Analysis of Retinal Images Using Detection of the Blood Vessels by Optic Disc and Optic Cup Segmentation Method

S. Beula Princy and Dr.S. Duraisamy

Abstract--- Retinal images are widely used for diagnostic purposes by ophthalmologists. Therefore, these images are suitable for digital image analysis for their visual enhancement and pathological risk or damage detection. In this paper, the optic disc segmentation and optic cup segmentation processes are used to detect and segment the blood vessels from the retinal image for indicate the normal and retinal disease diagnosis. The proposed system consists of following further steps for analysis of fundus images. At first the preprocessing of retinal image to enhance by using the Contrast Limited Adaptive Histogram Equalization CLAHE, before enhancement of the Retinal Image, which is filtered and removed unwanted noises from images using Median Filtering Method and after enhancement of the images, the Optic Disc segmentation is done by using Improved Markov random field (IMRF) and Optic Cup blood vessel segmentation using Artificial Neural Network (ANN) classifier. The proposed retinal image analysis system performance is analyzed by using publicly available retinal image dataset.

Keywords--- Contrast Limited Adaptive Histogram Equalization CLAHE, Median Filtering Method, Markov Random Field (IMRF), Optic Cup Blood Vessel Segmentation, Artificial Neural Network (ANN) Classifier

I. INTRODUCTION

Retinal images are influenced by all the factors that affect the body vasculature in general. The human eye is a unique region of the human body where the vascular condition can be directly observed. In addition to fovea and optic disc, the blood vessels contribute one of the main features of a retinal fundus image and several of its properties are noticeably affected by worldwide major diseases such as diabetes, hypertension, and arteriosclerosis. Further, certain eye diseases such as choroidal neovascularization [1] and retinal artery occlusion [2] also make changes in the retinal vasculature. The segmentation of retinal image structures has been of great interest because it could be used as a nonintrusive diagnosis in modern ophthalmology. The morphology of the retinal blood vessel and the optic disk is an important structural indicator for assessing the presence and severity of retinal diseases. The segmentation of blood vessels in retinal images can be a valuable aid for the detection of retinal diseases diagnosis.

One of the important tasks of analysis of the retinal images is segmentation of the Optic Discs (OD) and Optic Cup. Moreover, correct segmentation of the OD contour is a non-trivial problem. The natural variation in the characteristics of the OD is a major difficulty for defining the contour. Blood vessels may cross the boundary of the OD obscuring the rim of the disc, with edges of vessels also acting as significant distractors [3]. Another task of retinal image analysis is Optic cup segmentation, which is to determine the boundary of an excavation or depression in the optic disc. In [4], a method was described to segment the cup using pixel features from stereo disparity maps. Also, [5] described a deformable model which included depth information from images.Both optic disc segmentation [6] and optic cup segmentation [7] was able to utilize depth information from the imaging modality itself.

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In fundus image, the images captured without depth information, which increases the difficulty of detecting the cup contour accurately. In certain images, there is a difference in the color, or pallor, or the optic cup compared to the optic disc, and color [8] and edge-based methods [9] can be employed. However, another difficulty in the use of pallor is the clinical recognition [10] that there is a potential discrepancy between the actual size of the cup and its pallor. Furthermore, when there is no pallor difference between cup and disc, use of only pallor can lead to erroneous optic cup segmentation, particularly temporally.

In past years, several segmentation techniques have been employed for the segmentation of retinal structures such as blood vessels and optic disc and diseases like lesions in fundus retinal images. An automated segmentation and inspection of retinal blood vessel features such as diameter, color and tortuosity as well as the optic disc morphology allows ophthalmologist and eye care specialists to perform mass vision screening exams for early detection of retinal diseases and treatment evaluation. This could prevent and reduce vision impairments; age related diseases and many cardiovascular diseases as well as reducing the cost of the screening. However the acquisition of fundus retinal images under different conditions of illumination, resolution and field of view (FOV) and the overlapping tissue in the retina cause a significant degradation to the performance of automated blood vessel and optic disc segmentations. Thus, there is a need for a reliable technique for retinal vascular tree extraction and optic disk detection, which preserves various vessel and optic disk shapes.

