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Multi-Scale Retinal Vessel Segmentation Using Hessian Matrix Enhancement

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***Abstract*: In this paper an algorithm for vessel segmentation in retinal images is proposed. Firstly, on the basis of preprocessing of the retinal image, the contrast between retinal image vessel and background is improved. Then the multi-scale enhancement filter based on the Hessian matrix is used to enhance the retinal image, and finally the whole vessel network is binarized by using an iterative thresholding method.**

The experimental evaluation in the publicly available DRIVE database shows accurate extraction of vessels network. The average accuracy of 95.88 with 0.729 true positive rate and 0.194 false positive rate, which is very close to the manual segmentation rates obtained by the second observer. The proposed algorithm is compared also with widely used supervised and unsupervised methods, and the experimental results show the effectiveness of the method.

***Keywords*: Retinal image; Preprocessing; Hessian matrix; Iterative thresholding.**

1. INTRODUCTION

Vessel segmentation of retinal image can provide a good foundation for the three-dimensional reconstruction and measuring vessel parameters, so vessel segmentation results have important influence on the subsequent processing and analysis[1]. The vessel segmentation method, based on the characteristics of data of standard image or not, can be divided into supervised and unsupervised method. The supervision [2-6] method is through the standard image data previously obtained in the extraction of vessel characteristics, and the vessels are segmented. Unsupervised method [7-12] is used certain criteria to judge pixel point of the retinal images, and the image pixels are classified into vessels and background, including mathematical morphology method, vessel tracking method, the local adaptive threshold method and matched filtering method.

Through the analysis of existing vessel segmentation method of retinal image, most methods choose to treatment normal and good retinal images, but retinal images are more complex, and there are images with diseases, so most methods have problems that cannot completely and correctly segment the vessels with diseases in images, affecting the subsequent vessel quantitative analysis. According to the characteristics of vessels and the image quality, a hot research topic in the future is to find a vessel segmentation method with high quality and high automation.

This paper proposes a vessel image segmentation method based on Hessian matrix and multi-scale filtering. Based on the preprocessing, the contrast between vessels and background has been improved, so as to provide a good foundation for the subsequent retinal vessels segmentation, the diagram of the vessel segmentation method is shown in Figure 1.

