Automatic detection of Optic Disc based on Mathematical Morphology in Retinal Fundus Images

G. G. Rajput
Dept of Computer Science
Rani Channamma University, Belagavi,, Karnataka, India

B. M. Reshmi
Dept of Computer Science
Gulbarga University, Gulbarga, Karnataka, India

ABSTRACT
Optic disc segmentation is a prerequisite in automatic analysis of retinal disease in color fundus images. In this paper, an algorithm for detection of optic disc (OD) in fundus images is presented. Mathematical morphology is used for segmentation of candidate optic disc region, followed by determining its center and approximating the circular optic disc boundary using circular model. Proposed method is evaluated on public database, MESSIDOR. The proposed optic disc segmentation algorithm yielded an average overlapping score of 99.47% between true OD and segmented OD and success rate of 93%.

Keywords
diabetic retinopathy, fundus image, mathematical morphology, optic disc

1. INTRODUCTION
Detection of optic disc (OD) is a prerequisite to the following: identifying revascularization of the disc in the advanced stage of diabetic retinopathy (DR) and proliferative diabetic retinopathy; localizing other fundus features like fovea/macula [1]; localization of blood vessels [2]; deciding if the image is of the left or right eye; identifying exudates lesions in the retinal fundus image [3]; diagnosis of other eye diseases like glaucoma [4], optic neuropathies, optic neuritis, anterior ischemic optic neuropathy or papilledema, and optic disc drusen. In color fundus image (See Figure 1) OD appears as a bright spot of circular or elliptical shape, interrupted by outgoing blood vessels.

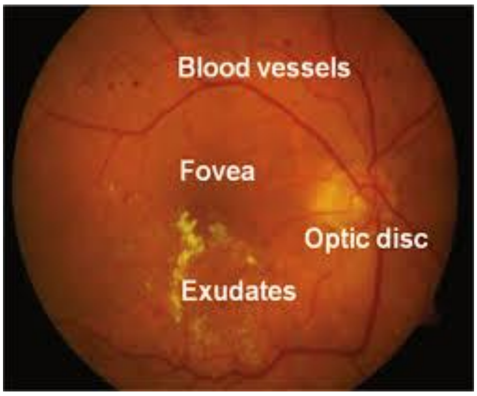

Fig 1: Typical fundus image of patient with DR

OD is located on the nasal side of the macula. The size of the OD varies from person to person. Identification of the OD is more complicated due to non uniform illumination, blood vessels occlusion, shape, size and color, and presence of disease like diabetic retinopathy. Many researchers have proposed OD detection methods. The template matching and directional matched filter is used for OD detection in [5]. In [6], authors have used intensity based approach to detect the OD boundary, given the OD center. In [7], the fundus image is decomposed into bit planes for detection of OD. Mathematical morphology and edge detection techniques, followed by circular Hough transform is used to obtain a circular OD boundary approximation. Many authors [5, 6, and 7] have used MESSODOR public database of fundus images for testing measures of the OD detection algorithms proposed. The other methods [8, 9, and 10] for OD detection exists based on public databases like, DRIVE, STARE and DIARETDB0. This paper presents a simple and effective method for OD segmentation based on mathematical morphology. This is a prerequisite for our study related to diabetic retinopathy. Firstly, the OD candidate region is segmented and then the center of the OD is obtained. Secondly, the circular OD boundary is approximated by using circular model. Rest of the paper is organized as follows. Section II presents the description of materials and methods used. Section III presents proposed algorithm for OD detection. Section IV provides a detail discussion on performance analysis resulting from tests on MESSIDOR public database consisting of both normal and DR fundus images. Conclusions are given in section V.

2. MATERIALS AND METHODS
2.1 Materials
The public database namely, MESSIDOR, containing fundus color images of the posterior pole acquired by the Hôpital Lariboisière Paris, the Faculté de Médecine St. Etienne and the LaTIM–CHU de Brest (France) are considered [11]. The database contains 1200 color fundus images of the posterior pole acquired by 3 ophthalmologic departments (400 images from each department). We have used 100 images for evaluation of the results. These images are of 2240X1488 pixels in size with 8 bits per color plane provided in TIFF format. The database consists of both normal and DR images.

