

An Efficient Glaucoma Screening Using CDR From 2-D Retinal Fundus Images

M. Kezia

M. Tech, Department of Electronics and Communication, JNTUA, Andhra Pradesh, India

ABSTRACT

Glaucoma is the second leading cause of blindness all over the world. Eye's optic nerve will be damaged as the result of glaucoma. Patients are also unaware of the disease because of its slow progression with very few symptoms. So detecting the disease in time is very important to avoid irreversible blindness. Automated optic nerve head (ONH) assessment from 2-D retinal fundus images is more promising for low-cost glaucoma screening. In this paper, super pixels classification based segmentation method is used for optic disc and optic cup boundary estimation. Subsequently, the CDR for testing fundus eye image is computed. The proposed method achieves good accuracy in large-scale population-based glaucoma screening.

Keywords: Glaucoma screening, super pixel classification, optic disc segmentation, optic cup segmentation, cup to disc ratio (CDR).

I. INTRODUCTION

Glaucoma is an eye disease in which the optic nerve head is damaged. It is predicted to affect nearly 80 million people by 2020 [1]. Glaucoma is called the silent thief of sight as it progresses with few signs and the vision loss from glaucoma is irreversible. Many glaucoma patients are unaware of the disease. Although it is irreversible, its progression can be slowed down through treatment. So screening of people at high risk for the disease is vital.

Clinically, there are three methods to detect glaucoma: 1) intraocular pressure (IOP) measurement, 2) visual field test, 3) optic nerve head assessment. The IOP measurement is not an effective screening tool because glaucoma can be present with or without increased IOP. Visual field test requires special equipment only present in specialized hospitals and therefore unsuitable for screening. Optic nerve head assessment is more promising for glaucoma screening which is done by a trained professional but manual assessment is time consuming, subjective and

expensive. Therefore, Automatic ONH assessment would be very beneficial for large-scale glaucoma screening instead of manual ONH assessment.

Binary classification between diseased and healthy image features is one strategy for automatic optic nerve head assessment [2]–[4] but selection of features is difficult and also challenging at pixel level [5]. Another strategy is to use the clinical indicators, such as the vertical cup to disc ratio (CDR) [6], disc diameter [7], ISNT [8] rule, peripapillary atrophy (PPA) [9], notching [10], etc. CDR is well known among ophthalmologists. A larger CDR value indicates a higher risk of glaucoma and vice versa. There has been some research on automated CDR assessment from 3-D images [11]–[14]. 2-D colour fundus images are still referred over 3-D images because of their availability and low cost [11]. This paper focuses on automatic glaucoma screening using CDR from 2-D fundus images.

The optic disc is the location where ganglion cell axons exit the eye to form the optic nerve head,

through which visual information of the photo-receptors is transmitted to the brain.

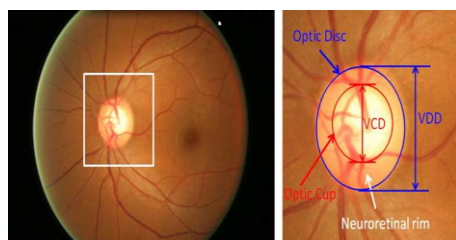


Figure 1. Major structures of the optic disc.

The region enclosed by the blue line is the optic disc; The central bright zone enclosed by the red line is the optic cup; And the region between the red and blue lines is the neuroretinal rim.

As shown in Figure 1, the disc can be divided into two distinct zones; namely, a central bright zone and a peripheral region. The central bright zone is optic cup and the peripheral region is neuroretinal rim. Clinically, CDR is the ratio of the vertical cup diameter (VCD) to vertical disc diameter (VDD). Therefore, accurate segmentation of disc and cup are essential for CDR measurement as shown in Figure 2.

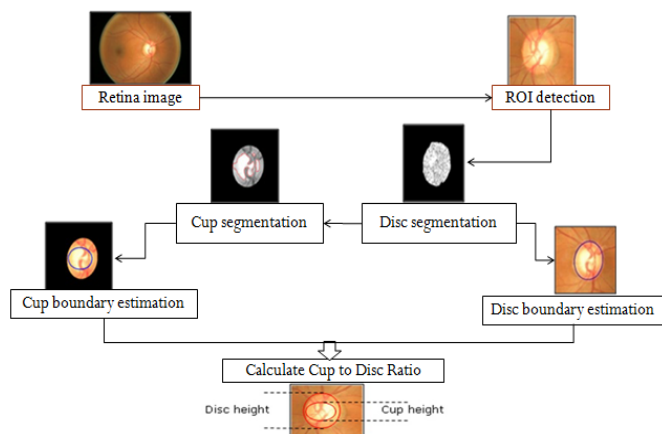


Figure 2. General procedure for CDR assessment.

