

DETECTION OF GLAUCOMA BASED ON K MEANS CLUSTERING

J.Surendiran¹Dr.T.Saravanan²

*Asst Prof., Department of Electronics and Communication Engineering¹,
Research scholar AMET University.*

Professor and Head ETC Department, Bharath University².

E-Mail: surenjaya1981@gmail.com

Abstract - Glaucoma is the leading cause of visual disability in the world. Over the years, extensive researches have been done for the detection of glaucoma. As glaucoma develops, neural tissues die, the nerve fiber layer thins, and the Cup-to-Disc Ratio (CDR) increases. Hence in the proposed system the measurement of CDR is used to detect the glaucoma

To measure the CDR, the Optic Disk (OD) and Optic Cup (OC) regions must be segmented from the whole fundus image. In the preprocessing stage, Region of Interest (ROI) is extracted from the fundus image which contains the OD region. This is done by selecting the maximum intensity pixels in the green plane as it provides best contrast than red and blue plane in the RGB fundus image. Before extracting the ROI region, the fundus image must be free from noise. Hence, median filtering is applied to de-noise the image.

To segment the OD region of the test image, we use K mean clustering technique. These features are fed into the trained classifier to segment the OD region. Then, the OC segmentation is done by again using k mean clustering techniques to the OD segmented image. The CDR is obtained from the diameter of segmented OD and OC region. The presence of glaucoma is detected based on the value of the CDR. The performance of the proposed system is evaluated using 100 fundus image.

Keyword – cdr, glaucoma, k mean clustering

I.INTRODUCTION

Glaucoma is one of the eye diseases where pressure inside the eyes increases enough so as to damage the optic nerve fibers and cause permanent blindness. This increase in blood pressure happens due to the passages that actually allow fluid in eyes to dry become clogged or blocked. So Glaucoma is also called as “silent thief of sight,” because this typically cause no pain and produce no symbol until we find vision loss occurs. Lowering of eye pressure is found based on the damage of optic nerve. In general, range of normal eye pressure is about 8 to 21 millimeters mercury (mmHg). In general an Ophthalmologist starts his treatment if and only if the pressure exceeds 30 mmHg. An ideal intraocular

Pressure (IOP) level of most glaucoma patients is about 14 mmHg or lower. Glaucoma is a progressive optic neuropathy characterized by structural changes of the optic nerve and retina that are associated with the development of visual functional defects. The temporal relation between structural signs of the disease with psychophysical measures such as visual field tests is important to clarify to determine the best methods to detect glaucoma and progressive glaucomatous damage in the clinical setting. Surgery for Glaucoma is generally considered as last resort when eye drops. Even laser treatments can't unable to lower the pressure in eyes sufficiently for preventing further optic nerve damage. Figure 1 illustrates the normal and glaucoma vision of a patient.

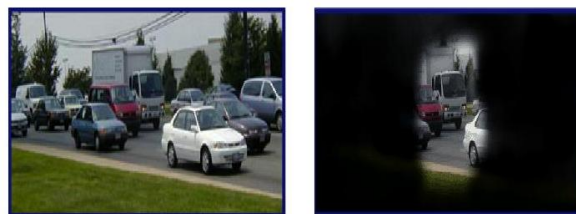


Figure 1 Vision of normal eye patients and glaucoma affected eye patient

Glaucoma is the second most common cause of blindness worldwide. Low awareness and high costs connected to glaucoma are reasons to improve methods of screening and therapy. A method for optic nerve head segmentation and its validation, based on morphological operations, Hough transform, and an anchored active contour model is proposed in [1]. A robust and computationally efficient approach for the localization of the different features and lesions in a fundus retinal image is presented in [2]. A constraint in optic disc detection is that the major blood vessels are detected first and the intersection of these to find the approximate location of the optic disc. A novel approach to automatically segment the OD and exudates is proposed in [3]. It makes use of the green component of the image and preprocessing steps such as average filtering, contrast adjustment, and thresholding. The other processing techniques used are morphological opening, extended maxima operator, minima imposition, and watershed transformation. An automated classifier based on adaptive neuro-fuzzy inference system (ANFIS) to differentiate between normal and glaucomatous eyes from the quantitative assessment of

summary data reports of the Stratus optical coherence tomography is presented in [4].