2.2 Methods
Mathematical morphology [12] is a tool for extracting geometric information from grayscale and binary images using sets. Objects in the image are represented by sets. Set corresponds to the pixels or points that belong to the objects in the image. In binary images, the sets are members of the 2D integer space Z^2, where each element of a set is a tuple whose coordinates are the (x, y) coordinates of a white (or black) pixel in the image. Gray-scale images can be represented as sets, whose components are in Z^3: two components are coordinates of a pixel, and the third – its discrete intensity value. In image processing mathematical morphology is used to find the interaction between an image and structuring element using the basic operations of erosion

and dilation. In binary images, with A and B as sets in Z^2, the erosion of A by B is defined as in equation (1):

$$\boldsymbol{A} \ominus \boldsymbol{B} = \{\boldsymbol{Z} | (\boldsymbol{B})\boldsymbol{z} \dot{\subseteq} \boldsymbol{A}\} \qquad (\mathbf{1})$$

The erosion of A by B is the set of all points z such that B, translated by z, is contained in A. We will assume that the set B is a structuring element.

The dilation can also be expressed as in equation (2):

$$\boldsymbol{A} \oplus \mathbf{B} = \{\boldsymbol{Z} | [(\widehat{\boldsymbol{B}})\boldsymbol{z} \cap \boldsymbol{A}] \dot{\subseteq} \boldsymbol{A}\} \qquad (\mathbf{2})$$

B is a structuring element and A is the set to be dilated.

We extend the basic operations of dilation, erosion to grayscale images. Assume that f(x,y) is a grey-scale image and b(x, y) is a structuring element and both functions are discrete. The erosion of f by a flat 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 the equation (3):

$$[\boldsymbol{f} \ominus \boldsymbol{b}](\boldsymbol{x}, \boldsymbol{y}) = \underbrace{\mathbf{min}}_{(\mathbf{s},\mathbf{t})\in\mathbf{b}} \{\mathbf{f}(\mathbf{x}+\mathbf{S}, \mathbf{y}+\mathbf{1})\} \qquad (\mathbf{3})$$

The dilation of f by a flat structuring element b at any location (x, y) is defined as the maximum value of the image in the window outlined by $\hat{b}$ when the origin of $\widehat{b}$ is at (x y). That is:

$$[\boldsymbol{f} \ominus \boldsymbol{b}](\boldsymbol{x}, \boldsymbol{y}) = \max_{(\mathbf{s},\mathbf{t})\in\mathbf{b}} \{\mathbf{f}(\mathbf{x}+\mathbf{S}, \mathbf{y}+\mathbf{1})\} \qquad (\mathbf{4})$$

Where $\widehat{b}$ =b(-x, -y).

From these basic operations, dilation and erosion, more complex transformations are constructed, as opening (dilate the result of an erosion) and, its dual operation, closing (erode the result of a dilation), to implement basic filters. We have used both binary and grayscale morphology.

3. PROPOSED METHOD

The proposed OD detection algorithm comprises several steps. The algorithm for OD detection is given below:

Algorithm: Input: Retinal fundus image

Output: Approximated OD boundary

1. Extract red channel of the original image and remove blood vessels by applying morphological closing operation with octagon shape structuring element. Then the image is inverted and contrast of the image is enhanced.

3. Extract candidate OD region by applying grayscale morphology operator, extended minima transform and remove unwanted regions from the image.

4. Mark the OD center and approximate the OD boundary.

All the steps required for OD detection are described in the following sub sections.

3.1 Extraction of red channel of the image

The optic disc is a brightest component of the fundus image (See Figure 2). In the red channel OD appear most contrasted against the background and has least vessel distractions. The red channel of the original RGB image is extracted (See Figure 3).

