Asian Journal of Electrical Sciences
ISSN: 2249 - 6297 Vol. 2 No. 2, 2013, pp. 31-37

Retinal Blood Vessels Segmentation Using the Curvlet Transform

M.C. John Wiselin and A. Prabin

[1]Academic Director, [2]Head of the Department,

Department of EEE, Travancore Engineering College, Oyoor, Kollam District, Kerala, India

E-mail: wiselin16@yahoo.com

(Received on 10 June 2013 and accepted on 18 July 2013)

***Abstract* - Retinal image having very vital information. It plays important roles in finding of some diseases in early stages, such as diabetes, and cardiovascular disease. In this proposed system a new algorithm used to detect the blood vessels effectively from the retinal image. The initial image enhancement is carried out by using Adaptive Histogram Equalization, followed by the curvelet Transforms are applied to the equalized image and the curvelet coefficients are obtained. The modifications to the Curvelet transform coefficients are carried out by suppressing all the coefficients of one band. This combined effect of the equalization and the Curvelet Transforms provides a better enhancement to the image. This enhanced image is used for the extraction of blood vessels. Afterward, eliminate the ridges not belonging to the vessels tree by morphological operators by reconstruction while trying to preserve the thin vessels unchanged. In order to increase the efficiency of the morphological operators by reconstruction, they were applied using multi-structure elements and local adaptive thresholding method along with connected components analysis (CCA) indicates the remained ridges belonging to vessels.**

***Keywords:* Blood vessel segmentation, connected component analysis, curvelet transform, multistructure elements morphology, retinal image**

I. Introduction

Digital fundus imaging in plays an important role in medical diagnosis of primary levels of diabetes and blood pressure as well as cardiovascular disease[1] .Some of the main clinical objectives reported in the literature for retinal vessel segmentation are the implementation of screening programs for diabetic retinopathy, evaluation of the retinopathy of prematurity, cardiovascular diseases, and computer-assisted laser surgery.

About 10% of all diabetic patients have diabetic retinopathy, which is the primary cause of blindness in the Western World. Since this type of blindness can be prevented with treatment at an early stage, the who advises yearly ocular screening of patients Other indirect applications include automatic generation of retinal maps for the treatment of age-related macular degeneration, extraction of characteristic points of the retinal vasculature for temporal or multimodal image registration, retinal image mosaic synthesis, identification of the optic disc position, and localization of the fovea. Furthermore, the network of retinal vessels is distinctive enough to each individual and can be used for biometric identification, although it has not yet been extensively explored [2].

The three most important structures of the human retina are Vessels, fovea, and optical disk, these structures mostly used for several applications such as retinal image registration, illumination correction, as well as pathology detection inside the retina. Detection of these important structures manually is time consuming and depends on the expertise of the user. As compare to all three vessels play vital role for apply many application. The segmentation of blood vessels from fundus photographs can be difficult for a number of reasons. The two most influential factors that make the segmentation difficult are the improper retinal image contrast and the uneven background illumination. The uneven illumination is from the acquisition process. The different vessels have different contrast with background. In other words, arteries have higher contrast than veins. Thick vessels also display a higher contrast with the background than do thin ones. Existing paper also has a deficiency of missing some thin blood vessels because of the simple thresholding method. There is a tradeoff between removing more false edges and preserving more pixels of small vessels.

In this paper, existing simple threshold is replaced by local adaptive threshold method; this is new proper approach threshold method. A method based on using curvelet transform is proposed to enhance and prepare the retinal image for better vessel detection. In the past decade, introduced the curvelet transform, a new multi scale transform. The second generation of curvelet transform, is faster and simpler than the first version. Therefore, the second generation of curvelet transform, discrete curvelet transform (DCT), and modified the DCT coefficients by a suitable nonlinear function are used. One way to increase the image contrast is to enhance the image ridges, which play an important role in enhancing image contrast. In order to simultaneously enhance the weak edges and eliminate the noise, the modifying function parameters are defined based on some statistic features of fast DCT (FDCT) coefficients.

Mathematical morphology using multi structure elements are applied to obtain the image ridges. Then, morphological opening by reconstruction helps to remove the detected ridges not belonging to the vessel tree while preserving the thin vessel edges. The morphological opening by reconstruction benefits from using multistructure elements, which helps to improve the performance of this step. There is a restriction on size of structure elements (SEs) concerning the blood vessels diameter. Therefore, the remaining false edges will be removed by means of connected components analysis (CCA) along with length filtering. In order to act locally, image is decomposed to several tiles and CCA, and length filtering is individually applied to each tile. Modified CCA is proposed to predict the length of the blood vessels dynamically. A result shows a promising performance in segmentation of the blood vessels. The quantitative performance results of both segmentation and enhancement steps show that our method effectively detects the blood vessels with better accuracy.