There have been several methods for automatic CDR measurement from 2-D fundus images, mainly pixel classification based methods [15]-[18], template based methods [19]-[21] and deformable model based methods [22]-[24]. This paper proposes super pixel classification based disc and cup segmentations for

glaucoma screening. Centre surround statistics were computed from super pixels and unify them with histograms for disc and cup segmentation. Based on the segmented disc and cup, CDR is computed. Whether glaucoma is present or absent is decided from computed CDR value as shown in Figure 3.

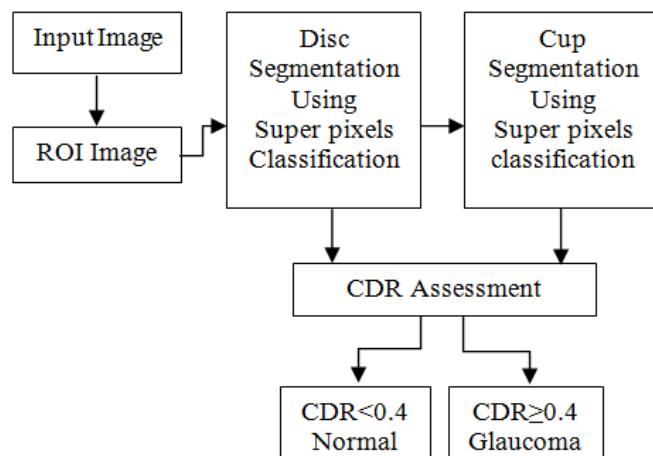


Figure 3. Block diagram of the proposed model

The paper summary is as follows. In Section II, description of Optic disc localization followed by ROI extraction. Section III describes super pixel classification based OD segmentation. Section IV explains super pixel classification based optic cup segmentation. Section V shows the experimental results including the accuracy for disc and cup segmentation as well as glaucoma screening. Conclusion is presented in final section.

II. OPTIC DISC LOCALIZATION

Localization of disc is very important step in automatic glaucoma detection. Localization means finding out the disc pixels in the entire image. The region containing disc pixels is the required region of interest. After finding disc pixels, automatic extraction of ROI is done by calculating correlation coefficient between mask and original image. The algorithm to local disc is as follows:

1. Resized original image to 256×256.
2. Applied mean smoothing filter to remove noise.
3. Binary image was generated by taking threshold.
4. Applied morphological operations (opening and closing) to binary image.
5. Labelled the image and calculated basic region properties (area, centroid, bounding box).
6. Correlation coefficient calculated between mask image and input image.
7. Pixels in the label with correlation coefficient = +1 are the required region of interest pixels.
8. Bounding box coordinates of required region were given to imcrop function to automatically crop the region of interest.

III. OPTIC DISC SEGMENTATION

Disc boundary estimation comes under segmentation which is a very challenging task due to variable imaging conditions, blood vessel occlusions, pathological changes around disc, etc. Edge detection followed by circular Hough transform initialization with an active shape model to segment the disc in [27]. Circular fitting for disc might lead to an underestimated disc because vertical diameter of disc is 7%–10% larger than the horizontal one. So ellipse fitting is often adopted for glaucoma detection [28]. The performance of the segmentation methods of disc depends upon the differentiation of edges from the disc and other structures, like PPA (region which looks like a part of the disc) [29] which makes to form another ellipse (often stronger) besides disc. To overcome the drawback of previous methods, a super pixel classification based method followed by deformable model is proposed. To compute local image features, super pixels work as a convenient primitive by capturing redundancy in the image. For initialization of disc boundary, super pixel classification is used and the deformable model is used to fine tune the disc boundary.

