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Research Article

An Improved Blood Vessel Extraction Approach from Retinal Fundus Images Using Digital Image Processing

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Abstract: Diseases like glaucoma, macular degeneration, hypertensive retinopathy and diabetic retinopathy has a major share in complete or partial vision loss in humans. Early diagnose of these diseases is possible through temporal examination of the shape and form, bifurcation patterns and growth of vessels present in the retinal fundus images. In this work, an efficient and rapid scheme to extract the retinal vasculature. In the first step only the green plane is considered and processed out of the RGB color space to accomplish the segmentation process. Contrast enhancement is achieved through applying sigmoid function followed by background exclusion. Finally vessels are extracted through hysteresis thresholding and morphological processing to enhance the fine details in the resultant image. Tradeoff between segmentation accuracy and time consumption of segmentation algorithm is minimized by producing promising accuracy and other metrics. The scheme is tested and evaluated on the retinal fundus images in the databases like STARE and DRIVE. The produced results evaluated and compared to the other state of the art work and proved to be better and outperformed in most cases.

Keywords: fundus, diabetic retinopathy, sigmoid function, Gaussian mixture model (GMM), support vector machine (SVM), contrast limited adaptive histogram equalization (CLAHE), Markov's random field (MRF)

1. INTRODUCTION

In ophthalmology, the vessels segmentation from retinal image is an unavoidable task for diagnosing some retinal diseases such that diabetic retinopathy, macular degeneration, arteriosclerosis, hypertensive retinopathy and glaucoma. These diseases can be diagnosed by analyzing thickness and width of vessels in fundus image. The glaucoma and diabetic retinopathy are one of the main roots of blindness in Pakistan [1] as well as rest of the world. Irregularity of blood vessel thickness could be the initial symptom of diabetic retinopathy or macula edema. Patients with macula edema have blood leakage in blood vessels in macula area, if detected earlier, it can be treated easily [2].

Retinal imaging is employed in multiple fields such as optical fundus retinal operations, diagnosis of diabetic retinopathy in the initial phases. Many diseases stand responsible for affecting the retina and its surroundings. These diseases can be diagnosed and treated through the retinal digital images which are known as fundus images acquired by digital fundoscope. After the image is acquired, further processing is performed. Blood vessels in fundus image originate and get divide in to main branches at the center of the optic disk. They are normally reddish orange in color because of rich blood supply. Fundus image contains several important parts such as an optical disk, macula and blood vessels tree which play a significant role in diagnosing diseases by ophthalmologists.

The early diagnosis of these diseases is of an enormous importance to prevent further their severe effects and for their fast treatment to prevent the vision related problems in initial stages. The extraction of vessels can assist the eye care specialists to diagnose these diseases and to carry out further clinical study.

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Thus for meticulous temporal examination and estimation of the blood vessel geometry and changing pattern depends on efficient segmentation of blood vessels. Extraction of retinal blood vessels is the initial requirement to get the features that assist in diagnosis in the first stage and for further treatment. An accurate segmentation and examination of the features of blood vessels such as width, color variations, and bifurcations as well as the morphology of optic disk assist ophthalmologists and to perform tests for the detection of various retinal diseases resulting in the avoidance and reduction of vision impairments, diseases related to growing age, and many heart diseases.

2. RELATED WORK

A lot of work is being done to address the issue of accurate extraction of blood vessels from fundus images. Broad categorization of vessel segmentation schemes may result in two main streams.