Fig 2: Original color fundus image

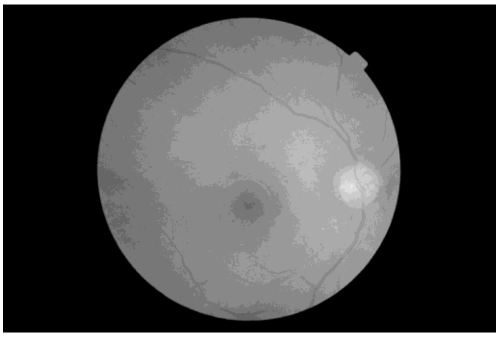

Fig 3: Red channel of the image

3.2 Removal of blood vessels

The OD region is fragmented into multiple sub regions by blood vessels. The blood vessels enter the OD from different directions with a general tendency to concentrate around the nasal side of the OD region. Therefore blood vessels are removed from the image by applying closing operation using octagon shape structuring element of size 3 to create fairly uniform region (See Figure 4). This operation contributes more towards better segmentation of OD where the vicinity of the blood vessels is more in the OD region. It is challenging to identify the vessels width with precision. If the structuring element is too large, it does not ensure that all trees of the vessels are removed. A very large structuring element may deform the OD boundary.

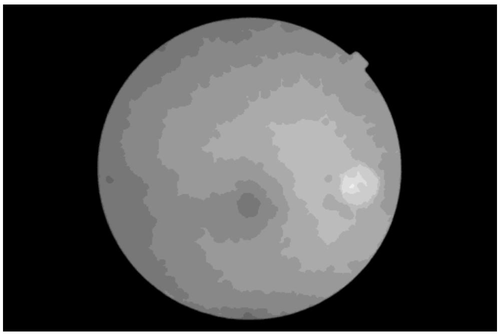

Fig 4: Blood vessels removed

3.3 Segmentation of the candidate OD region

Before segmentation of the candidate region of the OD, the image is inverted (See Figure 5). Then the contrast of the image is enhanced using histogram equalization (See Figure 6).

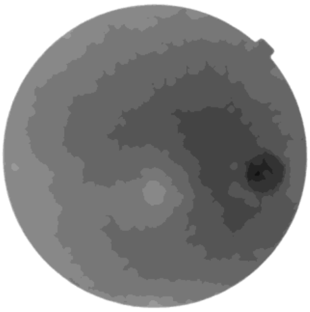

Fig 5: Inverted image

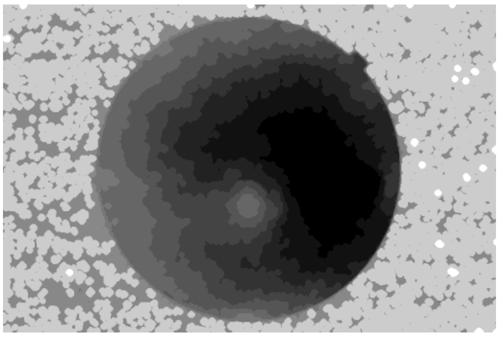

Fig 6: After contrast enhancement

Then the regions with minimum intensities using extended minima transform are identified. The extended-minima (h-minima) transform is the regional minima of h-minima transform. This transformation is a thresholding technique that brings most of the valleys to zero. The h-minima transform suppresses all the minima in the intensity image whose depth is less than or equal to a predefined threshold. The output image is a binary image with the white pixels representing the regional minima in the original image. Regional minima are connected pixels with the same intensity value, whose external boundary pixels all have a higher value. The extended minima transform on the f image with threshold value, h is shown in equation 5.

$$E = M(f, h) \quad (5)$$

where *E* is the output image.

The selection of threshold is very important where the higher value of h will lower the number of regions and a lower value of h will raise the number of regions. In the proposed method, h value (threshold height) is selected empirically and is set to 3. The output is a binary image (See Figure 7).

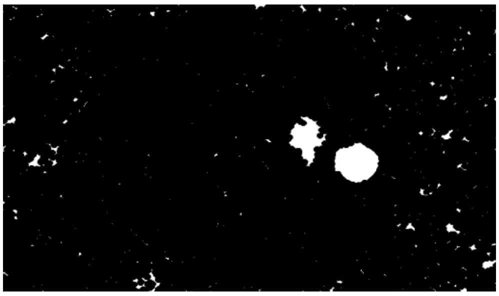

Fig 7: After applying extended minima transform

Morphological opening is applied using disk shaped structuring element of size 50 to eliminate the regions that are wrongly located. The mean intensities of the identified regions are computed. The region with the lowest mean intensity with largest area is then selected as the optic disc region (See Figure 8 and 9).

