Vessel Enhancement With Multiscale And Curvilinear Filter Matching For Placenta Images

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***Abstract*—Recently, placental pathology evidence has contributed to current understanding of causes of low birth weight and pre-term birth, each linked to an increased risk of later neuro-developmental disorders. Among various factors that cause such disorders, the vessel network on the placenta has been hypothesized to offer the most clues in bridging that connection. Herein lies the most essential step of the blood vessel extraction, which has only been done manually through laborious methods. In this paper, a filtering process that is partly based on images' second-order characteristics is proposed to highlight image pixels from locally curvilinear structures while simultaneously decrease non-vessel noise. Results are reported in Matthews Correlation Coefficient (MCC) against the pathologist's ground truth tracings and compared with an existing neural network approach. The proposed enhancement process consistently outperforms the multiscale and neural network approaches in both accuracy and efficiency. Since the process is completely automated, the algorithm is readily extendable to other medical images where vessel extraction is needed.**

I. Introduction

Placenta is the source of nutrition, oxygen, and blood for the developing fetus. Due to its importance, researchers in recent years started to believe that an analysis of the placenta may help predict risks for certain diseases that develop in the womb such as diabetes, autism, and heart disease [1], [2]. Ultimately, placenta research aims to develop mathematically quantifiable placental measurements that can be used to better understand how newborn, childhood, and potentially adult diseases have their genesis in gestational stress.

The structure of the placental blood vessels, which supply a fetus with all of its oxygen and nutrition, is believed to contain important medical clues. An essential step in the analysis of the vascular network pattern is the extraction of the blood vessels, which has only been done manually through a costly and time-consuming process. In practice, the large variation in the shape, color, and texture of the placenta makes it extremely difficult to apply standard image processing techniques. The only existing research in this field is documented in [3] with a neural network approach that requires a supervised training.

As one can see in Fig. 1(a), it is rather difficult to distinguish between a vessel and the vessel-like noise around it. Typical de-noising methods based on Gaussian smoothing can not be applied here since averaging erases the valley and peak structure exhibited by the small vessels which typically consist of very few pixels. Hence, the challenge for constructing a reliable method that outlines vessels on placenta images requires the ability to extract geometrically meaningful features.

Our proposed filter is built upon the success of an existing vessel enhancing filter, termed multiscale filter. It is based on the second-order characteristics of the image geometry and has been widely used in identifying vessels of varying sizes for MRI images [4], CT scans [5], and retinal images [6]. However, when the multiscale filter is applied to placenta images, the filter adversely picks up placenta's rough and irregular surface as part of the vessel network. This is true even on placenta images that are free of glare. To amend the fault caused by the multiscale filter, we propose the use of a match filter on the partial response returned by the multiscale framework to highlight locally curvilinear structure while penalize neighborhood pixels that present non-cohesive structure.

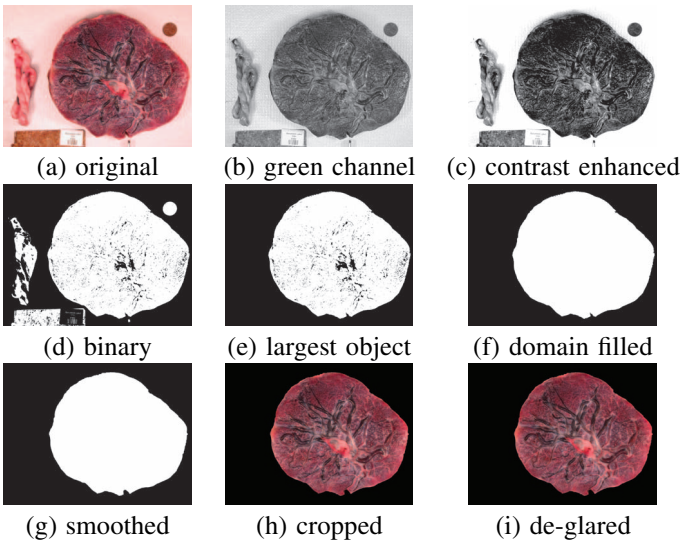
In the remainder of the paper, we will describe the proposed curvilinear filtering process in Section II and validate our proposed ideas with experimental results in Section III using images provided by Placental Analytics, LLC [2]. The paper is concluded with a summary of the work accomplished and a discussion of the significance in Section IV.

