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Cup to Disc Ratio(CDR) Assessment for Detecting Glaucoma Using 2-D Retinal Images

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***Abstract*—Glaucoma is a chronic eye disease which leads to vision loss. It is a silent theft of sight. Early detection of glaucoma can potentially reduce the risk of blindness. However many patients are unaware of the disease, because it progresses slowly without easily noticeable symptoms. In recent studies, there is no effective method for low-cost population-based glaucoma detection or screening. In this work, the propose method is cup to disc ratio (CDR) assessment, using 2-D retinal fundus images. First, the image is pre-processed by converting the image into HSI and applying the filter. Followed by, the optic disc is first segmented and reconstructed using a novel sparse dissimilarity-constrained coding (SDC) approach. Considers both the dissimilarity constraint and the sparsity constraint from a set of reference disc with known CDRs. Subsequently, the reconstruction coefficients from the SDC are used to compute the CDR for the testing disc.**

***Index Terms*—Color Image, Image Processing, Cup to disc Ratio (CDR), Glaucoma screening, Sparse dissimilarity-constrained coding (SDC).**

I. Introduction

Glaucoma is a complex eye disease where it lead to vision loss. Nearly 79 million peoples are going to affect up to coming year of 2020. As the symptoms only occur when the disease is quite advanced and very difficult to identify. Early detection and treatment by your ophthalmologist are the keys to preventing optic nerve damage and vision loss from glaucoma. Many of the people are unaware about the disease, so screening the glaucoma is important for everyone. Generally glaucoma assessment by Intra Ocular Pressure (IOP) measurement, visual field test and optic nerve head assessment, these are all promising ones, but these are all high cost, where screening glaucoma based on Cup Disc Ratio (CDR) is the low cost method. In [1], inappropriate for low-cost large-scale screening, and selection features and classification stage. In [2], the threshold based on intensity is used. In [3], challenges are there to finding the vessel bend, Yin et al. developed an active shape model (ASM)-based approach by combining prior knowledge with contour deformation.Gopal Joshi et al.proposed a method which make use of anatomical evidences such as vessel bends and local image parameters [5]. Jun Cheng et al. developed method based on super pixel classification by the use of histogram and centre surround statistics [4].

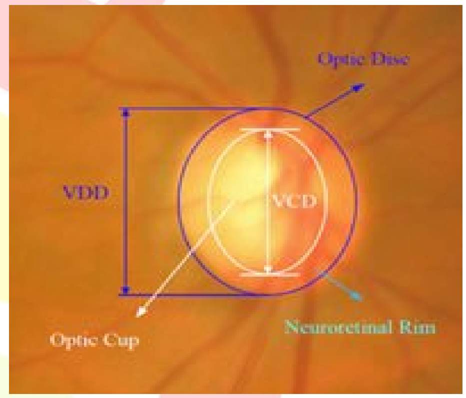

Fig. 1. Structure of an optic disc: optic disc boundary (blue), optic cup (white), neuroretinal rim (cyan), CDR is computed as VCD/VDD

In this proposed method Cup to Disc Ratio (CDR) can be estimated, based on the CDR the glaucoma stage is found. Usually the normal cup-to-disc ratio is 0.3. A larger CDR generally indicates a higher risk of glaucoma. The CDR is computed as the ratio of the **vertical** cup diameter to the vertical disc diameter. Overcome the limitations in [4], that is overestimates very small cups and underestimates very large cups. Here the Fig 1. Show structure of an optic disc. It shows the optic disc boundary, optic cup, neuroretinal rim and CDR computation.

Here, **CDR= VCD/VDD**

where, CDR is the Cup to Disc Ratio

VCD is the vertical cup diameter

VDD is the vertical Disc Diameter

Cup Disc Ratio is estimated where the cup is the one part of the disc

II. Methodology

The methodology shows the various steps in the process of the paper; starting from the image acquisition, enhancing the images using the Adaptive Histogram Equalization (CLAHE), segmentation of the images using the gradient features, localization, normalization, and to find the CDR assessment, the sparse dissimilarity is used. The flow diagram of the overall architecture is given in the fig.2.

