Detection of Vascular Intersection in Retina Fundus Image Using Modified Cross Point Number and Neural Network Technique

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Abstract

Vascular intersection can be used as one of the symptoms for monitoring and diagnosis of diabetic retinopathy from fundus images. In this work we apply the knowledge of digital image processing, fuzzy logic and neural network technique to detect bifurcation and vein-artery cross-over points in fundus images. The acquired images undergo preprocessing stage for illumination equalization and noise removal. Segmentation stage clusters the image into two distinct classes by the use of fuzzy c-means technique, neural network technique and modified cross-point number (MCN) methods were employed for the detection of bifurcation and cross-over points. MCN uses a 5x5 window with 16 neighboring pixels for efficient detection of bifurcation and cross over points in fundus images. Result obtained from applying this hybrid method on both real and simulated vascular points shows that this method perform better than the existing simple cross-point number (SCN) method, thus an improvement to the vascular point detection and a good tool in the monitoring and diagnosis of diabetic retinopathy.

Keywords: Fundus image, bifurcation, neural network, fuzzy c-means, cross point.

I. Introduction

Eye, an organ associated with vision in man is housed in socket of bone called orbit and is protected from the external air by the eyelids [1]. The cross section of the eye is as shown in Fig. 1.

Light entering the eye through the pupil is focused on the retina. The retina is a multi-layered sensory tissue that lines the back of the eye. It contains millions of photoreceptors that capture light rays and convert them into electrical impulses. These impulses travel along the optic nerve to the brain where they are turned into images. Optic disk is brighter than any part of the retina and is normally circular in shape. It is also the entry and exist point for nerves entering and leaving the retina to and from the brain.

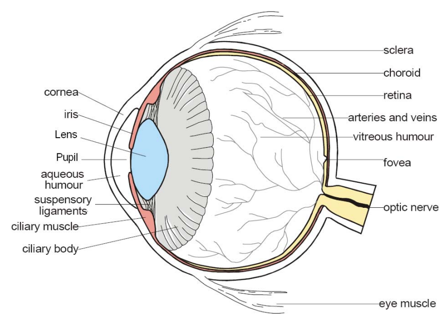

Fig. 1. Cross sectional diagram of human eye [2].

Neovascularisation can be described as abnormal growth of blood vessels in areas of the eye including the retina and is associated with loss of vision [4]. This occurs in response to ischemia, or diminished blood flow to ocular tissues. These new blood vessels have weaker walls and may break and bleed, or cause scar tissue to grow that can pull the retina away from the back of the eye. When the retina is pulled away it is called a retinal detachment and if left untreated, a retinal detachment can cause severe vision loss, including blindness [2], [5]. Associated with neovascularisation and bleeding are bifurcation and crossover points.

A typical fundus image of the retina is as shown in Fig. 2. The image shows the optic disc and the vascular network of the acquired fundus image.

Fig. 2. Retina Image

In this research work, the acquired retina fundus image (FI) was made to undergo preprocessing stage for illumination equalization and noise removal [5], [6]. The preprocessed image was then passed through the segmentation stage. Segmentation was achieved using fuzzy c means algorithm. The detection of bifurcation and cross points was achieved using a 5x5 window modified cross-point number (MCN) method and neural network (NN) techniques.

This paper is organized as follows; Section. I gives a brief introduction to diabetes and its associated terminology. Section. II discusses some of the reported work in relation to this research. In Section. III the proposed framework is discussed and this is shortly followed by experimental results in Section. IV, and Section. V concludes the paper.

II. RELATED WORK

In [7] an improvement was done to the tracking-based method reported in [11] by proposing a four step algorithm namely: matched filtering, local entropy thresholding, length filtering and vascular intersection detection for detection and extraction of blood vessels in retina images. The blood vessels were first enhanced by the use of matched filtering, based on the assumption that blood vessels usually have lower reflectance compared with the background. Entropy based threshold was then used to distinguished between background and vessels in the generated matched filter response (MFR) image of step one. Length filtering was later employed to eliminate misclassified pixels before the application of a 3x3 windows to probe for branching points and intersection or crossovers. The algorithm very well with the only problem of sever performance degradation in the presence of lesions.

