Abstract: The field of medical imaging gains its importance with increase in the need of accurate and efficient diagnosis over a short period of time. Since manual processes are tedious, time consuming and impractical for large data there is a need for automatic processing that helps community health workers. Segmentation of the vasculature in retinal fundus images plays an important role in the diagnosis of many eye diseases such as hypertension, arteriosclerosis and blindness caused by diabetes. A method is presented in this work for an automated segmentation of retinal vessels in the fundus images. This method uses a kernel based classifier such as Support Vector Machine to segment the vessels by classifying each pixel as vessel or nonvessel, based on the pixel’s feature vector. The feature vectors are composed of the pixel’s intensity and the Gabor wavelet responses measured at different scales. The performance of the segmentation is analyzed in terms of Specificity, Sensitivity and Segmentation Accuracy. The method’s performance is evaluated on publicly available databases of color fundus images with reference to the ground truth image provided in the database.

Index Terms: Retinal fundus images; Gabor Wavelet; Support Vector machine

I. INTRODUCTION

Digital fundus imaging in ophthalmology plays an important role in medical diagnosis of several pathologies like hypertension, diabetes, arteriosclerosis, cardiovascular disease and stroke [1]. Retinal vessel segmentation is a primary step towards automated analysis of the retina for anomaly detection and also image registration. Automated assessment of the retinal vasculature morphology can be used in a screening tool for early detection of diabetic retinopathy.

Different techniques are used for acquiring retinal images. Most common are colored or monochromatic photography and angiography using fluorescent dyes. The retinal vasculature is comprised of two complex networks - one of veins, the other of arteries - that spread out from the optic disk and branch successively to occupy different regions of the fundus. Retinal blood vessels are locally continuous with respect to position, curvature and width, with vessels widths gradually decreasing with the distance to the optic disk. Diabetic retinopathy screening involves assessment of the optic fundus with attention to a series of indicative features. Of great importance is the detection of changes in blood vessel structure and flow, due to either vessel narrowing complete occlusions or neovascularization. The retinal and choroidal vessel structures are used in biometrics for identification/verification of persons in security systems.

Segmentation of vessels in fundus images is performed manually by trained ophthalmologist but now there are many recent developments are employed to segment the vessels, since manual segmentation of images is a time consuming process and is susceptible to human errors. An automated assessment for pathologies of the optic fundus initially requires the precise segmentation of the vessels from the background, so that suitable feature extraction and processing may be performed. Several methods have been developed for automated vessel segmentation. Rawi et al. [2] proposed an improved matched filter by using an optimizing procedure to search for the best parameters for the method. Another technique for vessel extraction is the vessel-tracking method proposed by Can et al. [3], in which each vessel segment is defined by three attributes: direction, width, and center point. The density distribution of the cross section of a blood vessel is estimated
using a Gaussian shaped function. Elisa et al. [4] proposed a method for vessel segmentation using line operators and support vector machine. This method provides a good segmentation result but supervised based linear Support Vector Machine is used.

Soares et al. [5] proposed a simple and efficient method for segmentation using Gabor Wavelet and Gaussian mixture classifier. This method is conceptually simple and results efficient results but it does not perform well for large variations in lighting throughout an image and it has the inability to capture some of the thinnest vessels that are barely perceived by the human observers. Elisa et al. [6] proposed a method for vessel segmentation using cellular neural networks. This method is easy to use but results in low accuracy. Chin-Chen Chang et al. [7] proposed a classification mechanism for retinal images using SVM and this result in good accuracy. Dhruv Batra et al. [8] proposed a method for fingerprint classification using Gabor filter and Support Vector Machine.

From the above analysis of exiting method a new method is introduced in this work that uses Gabor wavelet and Support Vector Machine for retinal vessel segmentation. Gabor Wavelet is used for extracting the features and these features are used for pixel classification by using Kernel based classifiers such as Support Vector Machine.

The section II describes about proposed methodology of this work. Section III discusses about the results obtained. Section IV gives the conclusion of the work.

II. PROPOSED METHODOLOGY

The basic steps of the proposed methodology are shown in Figure 1.

A. Retinal Images

Retinal images used in this work are colored images and are obtained from the publicly available databases STARE [9]. The ground truths of the retinal images are also available in this Data Base.

B. Green Channel Extraction and Inversion

A colored image is made up of red, green and blue components. When these components are viewed separately the green channel shows the best vessel/background contrast, whereas the red and blue channels show low contrast and are very noisy. The green channel is inverted before the application of the wavelet transform to it, so that the vessels appear brighter than the background.