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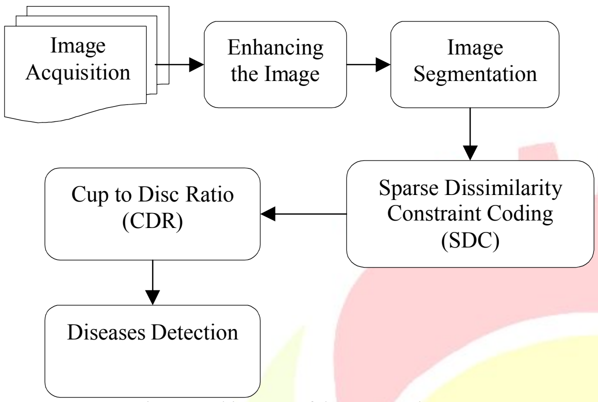

Fig. 2. Architecture of the Proposed System

III. IMAGE ACQUISITION

Every image processing application always begins with the image acquisition. The original image are received form ophthalmologists at the hospitals and store in database. For this study the eye images contain glaucoma disease will be chosen as an input image. Then the image-preprocessing techniques are applied to the acquired images to extract useful features that are necessary for further analysis. Then several techniques has been used for classify the images according to the specific problem in hand.

IV. IMAGE ENHANCEMENT

Image enhancement is helpful for easy understanding of human observation. Here in this firstly color conversion, extract I component, reduce noise, improve contrast, combine the image, and color conversion takes place. So fine images is found.

These steps are done, when preprocessing the image,

A. RGB to HIS conversion

B. Median Filtering

C. Improving Contrast using Adaptive Histogram Equalization (CLAHE).

V. IMAGE SEGMENTATION

Optic disk segmentation from a retinal image is a fundamental task in most of the diagnosis method related to retinal image. Features of Optic disk are more useful for number of eye disorder identification including glaucoma. In the determination of CDR ratio first we have to locate an optic disk in the eye image, then we can segment the disk.

A. Disc Localization

The disc localization focuses on finding an approximate location of the disc, very often the disc center. The disc localization is often achieved based on brightness [8], [9], anatomical structures among the disc, macula, and retinal BVs [10], [11]. In this paper, the disc is located using our earlier brightness – based method in [9], we segment the disc using the gradient value. Before proceeding with the self-assessed disc segmentation, the improved I component is combined with the H and S component. The located disc is shown in fig. 3.

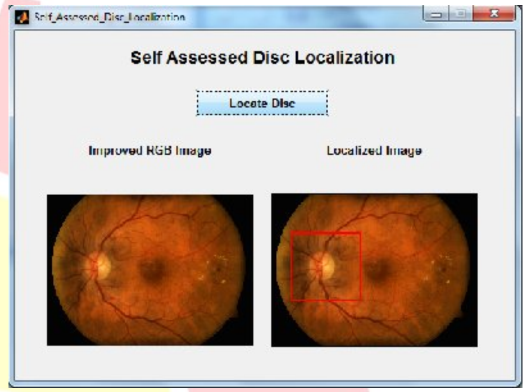

Fig. 3. Located Optic Disc in the Eye Image

B. Disc Segmentation

Here we propose a Self-Assessed Disc segmentation method which is used for segmenting the optic disc with good accuracy. The self-assessed disc segmentation proposed in [6], selects one result based on the outputs. This method is most reliable. [7], reported in the literature can be used. Here super pixel classification, elliptical Hough transform, etc., are used to segment the optic disk. The segmented optic disc is shown in fig. 4. For each segmentation method aself-assessment score is calculated. Based on the self-assessment score, only one segmented output is selected.