There are two methods to extract the disc automatically, as proposed in [5]. The component analysis method and Region of Interest (ROI) based segmentation are used for the detection of disc. For the cup, k mean technique method is used. Later the active contour is used to plot the boundary accurately. To automatically extract the disc, a variation level set method is proposed in [6]. For the cup, two methods making use of color intensity and threshold level set are evaluated. An automatic OD parameterization technique based on segmented OD and cup regions obtained from monocular retinal images is proposed in [7]. A novel OD segmentation method is proposed which integrates the local image information around each point of interest in multidimensional feature space to provide robustness against variations found in and around the OD region. A new template-based methodology for segmenting the OD from digital retinal images is presented in [8]. Morphological and edge detection techniques followed by the Circular Hough Transform are used to obtain a circular OD boundary approximation which requires a pixel located within the OD as initial information.

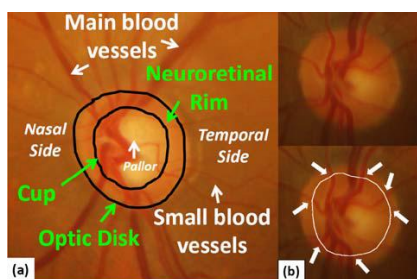


Fig 2 structure of eye with optic disc and cup

The optic disk generally appears as a bright circular or elliptic region. The methods of optic disk boundary detection can be separated into two steps: optic disk localization and disk boundary detection. Correct localization of the optic disk may improve the accuracy of disk boundary extraction.

II. EXISTING METHODS

Many existing approaches can be used to locate the optic disk with reasonable success. Sinthanayothin [1] located the position of the optic disk by finding the region with the highest local variation in the intensity.

Tamur [2] and Pinz [3] applied Hough transform to obtain optic disk center and the outer circle of disk boundary. Recently, a principal component analysis (PCA) model based approach was used in Ref. [4], and template matching was used in Refs. [5–7].

Hoover [8] utilized the geometric relationship between the optic disk and main blood vessels to identify the disk location, similar approaches were introduced in Refs. [9, 10]. Correctly locating the optic disk

is the first and essential step for optic disk segmentation. Subsequently the disk center is estimated and used to initialize the disk boundary. Interference of blood vessels is one of the main difficulties to segment the optic disk reliably and accurately.

This problem is very similar to other boundary detection and image segmentation problems in medical imaging area that still require robust solution. Currently, deformable models offer a reasonable approach for boundary detection and image segmentation which can be roughly classified into two categories: free-form deformable models, such as snakes, and parametrically deformable models, such as active shape models (ASMs).

Mendels et al. [11] and Osareh et al. [6] extracted the optic disk boundary by GVF-snake algorithm, in which the blood vessel was first removed by morphology in the preprocessing step.

Walter et al. [12] also used morphological filtering techniques to remove the blood vessels and then detected the optic disk boundary by means of shade-correlation operation and watershed transformation. Although the morphology preprocessing helps reduce the effect of blood vessels, it could not totally remove the effect. The resulted boundary was distorted in the regions with outgoing vessels.

Li and Chutatape [13, 14] used a PCA method to locate the optic disk and an ASM to refine the disk boundary. Although this approach could indirectly handle blood vessel occlusion problem with moderate accuracy, by using shape models, the fuzzy shapes of optic disk due to various pathological changes were not easy to be represented by a number of shape models, which might reduce the accuracy of the result. Parametrically deformable models (ASM method) are suitable for use when more specific shape information is available and the detected object has relatively uniform shape with limited variation.

However, in optic disk boundary detection, pathological changes may arbitrarily deform the shape of optic disk and also distort the course of blood vessels. Hence, deformable templates may not be able to sufficiently encode various shapes of optic disk from different pathological changes.

Lowell et al. [7] segmented the optic disk by a contour deformation method based on a global elliptic model and a local deformable model with variable edge-strength dependent stiffness. However, the authors indicated that the performance to the images with variably pathological changes still needed to be further improved.

