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Automated Retinal Vessel Segmentation based on Morphology and Random Forest classifier

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ABSTRACT : *An accurate extraction of the retinal vessel is one of the most important tasks in the field of medical image processing to diagnose various retinal as well as non-retinal diseases. This paper presents an automated method for the segmentation of retinal vasculature using morphological processing and the Random forest classifier. The proposed method starts with the extraction of the thin vessels using morphological processing. The Random Forest classifier utilizing 21-D feature vector is used to extract the major vessels. The final segmented image is obtained by combining both the major and the thin vessels. The feature vector for each pixel is constructed by using color component features (3-D), morphological features (10-D) and the Gabor filter responses (8-D).The performance of this method was evaluated and tested using the retinal images in the available retinal databases, namely, DRIVE, STARE and CHASE-DB1.*

KEYWORDS - *Bottom-Hat transformation, Gabor Transform , Random forest classifier, Retinal vessel segmentation.*

I. INTRODUCTION

The vascular structure of both the brain and the retina are similar in nature and hence the retinal vasculature analysis can also be used for the diagnosis of non-ophthalmic diseases like stroke diabetes, arteriosclerosis, hyper-tension and cardiovascular disease [1]. Apart from the medical field, due to the unique nature of the retinal vascular tree for each individual, retinal vasculature can also be used for biometric identification. Though the retinal vasculature can be segmented manually, the accurate automatic extraction can effectively assist the computer-aided diagnosis of ophthalmic and non-ophthalmic diseases with less time and complexity. Moreover, the accuracy of the segmentation results in manual process highly dependent on the expertise of the physician. So, an automatic method has been preferred for retinal vessel segmentation to avoid the manual interference and to reduce the error factors. In this paper, an automatic novel method using supervised random forest classifier and the morphological processing is proposed to extract the retinal vasculature. Since the green channel of the retinal image provides better vessel-background contrast[2], it is used as input for the proposed method.

The 21-D feature vector includes the Gabor filter responses (8-D) at different scales and orientations, morphological features (10-D) obtained by using bottom-hat transform, primary color component features (3-D), namely, red, green and blue channel. The ensemble Random Forest classifier utilizes this 21-D feature vector to classify the pixel as vessel or non-vessel. Mostly, the RF classifier segments the major vessels from the input retinal image. The thin vessels are extracted by applying bottom-hat transformation by varying the width of structuring element with the different orientations. The final segmented vessels are produced by combining the results of both the RF classifier and the morphological operation.

The rest of the paper is organized as follows: In the next section, some of the related works reported in the latest literature are discussed. Section 3 describes the public databases which are used for evaluation and section 4 provides a detailed description of the proposed method. The performance metrics and the robustness of the proposed algorithm along with the experimental setup are presented in section 5. At last, the conclusion and the future directions are explicated in section 6.

II. RELATED WORKS

The works about the retinal vessel extraction can be approximately categorized into five classes. They are machine-learning techniques, matched-filtering, tracking-based, morphology-based and multi-scale techniques. In Matched Filter (MF) techniques, the vessel features in the retinal images are enhanced using 2D-kernel based on Gaussian derivatives. The basic principle of the MF techniques strictly follows the fact that the cross-section of the blood vessels has a symmetric Gaussian intensity profile. Though the MF technique works well for the vessels which have the same standard deviation of the underlying Gaussian function, it fails to detect the vessels with the different intensity profile. So, MF technique performs well when it is used in conjunction with any other techniques. In tracking-based methods, the vasculature is extracted by following the center-lines of the vessels. Initially, the center-lines are identified by using various properties like width, tortuosity and gray-level intensity. Then, the complete vasculature is identified by tracking the pixels around the vessel center-lines. The basic idea behind morphology-based techniques is to probe an image with a template shape called Structuring Element (SE). Two main morphological algorithms used in image processing are Top-Hat and the watershed transformations. In multi-scale approach, different scales are used to extract information about the vessels having the various widths. The machine learning techniques are further classified into supervised and unsupervised classification. The supervised techniques need prior labelling information for classification whereas unsupervised techniques do not need any prior labelling information. Some of the articles which use supervised machine learning techniques to extract the retinal vasculature are discussed below.