The rest of the paper is organized as follows. In Section II, curvelet transform is briefly described. Then, multistructure elements morphology and morphology operators by reconstruction elaborated in Section III. Thereafter, the proposed method is explained in Section IV the experimental results are illustrated in Section V. Section VI concludes the works described in this paper.

II. Curvelet Transform

A. Curvelet transform

Candes *et al.*[3] introduced a new multi-scale transform, Curvelet transform. It can efficiently represent the edges along curves than the traditional transforms and also allows an optimal sparse representation of objects with C^2 singularities the best m-term approximation, fm for a smooth object, f with C^2 discontinuities along a generic smooth curve using Curvelet approximation, $\tilde{f}_m^n$ achieves

$$\hat{f}_{j,l}[n_1, n_2] = W(\tilde{U}_{j,l}, \tilde{f})[n_1, n_2] \quad (1)$$

B. Digital Curvelet Transform(DCT)

There are two methods to implement the second generation DCT: Wrapping method and Unequis paced Fast Fourier Transform (USFFT) method. Both methods are described detail in [3].

For the same accuracy, the wrapping method is faster and easier to implement than USFFT method. Here, we use the wrapping method in this paper. The architecture of Fast Discrete Curvelet Transform (FDCT) [4] via wrapping is as follows:

1. Apply the 2D FFT and obtain Fourier samples

$$\tilde{f}[n_1, n_2], -\frac{n}{2} \le n_1, n_2 < \frac{n}{2} \quad (2)$$

2. For each scale and angle, form the product

$$U_{j,l}[n_1, n_2]\tilde{f}[n_1, n_2] \quad (3)$$

Here, $\tilde{U}_{j,l}[n_1, n_2]$ is the discrete localizing window as said in the reference [5]

3. Wrap this product around the origin and obtain

$$\hat{f}_{j,l}[n_1, n_2] = W(\tilde{U}_{j,l}, \tilde{f})[n_1, n_2] \quad (4)$$

Where the range for n1 is now $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$ j; $L_{1,j} \sim 2^j$ and L $L_{2,j} \sim 2^{j/2}$ are constants.

4. Apply the inverse 2D FFT to each $\hat{f}_{j,l}$ hence collecting the discrete coefficients $C^D(j,l,k)$

III. Mathematical Morphology

A. Multistructure Elements Morphology

Since the size, shape, and direction of the SE determines the final result of morphological processing, the choosing of SE is a key factor in morphological image processing. Single and symmetrical SEs are normally selected in order to perform the morphological processing; such SEs are successful in detecting ordinary, simple, and straight edges of an image. While the edges complexities increase, their success in detection of such complex edges decrease. In order to deal with such edges and achieve a reliable precision, we need more advanced SEs. The basis of the multistructure elements morphology theory relies on gathering several SEs in one square window. In other words, decomposing an SE produces the s_i .

Therefore, such SE is capable of detecting different edges with different directions, efficiently.

Let $\{I(m,n) \mid m,n \in Z\}$ be a digital image; an SE in (2N +1) × (2N + 1) square window is defined as follows:

$$S_i = \{I(m+m_0, n+n_0, \theta_i = i \times \alpha \mid -N \le m_0, n_0 \le N\} \qquad (5)$$

where i = 0, 1, . . . , 4N − 1, $\alpha = {180^0}/{4N}$, and θi is the direction angle of Si . With regard to the required directional resolution α, the size of the SE windowis determined. Si for α = 15^0 and the 7 × 7 SE built from integration of all Si of all directions.

B. Morphological Operators by Reconstruction

Both morphology closing and opening leave the features larger than SE unchanged. However, the main drawback of conventional opening and closing is that they do not preserve edge information perfectly. Bangham *et al.* [6] introduced a new operator to address this defect, called M- and N-sieves. The new operator emphasizes only on the size of the features, but rejects the shape completely. Morphological operators by reconstruction are designed to address this problem and consider both shape and size of the features [7]. Opening by reconstruction and closing by reconstruction are denoted by $g \bar{\circ} S$ and $g \bar{\bullet} S$, respectively, and defined as

$$g \bar{\circ} S = \delta_f^{(rec)}(g \circ S) \qquad (6)$$

$$g \bar{\bullet} S = \in_f^{(rec)} (g \bullet S) \qquad (7)$$

Therefore, morphological opening by reconstruction in its first step eliminates bright features smaller than the SE. in the next step, it dilates iteratively to restore the contours of components that have not been completely removed by opening and it is performed by considering the original image as the reference. In a similar manner, closing by reconstruction is accomplished in case of dark features. Therefore, as a valuable result, producing new edges, edge drift and deforming the contours and edges, which often occur by applying conventional morphological opening and closing will not appear by applying opening and closing by reconstruction.