A 3x3 window with 8 neighboring pixels was applied in extracting retinal vascular feature from fundus image in [8]. The method work very well for the detection of bifurcation points compared with some of the existing methods (i.e. [9], [10]). This same algorithm was applied in this project and we observed that it sometimes convert a cross over points into two bifurcation points hence a need to improve this simple method and algorithm.

An improvement to [8] is hereby presented in this paper using Fuzzy c-means algorithm for segmentation, digital image processing technique to obtain MCN, and neural network techniques for bifurcation and cross-points detection. The present works make use of neural network technique in addition to MCN for the detection of bifurcation and cross-points. Thus, in this work, we propose an efficient FI segmentation technique and also a more accurate and reliable technique for detection of bifurcations and cross-points.

III. PROPOSED METHOD

A three stage bifurcation and cross-over points detection in FI is hereby presented. These stages are: image preprocessing, image segmentation and bifurcation and cross-over points detection.

The acquired image undergoes preprocessing stage as explained in Sec. III (A); for color space conversion, illumination equalization and noise filtering using a 5x5 median filter. Image segmentation stage clusters the image into two distinct classes and detection of candidate bifurcation and cross over points is done during the third stage using the MCN and neural network technique.

A. Image Preprocessing Stage

Image preprocessing involves six steps, these are:

Step-1 Color space conversion: Convert the input RGB image to HSI color using Eq. (1). For gray images, no conversion is needed.

$$\left.\begin{array}{l} H = \begin{cases} \theta, for B \le G \\ 360 - \theta, for B > G \end{cases} \\ S = 1 - \left\{ \dfrac{3}{R+G+B} \right\} \min(R,G,B) \\ I = \dfrac{1}{3}(R+G+B) \end{array}\right\} \quad \text{--- (1)}$$

Where

$$\theta = \cos^{-1}\left\{ \frac{[(R-G)+(R+B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}} \right\} \quad \text{and}$$

$\min(R,G,B)$ denotes the minimum value among of red, green and blue components of the image [12].

Step-2 Zero and edge padding: This involves edge padding and zero filling of the intensity matrix or the gray scale image depending on the output of step 1.

Step-3 Intensity value detection: This detects the maximum and minimum intensity present in the image.

Step-4 Filtering: Perform 5x5 median filtering on the resulted image.

Step-5 Zero and edge padding removal: Remove the zero padding introduced in step 2 and perform histogram equalization using Global-local adaptive histogram equalization using partially-overlapped windows (GLAPOW) method proposed in [6].

Fig. 3. Images at different stages (a). input image (left) and (b). preprocessed image (right).

The input and output images of preprocessing stage are shown in Fig. 3. Fig. 3(a) shows the input image while Fig. 3(b) is the output image of the pre-processing stage.

B. Image Segmentation Stage

Segmentation involves grouping image pixels into regions with same property or characteristics. Fuzzy-c mean algorithm is used in this stage. The steps involve are:

Step-1: Select number of clusters c, for $2 \le c \le n$. In our case $c = 2$.

Step-2: Choose an initial centers $v = [v_1, v_2, ..., v_n]$ and the termination criteria $\in$. Label each of the steps r, where $r = 1,2,...$

Step-3: Calculate the membership function.

Step-4: Update the membership function, v_1

Step-5: Repeat steps 3 and 4 until $\left\| v^{r+1} - v^{r} \right\| = 0$.

The output images from this section is referred to as segmented images.

C. Bifurcation and Crossover Points Detection

This involves accurately determining vascular intersection in FI. This is achieved by the use of MCN and NN.

