ENHANCEMENT OF VESSEL CONTOURS IN RETINAL ANGIOGRAMS

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ABSTRACT

Accurate and automatic assessment of angiograms has been sought as a powerful diagnostic tool in medical analysis, such as in diabetic retinopathy. These retinal angiograms images are characterized by poor local contrast. Applications of existing edge detection algorithms yield unsatisfactory results. In this paper, a set of cascaded linear directional filters is used to better enhance edges. Results show improvement in visual quality of the images.

keywords: *Retinal Digital images, Edge Detection, Angiograms, Vessel Enhancement, Vessel Detection*

1. INTRODUCTION

The quantitative computer based assessment of medical images plays an important role in clinical and research studies of a number of diseases. These images normally involve blood vessels trees that present information about the disease under question. In most cases the starting point of such kind of analysis of these images is the detection of vessels. This procedure can be seen as an edge detection procedure. Edge detection plays an important role in a number of image processing applications, such as scene analysis and object recognition.

There are various edge detection approaches in the literature. These methods fall under one of the following main categories.

1. Gradient-based schemes

   These schemes enhance discontinuities in images, using differential operators, for example. Then, the resulted image is thresholded. These schemes produce good results when the edges are sharp in the original image. However, the presence of noise highly degrades the performance of such schemes [1, 2, 3, 4].

2. Model-based schemes

   Algorithms belonging to this category attempt to match each edge segment in the image with a one of predefined edge-models. Then, the matched model is used to enhance these edge segments. Finally, the resulted image is thresholded. Thus the results of these algorithms are optimal for the chosen edge model and are less sensitive to noise. However, they are usually computationally expensive. Efforts have been made to simplify this approach [5, 6, 7].

In this work, a combination of edge/vessel detection techniques is proposed to achieve robust results. The organization of this paper is as follows. Section 2 describes the retinal angiograms, i.e. how they are produced and some of their properties. Some of the existing edge detection techniques are reviewed in Section 3. The proposed approach is presented in Section 4. Results are reported in Section 5. Finally some concluding remarks are given in Section 6.

2. BLOOD VESSEL DETECTION

2.1. Image acquisition

The acquisition of retinal angiograms is done by injecting fluorescein, a red crystalline dye that is visible in ultra-violet light, into the blood stream. The intention is to analyze the diffusion of the blood in the Retinal vascular system. A series of photos are collected and used in the examination of the patient. This procedure produces, along with the vascular tree, some undesired patterns in the image. These patterns can be categorized as follows [8]:

1. The noise occurring during the digitization process.

2. Noise due to the fluorescence of the layers below the retina. This is highly dependent on the anatomy of the eye.

3. Pathological disturbance of blood circulation in the Retinal layer.

4. Low random signals along the vessels, due to the late diffusion time.

2.2. Image Properties

In general, the retinal angiograms have been observed to have the following properties [5]:

1. Vessels usually have small curvatures. Therefore, they can be approximated as piecewise linear anti-parallel segments (anti-parallel since the gradient direction of the two edges composing the vessel are 180^o apart).

2. The vessels were observed not to have ideal step edges. The profile of the vessel was observed to have Gaussian like shape. The vessel can be approximated by the function

$$f(x,y) = A\left(1 - ke^{\left(\frac{-d^2}{2\sigma^2}\right)}\right),$$

   where d is the perpendicular distance between the point (x, y) and the center line of the vessel in the direction along its length. The parameter σ is the standard deviation of the modeled Gaussian. Parameters A and k are constants that depend on the shape of the model adopted.

3. Although vessels reduce in size as they travel radially outwards from the optical disk, such a change in the vessel caliber is a gradual one.

Normally, the use of general edge detection techniques blindly for any problem doesn't yield good results. This is very much true in the case of the retinal angiograms. Figure 1 shows a typical retinal angiograms image.

3. EDGE DETECTION

Lim [9] defines an edge in an image as a boundary, or a contour, at which a significant change occurs. In Section 1, we gave a brief introduction to edge detection were we divided the edge detection techniques into two categories: gradient-based schemes and model-based schemes. In this section we will elaborate more on these techniques.

