Segmentation of Blood Vessels in Retinal Color Images

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Abstract :

The appearance and structure of blood vessels in retinal images play an important role in diagnosis of eye diseases. This paper compares [3] [4] a computer based approaches for the detection of blood vessels using fundus images. Image preprocessing, morphological processing techniques, edge detection and postprocessing methods are applied on the fundus images to detect and extract the retinal blood vessels. The purpose of this study was to compare the effectiveness of two blood vessel segmentation algorithms. Fifteen fundus images from the STARE database were used to develop two algorithms using the CVIPtools.

This paper provides the comparisons for the reliable evaluation of automatic methods for detecting diabetic retinopathy in two algorithms. Here the comparison of two algorithms for segmentation of blood vessels in color retinal images for extraction of the minor blood vessels and major blood vessels in fundus images to help ophthalmologists.

The effectiveness of the developed algorithms are assessed by comparing its segmentations[4] to the segmentations [3] of two manually-developed algorithms using Signal-to-Noise Ratio (SNR), Root Mean Square (RMS) error and Pratt’s Figure of Merit (PFM) so that it helping ophthalmologists to detect the severity of eye-related diseases and prevent vision loss.

Keywords : Diabetic retinopathy, CVIP tools , SNR , Hough transform.

I. INTRODUCTION

In clinical ophthalmology color retinal images acquired from digital fundus camera are widely used for detection and diagnosis of diseases like diabetic retinopathy, hyper-tension and various vascular disorders. Retinal images provide information about the blood supply system of the retina. Diabetic retinopathy is a disorder of the retinal vasculature that eventually develops to vision loss of patient

Diabetic retinopathy (DR) is a common retinal complication associated with diabetes. It is a major cause of blindness in both middle and advanced age groups. Diabetic retinopathy has the three stages Background diabetic retinopathy, Proliferate diabetic retinopathy, Sever diabetic retinopathy where the retinal vessels swells in the primary stage and is weaker and damaged due to that fluid leaking from the blood vessels into the retina and settle at center of retina. In extreme cases, the patient will become blind. Therefore, early detection of diabetic retinopathy is crucial to prevent blindness. Early detection of the disease via regular screening is particularly important to prevent vision loss. In this process, an automated DR diagnostic system can assist in a big way since a large population has to be screened and that too repeatedly.

The timely diagnosis of diabetic retinopathy can prevent 98% of severe visual loss, for that, the patient has to undergo regular screening of eye for retinopathy. This process involves dilating the eyes with mydriatic drops and capturing the retinal image using standard digital color fundus camera. Screening program results in large number of retinal images needed to be examined by ophthalmologists. Manual diagnosis is usually performed by analyzing images from a patient, as not all images show signs of diabetic retinopathy. It increases the time and decreases the efficiency of ophthalmologists. Therefore, an automatic segmentation of an image could save workload of the ophthalmologists and may assist in characterizing the detected and to identify false positives [5]. Another important application of automatic retinal vessel segmentation is in the registration of retinal images of the same patient taken over period of time [6].

II. MATERIALS

A. Image Database:

Fifteen color retinal images were collected from the Structured Analysis of the Retina (STARE) image database.

B. Hand-Drawn Images: Images of 15 ophthalmologists’ hand-drawn tracings (ideal segmentations) of the retinal blood vessels in the color retinal images mentioned above, were also downloaded from the STARE.The ideally segmented images were used for vessels segmentation to compare to the CVIP-ATAT developed algorithm and to manually developed algorithms, to make an assessment of the comparative effectiveness of the three algorithms.

C. Software: The CVIP tools (Computer Vision and Image Processing tools) software libraries were used to perform all image processing operations, as well as to calculate the differences between the ophthalmologists' hand-drawn images and the segmented images generated by the algorithms [3,4]. The calculations used as metrics for algorithm effectiveness included Signal-to-Noise Ratio (SNR), Root Mean Square (RMS) error and Pratt's Figure of Merit (PFM). The CVIP-ATAT software was developed using CVIP tools' library functions.

III . RELATED WORK

Comparison of Two Algorithms in the Automatic Segmentation of Blood Vessels in Fundus Images [3] paper generates two methods for blood vessels segmentation in retinal images and compares the effectiveness of two methods. In this paper first method [3]A extracts most of the major vessels, while the second method [3]B extracts all of the major blood vessels and many of the minor ones. The comparison of two methods is done with respect to the SNR, FOM and RMS error.

Development of a New Algorithm for Blood Vessel Segmentation in Retinal Images [4] paper describes use of the Image Processing Algorithm Test which tested thousands (CVIP-ATAT) of permutations of parameter values in a retinal-image, blood-vessel-segmentation algorithm using Signal-to-Noise Ratio (SNR), Root Mean Square (RMS) error and Pratt's Figure of Merit (PFM).An improved matched filter for blood vessel detection of digital retinal images [7]. Retinal Image Blood Vessel Segmentation [8] the automated vessel segmentation technique for colored retinal image that enhances the vascular pattern using 2-D Gabor wavelet. The technique creates a binary mask for vessel segmentation applying adaptive thresholding on enhanced retinal image.