IV. Proposed Method

A. Image Selection

The images used here for the experimentation are obtained from the well known DRIVE database [8] . The gray scale version of these images is used. This grayscale coming from the green channel of the colored image because blood vessels in the green channel image of the original colored retinal image have the highest contrast. The blue channel tends to be empty and the red channel tends to be saturated.

B. Retinal Image Enhancement using Adaptive Histogram Equalization

Adaptive Histogram Equalization is an enhancement technique capable of improving an image's Local Contrast. It differs from ordinary histogram equalization in the respect that adaptive method computes several histograms each corresponding to distinct section of the image and uses them to redistribute the lightness values of image. It acts as a good tool for the enhancement of the edges. Comparison of the input and the enhanced image is shown in Figure (fig). 1

(a)

(b)

(c)

Fig.1 (a) Original Image (b) Gray Scale image
(c) Adaptive Histogram Equalized image

C. Vessels Contrast Enhancement Using FDCT

The curvelet transform is well adapted to represent the images containing edges; it is a good candidate for edge enhancement. Curvelet coefficients can be modified to enhance the edges in an image, which improves the image contrast. The aim of enhancement step is enhancing the thin vessels having low contrast to detect better in the edge detection step. Here contrast enhancement is carried out by means of Adaptive Histogram Equalization. It is a technique by which image brightness changes sharply.

Consequently, our proposed method to enhance the retinal image consists of following steps.

1. Applying FDCT via wrapping method, we get a set of scales S_j, each scale consists of a set of directional bands D_i containing coefficients.

2.. For each directional band in each scale D_{ji}, do the following:

   a) Calculate the noise standard deviation σ_{ij} ;

   b) Determine the value of m.

3. Multiply each coefficient individually by corresponding y.

4. Reconstruct the enhanced image using modified curvelet Coefficients.

Fig.2 FDCT Image

D. Edge Detection Using Multistructure Elements Morphology

In order to perform edge detection using multistructure elements morphology, the earlier SE of morphological edge detector should be replaced by new introduced SE and follow the following algorithm.

1) Produce the proposed SEs S_i with regard to the required directional resolution.

2) Apply the selected edge detector function F on the original image using the achieved SEs in 1 and get the sub edge image F(I)i .

3) Put the F(I)i obtained in 2) in the following equation to achieve the whole of detected edges:

$$F(I)\sum_{i=0}^{M-1}\omega_i F(I)_i \qquad (8)$$

where F(I) is the total edge image, M = 180/α is the number of S_i and ω_i is the assigned weight to each of subedge image.

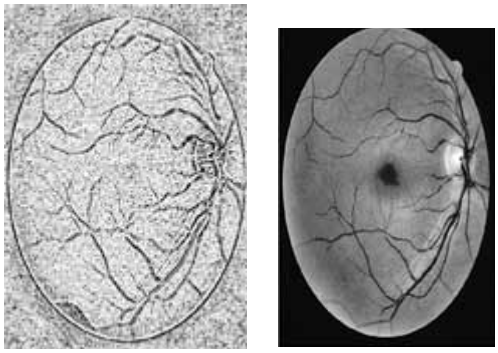
In order to have the same effect of each $F(I)_i$, the assigned weights can be defined as $\omega_i = 1/M$, or they can be calculated by other methods [9] as well. Also, if any information about the processed image exists, the weights can be assigned according to the degree of importance of information that may exist in each of F(I)i . we calculate the weights by

$$\omega_i = \frac{F(I)_i}{\sum_{i-0}^{M-1} F(I)_i} \tag{9}$$

E. False-Edges Removal Using Morphological Operators by Reconstruction

In the result image of edge detection step, there are edges not belonging to blood vessels but that arise from uneven background illumination. A simple method to eliminate these undesired objects is using morphological opening by reconstruction. Opening by reconstruction includes two steps: conventional morphological opening and reconstruction by dilation. In order to improve the performance of the morphological opening by reconstruction, the opening using multi structure elements is performed.