Chengzhang Zhu et al. (2016a) proposed a supervised retinal vessel segmentation algorithm using Extreme Learning Machine (ELM) classifier which utilizes 39-D feature vector for classification [3]. The 39-D feature vector is constructed by using the information like pixel intensity, morphological transformation, the vessel profile characteristics, phase congruency, Hessian and gradient vector field. The ELM classifier is a learning algorithm for single Hidden Layer Feed Forward Neural Networks. There is no need to spend much time in training since the input weights are randomly assigned and the output weights are determined accordingly. Additionally, the hidden nodes are completely independent of the training data. The retinal vasculature is extracted from the ELM output by removing the isolated regions with an area less than 30 pixels. The main advantage of this algorithm is its computational speed, that is, on an average it takes only ~12secs to process all the 20 images in the DRIVE database.

Erkang Cheng et al. (2014) proposed a retinal vasculature segmentation algorithm by combining heterogeneous context-aware features with a discriminative learning framework to extract retinal vessels [4]. This algorithm uses recently invented image features which very well capture the line-like structures, namely, Weber's local descriptor (WLD) [5] and the stroke width transform (SWT) [6]. Initially, a hybrid feature pool using SWT, WLD, intensity values, Gabor responses and vesselness measurements is created. The context information is encoded by utilizing the hybrid features from a sampled position inside the local context. Then, the hybrid features are classified using the Random Forest Classifier. Random Forest (RF) classifier has been chosen for classification by considering its flexibility of fusing heterogeneous features and its strong discriminative power.

Roychowdhury et al (2015) proposed a retinal vasculature extraction by using a hybrid approach using both the supervised Gaussian Mixture Model (GMM) classifier and the morphological algorithm [7]. The segmentation algorithm comprises of three stages. The number of pixels needs to be considered for supervised classification is significantly reduced by eliminating the major vessels. In the preliminary stage itself, the binary image containing major vessels is obtained by combining the binary images obtained by the high-pass filtering and top-hat transformation of the red region in the green channel image. For the remaining pixels, 8 features based on pixel neighbourhood and first and second-order gradient images are extracted. The 8-D feature vector is given as input to the GMM classifier and the result is combined with the major vessel to achieve the final segmented image.

Shuangling Wang et al (2015) proposed a supervised method to extract retinal vasculature by using classifiers, namely, Convolutional Neural Network (CNN) and Random Forest (RF) [8]. In this approach, CNN performs as a trainable feature extractor and RF classifier works as a trainable classifier. The method is able to automatically learn features from the raw images and those features are used by the RF classifier. Histogram equalization and Gaussian filtering are used in the pre-processing stage to remove the background variation and to uniformly distribute the gray-level values. For each pixel, a square window pixel values centered on it are given as input to the CNN. The elementary visual features such as end-points, oriented-edges and corners from the CNN layers are progressively combined together in order to capture higher-order features. Along with the features from the last output layer from the CNN, the features from the intermediate layers are also utilized by the RF classifiers. The decisions from three independent parallel RF classifiers are combined by the winner-takes-all method to make the final decision.

A new retinal vessel segmentation based on both the low and high-level features is proposed by Razieh Ganjee et al [9]. Initially, a preliminary vessel map is extracted based on the low-level features and non-vessel structures from the vessel map are removed by using the high-level features. The vessel map is obtained by combining the binarized result of both the Matched Filter (MF) and first-order derivative of Gaussian (FDOG) filter. Both filters are executed at different scales aiming both the wide vessels and thin vessels. Finally, the vessel map is generated by performing an OR function on the output obtained at different scales. Since the vessel map contains some of the non-vessel structures, the result is further classified by the SVM classifier. The shape- based features like elongation, solidity, extent and compactness which are extracted from the primary vessel map regions are given as input to the SVM classifier. The SVM with radial basis function kernel is used to categorize the region as vessel and non-vessel. The performance of the algorithm over the pathological images has been improved by 5.85%.

III. MATERIALS

Most of the existing retinal vessel extraction algorithms are evaluated on publically available databases, namely, DRIVE database, STARE database and the CHSE-DB1 database. The performance of the proposed work is also evaluated using the same databases.

3.1. DRIVE database

The retinal images of the DRIVE (Digital Retinal Images for Vessel Extraction) database were obtained by randomly selecting 40 photographs from the 400 diabetic subjects which were received for a diabetic retinopathy screening program in the Netherlands [10]. Out of the 40 images, 7 images show the sign of mild diabetic retinopathy whereas the remaining images are normal. The Canon CR5 camera with 45-degrees Field-Of-View (FOV) was used to capture the retinal images and the images were then digitized using 8 bits per color plane at 768 by 584 pixels resolution. The dataset contains two partitions, namely, the training-set and test-set. Both the sets have 20 images in each. The test-set has the manual segmentation of the retinal vasculature given by two physicians whereas a single manual segmentation data are available for the training-set images.