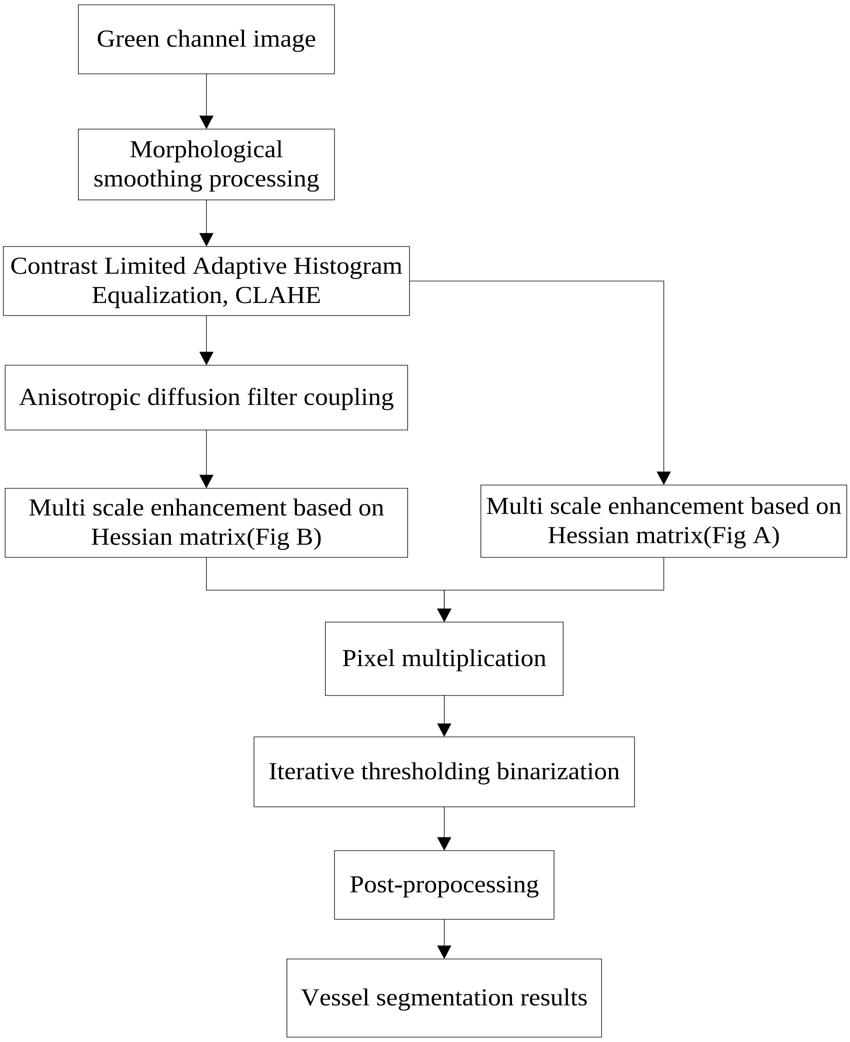

Fig.1 Diagram of the vessel segmentation method

2. MULTI-SCALE ENHANCEMENT FILTER BASED ON HESSIAN MATRIX

Retinal vessels are in partial lineage structure and their width varies, thus the Hessian matrix is used to detect retinal vessels as it is sensitive to lineage structure. For two-dimensional images, Hessian matrix[13] is a second-order matrix, which can be expressed as:

$$H(f)=\begin{bmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{bmatrix} \qquad (1)$$

f_{xx}, f_{xy} and f_{yy} are the second-order partial derivative of f respectively, $f(x,y;\sigma)=g(x,y;\sigma)*I(x,y)$, $g(x,y;\sigma)$ is a Gaussian function where the standard deviation is σ, σ is space scale factor, I is the original image, (x,y) is the position of pixel, $*$ represents the operation of a convolution.

The two characteristic values of H are as follows:

$$\begin{aligned} \lambda_1 &= a+b \\ \lambda_2 &= a-b \end{aligned} \qquad (2)$$

where $a=\dfrac{f_{xx}+f_{yy}}{2}$, $b=\dfrac{\sqrt{\left(f_{xx}-f_{yy}\right)^2+4f_{xy}^2}}{2}$.

For lineage structure, the corresponding characteristic vector of the two characteristic values of the Hessian matrix λ_1 and λ_2 ($|\lambda_2| > |\lambda_1|$) are orthogonal, $\lambda_2 > 0$ means the detection structure is a hidden structure, while $\lambda_2 < 0$ means the detection structure is an open structure. The characteristic vectors and characteristic values of the Hessian matrix can represent the intensity and direction of retinal vessels on the retinal image. The characteristic vector corresponding to high characteristic value is perpendicular to the blood vessel, while the characteristic vector corresponding to low characteristic value is parallel to the blood vessel.

After filtering, the blood vessels in the retinal image are enhanced. In order to extract the blood vessel from the filter results, this paper, according to the relationship between characteristic value of Hessian matrix and vascular structures, introduces the vascular confidence coefficient to describe the intensity of blood vessels. The confidence coefficient of single-scale blood vessel is defined as follows [14]:

$$Z_\sigma(x,y;\sigma)\begin{cases} 0 & \lambda_2<0 \\ \exp\left(\frac{-D^2}{2\beta^2}\right)\left(1-\exp\left(\frac{-S^2}{2M^2}\right)\right)\left(1-\exp\left(\frac{-|\lambda_1|}{\alpha}\right)\right) & \lambda_2 \ge 0 \end{cases} \quad (3)$$

