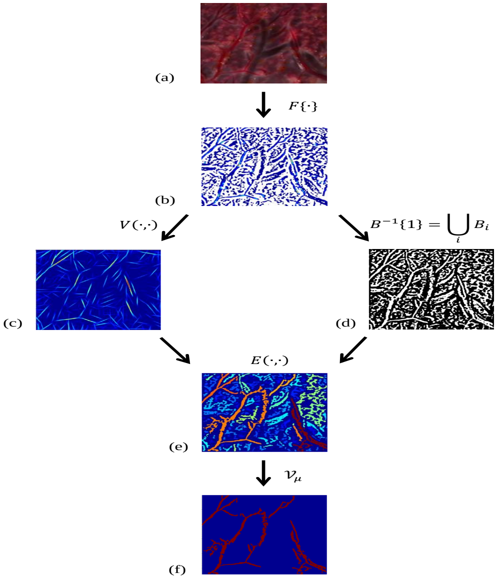
- The set of pixels identified as potential vessels by the multiscale filter, $B^{-1}\{1\}$, is the union of distinct connected components $\{B_i\}$. That is,

$$B^{-1}\{1\} = \bigcup_i B_i.$$

- For each $(x_0, y_0) \in B_i$, let $E(x_0, y_0) = \max_{(x,y)\in B_i} \{V(x, y), 0\}$ be the enhanced response.
- At the end of this enhancement process, there will be a collection of points that are identified as vessels:

$$\mathcal{V}_\mu = \{(x, y) \mid E(x, y) > \mu\}.$$

Visualization of the Method Flow



Experimental Design

[Materials] 16 randomly chosen 1600×1200 images with hand traces from the UNC placenta data provided by *Placental Analytics, LLC*.

[Method] The Matthew's Correlation Coefficient ($-1 \leq \mathrm{MCC} \leq 1$):

$$\mathrm{MCC}(x, y) = \frac{\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}}{\sqrt{(\mathrm{TP}+\mathrm{FN})(\mathrm{TP}+\mathrm{FP})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}}$$

TP: vessels identified as vessels	**FP**: non-vessels identified as vessels
TN: non-vessels identified as non-vessels	**FN**: vessels identified as non-vessels

[Benchmarks] *Neural Network approach* [1] and *Multiscale Vessel Enhancement* [2] alone.

[Results] A box plot of the maximum MCC values and a visual comparison.

Quantitative Results

It is clear that the proposed method consistently outperforms the two benchmarking algorithms on nearly all incidents.

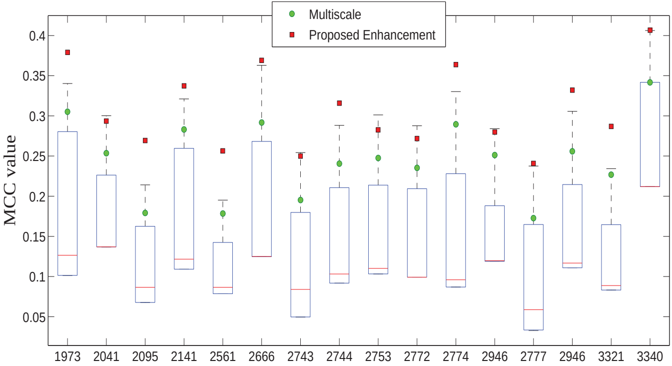
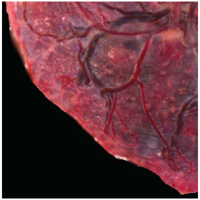


Figure: A box plot for the maximum MCC values with [1] on each of the 16 placentas (ID on horizontal axis). The best MCC value for [2] and the proposed enhancement method are also given for comparison.

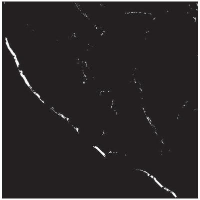
Qualitative Results

64-bit laptop w/Windows
Intel(R) Core(TM) i7-3770
@ 3.4GHz CPU, 8GB RAM
implemented in MATLAB
$\sigma \in \{4,6\}, \beta = 0.5, c = 15$
$\omega = 5, \ell = 14, \alpha = 0.04$
NN = 36.68s, MVE = 0.92s
C.L. Enhancement = 4.44s



(a) original

(b) hand traced



(c) neural network

(d) multiscale

(e) proposed

Figure: placenta ID 3355.

Summary

- A completely automatic routine to perform vessel enhancement on digital photographs of placenta was proposed.
- The method is shown to be superior than *all* existing methods in this line of research.
- Not only is the proposed method more accurate in identifying locations of vessel, it is doing so in a much faster way.

References

[1] N. Almoussa, B. Dutra, B. Lampe, P. Getreuer, T. Wittman, C. Salafia, and L. Vese, "Automated vasculature extraction from placenta images," *Proceedings of SPIE Medical Imaging Conference*, vol. 7962, 2011.

[2] A. Frangi, W. Niessen, K. Vincken, and M. Viergever, "Multiscale vessel enhancement filtering," in *LNCS*, vol. 1496. Germany: Springer-Verlag, 1998, pp.130-137.