RETINAL VESSEL SEGMENTATION USING ENSEMBLE CLASSIFIER OF BAGGED DECISION TREES

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Abstract

This paper presents a new supervised method for segmentation of blood vessels in retinal images. This method uses an ensemble system of boot strapped decision trees and utilizes a feature vector based on the orientation analysis of gradient vector field, morphological linear transformation, line strength measures and Gabor filter responses. The feature vector encodes information to handle the healthy as well as the pathological retinal image. The method is evaluated on the publicly available DRIVE and STARE databases. Method performance on both sets of test images is better than the 2nd human observer and other existing methodologies available in the literature. The incurred accuracy, speed, robustness and simplicity make the algorithm a suitable tool for automated retinal image analysis.

1 Introduction

Retinal, or fundus, photography is used to document the health of the eye and in the diagnosis of certain eye conditions. The high powered lenses of the fundus camera focus on the structures of the back of the eye allowing images of the optic nerve, macular, retina and the blood vessels to be taken. The morphological characterization of retinal blood vessels has been associated with cardiovascular and coronary disease in adult life [1] and with retinopathy of prematurity in premature infants [2]. Moreover, the blood vessels in retina have been shown to provide evidence in terms of change in diameter, branching angles or tortuosity, as a result of ophthalmic disease. The effectiveness of treatment for ophthalmologic disorders is reliant on the timely detection of change in retinal pathology. The manual labeling of retinal blood vessels is a time consuming process that entails training and skill. Therefore an automated reliable method of vessel segmentation would be valuable for the early detection and characterization of morphological changes in the retinal vasculature, which forms the backbone of many automated computer aided systems for screening and diagnosis of cardiovascular and ophthalmic diseases.

There is a substantial amount of work reported in the literature for detecting blood vessels in retinal images. A recent detailed review on retinal vessel segmentation methods can be found in [3]. These methods can be classified into two broad categories; the rule based methods and the supervised methods. The rule based methods can be further classified in to techniques based on matched filtering, morphological processing, vessel tracking, multiscale analysis and model based algorithms. The matched filtering methodology [4] exploits the piecewise linear approximation and the Gaussian like intensity profile of retinal blood vessels and uses a kernel based on a Gaussian or its derivatives to enhance the vessel features in the retinal image. The methods based on morphological processing [5, 6] for identifying vessel like shape have the advantage of speed and noise resistance. The tracking based approaches [7] segment a vessel between two points using local information and works at the level of a single vessel rather than the entire vasculature. The multiscale approaches for vessel segmentation are based on scale space analysis [8]. The model based approaches utilize the vessel profile models [9], active contour models [10] and geometric models based on level sets [11] for vessel segmentation. The supervised segmentation methods utilize ground truth data for the classification of vessels based on given features. These methods include the use of back propagation neural networks [12], K-Nearest Neighbor algorithm [13, 14] and Gaussian Mixture Model (GMM) [15] classifiers. In [15], 6 features are computed by employing a multiscale analysis using a Gabor wavelet transform and Gaussian mixture model (GMM) Bayesian classifier. Ricci [16] used line operators and support vector machine (SVM) classification with 3 features per pixel. Xu [17] combined wavelets and line operators to construct a 12 dimensional feature vector and used SVM to distinguish vessel segments. Lupascu [18] introduced a feature-based Ada-Boost classifier for vessel segmentation which utilizes a 41-D feature vector at different spatial scales for each pixel. In [19], a 7-D feature vector is computed by combination of moment invariant and gray level features and a five layer feed forward neural network is used for classification. X. You [20] computed the feature vector by using the steerable complex wavelet followed by calculating the line strength [16], the SVM is used for semi-supervised classification.