II. BACKGROUND STUDY

Optic disc is one of the most important parts of a retinal fundus image [11]. The Figure 1 shows that the sample retinal image s from the publicly available databases such as. The Structured Analysis of Retina (STARE) dataset [12], MESSIDOR [13] The Online Retinal Fundus Image Dataset for Glaucoma Analysis and Research (ORIGA) [14] and The Standard Diabetic Retinopathy Database Calibration level 0 DIARETDB0 [15]. There is also many numbers of datasets available for Retinal image analysis process.

OD detection is considered a preprocessing component in many methods of automatic image segmentation of retinal structures, a common step in most retinopathy screening procedures [16].The OD has a vertical oval (elliptical) shape [17] and is divided into two separate zones: the central zone or the cup and the peripheral zone or neuroretinal rim [16]. Changes in the color, shape, or depth of OD are indications of ophthalmic pathologies such as glaucoma [18]; therefore, OD measurements have important diagnostic values [19]. Accurate detection of the central point of OD is important in such measurements. Pathological cases occurring on the OD boundaries, such as papillary atrophy, influence the segmentation accuracy. Ingle andMishra [20] discuss the cup segmentation based on gradient method. Gradient is the variation in the intensity or color of an image. The gradient images were obtained from an original image convolved with a filter. Two methods were used to find the gradient: (1) linear gradient, (2) radial gradient. Wong et al. [21] described a novel technique for detecting blood vessel kinks for optic cup segmentation. The OD and OC segmentation technique proposed by Narasimhan and colleagues [22] implements the open CV library functions based on k-mean clustering and elliptic fitting to calculate CDR.

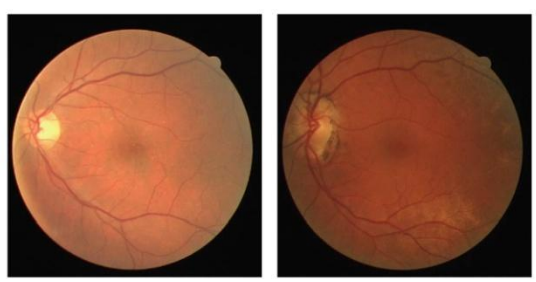

Figure 1: The Sample Normal and Pathological Images from the Datasets

III. PROPOSED METHODOLOGY

The proposed method has implemented to segment the blood vessel from the fundus retinal image with preprocessing technique, which consists of Contrast Limited Adaptive Histogram Equalization and median filtering method. This proposed methodology of the blood vessel optic disc and cup segmentation improves the robustness and the accuracy of the indication of the normal and retinal diseases from the retinal images. The Figure. 1 shows the illustration of the flow of the proposed methodology.

A. Preprocessing

In this fundus image analysis process, apply a contrast enhancement process to the green channel image similar to the work presented in [23]. The intensity of the image is inverted, and the illumination is equalized. The resulting image is enhanced using an advanced version adaptive histogram equalizer i.e. Contrast Limited Adaptive Histogram Equalization (CLAHE) in order enhance the image by using CLAHE, initially the unwanted noises of the retinal images are removed by using the Median filtering method, which are given in detail as follows

Median Filtering Method for Noise Removal

The Median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical preprocessing step to improve the results of later processing such as retinal image enhancement of this proposed methodology. The median filter is normally used to reduce noise in an image. However, it often does a better job than the mean filter of preserving useful detail in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images I_p and I_q

$$median\left[I_p + I_q\right] \neq median\left[I_p\right] + \ median\left[I_q\right] \ (1)$$

These filters smooths the image while keeping the small and edge details. The median is just the middle value of all the values of the pixels in the neighborhood. instead, the median has half the values in the neighborhood larger and half smaller. The median is a stronger "central indicator" than the average. In particular, the median is hardly affected by a small number of discrepant values among the pixels in the neighborhood. After reduce of noises from the retinal images, the image is enhanced for efficient segmentation purpose.

