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A Fast Supervised Retinal Blood Vessel Segmentation Using Digital Fundus Imaging

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Abstract— Digital fundus images (DFI) are obtained from the retina and graded by Ophthalmologists. Diabetic retinopathy (DR) is a common retinal complication associated with diabetes, that may result in permanent blindness. Progression of DR is assessed by its severity, which in turn determines the frequency of examinations. Computer assisted monitoring has been a demand of the hour as there is a significant shortage of professional observers. Fast assessment of blood vessel network plays an important role in a variety of medical disorders. To extract blood vessels from DFI, image enhancement techniques, morphological operations and post-segmentation processes were employed to generate a segmented binary image.

Keywords— Digital fundus image, Diabetic retinopathy, morphological operations.

I. INTRODUCTION

Digital fundus images (DFIs) are images captured through fundus photography, comprising of the optic disc, retina, macular regions and the posterior surface of an eye. Ophthalmologists use these regions during diabetic eye screening and diabetic retinopathy (DR) grading [1]. DR, a systemic disease, which affects up to 80 percent of all patients who have had diabetes for 10 years or more. Despite these intimidating statistics, research indicates 90% of these new cases could be reduced by proper, vigilant treatment & monitoring of the eyes. The longer a person has diabetes, the higher his or her chances of developing DR.

Diabetic Retinopathy is the leading cause of blindness in 20 to 55 year olds. Microaneurysms are the early signs that appear in retina at the initial stage of DR while the next signs are hemorrhages. Early diagnosis of both, hemorrhages and microaneurysms (HMAs) is crucial. Regular diabetic eye screening is a crucial step in detecting DR. Obtaining perfect contrast in analyzing the fundus surface can be done using the images obtained from Fluorescein Angiography (FA). This is an imaging technique which relies on the circulation of Fluorescein dye to show staining, leakage of the retinal vasculature. DFI has very low contrast between the retinal vasculature and the background. It makes visualization and analysis of small retinal vasculatures difficult [6]. The illumination is very frequently uneven or non-uniform which causes the presence of local luminosity and contrast variability in the images that may lead to difficulty to a human observer to visualize and diagnose lesions in certain areas. This in turn can seriously affect the diagnostic process and its product [7].

Therefore, to guarantee visualization of the retinal blood vessels, image enhancement is required. In [9], they used vessel central light removal and background equalization to enhance the images. Both methods were successful to remove brightness and standardize the intensity. Meanwhile, V.Saravanan et al. applied background subtraction after converting the fundus images to green channel and subtracted by median filtered gray scale image [10]. In addition, they also used adaptive histogram equalization to enhance the DFIs contrast. The above methods are considered as intensity normalization in the preprocessing stage.

This method focuses on DFI enhancement and blood vessel segmentation. Retinal vascular pattern facilitates the physicians for the purposes of diagnosing eye diseases, patient screening, and clinical study. Inspection of blood vessels provides the information regarding pathological changes caused by ocular diseases including diabetes, hypertension, stroke and arteriosclerosis.

II. METHODOLOGY

The database DRIVE & STARE were used which consists of 40 & 400 images respectively. Both the database's consists of good images as well as bad images. These database are freely available on the internet. They consists of the ground truth of image, which is used to check the accuracy of segmentation phase. The photographs for the DRIVE (Digital Retinal Images for Vessel Extraction) database were

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obtained from a diabetic retinopathy screening program in The Netherlands.