Since the multi structure elements are highly sensitive to edges in all directions, it helps to accurately eliminate the false edges. The SE used in this step is the same as in the edge detection step. The only difference is in assigned weight. Here, instead of assigning weights to each F(I)i , the maximum F(I)i is selected to construct the F(I). This method allows us to eliminate the weak false edges and prevent them from participating in construction of F(I).



(a) (b)

Fig.3 (a) Edge Detection image Using Multistructure Elements Morphology (b) Edges Removed image Using Morphological Operators

F. Length filtering with local adaptive threshold method

In order to obtain a clear final result without presence of pixels that do not belong to vessel tree, we use length filtering with the aim of removing the small pixel blocks. In this case, the concept of modified CCA is used where connected components pixels which are identified above a specific threshold and labeled using eight connected neighborhood and are considered as a single object. Modified CCA is used to predict the length of the blood vessels dynamically here the threshold value is automatically calculated. Considering the entire image in CCA and length filtering with simple threshold leads to inferior results. A kind of adaptive CCA, that is consider images in separate tiles and apply CCA and length filtering to each tile, individually. By this means, there is no large range of gray levels in each block, and a proper threshold can be chosen which separates the false edges from vessel edges efficiently. After applying modified CCA, all the small length blood vessels are identified. Finally, all of the results are integrated in a single image as the final blood vessel detection result.

Fig.4.a) Input Retinal image

b) Extracted blood vessels by simple threshold method

Still There is a tradeoff between removing more false edges and preserving more pixels of small vessels only because of simple threshold instead of that we use the local adaptive threshold method. it selects an individual threshold for each pixel based on the range of intensity values in its local neighborhood

Therefore, the algorithm is as follows.

1) Partition image into tiles of N × N pixels with 50% interpolation to avoid windowing effect.
2) Apply the described thresholding algorithm to each part individually and obtain the desired threshold of each tile.
3) Apply CCA to each tile with considering only the pixels whose gray levels are more than the corresponding threshold.
4) Apply length filtering to each tile individually and retain the components having length larger than the elements morphology was capable of detecting the corresponding threshold.
5) Gather all the results in one image.

(a)

(b)

Fig.5 a) Extracted blood vessels, b)Extracted blood vessels using local adaptive threshold

V. Experimental Results

We implemented our proposed method using MATLAB 7.1. We take DRIVE database image as an input image. As mentioned earlier, the green channel is the best choice to be processed. In the next step, the fundus region disk was

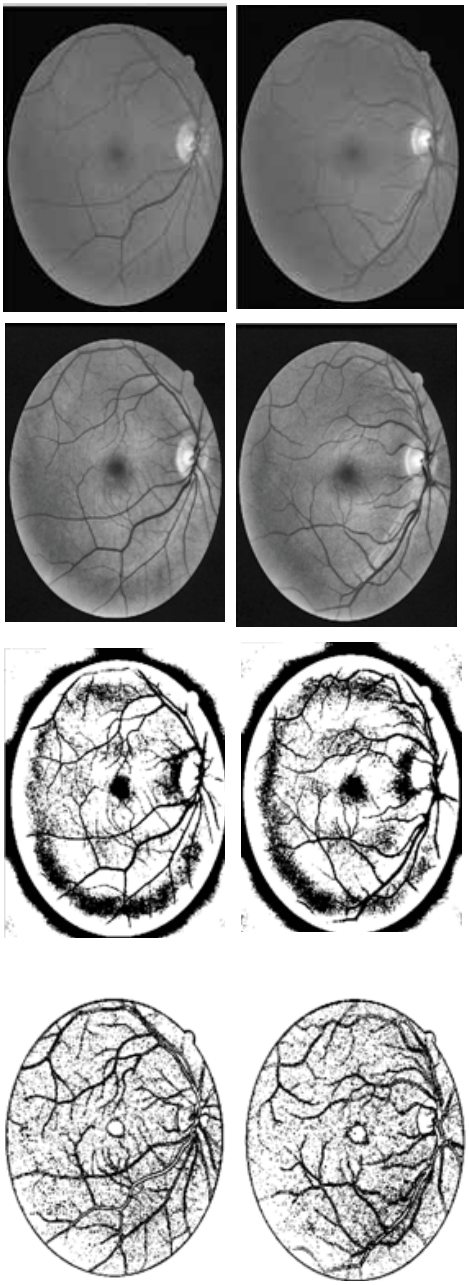


Fig. 6 Results of proposed method. (a),(b) are related to images 16 and18 of DRIVE database, respectively. From top to bottom they are the green channel, result of enhancement using FDCT, result of edge detection and last row are result of morphology operators by reconstruction and length filtering,respectively.

produced. Afterward, the FDCT was applied to the selected channel. This co-efficient is modified. hence the image vessels. Then, the edges of image were detected by modified top hat using the multistructure elements morphology. We used a 7× 7 SE with $\alpha = 15^0$. During edge detecting some of the undesired objects also found. This false edges are removed by the morphological opening by reconstruction. Finally the image is decomposed to several blocks and length filtering, and CCA are applied locally in order to better remove the remained false edges,The threshold value is find by local adaptive threshold method.

