British Journal of Applied Science & Technology
12(2): 1-12, 2016, Article no.BJAST.20116
ISSN: 2231-0843, NLM ID: 101664541

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A Hybrid Morphological Based Segmentation Method for Extracting Retina Blood Vessels Grid

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/BJAST/2016/20116
Editor(s):
(1) Samir Kumar Bandyopadhyay, Department of Computer Science and Engineering, University of Calcutta, India.
Reviewers:
(1) Anonymous, Universidade Federal do Rio Grande do Norte, Brazil.
(2) Anonymous, International Islamic University Malaysia, Malaysia.
(3) Romildo de Albuquerque Nogueira, Universidade Federal Rural de Pernambuco, Brazil.
(4) Praylin Selva Blessy Selvaraj Assley, Bethlahem Institute of Engineering, India.
Complete Peer review History: http://sciencedomain.org/review-history/11565

Original Research Article

Received 12th July 2015
Accepted 8th September 2015
Published 27th September 2015

ABSTRACT

The patterns of retinal blood vessels play major role in many different applications, such as diseases diagnosis and human identification. The accurate segmentation of vessels body appeared in retina images is vital to make successful human identification decisions. This paper presents a new method for vascular network extraction from color retinal images. The proposed method consists of three main stages: Preprocessing, segmentation, and post-processing. Preprocessing stage is applied to enhance the local appearance of blood vessels in retinal images; its main task is to make compensation for the global/local contrast variance over all parts of the retina area, such that the dynamic range for brightness levels of the vessels' pixels becomes narrow and lies in the dark region of brightness scale. In segmentation stage, the grid of retina vessels had been extracted using thresholding method; where the vessels appear dark, thin and connected bodies in retina area. Finally, post preprocessing stage is applied to eliminate the noise and to remove the produced disconnections in the extracted vessels due to thresholding.
The proposed method was tested on the two publicly available datasets: (i) DRIVE (Digital Retinal Images for Vessel Extraction) and (ii) STARE (Structured Analysis of the Retina). The test results indicated that the proposed method is efficient to segment the large vascular areas and

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outperforms of many introduced methods in the literature. The test results indicated that the attained accuracy of the proposed method was 97.41% in DRIVE dataset, and 97.43% in STARE dataset.

Keywords: Hybrid morphology; retinal blood vessel; contrast invariant; vascular network extraction; retina recognition.

1. INTRODUCTION

Vascular network is an important anatomical structure in human retina region, several blood vessel diseases requires accurate analysis for the vessels network [1]. The patterns of vascular blood networks of humans are unique and treated as high security area; for these two reasons they used as a biometric source of for human identification system [2,3]. The most important step in the identification system based on retina images is to detect and extract the blood vessels [4].

Automatic process of retinal blood extraction is better than manual based method because they can provide many benefits; including minimizes subjectivity and eliminating the required hard labor work. Beside to be a tedious task the manual detection is time consuming and it is unreliable task [5,6]. So, it is very useful to develop robust methods for automatic analysis of retinal images.

Different approaches for automated blood vessels segmentation have been proposed, they are classified as supervised and unsupervised methods [7]. Supervised methods requires a training set (or a collection of sets) and a machine learning and classification module (such as; support vector machine [8], neural network [9] or Bayesian classifier). While, unsupervised methods does not need a training set, it evaluates and assigns pixels to blood vessels according to some predefined criteria (e.g., vessels track [10,11] and threshold value). Supervised methods exploit the training pre-classified data, and they usually perform better than unsupervised methods. They generate very good blood vessels segmentation results without significant degradation [12].

This paper is organized into five sections. Section 2 presents the related literature review, section 3 illustrates the proposed methodology, and section 4 shows some of results attained during the tests applied on the taken two datasets. Finally, the conclusion is given in section 5.

2. LITERATURE REVIEW

Retinal blood vessel segmentation is a challenging task. It was in the focus of researches for many years ago. Some previous works relevant to the extraction of blood vessels are listed below:

Jiang et al. [13] presented an adaptive thresholding framework for human verification based on multi threshold probing scheme. They refer that blood vessels cannot be segmented using single global threshold due to the gradients in the background of the retinal image. They suggested probing the retinal image using different threshold values. Their presented method was evaluated on 20 images of the STARE dataset and the achieved accuracy value was 0.9212.