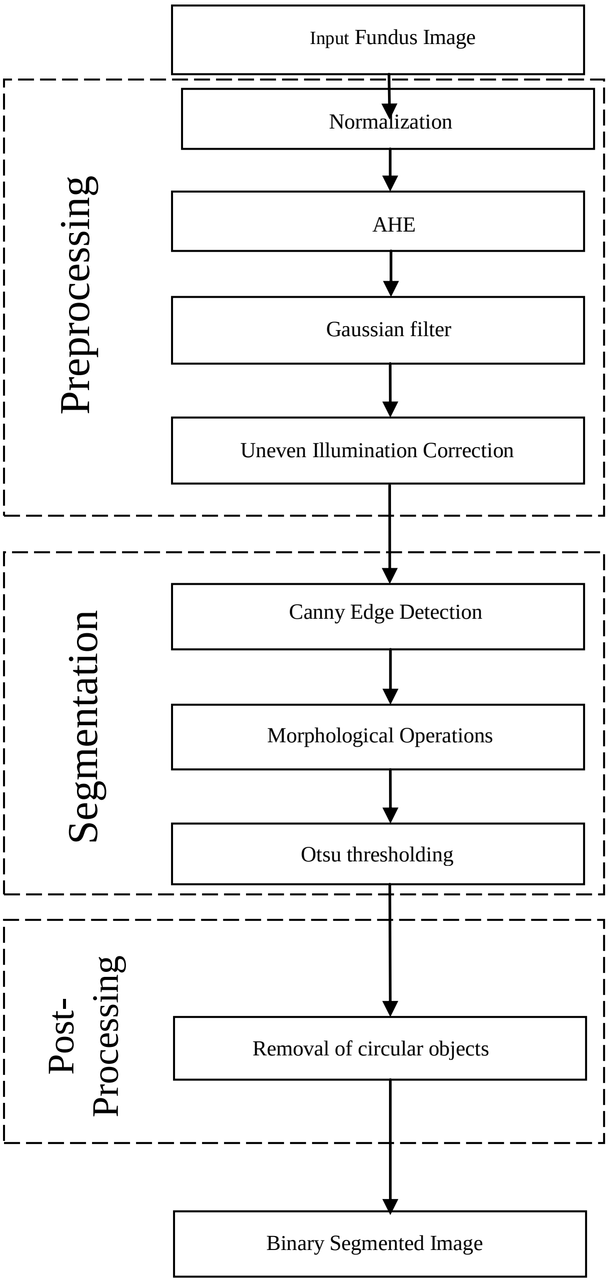

Fig 1. Block diagram of proposed method

The images were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 565 by 584. The STARE (Structured Analysis of the Retina) Project was conceived and initiated at the University of California, San Diego, USA. It consists of 400 raw images captured at 605 by 700 pixels.

A. Pre-processing

Initially, green channel was extracted from the DFI. In RGB DFI, the green channel typically shows the best contrast between the background and vessels whereas the other two channels produce more noise. As such, the gray images from the green channel are used since the retinal blood vessels in these images are more visible. Then, pre-processing techniques were executed with view of enhancement. Those techniques include normalization, Adaptive Histogram Equalization (AHE), Gaussian filter & uneven illumination correction. Normalization is a process that changes the range of pixel intensity values. Normalization transforms an n-dimensional grayscale image with intensity values in the range (Min, Max), into a new image with intensity values in the range (newMin, newMax).

$I : \{X \subseteq R^n\} \rightarrow \{Min, \ldots, Max\}$

$I_N : \{X \subseteq R^n\} \rightarrow \{newMin, \ldots, newMax\}$

The linear normalization of a grayscale digital image is performed according to the formula;

$$I_N = (I - Min)\frac{newMax - newMin}{Max - Min} + newMin \qquad (1)$$

Thus, each pixel intensity were brought in the range of 0 to 255. The adaptive histogram equalization method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. In general, AHE takes small blocks of the image and updates the central pixel using the histogram of the block as transfer function. The whole image is enhanced by sliding the block over the whole image. Gaussian Filter is a filter whose impulse response is a Gaussian function (or an approximation to it).

$$h_g(n_1, n_2) = e^{\frac{-(n_1^2 + n_2^2)}{2\sigma^2}}$$

$$h(n_1, n_2) = \frac{h_g(n_1, n_2)}{\sum_{n_1}\sum_{n_2} h_g} \qquad (2)$$

It returns a rotationally symmetric Gaussian low pass filter of size with standard deviation sigma. Illumination correction is based on background subtraction. This type of correction assumes the scene is composed of an homogeneous background and relatively small objects brighter or darker than the background. Correcting the illumination variation can be important both for accurate segmentation and for intensity measurements and was done using top-hat and bottom-hat transformation.

