RETINAL IMAGE SEGMENTATION FOR BLOODVESSELS EXTRACTION

K.Kavitha[1], M.Malathi[2]
PG scholar[1], Assistant Professor[2]
Department Of Computer Science and Engineering
Kalasalingam Institute of Technology, Krishnankoil.
Email id:kavisan07@gmail.com

ABSTRACT

Fundus imaging is a common clinical procedure used to record a viewing of retina. The manual examination of optic disk (OD) is a standard procedure used for detecting glaucoma. In this paper, we describe a process to automatically locate the optic nerve in a retinal image. The optic nerve is one of the most important organs in the human retina. Locating the OD position in fundus image is quite important for many reasons. Much important retinal pathology may affect the optic nerve. Since the OD may be easily confounded with large exudative lessions by image analysis techniques. The method is based on the preliminary detection of the main retinal vessels. All retinal vessels start from the OD and their path follows a similar directional pattern (parabolic course) in all images. Glaucoma detection typically considers the medical history, intra-ocular pressure and visual field loss tests of a patient together with a manual assessment of the OD, through ophthalmoscopy. blood vessels are extracted using line edge detection.

Keywords: Optic disc segmentation, optic cup segmentation, glaucoma screening, retina, blood vessels

I.INTRODUCTION

Glaucoma is one of the normal explanations for visual deficiency with about 79 million in the world likely to be afflicted with glaucoma by the year 2020 [1]. It is characterized by the progressive degeneration of optic nerve fibers and leads to structural changes of the optic nerve head, which is also referred to as optic disk, the nerve fiber layer and a simultaneous functional failure of the visual field. Since, glaucoma is asymptomatic in the early forms and the associated vision loss cannot be restored, its early detection and subsequent treatment is essential to prevent visual damage [2].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 non- contact tonometry (also known as the"airpufftest") is neither specific nor sensitive enough to began effective screening tool because glaucoma can be present with or without increased IOP. Color fundus imaging (CFI) is another modality that can be used for glaucoma evaluation. It has risen as a favored modality for large-scale retinal disease screening [4] and has already been established for large-scale diabetic retinopathy screening. It is possible to acquire fundus images in a non invasive manner which is suitable for large scale screening. To handle this, morphological-based preprocessing step is employed to suppress the vessel prior to template matching [30]. Assessment of the damaged optic nerve head is both additional guaranteeing, and better than IOP estimation or visual field testing for glaucoma screening. One strategy for automatic optic nerve head assessment is to use image features for a binary classification between [5][6][7]. Although different ophthalmologists have different opinions on the usefulness of these factors, CDR is well accepted and commonly used. A larger CDR indicates a higher risk of glaucoma. This paper proposes super pixel classification based disc and cup segmentations for glaucoma screening. A similar concept has been used for vessel segmentation [22]. We compute centre surround statistics from super pixels and unify them with histograms for disc and cup segmentation. We incorporate prior glaucomatous and healthy subjects knowledge of the cup by including location information for cup segmentation.

Based on the segmented disc and cup, CDR is computed for glaucoma screening. In addition, the proposed method computes a self-assessment reliability score forits disc segmentation result. The optic nerve head or the optic disc(in short, disc) is the location where ganglion cell axons exit the eye to form the optic nerve, through which visual data of the photo-receptors is transmitted to the mind. Most retinal pathology is neighbourhood in its punctual stages, not influencing the whole retina, with the intention that vision disability is progressively continuous. Conversely, pathology on or close to the nerve can have a more severe effect in early organizes, because of the need of the nerve for vision. Thus, an accurate segmentation of OD and cup is essential to get better localization of neuroretinal rim to enable new glaucoma evaluation methodologies which consider other factors in addition to CDR.

