VESSEL CENTERLINES EXTRACTION FROM FUNDUS FLUORESCEIN ANGIOGRAM BASED ON HESSIAN ANALYSIS OF DIRECTIONAL CURVELET SUBBANDS

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ABSTRACT

This paper presents a novel algorithm for automatic extraction of the blood vessels centerline in Fundus Fluorescein Angiography (FFA) images in different diabetic retinopathy (DR) stages. First, the background normalized images are enhanced by applying a morphological edge detector. Then each of the directional images resulting from curvelet sub-bands is individually processed using Hessian matrix and first order derivative of the directional images information in a multi-scale framework for extracting initial centerline segments. Every resulted candidate segment in previous step is confirmed or rejected based on the length and intensity features and eigenvalues analysis. The final vessels centerline segmentation is obtained by connecting the images subsets in a binary image. The proposed algorithm is tested on 70 FFA images from different DR stages and the performance of method in terms of true positive ratio (TPR) and false positive ratio (FPR) that are obtained .9017 and .0983 respectively.

Index Terms—Fundus Fluorescein Angiography, curvelet transform, match filter, Hessian matrix, eigenvalues analysis.

1. INTRODUCTION

Retinal vessel segmentation and quantification of blood vessels attributes, such as length, width, branching pattern and angles can be utilized for evaluation of the retinal disorders, macula and optic disk detection, diagnosis and screening of various cardiovascular and ophthalmologic diseases and as a tool for laser surgery **[1]**. Diabetic retinopathy (DR) is usually a leading cause of blindness and vision reductions in developed countries. A vision screening can be successful to detect retinopathy for people who are at risk for eye disease. Manually extraction of blood vessels is very time consuming in retinal images and its accuracy depends on the user skill level. So, automatic extraction of retinal blood vessels appears to be critical. According to [2], vessel segmentation methods can be divided in five main categories: (1) pattern recognition, (2) matched filtering, (3) vessel tracking/tracing, (4) mathematical morphology, (5) multi-scale approaches. In each category several methods are reported in [2]. Pattern recognition techniques can be divided in two categories: supervised methods and unsupervised methods. In [3] an approach based on back-propagation neural network is described for the segmentation of blood vessels in angiography. In **[4]** 2-D Gabor wavelet and supervised classification is used for retinal vessel segmentation. The feature vectors are formed by the pixels intensity and 2-D Gabor wavelet coefficients. In **[5]** an algorithm based on feeding a 7-D feature vector composed of gray-level and moment invariant-based features to a supervised neural network is described. The approach described in [6-8], can be considered as matched filter methods. In [6] a 2-D linear kernel with Gaussian profile is introduced for vessel detection. Because a vessel can be occurred in any angles, the kernel is rotated in 12 different directions and maximum response in each pixel is retained. In [7] the amplitude-modified second order Gaussian filter has been proposed for blood vessel segmentation. Also in [8] a 2-D Gaussian matched filter for vessel enhancement and then a neural network is applied for vessel detection. In [9] a tracking method with Gaussian and Kalman filters for vessel segmentation in retinal images is proposed. The second order matched filter is used for centreline estimation and then tracking process is stared, i.e., the Kalman filter is applied for estimation next vessel location. Also in **[10]** a modular supervised method for vessel segmentation is proposed. The image background is normalized for non-uniform intensity variations using scale space theory and a supervised optimization procedure is applied to determine the optimal scale.

This paper presents a novel algorithm for detection of the blood vessels centreline in FFA images. Usually the FFA images are degraded due to non-uniform illumination and low contrast between the background and the blood vessels. For this purpose, the images need pre-processing for enhancement of small and thin vessels. Then the directional subbands of curvelet transform of the image resulting from

pre-processing stage are computed to make set of directional images. Then the following two computations are performed for each one of the directional images in a multi-scales framework. First, eigenvalues of Hessian matrix analysis is computed and second the first order derivative of the directional images is evaluated. These features will be used to extract initial vessel centerlines as described in the following sections. Finally, each one of the initial vessel centerlines is confirmed or rejected based on the length and intensity features and eigenvalues analysis.

