A Robust Algorithm for Optic Disc Segmentation from Colored Fundus Images

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Abstract. Efficient and accurate optic disc (OD) segmentation is an essential task in automated diagnosis of different retinal diseases from digital fundus images. Due to presence of non-uniform illumination, noise, vessels and other lesions in the fundus images, it is challenging to come up with an algorithm which can accurately segment the OD from the fundus images. It is even more difficult to detect OD accurately for real time patient data in which the images are not captured in the very control environment. This paper presents a novel approach for efficient and robust OD segmentation even in presence of high retinal pathologies and noise. The proposed system consists of four modules i.e. preprocessing, candidate OD regions detection, vessel segmentation and OD detection based on vessel density in candidate regions. The proposed system is tested and validated on publicly available fundus image databases and images gathered locally for real patients. The experimental results show the validation of proposed system.

1 Introduction

Fundus image analysis is used to diagnose various eye diseases. An automated fundus image analysis system can be used as a tool to diagnose eye abnormality in its early stage which is a major help for ophthalmologists to treat the disease [1]. Optic Disc is a key component of retina. The information about the optic disc is used to detect severity of retinal diseases like glaucoma, diabetic retinopathy and papilloedema. Changes in the optic disc indicate the mildness or severity of the disease. So, automatic extraction of optic disc is very vital for computerized fundus image analysis systems [1]. Optic disc (OD) is one of the main features in digital fundus images. OD is a bright yellowish circular spot in the retinal image The brightest circle inside the optic disc is known as optic cup. It can also be used to detect other landmark features such as macula and fovea. All blood vessels of the retina emerge from optic disc.

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There are many methods presented in the literature for the automatic extraction of optic disc. Youssif et al. [2] detected OD from normalized fundus images using Gaussian matched filter. The directional vascular pattern is also considered in finding OD using this approach. The method is tested on publicly available DRIVE and STARE databases which showed 100% and 98.7% accuracy respectively. Sekhar et al. [3] proposed a method for OD localization by using morphological operations and Hough transform. The proposed method is tested on DRIVE and STARE databases showing 94.4% and 82.3% accuracy respectively. Statistical techniques are proposed by C. Kose et al. [4] for the automated detection of optic disc. A characteristic image is taken in this approach and statistical properties like intensity distribution, standard deviation, maximum and minimum intensity values and texture properties are taken into account for OD detection. The method is tested on STARE dataset and achieved 97% accuracy. H. Ying et al. [5] proposed a fractal based method for automatic OD localization. OD is segmented from fundus image using local histogram analysis. The approach is tested on DRIVE dataset and it showed 97.5% accuracy. R.J. Qureshi et al. [6] proposed an automatic OD segmentation method based on pyramidal decomposition, edge detection, entropy filter and hough transformation. The method showed 96.7%, 94.02% and 100% accuracies on Diaretdb0, Diaretdb1 and DRIVE databases respectively. A method based on vessel distribution and OD appearance characteristics is presented by D. Zhang et al. [7]. Horizontal and vertical projection appearance is used to extract OD using this method. This method is tested on publicly available four databases which are DRIVE, STARE, Diaretdb0 and Diaretdb1. The method showed 100%, 91.4%, 95.5% and 92.1% accuracies on these databases respectively. Lupascu et al. [8] proposed a method based on Hough transform for the segmentation of Optic Disc. The method is tested on DRIVE database giving 95% accuracy.

The exiting methods tends to fail to detect OD properly when fundus images contain a large number of lesions especially bright lesions (exudates) and some acquisition artifacts. In this paper, we present an automated system for detection of Optic Disc in colored fundus images. The proposed methodology consists of preprocessing stage in which background estimation is done and the noise is eliminated from the fundus image. The next stage is to detect candidate OD regions followed by extraction of blood vessels from the preprocessed image. Finally, OD is detected by measuring vessel density in candidate OD regions.

This paper comprises of four sections. Section 2 contains proposed methodology followed by experimental results in section 3. Section 4 contains conclusion.

