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Feature Analysis for Segmentation of Retinal Blood Vessels

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Abstract:
Retinal Vascular Segmentation proves useful for clinical purposes. From segmented blood vessel, tortuosity and diameter of vessels can be computed. Vessel tortuosity can be used for evaluation of hypertensive retinopathy whereas vessel diameter can be used to diagnose hypertension and cardiovascular diseases. In this paper, we have extracted the features for the detection of blood vessel. The extracted feature is vesselness measures, matched filter, Gabor filter and matched filter. Later these features are combined using multifeature analysis with the help of neural network for the segmentation of retinal blood vessels.

Key Words: Inverted green channel, Retinal Vascular Diseases, Retinopathy.

1. INTRODUCTION:

Retinal fundus images are used by ophthalmologists for the diagnosis of several disorders such as retinopathy of prematurity and diabetic retinopathy. Detection of blood vessels is an important initial step in the analysis of retinal fundus images and development of computer-aided diagnostic systems. It is possible to detect other anatomical landmarks such as the macula and optic nerve head (ONH) in the retina. The location and certain characteristics of such landmarks can help for the detection of abnormalities. A variety of methods have been proposed for the detection of blood vessels and some of these methods in the following paragraphs are reviewed.

Chaudhuri et al. [1] proposed an algorithm based on two-dimensional (2D) matched filters for vessel detection. Their method is based on three assumptions: (i) vessels can be approximated by piecewise linear segments (ii) Gaussian function approximates the intensity profile of a vessel and (iii) the width of vessels is relatively constant. The given image was convolved with the matched filter rotated in several orientations for detection of blood vessel.

Staal et al. [3] proposed the algorithm in which the ridges in the images that roughly coincide with the vessel centerlines was extracted. Feature vectors were then computed for every pixel using the line elements and characteristics of the partitions. The classification was done using *k*-nearest neighbor classifier with 20 test images of DRIVE database

Soares et al. [2] used complex Gabor filters and supervised classification for the detection of blood vessels in retinal fundus images. Here, magnitude outputs at several scales were obtained from 2D complex Gabor filters then these outputs were assigned to each pixel as a feature vector. A classification was done using Bayesian classifier for classification of the results into vessel or non vessel pixels.

Several types of vesselness measures have been developed for the detection of blood vessels based on the properties of the eigenvalues of the Hessian matrix computed at each pixel. The eigenvalues over all scales with the maximum response at each pixel is used for further analysis since blood vessels are of varying width. Frangi et al. [4] and Salem et al. [6] proposed different vesselness measures to highlight vessel-like structures.

Rangayyan et al. [8] performed multiscale analysis for the detection of blood vessels using Gabor filters and classified pixels using multilayer perceptron (MLP) neural networks with the test set of the DRIVE database.

In this work, we are detecting blood vessel using multiscale Gabor filters as proposed by [8], multiscale vesselness measures as proposed by [4] and [6], matched filters as proposed by [1] and a gamma-corrected [7] version of the inverted green channel. These will be further use for multifeature analysis for retinal blood vessel segmentation.

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2. OVERVIEW:

