Automated Detection of Vascular Abnormalities in Diabetic Retinopathy using Morphological Entropic Thresholding with Preprocessing Median Fitter

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Abstract

Diabetic retinopathy is one of the serious eye diseases that can cause blindness and vision loss. The complication of the diabetes associated to retina of the eye is DR. A Patient with the disease has to undergo periodic screening of eye. For the diagnosis, ophthalmologists use color retinal images of a patient acquired from digital fundus camera. Ocular funds image can provide information on pathological changes caused by local ocular diseases and early signs of certain systemic diseases. The present study is aimed at developing an automatic system for the extraction of normal and abnormal features in color retinal images. The Preprocessing median fitter is applied before the Morphology. Morphological filter is tuned to match that part of vessel to be extracted in a green channel image. To classify the pixels into vessels and non-vessels local thresholding based on gray level co-occurrence matrix is applied. The performance of the method is evaluated on two publicly available retinal databases with hand labeled ground truths. The performance of retinal vessels on DRIVE database, sensitivity 91% accompanied by specificity of 94%. While for STARE database proposed method sensitivity 92% and specificity 90%. The system could assist the ophthalmologists, to detect the signs of diabetic retinopathy in the early stage, for a better treatment plan and to improve the vision related quality of life.

Keywords: Vessel Segmentation, Image Processing, Diabetic Retinopathy, Preprocessing Median filter, Morphological filtering

I. INTRODUCTION

Diabetic Retinopathy (DR) is an eye disease which occurs due to diabetes. It damages the small blood vessels in the retina resulting in loss of vision. Automatic segmentation of blood vessels in retinal funds image plays an important role in the diagnosis of several pathologies, like hypertension, diabetes, and cardiovascular disease. Several morphological features of veins and arteries (e.g. diameter, length, branching angle, and tortuosity) have diagnosis relevance. Accurate vasculature segmentation is a difficult task for several reasons: The presence of noise, the low contrast between vessels and background, and the variability of vessels width, brightness, and shape. Moreover due to the presence of lesions, exudates, and other pathological effects, the image may have large abnormal regions. The risk of the disease increases with age and therefore, middle aged and older diabetics are prone to Diabetic Retinopathy.

Retinopathy is a progressive disease, which can advance from mild stage to progressive stage. There are three stages based on The National Screening Committee (NSC): (I) early stage or non-proliferate diabetic retinopathy (NPDR) or background retinopathy, (ii) maculopathy and (iii) progressive or proliferate retinopathy. The early stage is further classified as mild NPDR and moderate to severe NPDR [1], [2].In mild NPDR, signs such as microaneursyms, dot and blot haemorrhages and hard or intra retinal exudates are seen in the retinal images. Microaneury are small, round and dark, red dots with sharp margins and are often temporal to macula [1], [3]. Their size ranges from 20 to 200 microns i.e., less than $1/12^{th}$ the diameter of an average optic disc and are first detectable signs of retinopathy. Haemorrhages are of two types: Flame and Dot-blot haemorrhages. Flame haemorrhages occur at the nerve fibers and they originate from precapillary arterioles, which located at the inner layer of the retina [4]. Dot and blot haemorrhages are round, smaller than micro aneurysms and occur at the various levels of retina especially at the venous end of capillaries. Hard exudates are shinny, irregularly shaped and found near prominent micro aneurysms or at the edges of retinal edema. In early stage, the vision is rarely affected and the disease can be identified only by regular dilated eye examinations [5].

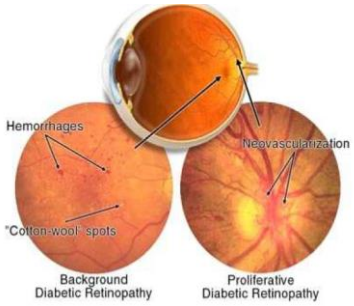

Fig. 1: Main stages of Retinopathy with the disorder

Fundus images are used for diagnosis by trained clinicians to check for any abnormalities or any change in the retina. They are captured by using special devices called ophthalmoscopes. A typical fundus image with its features marked is shown in the Figure 1. Each pixel in the fundus image consist of three values namely red, green and blue, each value being quantized to 256 levels. Diabetic Maculopathy is a stage where fluid leaks out of damage vessels and accumulates at the center of the retina called macula (which helps in seeing the details of the vision very clearly) causing permanent loss of vision. This water logging of the macula area is called clinically significant macular edema which can be treated by laser treatment.

