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SURVEY OF GLAUCOMA DETECTION METHODS

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Abstract- **G**LAUCOMA is a chronic eye disease that can damage optic nerve. According to WHO It is the second leading cause of blindness, and is predicted to affect around 80 million people by 2020. Development of the disease leads to loss of vision, which occurs increasingly over a long period of time. As the symptoms only occur when the disease is quite advanced so that glaucoma is called the silent thief of sight. Glaucoma cannot be cured, but its development can be slowed down by treatment. Therefore, detecting glaucoma in time is critical. However, many glaucoma patients are unaware of the disease until it has reached its advanced stage. In this paper, some manual and automatic methods are discussed to detect glaucoma. Manual analysis of the eye is time consuming and the accuracy of the parameter measurements also varies with different clinicians. To overcome these problems with manual analysis, the objective of this survey is to introduce a method to automatically analyze the ultrasound images of the eye. Automatic analysis of this disease is much more effective than manual analysis.

Keywords-Glaucoma, Optic cup segmentation, Optic disc segmentation, cup-to-disc ratio, active contour, vessel bend.

I. INTRODUCTION

Glaucoma is the second leading cause of blindness that can damage the eye's optic nerve, resulting in loss of vision and thereby cause permanent blindness. Though there is no cure, early diagnosis with adequate medication and care, it is possible to stop further impact on vision to a patient. With the predicted increase in life expectancy, the anticipated number of people becoming blind from the disease will rise substantially in the near future. Despite increasing public health awareness and the availability of advanced technology diagnostic tests in developed countries.

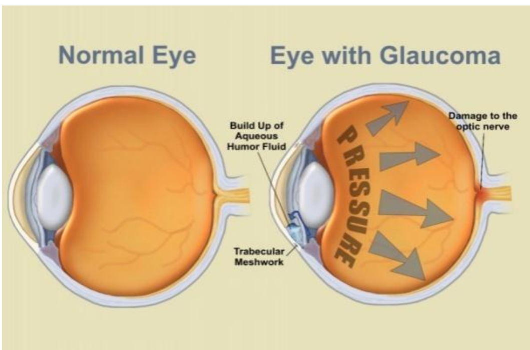


Figure 1. Normal eye and glaucoma effected eye

There are three methods to detect glaucoma
1) Assessment of raised intraocular pressure (IOP).
2) Assessment of abnormal visual field.
3) Assessment of damaged optic nerve head.

The IOP measurement using noncontact tonometry is neither specific nor sensitive enough to be an effective screening tool because glaucoma can be present with or without increased IOP. Visual field testing requires special equipment that is usually present only in hospitals. It is a subjective examination as it assumes that patients fully understand the testing instructions, cooperate and complete the test. Moreover, the test is usually time consuming. Thus, the information obtained may not be reliable. The assessment of optic nerve damage is superior to the other two methods. Optic nerve can be assessed by trained specialists or through 3D imaging techniques such as Heidelberg Retinal Tomography (HRT) and Ocular Computing Tomography (OCT). However, optic nerve assessment by specialists is subjective and the availability of HRT and OCT equipment is limited due to the high cost involved.

An automatic and economic system is highly desirable for detection of glaucoma in large-scale screening programs. The digital color fundus image is a more cost effective imaging modality to assess optic nerve damage compared to HRT and OCT, and it has been widely used in recent years to diagnose various ocular diseases, including glaucoma. An ophthalmologist will diagnose Glaucoma by measuring the CDR (Cup to Disc Ratio) which is the ratio of the vertical height of the optic cup and optic disc.

II. GLAUCOMA DETECTION METHODS

Glaucoma is a disease characterized by degeneration of optic nerves. So the fall in blood flow to the optic nerve give to the visual field defects associated with glaucoma. Drug therapy to control the elevated intraocular pressure and serial evaluation of the optical nerves are the principal method of curing the disease. Standard methods of evaluation of the optic nerve using ophthalmology or stereo photography or evaluation of visual fields. There are manual and automatic detection methods available. The survey is conducted on different glaucoma detection methods in image processing. This section briefly describes some of the techniques that are used for the detection of glaucoma.