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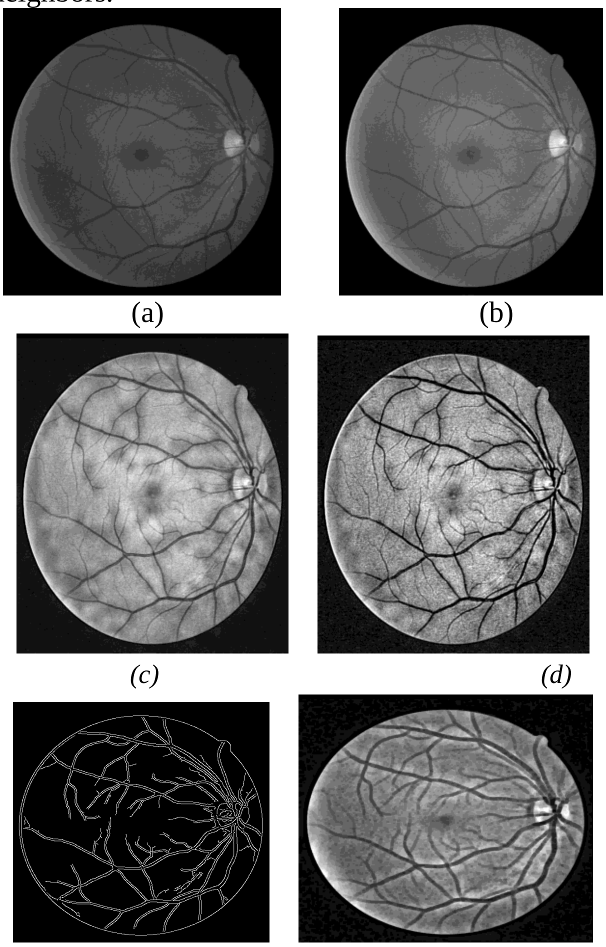
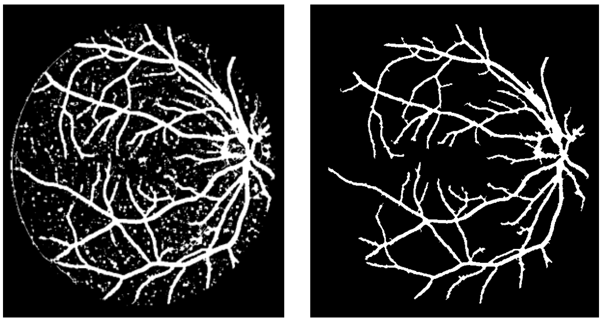
B. Segmentation

Edge detection is an important technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. Among the edge detection methods developed so far, canny edge detection algorithm is one of the most strictly defined methods that provides good and reliable detection. , This edge detection method finds edges by looking for the local maxima of the gradient of the input image. It calculates the gradient using the derivative of the Gaussian filter. The canny method uses two thresholds to detect strong and weak edges. It includes the weak edges in the output only if they are connected to strong edges. As a result, the method is more robust to noise, and more likely to detect true weak edges. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors.



(a) (b) *(c)* *(d)* *(e)* *(f)*



(g) (h)

Figure 2
(a) Green channel
(b)Normalization
(c)Adaptive Histogram Equalization
(d)Uneven Illumination Correction
(e)Canny edge detection
(f)Morphological Operations
(g)Otsu thresholding
(h)Removal of circular objects

By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image. The basic morphological operations used are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. Disk is the structuring element used. Opening morphological operation was used. Together with closing, the opening serves as a basic workhorse of morphological noise removal. Opening removes small objects from the foreground (usually taken as the dark pixels) of an image, placing them in the background, while closing removes small holes in the foreground.

