OPTIC DISC BOUNDARY SEGMENTATION IN RETINAL IMAGE USING MORPHOLOGY, EDGE DETECTION AND CIRCULAR HOUGH TRANSFORM

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Abstract—Image processing is technical analysis that breaks down the image to its basic features -shapes, textures, shadow, and lines to know what lies inside. Fundus photography involves capturing a photograph of the back of the eye i.e. fundus. Specialized fundus cameras that consist of an intricate microscope attached to a flashed enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc and macula. Diabetes is a disorder of metabolism. The effect of diabetes on the eye is called Diabetic Retinopathy (DR). It is known to damage the small blood vessel of the retina and this might lead to loss of vision. Accurate segmentation of fundus image is critical for mass screening and monitoring of ocular diseases. It provides a better source of information for studying the various ocular morphologies which helpful to improve clinical outcomes, prognosis, patient diagnosis and treatment planning. Optic disc detection is the first step of most vessel segmentation, disease diagnostic, and retinal recognition algorithms. For this purpose, circular boundary segmentation is proposed using Prewitt Operator and Circular Hough Transform. The algorithms were evaluated on the 217 images of the publicly available Db0 and Db1 database. The proposed algorithm was carried out in parallel in both red and green channel. The red channel yields better results out of the two with 81.56% efficiency as compared to green channel with 77% efficiency.

Keywords—Diabetic Retinopathy, Optic disc segmentation, Retinal imaging.

I. INTRODUCTION

Fundus is the bottom or base of anything. In medicine, it is a general term for the inner lining of a hollow organ. The ocular fundus is the inner lining of the eye made up of the Sensory Retina, the Retinal Pigment Epithelium, Bruch's Membrane, and the Choroid [1]. Fundus photography involves capturing a photograph of the back of the eye i.e. fundus. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc and macula [2]. The major leading causes of blindness and visual impairment that affect human eyes are DR, glaucoma, age-related macular degeneration (AMD) and Cataract. Diabetic Retinopathy (DR) is a disease which nowadays constitutes the primary cause of blindness in people of working age in the developed world. Early diagnosis of these two conditions is necessary as it can help to stop the progress of this disease thus keeping the sight and preventing blindness. DR is a complication in the retina due to diabetics. Its characteristic features are Microaneurysms (MA), Haemorrhages (H), and Exudates (hard exudates (HEx) and soft exudates (SEx)).

The benefits that a system for automatically detect early signs of this disease would provide have been widely studied and assessed positively by experts [3], [4]. In this sense, the OD plays an important role in developing automated diagnosis expert systems for DR as its segmentation is a key pre-processing component in many algorithms designed to identify
other fundus features. On the other hand, to segment the vascular tree, vessel tracking methods need an initial seed vessel point. For this, pixels of vessels within the OD or in its vicinity have been used [5], [6]. In addition, OD segmentation can be useful in diagnosing automatically some diseases caused by DR. Finding the OD can be used to decrease false positives in the detection of regions of retinal exudates [7]. These injuries are a diagnostic key to grading the risk of macular edema. OD segmentation is also relevant for automated diagnosis of other ophthalmic pathologies. One of them and maybe the most noteworthy is Glaucoma. In this paper we use Circular Hough Transform to approximate the circumference of OD boundary. The OD boundary is extracted by means of morphological and edge detection technique in both red and green channel. The channel that gives better result is finally selected.

II. LITERATURE SURVEY

There have been an increase in the use of digital image processing techniques for the screening of DR after it was recommended as one of the method for screening DR at the conference on DR held in Liverpool UK in 2005 [8]. With this increase more work have been done to improve some of the existing screening method while new methods have also been introduced in order to achieve better results. Study of fundus image is considered to be the best diagnostic modality available till date as it is reliable and easy to use. Although the OD has well-defined features and characteristics, localizing the OD automatically and in a robust manner is not an easy and straight forward process, since the appearance of the OD may vary significantly due to retinal pathologies. Consequently, in order to effectively detect the OD, the various methods developed should consider the variation in appearance, size, and location among different images [9].

