



# Automated Glaucoma Screening based on CDR Measurement

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**ABSTRACT:** Glaucoma is a disease that damages the optic nerve. It causes irremediable blindness if it is left untreated. This has made glaucoma detection as the main research topic in the field of medicine. Currently, there is no effective method that can be used for low cost population-based glaucoma detection or screening. Recent studies have shown that automated optic nerve head assessment from 2D retinal fundus images is capable of low cost population-based glaucoma screening.

The proposed system explains a method for cup to disc ratio (CDR) assessment using 2D retinal fundus images. In the proposed system, the optic disc is first segmented and cup to disc ratio is calculated. In this paper, the disc is located using earlier brightness based method, which performs well in our data sets for glaucoma. The segmentation estimates the disc boundary, but pathological changes around disc, blood vessel occlusions, and variable imaging conditions makes it a challenging task. Here, the disc is segmented using the self-assessed disc segmentation method, which is a combination of three approaches. It has been shown that the self-assessed method achieves more accurate disc segmentation than the individual methods.

**KEYWORDS:** CDR; Disc segmentation; Glaucoma; Self-assessed

## I. INTRODUCTION

Glaucoma is a persistent eye disease in which the optic nerve gets damaged gradually. It is one of the major causes of blindness, and it has been predicted that it may affect around 80 million people by 2020 [1]. Advancement of the disease leads to irreversible loss of vision, which occurs gradually over a long period of time. As the symptoms occur only at the lateral stage of disease, glaucoma is called the silent thief of sight. Glaucoma is incurable, but progression of this disease can be slowed down by treatment. Therefore, it is very important to detect glaucoma in time. However, many glaucoma patients are unaware of the disease until it has reached its advanced stage. Since glaucoma progresses with few symptoms and it causes irreversible vision loss, screening of people at high risk for the disease is important. Generally, Glaucoma screening is done by Intra-Ocular Pressure (IOP) measurement, visual field examination and optic nerve head assessment. Though, these all tests show good result and reliable, population screening with minimal cost not possible with these methods. There are various glaucoma risk factors, such as the vertical cup to disc ratio (CDR)[2], disc diameter[3], ISNT rule[4], notching, peripapillary atrophy (PPA) etc. Although on effectiveness of these factors there are different opinions, CDR is well acknowledged and most commonly used. Higher CDR represents Glaucoma.

## II. LITERATURE REVIEW

Some research provides automated CDR assessment from stereo images [5] and optical coherence tomography (OCT) images [6], [7], [8]. However, getting these stereo images is expensive, which makes it unsuitable for inexpensive large-scale screening [9]. Acquiring 2D retinal fundus images is inexpensive because such fundus cameras are widely available in eye centers, hospitals and in optical shops. Therefore, using existing fundus cameras it is possible to develop a Glaucoma screening programme with little added hardware cost.

In 2D fundus images, the optic disc is divided into the optic cup which is a central bright zone, also known as pallor and the neuroretinal rim, as shown in Fig. 1. The CDR is measured as the ratio of the vertical cup diameter to the vertical disc diameter. There are many methods that have been used for CDR assessment from 2D images. In [10], CDR

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assessment is carried out using intensity based thresholding. However, the cup boundaries are not distinguishable on intensity in many subjects. Later, cup detection is done by vessel bending [9]. But, to identify correct vessel bends is tedious.

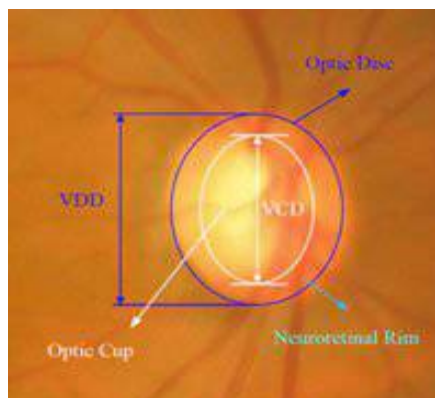


Fig. 1. Structure of an optic disc.

In [11], contour deformation is used for construction of active shape model. But, when the contrast between the rim and optic cup is weak then contour deformation becomes difficult. In [12], superpixel classification approach is used which includes superpixel generation which is quite useful in cup and disc detection. But it does not work well with very large sized and very small sized cups because at the time of training, medium sized cups dominate in number. In [13], cup detection from optic disc is performed using reconstruction based approach. In this method, reconstruction of the disc is carried out using locality-constrained linear coding (LLC) [14] with  $l_2$ - norm Gaussian distance regularization. CDR errors are minimized using this method. But the  $l_2$ - norm Gaussian distance undergoes noise.

