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DETECTION OF OPTIC DISC FROM DIGITAL FUNDUS IMAGES OF RETINA USING BOTTOM-HAT TRANSFORM AS PREPROCESSING FOR GLAUCOMA DETECTION

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ABSTRACT

Automated retinal image analysis is emerging as an important screening tool for early detection of eye disease. In this automated analysis some factors need to be considered in order to get better analytical results**.** We present in this paper methodology to extract exact boundary of OD in digital retinal fundus images. The method starts with preprocessing of digital fundus images by contrast normalization throughout the image, and removal of blood vessels which is major reason for distraction of finding OD candidate. Further processing is followed by detecting pixel located in OD by three different methods: Maximum difference method, Maximum Variance method & Low Pass filter method. Exact pixel location within OD among the three positions is estimated by Voting type algorithm. Using this point/pixel as seed point during segmentation procedure we extract exact boundary of optic disc using morphological methodology and edge detection techniques followed by circular Hough Transform. The proposed method was evaluated using MESSIDOR data set containing 100 digital fundus images of retina. This method succeeded in 94% of cases of MESSIDOR.

KEYWORDS: Bottom Hat Transform (BHT), Diabetic Retinopathy (DR), Hough Transform, Location Methods, Optic Disc (OD), Segmentation

INTRODUCTION

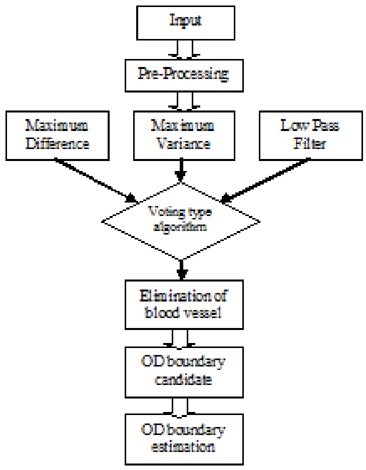
Diabetic retinopathy is a chronic disease. One of the most common cause of blindness is Glaucoma with which about 79 million is the world population likely to be affected with glaucoma by year 2020. The benefits that a system to automatically detect early signs of this disease would provide have been widely studied and assessed positively by experts [4], [5]. Thus OD plays an important role in developing automated diagnosis expert systems for glucoma as its segmentation is a key preprocessing component in many algorithms designed to identify other fundus features such as fovea, vascular tree. OD segmentation is also relevant for automated diagnosis of other ophthalmic pathologies [10], [11]. OD segmentation and analysis can be used to detect evidence of ophthalmic disease such as diabetic retinopathy. Slightly elliptical most bright region in an eye fundus image is OD. Its size may vary significantly researchers have given various estimations. Sinthanayothinet. al [6] stated that it occupies about one-seventh of the entire image, other researchers have pointed out that OD size varies from one person to another occupying one- tenth to one-fifth of the image.

OD segmentation job made harder mainly due to blood vessel occlusion, ill defined boundaries, image variations near the disk boundaries due to pathological changes and variable imaging conditions. Specifically, occurrence of similar regions near disk boundary, irregular shape and boundary are the most essential aspects to be addressed by a OD segmentation method. For better results we remove blood vessels using BHT. This paper presents BHT as preprocessing followed by template based method for OD segmentation. Firstly, image original image is enhanced using BHT then an

OD containing sub-image is extracted from enhanced image: a surrounding region wide enough to include the whole OD is selected. An OD location methodology is also proposed here. Then the OD boundary is extracted from green channel of this sub image by means of morphological and edge detection techniques. OD boundaries are approximated by a circumference using the Circular Hough Transform. The results of this study are used to verify suitability of circular approximation for OD boundary segmentation in view of digital fundus images of Indian population.

METHODOLOGY

The aim of this work is to validate methodology for OD segmentation that obtains a circular boundary approximation on local data base specific to Indian population.



Flow Chart of Implemented Algorithm

Pre-Processing (BHT)

Original image enhancement is done by applying bottom hat transform [26] to it. The figure 1 (b) significantly shows major blood vessels on the nasal side and small vessel in temporal side present a good amount of OD occlusion. We restore the disk region by significantly reducing the distraction caused by vessels as follows.

