Multi-Scale Vessel Extraction Using Curvilinear Filter-Matching Applied to Digital Photographs of Human Placentas

Marilyn Y. Vazquez, Nen Huyhn, and Jen-Mei Chang, Ph.D.

California State University, Long Beach, CA, U.S.A.

Why Study the Placenta?

- As the source of nutrients and outlet of waste, the placenta has a big impact on the development of the fetus, and studying it might give better clues on the causes of problems such as low birth weight and short gestational age.
- Features of the placenta that are being studied as potential predictors of pathologies are placental shape and vascular structure pervasiveness.

Question: Which one of following placentas is associated with a healthy baby?

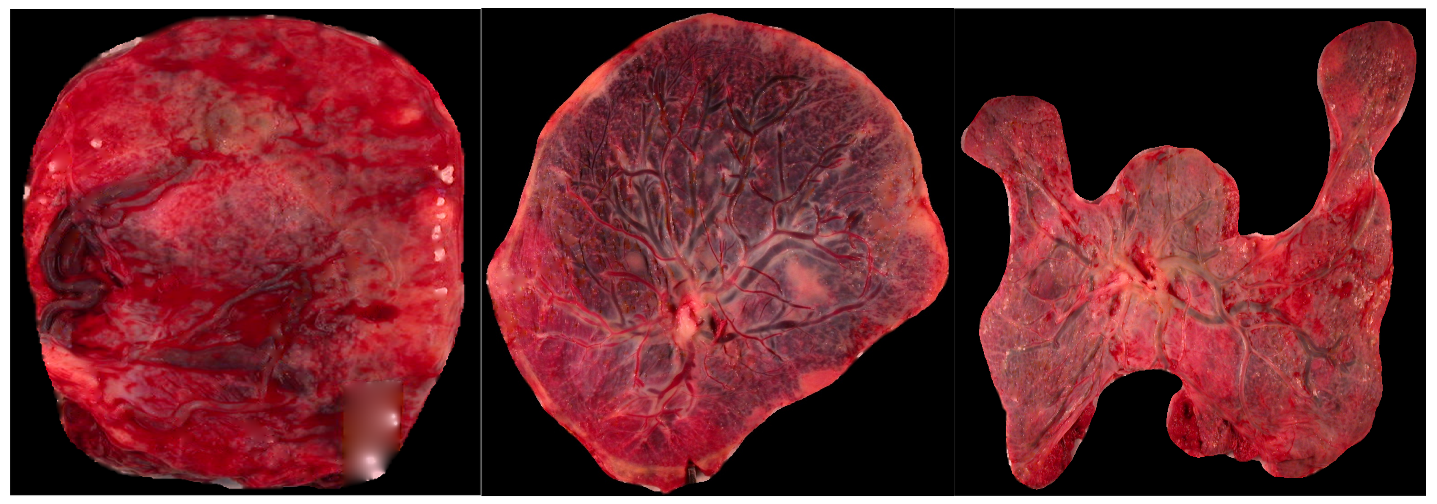


Figure: Sample digital placenta images in the UNC data set provided by Placental Analytics.

Overview

- The goal of this project is to develop an automated program that detects vessels in placenta images, which can be challenging because of the variations of color in the placenta and the non-uniform texture.
- To extract the vascular structure of the placentas, we use a multi-scale filter in combination with a line filter to take advantage of the second order characteristics and linear structure of the vessels.
- The results show an improved identification of vessels, measured by the Matthew's Correlation Coefficient, compared to the only other previous work in [1].

Image Representation and Filtering Process

- For implementation purposes, we used the green channel of the images so that $I(x,y)$ denotes the image function I and x, y the pixel location. For example, from (c) in the figure below, $I(104,43) = 6$ means that the pixel located at the position $(104,43)$ has a "green" intensity value of 6.

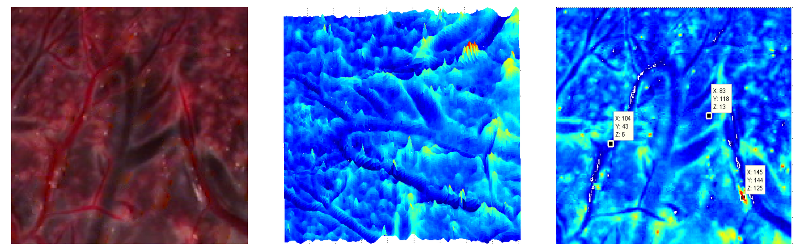


Figure: An image, its green channel tilted to show intensity map, some pixels labeled on the green channel, which is the one used for the implementations of this paper to create a better contrast, with some pixels labeled.