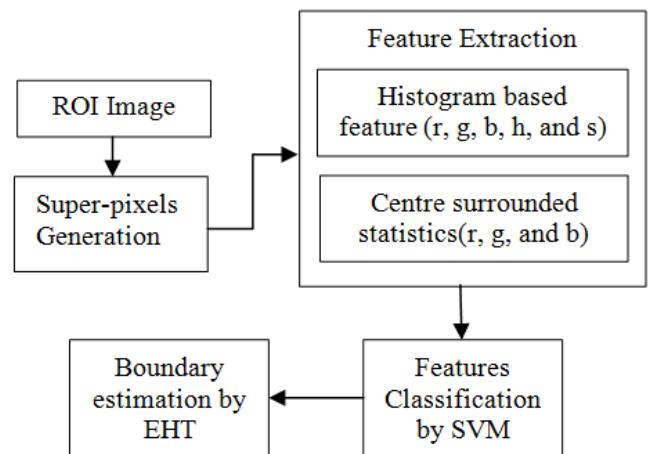


Figure 4. Super pixel based optic disc segmentation block diagram.

A. Generation of super pixels by SLIC

Simple linear iterative clustering [30] algorithm (SLIC) is used to aggregate nearby pixels into super pixels. Compared to other super pixel methods, SLIC is fast, memory efficient and very excellent at object's boundary adherence. SLIC operates on single parameter K i.e. the number of desired super pixels.

1. In the image with N pixels, Initial cluster centres C_k are sampled on regular grid step $S = \sqrt{N/K}$ pixels.
2. At first, centres moved towards the lowest gradient position in a 3×3 neighbourhood.
3. SLIC iteratively searches for its best matching pixel in $2S \times 2S$ neighborhood around C_k based on colour and spatial proximity.
4. Based on the found pixel new cluster centre will be computed.
5. The iteration continues until the distance between the new centres and previous ones is small enough.
6. In final step, Post processing is applied to enforce the connectivity.

B. Feature Extraction

1) Contrast Enhanced Histogram: Colour histogram from super pixels is an intuitive choice for feature extraction [31] because colour is one of the main

differences between disc and non-disc region. To form five channel maps, equalized histograms of red r, green g and blue b channels from RGB colour space and hue h and saturation s from HSV colour space are used. For retinal images, value v from HSV colour space is almost the same as the red channel. Hence v is not used. Histogram feature computed for the jth super pixel is

$$\begin{aligned} \text{HIST}_j \\ = [h_j(\text{HE}(r)) \ h_j(\text{HE}(g)) \ h_j(\text{HE}(b)) \ h_j(h) \ h_j(s)] \end{aligned}$$

where function of histogram equalization is denoted by $\text{HE}(\cdot)$ and the function to compute histogram is denoted by $h(\cdot)$ from jth super pixel SP_j . The histogram computation uses 256 bins and $256 \times 5 = 1280$ dimensional feature

2) Centre Surround Statistics: A texture feature is required to differentiate the PPA region which looks closer to the disc. PPA contains blob-like structure which varies largely in multiple scales whereas disc is constant with homogenous structure. Centre surround statistics (CSS) from super pixels work well to reflect the difference between PPA and disc. To compute CSS,

1. Gaussian pyramids are generated with a ratio from level 0 to level 8[32].
2. CSS is computed for 6 maps at 2-5, 2-6, 3-6, 3-7, 4-7 and 4-8 from an image channel using central levels $c = 2, 3, 4$ and surround levels (coarser) $s = c + d$, with $d = 3, 4$.
3. Feature map in centre level at $c = 2, 3, 4$ denoted as $I(c)$ and the feature map in surround level s as $I(s)$, interpolate $I(s)$ to be the same size as $I(c)$ and then interpolated map is denoted as $f_{s-c}(I(s))$.
4. The centre surround difference is then computed as $|I(c) - f_{s-c}(I(s))|$.
5. All the difference maps are resized to be the equal size with the original.
6. Compute $6 \times 3 = 18$ maps from r, g and b channels.

7. Then CSS features, $\text{CSS}_j = [\mu_j \ \text{var}_j]$ are computed as the first and second moments of these maps within super pixels where μ_j and var_j from Jth super pixel

$$\mu_j(i) = \frac{1}{n_j} \sum_{(x,y) \in \text{SP}_j} M_i(x,y) \quad (1)$$

$$\text{var}_j(i) = \frac{1}{n_j} \sum_{(x,y) \in \text{SP}_j} (M_i(x,y) - \mu_j(i))^2 \quad (2)$$

3) Final Feature: To classify the present super pixel, features from neighbouring super pixels are also included. For SP_j , features of four neighbouring super pixels SP_{j1} SP_{j2} SP_{j3} and SP_{j4} were computed. By moving horizontally to the left of the current super pixel SP_j , SP_{j1} is determined as the first super pixel. Similarly, SP_{j2} SP_{j3} and SP_{j4} are determined by moving right, up, and down, as shown in Fig. 5. For specific super pixel SP_j , CSS feature would be calculated as $\widehat{\text{CSS}}_j = [\text{CSS}_j \ \text{CSS}_{j1} \ \text{CSS}_{j2} \ \text{CSS}_{j3} \ \text{CSS}_{j4}]$ which has a dimension of $18 \times 2 \times 5 = 180$. Then $[\text{HIST}_j \ \widehat{\text{CSS}}_j]$ is the proposed feature.