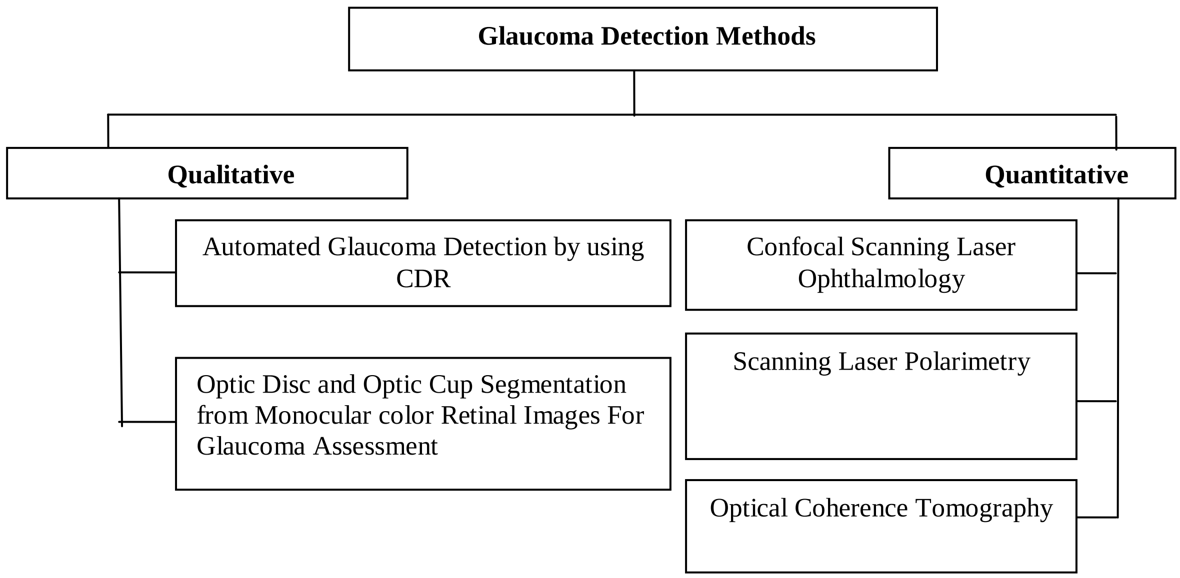


Figure 2. Classification of Glaucoma Detection Methods

A. Automated Glaucoma Detection by using CDR

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.

In [7] this method CDR is calculated automatically from nonsterographic retinal fundus photographs. To automatically extract the disc, two methods making use of an edge detection method and variational level-set method are proposed. For the cup, color component analysis and threshold level-set method are evaluated. To reshape the obtained disc and cup boundary from above mentationed methods, ellipse fitting is applied to the obtained image.

Methodology

To calculate the vertical cup to disc ratio (CDR), the optic cup and disc first have to be segmented from the retinal images. Figure 3 shows the framework for building the glaucoma detection system.

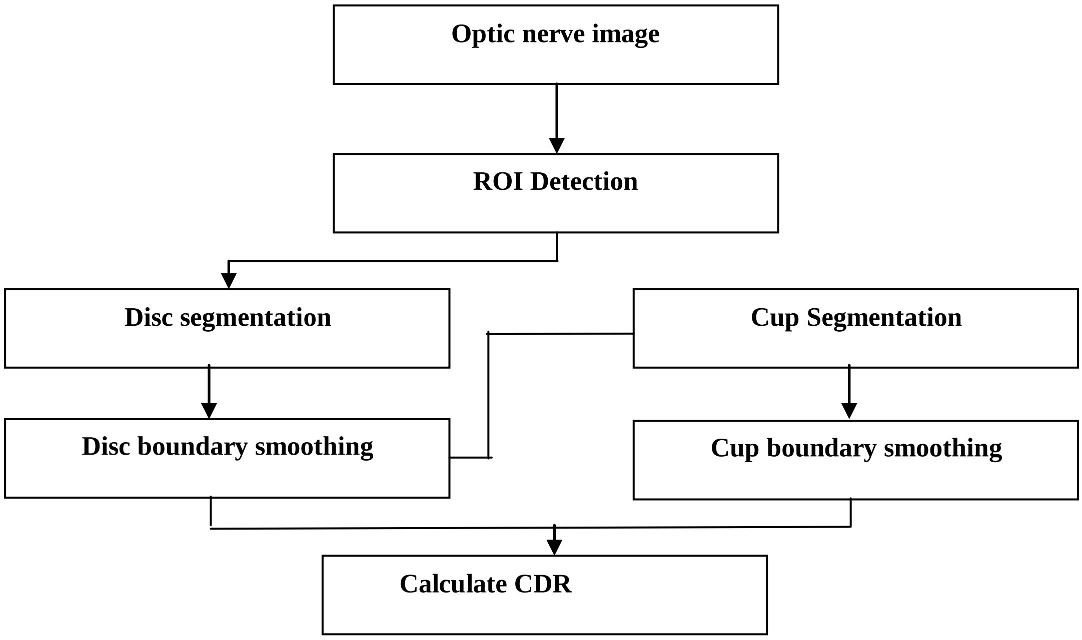


Figure 3. Framework for building the glaucoma detection system.

In order to extract the optic disc and cup, each retinal fundus image has been captured using a high resolution retinal fundus camera and saved as a 3072 x 2048 high-resolution digital image, as shown in Figure (a). Thus, the region of interest (ROI) around the optic disc must first be delineated.