II. ARCHITECTURAL DESIGN

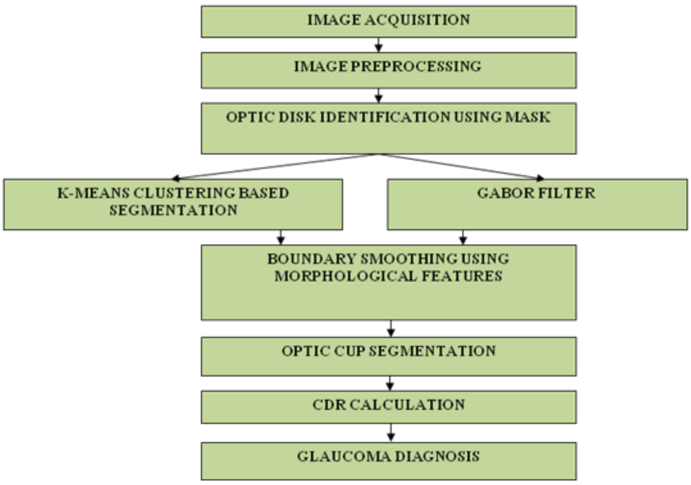


Fig 1: Architecture diagram

Figure shows the architecture of retinal fundus image. There are following parts

i) IMAGE ACQUISITION: It can be broadly defined as action of retrieving an image from some source.

ii) IMAGE PREPROCESSING: **I**t is mainly focus on noice removal process. Pre processing such as image filtration, color contrast enhancement are performed.

iii)OPTIC DISC: It evaluated using disc photography(DP) and optical coherence tomography(OCT).

Iv) K-MEANS CLUSTERING: It is unsupervised clustering algorithm i/p data points into multiple classes based on their inheritent distance.

v) GABOUR FILTER: Mainly focus on image processing application. It is used to accurate boundary delineation.

vi) MORPHOLOGICAL FEATURES: It is description of the shape of objects /regions. There are two operations are performed dilation and erosion.

vii) OPTIC CUP: We can use thresholding or binarization for optic cup segmentation process. This process will convert color image into B/W image.

viii) CDR CALCULATION: CDR value is greater than threshold, then it is glaucomatous otherwise healthy.

ix) GLAUCOMA DIAGNOSIS: We can find the disease condition of the patient, usually performed by optometrists and ophthalmologist.

III.OPTIC DISC SEGMENTATION

Image segmentation is the process of partitioning an image into multiple segments, as to change the representation of an image is more meaningful and easier to analyze. K-means clustering algorithm is applied for image segmentation. The segmentation estimates the disc boundary, which is a task due to blood vessel occlusions, pathological changes around disc, variable imaging conditions, etc. Circular Hough transform is used to the disc boundary. The segmentation estimates the disc boundary, which is a challenging task due to blood vessel occlusions, pathological changes around disc, variable imaging conditions, etc. Some approaches have been proposed for disc segmentation, which can be generally classified as template based methods[26][27][28],deformable model based methods [29][14][30][8][31][32]and pixel classification based methods [15][33].In [26][27],circular Hough transform is used to model the disc boundary because of its computational efficiency. We also presentation super pixel classification based approach using histograms [35] to improve the initialization of the disc for deformable models.

Both the template and deformable model based methods are based on the edge characteristics. The performance of these methods very much depends on the differentiation of edges from the disc and other structures, especially the PPA. 1) it looks similar to the disc;2)it screscent shape[36]makes it form another ellipse (often stronger) to gether with the disc.

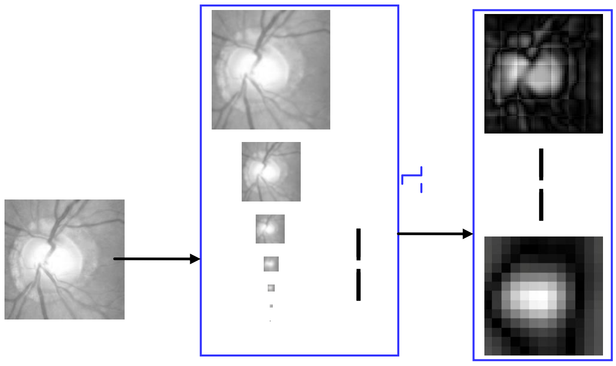


Fig 2: Segmentation

This paper uses the simple linear iterative clustering [47] algorithm (SLIC) to aggregate nearby pixels into super pixels in retinal fundus images. Compared with other super pixel methods, SLIC is fast, memory efficient and has excellent boundary adherence. SLIC is also simple to use with only one parameter, i.e., the number of desired super pixels *k*. Here we give a brief introduction of the SLIC algorithm while more details of the algorithms can be found in the SLIC paper [47]. Many features such as colour, appearance, gist, location and texture can be extracted from super pixels for classification [48]. Since colour is one of the main differences between disc and non-disc region, colour histogram from super pixels is an intuitive choice [35]. Motivated by the large contrast variation between images and the use of histogram equalization in biological neural networks [49], histogram equalization is applied to red r, green g, and blue b channels from RGB colour spaces individually to enhance the contrast for easier analysis. It is important to include features that reflect the difference between the PPA region and the disc region. The super pixels from the two regions often appear similar except for the texture: the PPA region contains blob-like structures while the disc region is relatively more homogeneous. The histogram of each super- pixel does not work well as the texture variation in the PPA region is often from a larger area than the super pixel [35].