The paper is organized as follows. The proposed algorithm is introduced in Section 2. Thereafter, the experimental results on the FFA images from different DR stages are presented in section 3 and finally section 4 is devoted to the main conclusions of this paper.

2. PROPOSED METHOD

2.1. Image pre-processing

The background intensity variational of the retinal images makes some of the characteristic in retinal images such as retinal capillaries to be hardly visible which often affected the outcome of the vessel segmentation. For this reason, the background intensity variations can be reduced by using nonlinear diffusion [11]. Then a median filter with proper size is applied to nonlinear diffusion output which omits the vessels successfully and preserves the image of background. This background image is subtracted from nonlinear diffusion output and then a top-hat transform using multi structure elements morphology is applied to the last result to enhance contrast of thin vessels. The detailed procedure of the morphological edge detector is available in [12]. Fig.1 shows the results of this stage.

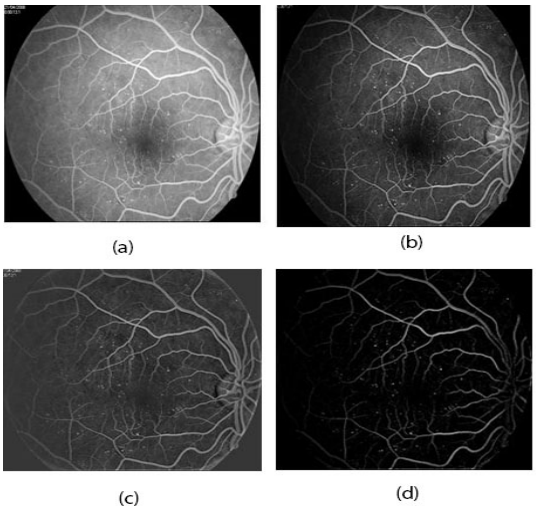

Fig. 1. (a) FFA image, (b) Output of nonlinear diffusion, (c) Background normalized image, (d) Output of the modified top-hat transforms.

2.2. Making a Set of Directional Images

Curvelet transform is a multi scale approach and multi directional decomposition [13-14]. In order to enhance the edges of image, curvelet coefficients are modified using a nonlinear function introduced in **[15]**. The curvelet enhancement algorithm can be described in the following steps:

1. Calculate the curvelet transform of the images resulting from the previous stage. So, a set of directional subbands is obtained in each scale.

2. The noise standard deviation of coefficients is calculated in the same subband and scale using the algorithm proposed in **[16]**.

3. For each subband:

- Calculate the maximum curvelet coefficients of the relative subband.

- Multiply each curvelet coefficient x by a nonlinear function defined in **[15]**:

$$K_c(x,\sigma_{ji})=\begin{cases}15; & x<c\sigma_{ji}\\ 2\left(\dfrac{x-c\sigma_{ji}}{c\sigma_{ji}}\left(\dfrac{m}{c\sigma_{ji}}\right)^p+\dfrac{2c\sigma_{ji}-x}{c\sigma_{ji}}\right); & c\sigma_{ji}\le x<2c\sigma_{ji}\\ 7\left(\dfrac{m}{x}\right)^p; & 2c\sigma_{ji}\le x<m\\ 10\left(\dfrac{m}{x}\right)^s; & m\le x\end{cases} \quad (1)$$

where σ_{ji}, p, s and c are respectively noise standard deviation, degree of nonlinearity, dynamic range compression, and normalization parameter. The parameter m is the value under which coefficients are amplified.