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, as shown in Figure (b). The intensity-weighted centroid method is proposed to find an approximate ROI centre. The boundary of the ROI is defined as a rectangle around the ROI centre with dimensions of twice the typical optic disc diameter, and is used as the initial boundary for the optic disc segmentation, as shown in Figure (c). The ROI is returned as an image of size 480x750 pixels as shown in Figure (d).

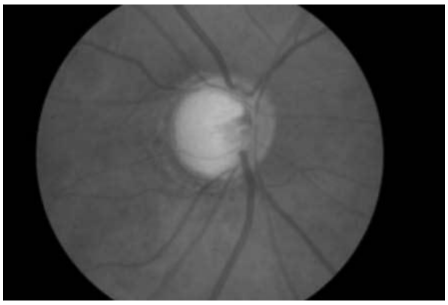


Figure (a)

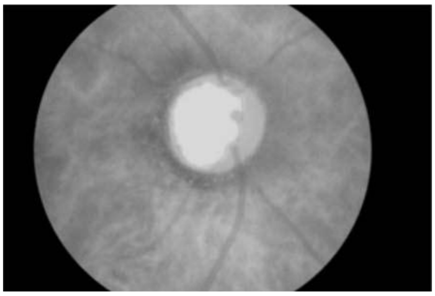


Figure (b)

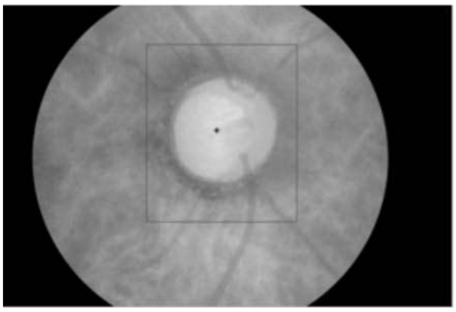


Figure (c)

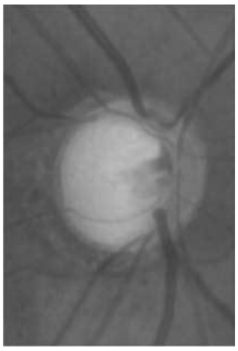


Figure (d)

Figure 4. a) Input image of size 3072 x 2048 pixels b) A brighter pallor detected (blue area) c) ROI localization d) ROI image of size 480 x 750 pixels.

1. Optic Disc Segmentation

To automatically extract an optic disc boundary, image pre-processing is introduced. Figure 5 shows a simplified workflow of optic disc segmentation.

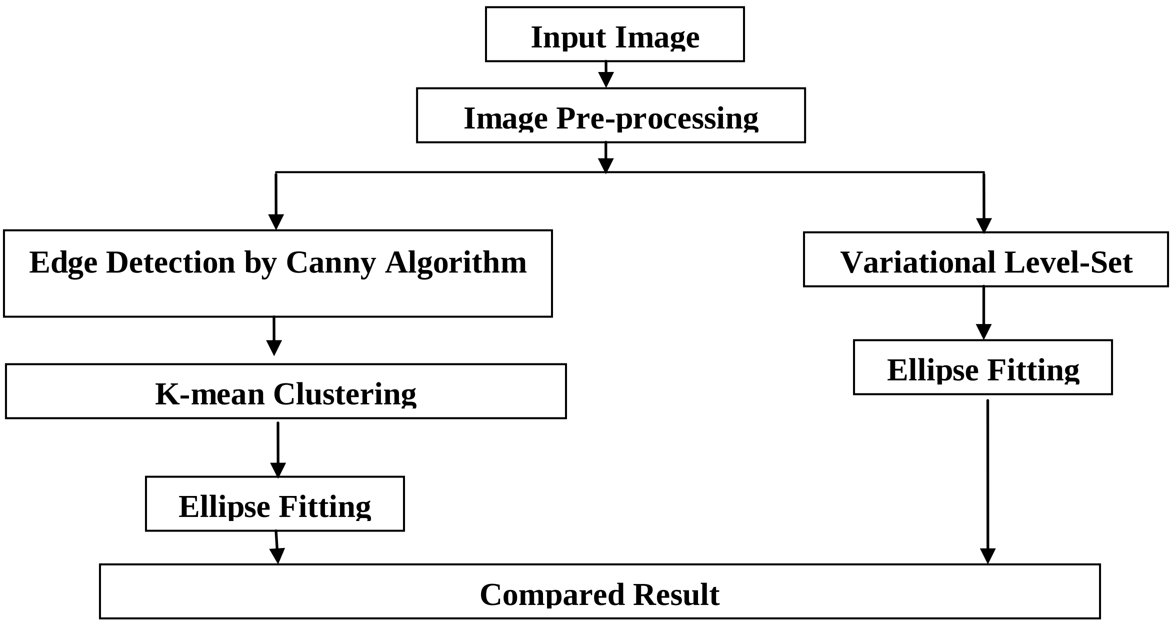
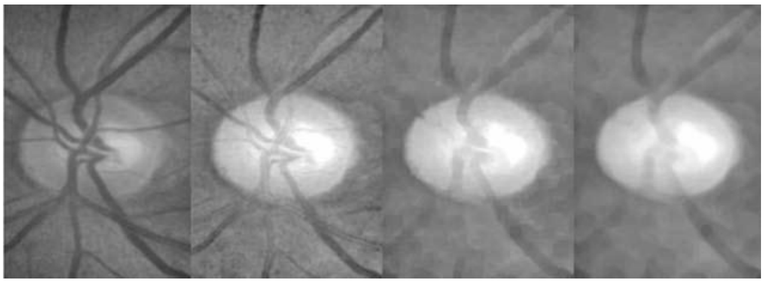