II. Proposed Method

A. Preprocessing

Many of the raw placenta images contain rulers and coins that were intended for scale information but are irrelevant to this task. Moreover, the majority of the placenta images have significant glare and low contrast due to the blood content and suboptimal imaging environment which present additional challenges for vessel extraction. In exploring color information of the images, we found that the green channel provides a much higher contrast than the red channel and is used in the subsequent preprocessing routine. Next, we illustrate with Figure 1 the steps we take to arrive at cropped and de-glared placenta images that are used for vessel extraction in the study. However, in the interest of space, readers who are interested in the detailed description of the algorithms used are referred to [3].

Starting with a raw placenta image (Fig. 1(a)), obtain the green channel information (Fig. 1(b)) and stretch the intensity distribution by a linear transformation to highlight the



(a) original (b) green channel (c) contrast enhanced

(d) binary (e) largest object (f) domain filled

(g) smoothed (h) cropped (i) de-glared

Fig. 1. The process of the implemented cropping and de-glaring algorithm on a sample placenta image.

extremely low and high intensities (Fig. 1(c)). The gray scale image is then converted to a binary image by thresholding about the mean intensity value (Fig. 1(d)). The largest object in the image content is detected (Fig. 1(e)) and filled in to create a continuous and compact domain (Fig. 1(f)). To create a smoother structure in the image boundary, a morphological erosion is applied (Fig. 1(g)). The resulting image serves as a mask template and is overlayed on top of the original image to arrive at a cropped placenta image (Fig. 1(h)). Glare is then removed using a modified in-painting algorithm described in [3]. The final image (Fig. 1(i)) is what we use to develop the proposed vessel extraction algorithms.

B. The Multiscale Filter

A vessel enhancing method based on second-order characteristics was first developed by Frangi et. al [4] which uses eigenvalues of the Hessian to determine locally the likelihood that a pixel belongs to a vascular region. Note that the following discussion is intended for dark curvilinear structures with a brighter background. For bright objects with a darker background, the conditions of the eigenvalues (or the images) should be reversed. For a 2D digital image $I(x, y)$, its Hessian matrix is given by

$$H(x,y) = \begin{pmatrix} \frac{\partial^2 I}{\partial x^2} & \frac{\partial^2 I}{\partial x \partial y} \\ \frac{\partial^2 I}{\partial y \partial x} & \frac{\partial^2 I}{\partial y^2} \end{pmatrix}. \tag{1}$$

Let $\mathbf{u}_1$ and $\mathbf{u}_2$ denote eigenvectors of H corresponding to eigenvalues λ_1 and λ_2 satisfying $|\lambda_1| < |\lambda_2|$, respectively. If we associate $|\lambda_i|$'s with the magnitude of curvatures, then $\mathbf{u}_1$ would likely point along with the direction where the vessel travels while $\mathbf{u}_2$ would point towards the edge of the vessel.

These eigenvalues can then be used to define two *vesselness* measures suited for medical images:

$$\begin{aligned} \text{(anisotropy)} \quad A &= \frac{|\lambda_1|}{|\lambda_2|}, \quad \text{and} \\ \text{(structureness)} \quad S &= \sqrt{\lambda_1^2 + \lambda_2^2}. \end{aligned}$$

The value of A is high if there is a large curvature in the direction of $\mathbf{u}_2$ and small curvature in the direction of $\mathbf{u}_1$. S will be low in the background where no structure is present and the eigenvalues are small for the lack of contrast.

With these two measures, the probability of a pixel being a vessel is given by

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

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

The multiscale filter works best when the background of the image has negligible overall concavity when viewed as a surface, i.e., the eigenvalues of the Hessian are small. However, discoloration in the background is typical in placenta images which produces significant concavity with similar magnitude when compared to actual vessels.