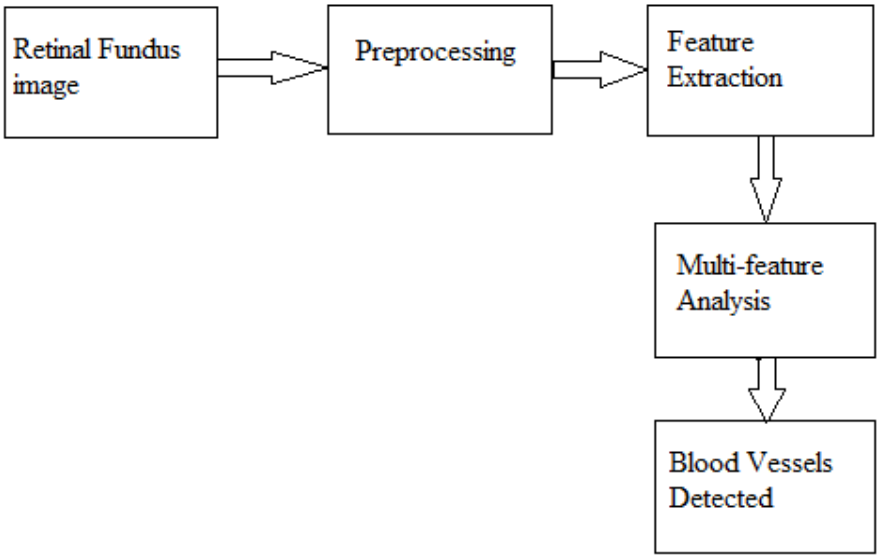


Figure 1: Block diagram of Retinal Blood Vessel Segmentation

A. Preprocessing

For efficient segmentation of retinal blood vessels, it is desirable to have high contrast between the retinal blood vessels and retinal background. Thus, highest weight is provided to green channel component to increase the contrast of blood vessel.

B. Feature extraction:

The features are extracted by various methods such as vesselness measure by Frangi and Salem, Multiscale Gabor filter and Gamma corrected version of inverted green channel. The techniques for feature extraction are explained briefly in upcoming section.

C. Multifeature Analysis:

In Multifeature analysis, combination of features are used to distinguish pixels belonging to blood vessel using MNN(Multilayer Neural Network). The number of input layer nodes is equal to the number of features being used and the output layer always contain one node.

D. Thresholding technique:

Further the thresholding technique like entropy thresholding will be used to get improved result.

3. FEATURE EXTRACTION:

In the present study, we review and implement several methods for the detection of blood vessels and investigate their combined application for multifeature analysis.

A. Vesselness Measures

A vesselness measure was defined by Frangi et al. [4] to detect pixels belonging to vessel like structures depending on the properties of the eigenvalues of the Hessian matrix. The numerical estimate of the Hessian matrix, *H*, at each pixel of the given image, $L(x,y)$ is obtained as:

$$H = \begin{bmatrix} \frac{\partial^2 L}{\partial x^2} & \frac{\partial^2 L}{\partial x \partial y} \\ \frac{\partial^2 L}{\partial y \partial x} & \frac{\partial^2 L}{\partial y^2} \end{bmatrix}$$

At multiple scales, the entries of *H* can be obtained by convolution the the image *L*(*x, y*) with the Gaussian kernel *G*(*x, y*; *σ*) of different scales *σ*.The Gaussian kernel at different scales is defined as:

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

Gaussian kernels can be used to generate a suitable scale space with an amplitude range of ¾ related to the range of vessel width. The width of retinal blood vessels varies from 50 μm to 200 μm in retinal fundus images, which translates to the range of about 2 to10 pixels, given a spatial resolution of 20 μm for the DRIVE images. By linear convolution of the image with the scale-normalized derivatives of the Gaussian kernel ,the multiscale derivatives of the image *L*(*x,y*) can be obtained as:

$$\frac{\partial^2 L}{\partial x^2} = L(x,y) * \sigma^2 G_{xx} = L_{xx}\,, \frac{\partial^2 L}{\partial x \partial y} = \frac{\partial^2 L}{\partial y \partial x} = L(x,y) * \sigma^2 G_{xy} = L_{xy} = L_{yx}\,, and\ \frac{\partial^2 L}{\partial y^2} L(x,y) * \sigma^2 G_{yy} = L_{yy}.$$

The symbol '*'represents the 2D convolution operation and $G_{xx}\,, G_{xy}\,, and\ G_{yy}$ are the second derivatives of the Gaussian kernel *G*.

