Retinal Vasculature Extraction using Wavelets

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Abstract

Retinal vasculature extraction helps in diagnosing the early detection of diabetic retinopathy to prevent blindness. In this work vasculature structure extraction is proposed which is based on vessel detection method. Retinal normal and abnormal images are first preprocessed to enhance the vessel information. Two methods i.e. wavelet transforms along with multiscale hessian-eigenvalue approach are considered for vessel extraction. Results are promising and it shows that the method performs well in extracting the vascular pattern. The comparative studies with manual based segmentation prove the effectiveness of our proposed method.

Keywords: Blood Vessel Extraction, Diabetic Retinopathy, Discrete Wavelet Transform, Hessian Matrix

1. Introduction

Retinal vasculature extraction plays an important role in the medical field. Retinal images help in early diagnosis of ophthalmic disorders such as diabetic retinopathy, glaucoma and macular degeneration. Diabetic Retinopathy is the most common reason of blindness. So treatment needs to be done at early stage to avoid visual loss and blindness in patients. It is caused mainly of the damaged blood vessels, which may leak blood and grow new weak vessels. So detection of blood vessels has to be very accurate to detect the disease. Manual detection is difficult since the blood vessels in the retinal images are complex and having low contrast. So proper automatic segmentation steps are required for concluding a decision. Several methods exist related to the retinal vasculature extraction. To improve the quality of the vascular network some problems have to overcome i.e. poor segmentation, poor detection of small vessel and detection of false vessels etc.[1]. It has been proved that wavelet transform gives good result in vessel segmentation. Akram et al.[2] proposed blood vessel enhancement using wavelet transform. Ceylan et al.[3] proposed Complex Wavelet Transform and Artificial Neural Network for blood vessel extraction from retinal images which gives better result compared to only wavelet transform. But it would be highly appreciable to make the method less complex and high in computation speed. Bankhead et al.[4] proposed a method of vessel segmentation using the wavelet thresholding. The

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overall performance of the algorithm was good and was computed in less time. But in less image contrast the proper zero-crossings may not be found at all locations along the vessel. Sengar et al.[5] proposed retinal vessel extraction by morphology based method. It provides good vessel structure and is computationally efficient. But in this method the threshold value is dependent on the image property. Kurilova et al.[6] also proposed a method based on morphology. It is less complex. But still focus has to be given in the number of false positive findings. Hence true vascular extraction is a challenging work. It has been noticed that multiscale hessian-eigenvalue approach is effective in retinal vessel enhancement[7-11].

In this work discrete wavelet transform is employed on the preprocessed retinal images and multiscale hessian based vesselness measurement is applied on sub-bands to identify the blood vessels. In the existing works both eigen values λ1 and λ2 have been used for vessel enhancement[7-10]. Here we proposed a new vesselness measure with only the minimum eigen value or λ min. We found that using only the smallest value is sufficient for vessel enhancement. Our preprocessing greatly enhanced the vessel part and reduced false positives of optic disc boundary. We apply our method on the images of STARE database and compare with ground truth images.

2. Mathematical Preliminaries

Wavelet transform provides the information of the frequency domain at time instance. So local features are described more clearly. Wavelet Decomposition decomposed a signal or an image into a hierarchical set of approximations and detail coefficients. The signal provides low and high frequency sub-bands. First the 1D or 2D signals are analyzed by low pass filtering and high pass filtering along the rows or vertically and down sampled, then the sub-bands are analyzed by low pass filtering, high pass filtering, down sampling along horizontally and so on for each level. We get 4 sub-bands; approximation (LL), Vertical (LH), Horizontal (HL) and diagonal (HH). Below Figure shown the 1-level decomposition.

This procedure can mathematically expressed as

$$\text{yhigh}(k)=\Sigma n\ p[n].q[2k-n] \tag{1}$$

$$\text{ylow}(k)=\Sigma n\ p[n].r[2k-n] \tag{2}$$

Where the original signal is p[n], half band high pass filter is q[n]and r[n] is half band low pass filter. Equation (1) and (2) are the outputs after sub-sampling by 2.

