Automated Vessels Detection on Infant Retinal Images

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Abstract: Retinopathy of Prematurity (ROP) is a common retinal neovascular disorder of premature infants. It can be characterized by inappropriate and disorganized vessel. This paper present a method for blood vessel detection on infant retinal images. The algorithm is designed to detect the retinal vessels. The proposed method applies a Lapalacian of Gaussian as a step-edge detector based on the second-order directional derivative to identify locations of the edge of vessels with zero crossings. The procedure allows parameters computation in a fixed number of operations independent of kernel size. This method is composed of four steps : grayscale conversion, edge detection based on LOG, noise removal by adaptive Wiener filter & median filter, and Otsu's global thresholding. The algorithm has been tested on twenty infant retinal images. In cooperation with the Digital Imaging Research Centre, Kingston University, London and Department of Opthalmology, Imperial College London who supplied all the images used in this project. The algorithm has done well to detect small thin vessels, which are of interest in clinical practice.

Keywords: Vessel Detection, Laplacian of Gaussian , Infant Retinal Images, Retinopathy of Prematurity (ROP)

1. INTRODUCTION

Retinopathy of prematurity (ROP) is characterized by inappropriate and disorganized vessel growth [1]. ROP may be indicated by the vessel properties such as engorgement and tortuosity [2] [3]. ROP diagnosis is based upon visual inspection of retinal blood vessels. Wallace et al. proposed a system where clinicians compare the video images with 5 reference images. Due to subjectivity of the comparison, this method can take as long as one hour per baby and for some cases there is high inter-physician disagreement [4]. Characterization of blood vessels can be used in preliminary grading of disease or used in a part of the process for automated diagnosis of diseases with ocular manifestation. Many automatic algorithms in the adult retina propose matched filtering used to emphasise vessels in a fundus images [5] [6] [7] [8] [9]. This method is quite effective to a point, but rarely useful alone, and need to be applied at several rotations. In addition, the kernel responds optimally to vessels that have the same σ the standard deviation of the underlying Gaussian function, and thus may not respond to thin vessels as well as wide vessels. In addition, the kernel, since it has a minimum length, may give weak responses for very tortuous vessels [10]. Martinez-Perez et al. have developed a region growing technique combined with scale-space analysis to extract blood vessels in the retina [11]. Leandro et al. use a continuous wavelet transform combined with morphological operators to segment blood vessels within the retina [12]. Aylward et al. which extracts blood vessels from 3-dimensional images using a scale space technique with sub-voxel accuracy [13]. Wood et al. equalizes image variabilities as a preprocessing step in their method to segment retinal vessels. Image equalization is achieved by computing a local two dimensional average and subtracting from each pixel [14]. Hoover et al. combine local and region-based properties to segment blood vessels in retinal images [15]. Goldbaum et al. describe their STARE (Structural Analysis of the Retina) image management system for the diagnosis and analysis of the retinal images. Segmentation of the images is achieved by employing rotating matched filters [16]. Staal et al. present a method to detect vessels in images of the retina. Instead of relying on pixel classification, as many detection algorithms do, and propose a more natural representation for elongated structures, such as vessels [17]. Heneghan et al. present a general technique for segmenting out vascular structures in retinal images, and characterizing the segmented blood vessels [18]. Chutatape et al. proposed scanning and tracking algorithms for detection blood vessel network in the retinal images. The framework of tracking designed the matched filter, tracking estimation and branch detection method [19]. Chanwimaluang and Fan introduced efficient methods for automatic detection and extraction of blood vessels and optic disc (OD) both of which are two prominent anatomical structures in ocular fundus images[20].

Many previous techniques have been shown to be successful on adult images but on infants this method will not suffice for solving vessel detection in infant images entirely. Because the main differences between the adult and infant images are : (a) Unlike adult retinal images two sets of vessels (retinal and choroidal) need to be distinguished. (b) The infant images are extremely noisy in comparison to the adult images, particularly in the periphery of the retina. (c) There is a massive range of image type, colour and quality, far more so than in adult retinal images [21] [22].