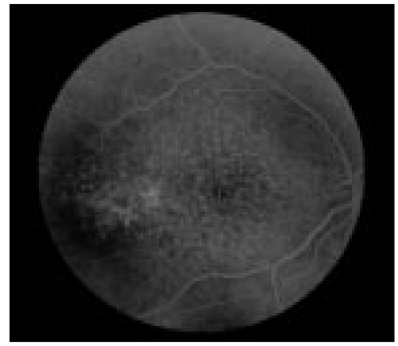


Figure 1: A typical retinal angiograms image

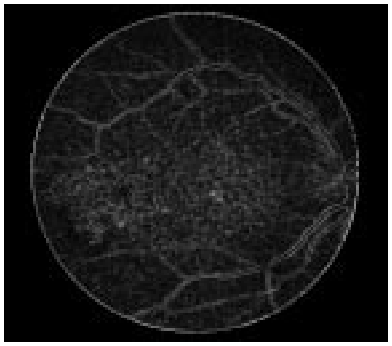
3.1. Gradient-based schemes

Edge points are characterized by change of slope. This can be measured using the derivative, e.g., the gradient. The magnitude of the derivative indicates the sharpness of the edge, where the edge occurs at the turning point of the gradient. An example of these operators is the Sobel [3] operator. Figures 2 (a) shows the effect of Sobel operator on the retinal angiograms image shown in Figures 1. Figures 2 (b) shows the thresholded version of Figures 2 (a).[1]

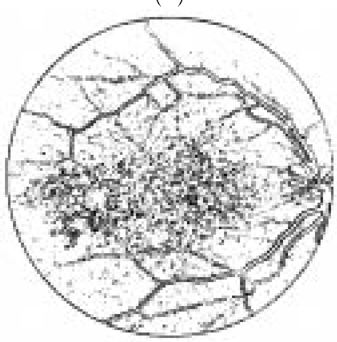
Since Sobel operator is based on the first derivative, it might not that straightforward to identify the actual location of edges, as well as to find the thresholding value. Instead of using the first derivative to identify edge pixels, the Laplacian operator uses the second derivative to do so [2]. In the Laplacian approach, edge pixels are located at the zero-crossing points. However, this approach is very sensitive to noise in the image and gives a lot of false edges. Figure 3 shows the output using the Laplacian operator.

A more sophisticated approach, which based on the Laplacian operator, was presented by Marr and Hildreth [4]. They apply a Gaussian *Low Pass Filter* (LPF) on the image before applying the Laplacian operator. The Gaussian LPF basically was to reduce the effect of noise by transforming the image to a lower resolution. However, these edge detection techniques do not show a reasonable amount of noise suppression that can allow for further segmentation of the image. It is worth mentioning that, there is a tradeoff between removing the noise from the image and destroying the vessel edges. Figure 4 shows the output using the Marr-Hildreth approach, where two different Gaussian LPFs are used.

[1] Note that, pixel values in any thresholded image in this paper is reversed to improve the printing quality.



(a)



(b)

Figure 2: Edge detection using Sobel operator. (a) Image after applying The Sobel operator; (b) Thresholded image at value = 48.

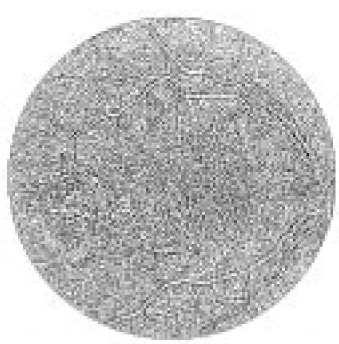
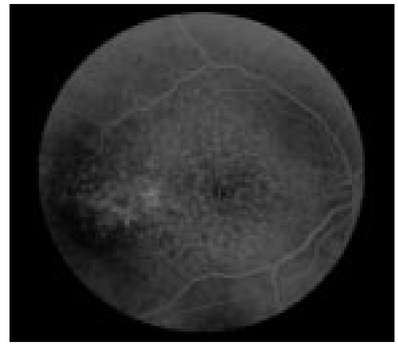
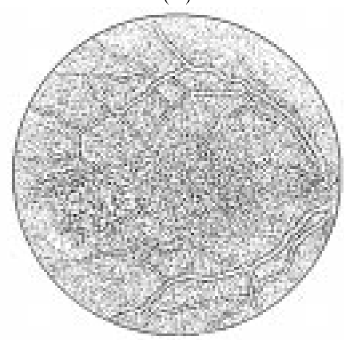