Both the algorithms enhance the details of image by using preprocessing methods so to smoothen the images. After preprocessing both algorithms used the edge detection and the median filter to extract the vessels from the image and also to enhance the details of blood vessels. There is several methodology use in both the algorithm to extract blood vessels from retinal color images.

IV. PROPOSED PROCESSES

A. Preprocessing:

In algorithms images were resized from fewer pixels to more pixels to provide greater resolution. The green band was extracted from the color fundus images because it has maximum contrast, is less affected by variations in illumination and consequently has the most pertinent visual information. A histogram stretch is [3]A to increase contrast between the blood vessels and the background (fundus) and consequently increase blood vessel details and resolution.

B. Mean Filter

Instead of a histogram stretch [3]B employed the method with an Yp mean filter to remove salt and pepper noise and to smooth the images. The Yp mean filter gives better noise removal and image smoothing than other filters.

$$Y_p Mean = \left[\sum_{(r,c)\epsilon W} \frac{(d(r,c)^P)}{N^2}\right]^{\frac{1}{p}} \text{..................} \quad (1)$$

Where d(r,c) are the degraded image pixel values, N is the filter window size and W is the current NxN window centered at d(r, c).

C. Morphological Filtering using a small structuring element:

A morphological-filtering opening operation with a size-5 rectangular structuring element was performed [3] A after the histogram stretch in Algorithm. An opening operation consists of image object erosion followed by dilation and eliminates all pixels in regions that are too small to contain the structuring element thereby "smoothing" the vessels' shapes and enhancing their fundamental geometric properties. "Opening" opens up (expands) holes and erodes edges. Also, noise patterns were removed, through opening due to its ability to erode small noise points. At the same time opening helps fill in small holes in the vessels while connecting disjoint parts that are supposed to be connected.

D. Detection:

The both algorithms employed a Laplacian edge detector to extract the blood vessels' features from the image. . Laplace Edge Detector is a gradient based operator which uses the Laplacian to take the second derivative of an image.

E. Post Processing:

Then, in postprocessing both the algorithm converted the images from color, to gray scale, to binary images on which a logical NOT operation was performed. At this point, because Algorithm is extracted most of the major and minor [3] A Vessels with some intersections and bifurcations missing, vessels segments were tried to reintegrate using the Hough transform.

Hough transform basically finds lines which are a collection of edge points that are adjacent and have same direction. The Hough algorithm takes a collection of n edges points found by the Laplacian edge detector and finds all the lines on which these edge points lie efficiently. In other algorithm after the Not operation instead of using a Hough Transform for collection of edge points, the output images from NOT step gives to the edge-linking [3]B contained pho tographic, image-edge artifacts which gives the better match with the ophthalmologist-segmented images.

For the better results and to remove the outer ring algorithm [4] proposed that the edge linking contained photographic image can be removing by subtracting edge linking out image into corresponding outer-ring masks from them this post processing step helped create a better match with the ophthalmologist-segmented images which had no edge artifacts. The outer-ring masks were threshold with a threshold value of 128.

The algorithm [3] A help to extract most of the major blood vessels and algorithm [3] B extract major and with that some minor blood vessels also extracted in that algorithm. But both the algorithms in paper [3] have the outer ring so to remove the outer ring generate the outer ring mask and subtract the outer ring mask with the edge linking output.

V. EVALUATION TOOLS

Both the algorithm compares there result on the basis of Figure of merit, Signal to noise ratio and Root means square error.

Pratt's Figure of Merit (FOM) measures the success of an edge detector by comparing the distance between edges in an original image to the edges in its edge-detected counterpart. It ranges from 0 –1. The FOM for a missing edge is 0 (0% edges detected). For a perfectly-detected edge it is 1(100%). The FOM takes into account the types of errors that can occur with edge detection methods.

The types of errors are: 1) missing valid edge points, 2) classifying noise pulses as valid Edge points, and 3) smearing of edges.

If these errors do not occur, we can say that we have Achieve success in edge detection.

The Pratt FOM is defined as:

$$FOM = \frac{1}{I_N} \sum_{i=1}^{I_F} \frac{1}{1+\alpha d_i^2} \quad \text{------------------} \quad \textbf{(2)}$$

Where *II* is the number of ideal edge points in the image, *IF* = the number of edge points found by the edge detector, *IN* is the maximum of *II* and *IF*, *α* is a scaling constant that can be adjusted to adjust the penalty for offset edges, and *di* is the distance between a found edge point to an ideal edge point. For this metric, the FOM will be 1 for a perfect edge. Normalizing to the maximum of the ideal (*II*) and found (*IF*) edge points guarantees a penalty for smeared edges or missing edge points. In general, this metric assigns a better rating to smeared edges than to offset or missing edges. This is done because techniques exist to thin smeared edges, but it is difficult to determine when an edge is missed.