Figure 5. Optic Disc Segmentation

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. To remove the blood vessels, a morphological closing operation is performed. After performing the closing operation, a median filter is applied to further smoothen the obtained image. The outputs of the image pre-processing are shown in Figure 6



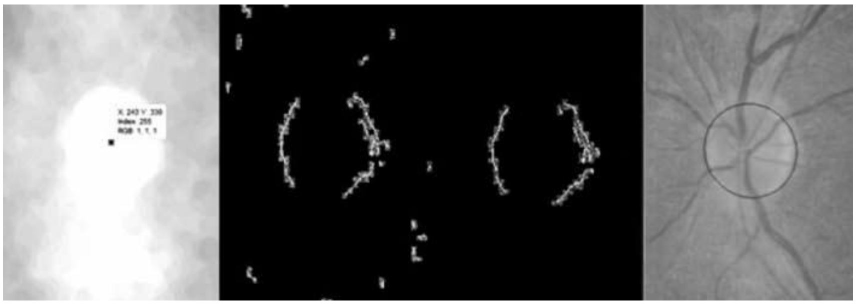
(a) (b) (c) (d)

Figure 6. a) Input Image b) Red channel c) Closing operation and d) Median filter

1.2 Edge Detection Approach

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.

In order to extract only a disc boundary, the edge image has to be classified into three groups based on the distance from the center of the optic disc as shown in below Figure 7(a). This classification is achieved by performing k-means clustering to the edge of the image 7(b). K-means clustering is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. Then, the group that contains only edge detection of a disc boundary is selected, and the noise can be rejected as shown in Figure 7(c).After that, the application of direct ellipse fitting is used to obtain boundaries in order to find a smoother contour. The outputs are shown in Figure 7(d).

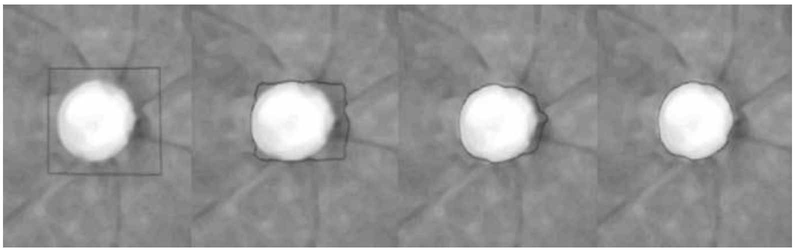


(a) (b) (c) (d)

Figure 7. a) Input image after performing the image pre-processing with the center of an optic disc b) Edge detection c) The result after noise is rejected d) Disc boundary smoothing.

1.3 Variational Level-Set Approach

The variational level- set algorithm is used as a global approach for the optimization of active contours for the segmentation of objects of interest from the background. This method is employed by initializing a curve centered at the detected optic disc location. The curve is evolved based on the average intensity value inside and outside the curve. The curve evolution always converges to the optic disc boundary irrespective of the shape or size of the initial contour.



(a) (b) (c) (d)

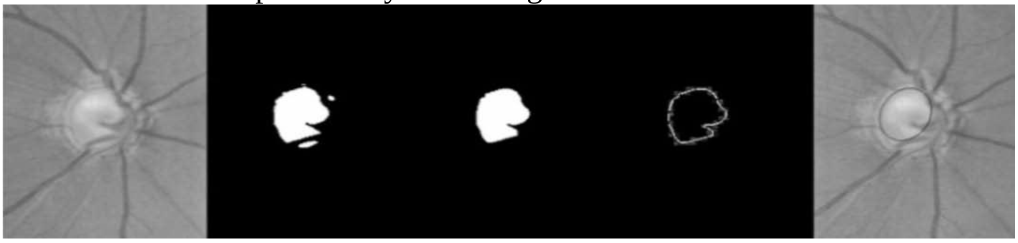
Figure 8. Sample Evolution Results at Different Iterations

2. Optic Cup Segmentation

Optic Cup Segmentation, two approaches are used .The color component analysis approach and threshold level set approach.