The detection of edges in an image has been an important problem in image processing. There are two main categories : gradient and zero-crossing based methods to detect edge. While the gradient approach uses the first-order directional derivatives of the image to compute a quantity related to edge contrast for edge detection, the zero-crossing approach requires computation of the second-order directional derivatives to identify locations with zero crossings. A very popular second-order derivative operator is the Laplacian operator. The problem with the second-order derivative approach is that the second-order derivatives tend to exaggerate noise twice as much. Some sort of noise suppression is needed. Marr and Hildreth [23] proposed the use of zero-crossings of the Laplacian of a Gaussian (LOG) for edge detection. The Gaussian serve the purpose of smoothing for noise reduction. Isotropic digital LOG kernels are used to convolve with an image to compute the Laplacian value of each pixel. Haralick [24] proposed the use of the zero-crossings of the second directional derivatives of the image brightness function. They also discuss zero-crossing edge operators, the performance characterization of edge operators and some line detectors.

In this work is only a part of a more extensive study about automatic vessel detection. We propose edge detection algorithm to detect blood vessels. Our method applies a Lapalacian of Gaussian to combind with our algorithm to detect a small thin vessels which is important for clinical diagnosis.

2. EDGE DETECTION

A number of method exist for detecting edges in images. Some of them are general in the sense that they can be used independently of the application, while others are specific for a particular application and make use of a priori information. The class of linear operators used for detecting edges in an image, which is of interest in the present study, has three essential operations : filtering, differentiation, and the subsequent detection of features such as peaks or zero crossings. The filtering or smoothing operation serves two purposes : it reduces the effect of noise on the detection of intensity changes and sets the resolution or scale at which intensity changes are to be detected. The second operation, differentiation, accentuates intensity changes and transforms the image into a representation from which properties of these changes can be extracted more easily. An intensity change along a particular orientation in the image gives rise to a peak in the first directional derivative of intensity measured perpendicular to the change, or a zero crossing in the second derivative. If directional operators are utilized, they should be applied for a number of directions in order to detect intensity changes at different orientations in the image. From a computational point of view, it would be efficient to apply a single no directional operator.

The Marr-Hildreth [25] operator, also known as the $\nabla^2 G$ operator, has provision for observing intensity changes at different scales and is one example of the class of linear operators used for detecting edges in images. It uses the Gaussian function for filtering and the Laplacian for differentiation and finally detects edges by detecting the zero crossings. The Gaussian function has the desired characteristic of being optimally localized in both the space and the frequency domain. Convolving an image $f(x,y)$ with the Gaussian function $g(x,y)$ effectively wipes out all structures at scales much smaller than the space constant σ of the Gaussian. The importance of Gaussian filtering and its similarities with filtering functions used in other edge detection operator are pointed out in [23]. The simplest nondirectional linear differential operator is the Laplacian. The first two operations in the Marr-Hildreth operator are combined into a single operation since both are linear. A single convolution of the image allows the detection of intensity changes at all orientations, for a given scale. Hence, for the detection of edges using a $\nabla^2 G$ operator, the required output is

$$f''(x,y) = \left[\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right) g(x,y)\right] ** f(x,y). \tag{1}$$

For the circularly symmetric 2-D Gaussian function,
Where ** indicates convolution.

$$g(r) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{r^2}{2\sigma^2}} \tag{2}$$

Where $r^2 = x^2 + y^2$ and σ is the standard deviation of the Gaussian function. The term in the square brackets in (1) evaluates to

$$g''(r) = \left(\frac{-1}{\pi\sigma^4}\right)\left(1 - \frac{r^2}{2\sigma^2}\right) \exp^{-\frac{r^2}{2\sigma^2}} \tag{3}$$

We base our algorithm on this edge detection formula. All the detail can be seen in section 3.

3. PROPOSED ALGORITHM

The proposed algorithm is composed of four steps. Grayscale conversion, edge detection based on LOG, noise removal by adaptive Wiener filter & median filter, and Otsu's global thresholding. Firstly, we apply the Laplacian of Gaussian to detect blood vessels with a modification step to include edge detection.

