RETINAL BLOOD VESSEL SEGMENTATION USING MULTIFEATURE ANALYSIS

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ABSTRACT:

The Detection of blood vessels in retinal fundus images is an important initial step in the development of systems for computer aided diagnosis of pathologies of the eye. In this study, we perform multifeature analysis for the detection of blood vessels in retinal fundus images. The vessel detection techniques implemented include Gabor filters, matched filters, Gamma Corrected version of inverted green channel and vesselness measures. Values of the area under the receiver operating characteristic curve of up to 0.9604 were obtained using the 20 test images of the DRIVE database.

Keywords: Vascular Architecture, Retinopathy, Neural Network, Segmentation.

[1] INTRODUCTION

Ophthalmologists uses Retinal fundus images for the diagnosis of several disorders such as retinopathy of prematurity and diabetic retinopathy. The structure of the blood vessels in the retina is affected by diabetes, hypertension, arteriosclerosis, and retinopathy of prematurity through modifications in shape, width, and tortuosity. Quantitative analysis of the architecture of the vasculature of the retina and changes as previously mentioned could assist in monitoring disease processes, as well as in evaluating their effects on the visual system. Images of the retina can also reveal pathological features related to retinopathy, such as microaneurysms, hemorrhages, exudates, macular edema, venous beading, and neovascularization. Automated detection and quantitative analysis of features as previously mentioned could assist analysis of the related pathological processes. In many applications of image processing in ophthalmology, the most important step is to detect the blood vessels in the retina.
We present a brief review of some of the previously proposed methods for the detection of blood vessels in the retina.

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. [2] 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. [4] 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. [5] and Salem et al. [6] proposed different vesselness measures to highlight vessel-like structures.

Lupascu et al. [11] done multifeature analysis using new features that represent information about the geometry of the vessels at different scales of length, local intensity, the structure of vessels and spatial properties combined with previously proposed features. They used a feature of 41 features obtained at different scales to train a classifier which was then applied to the test set using the 20 test images of the DRIVE database.

Rangayyan et al. [7] 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 perform vessel segmentation by multifeature analysis, using multiscale Gabor filters as proposed by [7], multiscale vesselness measures as proposed by [5] and [6], matched filters as proposed by [1] and a gamma-corrected [8] version of the inverted green channel.
[3] METHODS FOR DETECTION OF RETINAL BLOOD VESSEL

The methods for detection of Retinal Blood Vessel are explained below:

- Vesselness Measures: A vesselness measure was defined by Frangi et al. [5] 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:

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

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

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

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 $\lambda_1$ and $\lambda_2$ 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 $\lambda_2$ compared to $\lambda_1$ represents a vessel like structure. The larger eigenvalues of $\lambda_2$ corresponds to the maximum principle curvature at the location $(x; y)$. By solving the following equation, the eigenvalues and eigenvectors of the Hessian matrix can be computed as:

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

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where, \( \lambda \) represents the two eigenvalues \( \lambda_1 \) and \( \lambda_2 \). The eigenvalues \( \lambda_1 \) and \( \lambda_2 \) 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. [5] defined a vesselness measure to highlight pixels belonging to vessel-like structures as:

\[
V_F = \begin{cases} 
\exp\left(-\frac{R_\beta}{2\beta^2}\right) \left[1 - \exp\left(-\frac{s^2}{2\gamma^2}\right)\right] & \text{if } \lambda_1 \lambda_2 > 0 \\
0 & \text{otherwise}
\end{cases}
\]

(3)

Where, \( \beta=0.5, R_\beta = \frac{\lambda_1}{\lambda_2}, S = \sqrt{\lambda_1^2 + \lambda_2^2} \) is the Frobenius norm of the Hessian matrix and \( \gamma \) 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 \( e_1 \rightarrow \) and \( e_2 \rightarrow \) be the eigenvectors corresponding to the eigenvalues \( \lambda_1 \) and \( \lambda_2 \) respectively, and let \( \theta_1^e \) and \( \theta_2^e \) 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 \( \theta_1 \) is used to analyze the orientation of blood vessels. The orientation of the eigenvector \( e_1 \) can be represented as:

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

(4)

Detection of blood vessels can be accomplished by assuming that the value of \( \lambda_2(\lambda_{\text{max}}) \) over several scales, with \( \sigma = \{1, 2, ..., 6\} \) pixels, is the highest at the center of the vessel. Salem et al. [6] defined a vesselness measure as:
\[ V_S = \frac{\lambda_{max}}{\theta_{std} + 1} \] (5)

where, \( \theta_{std} \) is the standard deviation of \( \theta_1 \) 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.