3.2. STARE database

The STARE (Structured Analysis of the Retina) database images were captured by using a Topcon TRV-50 fundus camera at 35-degrees FOV and the images were digitized using 8 bits per color channel at 605×700 pixels resolution. The database is available online and can be downloaded from http://cecas.clemson.edu/~ahoover/stare/. The database contains two sets of images. The first-set has 81 images with the manual reference indicating the optic disc location whereas the second-set has 20 retinal images with the manual reference indicating the retinal vasculature.

3.3. CHASE_DB1 database

The retinal images in CHASE_DB1 database are acquired from 14 multi-ethnic school children in the program Child Heart And Health Study in England. The database has 28 images with two manual references of the retinal vasculature which were given by two independent observers. A Nidek NM-200-D camera was used to capture the images at 30-degrees FOV with the resolution of 1280×960 pixels. The database is available online at https://staffnet.kingston.ac.uk/~ku15565/CHASE_DB1/assets/CHASEDB1.zip.

IV. METHODOLOGY

A new supervised approach along with the morphology-based technique is used here for the extraction of retinal blood vessels. This work comprises of the following stages: 1) Feature Extraction 2) Major vessel extraction using RF classifier 3) Morphology-based thin vessel segmentation 4) Final vessel generation. In this proposed approach, the features are extracted from the green channel image due to its high contrast nature when compared to the image background. The schematic overview of the proposed approach, RF-Morpho Vessel Detection is shown in Fig. 1.

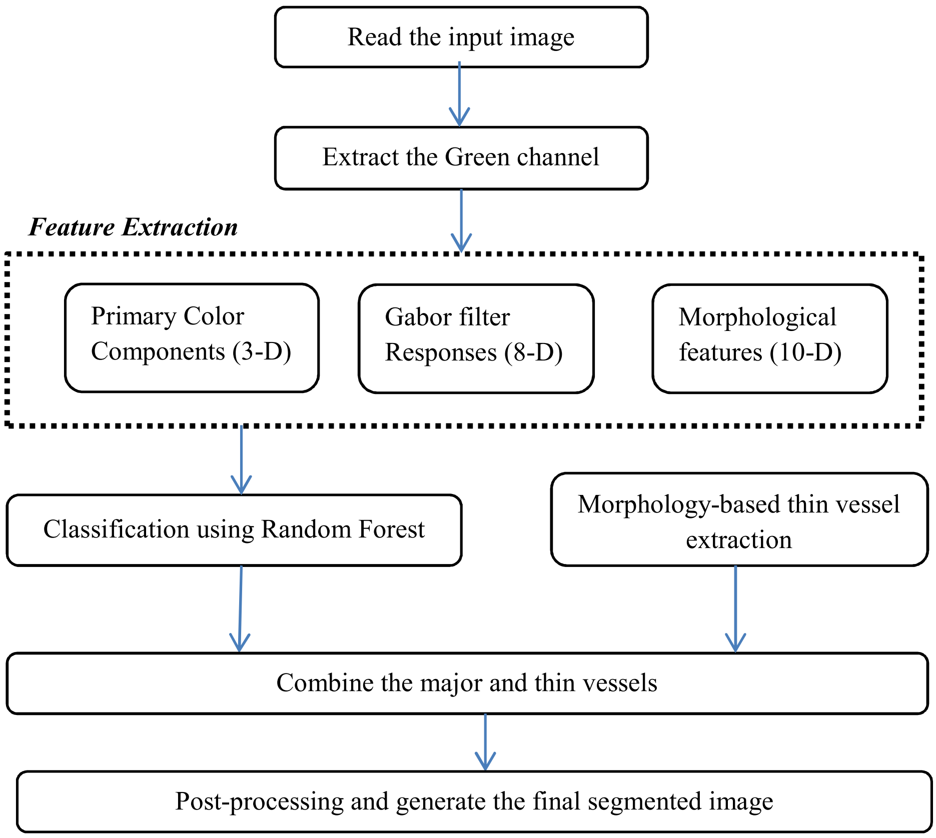


Fig. 1. Block diagram of the RF-Morpho Vessel Detection approach

The 21-D feature vector is constructed from the features extracted from the green channel image. The feature vector is given as input to the RF classifier and the output of it contains most of the major vessels. The morphological technique is used to extract the thin vessels and it is composed of three operations including (i) bottom-hat transform, (ii) summation and background removal (iii) binarization using the triangle-thresholding method. The vessel maps generated by both the RF classifier and the morphological extractor are combined to get the segmented image. The resultant image is further tuned by removing the isolated pixels. The following sections describe each stage in detail.