Since convolving it with a Gaussian kernel and then taking its Laplacian by convolving the result with a Laplacian kernel is exactly the same as taking the Laplacian of the Gaussian kernel (LOG) and convolving the image with it. The Laplacian of the Gaussian kernel is given by

$$LOG(x,y) = \left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right) \frac{1}{2\pi\sigma^2} e^{\frac{1}{2}\left(\frac{x^2+y^2}{\sigma^2}\right)} \tag{4}$$

$$LOG(x,y) = \frac{-1}{2\pi\sigma^4}\left[2 - \frac{x^2+y^2}{\sigma^2}\right] e^{-\frac{1}{2}\left(\frac{x^2+y^2}{\sigma^2}\right)} \tag{5}$$

The central negative area of the kernel is a disk of radius $\sqrt{2\sigma}$. The domain of the Laplacian of the Gaussian kernel must be at least as large as a disk of radius $3\sqrt{2\sigma}$. In actual practice, since only a zero crossing is being searched for, the Laplacian of Gaussian kernel is multiplied by some constant, and the resulting values are quantized to an integer, with some care being taken to do the quantization so that the sum of the positive entries equals the absolute value of the sum of the negative entries. One way of accomplishing this is to define.

$$LOG(x,y) = truncate\left[A\left(1 - k\frac{x^2+y^2}{\sigma^2}\right) e^{-\frac{1}{2}\frac{x^2+y^2}{\sigma^2}}\right] \tag{6}$$

After the definition of k, A, σ and the kernel size were found from experiments, the output of the LOG operator, is obtained by the convolution operation Eq.(6) Thus, the following two methods are mathematically equivalent:

1. Convolve the image with a Gaussian smoothing filter and compute the Laplacian of the result.

2. Convolve the image with the linear filter that is the Laplacian of the Gaussian filter.

The following steps are then applied

- Step 1. Convert the RGB values to NTSC coordinates, sets the hue and saturation components to zero.
- Step 2. Use a 2-D Laplacian of the Gaussian from Eq.(6) to design the kernel for blood vessel detection.
- Step 3. Convolving the image with output from kernel by Eq. (7)

$$c(n_{1,}n_2) = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} a(k_{1,}k_2)b(n_1 - k_{1,}n_2 - k_2) \qquad (7)$$

where a and b are functions of two discrete variables n_1 and n_2

- Step 4. Subtract the image with a constant value to reduce noise. We define a constant at (-3.5)
- Step 5. Noise removal by adaptive wiener filtering by estimating the local mean and variance around each pixel.

$$\mu = \frac{1}{NM} \sum_{n_1,n_2 \in \eta} a(n_{1,}n_2) \qquad (8)$$

$$\sigma_w^{\ 2} = \frac{1}{NM} \sum_{n_1,n_2 \in \eta} a^2(n_{1,}n_2) - \mu^2 \qquad (9)$$

where η is the N-by-M local neighborhood of each pixel in the image. Wiener filter using these estimates

$$b(n_{1,}n_2) = \mu + \frac{\sigma_w^{\ 2} - v^2}{\sigma_w^{\ 2}}(a(n_{1,}n_2) - \mu) \qquad (10)$$

where v^2 is the noise variance or the average of all the local estimated variances [26].

- Step 6. Apply median filter to remove noise of the image in two dimensions. Each output pixel contains the median value in the m-by-n neighborhood around the corresponding pixel in the input image. Median filtering pads the image with zeros on the edges, so the median values for the points within [m n]/2 of the edges may appear distorted.
- Step 7. Compute a global threshold to convert an intensity image to a binary image. By normalized intensity value that lies in the range [0, 1]. The threshold function uses Otsu's method, which chooses the threshold to minimize the intraclass variance of the black and white pixels [27].

The four steps shown in Fig.1 comprise the method described.

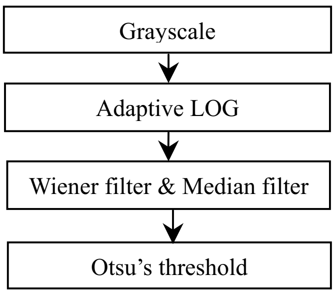


Fig.1 Flowchart of algorithm.

4. EXPERIMENT RESULTS

After running experiments of vessels detection algorithm, we found that the kernel of size 11×11 is the optimum size to detect blood vessel in infant retinal images. The optimum parameters σ = 1.4, A = 1, k=0.5 gave highest efficiency. The kernel and two dimensions profile of the 2-D Laplacian of the Gaussian from, Eq.(6) shown in table 1 and , Fig 2.