Staal et al. [14] have proposed an automated method for extracting the blood vessels from retinal color images. The vessels are extracted by considering vessels as ridges; they treated as natural indicators for blood vessels and they coincide approximately with blood vessel centerlines. The feature vectors were computed to reflect the properties of the patches and the ridges line elements. The extracted feature vectors are classified using neural network classifier and K-NN classifier. Their proposed method was tested on DRIVE dataset which consists of 40 manually labeled images. The method achieved an area under the receiver operating characteristic curve of 0.952.

Ricci et al. [8] presented a method for segmentation of retinal vascular using line operators and support vector classification (SVC). A line detector based on the evaluation of average grey level along the lines of fixed length is proposed. This detector is applied on the green channel of RGB image. In order to obtain unsupervised pixel classification, two orthogonal line detectors have been employed along with the grey level of the target pixel to construct a feature vector for supervised classification using a support vector machine (SVM). They referred that their method need few examples for training, and the introduced line detector was robust with respect to non-uniform illumination and contrast. The method was evaluated on DRIVE and STARE datasets, the achieved accuracy rate was 0.9595 & 0.9646 for DRIVE and STARE, respectively.

Perez et al. [15] presented a method for automatic segmentation of retinal vascular that based on multi-scale feature extraction. The local maxima over scales of the magnitude of the gradient and the maximum principal curvature of the Hessian tensor have been used in a multiple pass region growing procedure. Their approach is an extension of scale space algorithm [16]. The method was able to detect the retina traces different widths, lengths and orientations. The method was evaluated on DRIVE and STARE datasets. The achieved accuracy rate was 0.9410 for STARE dataset, and 0.9344 for DRIVE dataset.

Soares et al. [17] presented a method for segmentation of vascular blood vessels in color retinal images using 2D Gabor wavelet and supervised classification. The method classifies each image pixel as vascular or not vascular using the pixels feature vector. The feature vectors are composed of pixels intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales tuning to specific frequencies. Their method uses together Bayesian classifier and class conditional probability density functions in order to classify pixels. The proposed method was evaluated on DRIVE and STARE datasets, the achieved accuracy rate are 0.9466 for DRIVE dataset and 0.9480 for STARE dataset.

Akram et al. [18] proposed a method for vascular segmentation from colored retinal image. The 2D Gabor wavelet is used to enhance the vascular pattern. Then, the vascular edges are sharpened using filter mechanism. As next step, edge detection is applied to extract the vascular boundaries. Also, the morphological dilation operation is applied to fill the gaps between the detected boundaries. Their proposed method was tested on DRIVE database and the achieved accuracy rate was 0.9469.

Rahebi et al. [19] proposed a method to fine-tune the performance of matching filter in order to improve the accuracy of vascular segmentation. They propose using Gabor filter structure to classify each pixel as blood vessel or non-blood vessel depending on the output of matching filter beside to several other features extracted on the pixel level. Then, the blood vessels are extracted by applying thresholding on the matching filter response. The proposed method was tested on the STARE and DRIVE datasets. The achieved accuracy was 0.9482 & 0.9380 for STARE and DRIVE datasets, respectively.

Buadi et al. [20] proposed a method for blood vessel segmentation in retina images. Their method implies steps to avoid some potential problems; e.g. specular reflexes of thick blood vessels. The method consists of pre-processing, segmentation, and post-preprocessing stage. The preprocessing steps are applied on the green channel of the color retina image. Histogram stretching is applied to increase the contrast such that the task of detecting small brightness changes can be easily accomplished. After that, the bilateral filtering is applied as de-noising tool; it is used to smooth intensity changes, while preserving the boundaries of different regions. Then, they applied hessian matrix and specular reflex correction to reduce the effect of a bright specular reflex in the middle of thick vessels. After the blood vessel enhancement is completed on each resolution level, then the results are resized to the original resolution and applying hysteresis threshold in order to extract the blood vessels. Finally, the post processing steps are applied to fill the produced small holes in the blood vessel and to remove the small undesired objects. The method was evaluated using both STARE and DRIVE datasets, the attained accuracy rate was 0.9386 for STARE dataset, and 0.9572 for DRIVE dataset.