Let λ_1 and λ_2 represent the eigenvalues of the Hessian matrix, with the condition $|\lambda_2| \geq |\lambda_1|$. The Hessian matrix is symmetrical with real eigenvalues. The signs and ratios of the eigenvalues can be used as signatures of a local structure. A larger value of λ_2 compared to represents a vessel like structure The larger eigenvalues of λ_2 corresponds to the maximum principal curvature at the location (*x; y*). By solving the following equation, the eigenvalues and eigenvectors of the Hessian matrix can be computed as:

$$\begin{vmatrix} L_{xx} - \lambda & L_{xy} \\ L_{yx} & L_{yy} - \lambda \end{vmatrix} = 0,$$

where, λ represents the two eigenvalues λ_1 and λ_2. The eigenvalues λ_1 and λ_2 can be obtained as:

$$\lambda_1 = \frac{L_{xx} + L_{yy} - \alpha}{2},$$

and

$$\lambda_2 = \frac{L_{xx} + L_{yy} + \alpha}{2}$$

Where $\alpha = \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2}$. Depending on the property of the eigenvalues of the Hessian matrix, Frangi et al. [8] defined a vesselness measure to highlight pixels belonging to vessel like structures as:

$$V_F = \begin{cases} exp\left(-\frac{R_\beta^2}{2\beta^2}\right) & \left[1 - exp\left(-\frac{s^2}{2\gamma^2}\right)\right] \\ 0 \end{cases}$$

Where, β=0.5, $R_\beta = \frac{\lambda_1}{\lambda_2}$, S = $\sqrt{\lambda_1^2 + \lambda_2^2}$ is the Frobenius norm of the Hessian matrix and *γ* is equal to one-half of the maximum of all of the Frobenius norms computed for the whole image. The magnitude of the derivatives of the intensities will be small where no vessels are present and the eigenvalues are low, so the Frobenius norm is expected to be low in background areas. Otherwise, the Frobenius norm will become larger, in regions with high contrast as compared to the background because at least one of the eigenvalues will be large.

The vesselness measure proposed by Salem et al. [6] to detect the orientation of blood vessels uses the eigenvalues of the Hessian matrix. Let $\underset{e_1}{\rightarrow}$ and $\underset{e_2}{\rightarrow}$ be the eigenvectors corresponding to the eigenvalues $\lambda_1$and λ_2 respectively, and let $\theta_1$and θ_2 be the angles of the eigenvectors with respect to the positive *x*-axis. The orientations of the eigenvectors corresponding to the larger and smaller eigenvalues for every fifth pixel are shown in Figure 2. It can be noted from Figure 2 that the variation of the orientation of the eigenvectors corresponding to the smaller eigenvalues is smaller inside the blood vessels as compared to that outside the blood vessels. The eigenvectors corresponding to the smaller eigenvalues are mainly oriented along the blood vessels; hence, the angle θ_1 is used to analyze the orientation of blood vessels. The orientation of the eigenvector $\underset{e_1}{\rightarrow}$ can be represented as:

$$\theta_1 = arctan\left(-\frac{2L_{xy}}{L_{yy} - L_{xx} + \alpha}\right)$$

Detection of blood vessels can be accomplished by assuming that the value of $\lambda_2(\lambda_{max})$ over several scales, with σ = {1, 2, . . . , 6} pixels, is the highest at the center of the vessel. Salem et al. [9] defined a vesselness measure as:

$$V_S = \frac{\lambda_{max}}{\theta_{std} + 1}$$

where θ_{std} is the standard deviation of θ_1 over all scales used for the pixel under consideration. The larger the value of V_S for a pixel, the higher the probability that the pixel belongs to a vessel.

B. Gabor filters:

For the detection of blood vessels, Rangayyan et al. [8] applied multiscale Gabor filters by considering the fact that blood vessels are piecewise-linear, elongated or curvilinear structures with a preferred orientation.