- **Multiscale Gabor Filter**: For the detection of blood vessels, Rangayyan et al. [7] 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 \( \theta = -\pi/2 \) can be represented as:

\[
g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left[ -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) \right] \cos(2\pi f_0 x) \] (6)

In this equation, the frequency of the modulating sinusoid is given by \( f_0 \), and \( \sigma_x \) and \( \sigma_y \) 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 \( \tau \) is used to represent the average thickness of the vessels to be detected. The value of \( \sigma_x \) is defined based on \( \tau \) as \( \sigma_x = \frac{\tau}{2\sqrt{\ln 2}} \) and \( \sigma_x = l\sigma_x \), where \( l \) represents the elongation of blood vessels.

- **Gamma Corrected Version of Inverted Green Channel**: The inverted \( G \) component of the \( RGB \) color space provides high contrast for the blood vessels. Therefore, a gamma-corrected [8] version of the inverted \( G \) component is also used as a feature to improve the result of classification of blood vessels.

- **Matched Filter**: The method of Chaudhuri et al. [1], as explained in earlier Section 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 vessels. This 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:

\[
M(x, y) = -\exp \left( \frac{-x^2}{2\sigma^2} \right) \quad \text{for} \quad -L/2 \leq y \leq L/2
\] (7)
where $L$ represents the length of the vessel segment that is assumed to have a constant orientation and $\frac{1}{\sigma}$ is the STD of the Gaussian. 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] COMBINATION OF SEVERAL FEATURES

Using Multifeature analysis, combination of features are used to distinguish pixels belonging to blood vessel using MNNs (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. All the MNNs used in this work for multifeature analysis contain two hidden layers with 15 nodes per hidden layer. The number of input layer nodes is equal to the number of features being used and the output layer always contains one node. A tangent sigmoid (tansig) function was used as the training function for each hidden layer and a pure linear function was used at the output layer of the MNN. In each case, the MNN was trained using set of 20 images of the database. Sequential feed forward feature selection was used to determine which combination of the features listed as multiscale Gabor filters as proposed by [7], multiscale vesselness measures as proposed by [5] and [6], matched filters as proposed by [1] and a gamma-corrected [8] version of the inverted green channel would provide the best results for multifeature analysis. The feature selection method selected all available features.

[5] RESULTS

The performance of proposed method was tested with the set of 20 test images of DRIVE database. And set of 20 training images of DRIVE database was used to train Multilayer Neural Network. Results are evaluated in terms of the area under the curve (Az), TPR(True positive rate), FPR(False positive rate) and Accuracy.

Table I: Shows the outputs for combination of several feature

<table>
<thead>
<tr>
<th>Features</th>
<th>TPR</th>
<th>FPR</th>
<th>Accuracy</th>
<th>Az</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vesselness measures, Gabor Filter, Inverted Green channel.</td>
<td>0.8964</td>
<td>0.0946</td>
<td>0.9041</td>
<td>0.9614</td>
</tr>
<tr>
<td>Vesselness measures, Gabor Filter, Inverted Green Channel, Matched Filter</td>
<td>0.8978</td>
<td>0.0971</td>
<td>0.9022</td>
<td>0.9604</td>
</tr>
</tbody>
</table>

[6] CONCLUSION

In this paper, we have performed multiscale and Multifeature methods for the detection of blood vessels in retinal fundus images. The Multifeature analysis is done by combining these several features such as Vesselness measures, Gabor filter, Inverted Green channel and matched filter to get better accuracy for detecting blood vessels.
REFERENCES