Where $D = \arctan\left(\frac{\lambda_1}{\lambda_2}\right)$, β is the scale factor influencing D, $S = \sqrt{\lambda_1^2 + \lambda_2^2}$, M is the module value of Hessian matrix under the current scale, namely, $M = \|H\|$, α is the initial parameter of noise elimination. Equation (4) includes three parts: (1) in vascular structure, $|\lambda_2| > |\lambda_1|$, the value of $D = \arctan\left(\frac{\lambda_1}{\lambda_2}\right)$ is small, hence, a larger $\exp\left(\frac{-D^2}{2\beta^2}\right)$ can realize the enhancement of blood vessels; (2) $1-\exp\left(\frac{-S^2}{2M^2}\right)$ can realize the multi-scale judgment of blood vessels, as M is corresponding to scale factor σ, namely, the larger σ is, the larger the semi-diameter of Gaussian filter will be, and the larger the vascular diameter is, the larger Z will be; otherwise, the smaller σ is, the smaller the semi-diameter of Gaussian filter will be, and the smaller the vascular diameter is, the smaller Z will be. The function of $1-\exp\left(\frac{-|\lambda_1|}{\alpha}\right)$ is to eliminate noises. In the iteration process, the noise in some non-vascular areas are amplified, at the noise point in Hessian matrix, $\lambda_1 \approx 0$, hence, $1-\exp\left(\frac{-|\lambda_1|}{\alpha}\right)$ in Equation (4) has the function of eliminating noises.

Therefore, in order to describe the different scales of blood vessels, this paper, according to the scale space theory herein, employs multi-scale approach to enhance blood vessels. When the retinal image is proceeded iteratively with σ ($\sigma_{\min} < \sigma < \sigma_{\max}$), Z_σ under different scale will be achieved. For vascular vessels, only when the scale factor matches the vascular diameter to the largest extent can Z_σ reach its maximum value. The maximum value of Z_σ at each point is taken as the blood vessel confidence coefficient of the current point.

$$Z_o = \max_{\sigma_{\min}<\sigma<\sigma_{\max}} (Z_\sigma(x,y;\sigma)) \quad (4)$$

In order to test the different scales of the enhanced effect of vessels, the original color image is processed according to the paper [13] and a large number of experiments, the initial parameters are $\beta = 0.5$, $\alpha = 6$ .Comprehensive vessel Z_o with Single and multiple scales of vessel enhancement is separated shown in fig 2, Fig 2(a)is the original color image, Fig 2(b) is the green channel image, From Fig 2 (a)-(c) can be seen in single scale only corresponding diameter portion of the vessels are enhanced, Fig 2 (f) under the multi-scale interaction can be moderately enhanced the overall vessel, but not all of the vessels are enhanced, so before multi-scale enhancement based on Hessian matrix, there need to do preprocessing.

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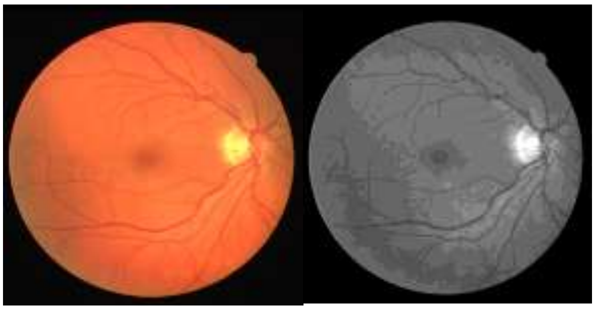
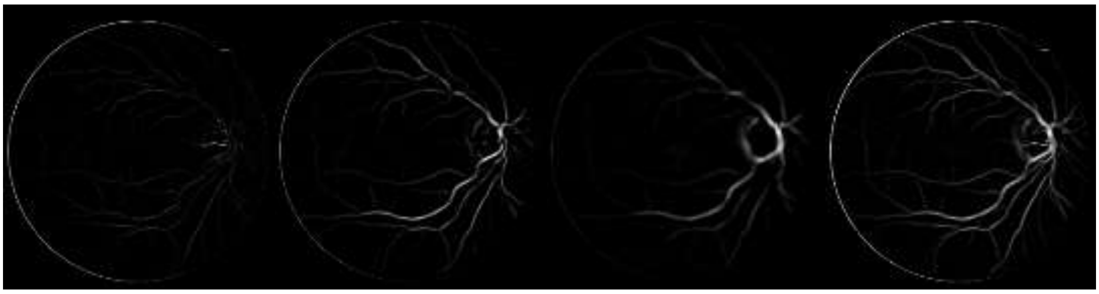