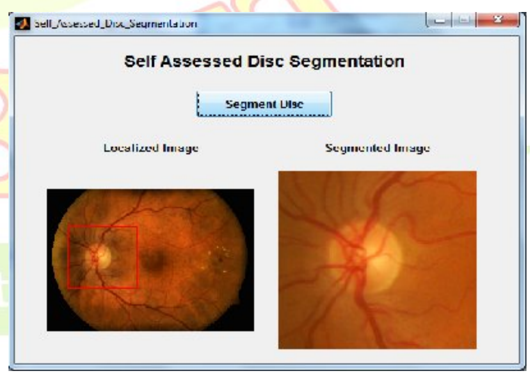

Fig. 4. Segmented Optic Disc from the Localized Image

VI. DISC NORMALIZATION

Green channel of the retinal color image is the most suitable one for CDR computation. The mean intensity is also removed to avoid the difference due to different illuminations in different disc images

Here two steps are done here

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A. BV Removal

It is important to remove BVs. Many automated vessel detection methods [18], [19] can be used. In this application, it is unnecessary to use a very complex and time consuming vessel segmentation to get precise BVs for the disc dissimilarity computation

$$BV(j,k) = \begin{cases} 1, & If\ |x(j,k) - \tilde{x}(j,k)| > \\ 0, & Otherwis \end{cases} \quad (1)$$

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

$$\hat{x}(j,k) = \begin{cases} \tilde{x}(j,k), & If\ BV(j,k) = \\ x(j,k), & otherwi \end{cases} \quad (2)$$

B. Uneven Illumination Correction

Uneven illumination across the optic disc is another factor that affects the dissimilarity computation and the disc reconstruction. In our method, we apply a linear mapping to correct the unbalance

We first compute the average intensity $\bar{x}_l$ and $\bar{x}_r$ from the first and last p columns of the disc $\hat{x}$. 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.

VII. SPARSE DISSIMILARITY CONSTRAINED CODING

Here, we introduce the proposed spare dissimilarity –constrained coding algorithm. Denote a set of *n* reference disc images $X = [x_1, \ldots. x$ and the correspondingCDRs as $r = [r_1, r_2, \ldots. r_n$, *i=1,2, ….n,* denotes the *i*th balance corrected disc computed above. Inspired from the reconstruction based method [26], we want to compute a linear reconstruction coefficient $w = [w_1, \ldots. w_n$ for a new testing disc image *y* while minimizing the reconstruction error. $\|y - Xw|$ is a few reference images that are closest to *y* are sufficient to estimate the CDR. Therefore, we want to limit the number of reference images used, i.e., we want to minimize thenonzeroelements in *w,* or $\|w$ Because -norm is a NP-hard problem,the -norm $\|w$ is used instead. Here finding the dissimilarity score is important for finding the variation in the disc.

A. Formulation of SDC

Combining the dissimilarity term $\|d \odot w\|^2$ and the sparsity term $\|w\|_1$ with the data term $\|y - Xw\|^2$, the objective function of the proposed SDC method is then given by

$$\underset{w}{argmin}(\|y - Xw\|^2 + \lambda_1 \cdot \|d \odot w\|^2 + \lambda_2 \cdot \|w\|_1) \quad (4)$$

where λ_1 and λ_2 are parameters controlling the weights of the two regularization items.

Rewriting the second item and merging it with the first item in we get

$$\underset{w}{argmin}(\|y - Xw\|^2 + \lambda_1 \cdot \|d \odot w\|^2 + \lambda_2 \cdot \|w\|_1)$$
$$= \underset{w}{argmin}(\|y - Xw\|^2 + \lambda_1 \cdot \|Dw\|^2 + \lambda_2 \cdot \|w\|_1)$$
$$= \underset{w}{argmin}\left(\left\|\begin{bmatrix} y \\ 0 \end{bmatrix} - \begin{bmatrix} X \\ \sqrt{\lambda_1} D \end{bmatrix} w\right\|^2 + \lambda_2 \cdot \|w\|_1\right)$$
$$= \underset{w}{argmin}\left(\|\hat{y} - \hat{X}w\|^2 + \lambda_2 \cdot \|w\|_1\right) \quad (5)$$

Where $D = diag(d)$ denotes a diagonal matrix with main diagonalelement $D(i,i) = d_i$, $i = 1, \ldots \ldots, n$, 0 is a vector of 0s with length *n,*

$\hat{y} = \begin{bmatrix} y \\ 0 \end{bmatrix}$ and $\hat{x} = \begin{bmatrix} X \\ \sqrt{\lambda_1} D \end{bmatrix}$

B. CDR Assessment

From the sparse dissimilarity constraint, the cup to disc ratio is calculated by identifying the cup and the disc in the eye image, which is shown in fig. 5. If the ratio is beyond the threshold level, then glaucoma is present. By this type of detection, the glaucoma can be detected in the earlier stage, which can controlled.