### III. METHODOLOGY

For the computation of CDR using proposed approach, the location and segmentation of the disc is essential. The disc localization is finding the location of the disc, which is mainly the disc centre. Very often, disc localization is accomplished based on brightness [15]. Other ways of locating disc are based on anatomical structures among the disc, macula, and retinal blood vessels [16], [17]. In the proposed system, earlier brightness based method in [15] for disc localization, which works well for glaucoma detection is used. The disc segmentation is done to estimate the boundary of the disc, but pathological changes around disc, blood vessel occlusions, and variable imaging conditions makes it a challenging task. There are some approaches for disc segmentation, which includes deformable model based approaches [6], [18], template based approaches [19], [20], and classification based approaches [21], [5].

In the proposed system, segmentation of disc is performed using the self-assessed disc segmentation method [22], which is a combination of three segmentation methods. The self-assessed method for segmentation is more accurate than the individual methods in [22].

#### A. Self-assessed disc segmentation

Optic disc segmentation from retinal fundus image is an important step in many applications such as automated glaucoma screening. In many cases, a method which works well for many images might not be adequate to some images. So it is hard to define single method which can give efficient segmentation results in all cases. Therefore, combined results from several methods can be used to minimize the risk of failure. The self-assessed disc segmentation method proposed in [22] selects one result from three individual disc segmentation methods. Each individual method, after obtaining disc boundary computes a self-assessment score that reflects a reliability of its automated result. Then whichever method gives better result according to self assessment score, output result from that method is taken.

The first individual method is the active shape model (ASM) based method [18]. Circular Hough transform of edge points in disc region is used to get contour. Then ASM is used for the deformation of the contour to the disc boundary.

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The self-assessment reliability score is calculated using the distance between the final boundary and the edge points in the image. The second method uses superpixel classification for the detection of the disc [21]. In this method, superpixel generation is done and then histograms and center surround statistics are used for the classification of superpixels to find whether it is disc or non-disc region. By evaluating the difference between the boundary obtained from superpixel classification and its best fitted ellipse [21], the self-assessment reliability score is calculated. The third method uses Elliptical Hough transform (EHT) [20] for detection of disc. This method includes detection of edges of the images and application of an EHT to find the disc boundary. By computing number of edge points present on the boundary of the disc, the self-assessment confidence score for EHT method is computed.

## B. Disc normalization

Disc representation can be done using many ways. Earlier research [5], [9], [11] shows that CDR computation by retinal images gives better results when green channel of the image is used. To differentiate between the left and right eye images, all the images of the right eyes are flipped horizontally. In order to make the images illumination invariant, the mean intensity is also removed. Besides that, removal of blood vessels and the correction of uneven illumination within the disc are needed.

1) *Blood vessel removal*: The blood vessels which are present inside the disc are different for different individuals. These blood vessels affect the reconstruction of the disc and dissimilarity computation. Therefore, to make reconstruction easier, it is essential to remove the blood vessels. For computing the disc dissimilarity blood vessel segmentation is useful. In the proposed system, Blood vessel estimation is carried out using a morphological closing process. Estimation of the blood vessels (BV) within the disc is given as:

$$BV(j, k) = \begin{cases} 1 & f|x(j, k) - \tilde{x}(j, k)| > T \\ 0 & otherwise \end{cases}, (1)$$

Where  $\tilde{x}$  = morph(x) represents the image after applying a morphological closing process on x. Then, after the replacement of the vessel pixels in x with the pixels in  $\tilde{x}$  the vessel removed image  $\hat{x}$  is obtained, i.e.,

$$\hat{x}(j, k) = \begin{cases} \tilde{x}(j, k) & \text{if } BV(j, k) = 1 \\ x(j, k) & \text{otherwise} \end{cases}, (2)$$

2) *Uneven illumination correction within the disc*: Another factor which affects the disc reconstruction and the dissimilarity computation is uneven illumination across the optic. Generally, the temporal side of the disc is brighter than the nasal side but for different discs of different individuals this unbalance is different. For the correction of this unbalance linear mapping is used. As shown in Fig. 2, average intensities  $\bar{x}_l$  and  $\bar{x}_r$  from the first and last p columns of the disc  $\hat{x}$  are computed. Then the balance corrected disc  $x_b$  is computed as:

$$x_b(j, k) = \frac{k - k_c}{k_{max} - p} (\bar{x}_l - \bar{x}_r) + \hat{x}(j, k), \quad (3)$$

Where  $k_c$  is the center column of the disc, and  $k_{max}$  is the maximum number of columns. The performance of the method is insensitive to the value of p.