Otsu’s method is then used which automatically performs clustering-based image segmentation. The gray level image is reduced to binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels or bi-modal histogram. It then calculates the optimum threshold by separating those two classes so that their combined spread is minimal.

C. Post-processing

Some post processing operation was needed to clean up the image obtained after converting the image to binary format by using Otsu thresholding. Noise in the form of circular objects was redundant and were eliminated using the concept of

Area of all connected regions was calculated along with the perimeter to compute the circularity.

$$f_{circ} = \frac{4\pi A}{P^2} \tag{3}$$

A threshold was set and all the regions found below the determined threshold level were eliminated. The ouput was now noise free.

III. EXPERIMENTAL RESULTS

Initially, the effect of different parameters of the proposed method was evaluated on images from publicly available DRIVE database [2]. In the second section of our experiments, the proposed method for blood vessel segmentation was tested on the STARE[3] database. The DRIVE database consists of 40 images along with manual segmentation of vessels. It has been divided into training and test sets, each of which contains 20 images. The hand-labeled images by the first expert human were used as ground truth. The STARE dataset consists of several retinal images that we selected 20 images. This set has same images used in Hoover et al. [3]. Two observers manually segmented all images. The hand-labeled images by the first observer were used as ground truth. The FOV mask images were manually generated by the first author. To evaluate the proposed vessel segmentation method, the detection performance is measured using true positive (TP), false positive (FP), true negative (TN) and false negative (FN) metrics. TP is defined as the number of vessel points correctly detected in the retinal images; FP is defined as the number of non-vessel points detected as vessel; TN is defined as the number of non-vessel points correctly detected; and FN is defined as the number of vessel points not detected by the system. By using these metrics we can obtain more meaningful performance measures like sensitivity, specificity and accuracy values as below:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{4}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{5}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

The sensitivity and specificity of the proposed method on DRIVE database are 0.6429 and 0.9859 respectively. For STARE database, the sensitivity and specificity were 0.7633 and 0.9611 respectively. Accuracy of this segmentation method on DRIVE and STARE databases were found to be 0.9548 and 0.9498 respectively.

Finally, the running time of the proposed method along with some state-of-the-art methods is given in Table 1, where the running times of the methods of Staal et al. [2], Marín et al. [17], Lam et al. [15], Mendonca et al. [16] and Soares et al. [18] were obtained from their papers. The proposed method competes with existing fast methods as it requires low computational cost. It will take about 13 seconds to process one image of the DRIVE database on a PC with a Intel(R) Core(TM) i5-3337U CPU and 4.0 GB RAM.

METHOD	TIME	SOFTWARE	PC CONFIGURATION
Staal et al. [2]	15 min	MATLAB	Pentium – III PC 1.0 GHz, 1.0 GB RAM
Marín et al. [17]	1.5 min	-	Intel Core2Duo CPU 2.13 GHz, 2 GB RAM
Lam et al. [15]	13 min	MATLAB	Dual CPU 1.83 GHz, 2 GB RAM
Mendonca et al. [16]	3 min	MATLAB	Pentium – IV PC 3.2 GHz, 960 MB RAM
Soares et al. [18]	3.2 min	MATLAB	PC 2167 MHz, 1 GB RAM
Fathi A. et al. [19]	1 min	MATLAB	Pentium-IV PC 3.2 GHz, 2 GB RAM
Proposed method	13 sec	MATLAB	Intel(R) Core(TM) i5-3337U CPU 1.8 GHz, 4 GB RAM

Table 1

IV. CONCLUSION

In this paper we proposed an efficient supervised algorithm for automatic blood vessel segmentation. The proposed method is based on common image enhancing techniques and basic morphological operations. The obtained average sensitivity and specificity of the vessel segmentation on both the DRIVE and STARE datasets are 70.31% and 97.35% respectively. Also the average accuracy value of it is 95.23%. The proposed method outperforms other existing vessel segmentation methods and also outperforms non-expert human segmentation. Also, the running time of the proposed method is better than other state-of-the-art methods. It can extract the vessel network of one image in just about 13 seconds(approx.).

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