1. Supervised segmentation methods
2. Unsupervised segmentation methods

In supervised classification methods, blood vessels are classified as vessels/non vessels on the basis of ground truth and training data. These methods use training images to extract features which forms basis for classification while unsupervised methods do not require any sort of training images. In supervised methods, the pixels are categorized manually as whether these pixels are relating to vessel category or non-vessel in training images. Here some of the images are used to train the classifiers to differentiate vessels on the basis of some features like line strength measures, morphological features [3] and GLCM features [4]. According to Singh et al. [5], the mostly used supervised classifiers are Bayesian classification, artificial neural network, support vector machine (SVM), Gaussian Mixture Model (GMM) etc. Fraz et al. [3] presented supervised classification for the extraction of vessels from retinal fundus images. Here a seven dimensional vector of features is achieved through results of linear morphological operations, strengths of lines and through orientation of Gabor filters at various scales. The vectors encode the pixel intensities according to vessel geometry at various scales. A Bayesian classifier along with the Gaussian mixture model (GMM) classifiers is used for further segmentation of vessels. Wankhede et al. [6] made use of the method known as graph cut, here mean filter is applied first and then performed convolution with Gaussian kernel followed by shade correction and for enhancement of blood vessels they used top hat transformation and at last graph cut segmentation is used to extract vascular structure. Minar et al. [2] used preprocessing by contrast limited adaptive histogram equalization (CLAHE) then using Laplace operator as a key point of proposed algorithm subsequently using erosion process to enhance the vessels more clearly. According to Caliva et al. [7], the arteries and veins in retinal images are shaped in tree like structures. Ordinary methods fail to completely segment all the vessels present in fundus image which produces broken segments of vessels. Reconstruction of these disconnected vessels adds more information features which have crucial importance. Their method includes neural cost functions to rejoin these disconnected regions. Awan et al. [8] proposed a method for extraction of blood vessels with lesions included. To deal with false vessels, there method consists of three major steps. Firstly extracted some features from the regions having vascular structures of prior extracted vessel pattern then a vector having discriminant features for every possible region is constructed and then features are selected to achieve best features and finally the support vector machine (SVM) classifier is used. Singh et al. [9] proposed local entropy threshold based method by making changes to the ordinary Gaussian matched filter. Chowdhury et al. [10] proposed a method having three stages. First of all the green channel of fundus image is processed by applying highpass filter to get a binary image and second image is formed by enhancement and morphological reconstruction to achieve vessel regions. The regions which are similar and common are referred as vessels and are decided to be major vessels. Secondly the remaining pixels are further classified through

Gaussian mixture model (GMM) classifier with the help of eight feature vector formed by first and second order gradients and pixel neighborhood. Finally the major vessels pixels and the (GMM) classified pixels are combined. Salazar-Gonzalez [11] first extracted vessels through a technique named graph cut, further these vessels assisted in estimating and locating optic disk. Optic disk is extracted using two schemes. The first scheme Markov random field (MRF) scheme extracts the optic disk by eliminating vessels pixels from optic disk portion of the image and compensation factor scheme extracts the optic disk through previous local intensity information of the vessel pixels. Osareh et al. [12] stated that for each and every pixel in the image, a vector having features is constructed which uses the characteristics of Gabor filters. Then classification is performed through generative Gaussian mixture model (GMM) and then discriminative support vector machines (SVM) classifiers. Phyo et al. [13] segmented the blood vessels and optic disk by morphological processing like closing, filling, morphological reconstruction and Otsu thresholding method. Joshi et al. [14] segmented the blood vessels by using mathematical morphology followed by contrast enhancement, thresholding and post processing. Wilkinson et al. [15] used two moving-window methods to segment blood vessels from skull images, for local thresholding they used flat or weighed windows with the threshold selected automatically. Wen-Huaxu et al. [16] presented a method in which enhancements are made non-uniformly in order to balance the background which is also non uniform; the image is further divided in parts. Thresholding is performed with optimal value on each and every part to extract vessels. Soares et al. [17] proposed a method in which classification is performed based on the feature vector which consists of the intensity and continuous 2D Morlet wavelet transform at various scales. The Morlet wavelet transform is able to be tuned at specific frequencies, which achieves both noise filtering and enhancement of vessels simultaneously. They use Bayesian classifier likelihoods as Gaussian mixtures for classification. Akhavan et al. [18] extracted blood vessels centerlines pixels. Final segmentation of vessels is achieved using a repetitive region growing scheme that combines the images which are binary and produced from center line detection part with the image resulting from fuzzy vessel segmentation part. In the post processing part they use morphological operations and median filtering. In Safarzadeh et al. [19] firstly, the reverse effect of bright lesions is reduced through K-means classification in a perceptive space. Then, a multi-scale line operator is used to extract vessels while ignoring some of the lesions which are dark having unlike structures from the vessels which are line-shaped.