Kaba et al. [21] presented a new approach to extract blood vessels by integrating a set of preprocessing techniques; e.g., bias correction and distance transform with probabilistic modeling expectation maximization (EM) segmentation method. Their proposed method implies two main stages (i.e., preprocessing and the probabilistic modeling). The first step in preprocessing stage is the bias correction to correct the intensity inhomogeneity of the retinal image. Then, the appearance of blood vessels pattern is enhanced using adaptive histogram equalization. Next, the blood vessels are extracted from image using probabilistic modeling that based on expectation maximization (EM) algorithm. Finally, the length filter is applied on the output of the EM algorithm to eliminate all the non-vessels pixels. The method was tested on the retinal images of

"STARE" and "DRIVE" datasets. The achieved accuracy rates are 0.9554 & 0.9410 for STARE and DRIVE datasets, respectively.

3. THE PROPOSED METHOD

The proposed method aims to extract the retinal vascular network from digital color retinal images. It consists of three main stages: (i) image preprocessing stage, (ii) extraction of the blood vessels pattern from the images, and (iii) finally, post processing stage to enhance the extracted vascular network. Fig. 1 shows the layout of the proposed segmentation method of retinal vascular network. Each module of the developed system is described in the following sub-sections.

3.1 Preprocessing

There are two important factors make the task of accurate blood vessels extraction from retinal fundus images too difficult; they are: (i) the improper contrast of a retinal image and (ii) uneven background illumination. Due to these two problems preprocessing is done to minimize the contrast variations in the background and foreground areas. The main targets of pre-processing stage are: (i) to produce a variant image has uniform background and (ii) to remove the unwanted area (i.e., flat white area and noise). The applied preprocessing stage consists of the following steps:

3.1.1 Color band analysis

An analysis for the local variability of pixels values in Red, Green & Blue color bands had been conducted; the results indicated that the blood vessels areas in the green channel are more informative (i.e., it shows higher local relative contrast with the surrounding background [22]) in comparison with the contrast cases in red and blue channels. The high relative contrast behavior in green channel makes the segmentation task easier and less challenging than the situation with red and blue bands (i.e., it requires less computation load [23]). Therefore the green channel of the retinal image (in RGB format) is chosen to apply the next steps of the proposed method. Fig. 2 shows the RGB bands of a fundus image.

3.1.2 Retina area allocation

It is important to distinguish between the surrounding background area and retinal vessels area (foreground), because the blood vessels detection method needs to localize the foreground areas which contain the vascular network. First of all, it is necessary to filter in the fundus area from the surrounding area in order to minimize the number of computational operations and, consequently, reduce the time required to accomplish all system stages. So, this preprocessing step aims to isolate the retinal area from surrounding background.