❖ Osareh proposed a method based on template matching for localizing the centre of optic disc. In this algorithm, some of retinal images in dataset were used to create a template and the correlation between each image and template is computed. The point which has the maximum correlation value is selected as the centre of optic disc [2].

❖ Alireza Osareh proposed the method of using colour morphology and snakes for optic disc localization. In the work, template matching provided an approximate location of the OD centre to automatically position a snake on a morphologically enhanced image. After applying a simple Lab space color morphology step, the system can localize the optic disc in all test images [7].

❖ A template-matching approach was implemented by Lalonde et al. The design relies on template-matching technique using edge maps, guided by pyramidal decomposition for large-scale object tracking. The proposed methods were tested with a dataset of 40 fundus images of variable visual quality and retinal pigmentation, as well as of normal and small pupils. An average error of 7% in positioning the centre of the ONH was reported [10].

❖ Hough transform; a technique capable of finding geometric shapes within an image was employed to detect the OD. In Abdel-Ghafar et al. employed the circular Hough transform (CHT) to detect the OD which has a roughly circular shape. The retinal vasculature in the green-band image was suppressed using the closing morphological operator. The Sobel operator and a simple Threshold were then used to extract the edges in the image. CHT was finally applied to the edge points, and the largest circle was found consistently to correspond to the OD [11].

❖ Aquino et al. used two independent methodologies to detect optic disc in retina images. Location methodology obtains a pixel that belongs to the optic disc using image contrast
analysis and structural filtering techniques. Then, a boundary segmentation methodology estimates a circular approximation of the optic disc boundary by applying mathematical morphology, edge detection techniques, and the circular Hough transform. This paper proposes a technique for measuring vessel width and tortuosity in the posterior pole of the retina, and shows how it can be used to demonstrate statistically significant changes in these parameters for ROP subjects. The technique firstly implements segmentation of the retinal vasculature. This is carried out using morphological pre-processing based on linear structuring elements, followed by enhancement using a smoothed second-derivative operator. A final stage of morphological post-processing is then used, prior to thresholding [12].

Arturo Aquino, Manuel Emilio Géndez-Arias, Diego Marín presented a new template based methodology for segmenting the OD from digital retinal images. This methodology uses morphological and edge detection techniques followed by the Circular Hough Transform to obtain a circular OD boundary approximation [13].

III. METHODOLOGY

This paper introduces a new methodology for OD segmentation that obtains a circular boundary approximation. Initially, the information of the coordinates pixel located within the OD is needed. A simple but reliable and very fast OD location methodology is also proposed to obtain the required OD pixel in order to complement the presented segmentation methodology. It must be stressed that any other location method could be used for this purpose.

A) Optic Disc Boundary Segmentation: The method proposed in this paper is performed on an RGB image of the original retinography. Although the green component of an RGB retinography is the one with highest contrast [14], the OD in the red field is often present as a well-defined white circular shape, brighter than the surrounding area. When contrast between the OD shape and its surrounding area in this color field is high enough, the OD can be segmented even better than in the green field. However, if the OD is not easily distinguishable from its environment, the green channel is preferred. The OD segmentation is performed side by side on the two components and the “better” of the two segmentations is ultimately selected. Blood vessels are eliminated by means of a special morphological processing. Then, a binary mask of the OD boundary candidates is obtained by applying edge detection and morphological techniques. Finally, the Circular Hough Transform is used to approximate the circular boundary of the OD.