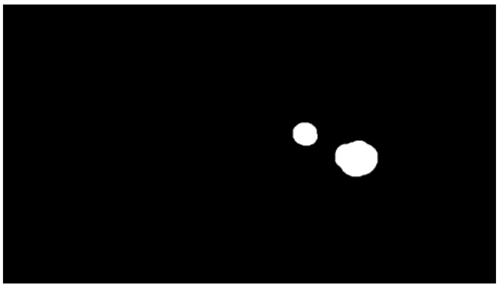

Fig 8: After applying opening operation

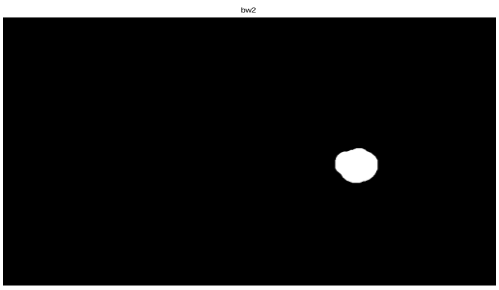

Fig 9: Extracting the region with largest area as OD

For the selected candidate optic disk region the centroid is computed (See Figure 10).

Fig 10: OD center marked

3.4 Detecting circular approximation of the OD boundary

Equidiameter is computed for the selected OD candidate region using equation 6. And then the circle is fitted (See Figure 11).

$$\text{Equidiameter} = \sqrt{(4 \times \text{Area}/\pi)} \qquad (6)$$

Fig 11: Circular approximation of the OD

4. EXPERIMENTAL RESULTS AND DISCUSSION

Experiments were performed on 100 images of public database consisting of both normal and DR images. To make evaluation of the algorithm performance on database possible, the OD boundary was manually delimited by expert ophthalmologist producing by this way a ground truth set. Algorithm performance was evaluated by measuring the overlapping degree between the true OD regions in "ground truth" images and the segmented candidate OD regions obtained with the proposed method. An overlapping score S is defined in equation (7) to measure the common area between the true OD region and the detected region.

$$S = \frac{n\,(T \cap D)}{n\,(T \cup D)} \qquad (7)$$

Where T corresponds to the ground truth in white, D is the segmented candidate region and n (.) is the number of pixels in a region. The measure S represents the accuracy. When compared with the hand labeled ground truth information from expert, for MESSIDOR database, the method is able to detect the OD pixels in all the images with an average overlapping score and success rate of 99.47% and 93% respectively.

Some sample segmentation examples are given in Figure 12. It is important to consider that the optic disc variations in appearance, size and location during the development of automatic detection optic disc detection (See Figure 13). The major OD detection error is due to the blood vessels (See Figure 13 (d)) that cut out the OD into several components (Our method uses global thresholding to extract OD). Our proposed method is sensitive to blurred OD (See Figure 13 (a)) and mylinated nerve fibre (See Figure 13 (b) which appear very bright region and are connected to the boundary of the OD. We will improve these issues in our future work.