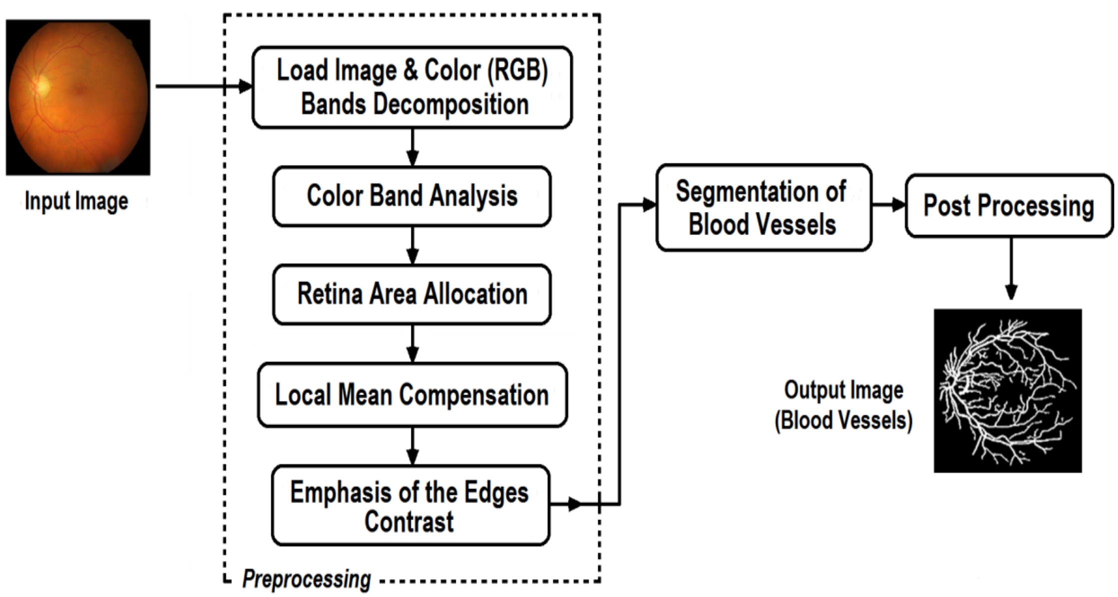


Fig. 1. The layout of the proposed method

This step is accomplished by calculating histogram for each the four corner regions of the green band image. Scan the histogram elements (starting from the second or third element of the histogram) to allocate the element shows the first local histogram peak value (as illustrated in Fig. 3B). Then, continue scanning to find the first element value (T) shows local histogram minimum; the element value (T) is taken as a threshold values to generate the binary image (mask). The binarization is accomplished by assigning value (0) for each pixel has green color component value less than (T) because it is considered as part of the surround pixels, otherwise the pixel assigned value (1). Fig. 3C presents an example of the constructed binary mask image.

3.1.3 Local mean compensation

Retinal images have low noise and non-uniform illumination. This processing step is applied to remove the low noise and to handle the non-uniform illumination in the green color band of the input retinal image. The sub-stage implies the following steps:

(1) The green band image, $G_{img}()$, is filtered using mean filter to eliminate the low noise may appear in $G_{img}()$. Then, the output image is divided into small non-overlapping blocks. The size of each block is set equal to (wxw). The mean value, $L_{img}()$, for each part is calculated and assigned as the mean value for all pixels belong to the block. The value of w was taken (13), because around this value successful segmentation results are met.

(2) Then, the subtraction process is applied by subtracting each pixel of $L_{img}()$ from the corresponding pixel value in $G_{img}()$. This step suppresses, up to suitable extent, the local lighting variation and, consequently, reduces the appearance of unwanted areas (for examples the optical disk).

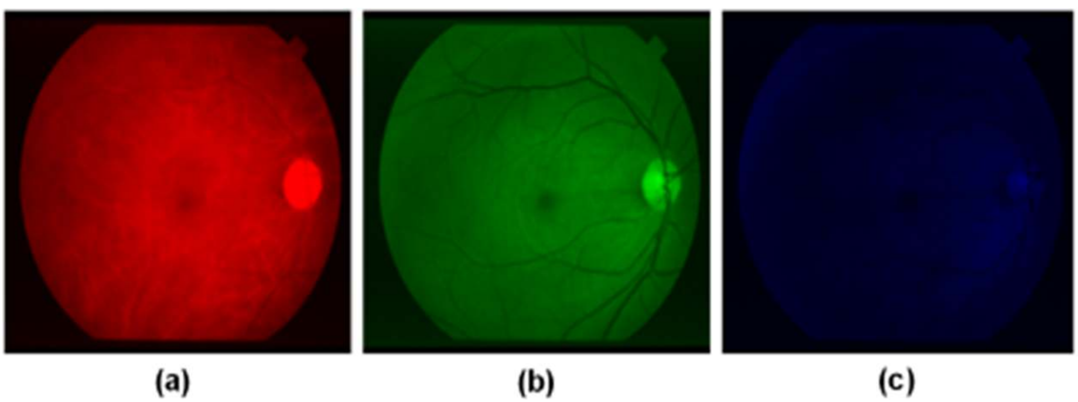
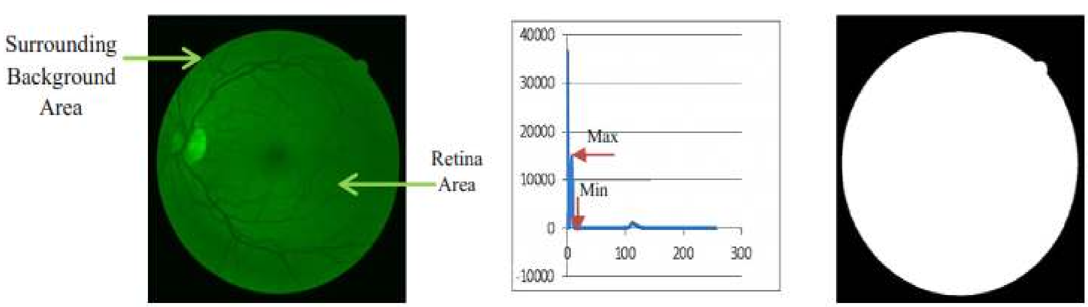