4.1. Feature Extraction

The feature extraction phase focuses on the extraction of the quantifiable measurements which better describe the vesselness nature from the input image and is used in the classification stage to determine whether the pixel belongs to the vessel or non-vessel. The 21-D feature vector is generated by using primary color components (3-D), Gabor filter responses at different orientations (8-D) and morphological transformations (10-D). The Gabor transformations and the morphological features are computed on the green channel image.

4.1.1. Features

4.1.1.1. Primary Color Components

The three primary color components from the input color RGB image, that is, red, green, blue are included in the feature vector. The green channel provides higher contrast between the vessel and the background while other channels are used to identify and classify non-vessel structures.

4.1.1.2. Gabor Filter Response Features

Generally, Gabor filter is considered for low-level edge discrimination due to the nature of the directional selectiveness capability and it's flexibility of fine tuning to the different scales and orientation. The 2-D Gabor function in the spatial domain can be represented as the product of Gaussian and an exponential function, it is given as follows

$$g(x,y) = exp\left[-\pi\left(\frac{Xc^2}{\sigma x} + \left(\frac{Yc^2}{\sigma y}\right)\right)\right] cos\ (2\pi f\, Xc) \quad (1)$$

where $X_c = X\, Cos\Theta + Y\, Sin\Theta$ and $Y_c = -X\, Sin\Theta + Y\, Cos\Theta$
The parameters Θ, f and σ represent the filter orientation, frequency and scale value at different orthogonal directions respectively. The Gabor filter bank *g(x,y)* is convolved with the green channel I_g image to generate the Gabor filter response *G(x,y)* and it can be given as

$$G(x,y) = g(x,y) * Ig(x,y) \quad (2)$$

where * represents the convolution. In the proposed work, maximum Gabor filter response over the angle 0 to 180 in steps of 15 degrees is computed for each pixel at different scales [2-5]. For each pixel in the green channel image, the maximum response across the orientation at each scale using different frequencies [0.125,0.225] is computed and taken as a feature. Thus, 8 Gabor responses are calculated for each pixel and are used for further classification.

4.1.1.3. Morphological Features

The morphological bottom-hat transform enhances the blood vessels and so used as prior step to construct the feature vector. The bottom-hat transform $Tb(I_g)$ over the green channel image I_g is calculated as follows

$$Tb(I_g) = I_g \otimes b - I_g \quad (3)$$

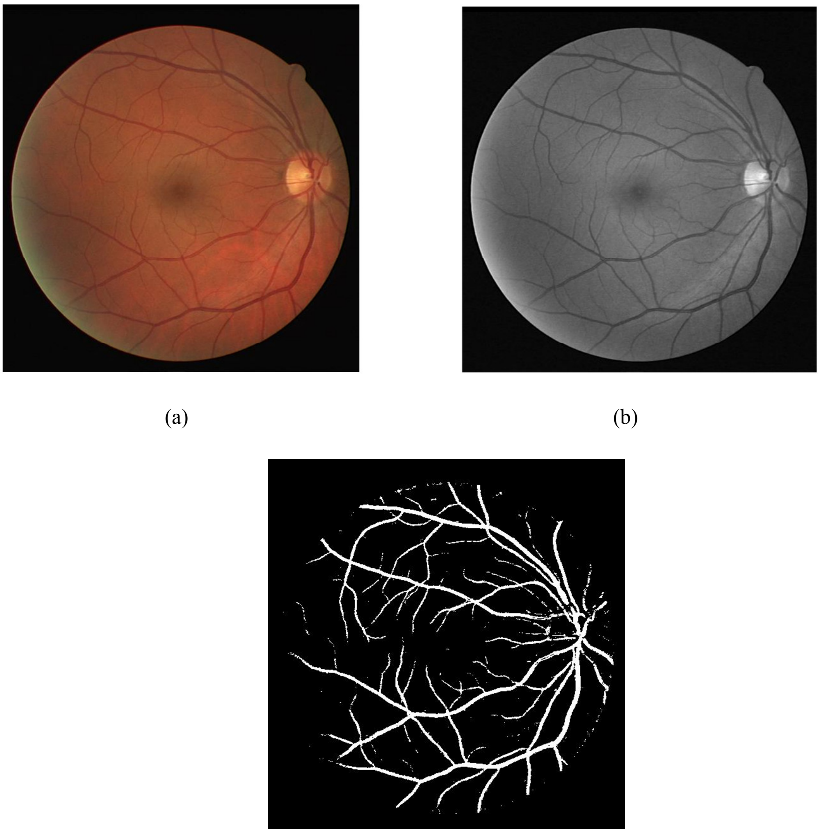
where $\boldsymbol{b}$ is the structuring element and $\otimes$ is a morphological closing operation. In this proposed work, the morphological operation is performed using linear structuring element oriented at different angles ranges from 15 to 180 in steps of 15. The bottom-hat transform is calculated by varying the structuring element length from

3 to 21 in steps of 2. For each length, the sum of the bottom-hat transform is calculated for all the orientations. The background from the reversal of the resultant sum is removed by using the average filter of size 45 X 45. Thus, in accordance with the length of the structuring element 10 such transformed images are created and included as features to the input feature vector.