This paper presents a new supervised method for segmentation of blood vessels by using an ensemble classifier of bagged decision trees. The feature vector is based on gradient orientation analysis, morphological linear transformation; line strength measures and the Gabor filter response which encodes information to successfully handle both normal and pathological retinas with bright and dark lesions simultaneously. The classifier based on the boot strapped decision trees is a classic ensemble classifier which has been widely used in many application areas of image
analysis, but has not been applied within the framework of retinal vessel segmentation for automated retinal image analysis. The obtained performance metrics illustrate that this method outperforms most of the state of the art methodologies of retinal vessel segmentation. The method is training set robust as it offers a better performance even when it is trained on the DRIVE [14] database and tested on the STARE [4] database, thus making it suitable for images taken in different conditions without re-training. This attribute is particularly useful when implementing the screening programs over a large multi-ethnic population where there is a large variability in the background pigmentation level of the acquired retinal images. Moreover, the algorithm is computationally fast in training and classification and needs fewer samples for training.

The paper is organized as follows. Section 2 illustrates the proposed methodology in detail. Experimental results of the algorithm on the image data sets are discussed in Section 3, and the paper is concluded in Section 4.

2 Methodology

The features are extracted from the inverted green plane of the colored retinal images, which has a higher contrast between the vessels and the background than the other channels. The vessel features of the training images are labeled using manual segmentation and are used to train the ensemble classifier. The classifier will be applied to the features generated from test images to compute the segmented vascular tree.

The feature vector contains the quantifiable measurement for each pixel in such a way that the classifier successfully differentiates the blood vessels and the bright and dark lesions. We have used a nine dimensional feature vector which includes the orientation analysis of gradient vector field (one feature) for removal of bright and dark lesions with vessel enhancement, morphological linear transformation (one feature) for eradicating bright lesions, line strength measures (two features) and a Gabor filter response at multiple scales (four features) for illuminating the dark lesions. The inverted green plane of the RGB colored image (one feature) is also included in the feature vector.

2.1 Orientation analysis of gradient vector field

The blood vessels are localized by analyzing the orientation of the gradient vector field. The unit gradient vectors of the image are highly discontinuous along the bilaterally symmetrical regions i.e. the linear structures which represent the blood vessels. Therefore the blood vessels are localized by finding the discontinuities in the gradient orientation. The feature extraction depends on the orientation of the gradient vector field, not its magnitude; therefore it is robust against low contrast and non uniform illumination [21].

The gradient vectors \( g_x(x, y) \) and \( g_y(x, y) \) are approximated by the first order derivative operators in the horizontal \( (k_x) \) and vertical \( (k_y) \) directions.

\[
\begin{align*}
  g_x(x, y) &= I(x, y) * k_x \\
  g_y(x, y) &= I(x, y) * k_y
\end{align*}
\]  

The gradient vectors \( g_x(x, y) \) and \( g_y(x, y) \) are normalized by dividing with their magnitude to compute the unit gradient vectors \( u_x(x, y) \) and \( u_y(x, y) \).

\[
\begin{align*}
  u_x(x, y) &= g_x(x, y) / \sqrt{g_x^2(x, y) + g_y^2(x, y)} \\
  u_y(x, y) &= g_y(x, y) / \sqrt{g_x^2(x, y) + g_y^2(x, y)}
\end{align*}
\]  

The unit vectors are assigned to zero if the gradient magnitude is too small (<3). The first derivatives of unit vectors are computed to find the discontinuities in gradient orientation, as:

\[
\begin{align*}
  d_{ux}(x, y) &= u_y(x, y) * k_x \\
  d_{uy}(x, y) &= u_x(x, y) * k_y \\
  d_{vx}(x, y) &= u_y(x, y) * k_x \\
  d_{vy}(x, y) &= u_x(x, y) * k_y
\end{align*}
\]  

The discontinuity magnitude in the gradient orientation \( D(x, y) \) is expressed in terms of the first derivatives of unit vectors as,

\[
D(x, y) = d_{ux}^2(x, y) + d_{uy}^2(x, y) + d_{vx}^2(x, y) + d_{vy}^2(x, y)
\]  

The \( D(x, y) \) actually contains the Gradient Orientation Analysis (GOA) map of enhanced blood vessels. There is a variance in vessel width as it travels radially from the optic disk. Therefore the first order derivative operator is employed at multiple scales \( \sigma = (\sqrt{7}, 2\sqrt{2}, 4) \) to generate the multiple GOA maps of blood vessels of different widths. The final GOA map which also serves as one of the chosen feature vectors is obtained by integrating the individual maps produced at multiple scales.