Table 1 An 11*11 Laplacian of Gaussian kernel σ = 1.4, A = 1, k=0.5

0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00
0.00	0.00	-0.01	-0.03	-0.04	-0.05	-0.04	-0.03	-0.01	0.00	0.00
0.00	-0.01	-0.04	-0.08	-0.12	-0.13	-0.12	-0.08	-0.04	-0.01	0.00
0.00	-0.03	-0.08	-0.14	-0.08	-0.01	-0.08	-0.14	-0.08	-0.03	0.00
-0.01	-0.04	-0.12	-0.08	0.29	0.58	0.29	-0.08	-0.12	-0.04	-0.01
-0.01	-0.05	-0.13	-0.01	0.58	1.00	0.58	-0.01	-0.13	-0.05	-0.01
-0.01	-0.04	-0.12	-0.08	0.29	0.58	0.29	-0.08	-0.12	-0.04	-0.01
0.00	-0.03	-0.08	-0.14	-0.08	-0.01	-0.08	-0.14	-0.08	-0.03	0.00
0.00	-0.01	-0.04	-0.08	-0.12	-0.13	-0.12	-0.08	-0.04	-0.01	0.00
0.00	0.00	-0.01	-0.03	-0.04	-0.05	-0.04	-0.03	-0.01	0.00	0.00
0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00

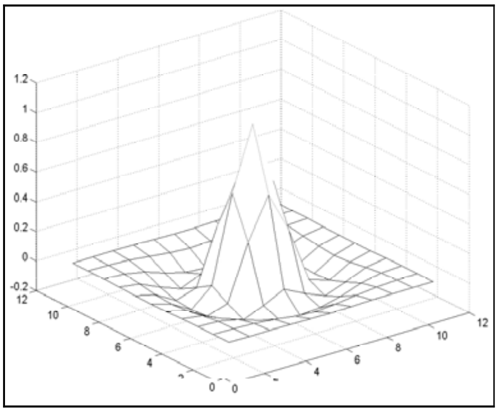


Fig.2 Two dimensions profile of LOG mask

Typical LOG masks are given in table 1. Smoothing is performed with a Gaussian filter, enhancement is done by transforming edges into zero crossing, and detection is done by detecting the zero crossings.

It can be shown that the slope of the zero crossing depends on the contrast of the change in image intensity across the edge. The problem of combining edges obtained by applying different-size operators to images remains. In the above approach, edges at a particular resolution are obtained. To obtain real edges in an image, it may be necessary to combine information from operators at several filter sizes.

The algorithm has been tested on 20 premature infants images (resolution 480*640 pixels; 256 gray levels). Experiments results show that the proposed method performs well in extracting blood vessels. The retinal in an infant is very thin and some choroidal vessels are visble and have been detected along with the retinal vessels. The algorithm requires further development to prevent this detection occurring. The final vessel detection output of the proposed algorithm is shown in Fig.(3) On a Pentium-4 PC with Matlab implementation, it takes about 5 seconds to accomplish blood vessel extraction for each image. The most time-consuming part is the removal noise by adaptive Wiener filtering and median filter.