Proliferate diabetic retinopathy, which is defined as the growth of abnormal new vessels (neovascularization) on the inner surface of the retina are divided into two categories: neovasculature of the optic disk

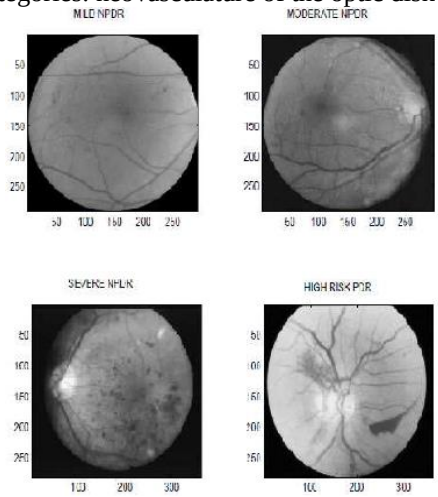

Fig. 2: Different stages of Diabetic retinopathy

Diabetic Maculopathy is a stage where fluid leaks out of damaged vessels.

II. DETECTION OF BLOOD VESSELS

There are different images-processing methods that can be used for capturing variation. Methods include image segmentation, edge or boundary detection, shape and texture analysis. The detection process can be carried out either on the original image or in the transform domain. Some of the transform, Fourier transform, And discrete cosine transforms (DCT). This paper utilizes preprocessing morphological filter for automated detection and classification of retinal images.

A. Preprocessing

In this pre-processing is used for better visualization. Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensity or reduce certain image details enable an easier or faster evaluation. In this work pre-processing is done with morphological filter for better visualization. Median Filter in images finds the median pixel value within the diameter that specified. It removes bright or dim features. Median filters are very effective in removing salt and pepper and impulse noise while retaining image details because they do not depend on values which are significantly different from typical values in the neighborhood. Median filters work in successive image windows in a fashion similar to linear filter. It sorts all the pixels in an increasing order and takes the middle one. If the number of pixels is even, the median is taken as the average of the middle two pixels after sorting.

B. Morphological Filter

The morphological operations include dilation, erosion, opening, closing etc.

1)*Dilation*

Dilation is a process that thickens objects in a binary image. The extent of this thickening is controlled by the Structuring Element (SE) which is represented by a matrix of 0s and 1s mathematically, dilation operation can be written in set notation as below

$$A \oplus A_S = \{Z|(A's)Z \cap A \neq \Phi\}$$

Where Φ is an empty element and as is the structuring element. The dilation of A by As is the set consisting of all structuring element origin locations where the reflected and transmitted As overlaps at least some portions of A. Dilation operation is commutative and associative.

2) *Erosion*

Erosion shrinks or thins the objects in a binary image by the use of structuring element. The mathematical representation of erosion is as shown below.

$$A \ominus A_S = \{Z|(As)Z \cap A \neq \Phi\}$$

Erosion is performed in MATLAB using the command imerode (Image Name, SE).

3) *Opening and Closing:*

In image processing, dilation and erosion are used most often and in various combinations. An image may be subjected to series of dilations and or erosions using the same or different SE. The combination of this two principles leads to morphological image opening and morphological image closing. Morphological opening can be described as an erosion operation followed by a dilation operation. Morphological opening of image X by Y is denoted by X O Y, which is erosion of X by Y followed by dilation of the result obtain by Y closing and opening

$$XoY = (X \oplus Y) \ominus Y$$
$$X \bullet Y = (X \ominus Y) \oplus Y$$

Morphological closing can also be described as dilation operation followed by erosion operation. Morphological Closing of Image X by Y is denoted by X Y, which is dilation of X by Y followed by erosion of the result obtained by Y. Image opening and image closing and are implemented in MATLAB by the use of imopen(image name) and imclose(image name) respectively