C. Curvilinear Filter Matching

Let $I : D \to \mathbb{R}$ be an image where $D \subseteq \mathbb{R}^2$ is the pixel window of the image. We treat I with the multiscale filter to identify potential vessels. For example, given a pixel (X, Y), we have a potential vessel at that location if $F\{I(X, Y)\} > \alpha > 0$. For convenience, we define the binary response function

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

to guide us in identifying pixels that are highly likely to be vessels. α is chosen so that the connected components of $B^{-1}\{1\}$ either identifies vessel regions or non-vessel noise. The choice of α does not need to be precise.

Now, to get rid of the non-vessel noise that is picked up by the multiscale filter while maintaining the connected components in the vessel network, a curvilinear filter is proposed to accomplish three desirable characteristics that are described next.

A pixel (X, Y) in the region of $B^{-1}\{1\}$, i.e., the set of marked pixels identified by the multiscale filter, is likely to be a part of a line of width $2w$ if there are orthogonal vectors $\mathbf{u}, \mathbf{v} \in \mathbb{R}^2$ with $\|\mathbf{u}\|_2 = w$ and $\|\mathbf{v}\|_2 > w$ so that:

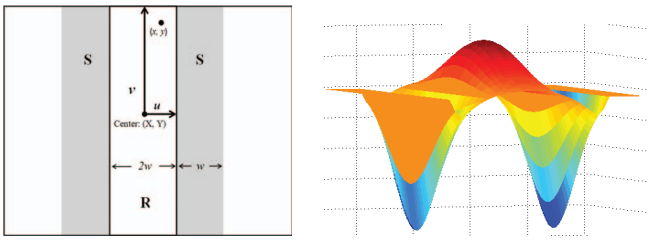
(i) $R = \{s\mathbf{u} + t\mathbf{v} + (X, Y) \mid -1 \le s, t \le 1\} \subseteq B^{-1}\{1\}$. That is, R is identified to be a vessel region.

(ii) $S = \{s\mathbf{u} + t\mathbf{v} + (X, Y) \mid |t| \le 1, 1 < |s| < 2\} \subseteq B^{-1}\{0\}$. That is, S is identified to be a non-vessel region.

(iii) And points in $R \cup S$ are inversely weighed based on their distances to pixel (X, Y). That is, points in $R \cup S$ contribute less to the vessel response if they are further away from (X, Y).

Fig. 2(a) depicts the ideas used in these three conditions.

Criteria (i) and (ii) motivate the use of a match filter as a way to reward pixels in region R and penalize pixels in



(a) (b)

Fig. 2. (a) An illustration for the conditions used in generating the proposed curvilinear filter. (X, Y) is the pixel being analyzed, R is the vessel region, and w is the width of the filter. (b) The proposed curvilinear filter function, generated with $w = 10$ and $\ell = 15$.

region S. To satisfy criterion (iii), we first note that the second derivative of the Gaussian function, i.e.,

$$-\frac{\partial^2 G}{\partial x^2}(x, y) = \left(1 - w^2x^2\right) \exp\left(-\frac{1}{2}\left(w^2x^2 + \ell^2y^2\right)\right) \quad (3)$$

has a structure with a centered peak, valley on the sides, and a leveling-out effect in the pixel region that is further away. Since vessels on placenta images tend to stay close to each other, the desired filter function should assign a large weight in $R \cup S$ and the drop off should be smooth. To accomplish this task, we replace the w^2x^2 term in Equation (3) with $\dfrac{3}{4 - w^2x^2}$. This way, $\exp\left(-\frac{1}{2}\left(\frac{3}{4-w^2x^2} + \ell^2y^2\right)\right)$ approaches 0 as $wx \to \pm 2$, hence the smoothness condition is accomplished.

With these, define the proposed curvilinear filter function

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

As shown in Fig. 2(b), this function highlights locally linear structure by controlling the width and length parameters, while penalizing neighborhood pixels that present non-cohesive structure. Notice that Ψ is a heuristic filter since it does not account for direction information. To that end, define the curvilinear template $W(x, y) = \Psi \circ T_{\mathbf{u}}(x, y)$ once the directions $\mathbf{u}$ and $\mathbf{v}$ are given, where $T_{\mathbf{u}}$ is a rotation that maps $\mathbf{u}$ to $(\|\mathbf{u}\|, 0)$. This allows us to apply the curvilinear filter in any orientation specified, hence the name curvilinear.

