An Efficacious Method of Cup to Disc Ratio Calculation for Glaucoma Diagnosis Using Super pixel

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Abstract: Glaucoma is a chronic eye disease that leads to vision loss. Since it cannot be cured, detecting the disease in time is important. The tests which are done to detect Glaucoma using intraocular pressure (IOP) are not sensitive enough for population based glaucoma screening. The assessment of Optic nerve head damage in retinal fundus images is both more promising and superior. In this paper the optic disc and optic cup segmentation using Superpixel classification for glaucoma screening. The SLIC (Simple Linear Iterative Clustering) algorithm is incorporated to segment the fundus retinal image into compact and nearly uniform superpixels. Unlike dividing an image into a grid of regular pixels, superpixels have the important property of preserving local boundaries. The segmented optic disc and optic cup are then used to compute the cup to disc ratio for glaucoma screening. The Cup to Disc Ratio (CDR) of the color retinal fundus camera image is the primary identifier to confirm Glaucoma for a given patient. Superpixels are becoming increasingly popular in computer vision applications because of improved performance over pixel-based methods.

Index Terms – intraocular pressure (IOP), superpixel, cup to disc ratio (CDR).

I.INTRODUCTION

Glaucoma is a group of eye diseases characterized by damage to the optic nerve. It is an eye disease which causes irreversible loss of vision. In its early stages, glaucoma may present few or no symptoms and can gradually steal sight. In fact, most people affected by Glaucoma do not know if they have the disease or not. If left undetected and untreated, glaucoma can lead to blindness. One of the high risk factors for glaucoma is elevated Intraocular pressure (IOP), or pressure inside the eye. A healthy and a normal eye secrete a fluid named aqueous humor, at the same rate at which it drains. The pressure is increased when the draining system is blocked and the fluid cannot exit at a normal rate. This increased IOP pushes against the optic nerve causing gradual damage, which may result in vision loss, usually starting with the peripheral, or side vision. Increased eye pressure is often associated with gradual damage to the nerve fibers that make up the optic nerve. In this paper optic disc and optic cup are segmented using superpixel classification for detecting Glaucoma. For automatic optic nerve head assessment we can use the image features for a binary classification between glaucomatous and healthy subjects. These features are normally computed at the image-level. CDR is commonly used because of its accuracy and simplicity. When CDR is greater than 0.65,

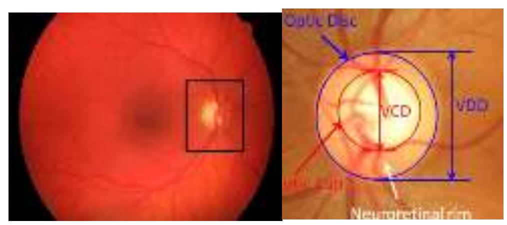

Fig. 1. Fundus retinal image showing the optic disc. The region enclosed by the blue line is the optic disc; the central bright zone enclosed by the red line is the optic cup; and the region between the red and blue lines is the neuroretinal rim.

then it indicates a high risk of glaucoma [10]. However, because 3-D images are not easily available, 2-D color fundus images are still referred to by most clinicians. Moreover, the high cost of obtaining, 3-D images make it inappropriate for a large-scale screening program. This paper focuses on automatic glaucoma screening using CDR from 2-D fundus images. The CDR is computed as the ratio of the vertical cup diameter (VCD) to vertical disc diameter (VDD) clinically.

II.PROBLEM STATEMENT

An early detection of glaucoma is particularly significant since it allows timely treatment to prevent major visual field loss and prolongs the effective years of usable vision. The diagnosis of glaucoma can be done through measurement of CDR (cup-to-disc ratio). Currently, CDR evaluation is manually performed by trained ophthalmologists or expensive equipment such as Heidelberg Retinal Tomography (HRT). However, CDR evaluation by an ophthalmologist is subjective and the availability of HRT is very limited. Thus, this paper proposes an intuitive, efficient and objective method for automatically classifying digital fundus images into either normal or glaucomatous types in order to facilitate ophthalmologists.