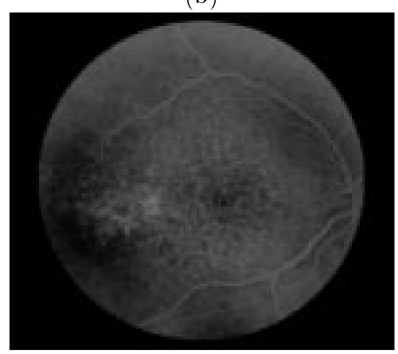
Figure 3: Edge detection using Laplacian operator.



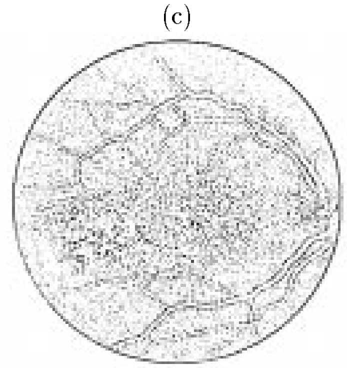
(a)



(b)



(c)



(d)

Figure 4: Edge detection using Marr-Hildreth approach. (a) and (c) After applying a Gaussian LPF with standard deviation = 0.6 and 1.0, respectively; (b) and (d) After applying the Laplacian operator, followed by thresholding, to images (a) and (c), respectively.

3.2. Model-based schemes

Algorithms belonging to this category attempt to match each edge segment in the image with a one of predefined edge-models. Then, the matched model is used to enhance these edge segments. Finally, the resulted image is thresholded.

The optimal model that can realize the properties of the vessels takes the shape

$$h_{opt} = e^{\left(\frac{-d^2}{2\sigma^2}\right)}.$$

Under the assumption of constant vessel width and additive white Gaussian noise, Chaudhuri, et. al. [5] proved that this is the optimal filter in the direction along the vessel.

When applying this to retinal angiograms images, we may run into the problem that the vessels run in different directions. This vessel orientation problem was solved by matching the image by the different alignments of the filter at an angle θ, where θ is the rotation angle applied of the filter. This will yield the peak response when the filter is aligned along the vessel center line.

4. THE PROPOSED FILTERING SCHEME

To improve and enhance the vessels in the retinal angiograms we propose the use of a structure of filters, as shown in Figure 5. This structure incorporates both a model-based filter and a Laplacian operator.

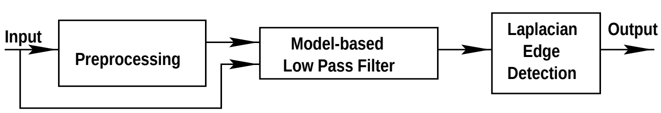


Figure 5: The proposed filtering block diagram

In this approach, a set of directional line filters is used to identify the direction of each vessel-segment. This line is centered, at the mask center, and rotated, according to pre-defined directions. The variance of pixels under the non-zero elements in each of these masks is calculated. The direction corresponding to the lowest variance is identified. This direction is chosen to be the direction for the vessel-segment in hand. Then, a model-based LPF filter in this direction is generated and filtered the pixel in hand to remove the noise and enhance the vessel.

Note that, removing the noise using a symmetrical Gaussian LPF may affect the sharpness of the vessel edges, since it doesn't really look into the continuation of the vessel. On the other hand, the proposed approach distinguishes between possible continuous vessels and noise in the image. Hence, it solves the tradeoff between removing the noise from the image and destroying the vessel edges.

