International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.7, No.2 (2014), pp.389-398
http://dx.doi.org/10.14257/ijsip.2014.7.2.36

Extraction of Optic Cup in Retinal Fundus images: A Compartitive Approach

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Abstract

Glaucoma which is a leading cause of blindness in the world is not a single disease but a group of disorders with diverse clinical manifestations. If not controlled at an early stage, it causes irreversible damage to vision. Careful evaluation of Optic nerve head structure and its documentation is extremely important for diagnosis of the disease and to monitor its progression. The optic nerve head comprises of the optic disc and the optic cup. 'Optic cup' is one of the imperative and crucial factors in disease diagnosis and monitoring. The aim of the research is to compare various existing optic cup segmentation methods and report their comparative performance. A modification in calculating threshold has been suggested which improves the accuracy.

Keywords: *Optic nerve head, optic cup, fundus image*

1. Introduction

Glaucoma is a disease caused by increased intraocular pressure (IOP). Glaucoma is progressive degeneration of the retinal ganglion cells and optic nerve axons. Left untreated, it causes irreversible damage to the optic nerve and retinal fibers resulting in a progressive, permanent loss of vision. Glaucoma is popularly known as silent thief of sight since it causes gradual lack of vision and symptoms are seen only at an advanced stage. Patients with an increased IOP may not always demonstrate optic nerve damage whereas in some cases patients with normal IOP may have optic nerve damage and visual field loss. However increased IOP is one of the major factors in causing optic nerve damage and visual field loss. Early treatment reduces rate of progression of the disease thus preventing visual field loss and blindness. Visual Field loss is the late manifestation of the disease. In Glaucoma, structural changes in the optic nerve head (ONH) precede functional changes in the visual field. Comprehensive examination of the patient's ONH helps in early Glaucoma diagnosis [1, 2]. Following optic nerve head analyzers are used for ONH evaluation.

1. Optical Coherence Tomography (OCT)
2. Confocal Scanning Laser Ophthalmoscopy (CSLO)
3. Scanning Laser Polarimetry (SLP)

Clinical assessment without ONH analyzers using ophthalmoscope is possible but this method suffers from drawbacks such as

1. Subjective opinion
2. Unnoticed subtle changes
3. Difficulty in documentation

ISSN: 2005-4254 IJSIP

Alternatively, a cost effective method is to extract relevant ONH parameters from fundus photographs using Image processing methods. This would eliminate the subjectivity in opinion and also make documentation easy.

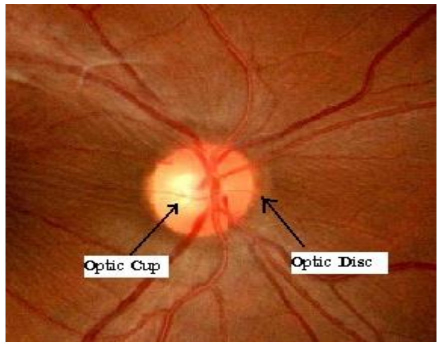


Figure 1. Fundus Image Depicting the Optic Nerve Head

The ONH structure comprises of the optic disc (OD) and the optic cup (OC). The cup to disc ratio is one of the vital parameters used for Glaucoma diagnosis. A Computer aided diagnostic (CAD) system can assist the ophthalmologists in computing this ratio. To compute this ratio the OD and OC need to be segmented. This work focuses on extraction of cup from ONH structure. A number of methods have been implemented and reported in different literature in this respect. [3] has used green channel of rgb image to extract OC. Binary thresholding with threshold value four times the standard deviation is used to segment OC . [4] has used color intensity based approach and threshold level set approach to segment OC followed by ellipse fitting. [5] has used opening and closing operations and component analysis method to segment OC. [9] has used Lab color space and K means clustering for this purpose. Efficient algorithms for localization and segmentation of OD are difficult to achieve due to variable appearance and occlusion due to optic nerves [10]. Secondly, a robust segmentation algorithm which would give correct segmentation results over a large database also seems to be difficult to achieve. The aim of the present work is to compare the performance of various segmentation methods in the context of said application. After studying the available literature, four segmentation methods have been implemented for optic cup segmentation. For ease of comparison they have been evaluated using a single database. In the fifth method, we propose a function for threshold calculation to improve the segmentation performance. It gives a method to calculate a threshold value which is robust enough to provide segmentation accuracy over a large database. All the methods use Canny edge detection for finding the boundary of OC and circle fitting to smoothen the boundary.