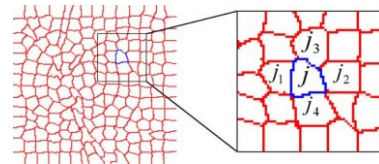


Figure 5. Illustration of neighbouring superpixels

C. Initialization and Deformation

A support vector machine with linear kernel is used as the classifier in this part. In the training, same number of super pixels from the disc and non-disc region from a set of training images with manual disc boundary.

1. The training is performed on the active set and returns a trained classifier model.
2. Then the trained classifier is used for further testing.
3. Output value of a super pixel is assigned to all pixels in that super pixel
4. Assign +1 and -1 to positive (disc) and negative (non-disc) samples, and the threshold is the average of them, i.e., 0.

5. After the binary decisions assignment for all pixels, a matrix with binary values with 1 as object and 0 as background is available.
6. Using morphological operation, largest connected object is obtained and its boundary is used as the raw estimation of the disc boundary.
7. The best fitted ellipse is computed as the fitted estimation using elliptical Hough transform [33].

IV. OPTIC CUP SEGMENTATION

Very few methods have been proposed for cup segmentation like thresholding [18], [19], level set based approach [20] and deformable model based method [34]. Cup boundary detection when the pallor is weak is the major challenge. In such cases, landmarks like intensity changes or edges are not present to estimate the cup boundary reliably. In super pixel classification method for cup segmentation we incorporate prior knowledge into the training of super pixel classification instead of relying on vessel bends. The procedure for cup segmentation is similar like disc segmentation with few modifications.

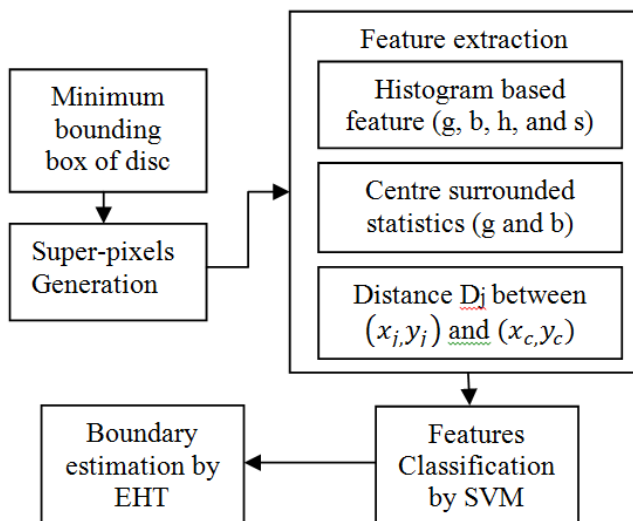


Figure 6. Block diagram of super pixel based optic cup segmentation.

A. Feature Extraction

The minimum bounding box of the disc is used for cup segmentation. While computing histogram feature $HIST_j^c$, we exclude red channel because only little information of the cup present in the red channel. Similarly, the center surround statistics $\widehat{CSS}_j^c$ can be computed. When the pallor is non-obvious, distance D_j is included as location information to obtain a reliable result, as illustrated in Fig. 7. D_j is normalized using the height and width of the disc to adapt the variation of disc size. Mathematically, D_j is computed as

$$D_j = \sqrt{\left(\frac{x_c - x_j}{h}\right)^2 + \left(\frac{y_c - y_j}{w}\right)^2} \quad (3)$$

Where (x_c, y_c) denotes the coordinate of the disc centre, (x_j, y_j) denotes the coordinate of the centre of SP_j , h and w denotes the height and width of the disc, respectively. Thus, the feature vector for cup segmentation is computed as $[HIST_j^c \ \widehat{CSS}_j^c \ D_j]$.