(a) (b) (c) (d)

Figure 1: Result of Preprocessing (a) Input Image (b) A Sample Cropped CFI (c) Image Obtained by Morphological Closing (d) BHT Result

The Bottom Hat Transform is applied on red channel of original image as blood vessels are red in color using linear structural element with different widths. Bottom hat transform is the residue between a closing and $I0$ defined as

$$\rho^{\theta}_{s}(I_o) = \varphi^{\theta}_{s}(I_o) - I_o \qquad (1)$$

Where φ_s^{θ} denotes morphological closing operation with a linear structuring element s of orientation θ. Morphological closing is nothing but dilation followed by erosion. The erosion of f by a structuring element b at any location (*x, y*) is defined as the *minimum* value of the image in the region coincident with *b* when the origin of *b* is at (*x, y*). Therefore, the erosion at (*x, y*) of an image f by a structuring element *b* is given by

$$[f\Theta\, b](x,y)=\min \{f(x+s,\, y+t)\} \quad (s,t)\in b \tag{2}$$

The dilation of I by as tructuring element *b* at any location (*x, y*) is defined as the maximum value of the image in the window outlined by b^- when the origin of b^- is

$$[f\Theta\, b](x,y)=\min \{ f(x+s,\, y+t) \} \; (s,t)\in b \tag{3}$$

The figure 1 (c) shows result when we apply morphological closing to original image. The figure 1(d) shows result after BHT.

Optic Disc Location

The location methodology obtains a pixel called Optic Disc Pixel (ODP) that belongs to the OD. It comprises three independent methods. Each method obtains its own OD candidate pixel. The final ODP is selected by taking into account the three previous candidate pixels and their locations with respect to their average point (centroid). For this, a voting procedure comprising the following cases is applied:

- **If the three OD Candidate Pixels are Close to the Centroid:** The selected ODP is the centroid.
- **If Only Two Candidates are Close to the Centroid:** The selected ODP is the average point in these two referred pixels.
- Otherwise, the selected ODP is the candidate pixel obtained with the most reliable method

The three developed methods work on the green channel of the RGB color space as this is the one that provides the best contrast [25]. This gray scale image will be denoted as I. These methods are illustrated in figure 4 and description of these methods is presented as follows:

- **Maximum Difference Method:** The OD usually appears as a bright region in eye fundus images. Moreover, the vascular tree formed by the “dark” blood vessels emerges in the disc. This is why the maximum variation of the gray level usually occurs within the OD pixel. But when we apply BHT preprocessing this tree disappears and results in performance degradation. Without applying BHT, if we apply this method on 100 ‘Messidor’ images, this method gives proper result for around 92 images. While this figure goes down, if apply BHT to original image, to 16.

A median filter of 21 x 21 is applied to I in order to remove non significant peaks in the image. If I_M denotes this filtered image, the OD pixel from this method is decided according to the following equation

$$\mathrm{ODP}=\max((I_M)_W^{MAX}(i,j)-((I_M)_W^{MIN}(i,j))) \tag{4}$$

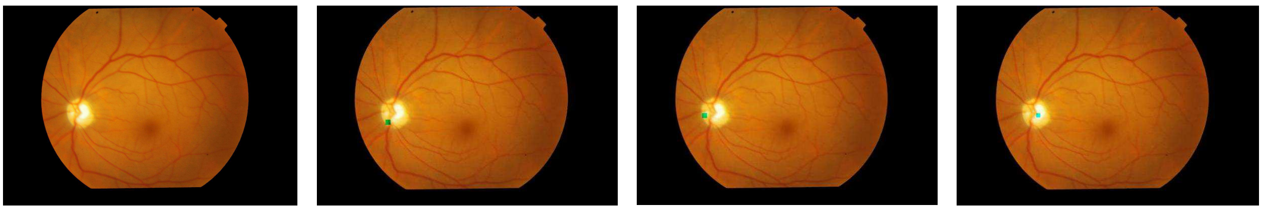
Where $(I_M)_W^{MAX}(i,j)$ and $(I_M)_W^{MIN}(i,j)$ are respectively, the maximum and minimum value of the pixels within a window of size 21 x21 centered on a pixel. Maximum Variance Method: This method is based on the same properties as the previous one. So applying BHT to original image before applying this method causes performance alteration. Effect on performance is not major as this method uses statistical variance not directly pixel value. Without using preprocessing, if we apply this method on 100 ‘Messidor’ images, gives proper results for 90 images while this figure goes down to 74 if we apply preprocessing. It calculates the statistical variance for every pixel by using 21 x 21 centered windows. On the other hand a set of “bright” pixels is obtained by automatic blue-channel thresholding by using canny edge detection. The window size is selected to compute the variance and to establish the neighborhood criteria.

$$\sigma(x,y) = \frac{1}{MN}\sum_{x=0}^{M}\sum_{y=0}^{N}\left[f(x,y)-m\right]^2$$