A level set approach was introduced in Ref. [15], which can segment the objects with arbitrarily complex shapes. The advantage of this approach is its ability to evolve the model in the presence of sharp corners, cusps, shapes with pieces and holes, etc. Nevertheless, many of these problems are different from those encountered in the boundary detection of optic disk.

III. ROI EXTRACTION:

The ROI Extraction stage is shown in Fig. 1. The retinal images have been taken by fundus camera in RGB mode. The size of the fundus image is 1504x1000 pixels. G plane is considered for the extraction of optic disc and optic cup, as it provides better contrast than the other two planes. Hence it is necessary to separate the G plane for further analysis.

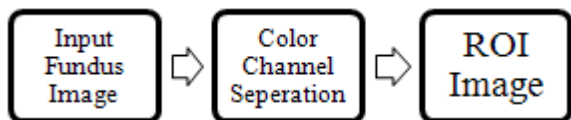


Fig 3 ROI extraction stage

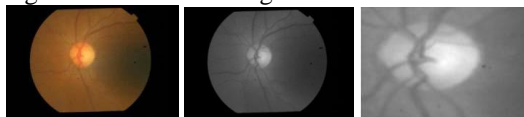


Fig 4 Retinal fundus image with defined ROI by masking

The optic disc is the entrance of the vessels and the optic nerve into the retina. In fundus images, the optic disc belongs to the brightest point of the image as mentioned by (Walter and Klein, 2005). Hence the maximum brightest point within the optic disc in the G plane is determined using *cvMinMaxLoc*. The approximate region around the identified brightest point is to be selected for initial optic disc region as ROI. As it takes more time to process an image of larger size, a square of size 360x360 pixels with the brightest pixel as the centre point is decided to consider as ROI. The initial ROI covers mainly the entire optic disc along with a small portion of other regions of the image. Figure 2 shows the images in ROI extraction stage.

IV. METHODOLOGY

A. K-MEANS CLUSTERING

K-means is one of the simplest learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different locations cause different results. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early grouping is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this

algorithm aims at minimizing an *objective function*, in this case a squared error function. The objective function

$$J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2$$

where $\|x_i^{(j)} - c_j\|^2$ is a chosen distance measure between a data point and the cluster centre is an indicator of the distance of the n data points from their respective cluster centres.

B. OPTIC DISC AND CUP SEGMENTATION

To calculate the vertical cup to disc ratio, the optic cup and disc first have to be segmented from the retinal images. The green plane of the registered image is extracted to choose mean value for background blood vessel, cup and disc are replaced for segmenting the image. Using concatenate function, the images are mapped in a set of 4 iterations to execute for the above set of mean values. The identified mean value is replicated with the mean value within each of the array and then the distance matrix is calculated.

Algorithm for k means clustering:

1. Compute the intensity distribution (also called the histogram) of the intensities.
2. Initialize the centroids with k random intensities
3. Repeat the following steps until the cluster labels of the image do not change anymore.
4. Cluster the points based on distance of their intensities from centroid intensities replicated with the mean value within each of the array and then the distance matrix is calculated.
 $C^{(i)} := \operatorname{argmin} \|x^{(i)} - \mu^j\|$
5. Compute the new centroid for each of the clusters.

$$\mu_i := \frac{\sum_{i=1}^m 1\{c(i) = j\} x^{(i)}}{\sum_{i=1}^m 1\{c(i) = j\}}$$

Where k is a parameter of the algorithm (the number of clusters to be found),
 i iterates over all the intensities,
 j iterates over all the centroids and μ_i are the centroid intensities