Fig. 2. The RGB retinal images (a) red, (b) green, (c) blue band



(A) Green channel **(B) Histogram** **(C) Mask image**

Fig. 3. The extracted binary mask image

3.1.4 Emphasis of the image contrast

To enhance the success rate of the proposed segmentation process of the blood vessels, the contrast of the retinal image should be increased. As next step the local contrast of the dark pixels is increased using modified gamma contrast stretching method. Contrast refers to the relative differences in the brightness of data values (i.e., increasing contrast means that the dark pixels become darker, and the bright pixels become brighter) [24]. When the brightness difference between any adjacent two different pixels increased, then, the contrast level of the whole image is increased. The process of contrast emphasis was done by applying the following steps:

1. Compute the mean (μ) and standard deviation (σ) values.
2. The average of low (L) pixels values and the average of high (H) pixels values of the image are assessed using statistical bases. These two values are less affected by the impulsive noise which may appear in the image. Taking into consideration that the output values of applying both minimum & maximum operators on the image array are greatly affected by impulsive noise; which causes bad reflectance on the process of brightness stretching. So, the use of statistically-based assessed values (i.e., L & H) leads to more robust brightness stretching results. In this paper work, the values of L and H are assessed using the following equations:

$$L = \mu - \alpha\sigma, \qquad H = \mu + \alpha\sigma \tag{1}$$

   Where, α is the dispersion ratio from the mean (μ) in terms of standard deviation (σ), in this work its value is set (1.1).

3. Apply the below modified gamma mapping equation just on pixels belong to fundus area:

$$G^{'}(x,y) = \begin{cases} 0 & If\ G(x,y) \leq L \\ 255 \times \left(\dfrac{G(x,y) - L}{H - L}\right)^{\gamma} & Othewise \\ 255 & If\ G(x,y) \geq H \end{cases} \tag{2}$$

Where G(x, y) is the input pixel value (i.e., the output of the local mean compensation step), G'(x, y) is the new pixel intensity and γ is the gamma value. In this work γ value is set (6.5). Fig. 5 shows an output sample of this gamma stretching process.

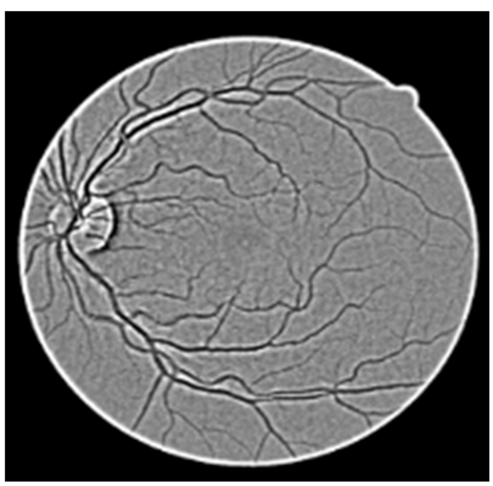
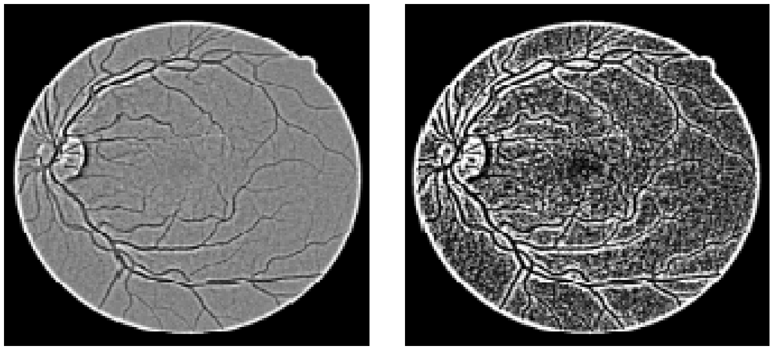


Fig. 4. Local mean compensation result



(a) Before **(b) After**

Fig. 5. The effect of contrast stretching

3.2 Segmentation

This stage is needful for extracting the blood vessels from retina image. Since, the pixels belong to blood vessels network are connected with each other; therefore, the region growing methodology can be used to collect the pixels of connected blood vessels. Region growing is a procedure that groups pixels in whole image into sub regions according to predefined criteria [25].