Since the orientation of the vessels varies across a single image, we create a library of curvilinear templates W_k's corresponding to a collection of various orientations $\{\mathbf{u}_k = (\cos\theta_k, \sin\theta_k)\}_{k=1}^n$, where $\theta_k = \frac{k\pi}{n}$ for some fixed n. Precisely, $W_k(x, y) = \Psi \circ T_k(x, y)$ where

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

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. This filtering process satisfies the desirable conditions since pixels in $B^{-1}\{1\}$ return a positive V_k response if they are in region R and return a negative V_k response if they are in region S and the term $\exp\left(-\frac{1}{2}\left(\frac{3}{4 - w^2x^2} + \ell^2y^2\right)\right)$ shrinks in value for points (x, y) that are further away from the center of the filter. This justifies the use of V_k to achieve the desired goal. Finally, from the collections of CLF responses, a point (x, y) is assigned the maximum CLF response $V(x, y) = \max\limits_{1 \le k \le n} V_k(x, y)$, which represents the amount of curvilinear structure the pixel possesses.

D. Vessel Enhancement

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

First, the set of pixels identified as potential vessels by the multiscale filter $B^{-1}\{1\}$ is the union of distinct connected components $\{B_i\}$. The connection is joined by one or more pixels. To mitigate the effect of noise, assign pixels in a component the maximum value of $V(x, y)$ in that component. That is, 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. The enhanced result prevents the occurrence of negative values. The rationale is that the vessel pixels have dominating curvilinear filter responses than the noise pixels. By picking a threshold value μ, we can remove components that do not have any pixel (x, y) satisfying $E(x, y) > \mu$, i.e., non-vessel regions.

At the end of this enhancement process, there will be a collection of points that are identified as vessels:

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

III. Experimental Results

In this section, we provide a quantitative and visual comparison of the proposed enhancement method against two baseline approaches that were described previously, i.e., the multiscale method [4] and the neural network approach [3] on a private placenta database fully described by [7] and provided by Placental Analytics LLC. Of the placentas photographed, 150 were traced by hand by a trained pathologist, hence providing the ground truth data for our experiments. Of the 150 traced images, 16 were chosen at random to benchmark the proposed work. Their corresponding placenta ID number is given in Fig. 3 for convenience.

While a Receiver Operating Characteristic (ROC) curve is typically used to evaluate the performance of a vessel extraction method, it is more appropriate to use the Matthews Correlation Coefficient (MCC) in reporting algorithm performance when we expect the accuracy to be low, which is indeed the case on placenta images. This choice is also intended to align with the results report in [3]. Formally, Matthews Correlation Coefficient is defined as

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

where TP gives the number of vessel pixels that are classified as vessel, TN gives the number of non-vessel pixels that are classified as non-vessels, FP gives the number of non-vessel pixels that are classified as vessels, and FN gives the number of vessel pixels that are classified as non-vessels.

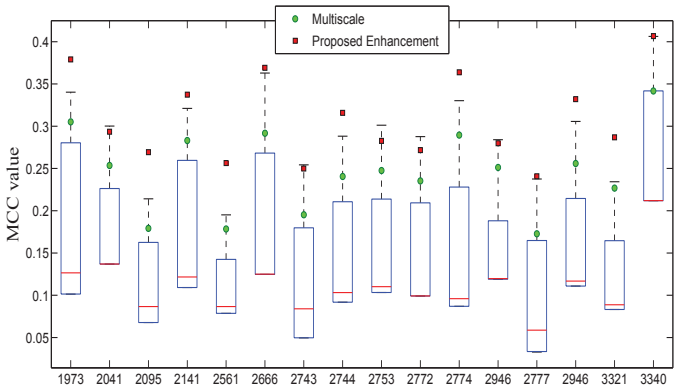


Fig. 3. A box plot for the maximum MCC values obtained through a neural network approach [3] on each of the 16 placentas tested (ID number is given on the horizontal axis). The best MCC value for the multiscale and the proposed curvilinear enhancement method are also given for comparison. It is clear that the proposed method consistently outperforms the two baseline algorithms on nearly all incidents.