- The linear filtering process can be viewed as a convolution of the image $I(x,y)$ with a filter function $f(x,y)$ with a moving convolution mask [3], illustrated in the following figure.

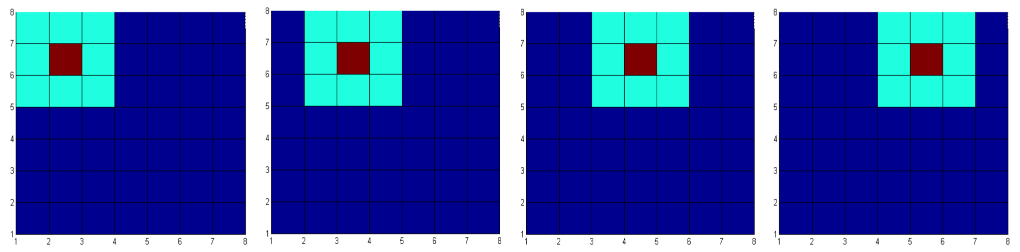


Figure: Convolution masks in light blue with red centers. These convolution masks move throughout the image as illustrated here from left to right.

The Multi-scale filter

- Let the 2D Gaussian filter be defined as follows

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

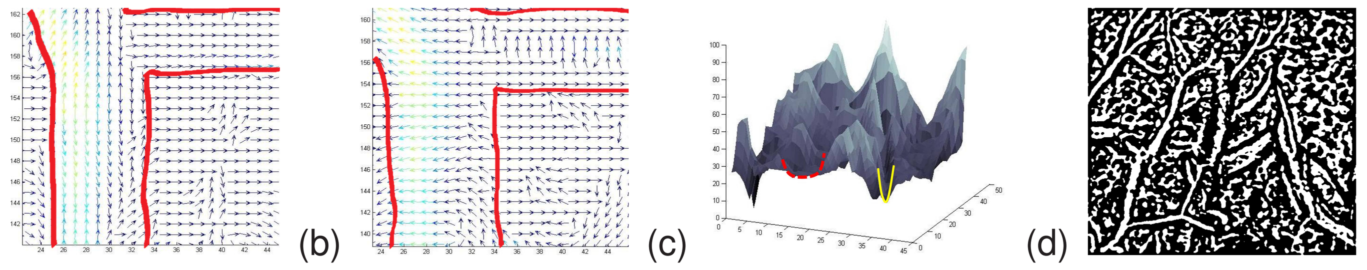
- If we let $I(x,y)$ be the image input and G_σ, be a Gaussian filter, the Hessian matrix is

$$H_\sigma = G_\sigma \star \begin{pmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{pmatrix}$$

- Since vessels appear as "valleys" in the image's intensity map, the eigenvalues of the Hessian are used to create a function that will output high values for pixels that are vessels and low values for those that are not.
- This likelihood equation, or"vesselness" equation, is defined in [2] as

$$V_o(s) = \begin{cases} 0 & \text{if } \lambda_2 < 0, \\ e^{-\frac{A^2}{2\beta^2}}\left(1 - e^{\frac{s^2}{2c^2}}\right) & \text{otherwise.} \end{cases}$$

where $A = \frac{\lambda_1}{\lambda_2}$ and c and β are thresholds that control the sensitivity of the line filter to A.
- However, due to the non-uniform texture of the placenta, this method detects background noise as vessels, as shown in the figure below.



(a) (b) (c) (d)

Figure: (a) Eigenvectors corresponding to the smallest eigenvalue of the Hessian, and (b) the eigenvectors corresponding to the other eigenvalue. (c) Intensity map rotated to magnify intensity values. Notice that a vessel, highlighted in yellow, and noise, highlighted in red, cannot be distinguished easily. (d) Multi-scale method applied on placenta patch.

Enhancing the Multi-scale Filter

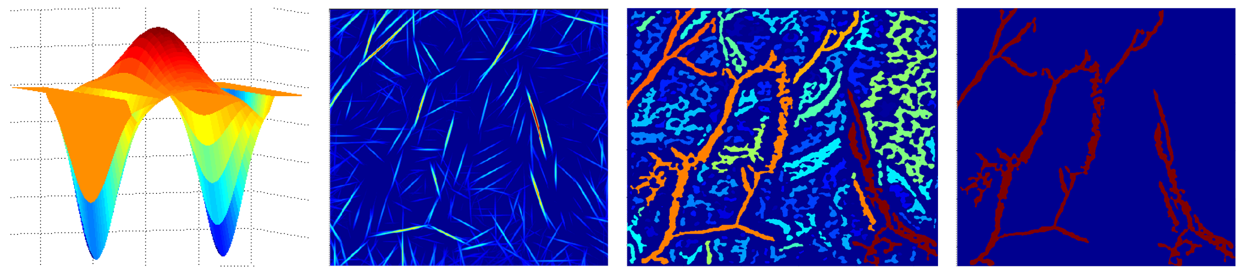
Linear Filter Matching

Since the multi-scale method identifies background noise as part of the vessel structure, we propose a new line filter to highlight linear structures already identified with the previous method and penalize surrounding pixels.