C. Feature Extraction and Normalization

It is the process of extracting significant information from an image. Features of the retinal images are extracted from the transformed coefficients. The wavelet transform is a powerful and versatile tool that has been applied to many different image processing problems, such as image coding, texture analysis and shape analysis. Continuous Wavelet Transform (CWT) in two or more dimension is a very efficient and flexible tool in image analysis. The continuous Wavelet Transform $T_\psi(b, \theta, a)$ is defined as

$$T_\psi(b, \theta, a) = C_\psi^{-1/2}(\psi_{b, \theta, a} | f)$$

$$= C_\psi^{-1/2} a^{-1} \int \psi(a^{-1} r_{\theta}(x - b)) f(x) d^2x$$

Where $C_\psi$, $\psi$, $b$, $\theta$ and $a$ denote the normalizing constant, analyzing wavelet, the displacement vector, the rotation angle, and the dilation parameter (also known as scale) respectively [10].

There are many analyzing wavelets, for instance the 2-D Mexican hat wavelet and the Optical Wavelet. Due to the nature of spatial locality, orientation, selectivity, and frequency characteristics, Gabor wavelets are used in this work as the analyzing wavelet. One of its most important properties is its capability of detecting and analyzing directional structures.

The 2-D Gabor wavelet is defined as

$$\psi_{\omega}(X) = \exp(ik_{\omega}x)\exp\left(-\frac{1}{2}(xAx)\right) + \text{correction}$$

where $A$ is a $2 \times 2$ positive definite matrix which defines the wavelet anisotropy, $B = A^T$ and $k_{\omega} \in \mathbb{R}^2$.

Figure 1: Proposed Methodology
defines the complex exponential basic frequency. The anisotropy matrix is given as

\[ A = \begin{bmatrix} e^{-1} & 0 \\ 0 & 1 \end{bmatrix} \] (4)

with elongation given by \( \varepsilon \geq 1 \).

In this work, the elongation parameter was set to \( \varepsilon = 4 \) and \( k_a = [0, 3] \). In order to detect vessels in any orientation, for each considered position and scale, the response with maximum modulus over all possible orientations is taken as pixel features

\[ M_x(b, a) = \max_b |T_x(b, a, \theta)| \] (5)

The Gabor wavelet transform is computed for \( \theta \) spanning from 0 up to 170 degrees at steps of 10 degrees and the maximum is taken (this is possible because \( |\Psi(b, a, \theta)| = |\Psi(b, a, \theta + 180)| \)). The maximum modulus of the wavelet transform over all angles for various scales is taken as pixel features.

The measures used as features may have ranges spanning different orders of magnitude. This can lead to errors in the classification process. A strategy to obtain a new random variable with zero mean and unit standard deviation, compensating for eventual magnitude differences, is to apply the normal transformation to each feature. The normal transformation is defined as

\[ \hat{V}_i = \frac{v_i - \mu_i}{\sigma_i} \] (6)

where \( v_i \) is the \( i \)th feature of each pixel, \( \mu_i \) is the average value of the feature and \( \sigma_i \) is the standard deviation of each feature.

D. Segmentation

Segmentation is done using pixel based classification methodology. Vessel segmentation method is proposed by exploring the Support vector Machine which has the ability of learning nonlinear distribution of the vessels without having any prior knowledge. Classifier used in this work is supervised method such as Support Vector Machine with Radial Basis Function (RBF) kernel which requires data for training and then used as reference for automatically classifying new data. SVM can produce accurate and robust classification results on a sound theoretical basis, even when input data are non-monotone and non-linearly separable.

In a linear classifier a \( p \)-dimensional vector is classified by a \( p-1 \)-dimensional hyper plane. Let \((x_i, y_i), i = 1, 2, \ldots, N \) represent the training examples of the classification problem, where \( x_i \in \mathbb{R}^n \) is the pattern to be classified and \( y_i \in \{-1, +1\} \), denotes its class labels. The problem is how to construct a classifier [i.e., a decision function \( f(x) \)] that can correctly classify an input pattern \( x \) that is not necessarily from the training set. There exists a linear function of the form

\[ f(x) = w^T x + b \] (7)

such that for each training example \( x_i \), the function yields \( f(x_i) \geq 0 \) for \( y_i = +1 \), and \( f(x_i) < 0 \) for \( y_i = -1 \). In other words, training examples from the two different classes are separated by the hyper plane \( f(x) = w^T x + b = 0 \).

For a given training set, there may exist many hyper planes that maximize the separating margin between the two classes. SVM finds the hyper plane that causes the largest separation between the decision function values for the “borderline” examples from the two classes. Mathematically, this hyper plane can be found by minimizing the cost function:

\[ J(w) = \frac{1}{2} w^T w = ||w||^2 \] (8)

Kernel representation offers an alternative solution by projecting the data into a high dimensional feature space to increase the computational power of the linear learning machines. A kernel is a function \( k \), such that for all \( x, z \in X \)

\[ k(x, z) = (\varphi(x), \varphi(z)) \] (9)

where \( \varphi \) is a mapping from \( X \) to an (inner product) feature space \( F \) [11].