4.2. Classification using Random Forest

Random forest is proposed by Breiman [11] and is a widely used ensemble learning methodology which can be used for both classification and regression. This ensemble classifier consists of many decision trees and the trees are constructed using randomized configuration. Since each tree is fed with a randomly selected subset of the whole training data, RF works well with huge training samples. In the proposed method 150 trees are used in the random forest and 5 features are randomly selected at each node. The number of trees and the size of the feature subset for the random forest are fixed using a grid search. Initially, each tree is grown with a bootstrap sample of the training observations. A random subset of predictor variables is used to provide the best split at each node and for different trees, different variables are used at each split. The final prediction of the Random forest is the class with the maximum votes.

The 21-D feature vector retrieved from a training image is given as input to the RF classifier. The training phase creates an ensemble of 150 bagged binary decision trees trained using the features from the input feature vector. This ensemble of binary decision trees is used for the classification. The initial segmentation result for an input sample image using RF classifier is shown in Fig. 2.



(a) (b)

(c)

Fig. 2. RF classification (a) Sample input image (b)green channel image (c) Random Forest output image

4.3. Thin Vessel Detection

Though the RF classifier results with a better performance, sometimes it fails to detect the thin vessels. In order to cover the thin vessels, a morphology-based approach is used in this proposed work. The algorithm to detect the thin vessels is described as Algorithm 1. To avoid the misclassification of the border pixels as thin vessels, the border of the green channel image is extended by 50 pixels by using the border extension algorithm as described by George Azzopardi (2015) [12].

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Input : Homogenized Image (I_h)

Output : Thin vessels segmented Image (I_t)

Variables :

RES – Response; SE_LENGTH – Linear Structuring Element Length; ORIENT – Orientation; BHF – Bottom _Hat Transform; SUM_RES – Summation of Responses;

Algorithm :

RES = 0;

For SE_LENGTH = 1 to 5

For ORIENT = 10 to180 in steps of 10

Calculate the Bottom-Hat transform(BHF) of the I_g using the structuring element of length SE_LENGTH and for the orientation ORIENT;

RES = BHF + RES;

End

End

Calculate the summation of RES (SUM_RES) corresponding to all the SE_LENGTH i.e. 1 to 5 ;

Find the complement (I_c) for SUM_RES image;

Subtract the background using the average filter of size 9 x 9 and create the resultant image (I_r);

Binarize the resultant image using the Triangle-Thresholding method to derive thin vessels segmented image (I_t);

Algorithm 1. Thin-Vessel segmentation

To avoid the over-amplification of noise and uniformly distributes the used grey-level values the contrast limited adaptive histogram equalization (CLAHE) is applied over the border extended green channel image and the resultant homogenized image (Ih) is used as input for the thin-vessel detection algorithm. Since this algorithm mainly focuses on the extraction of the thin vessels, the length of the structuring element is set in the range of 1 to 5. The sum of Bottom-Hat response for each length at all orientations i.e. 10-180 degrees is calculated. The orientation value is incremented in steps of 10 degrees. The responses at each length are added up to get the final response image. The reversal of the response-image is calculated and the image is further tuned by removing the background using the average filter of size 9 x 9. Thin vessels are extracted from this resultant image by binarizing the image using triangle-thresholding algorithm.

In the proposed algorithm, the triangle-thresholding method has been chosen for binarization by comparing the performance of this algorithm with some of the other algorithms. It is found that the performance of the triangle-thresholding methodology is better when compared with other algorithms. Though 16 existing algorithms for binarization have been tried, the binarized results for a sample resultant-image (Ic) using few of the thresholding methodologies are shown in Fig. 3