To achieve this goal, we constructed the following equation from the second derivative of the Gaussian function:

$$\Psi(x,y) = \begin{cases} \frac{1-w^2x^2}{4-w^2x^2}\mathrm{e}^{\left(-\frac{1}{2}\left(\frac{3}{4-w^2x^2}+l^2y^2\right)\right)} & \text{if } |x|<2w \\ 0 & \text{if } |x| \geq 2w \end{cases}$$

Then, we divided the multi-scale result in components and kept only components with linear values higher than a threshold, as shown in the following figure.



(a) (b) (c) (d)

Figure: (a) The proposed linear filter and (b) the results of applying this filter to the placenta patch. (c) The multi-scale result, and (d) the combination of both using a threshold of 40.

Empirical Results

The Matthew's Correlation Coefficient

To test the effectiveness of the filtering process, we used the confusion matrix to compare our results to the hand tracings of the placenta images done by pathologist. The confusion matrix can be constructed in the following form:

		True ID	
		True	False
Labeled ID	True	True Positive	False Positive
	False	False Negative	True Negative

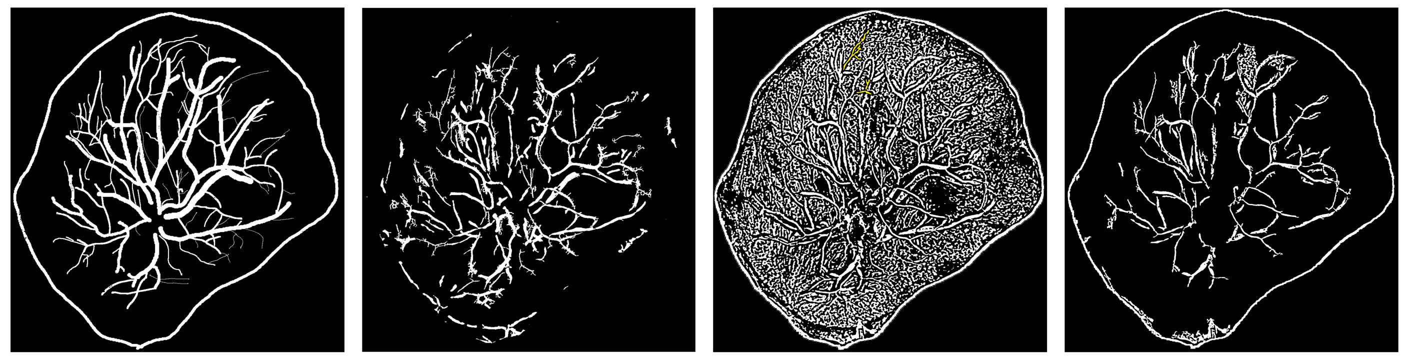
The Matthew's Correlation Coefficient (MCC) metric is defined as follows:

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

This metric is a correlation measure with values between -1 and 1 that for our case will be measuring how related the our identification of the vessels are to the actual vessel locations. Since the MCC gives an idea of how well the filtering process identified the vessels for the given parameters, it can be plotted against different threshold values to compare the overall accuracy of the our proposed filtering process. Then, the area under the MCC curve can be calculated to have a single value to compare results.

The Results

The best results were given by **experiment 1**, shown in Figure 6(e), with parameters: resizing = 3, Frangi scale = 5, Ridgelet width = 14, length = 36, number of filters = 12. The MCC values are given in Table 1



(a) (b) (c) (d)

Figure: (a) Hand tracing, (b) results from neural networks, (c) Frangi results with a threshold of 0, and (d) Frangi-Ridgelet with resizing = 3, Frangi scale = 5, Ridgelet width = 14, length = 36, number of filters = 12.

Method	Highest MCC value	Area Under the MCC curve
Neural Networks	0.345	0.22
Frangi	0.2552	0.1216
Experiment 1	0.3539	0.25

As seen in the table above, our proposed method is able to detect vessel pixels better than the neural networks method and the multi-scale vessel on its own.

Acknowledgements

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References

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Department of Mathematics and Statistics, California State University Long Beach, Long Beach, CA 90840

marilyn.vazquez@student.csulb.edu