To overcome the problem, we adopt a bootstrapping strategy [55].The active shape model employed in [31] is used to fine tune the disc boundary.

IV.CLUSTERING ALGORITHM

It is unsupervised clustering algorithms that classify the i/p data points into multiple classes based on their inherent distance from each other. K -means clustering algorithm to determine the number of clusters in the data. These clusters are multidimensional measurement space. The algorithm assumes that the data features form a vector space and tries to find natural grouping in them. The focuses are grouped around centroids µiAi = 1…k which are obtained by minimizing the objective.

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

Where $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j , is an indicator of the distance of the n data points from their respective cluster centers. Where 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. Compute the intensity distribution (also called the histogram) of the intensities. Initialize the centroids with k random intensities. Cluster the points based on distance of their intensities from centroids intensities replicated with the mean value within each of the array and then the distance matrix is calculated. Compute the new centroids for each of the clusters. Where k is a parameter of the algorithm (the number of clusters to be discovered), i emphasizes over the all the intensities, j iterates over all the centroids and are the centroids intensities.

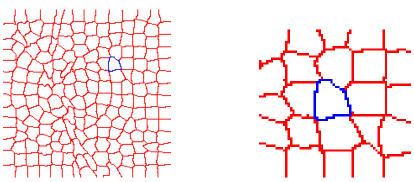


Fig 3: Neighboring superpixels

Slic: the simple linear iterative clustering algorithm (SLIC) to aggregate nearby pixels into super pixels in retinal fundus images. Compared with other super pixel methods. SLIC is fast, memory efficient and has excellent boundary adherence. SLIC is also simple to use with only one parameter.

V.GABOUR FILTER:

Gabour filter is a linear filter used for edge identification. Recurrence and introduction representations of Gabor filters are similar to those of the human visual framework, and they have been discovered to be especially appropriate for texture representation and discrimination. In the spatial domain, all filters can be generated from one mother wavelet by dilation and transformation. Gabor filters are directly related to Gabor wavelets, since they might be intended for a number of dilations and turns. Nonetheless, when all is said in done, development is not applied for Gabor wavelets, since this requires processing of bi-orthogonal wavelets, which may be very time consuming.

VI.OPTIC CUP SEGMENTATION

We can use thresholding or binarization for Optic Cup segmentation Process. This process will convert our image into a B/W (Black & White) image where we can easily get our Optic Cup. Detecting the cup boundary from 2D fundus images without depth information is a challenging task as depth is the primary indicator for the cup. Boundary. Thresholding is used to determine the cup in [18][19][56], relying on intensity difference between cup and neuroretinalrim. This method and thresholding based methods are essentially based on pallor information. The main challenge in cup segmentation is to determine the cup boundary when the pallor is non obvious or weak

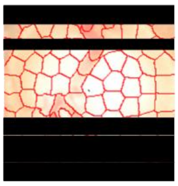


Fig 4: Distance b/w center of superpixel and center of disc

Retinal nerve bers converge to the optic disk (OD) and form a cup-shaped region known as the cup. Enlargement of this cup with respect to OD is an important indicator of glaucoma progression and hence ophthalmologists manually examine the OD and cup for evaluation. An automatic assessment of cup region from Colour fundus image (CFI) could reduce the workload of specialists and help objective recognition of glaucoma.

VII.CUP TO DISC RATIO

The ratio of the vertical cup diameter into vertical disc diameter .Retina is affected to the glaucoma.

After obtaining the disc and cup, various features can be computed. We follow the clinical convention to compute the CDR. As mentioned in the introduction, CDR is an important indicator for glaucoma screening computed as indicator for glaucoma screening computed as

CDR=VCD/VDD

The computed CDR is used for glaucoma screening. When CDR is greater than a threshold, it is glaucomatous, otherwise healthy.