2. Methodology

2.1. Method 1: Binary Thresholding and Entropy filtering

The Color fundus image consists of red, green and blue components. The green component enhances the cup region and is useful for extraction of cup using thresholding [3-5]. It appears as the region with highest brightness. Hence the green component is filtered. The cup region is segmented by converting the image to binary by single thresholding. A grayscale image is turned into a binary image by choosing a grey level T in the original image, and then turning every pixel black or white according to whether its grey value is greater than or less than T

[7]. A pixel becomes white if its grey value is greater than or less than value is greater than or less than T. The threshold value T is determined from the mean pixel value. The thresholded image is defined as

$$g(x,y) = \begin{cases} 1 \; if \; f(x,y) > T \\ 0 \; if \; f(x,y) < T \end{cases}$$

where f(x,y) is the original image and T is the threshold.

The binary image is entropy filtered. Output of entropy filter is an array wherein each output pixel contains the entropy value of the 9 by 9 neighborhood around the corresponding pixel in the input image. Entropy is a measure of information. It is defined as the minimum number of bits per pixel required to encode the image with no loss of information. Entropy H is given as

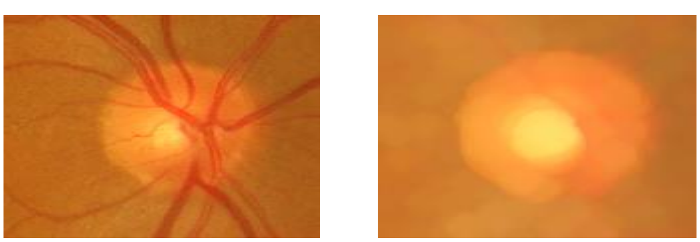
$$H = \sum_{0}^{L-1} pi \; log_2(pi)$$

where the index i is taken over all grayscales of the image, and pi is the probability of gray level occurring in the image [6].

The output image J is the same size as the input image I. For pixels on the borders, entropy filter uses symmetric padding. The values of padding pixels are a mirror reflection of the border pixels in I.

2.2. Method 2: Elimination of Blood Vessels

The cup is occluded by blood vessels and the shape extracted by method 1 is affected. This causes reduction in size of the extracted cup area. [3] has used closing operation followed by opening operation to remove the blood vessels. [5] has used dilation and erosion for the same purpose. We subjected the color fundus image to dilation alone so as to minimize the effect of blood vessels. Dilation is one of the fundamental morphological operations. Dilation adds pixels to the boundaries of objects in an image. Thus it enlarges the boundaries of regions of foreground pixels. The number of pixels added depends on the size and shape of the structuring element. Where A is the input image to be processed and B is the structuring element, B is a nonflat, ball-shaped structuring element whose radius in the X-Y plane is 10 and whose height is 10. Figure 2 shows the effect of dilation on blood vessels. It is clearly seen that their effect is minimized after dilation. All the steps of processing mentioned in method 1 are performed after dilation.



Original Image Dilated image

Figure 2. Effect of Dilation on Blood Vessels

2.3. Method 3: Lab Color Space and K Means Clustering

The original Color fundus image is in RGB format. It is converted to CIE L*a*b model. The equations for L*a*b color conversions are reported by [7]. The* component specifies the color as Green or Magenta hue, the b* component specifies the color as Blue or Yellow hue and the L* component specifies luminosity or the black and white tones of the image. The a component is used to extract the cup region. Cup region appears to be more enhanced in a* component of the image [8]. It is subjected to K means clustering algorithm proposed by [9]. Number of clusters is chosen as k. Initially cluster centroids are C_1, C_2, $C_3 \ldots C_k$ respectively. The initial seeds were selected by [9] from local maximum of color histogram of CIE L*a*b color space. However we modified this selection by choosing initial centroids equally spaced in the range of values of a* component. Data points are grouped into k clusters. For each data point, the centroid which is nearest is found. The data point is now assigned to the cluster of the nearest centroid. The new centroid is found by taking mean of all the data points in the cluster. The cluster corresponding to a centroid with minimum value matches the cup region.