1) Elimination of Blood Vessels: Consider the gray-level image from the red or green field of the fundus image. The blood vessel within the OD lowers the efficiency of the OD detection since they act as distractors, so they should be erased from the image beforehand. The vasculature is piecewise linear and can be considered as a structure composed of many such connected linear shapes with a minimum length $L$ and a maximum width $W$, where usually $W << L$ (see Heneghan et al. [15]). These linear shapes, as a general rule, comprises of a set of pixels with an almost constant gray-level. The value of these set of pixels is somewhat lower than the gray-level values of non-vessel pixels in their vicinity. Thus vessels can be removed.
from image $I$ using morphological closing. In mathematical morphology, the closing of a set (binary image) $A$ by a structuring element $B$ is the erosion of the dilation of that set,

$$A \bullet B = (A \oplus B) \ominus B$$  \hspace{1cm} (1)

Where $\oplus$ and $\ominus$ denote the dilation and erosion, respectively. In image processing, closing is, together with opening, the basic workhorse of morphological noise removal. Opening removes small objects, while closing removes small holes [16].

2) Obtaining OD Boundary Candidates:
The OD boundary represents the frontier between the OD and the background of the fundus image. The gray levels vary considerably within retinal image, with the higher values within the OD and lower levels corresponding to its surroundings. So, the OD boundary can be detected by measuring the gradient magnitude of gray-level changes in small neighborhoods of the image. Firstly, a mean filter is applied to eliminate pixel values unrepresentative of their environment. Then, the Prewitt edge detector [17] is used to obtain a gradient magnitude image (hereafter $I_{GM}$).

The operator uses two $3 \times 3$ kernels which are convolved with the original image to calculate approximations of the derivatives one for horizontal changes, and one for vertical which estimates image edge and orientation. We take the module of partial derivative values for every pixel and then the gradient image is obtained. Thus, $I_{GM}$ is an image which contains information on edges, specifically on the location and intensity of local gray-level variations (Figure 1, images R-2 and G-2). As the blood vessels were removed in the initial stages, in general the most significant edges in the gradient image correspond to the OD boundary. Thus, a binary mask of OD boundary candidates can be produced by thresholding the image in $I_{GM}$. As stated before, there is great inconsistency in OD appearance, and the contrast level between the OD and the background may vary quite significantly. Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. The simplest thresholding methods replace each pixel in an image with
a black pixel if the image intensity $I_{i,j}$ is less than some fixed constant $T$ (that is, $I_{i,j} < T$), or a white pixel if the image intensity is greater than that constant. Using this threshold, a first binary mask of OD boundary candidates is given by a simple binarization operation. This image $IGM$ can contain some noise caused by small rims present in the original image and detected in $IGM$. So, the final binary mask of OD candidate is obtained by cleaning $I_B$ by means of morphological erosion(Figure 2, images R4 and G4),

$$I_{BM}(i, j) = (I_B)_{C_{MIN}}(i, j)$$

where $C$ is a circular structuring element with a radius 1 pixels.

B) Final OD Boundary Segmentation: The Hough Transform finds its applications in Computer Vision and Pattern Recognition for detecting geometrical shapes that can be defined by parametric equations. Based on the primitive Hough Transform [18], the Circular Hough Transform was outlined by Duda et al. [19] and later improved and extended by Kimme et al. [20]. Circular patterns within an image can be obtained by this method. A set of feature points in the image space is transformed into a set of accumulated votes in a parameter space. Then, for each feature point, the accumulator array stores the accumulated votes for all parameter combinations. The array elements that contain the highest number of votes indicate the presence of the shape. A circumference pattern is described by the parametric equation of the circumference, defined as

$$(x - a)^2 + (y - b)^2 = r^2$$

where $(a, b)$ are the coordinates of the circle center and $r$ is the radius. So, the circular shapes present in $I_{BM}$ can be obtained by performing the Circular Hough Transform on this image. It can be defined as