2.1 Color Component Analysis Approach.

In the color component analysis method, RGB components of the input images are analyzed, and it is found that the optic cup is more easily discriminated in the green image because the visibility and contrast of the optic cup is superior and its pixels are of higher intensities, while the neuroretinal rim and the retinal vessels are often of lower intensities. The next step is to use morphological opening operation in order to remove noise around the cup region. Then the edge detection and ellipse fitting is proposed to obtain the cup boundary smoothing.

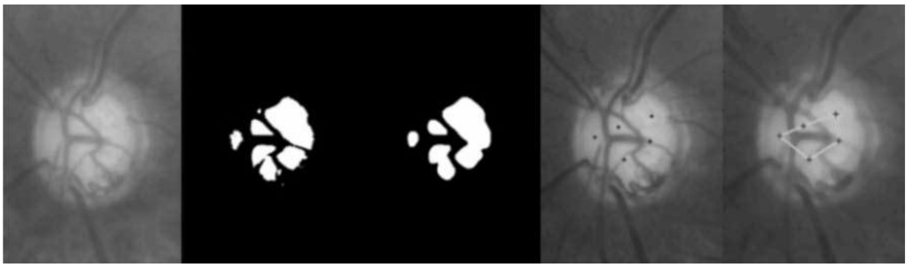


(a) (b) (c) (d) (e)

Figure 9. a) Input Image b) Color Green Detected c) Morphological Opening Operation d) Edge Detection e) Cup Boundary Smoothing

2.2 Threshold Level Set Approach

In this approach, the green channel of the input image is selected as the basis for further segmentation due to the optimum observed contrast between the cup and disc boundaries in this channel. The method to select the top 1/3 of the grayscale intensity is to find the threshold value from the normalized cumulative histogram and then compare it with all the intensity values of the input image. Then an intensity value is that is greater than the threshold value is selected.Text step is to use a morphological opening operation in order to remove noise around the cup region.Next, the intensity-weighted centroid method is proposed to find an approximate initial point. This is found to give a good initial approximation for the initial cup region. Then, a threshold level-set algorithm is applied to segment the optic cup.



(a) (b) (c) (d) (e)

Figure 10. A) Input Image B) Color Green Detected C) Morphological Opening Operation D) The Initial Point Of Cup Region E) The Initial Cup Contour.

3. Ellipse Fitting for Optic Disc and Cup

Ellipse fitting algorithm can be used to smooth the optic cup and disc boundary. Ellipse fitting is usually based on the least square fitting algorithm which assumes that the best-fit curve of a given type is the curve that has the minimal sum of the deviations squared from, given data points. Direct Least Square Fitting Algorithm is chosen to fit the optic disc from popular ellipse fitting algorithms. It is ellipse specific, thus the effect of noise (ocular blood vessel, hemorrhage, etc.) around the disc area can be minimized while forming the ellipse. It can also be easily solved naturally by a generalized Eigen system.

4. Calculate CDR

The ratio of the size of the optic cup to the optic disc, also known as the cup-to-disc ratio (CDR), the value of CDR which is more than 0.65 is used to assess a patient as a possible glaucoma case.

B. Optic Disc and Optic Cup Segmentation from Monocular Color Retinal Images for Glaucoma Assessment

Interest in OD segmentation is not limited to glaucoma detection. It is a fundamental task for automatic processing of retinal images such as image sequence registration, and automatic measurements for treatment evaluation or for diabetic retinopathy diagnosis. Initial attempts have been made with shape-based template matching in which OD is modelled as a circular or elliptical object. This matching is performed on an edge map extracted from the underlying image. This approach suffers due to vessel edges present in and around the OD region. To handle this, morphological-based pre-processing step is employed to suppress the vessel prior to template matching[1].

1. Localised and vector-valued C-V active contour model

This model assumes that an image consists of statistically homogeneous regions and therefore lacks the ability to deal with objects having intensity inhomogeneity. Intensity inhomogeneity is very common in natural images, especially in OD region it is a frequently occurring phenomena. In computer vision, there have been some attempts to improve C-V model for such situations. Here, the basic idea is to use local instead of global image intensity into the region-based active contour model.

These methods report significant improvement in the segmentation over original C-V model for segmenting objects with heterogeneous intensity statistics. However other than intensity heterogeneity within OD, smooth region transition at boundary locations and occurrence of similar characteristic regions near the OD boundaries (atrophy) make OD segmentation a much more difficult case altogether. The local intensity based statistics is not sufficient to discriminate between the OD and atrophy regions. We propose a region-based active contour model which uses local image information at a support domain around each point of interest (POI) inspired by localised C-V models by using a richer form of local image information gathered over a multi-dimensional feature space. The intention is to represent the POI more holistically by including descriptions of the intensity, colour, texture, etc. This approach should yield a better representation of image regions and make the proposed model robust to the distractions found near the OD boundaries.