2.4. Method 4: Addition of Dilated and Original Image

The Color fundus image consists of red, green and blue components. The preprocessing step consists of adjusting the mean value of these components. The preprocessed image is subjected to dilation with a non flat ball shaped structuring element in order to remove blood vessels. A color image f(x,y) is derived by addition of the dilated image with the original image. Since the cup region is the brightest area, in the resultant image, pixels in the cup region have red and green component values equal to 255 and blue component values greater than 130. These values were found by experimentation and observation. Thus the cup region is segmented. The image is converted to binary with cup as bright area and background as dark. The binary image *g(x,y)* is derived from the color image *f(x,y)* using the function

$$g(x,y) = \begin{cases} 1 \quad if \quad (fr(x,y) = 255 \\ \quad AND\ fg(x,y) = 255 \\ \quad AND\ fb(x,y) > 130\ ) \\ 0 \quad otherwise \end{cases}$$

where *fr(x,y), fg(x,y)* and *fb(x,y)* are the red, green and blue components of *f(x,y).*

2.5. Method 5: Proposed Method

The Color fundus image consists of red, green and blue components. The preprocessing step consists of adjusting the mean value of these components. The preprocessed image is subjected to dilation with a non flat ball shaped structuring element in order to remove blood vessels. Cup area is segmented from the dilated image using thresholding. The binary image *g(x,y)* is derived from the dilated color image *f(x,y)* consists of cup region as the bright part. Maxima of red, green and blue components are used to extract cup region. Image *g(x,y)* is derived using the function

$$g(x,y) = \begin{cases} 1 \quad if \quad (fr(x,y) = mr \\ \quad AND\ fg(x,y) \geq mg - 30 \\ \quad AND\ fb(x,y) \geq mb - 30\ ) \\ 0 \quad otherwise \end{cases}$$

where *fr(x,y), fg(x,y)* and *fb(x,y)* are the red, green and blue components of *f(x,y)* and

$$mr = \max(fr(x,y)$$
$$mg = \max(fg(x,y)$$
$$mb = \max(fb(x,y)$$

The above function has been derived from experimentation and observation.

3. Extraction of OC Boundary

In all the above methods (except method 1) the boundary of the segmented OC region extracted is determined using Canny Edge Detection method. The Canny method finds edges by looking for local maxima of the gradient of I. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and iincludes the weak edges in the output only if they are connected to strong edges. This method is therefore more immune to noise. Canny edge detector follows the following steps [11].

- Elimination of noise by smoothing of the image.
- Finding gradient to mark regions with high magnitude gradients.
- Amongst the marked regions it suppresses the non maximum pixels.
- Double thresholding is done with hysteresis. If the magnitude is above the high threshold, it is marked as an edge.

The OC boundary is approximated as a circle using circle fitting algorithm. This smoothens the OC boundary.

4. Experimentation and Results

Detection and quantification of optic cup is one of the crucial factors in glaucoma diagnosis. Five methods mentioned have been implemented on using a set of 370 retinal images from Messidor database, kindly provided by the Messidor program partners (see http://messidor.crihan.fr) The database consists of retinal fundus images acquired using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field of view. The database was divided into two sets. 40% images were used in dataset 1 for training purpose and 60 % images were used in dataset 2 for testing purpose. The OC boundary for the images in dataset was drawn by experts in ophthalmology. The results obtained were compared using the following performance parameters.

$$Percent\ accuracy = \frac{A}{B} \times 100$$

where A represents the number of images for which the calculated boundary was exactly matching with that drawn by experts and B represents total number of images in the experiment.

$$Disparity = C - D$$

where C indicates clinical radius of optic cup and D indicates calculated radius of optic cup

Results of different segmentation methods (for a sample image) are shown in Figure 3. Figure 4 shows comparison of segmentation accuracy of all the methods. Figure 5 shows comparison of clinical and computed radius of cup region. Figure 6 depicts and disparity (from clinical values) for a sample image for all the methods.