The seed filling algorithm was applied as region growing tool. The applied seed filling steps are:

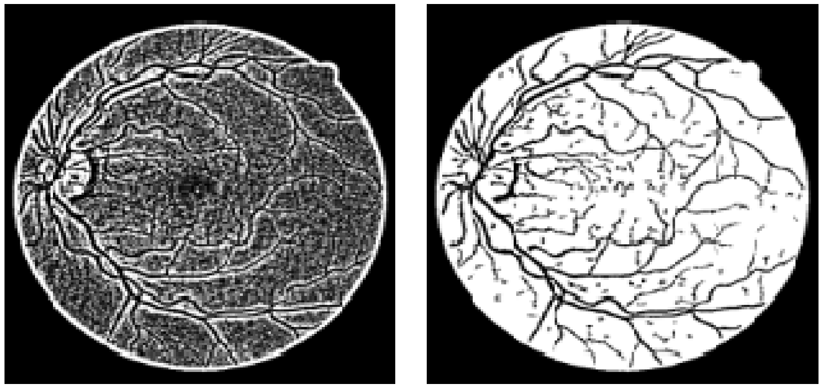
(1) Scan all pixels of the binary mask image, and check each one, if it is black pixel (0) then this pixel is considered as a seed point of a segment; and add it to certain points buffer,
(2) Then, test the four connected (i.e. in up, down, right and left) neighbors of the pixel added to points buffer. If each one of the four connected pixels is black then add it to the point buffer; each point added to the points buffer if flagged in the image array as visited point (i.e., assigned a value 2) in order to avoid repeat visiting.
(3) Step (2) is repeated to all points listed in point's buffer, till all the pixels of the buffer are scanned and no further neibors pixels are added to the buffer.
(4) After collecting a segment that contains the connected black pixels to the seed black pixels. Then, check the size of the segment. In case the size (i.e., number of segment pixels) is very small then all points of this segment are converted to black pixels. The threshold value for the minimum number of pixels of the kept segments is taken 10.
(5) Then continue the pixels scanning till finding a need seed for next segment. Otherwise the scanning is continued till reaching the last pixel in image mask array and no new seed is met.

Fig. 6 presents a sample of results after apply seed filling algorithm.

3.3 Post Preprocessing

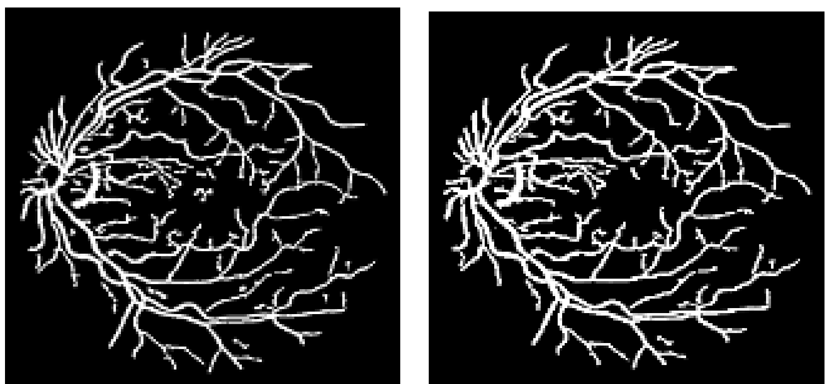
The previous stage is vascular segmentation. It provides the true segments of the blood vessels network with some unwanted segments (i.e., small islands and gaps), as shown in Fig. 7a. Due to the appearance of islands and gaps post preprocessing is required for filling pixels gaps (black) and removing small island pixels (white). For accomplishing this task the two morphological operations (i.e., erosion and dilation) have been applied [26]. Before the application of erosion and dilation, the segmentation output image is subjected to binary color inversion to ensure that the pixels belong to region of interest (i.e., vascular network) are represented white (1s valued) and the background pixels as black (0s valued). These two morphological processes are applied as follows:

a) Firstly, for each white pixels (1) inside retina area open the structure element around it, then count the number of all adjacent white pixels (CW); then if the value of CW is less than a threshold value (q), then the pixel will considered as island point and converted to black (0); otherwise it is kept white (1).
b) Secondly, for each black pixels (0) inside retina area open the structure element around it, then count the number of all adjacent white pixels (CW); if the value of CW is more than threshold value (q), then the pixel will considered as gap point and converted to white (1); otherwise is kept black (0).



(a) Before **(b) After**

Fig. 6. The effect of wide areas removal: (a) before & (b) after region growing



(a) After color inversion **(b) After tiling and erosion**

Fig. 7. Enhancement of segmentation result using tiling and erosion process

Fig. 7 presents a sample of output image after applying erosion and tiling processes. This process can be repeated more than one time to get better result. In the proposed work a best result obtained when structure element size is taken (3×3) and threshold value is q=5.