2 Proposed Methodology

Optic Disc is the bright circular region of the human retina. It is the location on the human retina from where the optic nerve and blood vessels enter the eye [9]. Automatic Optic Disc detection is an important step while designing automated systems for screening of diabetic retinopathy, glaucoma or papilloedema. Localization of OD is also essential for checking the severity of these retinal diseases [10].

OD detection is challenging in the presence of other bright lesions in the retina or if the images are not captured in a very controlled environment. So there is need for an accurate algorithm which can locate the OD correctly. Keeping in mind the above issues, we propose a system which segments the OD in efficient and accurate manner. The main steps involved in the detection of the OD in the proposed algorithm are; Preprocessing, Segmentation of candidate OD regions, Vessel detection and finally OD detection. First of all preprocessing is applied on the fundus image followed by segmentation of candidate OD regions. After the segmentation, the number of regions which are greater than one are checked. If there are, then vessel segmentation is done on the image otherwise vessel segmentation is skipped to improve the efficiency of the system. Finally, vessel density with in a bounding box is checked in each candidate region and a region with highest vessel density is called as "OD". The flow diagram in figure 1 shows the sequence of the steps as used in our proposed method.

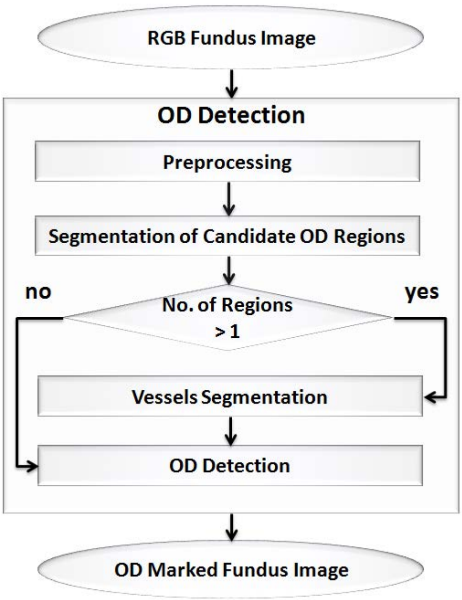

Fig. 1. Flow diagram of proposed system

2.1 Preprocessing

The initial step of our system is preprocessing and its goal is to segment a background (BG) mask. There are two stages of our proposed preprocessing algorithm. The steps for first stage of preprocessing are as follows;

- An initial threshold is applied on the red plane of fundus image and morphological operations are used to remove holes and false regions.

- Labeling of the objects that are present in the binary image is done using connected component labeling algorithm [11].
- Select the object having the largest area [12] as the fundus region. Figure 2(b) shows the result of background segmentation.

The steps for the second stage of preprocessing are listed below;

- Convert the colored fundus image to grayscale either by selecting red channel from original colored image or by converting colored image in gray scaled using equation 1 [13]. This selection depends on the saturation level of red channel.
$$F = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \tag{1}$$
where F, R, G and B are the grayscale image, the Red plane, Green plane and the Blue plane of RGB fundus image.
- Apply padding technique to increase the fundus region of the gray scaled image. The main reason for this step is that the edge detection filter has highest response near the boundary of fundus region due to a sharp change which causes error in OD detection if it is present near the boundary.
- Resize the gray scaled image by using bilinear interpolation, crop it and then apply masking on it with the negative of the BG mask in order to obtain a ring, that we add with the grayscale image (fig-2(c)).
- Apply adaptive histogram equalization to enhance the bright regions of the image (fig-2(d)).

2.2 Candidate OD Region Segmentation

For candidate OD region segmentation, Laplacian of Gaussian (LoG) kernel is applied to enhance the bright regions present in the image [13]. Equations 2 and 3 represent mathematical expression for LoG [13]

$$h_g(n_1, n_2) = e^{\frac{-(n_1^2+n_2^2)}{2\sigma^2}} \tag{2}$$

$$h(n_1, n_2) = \frac{-(n_1^2 + n_2^2 - 2\sigma^2)h_g(n_1, n_2)}{2\pi\sigma^6 \sum_{n_1} \sum_{n_2} h_g} \tag{3}$$

Where σ, n_1 and n_2 are standard deviation of the LoG kernel, the n_1^{th} row and n_2^{th} column respectively.