III. EXTRACTION OF VESSELS

The enhanced vessel segments in the morphological filter response image, an effective thresholding scheme is required. The entropy based thresholding using gray levels co-occurrence matrix is employed. It computes optimal threshold by taking into account the spatial distributions of gray levels that are embedded in the co-occurrence matrix. The GLCM contains information on the distribution of gray level and edge information, as it is very useful in finding the threshold value. The gray level co-occurrence matrix is a $L \times L$ square matrix of the gray scale image I of spatial dimension $M \times N$ with gray levels in the range [0, 1…L-1]. It is denoted by $T = [t_{i,j}]L \times L$ matrix. The element of the matrix specifies the number of transitions between all pairs of gray level in a particular Way. For each image pixel at spatial co-ordinate (m, n) with its gray level specified by $f(m,n)$, it considers its nearest four neighbouring pixels at locations of $(m+1,n)$, $(m-1,n)$, $(m,n+1)$, and $(m,n-1)$. The co-occurrence matrix is formed by comparing gray level changes of $f(m,n)$ to its corresponding gray levels, $f(m+1,n), f(m-1,n), f(m,n-1)$ and $f(m,n+1)$. Depending upon the ways in which the gray level i follows gray level j, different definitions of co-occurrence matrix are possible. The co-occurrence matrix by considering horizontally right and vertically lower transitions is given by

$$t_{i,j = \sum_{m=1}^{M} \sum_{n=1}^{N} \delta}$$
$$\delta = 1 if \begin{cases} f(m,n) = i \ and \ f(m,n+1) = j \\ f(m,n) = i \ and \ f(m+1,n) = j \end{cases}$$
$$\delta = 0 \ otherwise$$

Where, the total number of transitions in the co-occurrence matrix, a desired transition probability from gray level i to gray level j is obtained as follows

$$P_{i,j} = \frac{t_{i,j}}{\sum_{i=1}^{L} \sum_{j=1}^{L} t_{i,j}}$$

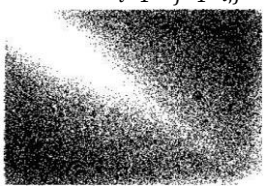

Fig. 3: Gray level co-occurrence matrix

IV. ENTROPY THRESHOLDING

Based on the gray level variations wit in or between objects and background, the gray quadrants. Let T_h be the threshold within the range $0 \leq T_h \leq L-1$ that partitions the gray level co-occurrence matrix into quadrants, namely A, B, C and D.

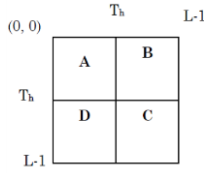

Fig. 4: Four quadrants of co-occurrence matrix

Quadrant A represents gray level transition within the objects while quadrant C represents gray level transition with in the background. The gray level transition between the object and the background or across the object's boundary is placed in quadrant B and quadrant D. These four regions can be further grouped into two classes, referred to as local and joint quadrant. Local quadrant is referred to quadrant A and C as the gray level transition arises within the objects or the back ground of the image. Then quadrant Band D is referred as joint quadrant because the gray level transition occurs between the object and the background of the image.

The local entropic threshold is calculated considering only quadrant A and C. The probabilities of object class and background class are defined as the normalized probabilities of the object class and background class are functions of threshold vector (T_h, T_h) are defined as

$$P_A = \sum_{i=0}^{T_h} \sum_{j=0}^{T_h} P_{i,j}$$

$$P_C = \sum_{i=T_h+1}^{L-1} \sum_{J=T_h+1}^{L-1} P_{i,j}$$

$$P_{i,j}^A = \frac{P_{i,j}}{P_A}$$

$$P_{i,j}^C = \frac{P_{i,j}}{P_C}$$

The second order entropy of the object is given by

$$H_A(T_h) = -\frac{1}{2} \sum_{i=0}^{T_h} \sum_{j=0}^{T_h} P_{i,j}^A \, log_2 P_{I,J}^A$$

The local transition entropy A denoted by $H_A(T_h)$.Similarly, the second-order entropy of the background is given by

$$H_C(T_h) = -\frac{1}{2} \sum_{i=T_h+1}^{L-1} \sum_{j=T_h+1}^{L-1} P_{i,j}^C \, \log_2 P_{i,j}^C$$

Up the local transition entropies, the total second-order local entropy of the objects and the background is given by

$$H_T(T_h) = H_A(T_h) + H_C(T_h)$$

Finally, T_E the gray level corresponding to the maximum of $H_T(T_h)$ over T_h gives the optimal threshold for value

$$T_E = arg \left[\max_{T=0 \ldots L-1} H_T T_h \right]$$

It can be seen that there exist small unconnected pixels in the threshold image. These isolated pixels are removed by performing length filtering based on connected pixel labelling. The result of removing these unconnected pixels can be seen in the final segmented image. To ensure that only the section of the image containing data is considered during image processing and analysis, a mask image is generated for each image. It is applied to remove any artefacts present outside the region of interest.

