Automatic Blood Vessels Detection of the Retinal Image of Premature Infant

Gantana Sukkaew

Department of Information System, Faculty of Business Administration,
Rajamangala University of Technology Srivijaya,
Songkhla, Thailand

E-mail: gantana.s@rmutsv.ac.th

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 presents a method for blood vessel detection on infant retinal images. We proposed a set of automatic methods to extract skeletonized structure of premature infant’s low-contrast retinal blood vessel network. The method is composed of four steps: Statistically optimized Laplacian of Gaussian filter for edge detection, Medial Axis Skeletonization, Image Pruning, and Spur Removal by morphological Opening. The algorithm has been applied to test on 40 infant retinal images. The result from the algorithm was compared with ophthalmologists’ hand-drawn ground truth and it can detect the blood vessel with a high specificity of 0.913 and sensitivity of 0.982.

Keywords: Vessel Detection, Laplacian of Gaussian, Infant Retinal Images

I. INTRODUCTION

Retinopathy of Prematurity (ROP) is one of those diseases frequently affects to the eyes of those premature babies. When a fetus baby is growing inside mother’s womb, the babies are in protective environment. Then the babies are developed slowly, until they are able to continue growing outside the wombs. The retina is inner lining on the posterior wall of the eyeball. The retina is part of eyes that receives sight through the pupil and sends to the brain. The retina receives blood through blood vessels. These blood vessels are the posterior part of the eyes to develop just before a mature baby is born. The retinas of baby’s eyes are not completely developed, when a baby born prematurely. On retinal image normally, the blood vessels are straight or gently curved. Some diseases, the blood vessels become dilated with tortuosity as of serpentine paths. Many disease classes generate tortuosity, including high blood flow, and blood vessel congestion. Information about disease severity or change of disease with time may be inferred by measuring the tortuosity of the blood vessel network. Blood vessel appearance is an important indicator for many diagnoses in retina and there are multiple eye diseases that affect the vasculature in the eyes, particularly in retinal vessels. These diseases can cause physical changes to existing vessels, such as changes in the width, color, and path of the vessels. One of those symptoms of diseases in retinopathy is the presence of new vessel formation, often appears as tortuous vessel. Abnormal blood vessels may develop, which can subsequently lead to bleeding and scar tissue formation. This may stretch the retina pulling it beyond its position and finally visual loss may occur.

Chaudhuri et al [1] introduced a simple operator for feature detection based on the optical and spatial properties of objects to be recognized. The proposed scheme retains the computational simplicity of the enhancement/thresholding type of edge operators, and at the same time incorporates the advantages of using model-based edge detectors. Wood et al [2] 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. This procedure normalizes the variation in the background level before edge detection. Mao et al [3] describe their algorithm to extract structural features in digital subtraction angiograms. The algorithm is based on the visual perception modeling which states that the relevant parts of objects in noisy scenes are usually grouped together. The problem with this algorithm is that it does not successfully solve all the 2D ambiguities such as crossing or forking situations. Hoover et al [4] combine local and region-based properties to segment blood vessels in retinal images. The method examines the matched filter response (MFR) [1], using a probing technique. The technique classifies pixels in an area of the MFR as vessels and non-vessels by iteratively decreasing the threshold. Tolias and Panas [5] develop a fuzzy C-means (FCM) clustering algorithm that uses linguistic descriptions like “vessel” and “nonvessel” to track fundus vessels in retinal angiogram images. Their algorithm uses only (fuzzy) image intensity information and makes no assumptions for the shape of the vessels. Zhou et al [6] develop a method to detect and quantify retinopathy in digital retinal angiograms. Their method relies on a operator. The proposed method retains the computational simplicity while achieves high accuracy and fast results.

II. METHODS

We have experimented with the application of many algorithms that work on adult images to infant retinal images. A successful combination of those algorithms which are statistically optimized for the infant retinal vessels classification problem is explained in this section.

A. Statistically optimized Laplacian of Guassian filter for edge detection

The edges in an image give structural information about its boundaries. In order to detect blood vessels, edge information will also be significantly important because the vessels should be clearly visible in an edge image. Our first step is to extract edge information from the original infant retinal image. After qualitative comparison of the performances between many public domain edge operators with our set of infant images, we found that Laplacian of Guassian (LOG) is the most suitable operator. The LOG operator is described by equation “(1)”. Statistically, we found that a \(\sigma = 1.4\) at the operator size of 11x11 yielded the best performance.