Gabor filters are sinusoidally modulated Gaussian functions. They provide optimal localization in both the frequency and space domains which are suitable for the analysis of oriented structures. The real Gabor filter kernel oriented at the angle $\vartheta = -\pi/2$ can be represented as:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right]\cos(2\pi f_0 x)$$

In this equation, the frequency of the modulating sinusoid is given by f_0, and σ_x and σ_y are the standard deviation values in the *x* and *y* directions. In the present work, a set of 180 Gabor filters over the range [$-\pi/2$, $\pi/2$] is prepared by rotating the main Gabor filter kernel. For simplicity of design, a variable τ is used to represent the average thickness of the vessels to be detected. The value of σ_x is defined based on τ as $\sigma_x = \frac{\tau}{2\sqrt{2\ln 2}}$ and $\sigma_x = l\sigma_x$, where *l* represents the elongation of blood vessels.

C. Gamma-corrected version of the inverted green channel.

The inverted *G* component of the *RGB* color space provides high contrast for the blood vessels. Therefore, a gamma-corrected version [7] of the inverted *G* component is also used as a feature to improve the result of classification of blood vessels.

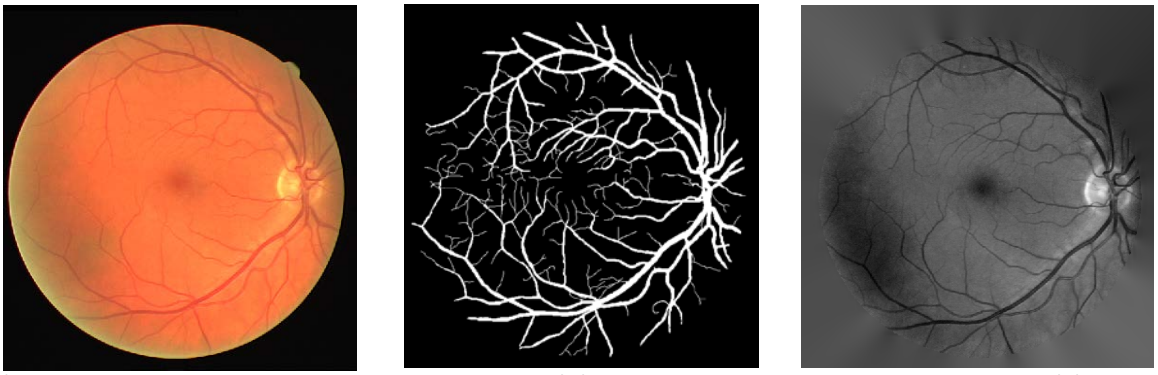
D. Matched Filters

The method of Chaudhuri et al. [1], as explained in Section 1, was implemented in the present work for the detection of blood vessels. The method assumes that blood vessels have a negative contrast with respect to the background, so the Gaussian template will need to be inverted. The main kernel of the matched filter is expressed as:

$$M(x,y) = -\exp\left(\frac{-x^2}{2\sigma^2}\right) \qquad for\ -L/2 \le y \le L/2$$

where *L* represents the length of the vessel segment that is assumed to have a constant orientation .The main kernel of the filter is oriented along the *y*-axis; in order to detect blood vessels at different orientations, the main kernel is rotated at multiple angles.