The first row in Figure 1 illustrates the green channel of retinal images and the second row is the GOA maps containing the enhanced blood vessels. It is observed that only the curvilinear shaped blood vessels are enhanced despite the presence of irregular shaped bright lesions in the first two images and the dark lesions in the third image.

2.2 Morphological linear transformation

The morphological opening using a linear structuring element oriented at a particular angle will eradicate a vessel or part of it when the structuring element cannot be contained within the vessel. This happens when the vessel and the structuring element have orthogonal directions and the structuring element is longer than the vessel width. Conversely, when the orientation of the structuring element is parallel with the vessel, the vessel will stay nearly unchanged.

\[
\begin{align*}
  I_{th}^0 &= I - \sum_{\sigma \in \mathcal{L}} I_{th}^\sigma \\
  I_{th}^\sigma &= \sum_{\alpha \in \mathcal{A}} I_{th}^{\sigma_\alpha}
\end{align*}
\]

The morphological top-hat transformation is shown in Equation (5) where \( I_{th} \) is the top-hat transformed image, “I” is the image to be processed and “\( S^\sigma \)” is structuring elements for morphological opening, “\( \alpha \)” and “\( \sigma \)” is the angular rotation of the structuring element. If the opening along a class of linear structuring elements is considered, a sum of top-hat along each direction will brighten the vessels regardless of their direction, provided that the length of the structuring elements is large enough to extract the vessel with the largest diameter. Therefore, the chosen structuring element is 21 pixels long 1 pixel wide and is rotated at angle spanning [0-
\( \frac{\pi}{8} \) in steps of \( \frac{\pi}{8} \). Its size is approximately in the range of the diameter of the largest vessels in the retinal image. The sum of top-hat is depicted in Equation (5), where \( I_{5x} \) is the sum of the top-hat transformation performed with structuring element oriented at “0” degrees. The set “A” can be defined as \( \{ x \mid 0 \leq x \leq \pi \text{ and } x \mod (\pi/8) = 0 \} \). The sum of the top-hat on the retinal image will enhance all vessels whatever their direction, including small or tortuous vessels eliminating the bright zones as depicted in Figure 1(g).

\subsection*{2.3 Multiscale Gabor filter}
A Gabor filter is a linear filter and has been broadly used for multi-scale and multi-directional edge detection. The Gabor filter can be finetuned to particular frequencies, scales and directions and therefore acts as low level feature extractor and background noise suppressor. The impulse response of a Gabor kernel is defined by the product of a Gaussian envelope and a complex sinusoid. It can be expressed as

\[
g(x, y) = \exp \{-0.5(x^2 + y^2)/\sigma^2\} \exp \{i(2\pi x \lambda / \lambda_0 + \psi)\} \tag{6}
\]

where, \( \lambda_0 \) is the wavelength of the sinusoidal factor, \( \theta \) is the orientation, \( \psi \) is the phase offset, \( \sigma \) is the scale of the Gaussian envelope, \( \gamma \) is the spatial aspect ratio,

\[
x' = x \cos \theta + y \sin \theta \quad \text{and} \quad y' = -x \sin \theta + y \cos \theta.
\]

The Gabor filter response to the inverted green channel of the colored retinal image is obtained by a 2-D convolution operator and is computed in the frequency domain. The detailed procedure can be seen in [15, 22]. The maximum filter response over the angle \( \theta \), spanning \([0, \pi] \) in steps of \( \pi/18 \) is computed for each pixel in the image at different scales \( \sigma = \{2, 3, 4, 5\} \). The maximum response across the orientation at a scale is taken as pixel feature vector. The filter response of the image containing dark lesions is shown in Figure 1(h) illustrating the removal of dark lesions while enhancing the blood vessels.