VI. Conclusion

In this paper, a new most efficient method for the retinal vessel segmentation has been presented; all sections are upgraded with efficient technique such that adaptive histogram in image enhancement with curvlet transform, Modified top hat transformation is used as an edge detector in edge detection and local adaptive threshold technique in threshold method. All these modifications are combined and moulted as a most efficient one. And it has concluded that proposed technique is giving much better results than existing ones.

Hence, our future work is modifying this threshold method with a more proper approach to increase accuracy of the method and deal with the problem of presence some severe lesions in retinal images.

References

[1] S. Dua, N. Kandiraju, and H.W. Thompson, "Design and implementation of a unique blood-vessel detection algorithm towards early diagnosis of diabetic retinopathy," *in Proc. IEEE Int. Conf. in Inf. Technol., Coding* Comput., 2005, pp. 26–31.

[2] A.M.Mendonc¸a and A. Campilho, "Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction," *IEEE Trans. Med. Imag.,* vol. 25, no. 9, pp. 1200–1213, Sep. 2006.

[3] E. Cand`es, L. Demanet, D. Donoho, and L. Ying, "Fast discrete curvelet transforms," *Multiscale Model. Simul.,* vol. 5, no. 3, pp. 861–899, 2006.

[4] Stephen N.Pizer, E. Philip Amburn, John.D.Austin, Robert Cromatie, Ari Geselowitz, Trey Greer, Brat Ter Haar Romeny, John.B.Zimmerman and Karel Zuiderveld ,—Retinal Image Analysis using Curvelet Transform and Multi structure Element Morphology by Reconstruction. Mohammad Saleh Miri and Ali Mahloojifar.

[5] E. J. Candès and D. L. Donoho, 1999 Curvelets A Surprisingly Effective Nonadaptive Representation For Objects with Edges, Curves and Surfaces.

[6] J. A. Bangham, R. Harvey, P. D. Ling, and R. V. Aldridge, "Morphological scale-space preserving transforms in many dimensions," *J. Electron. Imag.,* vol. 5, no. 3, pp. 283–299, Jul. 1996.

[7] S. Mukhoopadhyay and B. Chanda, "Multiscale morphological segmentation of gray-scale images," *IEEE Trans. Image Process.,* vol. 12, no. 5, pp. 533–549, May 2003

[8] Available at: http://www.isi.uu.nl/Research/Databases/DRIVE/.

{9] Y. Ma,M. Yang, and L. Li, "A kind of omni-directional multi-angle structuring elements adaptive morphological filters," *J. Chin. Inst. Commun.,* vol. 25, no. 9, pp. 86–92, 2004.

[10] Ch. Wu, G. Agam, and P. Stanchev, "A general framework for vesselsegmentation in retinal images," *in Proc. IEEE Int.Symp.* Comput. Intel.Rob. Autom., Jun.2007, pp. 37–42.

[11] E. J. Cand`es and D. L.Donoho, "Curvelets—A surprisingly effective nonadaptive representation for objects with edges," in Curves and Surfaces. Nashville, TN: Vanderbilt Univ. Press, 1999, pp. 123–143.

[12] Y. Zhao, W. Gui, and Zh. Chen, "Edge detection based on multi-structure elements morphology," *Proc. 6th World Congr. Intell. Control Autom.,* pp. 9795–9798, 2006.

[13] S. Mukhoopadhyay and B. Chanda, "Multiscale morphological segmentation of gray-scale images," *IEEE Trans. Image Process.,* vol. 12, no. 5, pp. 533–549, May 2003.

[14] Zh. B. Zhao, J. Sh. Yung, O. Gao, and Y. H. Kong, "Wavelet image denoising method based on noise standard deviation estimation," in *Proc. Int. Conf. Wavelet Anal. Pattern Recog.*, 2007, pp. 1910–1914.

[15] J. Starck, F. Murtagh, E. J. Cand`es, and D. L. Donoho, "Gray and color image contrast enhancement by the curvelet transform," *IEEE Trans. Image Process.*, vol. 12, no. 6, pp. 706–717, Jun. 2003.