3. METHODOLOGY

Accuracy of segmentation is highly desirable for accurate examination of blood vessels of fundus imagery for diagnosing of retinal diseases. A huge tradeoff exists between accuracy of segmentation and algorithm computational overhead. Almost all of the algorithms developed so far are either computationally complex creating huge overhead if producing high accuracy or much low accuracy in case of simple algorithms. An efficient, fast and accurate blood vessel segmentation method is proposed with fewer computations having higher accuracy in its stream of methods. Fig. 1 shows the block diagram of our method.

3.1 RGB to Green Channel Conversion

In our method, green channel of a fundus retinal image is selected for further processing such as

Fig. 1. Block diagram of the proposed scheme.

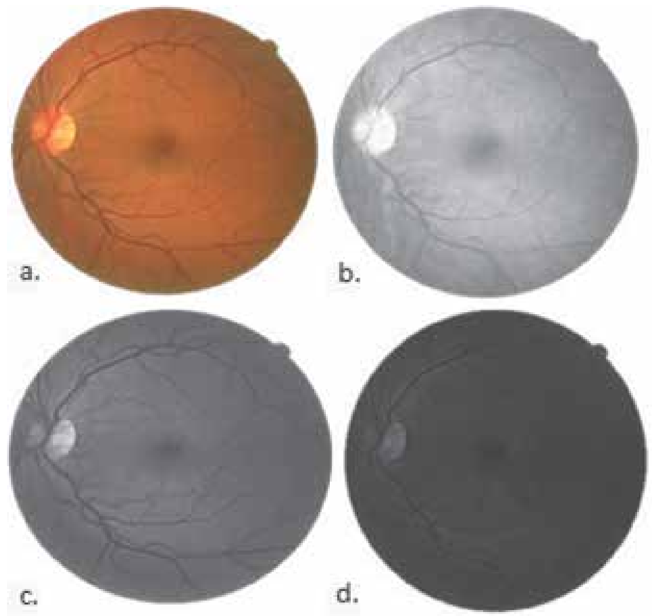

Fig. 2 (a). Original image; (**b**). Red channel; (**c**). Green channel; (**d**). Blue channel.

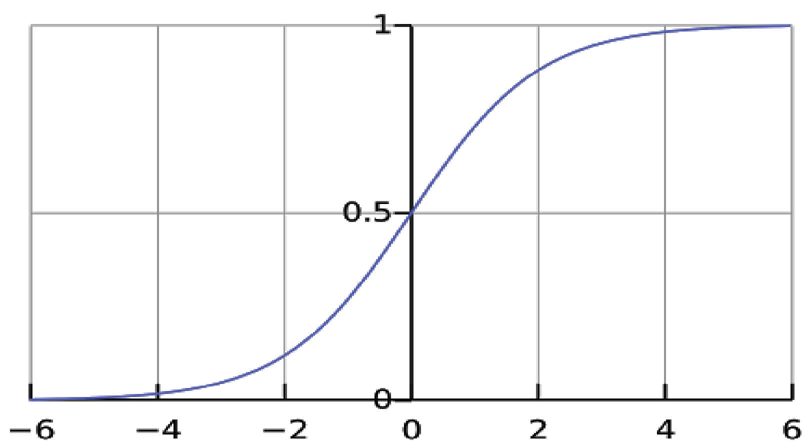

Fig. 3. Plot of sigmoid function.

according to Osareh et al. [12] it provides maximum contrast between vessels and background area and secondly it would reduce computational overhead if a single green channel is used for vessel detection in lieu of all the three red, green and blue channels. According to Fig. 2(c) it is clearly shown that green channel produces high contrast and vessels are clearly differentiable from background while in red and blue channels vessels are not much different and showing similar shades as background

3.2 Contrast Enhancement

Contrast of any fundus image is normally very low due to many reasons, like insufficient or varying lighting condition while capturing retinal images, low dynamic or nonlinear range of the imaging sensor such that non-uniform distribution of illumination within the image. So it is important to make the contrast high to make the edges of vessels more visible and separable from background, For this reason many contrast enhancement methods are applied in literature [20], i.e., methods based on spatial domain and histogram based techniques like histogram equalization technique, Contrast limited adaptive histogram equalization technique, Adaptive histogram equalization technique and