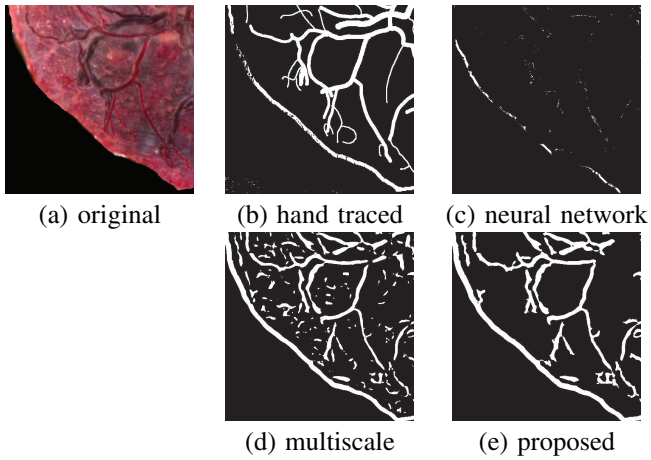


Fig. 4. A visual comparison between the proposed and existing methods on a randomly chosen placenta patch (placenta ID 3355).

Because the neural network results vary depending on a random seed, its results over 400 runs is given in Fig. 3 to summarize its performance statistics. It is evident that the proposed method consistently outperforms, with a significant margin, the two baseline algorithms on nearly all incidents. This is especially true for vessel images with a noisy background. Fig. 4 provides a visual clue to support the quantitative outcome described in Fig. 3. While Fig. 4(c) is obtained with the best MCC score out of the 400 runs, it fails to capture most of the vessels present in Fig. 4(a). On the other hand, the result from the multiscale vessel enhancement, as shown in Fig. 4(d), consists of many disconnected components that are not part of the large vessel network. These false positives are successfully corrected by the proposed curvilinear filter, as shown in Fig. 4(e).

The computational time we report here is done on 1600×1200 placenta images as shown in Fig. 1(i). All experiments are implemented in MATLAB and computed on a 64-bit laptop running Windows with Intel(R) Core(TM) i7-3770 at 3.40 GHz CPU and a 8GB RAM. On average, it takes 0.92 seconds to produce an enhanced image with the multiscale vessel enhancement using $\sigma \in \{4, 6\}$, $\beta = 0.5$, and $c = 15$. Along with these parameters, let $w = 5$, $\ell = 14$, and $\alpha = 0.04$, the proposed enhancement with the curvilinear filter takes an average of 4.44 seconds. This is an eightfold gain in computational efficiency when compared to the 36.68 seconds for the neural network approach having exactly the same parameters used in [3]. Most importantly, the entire process of vessel enhancement is automated without training, hence making real-time medical diagnosis feasible.

Technically, the values of the width, w, and the length, ℓ, may be visually approximated and if necessary, the best pair of the width and the length may be learnt from a single placenta. The threshold parameter, α, can be set as low as 0.04 to remove most of the noise in the background. Typically, the bottleneck of these calculations is due to the slow speed of convolution; however, an approach that is inspired by the Singular Value Decomposition [8] was implemented here to remedy the issue.

IV. Summary

In this study, we propose a vessel enhancement method based on a modified Gaussian function that is excellent in mitigating noisy vessel structures. Our work is inspired by the success of the multiscale filter on various medical imaging problems and results illustrated in this paper show promises of the proposed method in advancing the collective knowledge in the difficult field of vessel extraction from placenta images.

The proposed study breaks new ground by being the first to implement an automatic routine in vessel enhancement from digital images of placental surfaces. Not only is the proposed method more accurate in identifying locations of vessel, it is doing so in a much faster way. The impact of this study, if successful, will not only make it one step closer to the task of automatic vessel extraction on placental surfaces but also provide a blueprint to other medical imaging problems that require general vessel extraction.

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