Hessian Matrix, a square symmetric matrix gives the magnitude of an image. This matrix is well known for providing second order derivative. So to get the information of concavity and the local curvature hessian matrix has applied. The hessian matrix h(x, y) is defined as

$$\mathrm{H}\,h(x,y)=\begin{bmatrix} hxx & hxy \\ hyx & hyy \end{bmatrix} \tag{3}$$

Eigen values provide a clear idea about the information of the matrix. So to get the surface information of hessian matrix we compute eigen values. Eigen values of $\begin{bmatrix} X & Y \\ Y & Z \end{bmatrix}$ is calculated as

$$\lambda=\frac{\mathrm{X}+\mathrm{Z}\pm\sqrt{(X-Z)^2+4Y^2}}{2} \tag{4}$$

Let (x0, y0) be a critical point of h, and let λ1 and λ2 be the eigenvalues.

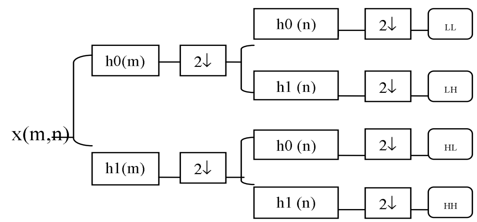

Figure 1. Wavelet decomposition flow chart.

- If λ1 < 0 and λ2 < 0 then critical point is local minimum.
- If λ1 < 0 and λ2 > 0 or if λ1 > 0 and λ2 < 0 then there is a saddle point.
- If λ1 > 0 and λ2 > 0 then it is local maximum.
- If either λ1 = 0 or λ2 = 0 or both, then no conclusion.

3. Proposed Methodology

The block diagram of the proposed method has shown below

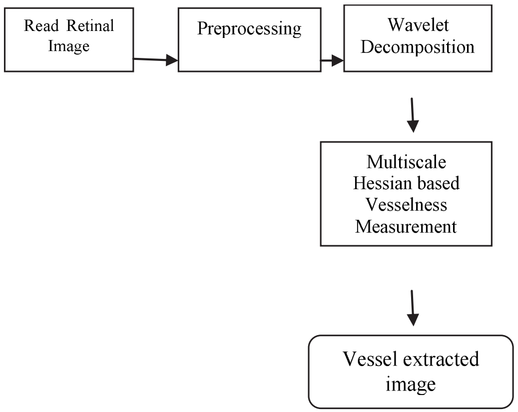

Figure 2. Proposed method.

The main two phases of proposed method are preprocessing and vessel extraction which is explained subsequently.

3.1 Preprocessing

Pre-processing is the first essential step which helps in simplifying the segmentation. The steps are described as below flowchart.

The green component of the RGB image has been extracted because it provides better contrast and energy compared to blue and red

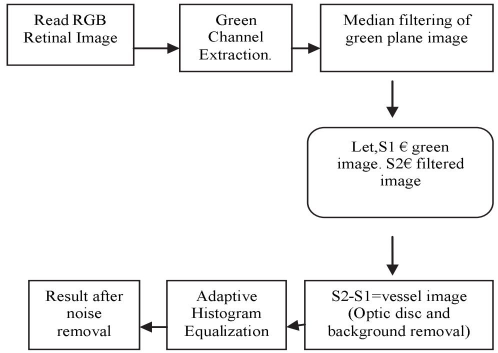

Figure 3. Preprocessing steps.

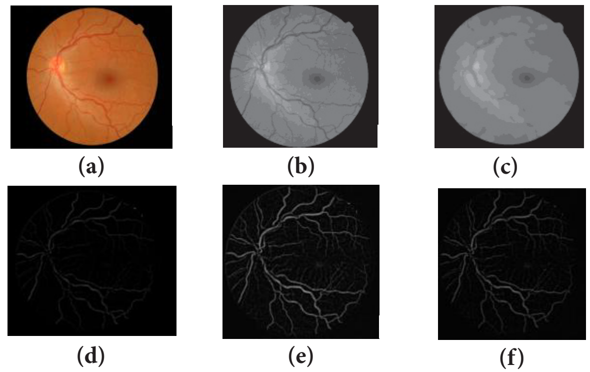

Figure 4. **(a)** RGB image **(b)** Green channel extraction **(c)** Filtering **(d)** Subtraction **(e)** Contrast enhanced image **(f)** Noise removal.

component; as a result we get better vessel background contrast. Median filtering is used to highlight the optical disc and background and filtered the vessel. Next, subtract from green plane image to get the vessel part of the image. To visible more vessel part adaptive histogram equalization technique is used. Finally, again median filtering is used for noise removal. The below Figure shows the output of the above procedure.