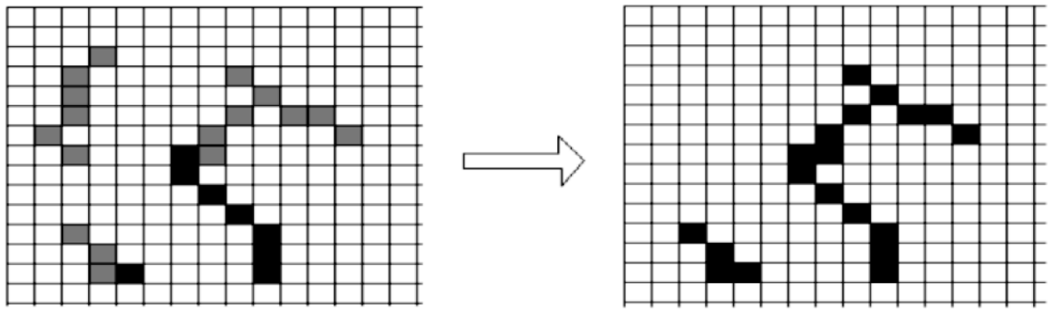

Fig. 4. Graphical representation of hysteresis thresholding.

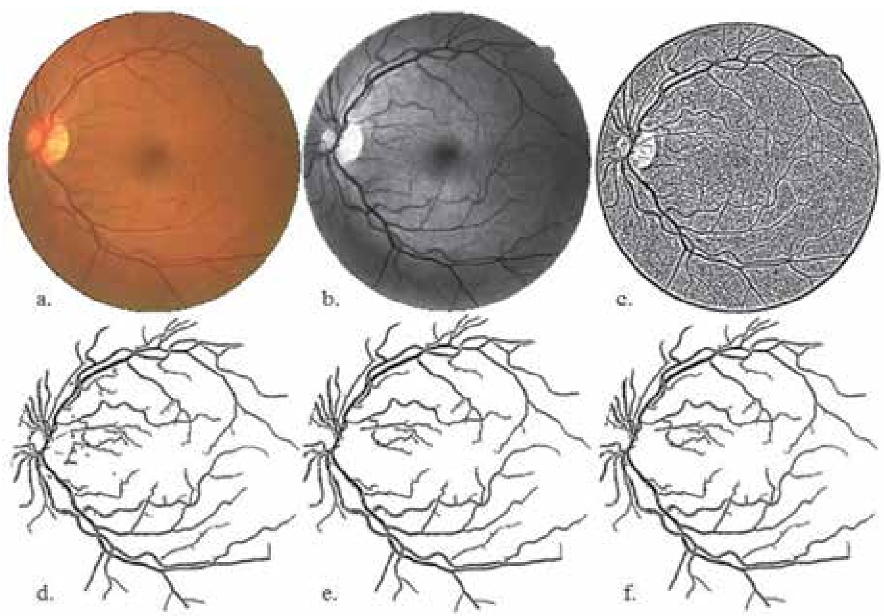

Fig. 5 (a). Original image; (**b**). Contrast enhancement of green channel; (**c**). Background removed; (**d**). Hysteresis thresholding; (**e**). Morphological opening; (**f**). Morphological opening.

local and global contrast stretching techniques etc. However, we made use of sigmoid function based contrast enhancement technique [21-24] which is a key and distinguishing part of our method. A sigmoid functions is a mathematical function which has "S" like shape as shown in Fig. 3 It is the logistic function's special case and having the formula:

$$f\ x\ = \frac{1}{1+e^{\ g\ x}} \qquad (1)$$

Where "g" is the gain and it controls the actual contrast and "x" is the cutoff which denotes the normalized greyness factor and its value is varied around it. Its normal initial value is 0.5 which is the mid of the greyscale. Different images may require different value of g to be enhanced. This function has the property of continuous function. Its output ranges between 0 and 1. It is differentiable and a real-valued function, bearing a first derivative which is either non-positive or non-negative . It is widely used in algorithms based on neural networks. In our method we use 15 and 0.5 for gain and cutoff respectively. Original image is shown in Fig. 5 a. while enhanced contrast image through sigmoid function is shown in Fig. 5 (b).