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

B. Medial Axis Skeletonization

The skeletonized structure is useful information because it provides a simple and compact representation of a shape and preserves many of the topological and size characteristics of the original shape at the same time. The length of a shape can be calculated by considering just the end points of the skeleton and finding the maximally separated pair of end points on the skeleton. The edge image from the previous step will be thresholded and skeletonized in this section. Before the resulting edge image from the previous step is skeletonized with Medial Axis Skeletonization algorithm, Otsu’s thresholding algorithm was applied to binarise the image into 2 classes, black and white. Otsu method automatically chooses the threshold to minimize the intra class variance of the black and white pixels [10].
The Medial Axis Skeletonization algorithm is chosen from quantitative experiments and applied to the binary image in this step in order to extract structure of the blood vessels. The vessel tree is then created by connecting these centerlines Medial Axis Transform is defined as the locus of the centre of all the maximal inscribed circle of the object as described in equation “(3)”. The medial axis transform of a set \( A \) is determined by the medial axis of \( A \) and the medial axis distance function \( f \) defined on the medial axis of \( A \). The medial axis function is directly related to the generalized distance. For the following definition of the morphological skeleton of a set \( A \) with respect to a structuring element \( K \) by the sets \( \{S_0,...,S_N\} \)\(^{[11]} \) where

\[
S_n = A \ominus K - (A \ominus K) \delta K \; \text{and} \; A \ominus K = A \\
\text{…………….. 2}
\]

The skeleton of \( A \) is then given by

\[
S(A) = \bigcup_{n=0}^{N} S_n \\
\text{…………….. 3}
\]

( \( \ominus \) denotes erosion operator with \( n \) iteration and \( o \) is an opening operator)

After the algorithm is applied, the blood vessels (including other artifacts) are thinner and can be visibly observed. The resulting skeleton is located at the central line of the original image. This result shows that the skeletonized image can clearly maintain the blood vessel topology and the blood vessel network as illustrated in figure 1. This valuable information is important when we later calculate other properties, like tortuosity of the blood vessel.

C. Image Pruning

In order to reduce the size of the noise that is smaller than a specific size, we can make use of a series of morphological operations. One set of the series is known as image pruning is used in this step. The resulting image from the previous step is processed with image pruning as defined by steps from equation “(4)” to equation “(7)”.

\[
X_1 = A \ominus \left[ B \right] \\
\text{…………….. 4}
\]

\[
X_2 = \bigcup_{n} (X_1 \ominus B^n) \\
\text{…………….. 5}
\]

\[
X_3 = (X_2 \ominus K) \ominus A \\
\text{…………….. 6}
\]

\[
X_4 = X_2 \cup X_3 \\
\text{…………….. 7}
\]

Where \( 4 \times \) is the result of the pruning set \( A \) with structuring element \( B \)\(^{[112]} \). \( X_1, X_2 \) and \( X_3 \) are resulting images of the intermediate process. \( \ominus \) Denotes a morphological thinning operator while \( \oslash \) is a dilation operator.

\( \oplus \) Denotes hit or miss transform.

D. Spur Removal by morphological Opening

Our last step in the process is to remove isolated noise, or spurs, a cluster of pixels that has a size less than 15 pixels. Morphological opening is chosen to use in this step because it is robust, fast and quite easy to
implement. This island removal algorithm utilizes Erosion (\(\ominus\)) and Dilation (\(\oplus\)) (erosion followed by dilation) as in the following equation.

\[
S = A \ominus B = (A \ominus B) \oplus B \tag{8}
\]

where \(S\) is the result after spur removal. Figure 1 illustrates results from this step.

We applied the series of methods we proposed on all the 50 images and some of the results are shown in figure 1.

![Figure 1. (a) an original images (b) resulting images](image)

III. RESULTS AND EVALUATION

To measure the performance of our method, we created ground truth images manually by drawing lines on vessel of original images. This is under supervision of a trained clinician. These 40 hand-drawn ground truth images are essential for performing a quantitative analysis of an algorithm’s results. Both the ground-truth images and final result images are binary images, so they can be compared easily by using Exclusive-Or function. We can calculate 4 different values from the comparison, namely, true positives (TP) or a number of pixels correctly detected as vessel pixels, false positives (FP) or a number of pixels incorrectly flagged, true negatives (TN) or a number of pixels correctly detected as non-vessel and, finally, false negatives (FN) or number of pixels incorrectly flagged as non-vessels.

We then used the 4 values from previous calculation to calculate performance measurement values, sensitivity (Se) and specificity (Sp) as follows

\[
Se = \frac{TP}{TP+TN} \tag{9}
\]

\[
Sp = \frac{FN}{FN+FP} \tag{10}
\]

**TABLE I. The algorithm has been tested on 40 premature infant’s images and all the results are shown in table**
IV. CONCLUSION

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 image and images with obscured blood vessel appearance. Efficiency of the method is measured and the results were in a high specificity of 0.913 and sensitivity of 0.982. The next step in this project is to employ this approach to support tortuous-based classification of ROP disease.

REFERENCES