III.METHODOLOGY

The first step is preprocessing, which involves preparing the images for feature selection and correspondence. Using methods such as scale adjustment, noise removal, and segmentation we can perform the Preprocessing. When pixel sizes in the images to be registered are different but known, one image is resampled to the scale of the other image. This scale adjustment facilitates feature correspondence. If the images are noisy, they are smoothed to reduce the noise. Image segmentation is the process of partitioning an image into regions so that features can be extracted. The superpixel algorithms represent a very useful and increasingly popular preprocessing step for a wide range of computer vision applications. The grouping of spatially coherent pixels sharing similar low-level features leads to a major reduction of image primitives, which results in an increased computational efficiency. The normal fundus image is converted to binary image by thresholding. Thresholding can be divided into two categories, namely global thresholding and local thresholding, depending on the threshold selection [13]. To do this, it converts the input image to gray scale format (if it is not already an intensity image), and then converts this gray scale image to binary by thresholding. The next step is to extract the features for improvised segmentation. The features used in image registration are corners, lines, curves, templates, regions, and patches. The type of features selected in an image depends on the type of image provided. To facilitate feature selection, it may be necessary to enhance image intensities using smoothing or deblurring operations. Image smoothing reduces noise but blurs the image. Deblurring is the process where it reduces blur but enhances noise. The size of the filter selected for smoothing or deblurring determines the amount of smoothing or sharpening applied to an image.The Region of Interest (ROI) localization was performed in order to reduce the computational requirements by only focusing on an appropriate region. The region of interest (ROI) around the optic disc must first be delineated. The correct identification of ROI results in a small image which helps speeding up the calculation of the CDR, since its size is usually less than 11% of the entire retinal fundus image. ROI localization requires very less human intervention and has potential for population based automatic screening. In this paper, the set of fundus images are firstly examined, and it is found that the optic disc region is usually of a brighter pallor or higher color intensity than the surrounding retinal area. The fundus images with the highest intensity are selected as potential candidates for the optic disc center. The intensity-weighted centroid method [8] is proposed to find an approximate ROI centre. The boundary of the ROI localization is defined as a rectangle around the ROI centre with dimensions of twice the typical optic disc diameter, and it is used as the initial boundary for the optic disc segmentation. To calculate the vertical cup to disc ratio (CDR), the optic cup and disc first have to be segmented from the retinal images. Fig. 2 depicts the framework for building the proposed methodology for CDR calculation for Glaucoma screening.

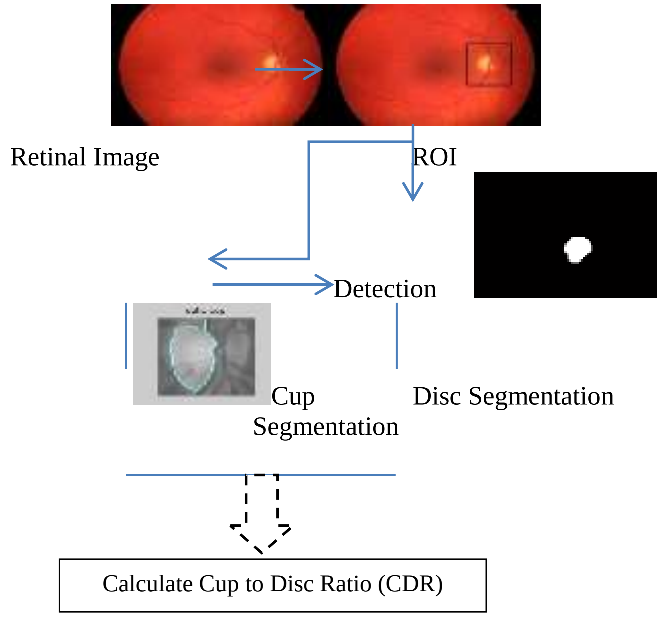

Fig. 2. CDR Calculation for screening Glaucoma

IV.SUPERPIXEL GENERATION

Image Segmentation is the process where the digital image is divided into multiple segments such as pixels or set of pixels known as Superpixels. The superpixel is the one which has same or similar color and brightness. The term superpixel was introduced by Ren and Malik [7] and illustrates the over segmentation of an image into homogeneous regions that align well with object boundaries. This allows to represent an image with only a couple of hundred segments that function as atomic building blocks instead of tens of thousands of pixels. The Simple Linear Iterative Clustering (SLIC) algorithm is used here to generate the superpixels [1]. It is a simple and efficient method to decompose an image in visually homogeneous regions and adherence to image boundaries on the Berkeley benchmark [6] . It is based on a spatially localized version of k-means clustering. SLIC takes two parameters: 1) the normal size of the regions and 2) the strength of the spatial regularization. The comparison of five state of- the-art superpixel methods [2], [5], [9], [11], [12], evaluating their speed, ability to adhere to image boundaries, and impact on segmentation performance. The properties of the Superpixel are:

- Superpixels should cling onto the image boundaries.
- It should be fast enough for the preprocessing step in order to reduce the computational efficiency.
- It should be memory efficient, and simple to use.
- When used for segmentation purposes, superpixels should both increase the speed and improve the quality of the results.