Finally, the Laplacian operator is applied to the image to further improve the sharpness of the edges.

5. RESULTS

Figure 6 shows the direction image generated from the preprocessing stage. In this image, each direction is categorized by a specific gray level. In this work, θ is set to 15^0, which allows 12 different directions. The information in this image helped the model-based LPF filter to orient itself in the vessel-segment direction.

Figure 6: The direction generated from the preprocessing stage, where each gray level represents a direction.

Figure 7 shows the output using the proposed approach, where two different sets of directional Gaussian LPFs are used.

Figure 7 (a) and (c) show improvement in in visual quality of the images, if it is compared with the original image in Figure 1.

Comparing the images in Figure 7 (b) and (d), to that achieved by the Sobel operator (Figures 2 (b)), the Laplacian operator (Figure 3), and Marr-Hildreth approach (Figure 4 (b) and (d)), it is observed that:

- More real vessels has been detected. Note that, there are many minor vessel at the center of the image. These vessels have less continuity as compared with the major blood vessel tree.
- The proposed scheme produces more continuous edges.
- The level of noise is suppressed in the produced output of the proposed scheme. This is especially true within the vessel tree area.

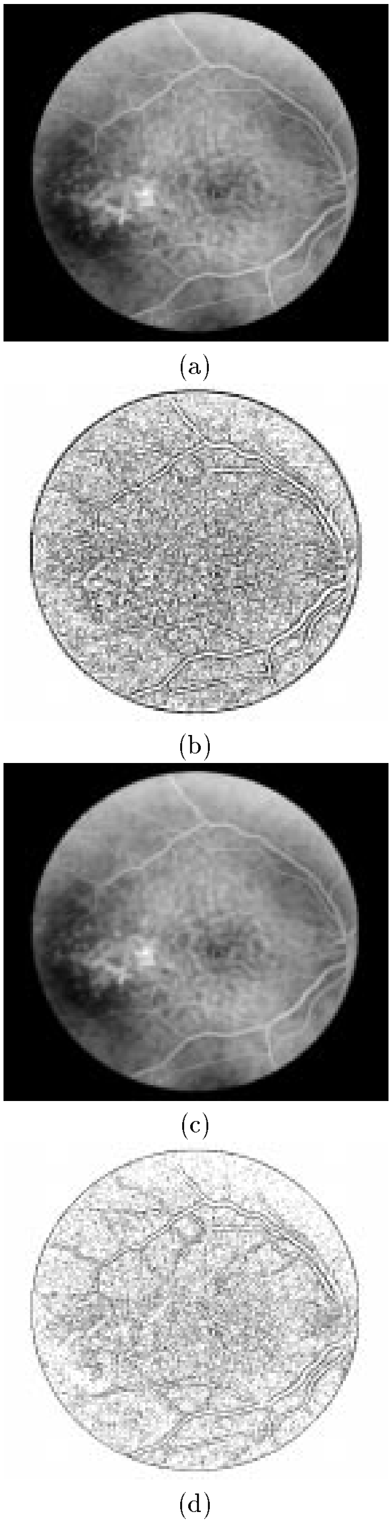


Figure 7: Edge detection using the proposed scheme. (a) and (c) After applying a set of directional Gaussian LPF with standard deviation = 0.25 and 1.00, respectively; (b) and (d) After applying the Laplacian operator, followed by thresholding, to images (a) and (c), respectively.

6. CONCLUSION

For images of a complex nature like the retinal angiograms, simple image processing techniques are inappropriate. To achieve any progress in the analysis of such images, a combination of tailored solutions must be developed. In this paper, we proposed a set of cascaded linear directional filters to better enhance/detect vessel edges. The results presented show an improvement on the visual quality of the edges, and at the same time a reduction in the noise level. This reduction in the amount of noise will improve the performance of any tracking algorithm that will be applied to the image to extract the vessels.

7. REFERENCES

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