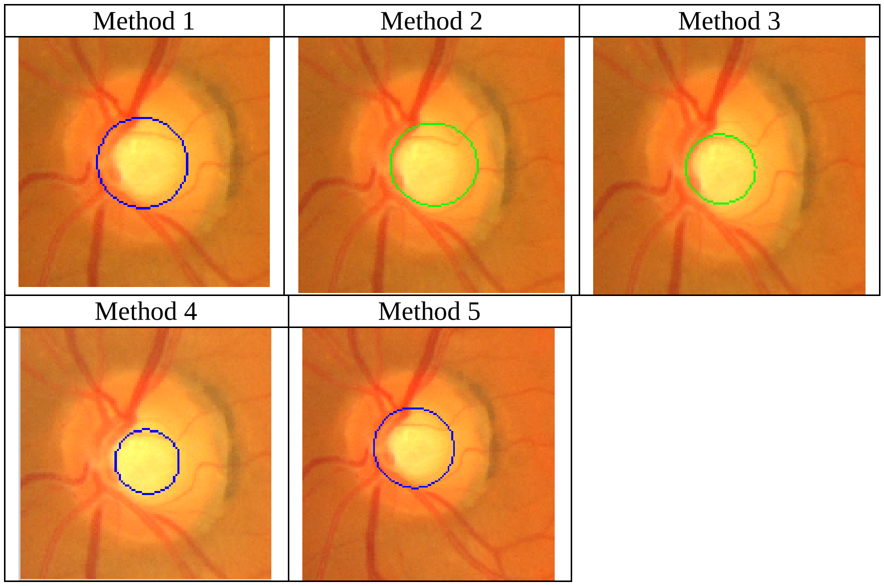
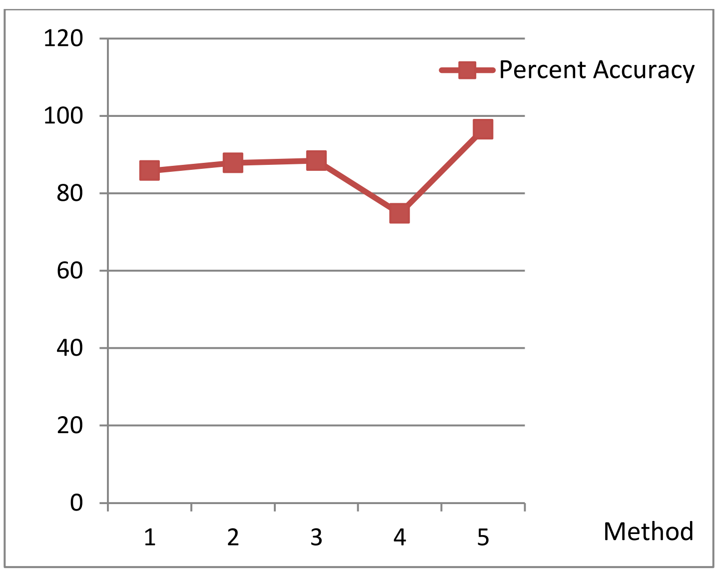