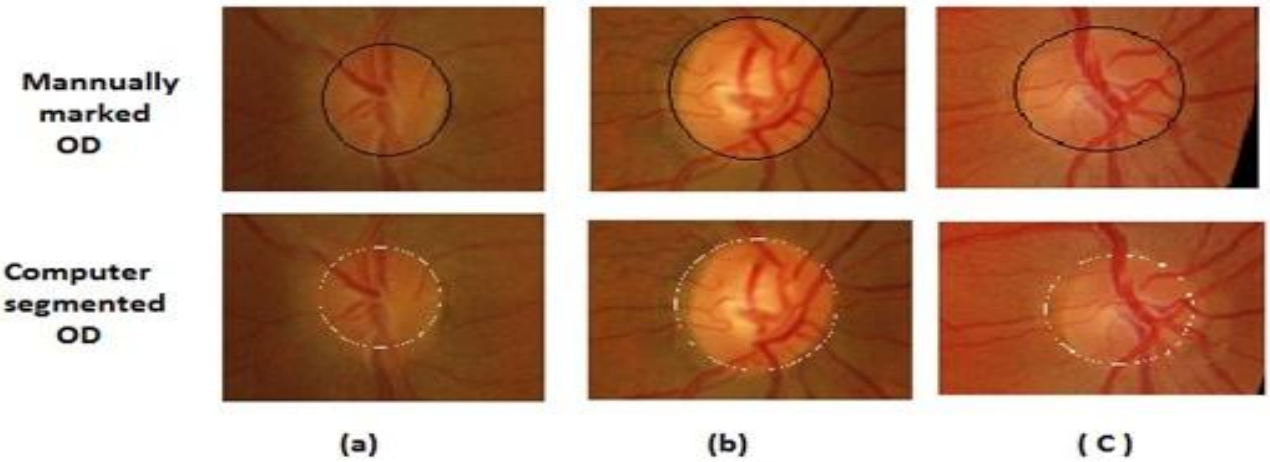

Fig 12: (a) S=99.60% (b) S=99.49 % (c) S=99.29%

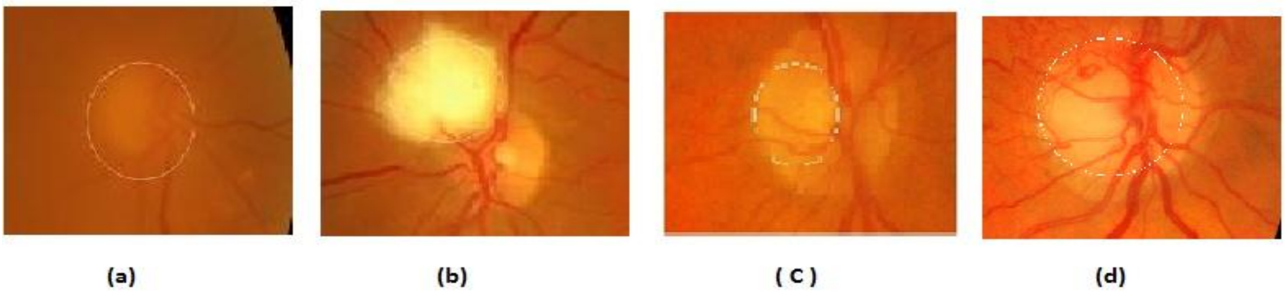

Fig 13: (a) Blurred OD (over segmentation) (c) Myelinated nerve fibers connected to OD boundary (OD is not detected) (C) and (d) Blood vessels that cut out the OD into several components of OD (Under segmentation)

Table 1 presents the results according to the level of diabetic retinopathy grades as given by MESSIDOR specialists. Grade 0 indicates no retinopathy, grades 1 and 2 correspond to patients with non-proliferative retinopathy, and grade 3 corresponds to patients with severe non-proliferative retinopathy or proliferative diabetic retinopathy.

Table 1: DR grade and OD detection results

DR Grade	No of images	OD Detected
0	32	30
1	13	12
2	12	11
3	43	40
Total	100	93

Table 2 presents the results according to the risk of macular edema, graded by the presence of exudates in the retinal fundus image. Grade 0 corresponds to normal images (no exudates), grade 1 to images with exudates located more than 1 disc-diameter away from the fovea, and level 2 to images with exudates located within 1 disc-diameter away from the fovea.

Table 2: Macular edema grade and OD detection results

DR Grade	No of images	OD Detected
0	32	30
1	13	12
2	12	11
3	43	40
Total	100	93

From the table 1 and 2, it shows that the proposed method has achieved highest success rate in all the grades of DR and macular edema. To compare the results obtained by the authors in [5], we obtained an average overlapping score of 99.47% which is 16.47% more than one obtained in [5]. The average computation time for optic disc segmentation was 6.10 seconds per image.

5. CONCLUSION

A novel approach for OD segmentation by means of a mathematical morphology is presented. In addition, an OD location methodology for obtaining the OD position needed by the segmentation algorithm as initial information is also proposed. The results presented in this paper show that the proposed methodology offers a reliable and robust solution for OD segmentation. An average overlapping between the “true” OD region and the one segmented by our algorithm is 99.47% with success rate of 93% (93/100) is obtained.

The proposed method of OD detection is simple and efficient, thus reducing the computational time. The method successfully detects OD boundary that are irregular, varying sizes and is independent of locations of OD. The proposed method yielded encouraging results for both normal and DR fundus images. In future, the success rate should be improved by considering the effects of myelinated nerve fibers, blurred OD and blood vessels. Also, the proposed algorithm will be evaluated on more number of images.

6. ACKNOWLEDGMENTS

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