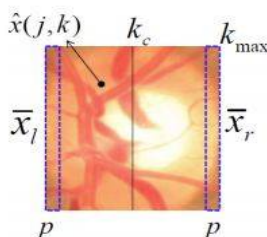


Fig 2. Illustration of unbalance correction



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## C. CDR Assessment

Once the disc and cup boundaries are located, the vertical height of the cup (VCD) and vertical height of the disc (VDD) are computed. This VCD and VDD are further used for CDR measurement.

$$CDR = \frac{VCD}{VDD} \quad (4)$$

## IV. EXPERIMENTAL RESULTS

### A. Data set

For the evaluation of proposed system the database used has 45 different retinal images of 45 different subjects acquired using Canon CR-DG digital retinal camera. This database is provided by the Friedrich-Alexander University Erlangen-Nuremberg (Germany), Pattern Recognition Lab (CS5), Department of Biomedical Engineering, the Department of Ophthalmology, and the Brno University of Technology, Faculty of Electrical Engineering and Communication, Brno (Czech Republic). The database has 3 different categories viz., images of healthy persons, and images of diabetic retinopathy and glaucoma patients. For the location of the disc and determining the region of interest (ROI), the disc localization method in [15] is used. It successfully locates the disc in all 45 images.

The accuracy of CDR assessment is evaluated using the following criteria: 1) CDR error, computed as  $\delta = |CDR_m - CDR|$  where  $CDR_m$  denotes the manual CDR; 2) The glaucoma detection accuracy. In diagnostic tests, sensitivity and specificity are used for measuring accuracy. But more the sensitivity, less the specificity and vice versa so there is a tradeoff between the specificity and sensitivity of a test.

### B. Comparison with other techniques

For the comparison of proposed method with other methods, first two state-of-art methods used are superpixel and LLC. For better comparison results it is also compared with locally linear embedding (LLE) and sparse coding. CDR of all images is computed manually by an expert ophthalmologist. Result from the expert is referred as 'Expert'.

CDR error is computed in all methods. The CDR error for all methods is given in Table I. Table I shows that proposed method provides better results with lower CDR error than other methods. CDR error is reduced by 18.0% and 11.1% than superpixel and LLC methods respectively.

Figure 3 shows comparison for segmentation of the disc by the proposed method with previous method. It shows that due to self-assessed segmentation method whichever segmentation gives better result is taken as segmentation method for that particular fundus image.

TABLE I  
PERFORMANCE BY VARIOUS METHODS.

Method name	CDR error
Superpixel	0.078
LLE	0.080
SC	0.071
LLC	0.072
Proposed	0.064

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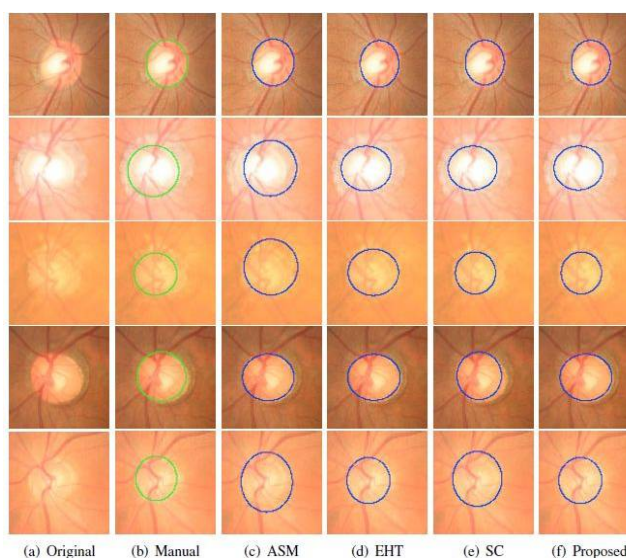


Fig 3- comparison of all methods

## V. CONCLUSION

This method gives better results in CDR computation with reduction in CDR error than previous methods. As manual CDR assessment is time consuming and cannot be implemented for large scale population screening, the proposed method can be used to replace manual CDR computation method. Therefore, the proposed method has great potential for inexpensive glaucoma screening in polyclinics, eye centers, and especially in optical shops, according to discussions with clinicians and ophthalmologists. But CDR computation from 2D retinal images has limitations because depth information is missing which mainly contains the information about the optic cup. 2D images are relying on intensity changes for cup detection. Future work will explore more factors related to CDR for better screening of glaucoma.

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