(a) (b)

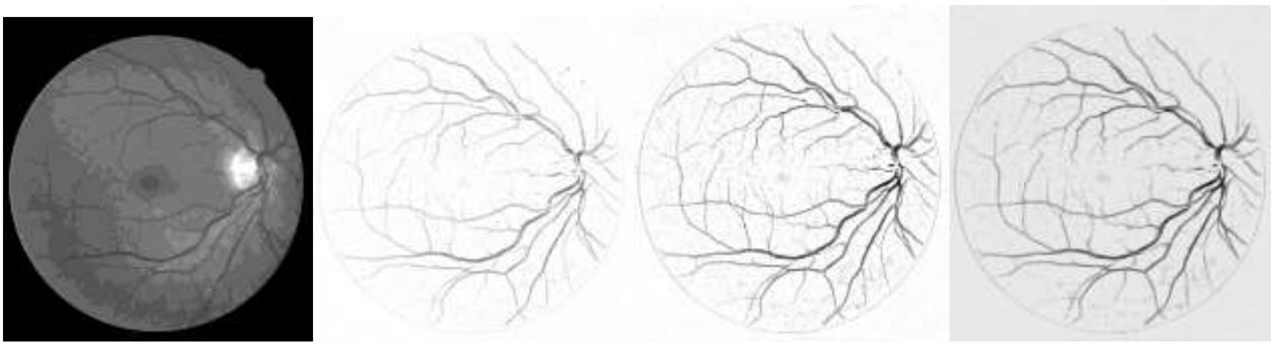


(c) $\sigma = 1$ **(d)** $\sigma = 3$ **(e)** $\sigma = 5$ **(f)** $\sigma : [1:10], \sigma_s = 0.5$

Fig 2 Single and multiple scales of vessel enhancement

3. PREPROCESSING

The main purpose of the preprocessing is to improve the quality of retinal images, enhance vessel information and suppress background noise and other interference factors. The preprocessing includes morphological smoothing processing, contrast limited adaptive histogram equalization(CLAHE), the anisotropic diffusion equation coupled filter. Morphological smoothing is to highlight vessel and weaken background noise, suitable for low contrast images, the anisotropic diffusion equation coupled filter can not only protect vessel edge information, but also can enhance the effect of image smoothing, provide the basis for the subsequent processing. The preprocessing results are shown in Figure 3.



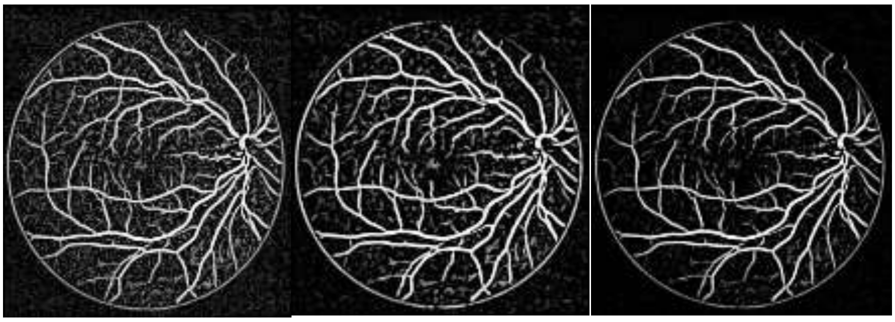
(a) (b) (c) (d)

Fig 3 Preprocessing results

(a)Green channel image; (b)Morphological smoothing processing; (c)CLAHE processing; (d)The anisotropic diffusion equation coupled filter processing

4. VESSEL SEGMENTATION METHOD

Based on the preprocessing, no matter whether the image filtering or not by the anisotropic diffusion equation coupled filter processing, the vessels are extracted using multi-scale enhancement based on Hessian matrix($\sigma \in [0.5, 10], \sigma_s = 0.5$),shown in fig 4(a) and (b). The two results are multiplied with pixel level, shown in fig 4(c).