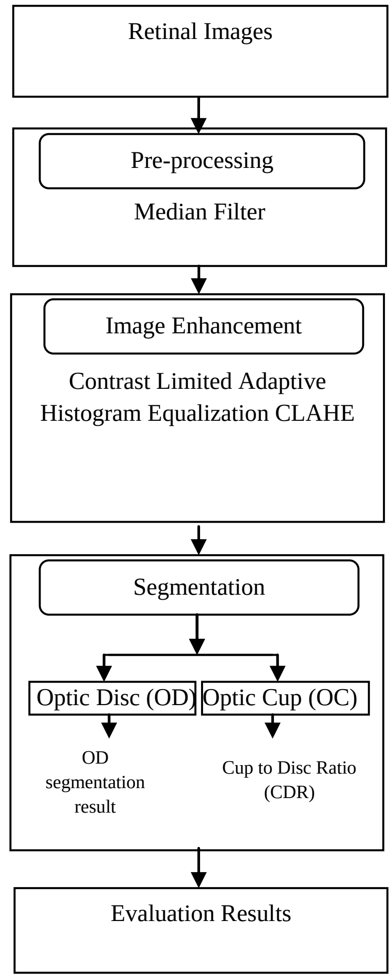

Figure 2: Flow of the Proposed Methodology for Retinal Image Analysis

B. Image Enhancement Using Contrast Limited Adaptive Histogram Equalization CLAHE

Adaptive histogram equalization (AHE) transforms each pixel in a gray-scale image using a transformation function that is derived from a neighborhood region. Simply, each pixel is transformed based on the histogram of a square surrounding the pixel. The transformation function derived from the histograms is similar to those of the ordinary HE, where the transformation function is proportional to the pixel values cumulative distribution function (CDF) in the neighborhood. AHE enables information with various intensities to be analyzed simultaneously [24]. This method is also automated and reproducible. However the results of AHE are image dependent and limited to images with low contrast variation only. CLAHE uses RGB images directly and as such, the noise content of an image is not excessively enhanced in the resulting image, nevertheless visualization of the structures within the image is made by the sufficient contrast enhancement. This is achieved by limiting the contrast enhancement of AHE when the contrast amplification around a given pixel value is obtained according to the slope of the transformation function [25]. Thus, limiting the slope of the CDF is done by CLAHE when it limits the amplification by clipping the histogram at a predefined value before computing the CDF. The clip limit depends on the size of the neighborhood region and the normalization of the histogram. Images tend to appear more natural when processed with and can facilitate the comparison of different areas of the image [26]. However, the ability of an observer to detect the presence of some significant gray-scale contrast may be hindered because of the reduced contrast enhancement of CLAHE [27]

C. Blood Vessel Segmentation

Optic Disc Segmentation

The optic disk segmentation starts by defining the location of the optic disk. This process used the convergence feature of vessels into the optic disk to estimate its location. The disk area is then segmented using two different automated methods (Improved MRF image reconstruction and compensation factor) and also another optic cup segmentation method. First two methods use the convergence feature of the vessels to identify the position of the disk. The IMRF method is applied to eliminate the vessel from the optic disk region. This process is known as image reconstruction and it is performed only on the vessel pixels to avoid the modification of other structures of the image. The reconstructed image is free of vessels and it is used to segment the optic disk via graph cut. In contrast to IMRF method, the compensation factor approach segments the optic disk using prior local intensity knowledge of the vessels and The OC algorithm provides the cup and disc area in all directions of the images as well as CDR, instead of relying on the accuracy only in one direction, which is provide the high segmentation accuracy result of this proposed method.

Optic Disk Location

Inspired by the method proposed in [28], which effectively locates the optic disk using the vessels, and use the binary image of vessels segmented to find the location of the optic disk. The process iteratively traces toward the centroid of the optic disk. The vessel image is pruned using a morphological open process to eliminate thin vessels and keep the main arcade.