The image is first divided into grids and then the center of each grid tile is then used to initialize the corresponding k-means. After the k-means step, SLIC removes any segment whose area is smaller than the threshold by merging them into larger ones. The CIELAB is the complete color space which is specified by the International Commission on Illumination. The CIELAB, the lab color space is given as the input. For the retinal color images in the CIELAB color space, the k-means clustering procedure begins with an initialization step where k initial cluster centers $C_i = [l_i\ a_i\ b_i\ x_i\ y_i]^T$ are sampled on a regular grid spaced S pixels apart.

V. OPTIC DISC SEGMENTATION

The use of OD detection is not limited to glaucoma detection. Diagnosis of other diseases, such as diabetic retinopathy and pathological myopia, also requires OD detection. Therefore, it is a fundamental task in retinal image processing. To detect an optic disc boundary, image pre-processing is introduced. Firstly, a coarse localization of optic disc region is presented using the red channel. The red component is utilized as it is found to have higher contrast between the optic disc and non-optic disc area than for other channels. The RGB image, shown in Fig.3 is converted into Gray scale intensity image, as shown in Fig.4 which is very useful since it has only the luminance or intensity information. The input gray image is filtered in-order to remove the noise which is necessary in edge detection in image processing. The filtered gray image is converted into binary image using thresholding. It produces a binary image from the filtered image which has value 0 for all pixels in the input image with intensity values less than the Threshold and value 1 for rest of the pixels. The smoothed decision values are then used to obtain the binary decisions for all pixels with a threshold. In the experiments, assign +1 and-1 to positive is for disc and negative is considered for non-disc samples, and the average of them is said to be the threshold .i.e., zero.

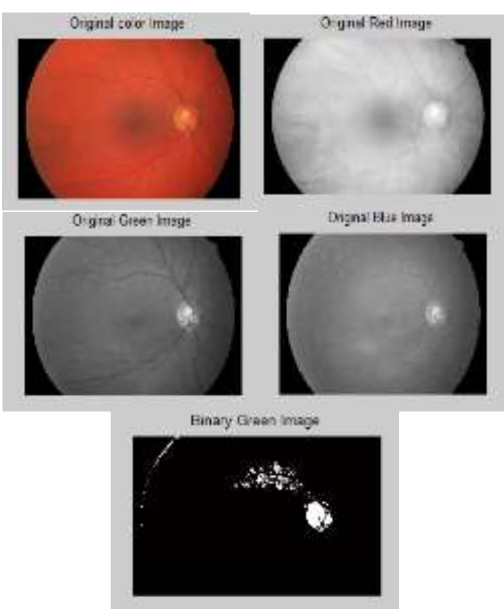

Fig. 3. The original fundus retinal image and its RGB color model with binary green image.

After getting the binary decisions for all pixels have a matrix with binary values with 1 as object and 0 as background. The largest connected object, i.e., the connected component with largest number of pixels, is obtained through morphological operation and its boundary is used as the raw estimation of the disc boundary. The morphological structuring element is created for the disc which also removes the blood vessels. The dilation is followed by erosion, and it tends to enlarge the boundaries of foreground regions in an image and shrink background color holes in such regions. Due to dilation operation the small interfering blood vessels are removed. This results in slight blurring of the input image. Following to that, erosion is done to restore the boundaries to their former position. The optic disc can be detected using all these methods and it shows an obvious result of clearly identifying the disc in this fundus retinal images.

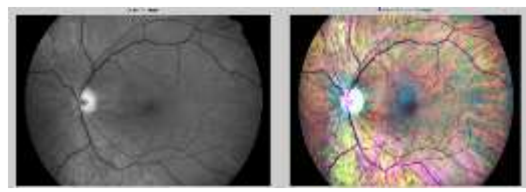

Fig. 4. Gray scale intensity image and its enhanced image

The Optic Disc is segmented, shown in Fig.5 using filtered image by thresholding and this segmented image are further used for the calculation of Cup- to- Disc Ratio (CDR). The best fitted ellipse using elliptical Hough transform is computed as the fitted estimation.