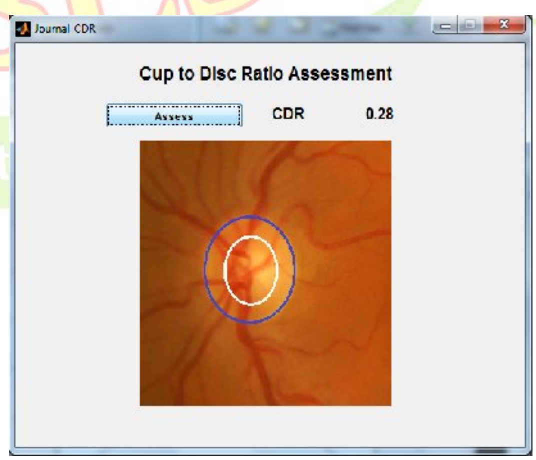

Fig. 5. Detection of the Optic Cup (White) and the Optic Disc (Blue)

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VIII. Experimental Results

The proposed system is checked on various images, it shows only insignificant errors compared with the many optic cup detection techniques like Locally Linear Embedding (LLE), Sparse Coding (SC), etc. The performance evaluation of the proposed system is calculated and shown in fig. 6 and fig. 7.

A. Accuracy

The following graph shows the accuracy of the proposed method, which shows a better result compared with other methods.

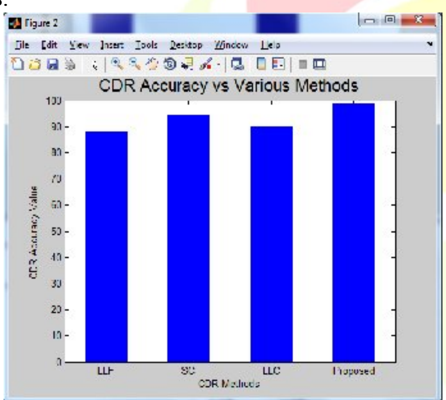

Fig. 5. Cup to Disc Ratio Accuracy between various methods detection techniques

B. CDR Errors

The graph shows the error report of various CDR methods. From the figure our proposed method got very less errors compared to other methods.

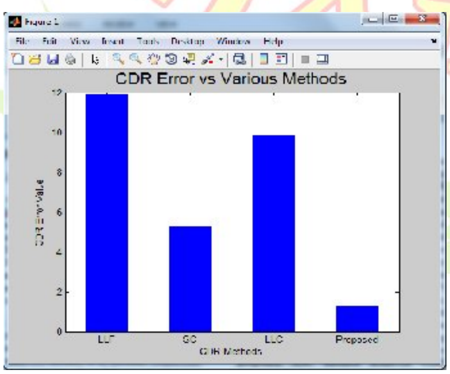

Fig. 5. Cup to Disc Ratio Error Rate between various methods detection techniques

IX. Conclusion

In this paper, we propose the SDC for CDR assessment. The proposed method significantly improves the CDR computation compared with other reconstruction – based methods such as LLE, SC and LLC. The proposed method can be potentially used to replace manual CDR assessment to save time and reduce cost. The CDR – based screening from 2-D images has its limitations. The proposed SDC method achieves CDR computation and glaucoma detection accuracy comparable with manual CDR assessment. The proposed method can be used to replace the time consuming and expensive manual CDR assessment. Therefore, the proposed method has great potential for low – cost glaucoma screening in polyclinics, Eye Centre, and especially in optical shops.

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