2.2 Background Exclusion

The basic goal of this step is to remove differences in background brightness of the image so that the vessels present in foreground become more visible for next step in our algorithm. In most of the image processing applications, the exclusion of background is achieved by the subtraction of the input actual image from the image filtered through averaging filter or smoothed image. We also adopted the same method. Averaging filter is also known as lowpass filter which is widely used in image processing algorithms for various purposes, Moving average filter substitute the center pixel value by the mean value $\hat{p}$ of a neighboring pixels $p_i(x, y)$ which is predefined as shown in Eq. 2

$$\hat{p}(x,y) = \frac{1}{N\times M}\sum_{i=1}^{N\times M} p_i \quad (2)$$

Subtraction operation is performed by subtracting the original image "$p(x,y)$" from its smoothed version $\hat{p}(x,y)$. The difference image $z(x, y)$ is achieved by calculating the difference 'dn' between the corresponding pixels in both images $p(x, y)$ and $\hat{p}(x,y)$ as,

$$z(x,y) = \begin{cases} dn & \hat{p}(x,y) - p(x,y) > 0 \\ 0 & else \end{cases} \quad 0\ 255 < d \leq 255 \quad (3)$$

Image, with removed background, is shown in Fig. 5 (c).

3.3 Hysteresis Thresholding

The goal of this part of the scheme is to create a binary image contains only vessels where the blood vessels are marked as 1 and the background is marked as 0. But, unluckily there do not existed any thresholding scheme for calculating an optimal value for threshold yielding perfect results in extracting vessels in all circumstances. However, in the proposed scheme, we employ hysteresis thresholding scheme which works perfectly in vessel segmentation from fundus image problem by producing a binary image as follows, Two threshold values are selected initially, i.e., T1 and T2. Values above the T1 are considered as object or foreground or to be more accurate as edges and values below T2 are considered as background and the value in between are decided to be the weak edges which then further included in the stronger edges part of the retinal image. Fig. 4 explains better and helps in understanding the hysteresis thresholding technique. After extensive simulations, value for T1 ranges between 1 and 12 while value for T2 is 40 for fundus imagery. After applying hysteresis thresholding to Fig. 5(c) the resultant image is shown in Fig. 5(d).

3.5 Morphological Processing

After applying thresholding, some undesirable pixels forming dots and very thin lines emerged as noise which is referred as false positive in the produced binary image, so in order to remove these undesirable pixels, some further processing have to be performed for improving the image and maintaining the wanted blood vessel pixels as a post processing step. To accomplish this task, an image opening (morphological operation) is used to eliminate the undesired pixels that is limited to or less than 90 pixels. Now due to image opening, little gaps between vessels are appeared which is removed to some extent with image dilation. Imagesin Fig. 5(e) and Fig. 5 (f) are showing results of image opening and dilation, respectively.

4. EXPERIMENTAL RESULTS AND DISCUSSION

To assess and determine the performance of the proposed scheme, the color fundus images with ground truth or hand labeled images have been taken from two publically available DRIVE [25] and STARE [26] database. DRIVE database is comprised of total forty images which are separately grouped into training and test images, each group is comprised of 20 images, respectively. All of these images were captured using Canon CR5 non-mydriatic 3CCD camera having a 45 degree field of view (FOV) and using 8 bits per channel. Resolution of all the images in the database is 768×584 pixels. It also contains masks in order to extract field from the remaining fundus image. Manually segmented vessels are included as ground truth images. The STARE database of fundus images has twenty images; out of them ten has pathology. All of the images are acquired by TopCon TRV-50 camera at 35° field of view. Resolution of these images is 605 ×700 pixels, having 8 bits per channel. The proposed scheme

Table 1. Performance evaluation and comparison of the proposed scheme with various other schemes on DRIVE and STARE data sets.