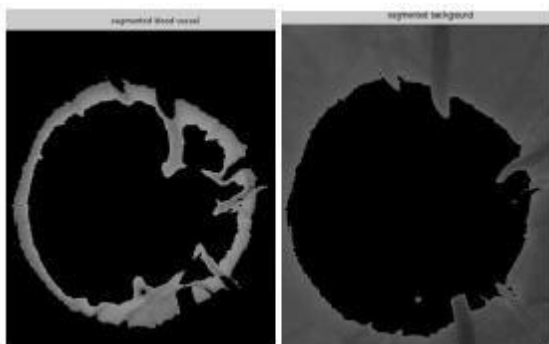


Figure 5: Segmented blood vessel & background using K-Means clustering

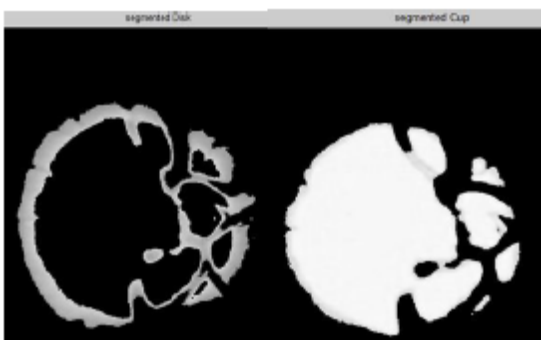


Figure 6: Segmented disc & cup using K-Means clustering

C. OPTIC DISC AND CUP SMOOTHING

The disc boundary detected from the above step may not represent the actual shape of the disc since the boundary can be affected by a large number of blood vessels entering the disc. Therefore morphological features are applied to reshape the obtained disc boundary. After the cup boundary detection, morphological feature is again applied to eliminate some of the cup boundary's sudden changes in curvature.

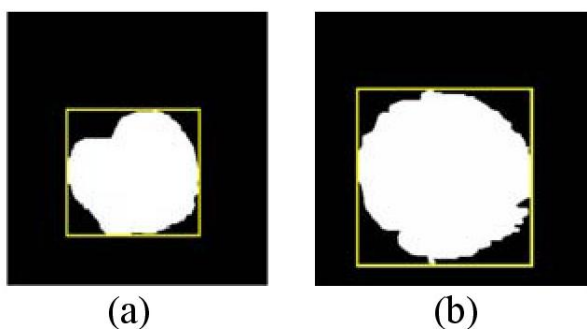


Fig 7: Rectangle of optic disc and cup region

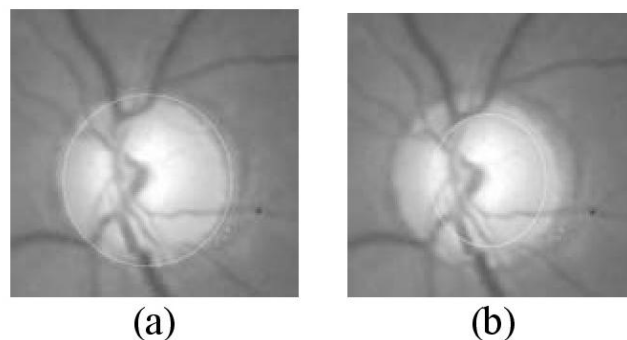


Fig 8: Optic disc and cup

v. CDR CALCULATION:

The cup-to-disc ratio (CDR) is a measurement used in ophthalmology to assess the progression of glaucoma. The cup-to-disc ratio compares the diameter of the "cup" portion of the optic disc with the total diameter of the optic disc. Cup and Disc area is calculated by taking the number of white pixels from the segmented image. If the CDR ratio exceed 0.65 then it is considered to be glaucoma.

TABLE 1: COMPARISON OF CLINICAL CDR VALUE WITH OUR RESULT

Images	Clinical CDR Value	K-Means Clustering
G1	0.65	0.62
G2	0.66	0.64
G3	0.69	0.66
G4	0.7	0.68
G5	0.8	0.79
G6	0.62	0.59
G7	0.58	0.6
Normal	0.3	0.29
Normal	0.29	0.27
Normal	0.3	0.29

VI. CONCLUSION

This paper is presented and evaluated for Glaucoma detection in patients, a global leading cause for blindness. Boundary delineation is the key to determine CDR (Cup to Disc Ratio) and is obtained using multimodalities including K -Means and Fuzzy C Means Clustering of the color fundus camera image. If the CDR ratio exceeds 0.6, it shall be recommended for further analysis of a patient to the ophthalmologist. This shall help in patients worldwide by protecting further vision deterioration through timely medical intervention and subsequent treatment.

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