The data with linear separability may be analyzed with a hyper plane, linearly non separable data are analyzed with kernel function such as higher order polynomials, Gaussian RBF and tan-sigmoid. In this study, RBF kernel is used for classification of pixels in the retinal images. The main advantage of RBF kernel is their localized and finite responses. RBF kernel nonlinearly maps samples in to higher dimensional space so, it unlike the linear kernel can handle the case when the relation between class labels and attributes is non linear. The Radial Basis Function (RBF) is defined as

\[ k(x, z) = \exp(-||x - z||^2 / \sigma^2) \] (10)

where the \( \sigma \) is Gaussian kernel constant (standard deviation).
E. Performance Measures

All classification results could have an error rate and an occasion will either fail to identify a vessel which may be very thin. It is common to describe this error rate by the terms true and false positive (TP & FP) and true and false negative (TN & FN). The performance of vessel segmentation is measured by Segmentation accuracy and ROC curve.

Accuracy

Accuracy reflects the overall correctness of the classifier.

\[
\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}
\]

III. RESULTS AND DISCUSSION

In order to facilitate comparisons with other methods, the methodology described in this work was tested using the publicly available database, the STARE database in which colored retinal images and the corresponding manual segmentations are available.

A. STARE Data Base

The STARE database [9] was collected by Hoover et al. and consists of 20 digitized slides captured by a TopCon TRV-50 fundus camera at 35° FOV. The slides were digitized to 700 × 605 pixels, 8 bits per color channel. The FOV in the images are approximately 650 × 550 pixels in diameter. There are many normal and pathological images are available in this database. The ground truths of two observers for these images are also available in this database. In this work first observer’s manual segmented results are taken as gold standard.

B. Green Channel Extraction and Inversion

Green channel image is extracted from the colored retinal images. Fig. 2 shows the original colored retinal image and the three different channels such as red, green and blue channel. The extracted green channel image is inverted so that the vessels appear brighter than the background. Fig. 3 shows the inverted green channel image.

C. Feature Extraction and Normalization

The green channel intensity is considered as one of the pixel features. The other features are the maximum modulus of the wavelet transforms coefficients calculated using the “Eq (5)” over the angles 0 to 170 degrees for the scale 2, 3, 4 and 5. These five features constitute the feature vectors. Maximum modulus of the wavelet transforms Coefficient for scales 2, 3, 4 and 5 are shown in Fig 4 (a), (b), (c) and (d) respectively.

The features thus obtained are normalized using the “Eq (6)” which uses the features mean and standard deviation in order to compensate for the eventual magnitude differences. Then this normalized feature vector is used for segmentation of vessels and non vessels.

D. Segmentation

In pixel based segmentation the normalized feature vectors of an image and their corresponding ground truth image is needed for training.

The Figure 5 shows the original image along with the ground truth image that is used for training. For training randomly chosen two lakh samples and their corresponding manual segmentation samples are used. Manually segmented image is in the form of binary image i.e., vessels are represented as one and nonvessels are represented as zero.

For testing a set of seventeen images (nine normal images and eight pathology images) are taken and its features are calculated. Then these features are used by the SVM for segmentation. The

Figure 2: Green Channel Extraction (a) Input colored retinal Image, (b) Red Channel, (c) Green channel, (d) blue channel
segmentation results for some of the normal and abnormal images are given in Figure 6 and 7 respectively.

For quantitative analysis of the proposed method performance measures such as Sensitivity, Specificity and Accuracy are calculated and are tabulated in Table I and Table II for Normal and Abnormal Retinal Images respectively. The ROC curve for the Performance measure is given in Figure 8.
Table I

<table>
<thead>
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<th>Test Images</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>0.7837</td>
<td>0.9624</td>
<td>0.9481</td>
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<tr>
<td>Image 2</td>
<td>0.7611</td>
<td>0.9625</td>
<td>0.9475</td>
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<td>Image 3</td>
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<td>Image 4</td>
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<td>0.9648</td>
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<tr>
<td>Image 7</td>
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Table II

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<td>0.9802</td>
<td>0.9529</td>
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</table>

IV. CONCLUSION

In the proposed work, segmentation by SVM classifier is trained through supervised learning for the features extracted using Gabor wavelet to segment the vessels in the retinal images. The retinal images used in this work are obtained from the publicly available Data Base-The STARE. The features are individually and collectively given to kernel classifier (i.e., SVM) and performance measures are measured. For normal and abnormal images the accuracy obtained are 94.4% and 94.77% respectively. The developed system will lend a helping hand to ophthalmologist as second opinion to do very accurate diagnosis.

REFERENCES