Optic Disk Segmentation with IMRF Image Reconstruction

The high contrast of blood vessels inside the optic disk presented the main difficulty for its segmentation as it misguides the segmentation through a short path, breaking the continuity of the optic disk boundary. To address this problem, the IMRF based reconstruction method presented in [29] is adapted in this work. In this proposed work have selected this approach because of its robustness. The objective of our algorithm is to find a best match for some missing pixels in the image; however, one of the weaknesses of the IMRF-based reconstruction is the requirement of intensive computation. To overcome this problem,have limited the reconstruction to the ROI, and using prior segmented retina vasculartree, the reconstruction was performed in the ROI.

Optic Disk Segmentation with a Compensation Factor

In contrast to the MRF image reconstruction, we have incorporated the blood vessels into the graph cut formulation by introducing a compensation factor V_{ad}. This factor is derived using prior information of the blood vessel. The energy function of the graph cut algorithm generally comprises boundary and regional terms.

The boundary term defined by,

$$b(G) = \sum_{p,q \in N} b_{p,q} . \emptyset(G_p, G_q) \ (2)$$

Where, $\emptyset(G_p, G_q)$=1 for $G_p \neq G_q$ and 0 otherwise, which is used to assign weights on the edges (n-links) to measure the similarity between neighboring pixels with respect to the pixel proprieties (intensity, texture, and color). Therefore, pixels with similar intensities have a strong connection. The regional term given by

$$R(G) = \sum_{q \in Q} R_q(G_q) \ (3)$$

Which is derived to define the likelihood of the pixel belonging to the BG or the FG by assigning weights on the edges (t-link) between the image pixels and the two terminals BG and FG seeds $R_q(G_q)$ specifies the assignment of pixel p to either the FG or the BG. $b_{p,q}$ defines the discontinuity between neighboring pixels, and its value is large when the pixel intensities $Ip \ and \ Iq$ are similar and close to zero when they are different. The value of $b_{p,q}$ is also affected by the Euclidean distance dist (p, q) between pixels p and q.

The intensity distribution of the blood vessel pixels in the region around the optic disk makes them more likely to belong to BG pixels than the FG(or the optic disk pixels). Therefore, the vessels inside the disk have weak connections with neighboring pixels making them likely to be segmented by the graph cut as BG. And this work introduce in

$$S_l = \begin{array}{l} -\ln p_r \ \frac{I_p}{FG_{seeds}}\Big) if P \neq vessel \\ -\ln p_r \ \frac{I_p}{FG_{seeds}} \ + Vad \ if P = vessel \end{array}$$

$$\text{and } T_l = \begin{array}{l} -\ln p_r \ \frac{I_p}{BG_{seeds}}\Big) if P \neq vessel \\ -\ln p_r \ \frac{I_p}{BG_{seeds}} \ \ if P = vessel \end{array} \quad (4)$$

Where $V \ ad$ is the compensation factor, P is the pixel in the image, FG seeds is the intensity distribution of the FG seeds, BG seeds represents the intensity distribution of the BG seeds a compensation vector to all t-links of the FG for pixels belonging to the vascular tree to address this behavior. Consequently, vessels inside the optic disk are classified with respect to their neighborhood connections instead of their likelihood with the terminals FG and BG seeds. The segmentation of the disk is affected by the value of $V \ ad$, and the method achieves poor segmentation results for low value of $V \ ad$. However, when the value of the $V \ ad$ increases, the performance improves until the value of $V \ ad$ is high enough to segment the rest of the vessels as FG.

Optic Cup Segmentation

Optic Cup segmentation is also a challenging task in fundus images which do not carry depth information, which is the primary indicator of the cup boundary. Another segmentation method used in this work, which can be extended to differentiate between the abnormal and normal images. The automatic detection of the optic cup is based on vessel kinking. To detect the kinks, first the vessels must be detected.The smaller vessels are harder to detect. Therefore, a segmentation technique for small vessel detection was introduced by fusing pixel features and a Artificial Neural Network classification. Patches of interest (POI) were generated within the optic nerve head. Then features for detecting small vessels were generated, where the green channel was chosen for the feature generation due to its better visibility for the vessels. A wavelet transform was generated for each POI using Modified Gabor filter to detect the overall architecture of vessels. A sobel edge detector was applied to detect all possible vessels. Finally, the feature in the vessels segment based approach was fused instead of pixel classification for the vessels and non-vessels. Kinking was localized by analyzing the identified vessels segments and locating points of maximum curvature on the vessels (i.e., to fit the segment to a curve).The obtained kinks are combined with pallor-based information to determine the optic cup and which is used to indicate the retinal image as normal or abnormal.