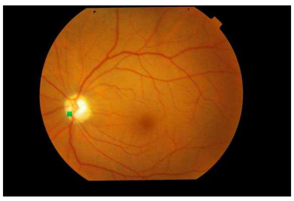
- **Low Pass Filter Method:** The OD pixel of this method is the maximum gray level pixel in a low pass filtered image. Major distraction for finding this pixel, blood vessels, is removed by BHT. Although the OD is usually the brightest area in a retinography, the pixel with the highest gray level could not be located within it.In many cases, this pixel may be inside other small bright regions. In order to smooth out these distracters, the image I is transformed to the frequency domain and filtered by the Gaussian low-pass filter defined as follows

$$H(u,v) = \exp\left(\frac{-D^2(u,v)}{2Do^2}\right)$$

Where D (u, v) is the Euclidean distance between the point (u, v) and the origin of the frequency plane, and D_{0} is the cut-off frequency with a value of 25 Hz. The highest gray-level pixel in the filtered image returned to the spatial domain is the result of this method. In major cases, due to preprocessing, the OD pixel found by this method is center of OD. So this method can solely be used for further segmentation process means we can skip above mentioned two methods and voting type algorithm also. Preprocessing shows major effect in this method. Without applying BHT, if we apply this method on 100 ‘Messidor’ images, this method gives proper result for around 90 images but in most the cases the OD pixel is not near to center. While this figure goes up, if apply BHT to original image, to 98 also result is more accurate as OD pixel is closer to center. The result of the final ODP selection process is illustrated by the examples of application of the methodology. In the first example (Figure 5, image d), pixel located by maximum difference is shown, figure 5f displays pixel located by maximum variance method, whereas figure 5h highlights pixel located by low pass filter method for the input image shown in figure 5a. the three OD candidate pixels are close to centroid, so the location of the ODP is nearto their centroid.



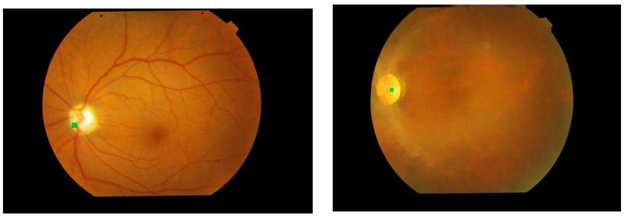
(a) (b) (c) (d)



(e)

Figure 2: Result of Pixel Location Methodologies. (a) Input Image (b) Image Highlighting OD Pixel Located by Maximum Difference Method (c) Image Highlighting OD Pixel by Maximum Variance Method (d) Image of Low Pass Filter Method (e) Final OD Selection by Voting Type Algorithm

Above figure (figure 2) shows result of pixel location methodologies for original image. These results can be improved by pre-processing original image. These pre-processing methods enhances various image properties such as contrast, hue, brightness and also removes blood vessels etc. here we implemented BHT for pre-processing an original image. Figure 3 illustrates comparison of ODP location of pre-processed image with the ODP location of the original image.



(a) (b)

Figure 3: Comparison of ODP Location Selection by Voting Type Algorithm (a) ODP Selection for Original Image (b) ODP Selection for Pre-Processed Image

Figure 3(a) shows ODP selection for original image and figure 3b shows ODP selection with BHT as preprocessing.

Optic Disc Boundary Segmentation

The method proposed in this paper is performed on RGB sub-image of the original retinography. This increases the robustness and efficiency in OD segmentation and also reduces the search space and decreases number of artifacts. We can apply proposed method on an RGB sub-image of the original retinography which reduces the search area and no. of distracters present in the image. So, as a first step, a 150X150 RGB sub-image is extracted centered on an OD pixel provided by the OD location methodology previously presented. Then a binary mask of the OD boundary candidates is obtained by applying edge detection techniques. Finally, the Circular Hough Transform is used to calculate the circular approximation of the OD.

Obtaining OD Boundary Candidate

The OD boundary represents the frontier between the OD and the background. It is characterized by a sudden variation in gray levels, with these values higher within the OD than in 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 is used to obtain a gradient magnitude image (hereafter I_{GM}). This operator estimates image edge and orientation by convolving two 3x3 kernels which approximate derivatives for horizontal and vertical changes. The gradient magnitude image is finally obtained by taking the module of partial derivative values for every pixel. Thus, I_{GM} is an image which contains information on edges, specifically on the location and intensity of local gray-level variations. As the blood vessels were previously erased, 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 I_{GM}.

The Otsu thresholding method automatically decides a threshold for a gray-level image by assuming that it is composed of two sets, the background and the foreground. Then, the method establishes the optimum threshold TOTSU by maximizing the between-class variance. Using this threshold, a first binary mask of OD boundary candidates is given by a simple linearization operation

$I_B(i,j)=\{\ 0,\ \text{if } I_{GM}(i,j)<T_{OTSU}$ (5)

$\{\ 1,\ \text{if } I_{GM}(i,j)>T_{OTSU}$

The noise in image 5 is removed by morphological operations and binary mask of OD boundary is obtained.