Source	Acc	Time	Acc	Time	Platform
Singh et al. [9]	0.9459	-	-	-	-
Sohoni et al. [10]	0.952	3.11s	0.951	6.7	2.6 GHz Processor, 2 GB RAM
Gonzalez et al. [11]	0.9412	-	0.9441	-	-
Soares et al. [17]	0.9473	3 min	0.9349	3 mins	2.17 GHz Processor, 1 GB RAM
Razieh et al. [18]	0.9513		0.9537		-
Staal et a.l [25]	0.944	15 min	0.952	15 mins	1 GHz Processor, 1 GB RAM
Hoover et al. [26]	-	-	0.927	5 mins	Sun SPARCstation 20
L. Xu et al. [27]	0.9328	-	-	-	-
You et al. [28]	0.9434	-	0.9497	-	-
Marin et al [29]	0.945	90s	0.952	90s	2.13 GHz Processor, 2GB
Jiang et al. [31]	0.891	8-36s	0.901	8-36s	600 MHz Processor
Mendonca et al. [33]	0.945	2.5 min	0.944	3 mins	3.2 GHz Processor, 980 MB RAM
Miri et al. [35]	0.943	50s	-	-	3 GHz Processor, 1 GB RAM
LAM et al. [37]	-	-	0.947	8 mins	1.83 GHz Processor, 2GB RAM
Saffarzadeh et al. [38]	0.9387	-	0.9483	-	-
Al Diri et al. [39]	-	11 min	-	-	1.2 GHz Processor
Chaudhuri et al. [40]	0.8773	-	-	-	-
Zana et al. [41]	0.9377	-	-	-	-
Lam et al. [42]	0.947	13 min	0.957	13mins	1.8 GHz Processor, 2GB RAM
Budai et al. [43]	0.949	11s	0.938	16s	2.0 GHz Processor, 2GB RAM
Budai et al. [44]	0.957	1.04s	0.938	1.31s	2.3 GHz Processor, 4 GB RAM
Fraz et al. [45]	0.948	100s	0.953	100s	2.27 GHz Processor, 4 GB RAM
Proposed Method	**0.952**	**2.04 s**	**0.9383**	**2.18 s**	1.66 GHz Processor, 2GB RAM

was applied and tested on all the images of DRIVE and STARE databases on Intel atom 1.67 GHz processor with 2GB of RAM on Windows 7 and using Matlab R2008b. The quantitative study of blood vessel extraction is carried out by comparing the blood vessels segmented out through our scheme with the respective manually segmented blood vessels in ground truth images of DRIVE and STARE databases. For quantitative study we used the segmentation accuracy as a metric to compare and assess our scheme with other schemes .Accuracy incorporates the number of true positive, true negative, false positive, false negative pixels. If the pixel is classified as vessel and the same pixel is also labeled as vessel in the ground truth image then it is said to be true positive (TP). If the pixel is classified as non-vessel and also it is not a vessel pixel in ground truth image then it is called true negative (TN). Similarly If a pixel is decided to be a vessel by the classifier and respectively it is a non-vessel pixel in ground truth image then it is termed as false positive (FP) and if a pixel is not classified as vessel and it is a vessel pixel in the ground truth image then it is called false negative (FN).

While formula for accuracy is given by Eq. 4

$$Accuracy = \frac{True\ Positive\ TP + True\ Negative\ TN}{True\ Positive\ \ TP + True\ Negative\ TN + False\ Positive\ FP + False\ Negative\ FN} \quad (4)$$

Accuracy of the proposed scheme is compared with previous work done and is shown in the Table 1. According to the Table 1 our method has outperformed almost all the methods using DRIVE database except from the results of Budai et al. [3], which are produced through simulations in C. While using STARE database our method also produces promising results though its accuracy is not much impressive but with a method having low computational overhead, it achieved a much better performance while comparing with methods of its own nature, i.e., methods involving morphological processing. However the mean time to perform a single segmentation operation is lowest which makes our method superior to other methods.

5. CONCLUSIONS

In ophthalmology segmentation of blood vessels through computers play a significant role in diagnosing various eye related diseases. Accurate extraction of blood vessels from retinal fundus image while keeping the algorithm simple, always remain a challenging task for researchers. For this reason we proposed a method which achieved a promising accuracy through fewer computations as compared to previous methods. The method acquire green channel of fundus image followed by contrast enhancement by sigmoid function. Background is removed to make vessels more visible. After hysteresis thresholding some morphological operations are performed as post processing the resultant image. The scheme was applied to DRIVE as well as STARE databases. A single limitation of the proposed method is that during hysteresis thresholding stage, changing the lower threshold value which ranges between 1 and 12 may change result. In future our work can be extended by automatic selection of lower threshold producing best result.

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