Due to the presence of non-uniform illumination, it is not efficient to detect the bright regions by only applying global thresholding. So, LoG kernel is used in frequency domain to increase the efficiency of the system. As OD is the circular shaped bright spot, so an inverted log kernel is used which is a circular shaped template having bright peak at its center to enhance the location of OD. Figure-2(e) shows the enhanced image from inverted Gaussian Kernel.

A threshold value is calculated using $T = 0.6 * Gkmx$, where T and Gkmx are calculated Threshold Value and the maximum value in Gaussian Kernel-Processed Image respectively. This selects pixels having top 40% response from

Gaussian kernel. Morphological opening is applied to remove noisy regions from thresholded image. Connected component labeling algorithm [11] is applied for labeling on the binary image and small objects present in the image are removed having area [12] less than a certain threshold which is variable for different databases. This gives some segmented regions which may or may not be candidate OD regions particularly when there is more than one region present in the image. Figure-2(f) shows the candidate OD regions.

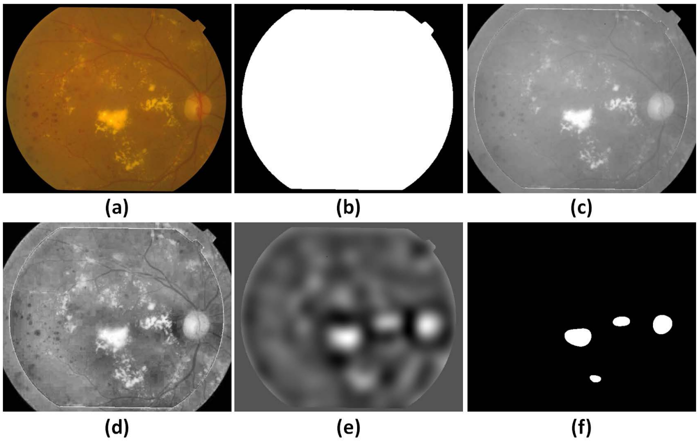

Fig. 2. Preprocessing and candidate od region segmentation. a) Original retinal image; b) Background mask; c) Padded gray scaled image; d) Contrast enhanced image; e)Enhanced image using inverted Gaussian kernel; f) Binary image containing candidate regions.

2.3 Vessel Segmentation

The next step is extraction of blood vessels to measure vessel density in each candidate OD region. In proposed system, vascular pattern is enhanced by using 2-D Gabor wavelet for their better visibility. Gabor wavelets have directional selectiveness capability and since the vessels have directional pattern so Gabor wavelets enhance the vessels very well. The second step which is used in vascular extraction is the segmentation. In order to increase the accuracy of vessel segmentation, the proposed system uses multilayered thresholding approach to make sure the extraction of small vessel along with large ones [18]. Figure 3(a) and 3(b) show the result of blood vessels enhancement and segmentation.

2.4 OD Detection

The final step of this system is optic disc detection. If there is only one candidate OD region, the proposed system considers it as OD. In case of multiple regions,

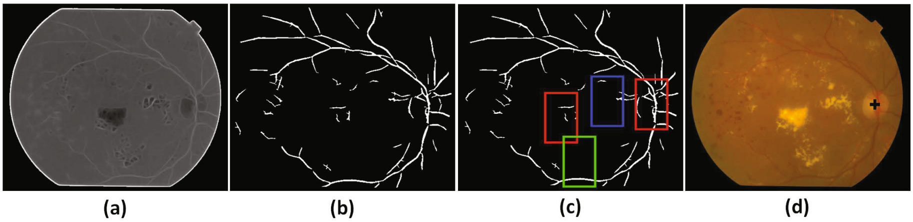

Fig. 3. a) Enhanced vessel using Gabor wavelet; b) Binary blood vessels; c) Segmented Candidate Regions Marked on the Vessels Mask; d) Region with highest vessel density marked as OD

vessel density is checked with in each candidate region and considers a region as OD that has maximum vessel density. The figure 3 (c) and 3 (d) shows the results of OD detection.