(a) (b) (c)

Fig 4 Enhancement results

(a)Multi-scale enhancement based on Hessian matrix after CLAHE processing; (b) Multi-scale enhancement based on Hessian matrix after the anisotropic diffusion equation coupled filter processing; (c) Pixel level multiplication

5. ITERATIVE THRESHOLDING BINARIZATION

In this section the vessel is binarized by iterative thresholding, and then disposed by post-processing, shown in fig 5. The whole vessel network is segmented.

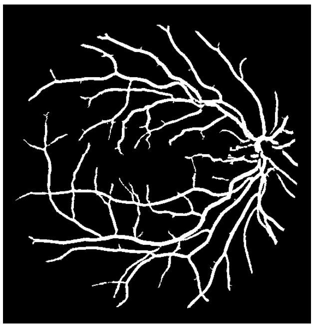


Fig 5 Vessel segmentation result

6. EXPERIMENTAL EVALUATION

A. Materials:

The retinal vessel segmentation methods is evaluated on two publicly available data sets. Both the DRIVE database and the STARE database have been widely used by researchers to test their vessel segmentation methodologies, since they provide manual segmentations for performance evaluation.

The DRIVE database[15] contains 40 color retinal images, which have been divided into a test set and a training set, both containing 20 images. Each of the twenty training images has been carefully labeled by an expert, by hand, to produce ground truth vessel segmentation. The images were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45° FOV. Each image was captured using 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels. For this database, the images have been cropped around the FOV. For each image, a mask image is provided that delineates the FOV.

The STARE database[16] contains 20 colored retinal images, with 700 × 605 pixels and 8 bits per RGB channel, captured by a TopCon TRV-50 camera at a 35° FOV. Two manual segmentations by Hoover and Kouznetsova[16] are available. The first observer marked 10.4% of the pixels as vessel, the second one 14.9%. The performance is computed with the segmentations of the first observer as a ground truth. The comparison of the second human observer with the ground truth images gives a detection performance measure, which is regarded as a target performance level.