2. OD localisation and contour initialisation

The first step is to localise the OD region and extract a region of interest for further processing. The red colour plane of CFI gives good definition of OD region and thus is a good choice for the OD localisation task. The contour initialization is the next essential step to initiate the active contour evolution. In our method, we perform localisation and initialisation steps together by performing circular Hough transform on the gradient map.

The vessel segments are identified using a curvature-based technique. These regions are suppressed and inpainted by performing selective morphological closing in 8 directions and retaining maximum response for each vessel pixel. Next, a Canny edge detector at a very low threshold is applied on the pre-processed (vessel-free) image to get edge points. On these points, a circular Hough transform is applied for a range of expected OD radius (*rmin* to *rmax*). This range is chosen based on the retinal image resolution. We select the OD center which has maximum value in the accumulator matrix while performing Circular Hough transform. Next, the edges near the identified center location in the image domain are used to estimate the radius of the circle. The circle points are identified using estimated radius and used to initialise the active contour mentioned in section

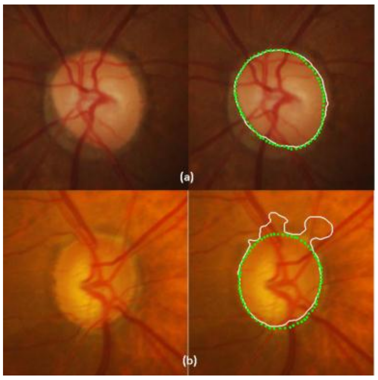


Figure 11. Sample Results of C-V Active Contour.

2.1 Segmentation in multi-dimensional feature space

A multi-dimensional image representation is obtained from colour and texture feature space. In normal image conditions, red colour plane gives a better contrast of the OD region. To better characterise OD in pathological situations, two different texture representations are derived.

3. CUP Segmentation

The objective is to segment the cup region by using both vessel bends and pallor information. vessel bends can occur at many places within the OD region. However, only a subset of these points define the cup boundary. It refer to this as relevant vessel bends or r-bends. The first problem at hand is to find this subset. We use multiple sources of information for this purpose: the pallor region which spatially defines the inner limit of r-bends, bending angle and location in the OD region.

3.1 Cup segmentation using r-bends information

The objective is to segment the cup region by using both vessel bends and pallor information. cyan points in figure 13, vessel bends can occur at many places within the OD region. However, only a subset of these points defines the cup boundary. this is relevant vessel bends or *r-bends*. The first problem at hand is to find this subset, multiple sources of information is use for this purpose: the pallor region which spatially defines the inner limit of *r-bends*, bending angle and location in the OD region.

A second problem is that the anatomy of the OD region is such that the r-bends are non-uniformly distributed across a cup boundary with more points on the top and bottom; they are mostly absent in the nasal side and very few in number in the temporal side. We propose a local interpolating spline to naturally approximate the cup boundary in regions where *r- bends* are absent.

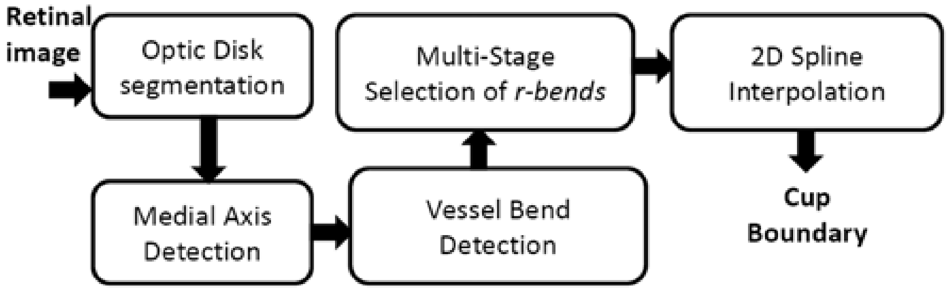


Figure 12. The Proposed Cup Segmentation Method

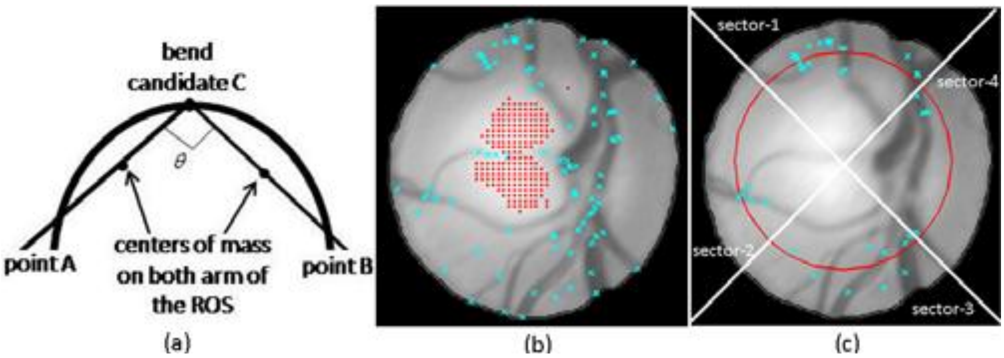


Figure 13. a) Angle of a vessel bend, b) uniform pallor samples(red), bend points(cyan) and c) fitted circle(red) and potential r-bends