4. Retain all coefficients in a specific direction in different scales and set the others to zero in order to reconstruct set of directional images from the modified curvelet coefficients. In this paper, curvelet transform via wrapping is applied in 5 scales, and 16 directions is defined in the second scales, which makes 32 directions in 3rd and 4th scales, and 64 directions in 5th scale. Under this framework, number of directional images would be the half number directions in the second scale. So, for each $1 \le i \le 8$, a directional image containing frequency content $[3\pi/4-(i-1)\pi/8 \quad 3\pi/4-i\pi/8]$ is obtained, i.e., each of these images is averagely directed in specific angle by:

$$\theta(i)=\frac{(2\pi/8-(i-1)\pi/8)+(2\pi/8-i\pi/8)^o}{2} \quad 1\le i\le 8 \quad (2)$$

2.3. Detection of Initial Candidate Centreline Segments

Since retinal blood vessels have a range of different sizes and also can occur in different direction, our algorithm is designed based on the multi-scale techniques and directional image analysis. Based on the vessel structure characteristics, the radius of blood vessels changes logarithmically as follows **[17]**:

$$S(i)=\exp\left(\log(a)+\frac{(i-1)\left(\log(b)-\log(a)\right)}{(Ns-1)}\right) \quad (3)$$

where N_s is the number of scales, and a and b are minimum and maximum radius of the vessels. In this paper a, b and N_s are considered 0.4, 3 and 5 respectively.

Accordingly, one pixel of the directional image can be belonging to the initial centreline segment if the following conditions are satisfied:

1. **Eigenvalue analysis:** Given the structure of the vessel, each one of the directional images contains negative or positive intensity values according to variational intensity in the same direction. So, the pixels intensity value of the directional images is positive inside the vessel and negative outside the vessel. Also, a pixel from the directional image is belonging to vessel if the largest eigenvalue from Hessian matrix is negative [18]. So, each of the eight directional images is searched for the positive intensity values and negative eigenvalues with maximum magnitude in different scales (as defined in (3)).

2. **Gradient analysis**: Another feature is the magnitude of the gradient of the resulted image in section 2.1 (Fig. 1. (d)). Based on assuming Gaussian profile for blood vessels, magnitude of the gradient is increased from vessel centreline to both sides of the vessel. So, on perpendicular direction to the vessel, the search is performed on a line with a width proportional to the radius of the vessel, which is approximated by $2S(i)$.

3. **Evaluation of the first order derivative of directional images**: The directional images resulting from the convolution with the first order derivative of the Gaussian filter along the x-axis would have a change of sign on perpendicular direction of the pixel belonging to the vessel centreline.

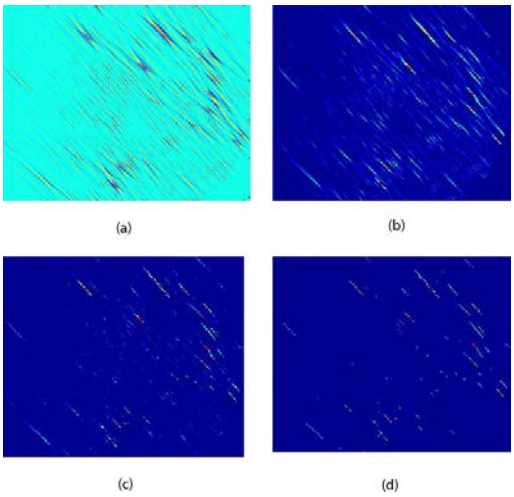

Fig. 2. (a) 5th directional image, (b) Directional image resulting from condition 1, (c) Directional image resulting from conditions 2 and 3, (d) Initial centerline vessel segments after condition 4.

4. **Image histogram analysis by Otsu threshold algorithm**: The image resulting from condition 3 is assessed based on adaptive thresholding of the image histogram. The histogram is automatically divided into two classes using Otsu threshold algorithm. Intensity values greater than Otsu threshold belong to an initial centerline segment. For those pixels which are below the Otsu threshold, their mean and standard division are calculated and each pixel which is greater than the sum of mean and standard deviation is assigned to an initial centreline segment. Fig. 2 shows the results of this section for 5th directional image and $s(1)$.