3.2 Vessel Extraction

Accurate vessel extraction is the vital part in this work.It involves the following steps

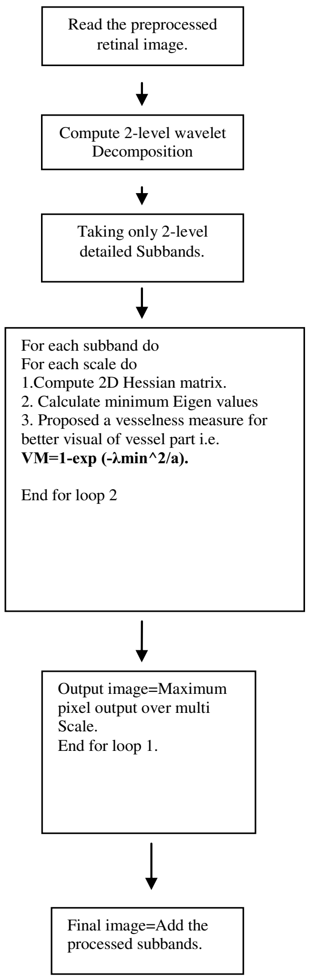

Figure 5. Block diagram of vessel extraction.

3.2.1 *Wavelet Decomposition*

Wavelet transform represents the space-frequency information. So local features are more prominent with wavelets. In our work we apply 2-level discrete wavelet decomposition on the preprocessed image. We know in wavelet decomposition images are first analyzed into low-frequency and high-frequency sub-bands along the rows and then down-sampled by factors of 2. Each of the resulting sub-bands is then analyzed into the low and high-frequency sub-bands along the columns and so on. We perform the 2-level decomposition. But we take only the detail sub-bands of the second level. We use Haar wavelet in our work. The result of 2-level wavelet decomposition has shown below.

3.2.2 *Multiscale Hessian based Vesselness Measurement*

We compute 2D Hessian to the smoothing function i.e. Gaussian function and convolve the image. It gives better result than applying Hessian directly to the image. It gives the gradient of an image.

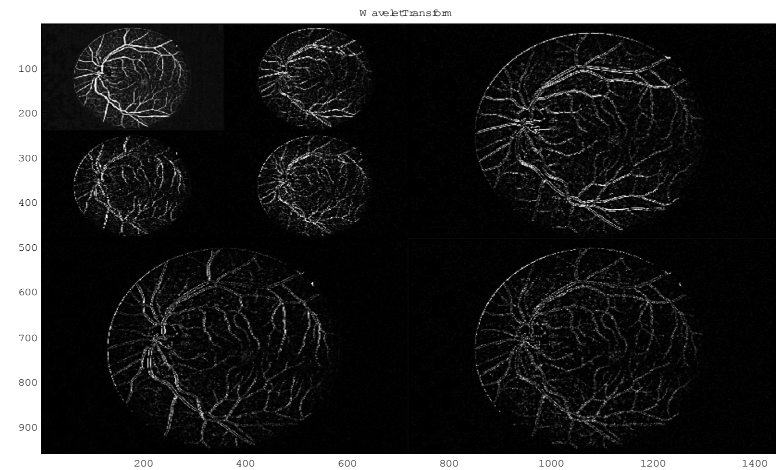

Figure 6. Wavelet decomposition.

$$G(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp - \left(\frac{x^2 + y^2}{2a^2} \right) \quad (5)$$

$$H(x, y) = \begin{bmatrix} Fxx & Fxy \\ Fyx & Fyy \end{bmatrix} \quad (6)$$

$$\mathrm{Fxx} = \mathrm{Gxx} * \mathrm{Ixx} \quad (7)$$

$$\mathrm{Fxy} = \mathrm{Gxy} * \mathrm{Ixy} \quad (8)$$

$$\mathrm{Fyx} = \mathrm{Gyx} * \mathrm{Iyx} \quad (9)$$

$$\mathrm{Fyy} = \mathrm{Gyy} * \mathrm{Iyy} \quad (10)$$

where, '∗' is the convolution operation; Gxx, Gxy, Gyy are second derivatives of the Gaussian function G. Next the eigen values $\lambda 1$ and $\lambda 2$ are calculated from hessian matrix H, where $\lambda 1 <= \lambda 2$. We found that existing works[7-10] used both the eigen values for vessel enhancement.