3.1.1 Medial axis detection

The OD region has both thick and thin vessels. Detecting both reliably is difficult in the presence of inter-image intensity variations. This method formulates the blood vessel detection as a problem of trench detection in the intensity surface. The selection of this space gives robustness to the image variations and detection is solely driven by the shape of trench and directional continuity associated with a vessel structure. Trenches are regions characterized by high curvature, oriented in a particular direction.

3.1.2 Vessel Bend detection

The amount of bending in vessels varies according to the caliber of vessel. Thin vessels show significant bending compared to a thick vessel. This is due to the fact that thick vessels are more rigid. The selection of appropriate scale for detecting bends in both types of vessels is crucial because bend in a thick vessel is apparent only at a larger scale compared to a bend in thin vessel. We employ a scheme based on the concept of dynamic region of support (ROS) which has been proposed for corner detection to find the appropriate scale to analyse a candidate point. This is explained below.

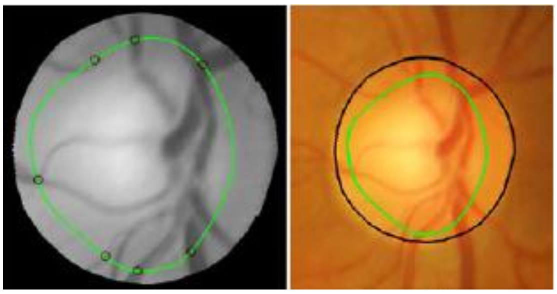
First, we extract vessel segments terminated by end and/or junction points. For each segment, we compute 1D shape (curvature) profile and locate the local maxima. These local maxima constitute a candidate set of bends *bi*. A ROS for any *bi* is defined as a segment of vessel around *bi* and bound on either side by the nearest curvature minimum. Choosing the bounds to be based on curvature minima automatically ensures the size of the ROS to be large for thick vessels and small for thin vessels.

The angle of bend θ is then computed as the angle between the lines joining a bend point and the center of mass on both sides of the ROS. The center of mass of an arm is defined by the mean position of pixels on the arm. Since only vessels bending into the cup are of interest, bends above $\theta =$

170◦ are eliminated from the candidate set. The detected vessel bends in a sample image are highlighted in figure(13) with cyan markers.

3.1.3 Multi-stage selection of r-bends

The task of identifying the *r-bends* from *bi* is performed in two stages to reduce the required analysis, by utilizing anatomical knowledge associated with *r-bends*. In the first stage, a coarse selection is done based on a bend's proximity to the pallor region. In the second stage, the spatial position and bending information are used to identify the set of *r-bends*.



(a) **(b)**

Figure 14 a)Estimated Cup Boundry b)Final Cup Boundry

3.1.4 2D spline interpolation

Typically, *r-bends* are sparse and not uniformly distributed across the sectors. In their absence, experts use their clinical knowledge (experience of direct 3D cup examination) to approximate a cup boundary. Hence, it is difficult to get the cup boundary in the regions with no *r-bends*. We choose a *local*, cubic cardinal spline, which is a generalisation of Catmull-Rom spline, with a shape parameter *t*. The parameter *t* helps control the bending behaviour and thus the shape according to the sector. The value of *t* is kept high in sectors 2&4 as they usually have low vessel density (*r-bends*) compared to sector 1&3. A closed-form 2D spline curve is obtained by considering, sequentially a subset of *r-bends*. Figure 7(a) shows the interpolated cup boundary passing through the *r-bends* and Fig. 7(b) shows final obtained boundaries for a sample OD region.

C. Confocal Scanning Laser Ophthalmology

In [6] Confocal scanning laser ophthalmoscopy (CSLO), a laser based image gaining which is proposed to improve the quality of the examination compared to ordinary ophthalmologic examination. A laser id scanned across the retina along with a detector system. Once a single spot on the retina is illuminated at any time, ensuing in a high-contrast image of great reproducibility that can be used to estimate the width of the RNFL. In addition, this technique does not need maximal mydriasis, which may be a problem in patients having glaucoma. The Heidelberg Retinal Tomography is possibly the most common example of Confocal scanning laser ophthalmoscopy (CSLO).