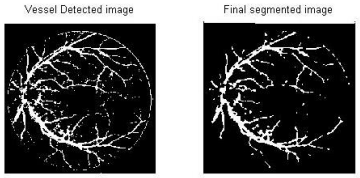

Fig. 5: Segmented vessels; Threshold response image, final segmented image after removing unconnected pixels.

V. RESULT

The retinal images from the DRIVE database and STARE database segmentation method. The manually segmented vessels provided in both the databases are used as gold standard Figure and Figure illustrates the result of vessel segmentation on one of

the images in each database. The entire process of segmenting vessels was performance on Intel PC with 1.66GHz CPU and 512MB memory using MATLAB7.10. The processing of each image including convolution and thresholding took about 30 seconds. Morphological filtering is used to enhance the multi-oriented vessels. True positive are pixels Marked as vessels in both the segmentation given by a method and the manual segmentation used as ground truth. False positives are pixels marked as vessels as by the method, but that are actually negatives are pixels marked as background in both images. And false negatives are pixels marked as background by the method, but actually are vessels pixels

Tab1e – 1

Performance analysis using Ground Truth Table

	Ground truth		
		Positive	*Negative*
Method result	*Positive*	*True positive*	*False Positive*
	Negative	*True Negative*	*False Negative*

From these sensitivity and specificity evaluated. Sensitivity gives the percentage of pixels correctly classified as vessels by the method and specificity gives the percentage of non-vessels pixels classified as non-vessels by the method as follows

$$\text{Sensitivity} = \frac{T_p}{T_p + F_n} \quad \text{Specificity} = \frac{T_n}{T_n + F_p}$$

Where T_p is true positive, T_n is true negative, F_p is false positive, and F_n is false negative at each pixel. The method is compared with the matched filter based method of using the DRIVE database Table shows that preprocessing Morphological filter is better in classification of vessels with less false positive fraction rate.

Table – 2

Performance of retinal blood vessels segmentation method on DRIVE database

Method	*Sensitivity (%)*	*Specificity (%)*
Proposed Method	*91*	*94*
Morphological filter	*86*	*91*
Gabor filter	*85*	*90*

The STARE database and the result are depicted in Table. Here also the proposed method performs better with lower specificity even in the presence of lesions in the abnormal images

Table – 3

Comparison of vessel segmentation results on STARE database.

Method	*Sensitivity (%)*	*Specificity (%)*
Proposed Method	*92*	*90*
Hoover et. Al	*75*	*92*

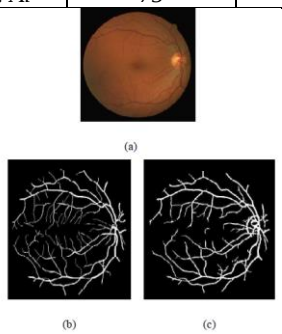

Fig. 6: DRIVE database; (a) Input image; (b) Manual segmentation by expert; (c) Automatic Segmentation by the method

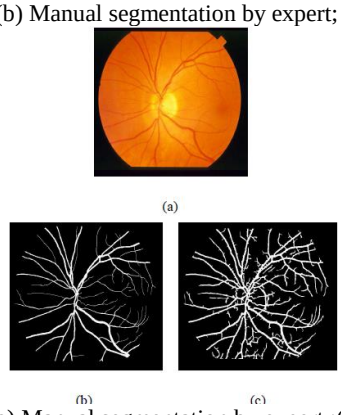

Fig. 7: STARE database; (a) Input image; (b) Manual segmentation by expert ;(c) Automatic Segmentation by the method.

VI. CONCLUSION

In this paper the sensitivity and specificity can be determined for diabetic retinopathy effected image and normal fundus images. The method Success for all images due to the presence of preprocessing technique. It was found that the number of miss classified pixels was less compared to other filter methods.

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