Figure 3. OC Segmentation using Different Methods



Method	Percent Accuracy
1	85.82
2	87.82
3	88.4
4	74.8
5	96.5

Figure 4. Segmentation Accuracy of Different Methods

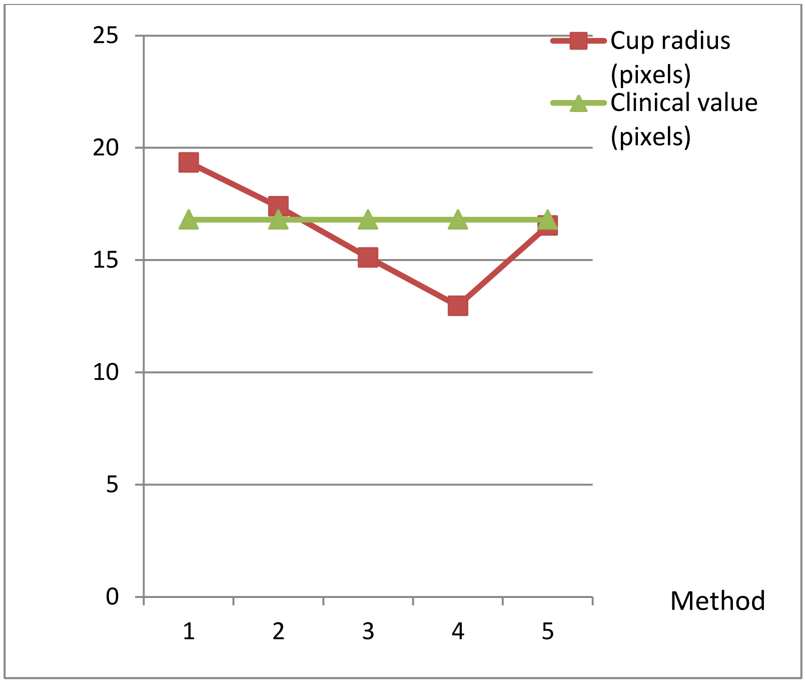


Figure 5. Clinical and Computed Cup Radius (A sample case)

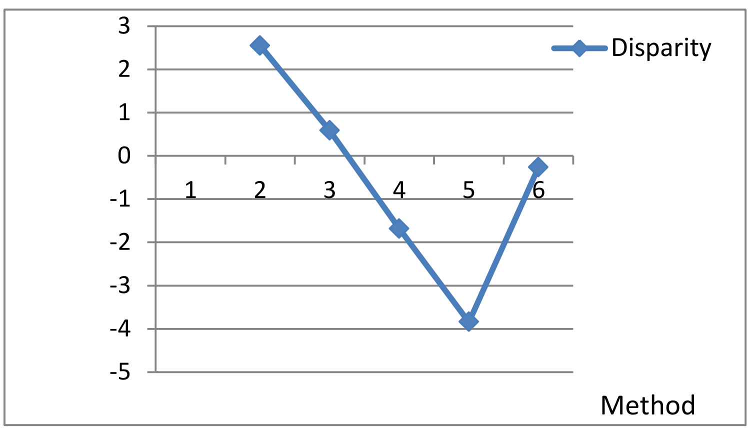


Figure 6. Disparity in Computation of Radius Compared to Clinical Values (A Sample Case)

4. Conclusion

A Computer aided diagnostic (CAD) system can assist the ophthalmologists in computing the cup to disc ratio, which is a vital parameter in glaucoma diagnosis. Thus OC extraction is a vital issue in this regard since it contributes to calculation of cup to disc ratio. The aim of the research is to compare the various existing methods for OC segmentation and report their comparative performance. Amongst method 1 and 2 the performance of method 2 is better. This Improvement in method 2 is on account of removal of vessel structures causing occlusion in OC structure are removed in method 2. A modification in the method of threshold calculation has been suggested in method 4 and 5. Method 4 exhibits a lower accuracy. However method 5 outperforms all other methods and shows an improved accuracy of 96.5 %.

Acknowledgements

The authors are thankful to the Messidor program partners (see http://messidor.crihan.fr) for making the database available. The sample images in this publication are taken from the same database. We acknowledge the help of Dr. Medha Prabhudesai and Dr. Mandar Paranjpe, Ophthalmologists for their guidance in understanding glaucoma and its diagnosis procedure. We also acknowledge the help of Dr. Mandar Paranjpe in validation of results.

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