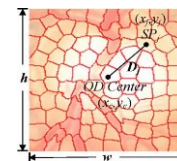


Figure 7. Illustration of distance D_j

B. Superpixel Classification for Optic Cup Estimation

The SVM classifier with linear kernel is used again to classify cup and non cup regions. In the training step, the same number of super pixels from the cup and non-cup regions was generated from a set of training images with manual cup boundary. The output value for each super pixel is used as the decision values for all pixels in the super pixel and then mean filter is applied on the decision values to compute smoothed decision values. The largest connected object is obtained and its boundary is used as the raw estimation after the smoothed decision values are used to obtain the binary decisions for all pixels. Here, the best fitted ellipse is computed as the cup boundary which overcomes the noise introduced by vessels

especially from the inferior and superior sector of the cup.

$$CDR = VCD/VDD \quad (4)$$

C. Cup to Disc Ratio

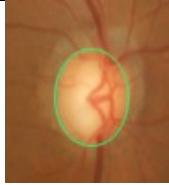
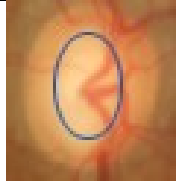
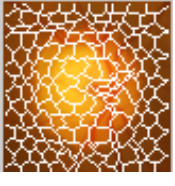
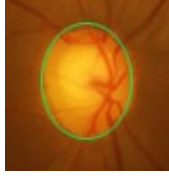
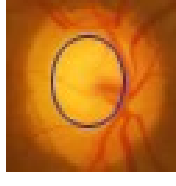
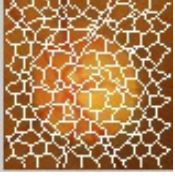
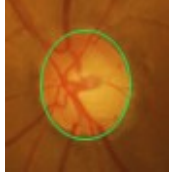
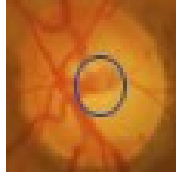
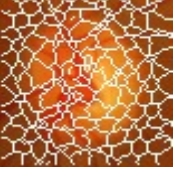
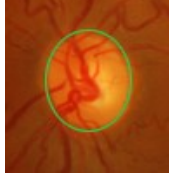
After obtaining the disc and cup, CDR can be calculated. As mentioned in the introduction, CDR is an important indicator for glaucoma screening computed as

If the computed CDR is greater than a threshold, it is glaucomatous eye, otherwise, healthy eye.

V. EXPERIMENTAL RESULTS

A. Simulation Results

Table 1. Simulation results of input images for glaucoma screening

INPUT IMAGE	LOCALIZED ROI	DISC ROI WITH SUPERPIXELS	DISC BOUNDARY ESTIMATION	CUP BOUNDARY ESTIMATION	Cdra	DIAGNOSIS
					0.72	Glaucoma
					0.69	Glaucoma
					0.31	Normal
					0.39	Normal

B. Performance Evaluation

1. Mean CDR Error:

To evaluate the accuracy of the proposed CDR, the CDR error is computed as

$$\delta = |CDR_m - CDR_a| \quad (5)$$

Where CDR_m denotes the manual CDR from trained professionals and CDR_a denotes the automated CDR.

$$\text{Mean CDR Error} = \frac{1}{N} (\sum \text{CDR Errors}) \quad (6)$$

Here, N denotes the total number of images in dataset.

2. Overlapping error for Optic Disc and Optic Cup:
The overlapping error is computed as the evaluation metric for segmentation accuracy

$$E = 1 - \frac{\text{Area}(S \cap G)}{\text{Area}(S \cup G)} \quad (7)$$

Where S and G denote the segmented and the manual “ground truth” disc or cup, respectively.

Table 2. MEAN CDR ERROR , Mean overlapping error of Disc and Cup BETWEEN PROPOSED METHOD AND PREVIOUS METHOD

Metric Method	Mean overlapping Error for Disc	Mean overlapping Error for Cup	Mean CDR Error
EHT	0.14	0.25	0.15
SP	0.11	0.18	0.09
SP+EHT (proposed)	0.07	0.11	0.06

VI. CONCLUSION

Super pixel classification based methods for disc and cup segmentations have been demonstrated that HIST and CSS are beneficial for both disc and cup segmentation. In disc segmentation, CSS responds to blobs and provides better differentiation between PPA and discs compared with histograms. In cup segmentation, the benefit of CSS and Dj is even larger than that in disc segmentation, because the colour change from cup to neuroretinal rim is much smaller. The obtained CDRs for very large cups are still high and the CDRs for very small cups are still small, so the proposed method achieves high classification accuracy when differentiating glaucomatous subjects from healthy ones. The accuracy of the proposed method is

already much better than the air puff IOP measurement and previous CDR based methods [27].

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