Peak Signal-to-Noise Ratio (SNR) is used to measure the amount signal compared to the noise in the signal. Here, we use it to measure the amount of correct signal (correct segmentation) in the output image as it compares with the amount of segmentation inaccuracy (error). SNR is highest when the output image more perfectly matches the hand-drawn image. A higher SNR means there is more signal strength or more accurate segmentation in the output.

$$SNR = 10 log_{10} \frac{(L-1)^2}{\frac{1}{N^2}\sum_{r=0}^{N-1}\sum_{r=0}^{N-1}[f(r,c)-I(r,c)]^2} \quad \text{.....................} \quad \textbf{(3)}$$

Where L is the number of gray levels in the image (e.g., L = 256 gray levels is facilitated by 8 bits) **The Root Mean Square (RMS) Error is found by taking the square root of the error squared divided by the total number of pixels in the image:**

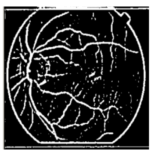
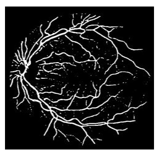
$$e_{RMS} = \sqrt{\frac{1}{N^2}\sum_{r=0}^{N-1}\sum_{r=0}^{N-1}\left[f(r,c)-I(r,c)\right]^2} \ldots \quad \text{............................} \quad \textbf{(4)}$$

VI. EXPERIMENTAL RESULTS:

These results [2] In terms of SNR, the improvements of the CVIP-ATAT-developed algorithm over manually-developed Algorithms A and B in [3] were 11.40 % and 9.95 % respectively. In terms of RMS error, the improvements of the software's algorithm over Algorithms 1 and 2 were 69.13 % and 70.06 %, respectively. In terms of PFM, the improvements were 48.84 % and 54.27 %, respectively.

As the outer ring removed from the resulted segmented image [4] SNR percentage increases for CVIP-ATAT for Algorithm [3] is 31.63% and RMS Percent Decrease for CVIP-ATAT [4] vs. Algorithm [3] is -18.9. Figure 2 shows the blood vessels [3] extracted image for algorithm 1 and Figure 3 shows the blood vessels [4] extracted image for algorithm 2.

TABEL 1: RRESULS OF TWO ALGORITHMS

	Algorithm 1	Algorithm2
Figure of merits	54.27 %	81.10 %
Avg.Signal to noise ratio	9.959 %	13.109 %
Root means error square	70.06 %	56.816 %
Output		

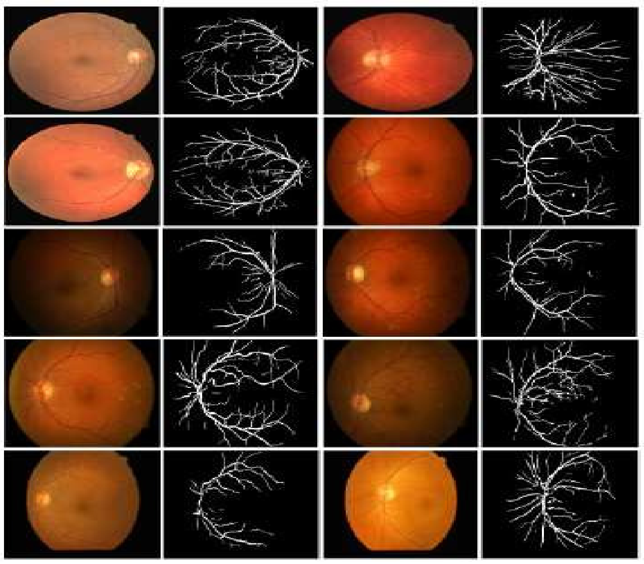


Fig1. Results of Algorithm 2 for random samples of Original and Segmented Images

VII. CONCLUSION

Algorithm 1 extracted most of the major vessels, while Algorithm 2 extracted *all* of the major blood vessels and many of the minor ones.it should be apparent by observation that both Algorithms 1 and 2 areextracting most (approximately 90-95%) of the vessels. Algorithm 2 has an FOM that is 10% higher thanAlgorithm1. Algorithm 2 also has a 6%-higher SNR than Algorithm1. Although Algorithm 2 has 1.3%more RMS error than Algorithm 1, this comparative amount of error is negligible. Algorithm 3 extracts most of the major and minor blood vessels and the outer ring is subtracted so the FOR is increase by 27% and RMS is reduce to 14 %.

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