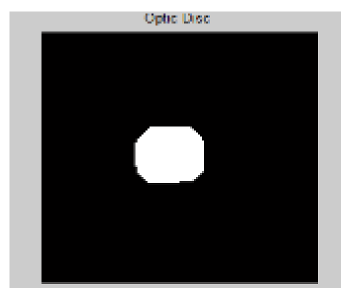

Fig. 5. Segmented Optic Disc

VI. OPTIC CUP SEGMENTATION

Detecting the cup boundary from 2-D fundus images without depth information is a challenging task, as depth is the primary indicator for the cup boundary. In 2-D fundus images, one land- mark to determine the cup region is the pallor, defined as the area of maximum colour contrast inside the disc. The main challenge in cup segmentation is to determine the cup boundary when the pallor is non-obvious or weak. In such scenarios, we lack landmarks, such as intensity changes or edges to estimate the cup boundary reliably. Although vessel bends are potential landmarks, they can occur at many places within the disc region and only one subset of these points defines the cup boundary.

Besides the challenges to obtain these points, it is also difficult to differentiate the vessel bends that mark the cup boundary from other vessel bends without obvious pallor information. The proposed method in [4] uses manual threshold analysis, color component analysis and ROI (Region of Interest) based segmentation for the detection of the cup. Once after the Optic Disc is segmented, the Optic Cup (OC) is segmented. The green channel is well suited for extracting the optic cup since it has better contrast when compared to the red and blue planes. The Region of Interest (ROI) is considered and given as input for the Contour detection. The contours are examined by thezero – crossings of the Laplacian of Gaussian Filtered image and the contour strengths are encoded in the pixel intensities. The strengths are taken to be the proportional to the magnitude of the gradient at the zero – crossing determined by the Sobel filter. The Canny Edge detection is performed in-order to extract the optic cup from the fundus image. The Canny method is specified for edge detection because the Canny algorithm can detect edges with noise suppressed at the same time. This method uses two thresholds, to detect strong and weak edges, and it includes the weak edges in the output only if they are connected to strong edges. The optimum threshold of the each input retinal image is found to be different due to the variant intensities in each image. The Optic Cup is segmented as shown in Fig.6.

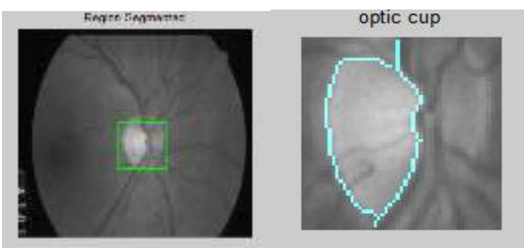

Fig. 6. Segmented Optic Cup

VII. ELLIPSE FITTING FOR OPTIC DISC AND CUP

The ellipse fitting algorithm can be used to smooth the disc and cup boundary. Ellipse fitting is usually based on least square fitting algorithm which assumes that the best-fit curve of a given type is the curve that minimizes the algebraic distance over the set of N data points in the least square. By minimizing the algebraic distance subject to the constraint $4ac\ b2 = 1$, the new method incorporates the ellipticity constraint into the normalization factor. B2AC (Direct Least Square Fitting Algorithm) [3] is the best to fit the optic disc and cup since it minimizes the algebraic distance subject to a constraint, and incorporates the elliptic constraint into the normalization factor. It is ellipse-specific, so that effect of noise (ocular blood vessel, hemorrhage, etc.) around the cup area can be minimized while forming the ellipse. It can also be easily solved naturally by a generalized Eigenvalue system.

VIII. CUP TO DISC RATIO CALCULATION

The developed methodology is tested on 30 different fundus images obtained from the patients. The Cup to Disc ratio (CDR) value is obtained using the formula,

$$CDR = VCD/VDD \qquad (1)$$

where VCD is the Vertical Cup Diameter and VDD is the Vertical Disc Diameter. The CDR values for all the images have been calculated by the developed method and they are listed in the Table 1. In the tables, the first column shows the subject i.e., the Normal Eye and the Glaucoma Eye and the second column indicates the CDR values that are calculated by the present methodology.

SUBJECT	CDR VALUE
Glaucoma Eye	0.682
Normal Eye	0.312

Table 1:- CDR values

IX. CONCLUSION

The cup to disc (CDR) ratio is an important indicator of the risk of the presence of glaucoma in an individual. In this paper, we have presented a method to calculate the CDR from fundus images using segmentation of optic disc and the segmentation of optic cup. After obtaining the contours, an ellipse fitting step is introduced to smooth the obtained results.

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