4. RESULTS

Two public datasets have been used for performance evaluation of the proposed method; they are: DRIVE [27] and STARE [28] datasets. Beside to whole 70 images belongs to these two data sets; other 70 manually labeled images have been used for purpose of performance evaluation. The DRIVE dataset consists of 40 images with (768×587) pixels of resolution, they divided into 2 subsets, each consists of 20; the first subset is for training and second is for testing. The STARE dataset consists of 30 RGB color images of retina, each image is of size (605×700) pixels. The 70 samples (i.e., 40 from DRIVE and 30 from STARE) have been subjected to various linear and non- linear radiometric conversions to produce 10 different variants for each of the 70 samples.

Our proposed method gave better segmentation results when compared with the methods listed in literature review section. The performance of the proposed method is evaluated by comparing its segmentation results with those produced by other retinal vascular segmentation methods; the evaluation was based on using three segmentation performance measures: (i) true positive rate (TPR), (ii) false positive rate (FPR), and (iii) accuracy (ACC); they defined as [14-17]:

$$TPR = \frac{TP}{TP + FN} \tag{3}$$

$$FPR = \frac{FP}{FP + TN} \tag{4}$$

$$ACC = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

Where TP is the number of vascular points identified correctly, TN is the number of fundus background points identified correctly, FP is the number of fundus background points identified as vascular (i.e., pixels not belong to vascular but recognized as vascular), and FN is the number of vascular point identified as background (i.e., pixels belong to vascular but they recognized as background).