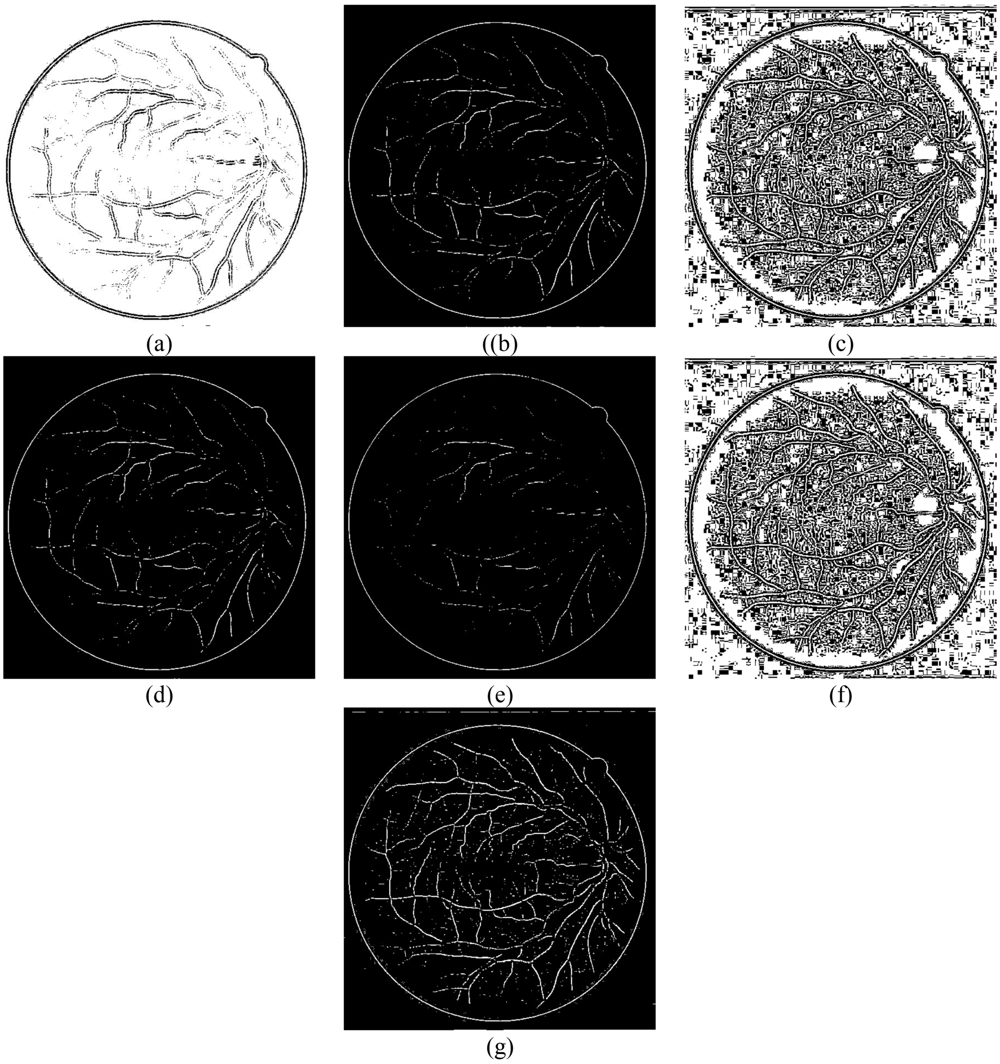

Fig. 3. Binarization (a) IsoData (b) Li's Minimum Cross Entropy (c) Mean (d) Tsai's moments (e) Otsu (f)Dyle's Percentile (g) Triangle

4.4. Final Segmentation

The segmented image is created by combining the major vessels which are detected using RF classifier with the thin vessels. As a post-processing step, morphological operations are performed over the segmented image to connect the disconnected vessels and to remove small unwanted isolated pixel areas. An output of a segmented image for a sample input image is shown in Fig. 4.

4.5. Experiment and Result

The proposed approach is implemented in Matlab 2015 on a PC with Intel Core i7 processor system (3.60GHz, 20 GB RAM). The Auto Threshold plugin in ImageJ 1.5 software tool is used to perform the triangle-thresholding technique for binarization. The performance of the proposed method is evaluated by comparing the results with the manually segmented results available for retinal datasets like DRIVE, STARE and CHASE-DB1. The performance is evaluated on the basis of sensitivity, accuracy, specificity and Area Under the Curve (AUC). The performance metrics are calculated as follows