\subsection*{2.4 Line strength measures}
The retinal vasculature appears as piecewise linear features, with variation in width and their tributaries visible within the retinal image. The concept of employing line operators for detection of linear structures in medical images is introduced in [23] which is modified and extended in [16] to incorporate the morphological attributes of retinal blood vessels. The average grey level is measured along lines of a particular length passing through the pixel under consideration at 12 different orientations spaced by 15 degrees each. The line with the highest average gray value is marked. The line strength of a pixel is calculated by computing the difference in the average gray values of a square sub-window centred at the target pixel with the average gray value of the marked line. The calculated line strength for each pixel is taken as pixel feature vector. The line strength image can be observed in Figure 1(i) where the elimination of dark lesions can be observed with the enhanced blood vessels map.

\subsection*{2.5 Ensemble classifier}
Ensemble classification [24] is the process by which multiple classifiers are strategically generated and combined to solve a particular machine learning problem. Ensemble learning is primarily used to improve the classification or prediction performance of a model, or reduce the likelihood of a poor or unfortunate selection. The ensemble methods use multiple models or classifiers to obtain better predictive performance by combining the results from many weak learners into one high-quality ensemble predictor. In this approach, we have used decision trees as the classification model and the results of these weak learners are combined using Bootstrap aggregation also known as Bagging [25].

The decision trees are grown on the bootstrap replicas of the training dataset which are generated by randomly selecting M observations out of N with replacement, where N is the training set size. The predicted responses of the Individual classifiers are then combined by taking a majority vote of their decisions. For any given instance, the class chosen by most classifiers is the ensemble decision. Picking up the M out of N observations with replacement omits on average 37% of observations for each decision tree. These are "out-of-bag" observations and can be used to estimate the predictive power of the classifier during training and without supplying the test data. Therefore, in order to find the optimal number of training samples and the number of weak learners, we have created the ensembles of 300 bagged trees and trained with the samples in the range of 100 thousand and 300 thousand. The out-of-bag classification error is then computed for each of the ensemble classifiers. The relationship among the number of weak learners (the decision trees) used to construct the ensemble; number of samples used for ensemble training and the out-of-bag classification error is illustrated in Figure 2. We have constructed the ensemble with 200 decision trees and trained it on 300 thousand randomly selected pixels from twenty test images of the image database.
3 Results and Discussion

The outcome of the ensemble classifier is a vessel probability map, where each value corresponds to the confidence measure of each pixel to be a part of the vessel or not. The probability map is often considered as a grayscale image such that the bright pixels in this image indicate a higher probability of being vessel pixel as shown in Figure 3.

A thresholding scheme on the probability map is used to decide whether a particular pixel is part of a vessel or not. This procedure assigns one of the classes $C_v$ or $C_{nv}$ to each candidate pixel, depending on whether its’ associated probability is greater than a threshold $T_b$. A resultant binary vessel image is obtained by associating classes $C_v$ and $C_{nv}$ to the values 1 and 0 respectively. Mathematically,

$$I_{bc}(x,y) = \begin{cases} 1(=C_v), & \rho(C_v \mid F_v(x,y)) \geq T_b \\ 0(=C_{nv}), & \text{otherwise} \end{cases}$$

(7)

Where $\rho(C_v \mid F_v(x,y))$ is the probability of a pixel $(x,y)$ belongs to class $C_v$ given the feature vector $F_v(x,y)$.