In Fig.(3) we show the result of particular steps in the process

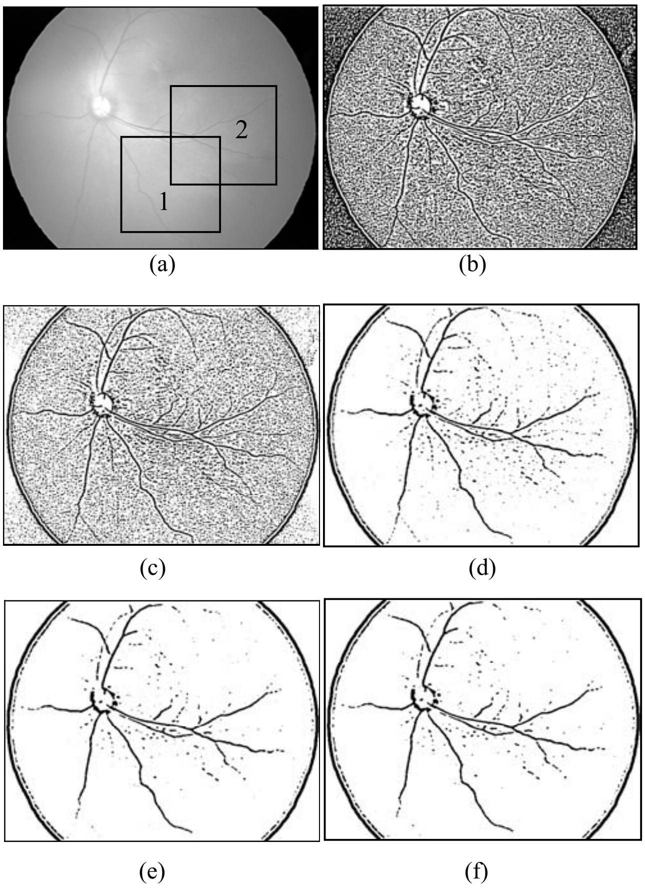
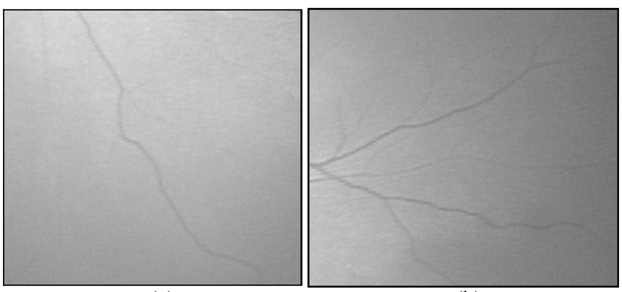
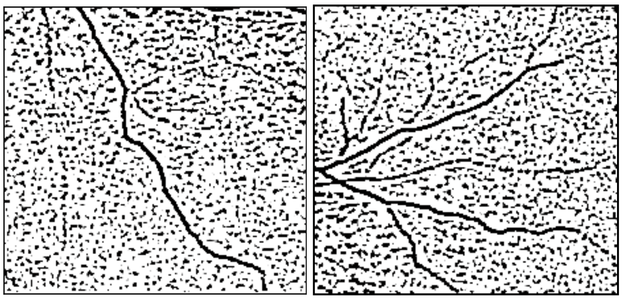


Figure 3 (a) An original infant retinal images in grayscale. (b) Vessels detection result from Eq.(6) (c) Subtract image from constant value (-3.5) (d) Noise removal by adaptive Wiener filtering. (e) After noise removal with median filter. (f) After image thresholding with Otsu's method.

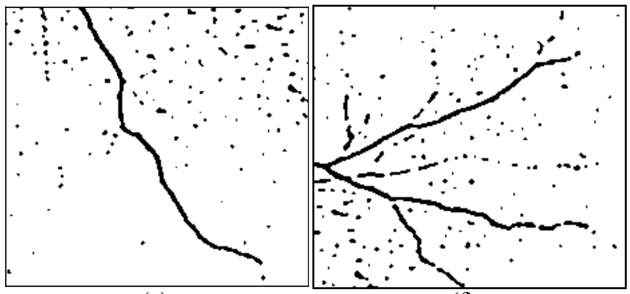
Figure 4 shows the results of area 1 and area 2 as indicated in Fig.3-(a).



(a) (b)



(c) (d)



(e) (f)

Figure 4 (a) Image of area 1 from Fig.3-(a). (b) Image of area 2 from Fig.3-(a). (c) Vessels detection result from Eq. (6) for area 1 (d) Vessels detection result from Eq. (6) for area 2 (e) Output image form area 1 (f) Output images form area 2

5. CONCLUSIONS

Retinopathy of Prematurity (ROP) is a major risk for permanent visual loss in extreme premature infants. In this paper, we have introduced an efficient combination of algorithms for automated blood vessel detection in infant retinal images. The proposed method retains the computational simplicity while it can achieve accurate results in the case of normal infant retinal images and images with obscured blood vessel appearance. In the case of certain images some choroidal vessels are also detected in addition to retinal vessels. One particularly encouraging sign is that the algorithm has done well to detect small thin vessels, which are of interest in clinical practice. In the future, we expect to improve the noise removal algorithm for blood vessel detection.

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