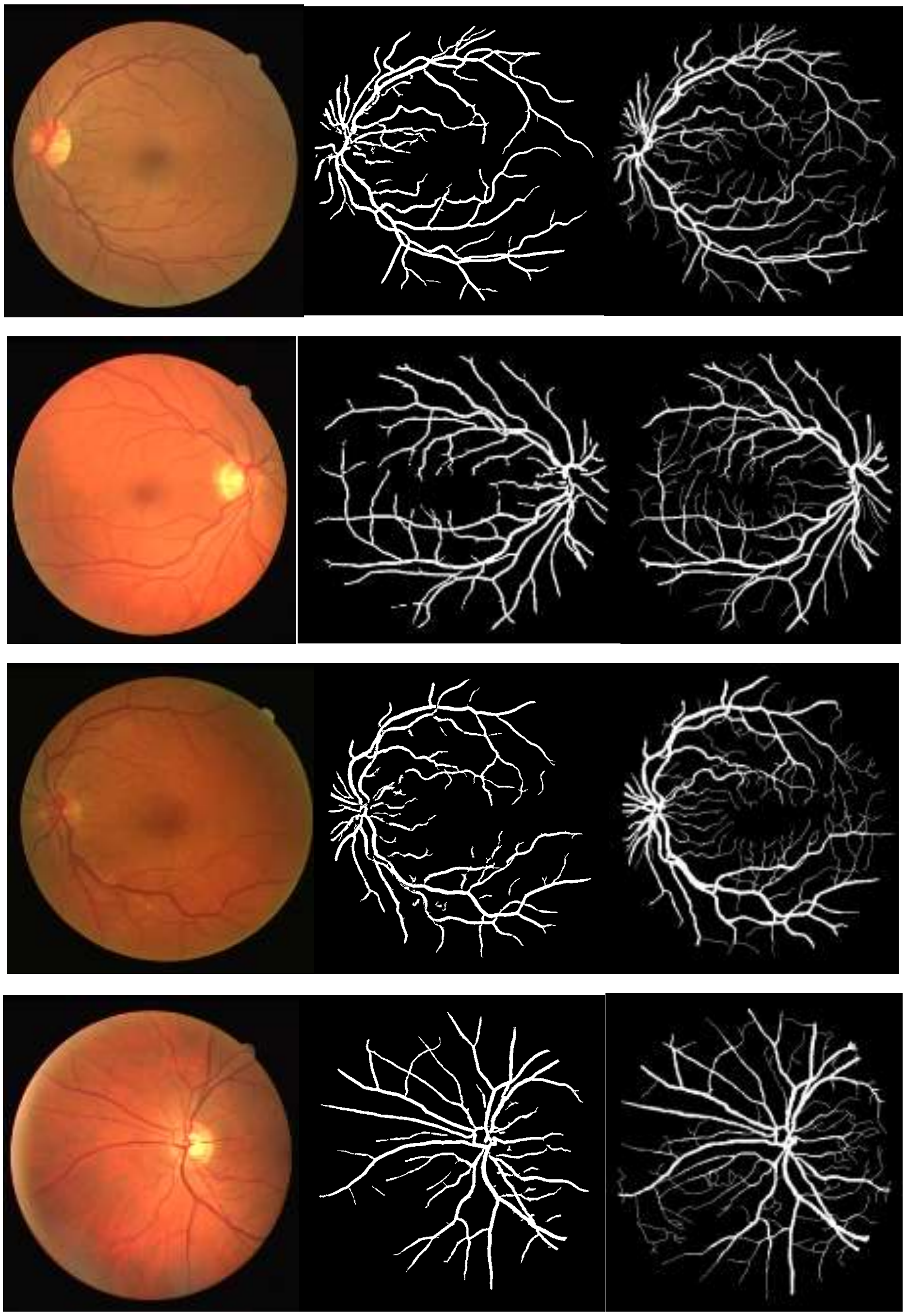
B. Performance Measures:

In order to quantify the algorithmic performance of the proposed method on a retinal image, the resulting segmentation is compared to its corresponding ground truth image. Any pixel that is identified as a vessel in both the ground truth and the segmented image is marked as a true positive (TP). Any pixel that is marked as a vessel in the segmented image, but not in the ground truth image, is counted as a false positive (FP). The performance can be described by true positive rate (TPR), false positive rate, (FPR), and accuracy (ACC).

$$TPR = \frac{TP}{TP+FN}, FPR = \frac{FP}{FP+TN}, ACC = \frac{TP+TN}{TP+FP+TN+FN} \quad (5)$$