The algorithm is evaluated in terms of Accuracy (Acc), Sensitivity (SN), Specificity (SP), Positive Predictive Value (PPV), and False Discovery Rate (FDR). These metrics are defined in Table 2 based on the terms in Table 1. The accuracy (Acc) is measured by the ratio of the total number of correctly classified pixels (sum of true positives and true negatives) by the number of pixels in the image FOV. Sensitivity (SN) reflects the ability of an algorithm to detect the vessel pixels. Specificity (SP) is the ability to detect non-vessel pixels. It can be expressed as 1 – FPR. The Positive Predictive Value (PPV) or precision rate gives the proportion of identified vessel pixels which are true vessel pixels. It is the probability that an identified vessel pixel is a true positive.

In addition, the method performance is also measured with the area under receiver operating characteristic (ROC) curve (AUC). An ROC curve is a plot of true positive fractions (SN) versus false positive fractions (1-SP) by varying the threshold on the probability map. The closer a curve approaches the top left corner; the better is the method performance.

3.2 Method evaluation

The average of the selected performance metrics obtained for the DRIVE and STARE databases is tabulated in Table 3.
accuracy values and precision rates of vessel segmentation incurred by the algorithm are more than the 2nd human observers for DRIVE and STARE databases. The specificity values for the algorithm are also higher than the 2nd human observer that shows the low false positive rate of the methodology as compared with the 2nd human observer which in turn indicates that the algorithm has identified less number of background pixels or pathological area pixels as part of a vessel than the 2nd human observer.

3.3 Training set independence
The methodology is also tested for its dependency on training data and its suitability to be applied to any retinal image in a more realistic way, such that the classifier is trained on DRIVE and evaluated on STARE and vice versa. The performance metrics for cross training are shown in Table 4.

<table>
<thead>
<tr>
<th>Database</th>
<th>AUC</th>
<th>Acc</th>
<th>SN</th>
<th>SP</th>
<th>PPV</th>
<th>FDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRIVE (trained on STARE)</td>
<td>0.9697</td>
<td>0.9456</td>
<td>0.7242</td>
<td>0.9792</td>
<td>0.8478</td>
<td>0.1522</td>
</tr>
<tr>
<td>STARE (trained on DRIVE)</td>
<td>0.9660</td>
<td>0.9495</td>
<td>0.7010</td>
<td>0.9770</td>
<td>0.8123</td>
<td>0.1876</td>
</tr>
</tbody>
</table>

Table 4: Average Performance Measures on DRIVE and STARE with Cross Training

There is a slight decrease in performance as the AUC falls to 0.9697 from 0.9747 for DRIVE and to 0.9660 from 0.9768 for the STARE database. There is a fractional decrease in accuracy observed of 0.0008 for DRIVE and 0.0039 for the STARE database. The same pattern is observed in the specificity, sensitivity and the precision rate of vessel segmentation.

3.4 Comparison to other methods
The performance of the proposed methodology is compared with state of the art algorithms published in the last decade in Table 5 and Table 6 for DRIVE and STARE respectively.

4 Conclusion
In this paper, we have presented an effective retinal vessel segmentation technique based on supervised classification using an ensemble classifier of bagged decision trees. We have used a nine dimensional feature vector which consists of the vessel map obtained from the orientation analysis of gradient vector field, the morphological linear transformation; line strength measures and the Gabor filter response which encodes information to successfully handle both normal and pathological retinas. The total time required to process a single image is less than approximately one minute and twenty seconds, running on a PC with an Intel Core2Duo CPU at 2.27 GHz and 4 GB of RAM. The demonstrated performance, effectiveness and robustness along with its simplicity and speed in training as well as in classification, make this ensemble based method for blood vessel segmentation a suitable tool to be integrated into a complete retinal image analysis system for clinical purposes and in particular for large population studies. In future we aim to incorporate the vessel width and tortuosity measures in the algorithm and to develop an interactive vessel analysis software tool for ophthalmologists.

References

Figure 5 : ROC plot for DRIVE and STARE databases