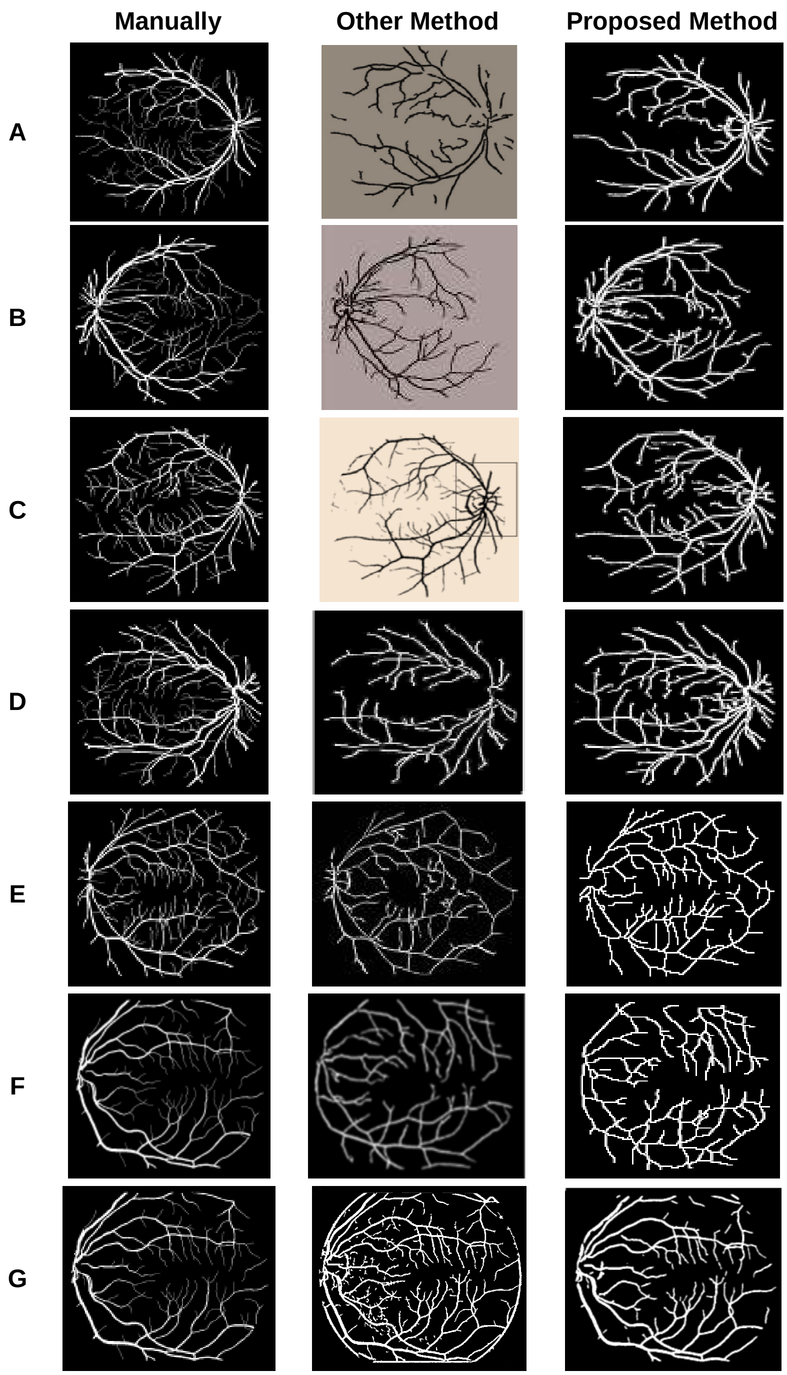


Fig. 8. The results samples of the proposed method and other methods: (A) Jiang et al. [13], (B) Budai et al. [20], (C) Ricci et al. [8], (D) El Abbadi et al. [29], (E) Hoover et al. [30], (F) Kaba et al. [21], (G) Rahebi et al. [19]

As shown in the following figure and tables, the proposed method is more accurate in extracting vascular blood vessels in comparison with other published methods in literature. For example Jiang et al. [13] and Budai et al. [20] methods haven't extracted the small and thin blood vessels properly, as shown in Fig. 8A & 8B; and they achieved accuracy less than accuracy of our proposed method.

The proposed method shows False Positive Rate less than other methods. For example, although Rahebi et al. [19] method showed good extraction result for of small vascular segments; but their method added many false pixels (FP). Also, Ricci [8] method was able to segment large part of thinner vascular, but it shows very high false detection around the border of the optic disc (OD), as shown in fig. 8G & 8C.

Also, our proposed method requires less relatively short computation time for extracting vascular than other methods. For example Staal et al. [14] and Soares et al. [17] methods showed good segmentation accuracy performance for detecting the small vascular areas; but take long computation time to accomplish segmentation. Staal method [14] takes 900 second, while Soares [17] takes 180 second to accomplish segmentation for both STARE and DRIVE datasets. While our proposed method requires 5.2 seconds to accomplish accurate vascular extraction for DRIVE dataset and 6.8 seconds for STARE dataset.

Fig. 8 presents some samples of segmentation results published by some authors. The figure gives a visual description to facilitate the task of making comparisons between the results produced by other methods and the attained results of our proposed method.

Tables (1) and (2) present the performance parameters (TPR, FPR and accuracy) achieved by some previously published works and our proposed work. The listed results in both tables indicate that the proposed method leads to less false detection rate, and can capture both thick and thin blood vessels with less computational requirement. Also, the comparison with manually labeled images indicated that some parts of thin blood vessels cannot be extracted it. So, in future an enhancement for the pre-processing stage is required to raise its capability to collect the thin and small vascular segments.

Table 1. Vessel extraction results for the DRIVE dataset

Method	TPR	FPR	Accuracy
Staal [14]	0.7194	0.0227	0.9442
Soares [17]	0.7283	0.0212	0.9466
Kaba[21]	0.7466	0.0317	0.9410
Jiang [13]	-	-	0.9212
Rahebi [19]	0.7110	0.0278	0.9380
Ricci [8]	-	-	0.9595
Perez [15]	0.7246	0.0345	0.9344
Budai [20]	-	-	0.9572
Proposed method	**0.7915**	**0.0018**	**0.9741**

Table 2. Vessel extraction results for the STARE dataset

Method	TPR	FPR	Accuracy
Hoover [30]	0.6751	0.0433	0.9267
Soares [17]	0.7165	0.0252	0.9480
Ricci [8]	-	-	0.9646
Rahebi [19]	0.7170	0.0250	0.9482
Perez [15]	0.7506	0.0431	0.9410
Budai [20]	-	-	0.9386
Kaba [21]	0.8506	0.0300	0.9554
Proposed method	**0.8675**	**0.0051**	**0.9743**

5. CONCLUSION

In this paper, an accurate segmentation method is proposed for vascular network extraction from retina color images. Many tests have been conducted on the method using different retinal images which have different qualities. The tests results indicated that the proposed method is capable to extract retina vessels grid with accuracy competitive with those achieved by other methods introduced in the literature. Also, the method requires reasonable computational requirements.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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