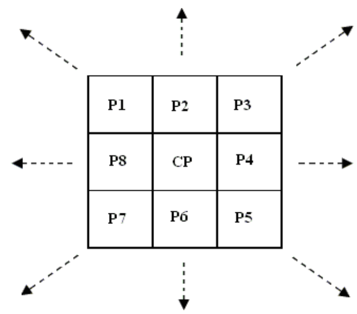

Fig. 4. Simple cross-point number.

a) Simple Cross-point Number Method: In the simple cross-point number (SCN) method a 3x3 window with 8 neighboring pixels (See Fig. 4) were used in detecting bifurcation and cross-over points [8]. The criterion used was; any point will be a cross-over point if $(cpn = 4)$ and it will be a bifurcation point for $(cpn = 3)$, where cpn can be found using Eq. (2) with $P_9 = P_1$. The possible cross-points in a 3x3 pixels window are shown in Fig. 5.

$$cpn = \frac{1}{2}\sum_{n=1}^{8} \left| P_n - P_{n+1} \right| \qquad \text{--- (2)}$$

The algorithm works well in detecting bifurcation points but sometimes fails in detecting cross-over points due to morphological operations performed on the image. The process of skeletonization or thinning

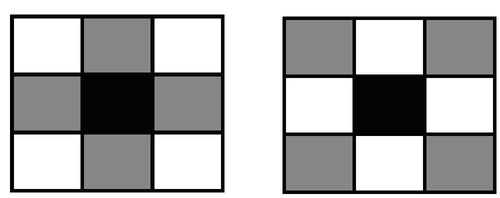

Fig. 5. Possible cross-over points using a 3x3 window (cnp = 4) in SCN method.

converts lots of single cross-over points into two bifurcation points depending on the angle and thickness of the crossing veins, thereby making the use of SCN inappropriate for total detection of cross-over points, hence a need for more appropriate method. A cross-over point (See Fig. 8) is turned into two bifurcation points during the skeletonization as can be seen in Fig. 9. It is obvious from Fig. 9 that using a 3x3 window (shown in green in Fig. 9), $(cpn = 2)$, hence unable to detect this cross-over using SCN method.

b) Modified Cross-point Number Method: Modified cross-point number (MCN) method uses a 5x5 window with 16 surrounding pixels (See Fig. 6) to the central

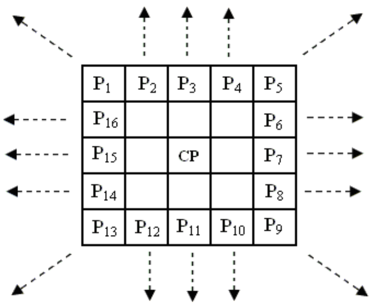

Fig. 6. Modified cross-point method

pixel in detecting bifurcation and cross-over point. The criterion here for a cross-point is slightly modified $(cpn \geq 4)$ and cpn can be calculated using Eq. (3), with $P_{17} = P_1$.

$$cpn = \frac{1}{2}\sum_{n=1}^{16}\left|P_n - P_{n+1}\right| \qquad \text{--- (3)}$$

Typical examples of cross-overs for a 5x5 window fulfilling $(cpn \geq 4)$ are as shown in the Fig. 9. With the use of MCN method, cross-over points which changed to bifurcation points were easily detected and subsequently reduced error associated with SCN method. Fig. 9 illustrates an example of cross-over

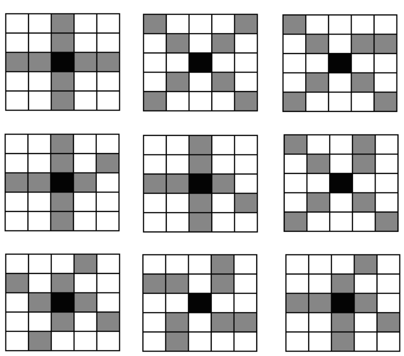

Fig. 7. Typical cross-over points using 5x5 window ($cpn \geq 4$) in MCN method

point which was un-detected by the use of SCN while MCN was able to detect such a point by using 5x5 window (shown in red).

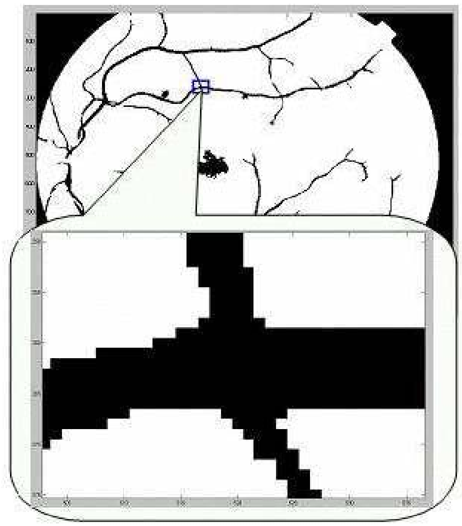

Fig. 8. Vein cross-over point.

c) Addressing other Issues of MCN: Despite the advantages associated with the use of 5x5 windows in MCN, it introduces two new errors, these are:

1) False detection due to the traces of other nonintersecting veins in the 5x5 window.
2) Detection of one crossover point at more than one pixel positions thus increasing the counts of false positive (false detections).