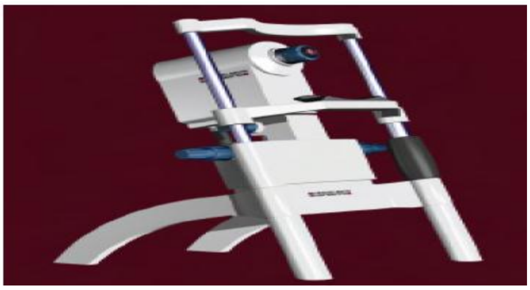


Figure 15. HRT Machine

D. Scanning Laser Polarimetry

RNFL is birefringent, which causes a change in the state of divergence of a laser beam as it passes. It uses a 780-nm diode to illuminate optic nerve. The polarization state of the light emerging from the eye is then evaluated and linked with RNFL thickness. Unlike CSLO, scanning laser polarimetry (SLP) can unswervingly measure the thickness of the RNFL[6]. GDx® is an ordinary example of a scanning laser polarimeter. GDx®contain a normative database and statistical software package to permit comparison to age-matched normal subjects of the same racial origin.

The advantages of this system are that images can be obtained without pupil dilation, and evaluation can be done roughly in 10 minutes. Modern instruments have added improved and erratic corneal compensation technology to account for corneal polarization.

Figure 16. GDx VCC

E. Optical Coherence Tomography

Optical coherence tomography (OCT) uses near-infrared light to provide direct crosssectional measurement of the RNFL [6]. The principles employed are alike to those used in B-mode ultrasound except light, not sound, is used to create the 2-dimensional images.

The light source can be directed into the eye through a conservative slit-lamp biomicroscope and focused on the retina through a distinctive 78-diopter lens. This system requires dilation of the patient's pupil. OCT is an example of this technology.

Figure 17. OCT

III. CONCLUSION

Glaucoma is a silent disease that comes with no symptoms and warning. Initially no one can say that the patient is having any sort of problem either by looking and touching the eye. Hence its detection and diagnosis are very essential.

When Glaucoma increases, the pressure inside the eye (>21mm of Hg) also increases which makes the patient feel uncomfortable (symptoms) and needs to consult a doctor. In this survey different Qualitative and Quantitative glaucoma detection methods and their comparisons are discussed here. But the quantitative methods need special equipments which may available in territory hospitals and it is expensive and not easily available. Therefore, qualitative methods are advantageous for accuracy and early diagnosis of glaucoma. Quantitative imaging techniques provide comprehensive RNFL assessment to aid the clinician in the diagnosis of glaucoma. Qualitative glaucoma detection provide early detection and prevents the human from virtual impureness.

REFERENCES

[1] Joshi GD, Sivaswamy J,Krishnadas SR "Optic disk and cup segmentation from monocular color retinal images for glaucoma assessment,". *IEEE Trans. Med. Imag.*, vol. 30, no. 6, pp. 1192–1205,Jun. 2011.

[2] S. Chandrika 1, K. Nirmala *2* "Analysis of CDR Detection for Glaucoma Diagnosis," (IJERA) ISSN: 2248-9622 National Conference on Advanced communication & Computing Techniques (NCACCT-19 March 2013.

[3] Screening Jun Cheng*, Jiang Liu, Yanwu Xu, Fengshou Yin, Damon Wing Kee Wong, Ngan-Meng Tan, Dacheng Tao,Ching-Yu Cheng, Tin Aung, and Tien Yin Wong "Superpixel Classification Based Optic Disc and Optic Cup Segmentation for Glaucoma," IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 32, NO. 6, JUNE 2013.

[4] Subi. P .P "Glaucoma screening based on superpixel classification and detection of macula in human retinal imagery," IJCAT International Journal of Computing and Technology, Volume 1, Issue 5, June 2014.

[5] R. Bock, J. Meier, L. G. Nyl, and G. Michelson, "Glaucoma risk index: Automated glaucoma detection from color fundus images,*"Med. Image Anal.*, vol. 14, pp. 471–481, 2010.2007.

[6] Saja Usman1, Dimple Shajahan "A REVIEW ON DIFFERENT GLAUCOMA DETECTION METHODS," International Journal of Advanced Research in Engineering Technology (IJARET), ISSN 0976 –6480(Print), ISSN 0976 – 6499 (Online) Volume 5, Issue 2, February (2014), pp. 95-100, © IAEME.

[7] *Chalinee Burana-Anusorn1, Waree Kongprawechnon1, Toshiaki Kondo1, Sunisa* Sintuwong2and KanokvateTungpimolrut3 Thammasat "Image Processing Techniques for Glaucoma Detection Using the Cup-to-Disc Ratio," International Journal of Science and Technology, *Vol. 18, No. 1, January-March 2013.*

[8] S.Kavitha1, K.Duraiswamy "Automated Glaucoma Screening Using CDR From 2D Fundus Images Glaucoma in fundus images using ANFIS," Jan 2012.©IJAET ISSN: 2231-1963.