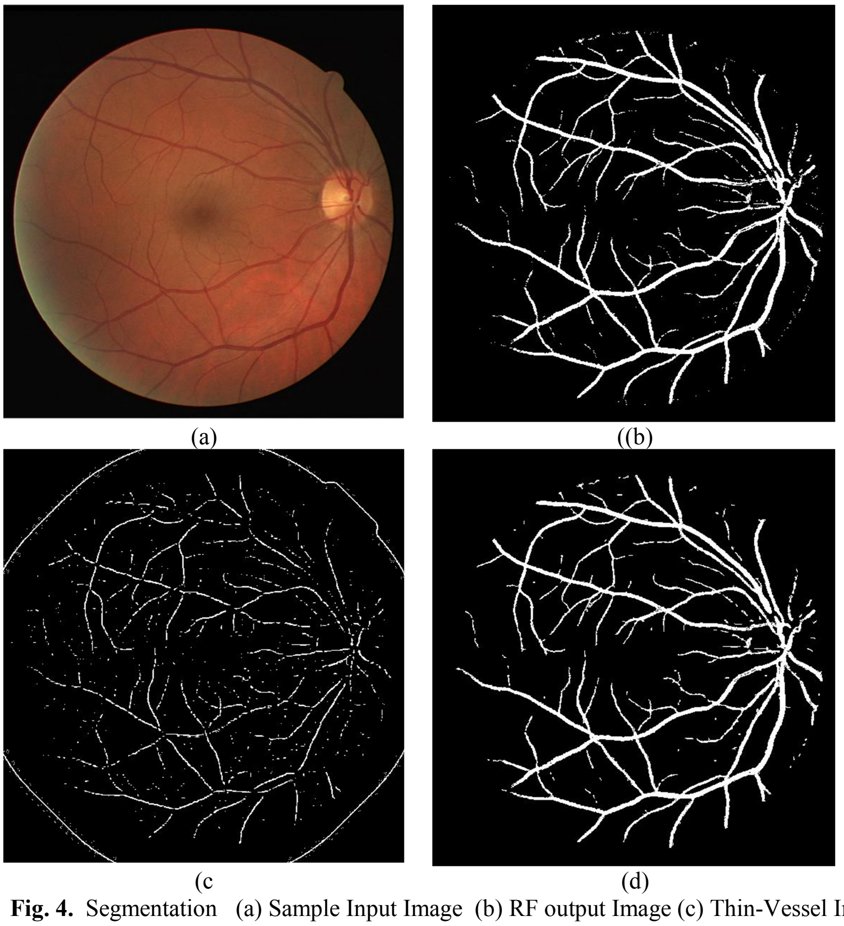

Fig. 4. Segmentation (a) Sample Input Image (b) RF output Image (c) Thin-Vessel Image (d) Final Segmented Image

$$\text{Sensitivity} = TP/(TP+FN) \tag{4}$$

$$\text{Specificity} = TN/(FP+TN) \tag{5}$$

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \tag{6}$$

where TP, TN, FP, FN are the True-Positive, True-Negative, False-Positive and False-Negative respectively. True-Positive represents the number of image pixels which are correctly classified as vessel pixels.True-Negative is the number of pixels belongs to non-vessels which are detected correctly. False-Negative is the numbers of vessel pixels which are missed by the algorithm, whereas False-Positive is the number of non-vessel pixels which are misclassified as vessel pixels. AUC measure is derived from the Receiver Operating Characteristic (ROC) curve plot. The average values of the performance metrics for all the three databases are given in Table 1.

Table 1. Performance measures for DRIVE, STARE and CHASE-DB1

Measure	DRIVE	STARE	CHASE-DB1
Accuracy	0.9448	0.9236	0.8877
Sensitivity	0.7154	0.6534	0.6810
Specificity	0.9786	0.9720	0.9111
AUC	0.8870	0.8235	0.8032

The proposed algorithm is very fast and the average processing time for the databases is given in Table 2. Though the proposed algorithm segments most of the major and thin vessels, the sensitivity is low due to the presence of false positives. The post-processing phase will be further enhanced in future to reduce the False Positives Ratio (FPR) which in-turn increases the sensitivity.

Table 2. Processing Time for DRIVE, STARE and CHASE-DB1

Processing Time (seconds)	DRIVE	STARE	CHASE-DB1
Classification Time	35.48633	43.6015	85.47475
Feature Extraction Time	9.044158	11.81396	22.6960