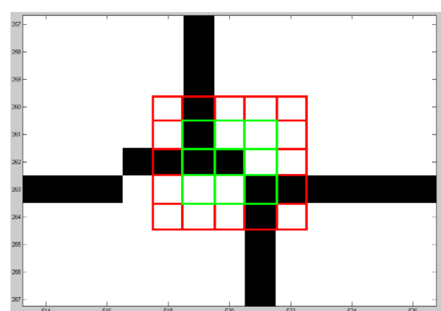

Fig. 9. Cross-over been turned into bifurcation as a result of thinning.

Both issues were resolved as follows; To prevent false (positive) detections due to traces of non-intersecting veins, all unconnected pixels to the central pixel were removed before the calculation of cpn. To prevent multiple detections for a single cross-over point, the cross-over image (i.e. the binary image with the same size as the input image but having only cross-over point pixels as value one and all other pixels as zero) was dilated. This reconnects the crossovers points that are very close to each other and such a point can now be considered as a single cross-over point.

d) Artificial Neural Network method: This section involve the development of artificial neural network (ANN) approach to the detection of bifurcation and vascular intersection points in FI based on the technique of MCN.

A multilayered feed forward neural network (MFN) was developed using MATLAB toolbox. The network architecture comprises of 25 neurons at the input layer and 2 neurons at the output layer.

IV. Results obtained

To evaluate the method of MCN and neural network introduced in this paper, we applied the three methods (SCN, MCN and NN) to two different set of images, each comprises of simulated images and real FI. The result obtained by comparing the detection rate of SCN to MCN is provided here using a bar chart in Fig. 10. The two methods never gave a false detection but SCN sometimes fails to detect cross points. The two methods were later applied to real fundus images and the result obtained is similar to that obtained for simulated images.

In a similar way, comparing the method of MCN and NN, the result obtained is as shown using bar chart in Fig. 11. The NN technique was able to perform better than both MCN and SCN in detecting cross-points. Detection of false cross-points was noticed in MCN in images 1 and 2, while both failed to detect cross-points in some others images. The results obtained in this work show that the use of NN technique provide better and more accurate detection technique for both bifurcation and cross points than the use of MCN and SCN, though MCN performs far better than SCN and need prior training as NN technique.

This improvement in detecting vascular intersections in the fundus images plays a critical role in automatic diagnosis of DR thus leading to increase in efficiency of such a task. It is also a vital tool in development of a tool for diagnosing vascular disorders related diseases such as DR.

V. Conclusion

In this paper we have presented a new simple and efficient method of detecting vascular intersection such as bifurcation and cross-over points in FI. Our approach uses a 5x5 window with 16 neighborhood in detecting candidate cross points. The algorithm was applied to both simulated cross points and real cross points obtained from FI. The result obtained is better than that obtained from the use of SCN method. In addition, the neural network technique proved to be best among the three used here in this work.

This newly developed method can be of great benefit to ophthalmologist in the diagnosis, monitoring and screening of diabetes retinopathy. Furthermore, the idea developed in this paper can also be applied to other images in which it is of interest to detect the vascular objects present in it.