$I_{BM}(i,j)=(I_B)_C^{MIN}(i,j)$ (6)

Where, C is circular structuring element with diameter of pixels.

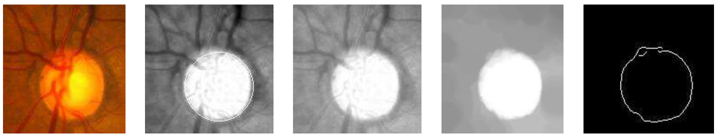


Figure 4: Illustration of the Circular OD Boundary Approximation

Final OD Boundary Segmentation

The circular shapes present in the image I_{BM} can be obtained by performing the Circular Hough Transform on this image. It can be defined as

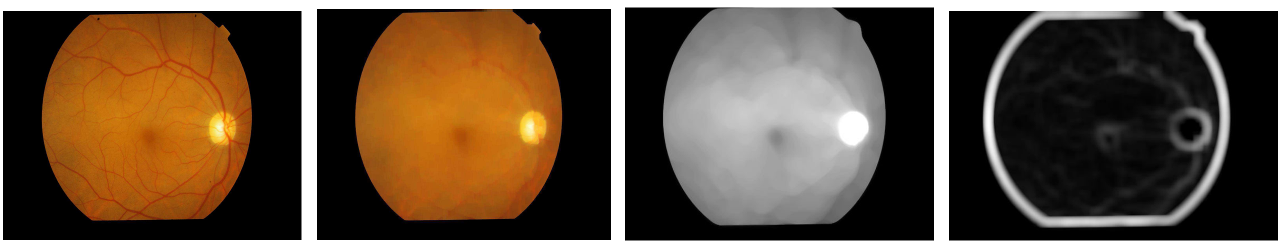
$(Pc,r)=CHT(I_{BM},r_{min},r_{max})$ (7)

Where, Pc =(ic, jc) 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 divided by two (as these measurements refer to OD diameter estimation).

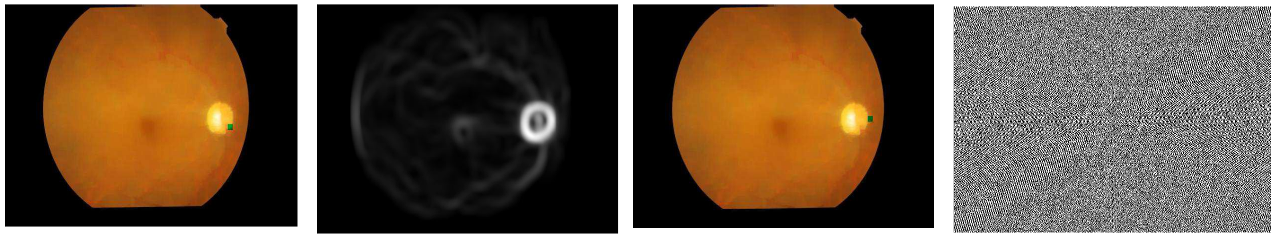
TESTING AND RESULTS

We tested these methods on the publicly available MESSIDOR data base and NIOP data base which we obtained from Local hospital, National Institute of Ophthalmology, Pune. The NIOP images are 400 x600 pixels in size and 8-bit per color plane and are provided in JPEG format. We have tested the algorithms on 100 images from MESSIDOR database and 50 images from NIOP data base. To make evaluation of the algorithm performance on this data base possible, the OD rim was manually delimited by experts this way a gold standard is set.

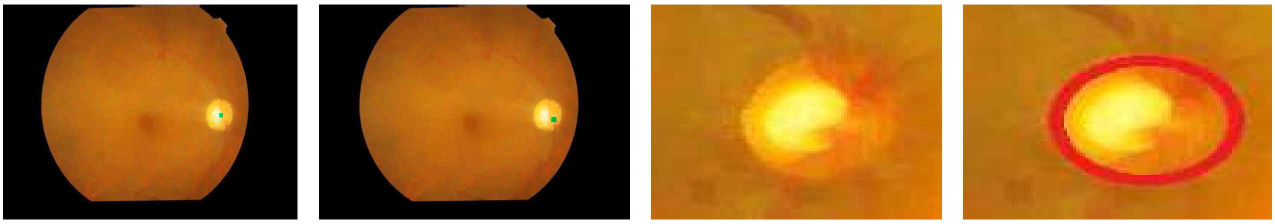
Performance of algorithm was evaluated by measuring the overlapping degree between true OD region in "gold standard" images and approximated regions obtained with the described approach. Overlapping between the hand-labeled OD region and one segmented by Circular Hough algorithm is higher than or equal to 0.80% for 95% of the images in the data base