$$(P_c, r) = CHT(I_{BM}, r_{min}, r_{max})$$

where $P_c = (i_c, j_c)$ and $r$ are respectively the center position and the radius that define the circular shape with the highest punctuation in the Circular Hough Transform implemented by $CHT$. The radius $r$ is restricted to be between $r_{min}$ and $r_{max}$, values which are one tenth and one fifth of the image [5] divided by two (as these measurements refer to OD diameter estimation). The minimum radius restriction reduces the possibility of considering the OD cup, while the maximum radius restriction eliminates candidates with too wide areas. The obtained $r$ value must be corrected due to the effects of (1) and (2). The vessel elimination performed in (2) enlarged the OD pixels and the erosion operation in (2) produced pixel reduction. As previously commented, this processing is applied in parallel to the green and red channels. Thus, two OD approximations are obtained. The one with the higher score in the Circular Hough Transform algorithm is then selected as the definitive circular OD boundary approximation (Figure 2, images R5 and G5). This score measures the point by point matching degree between the estimated circumference and the fitted shape in $I_{BM}$. Therefore, higher scores generally involve better OD border extraction and, hence, better segmentation quality. Moreover, the selection of the correct candidate is also favoured by the fact that the score of this algorithm is an absolute and not a relative measure. This implies that the selected maximum-score criterion tends to select longer candidate circumferences. This is especially useful when the OD cup is wide enough to be considered a candidate, as it
leads to an increased probability of selecting the correct candidate between the cup and the true OD boundary.
Fig. 2. Illustration of the process for the calculation of the circular OD boundary approximation: (C): Initial RBG sub-image containing an OD. (R) and (G) are sub-images extracted from the red and green channels of (C), respectively. (R1) and (G1): Vessel elimination. (R2) and (G2): Gradient magnitude image. (R3) and (G3): Binary image. (R4) and (G4): Cleaner version of the binary image. (R5) and (G5): Circular OD boundary approximation. The scores obtained in the Circular Hough Transform algorithm out of 130 images in Db0 are 106 for segmentation in (R5) and 104 for segmentation in (G5), so the segmentation selected would be the one performed on the red channel. For database Db1 which contains 87 images, the score is 71 for segmentation in (R5) and 63 for (G5).

IV. TESTS AND RESULTS

We have used a dataset of 217 images for evaluating the algorithm. The images were taken from different sources so they have different variations in color, illumination and quality. The images are 1500x1152 pixels in size and 24 bit depth and are provided in PNG format. 130 images were taken from DB0 database and 87 images were taken from DB1 database which were publicly available. The entire algorithm was run on the database and results for optic disk localization and vessel segmentation were obtained. Experiments are carried out using Matlab 2016a on Db0 and Db1 images. The MATLAB code takes 5 seconds per image on an average to run. Table I summarizes the results of our optic disk detection algorithm on the dataset. If the radius range defined by the Circular Hough Transform algorithm falls within the optic disk boundary then it is considered a correct detection and vice versa. The test was carried out in both red as well as green channel of the RGB image. The red channel yields better results than the green channel because it eliminates the blood vessels which act as strong distractors. However for those images with poor illumination, green channel is preferred because it provides higher contrast.

| TABLE I. RESULTS OF OPTIC DISK BOUNDARY DETECTION USING MORPHOLOGY, EDGE DETECTION AND CIRCULAR HOUGH TRANSFORM ON STANDARD RETINAL DATASET |

IJRIS| www.ijrise.org|editor@ijrise.org [56-64]
| Standard Database | Number of images used for testing | Number of images that correctly detects OD boundary | Percentage  
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<tbody>
<tr>
<td>Db0(red channel)</td>
<td>130</td>
<td>106</td>
<td>81.53%</td>
</tr>
<tr>
<td>Db0(green channel)</td>
<td>130</td>
<td>104</td>
<td>80%</td>
</tr>
<tr>
<td>Db1(red channel)</td>
<td>87</td>
<td>71</td>
<td>81.6%</td>
</tr>
<tr>
<td>Db1(green channel)</td>
<td>87</td>
<td>63</td>
<td>72.4%</td>
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V. CONCLUSION

In this paper, a simple and efficient scheme for early detection of Diabetic Retinopathy has been developed. The performance results obtained by the proposed methodology on a standard digital retinal database indicate that basic image processing techniques seem to satisfy for OD location and segmentation. The optic disk is detected by combining mathematical morphology and edge detection techniques. A circular modelling for the final detection of OD boundary is obtained by using Circular Hough Transform. Our techniques may further be combined with some learning methods for possibly even better results.

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REFERENCES