The proposed retinal image analysis based on the detected cup, cup-to-disc ratio(CDR) and optic disc segmentation is efficiently indicated for assessing the presence and severity of retinal diseases such as diabetic retinopathy, hypertension, glaucoma, hemorrhages, vein occlusion, and neovascularization or normal.

IV. EXPERIMENTATION RESULTS

Performance Analysis

For performance analysis of this proposed the vessel segmentation method, used public datasets, DRIVE with a total of 40 images. The optic disk and optic cup segmentation algorithm was tested on DRIVE, consisting of 60 images in total. The performances of these methods are tested against a number of alternative methods. To facilitate the performance comparison between proposed method and existing retinal blood vessels segmentation approaches, parameters such as the true positive rate (TPR), the false positive rate (FPR), and the accuracy rate (ACC) are derived to measure the performance of the segmentation.

Accuracy: It is defined as the sum of the true positives (pixels correctly classified as vessel points) and the true negatives (nonvessel pixels correctly identified as nonvessel points), divided by the total number of pixels in the images.

True Positive Rate (TPR): It is defined as the total number of true positives, divided by the number of blood vessel pixels marked in the ground true image.

False Positive Rate (FPR):The FPR is calculated as the total number of false positives divided by the number of pixels marked as nonvessel in the ground true image.

The table 1 shows that the performance of the proposed and existing retinal segmentation methods comparison through the DRIVE Dataset Images.

Table 1: Comparison of the Performance of the Proposed and Existing Methods in the Drive Dataset

METHODS	DRIVE Dataset Images		
	TPR	FPR	ACCURACY
MF-FDOG	66.98	70.15	85.23
Multithreshold probing	69.81	73.25	89.48
Multiscale feature extraction	77.47	79.98	91.59
Proposed OD-OC Method	79.43	78.23	95.89

The figure 3 show that the accuracy result comparison of the proposed and existing methods. The graphical representation proves that proposed OD-OC based blood vessel segmentation method provides the high accuracy values than the existing methods.

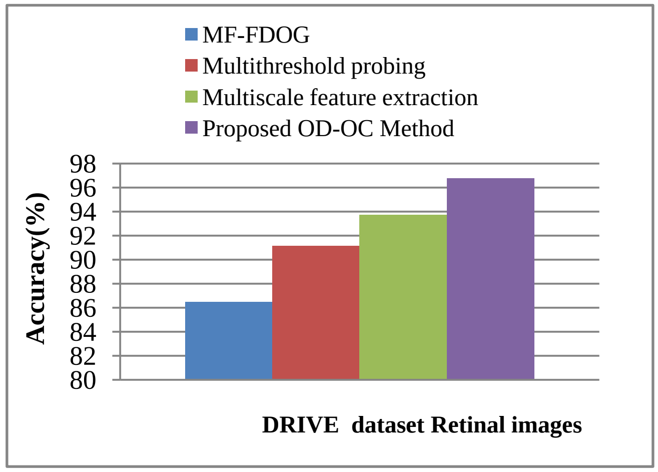

Figure 3: The Accuracy Results of the Proposed and Existing Methods in the Drive Dataset

V. CONCLUSION AND FUTURE WORK

An important task for diagnosis of retinal diseases at earlier stage is used the blood vessel segmentation. The retinal optic disc and optic cup segmentation is proposed in this work to detect and segment the blood vessels from the retinal image .The retinal image is filtered and enhanced by Median filter and Contrast Limited Adaptive Histogram Equalization CLAHE. Further process of this proposed method is segmented blood vessels using optic disc and optic cup segmentation methods and the results in the retinal fundus images shown the efficiency of the proposed blood vessel segmentation method for identification of retinal diseases and normal images. In future work includes the blood vessels features extraction method and add large number of dataset images for increasing accuracy of segmentation which is more accurately to indicate the retinal diseases and normal retinal images.

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