2.4. Evaluation of Centerline Candidate Segment

Maximum intensity and maximum eigenvalues of the eight directional images resulting from the previous stage are calculated on all scales of the Gaussian kernel. Directional images which belong to a limited range of angles are combined together. Therefore according to Table 1 there will be just four directions for the images. Fig. 3 shows four directional images obtained from this stage. Every centreline segment is confirmed or rejected based on the evaluation of the eigenvalues, intensity and length features.

Table 1: Angle of directional image analysis

i	$\theta(i)$	Angle approximated
1,8	$33.75^o, 56.25^o$	45^o
2,3	$11.25^o, 168.75^o$	0^o
4,5	$146.25^o, 123.75^o$	135^o
6,7	$101.25^o, 78.75^o$	90^o

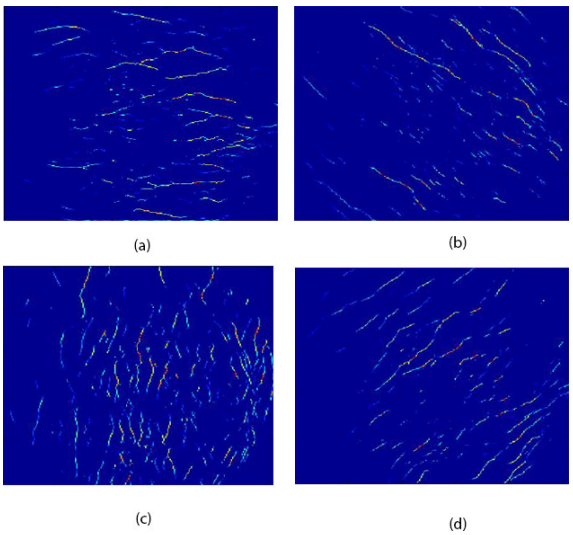

Fig. 3. Initial centerline segments (horizontal, diagonal 135^o and vertical, diagonal 45^o).

Evaluation of the eigenvalues: this process is experimentally applied on the connected components with length smaller than 6 in each of the directional images. Then the candidate segments with eigenvalue smaller than the difference between the mean and multiple of the standard deviation are rejected.

Evaluation of the intensity and length features: Intensity of the segment is calculated using the geometric mean between the mean and maximum intensity values of the segment candidate **[19]**, and length of the segment is calculated by maximum number of the pixels in vertical or horizontal direction. The validation step is applied on each of the

candidate segments from set of the directional images by combining its intensity and length features with its reference values. The detailed procedure of evaluation of the intensity and length is available in **[19]**. Finally, a binary image containing vessels centerline is made by cleaning the connected components smaller than 9. The final image of the vessel centerline is shown in Fig. 4.

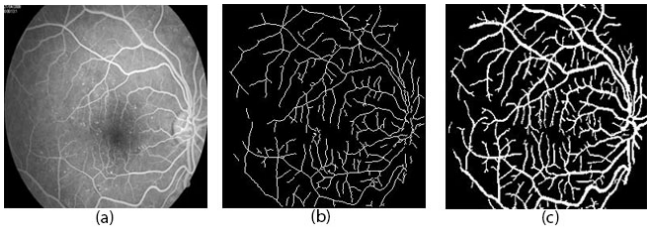

Fig. 4. (a) FFA image, (b) Vessel centerlines, (c) Ground truth image.