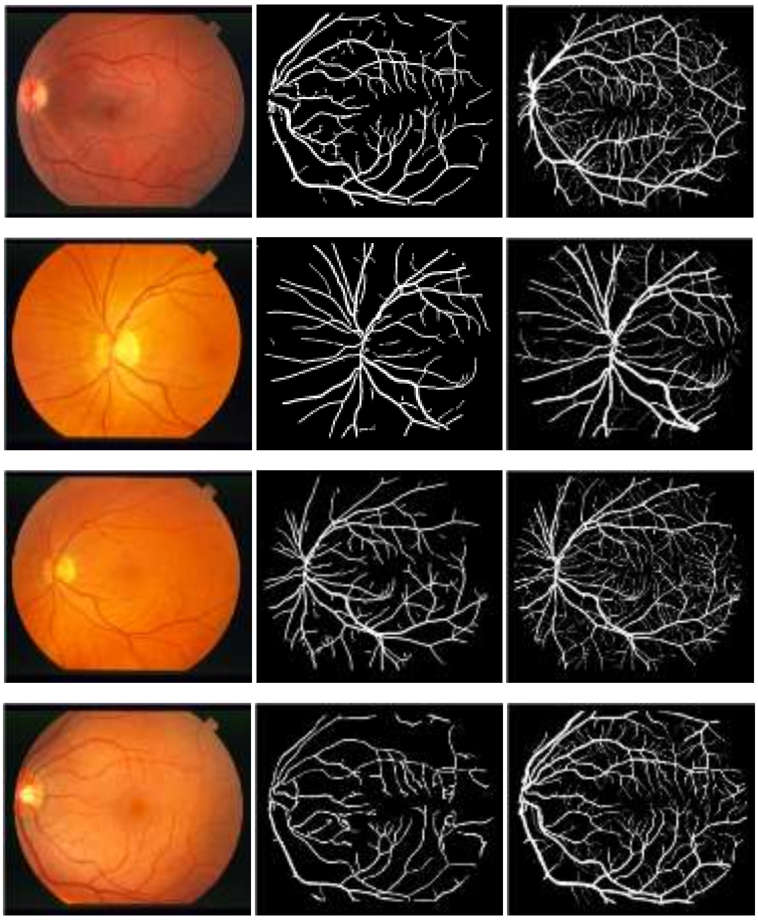
C. Vessel Segmentation Results:

In this section we give the vessel segmentation results, showing in fig 6 and 7, the first column is the original color image, the second column is our results, the last column is the ground truth. Our results can get a whole vessel network. Our method can get a good segmentation.



(a) **(b)** **(c)**

Fig 6 Segmentation results of DRIVE database



(a) **(b)** **(c)**

Fig 7 Segmentation results of STARE database

In order to further illustrate the effectiveness of this vessel segmentation method, TPR, FPR and ACC of the different methods with DRIVE database and STARE database are showed in table 1(a) and 1(b).Our method can get a good TPR, FPR and ACC compared with other method.

Table 1(a) TPR, FPR and ACC in different segmentation with DRIVE database

Method type	Method	TPR	FPR	ACC
Unsupervised	Jiang et al.[7]	-	-	0.9212
	Martinez-Perez et al.[8]	0.7246	0.0345	0.9344
	Zhang et al.[9]	0.7120	0.0276	0.9382
	Uyen T.V.Nguyen et al.[10]	-	-	0.9407
	Emanuele Trucco et al.[11]	-	-	0.9461
	Frank Y. Shih et al.[12]	0.7354	0.0211	0.9477
Supervised	Marin et al.[6]	0.7067	0.0199	0.9452
	Niemeijer et al.[2]	0.6898	**0.0304**	0.9417
	Soares et al.[3]	0.7230	0.0238	0.9446
	Ricci et al.[4]	-	-	0.9595
	Staal et al.[5]	0.7194	0.0227	0.9442
Our method		0.7286	0.0194	0.9588

Table 1(b) TPR, FPR and ACC in different segmentation with STARE database

Method type	Method	TPR	FPR	ACC
Unsupervised	Martinez-Perez et al.[8]	0.7506	0.0431	0.9569
	Zhang et al.[9]	0.7171	0.0247	0.9484
	Uyen T. V. Nguyen et al.[10]	-	-	0.9324
	Emanuele Trucco et al.[11]	-	-	0.9521
	Frank Y. Shih et al.[12]	0.7354	0.0233	0.9477
Supervised	Staal et al.[5]	0.6970	0.0190	0.9516
	Soares et al.[6]	0.7103	0.0263	0.9480
	Ricci et al.[4]	-	-	0.9646
Our method		0.7286	0.0194	0.9588

7. CONCLUSIONS

In this paper, an effective retinal vessel segmentation method has been proposed, Experimental results have shown that our method can segment these close vessels, and has the ability to deal with these centers of central reflex vessels. Being an unsupervised method, our method has produced comparable accuracy. The demonstrated effectiveness and robustness, together with its simplicity, make theproposed blood vessel segmentation method a suitable tool for being integrated into a computer-assisted diagnostic system for ophthalmic disorders.

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