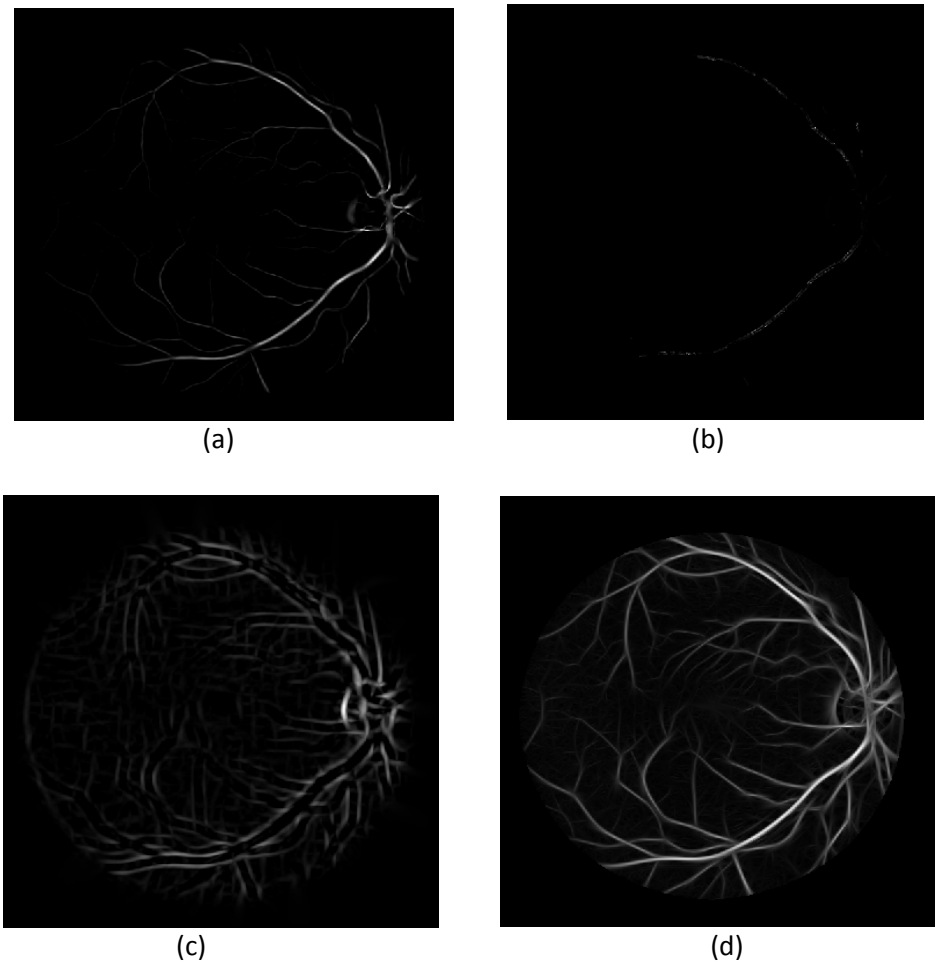
4. RESULTS AND DISCUSSION:



(a) (b) (c)

Figure 2: (a) Fundus Image (b) Ground Truth (c) Preprocessed Image

Figure 2 (a) and (b) shows Fundus image and ground truth image of drive database respectively.The fundus image is preprocessed to increase the contrast of blood vessel and the out of preprocessing is shown in figure 2(c)



(a) (b)

(c) (d)

Figure 2: Features
(a) Result of Vesselness measure by Frangi *et.al*
(b) Result of Vesselness measure by Salem *et al*
(c) Result of Matched filter
(d) Result of Gabor filter
.

Figure 2 shows the results of various features. These features are obtained from preprocessed fundus image. Fig. 2(a) shows result of vesselness measure by Frangi [4] while Fig.2 (b) shows result of vesselness measure by Salem[6]. Again, Fig.2(c) and Fig.2(d) shows the result of matched filter and Gabor filter respectively. These features will be used further for multifeature analysis to segment retinal blood vessel. By subjective Analysis of features, shown in fig.2, we can see that the blood vessels are more properly detected by Gabor and resemble ground truth. Small blood vessels which are missed in other feature are detected properly in Gabor.

5. CONCLUSION:

In many applications of ophthalmology, the most important step is to detect the blood vessels in the retina for diagnosing various vascular diseases. For proper diagnosis of the diseases, it is important to segment blood vessels more accurately. Thus, multifeature analysis is proposed to improve accuracy of retinal blood vessel segmentation. In this paper, we have obtained the various feature like vesselness measure, gabor filter and matched filter. Later, Multifeature analysis will be done by combining these several feature for detecting blood vessel more precisely. Also the thresholding techniques like entropy thresholding will be used for further modification of results.

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