3. EXPERIMENTAL RESULTS

Our proposed algorithm for vessel centreline segmentation was tested on the 70 FFA images of size 576×720 pixels from angiography unit of Isfahan Feiz hospital from different DR stages. These images can be downloaded from http://misp.mui.ac.ir/data/eye-images.html. The detailed results of the proposed algorithm for a sample FFA image are illustrated in Fig. 5. In this figure, correctly detected centreline pixels, false detected centreline pixels and lost detected centreline pixels are shown in orange, white and red respectively. The proposed algorithm in this paper is performed by MATLAB version 8 by applying fast curvelet transform via wrapping (which the source codes is downloadable from http://www.curvelet.org) in 5 scales and 16 directions in the second scales (which makes 32 directions in 3rd and 4th scales and 64 directions in 5th scale). The modified coefficients were produced using nonlinear function (1) by parameters $l=0.2 \quad c=4 \quad p=0.5 \quad s=0$. As mentioned earlier, each one of the directional images is individually processed for extracting centreline segment. To evaluate our results, true positive rate (TPR) can be calculated as the ratio of the intersection of the centreline pixels in detected vessel centrelines by our algorithm and pixels belonging to the vessels in ground truth image to the total number of detected pixels. The ratio of the number of false detected centreline pixels to the total number of detected pixels can be defined as false positive rate (FPR). Table 2 shows the performance of the above algorithm in terms of TPR and FPR on defined dataset. In Fig. 6, the results of applying our vessel detection method for several FFA images are compared with ground truth images.

Table 2: Performance of the method

	TPR	FPR
FFA images	.9017	.0983

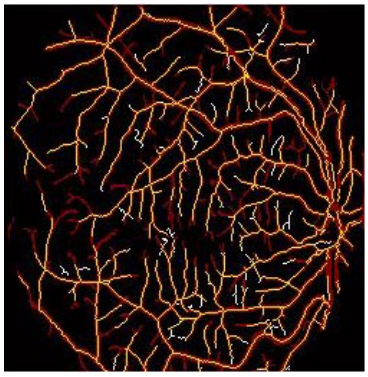

Fig. 5. Displayed pixels in terms correctly detected centerline (orange), false detected centerline (white) and lost detected centerline (red).

4. CONCLUSION

In this paper a novel algorithm in curvelet domain for vessel centreline extraction is introduced. For this purpose, set of directional images of curvelet sub-bands is individually processed in order to select vessel centreline segments using length and intensity features and eigenvalues analysis. The final vessel segmentation results is obtained by combining all resulted segments and removing false detected edges. Since curvelet transform is a multi-directional decomposition approach, detection of thin and low contrast vessels is successfully done in each of the directional images. The results are shown that proposed method has enough accuracy to extract small and low contrast vessels that are visible hardly. There is a trade-off between extracting thin vessels and removing the false edges and background noise. The deficiency of the proposed algorithm in missing some thin vessels and remaining false edges detected is duo to the simple thresholding algorithm. Also, we can extend this approach for segmentation of other important features in retinal images such as optic disk, exudates and fovea in both colour fundus and FFA images.

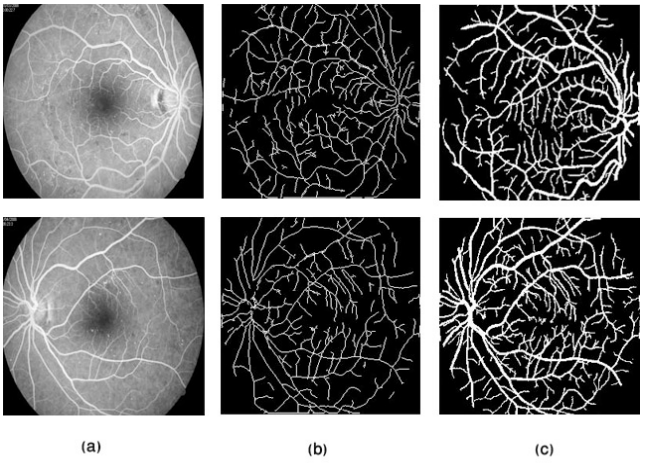

Fig. 6. (a) FFA images, (b) Vessel centerline, (c) Ground truth images.

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