Here a vesselness measure has been proposed where we use only the minimum or smallest eigen value. It has been noticed that it is adequate to fulfill the aim.

$$\mathbf{VM = 1 - exp\ (-\lambda min^{2/a})} \quad (11)$$

where, a is a threshold value which controls the filter sensitivity. Vessels are of different diameters, so this Hessian based computation has been applied at different scales. After processing the maximum value over all scale is taken which is required to get the continuity of thin vessel picture. The whole hessian based approach has been applied to all the detailed sub-bands and finally compute the summation of all the sub-bands to keep the value of all the coefficients.

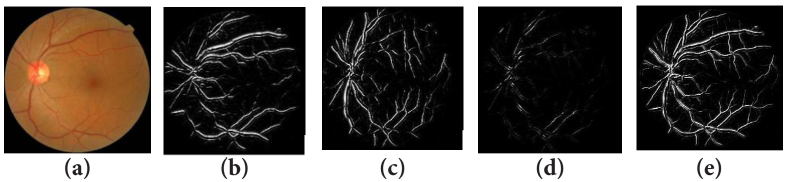

Figure 7. Result of the vesselness filter **(a)** Original image **(b)** Filtered LH2 Sub-band **(c)** Filtered HL2 Sub-and **(d)** Filtered HH2 Sub-band **(e)** Final output of summation of all the filtered Sub-bands.

4. Experimental Result

The method is applied to the images from the STARE database and the results are compared with the ground truth images in the database. This database provides two sets of manual segmentations made by two different specialists. We use the images provided by the first observer for our experiment. The sample results are shown below.

In the Figure 8, we are showing 5 sample results. The first column shows the original retinal images, second the ground truth images and

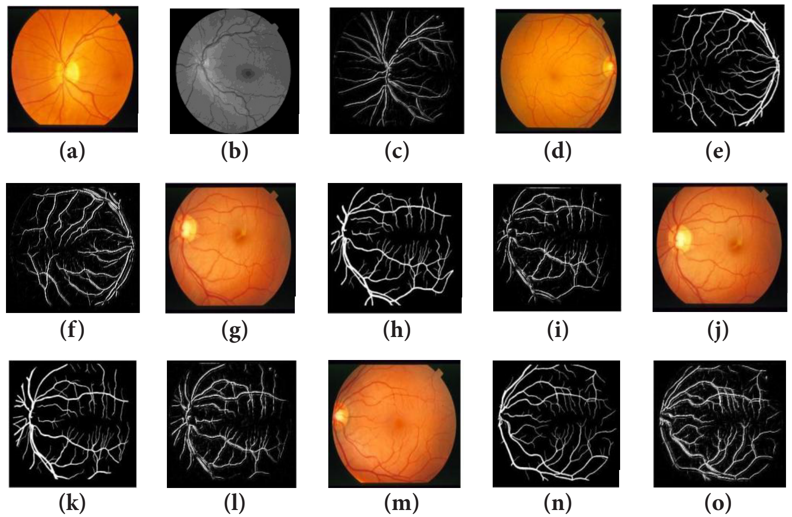

Figure 8. Sample results for the images of the STARE database. **(a),(d),(g),(j),(m)** Original image, **(b),(e),(h),(k),(n)** ground truth image, **(c),(f),(i),(l),(o)** proposed method.

Table 1. Mean square error

Retinal images of Figure. 8	Mean Square Error
Image1	0.1470
Image2	0.1507
Image3	0.1539
Image4	0.1560
Image5	0.1578

third shows the vessel extraction results by the proposed method. It has been noticed that we get quite a good result. Maximum vessels have been detected comparing with the ground truth images. The outer ring artifact and the optic disc have been removed in preprocessing itself, which helps in removing false positives. But in the above figure we see that some of the small vessels are missing. We will work on these drawbacks in the near future.

The quality of the vascular structures has been analyzed by the mean square error between the proposed results and the ground truth images. We convert both into binary format and find the result. The below Table shown the error result of above sample images.

5. Conclusion

We proposed 2D discrete wavelet decomposition and Hessian-Eigen value based approach for retinal vascular extraction. Here we first remove the optic disc by the preprocessing technique. The results of the vascular extraction are compared with the ground truth images. We use STARE database for this purpose. By visual comparison with the ground truth images it can be said that our method is quite impressive. The blood vessel visualization is appreciable which helps to find out the abnormalities of retina.

6. References

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