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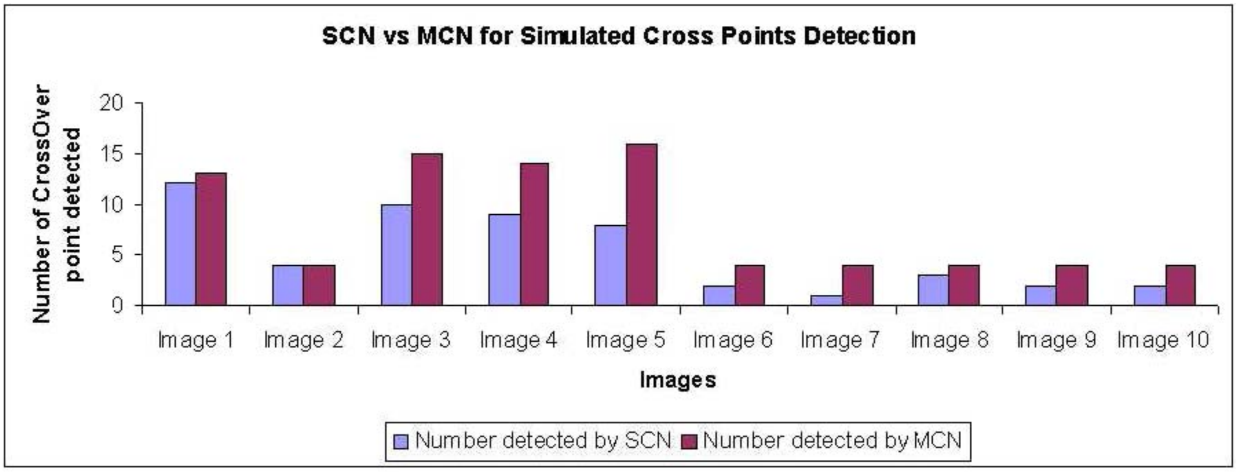

Fig. 10. Comparison between SCN and MCN for simulated cross-over points

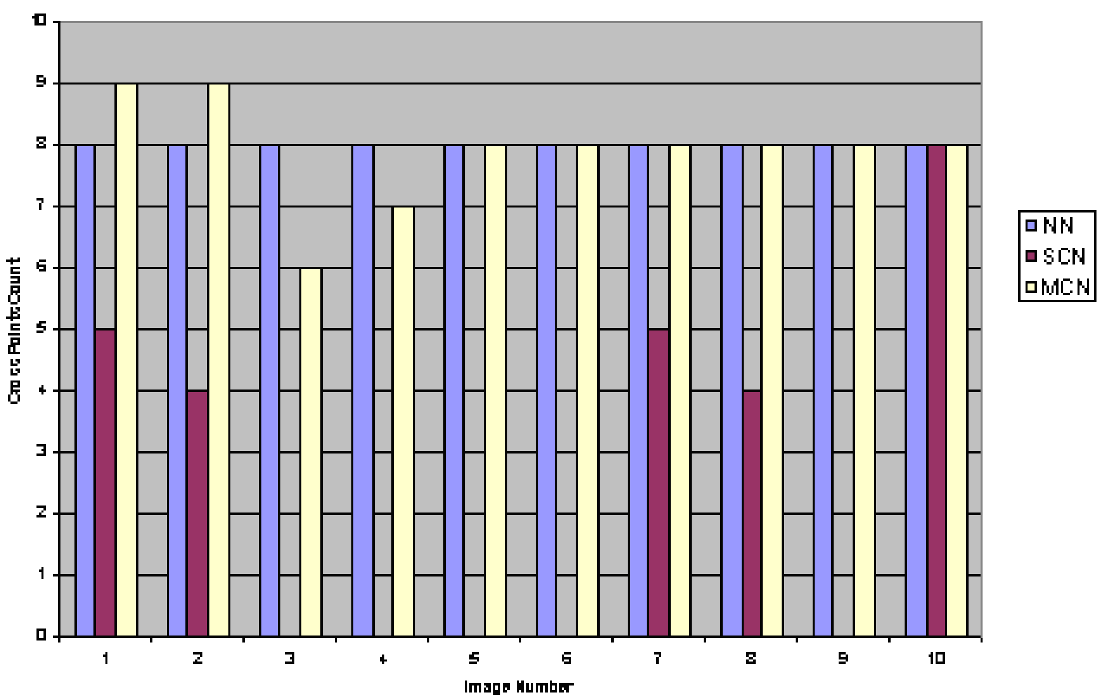

Fig. 11. Comparing SCN, MCN and neural network technique for simulated cross-over points