3 Results

The quantitative assessment of the proposed system of OD detection is done by using publicly available databases such as DRIVE, STARE and DiaretDB. We have also tested our system on some locally collected data with large number of pathologies and variety of noise. DRIVE database has 40 retinal fundus images of size 768 $\times$ 584 [19]. The images were captured using Canon CR5 Non-Mydriatic

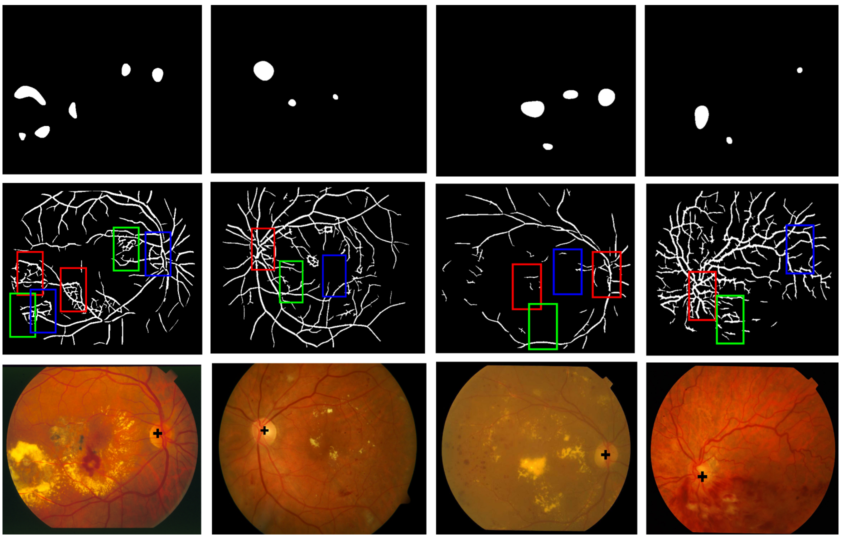

Fig. 4. Row1: Candidate regions, Row2: Bounding box marked on segmented vessels showing vessel density calculation, Row3: OD Detection and marked with cross on it

retinal camera with a 45 degree Field of View (FOV). STARE database has 400 retinal images which are acquired using TopCon TRV-50 retinal camera with 35 degree FOV having size of 700 $\times$ 605 [20]. DIARETDB (DIAbetic RETinopathy DataBase) is a database which is designed to evaluate automated lesion detection algorithms [21]. It contains 89 retinal images with different retinal abnormalities. The images are captured with a 50 degree FOV and a resolution of 1500$\times$1152. Furthermore, we have used some locally collected images i.e. 462 images with a resolution of 1504 $\times$ 1000 and 100 images with a resolution of 1936 $\times$ 1296. Figure 4 shows results on different retinal images using proposed methodology.

A MATLAB based annotation tool is designed and OD centers are marked for all images with help of an ophthalmologist. These OD centers are considered as ground truths and the distance of automatically detected OD centers are calculated from these ground truths. OD is considered as correctly detected if the difference between automated and ground truths centers is less than 10 pixels.

4 Conclusion

Optic disc is a major landmark in digital fundus images and its automated detection helps in segmentation of other retinal landmarks. A novel and robust optic disc detection algorithm is presented in this paper. The proposed system consisted of four phases i.e. preprocessing, candidate regions for OD segmentation, retinal vessel segmentation and finally OD detection. The main contribution is that the proposed system is robust even in the presence of noise and large number of retinal abnormalities. The accuracy of the proposed system is 100%, 97.50%, 100% and 95.85% on DRIVE, STARE, DiaretDB and local images respectively. This algorithm can be used for automated detection of OD for grading of diseases like diabetic retinopathy, glaucoma and papilloedema.

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