Table 3. Processing Time for DRIVE, STARE and CHASE-DB1

Method	Accuracy	Sensitivity	Specificity	AUC	Processing Time
Chengzhang Zhu et al, 2016 [3]	0.9607	0.7140	0.9868	0.9086	-
Erkang Cheng et al, 2014 [4]	0.9474	0.7252	0.9798	0.9648	~<1min
Roychowdhury et al, 2015[7]	0.9520	0.7250	0.9620	0.8440	3.11s
Lupascu et al, 2010 [13]	0.9590	0.7200	-	-	-
Marin et al, 2011 [14]	0.9450	0.7060	0.9800	0.8430	~90s
Miri et al, 2015[15]	0.9430	0.7150	0.9760	0.8460	~50s
Melinscak et al, 2015[16]	0.9466	0.7276	-	-	452.21s
Wang et al, 2013 [17]	0.9461	-	-	-	-
Javad Rahebi et al , 2014[18]	0.9461	0.7365	0.9707	0.9564	-
Chengzhang Zhu et al, 2015 [19]	0.9581	0.6565	0.9895	-	-
Wendeson et al, 2016 [20]	0.9464	-	-	-	-
RF-Morpho Vessel Detection Method	**0.9448**	**0.7154**	**0.9786**	**0.8870**	**~44s**

Table 4 Performance results on DRIVE database images

Image No.	Accuracy	Sensitivity	Specificity	AUC
1	0.9440	0.7953	0.9665	0.8809
2	0.9489	0.7724	0.9799	0.8876
3	0.9343	0.6904	0.9759	0.8856
4	0.9467	0.6704	0.9892	0.8923
5	0.9430	0.6886	0.9829	0.8891
6	0.9366	0.6227	0.9882	0.8918
7	0.9354	0.7015	0.9711	0.8832
8	0.9388	0.6448	0.9810	0.8882
9	0.9471	0.6359	0.9886	0.8919
10	0.9483	0.7339	0.9774	0.8864
11	0.9427	0.7070	0.9778	0.8866
12	0.9475	0.7120	0.9812	0.8883
13	0.9404	0.6626	0.9863	0.8908
14	0.9476	0.7786	0.9702	0.8828
15	0.9382	0.8063	0.9534	0.8744
16	0.9477	0.7028	0.9846	0.8900
17	0.9461	0.6706	0.9848	0.8901
18	0.9486	0.7256	0.9776	0.8865
19	0.9611	0.8289	0.9791	0.8872
20	0.9528	0.7572	0.9762	0.8857
Average	**0.9448**	**0.7154**	**0.9786**	**0.8870**

Table 5 Performance results on STARE database images

Image No.	Accuracy	Sensitivity	Specificity	AUC
1	0.9094	0.6749	0.9432	0.8091
2	0.9119	0.7020	0.9292	0.8020
3	0.9138	0.7236	0.9300	0.8024
4	0.9234	0.5870	0.9606	0.8177
5	0.9145	0.6612	0.9568	0.8158
6	0.9202	0.6097	0.9725	0.8237
7	0.9331	0.7195	0.9793	0.8271
8	0.9129	0.6233	0.9801	0.8275
9	0.9265	0.6810	0.9759	0.8254
10	0.8891	0.5862	0.9693	0.8221
11	0.9309	0.6672	0.9801	0.8275
12	0.9446	0.7432	0.9826	0.8287
13	0.9219	0.6512	0.9870	0.8309
14	0.9265	0.6848	0.9804	0.8277
15	0.9346	0.6722	0.9888	0.8318
16	0.8961	0.5488	0.9879	0.8314
17	0.9291	0.6656	0.9869	0.8309
18	0.9651	0.6910	0.9905	0.8327
19	0.9528	0.6581	0.9806	0.8277
20	0.9162	0.5166	0.9792	0.8271
Average	**0.9236**	**0.6534**	**0.9720**	**0.8235**

Since most of the existing algorithms are evaluated on the DRIVE database images, the average performance measure of the proposed work in comparison with several existing approaches for DRIVE database is given in Table 3. The time complexity of the proposed work is low and it gives better performance in less time when compared with several existing approaches. The image-wise performance measure for the images in DRIVE and STARE databases are given in Table 4 and Table 5 respectively.

V. CONCLUSION AND FUTURE WORK

In this proposed RF-Morpho vessel detection method, the retinal vessels are segmented by using the combination of RF classifier and morphology based thin vessel detector. The 21-D feature vector is constructed by extracting the pixel-wise features from the input image. The trained RF classifier extracts the major vessels in the input retinal image by taking this 21-D feature vector as input. The enhanced Bottom-Hat transform along with the triangle-thresholding method is used to segment the thin vessels in the input image. The final segmented image is obtained by combining the results of both the RF classifier and the morphology-based thin-vessel detector. This algorithm performs well for the healthy images and demonstrates the performance advantage in terms of accuracy and processing time. Though the morphological operations used in this work very well extract the thin vessels, it also produces artifacts due to the presence of non-vessel structures in the retina. So, the future work will be carried out to handle this drawback and an enhanced post-processing stage will be followed to reduce the False Positives in the final segmented image.

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