(a) (b) (c) (d)



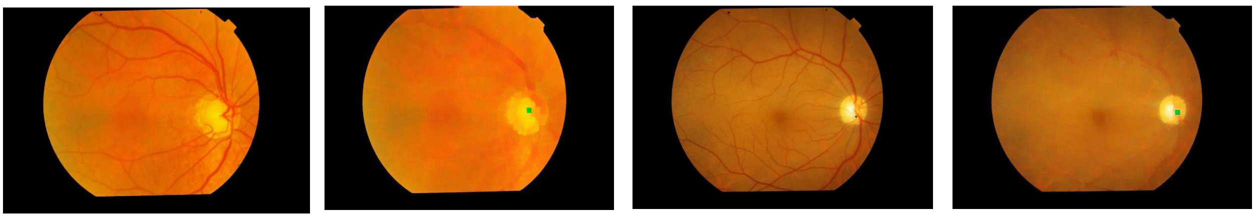
(e) (f) (g) (h)



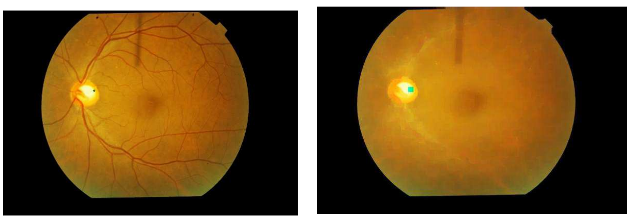
(i) (j) (k) (l)

Figure 5: Results of the Algorithm - (a) Eye Image (b) Preprocessed Image (c) Image with Application of Median Filter (d) Image with Maximum Difference Method (e) OD Pixel Located with Maximum Difference Method (f) Image with Max Variance Method (g) OD Pixel Located with Max Variance Method (h) FFT of Image (i) OD Pixel Located with Low Pass Filter Method (j) OD Pixel Located with Voting Algorithm (k) Sub Image Extracted from Retinal Image Containing OD (l) OD Image of Segmented Using Circular Hough Transform

In addition to the above results, we get better results from pre-processed images as compared to original image. This result can be illustrated using figure 6. In this figure, (a) shows the ODP selection for original image using voting type algorithm whereas (b) represents ODP selection for BHT processed images. It is seen that there is difference between ODP locations of both image. The ODP location in original image is near to the centroid (figure 6a) but when this original image is pre-processed and ODP location is determined for pre-processed image. It is seen that ODP location is changes to new location which is close to centroid as compared to previous location. So it will give better results as compared to the original image.



a(1) b(1) a(2) b(2)



a(3) b(3)

Figure 6: Comparison of ODP Location Selection by Voting Type Algorithm (a) ODP Selection for Original Image (b) ODP Selection for Pre-Processed Image (BHT)

Table 1: Illustrates the Average Execution Timing per Sample Image and no. of Images with Expected Results off Total 100 Images from MESSIDOR Database

Sr No.	Algorithm	No. of Images with Expected Results	Execution Timing/Image (Avg) in Secs
1	Pre-processing (BHT)	100	1.0596605
2	MDM	16	12.378558
3	MVM	74	0.613595
4	LPF	98	0.686599
5	VTA	96	1.143222
6	ROI	96	0.042135
7	Optic Disk Segmentation	89	0.482463

CONCLUSIONS

The Bottom Hat Transform as preprocessing gives better results in low pass filter method (98%) as compared to results without preprocessing (84%). In this way, BHT methods gives better ODP location as compared to original image.

The maximum difference method works well with non pathological images or pathological images with small area of exudates except noisy images. The maximum variance method works for images same as maximum difference method but variance method can locate the OD pixel more accurately than maximum difference method since variance is stronger function than difference. The low pass filter method can falsely locate the OD pixel if the bright spot is created by camera flash. The voting type algorithm locates the OD pixel even if one of the methods fails to locate OD pixel. The segmentation method used circular approximation to segment OD boundary, which gives better results than the elliptical approximation in most of the cases (Poor OD border contrast). The circular OD approximation is succeeded in 80% of the images in the database.

This work is further extended through C implementation to optimize its mathematical computations and processing time.

This work can in future be extended in the implementation of a complete automatic diabetic retinopathy diagnostic system, and the OD detection will be the seed point in the diabetic retinopathy analysis.

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