VIII.GLAUCOMA DIAGNOSIS AND SCREENING

Screening for glaucoma is usually performed as part of a standard eye examination performed by optometrists, orthoptists, and ophthalmologists. Testing for glaucoma may as well incorporate estimations of the intraocular pressure through tonometry. Changes fit as a fiddle of the eye, foremost chamber point examination additionally gonioscopy. And examination of the optic nerve to search for any visible harm to it, or change in the glass to-disc proportion and additionally rim appearance and vascular change. A formal visual field test ought to be performed. The retinal nerve filament layer might be surveyed with imaging techniques such as optical intelligibility tomography, filtering laser polarimetry, or examining laser ophthalmoscopy.

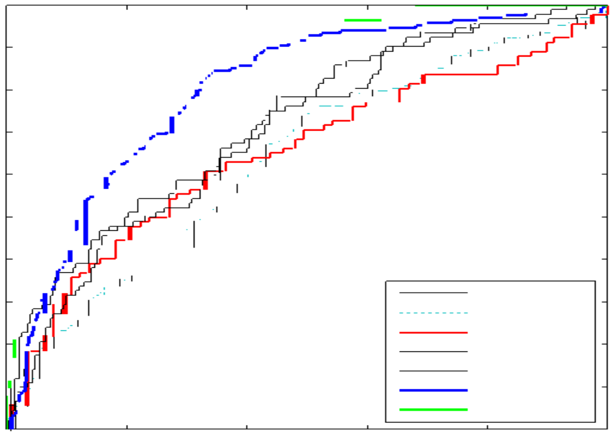
X.RESULT

There are glaucoma screening for optic disc and optic cup segmentation for the area under curve (AUC) of the ROC curves by various cup segmentation methods. Therefore, the AUC significantly larger than IOP, threshold, r-bend, ASM, and regression methods.

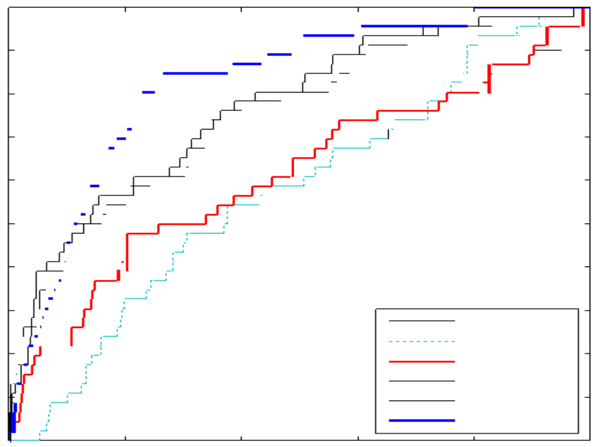
The results show smaller CDR errors in CDR measurement and higher AUC in glaucoma screening by the proposed method, compared with previous methods. The proposed disc and cup segmentation methods achieve an AUC of 0.800, 0.039 lower than AUC of 0.839of the manual CDR computed from manual disc and manual cup.

In the results for the SCES dataset, the proposed method achieves AUC 0.822 in the screening SCES data, which is much higher than 0.660 by the currently used IOP measurement. From the discussions with clinicians, the accuracy is good enough for a large-scale glaucoma, it is important to know how different partition affects the performance.

ROC curves of glaucoma screening by previous and proposed cup segmentation methods in (a) SiMES (b) SCES



(a)SiMES



(b)SCES

In the cross-validation, set *A* is first used to train new models for disc and cup segmentation and set *B* is used for testing. Then set *B* is used for training and set *A* is used for testing. For SCES data set, it remains the same in each test and only the models are updated each time. The AUC in each testis computed. Therefore we get 20 different results for both SiMES and SCES from the 10partitions.

X.CONCLUSION

In this paper we presented super-pixel classification based disc and cup segmentations for glaucoma screening. This paper is presented and evaluated for Glaucoma detection in patients using multimodalities including CSS, Contrast Enhanced Histograms, K-Means clustering, SLIC and Gabor wavelet transformation of the color fundus camera image to obtain accurate boundary delineation. Using structural features like CDR (Cut to Disc Ratio), eccentricity and compactness the ratio value exceeds 0.6 shall be recommended for further analysis of a patient to the ophthalmologist.

REFERENCES

[1] World health organization programme for the prevention of blindness and deafness- global initiative for the elimination of avoidable blindness World health organization, Geneva, Switzerland, WHO/PBL/97.61 Rev.1, 1997.

[2] G. Michelson, S. Wrntges, J. Hornegger, and B. Lausen, "The papilla as screening parameter for early diagnosis of glaucoma," DeutschesAerzteblatt Int., vol. 105, pp. 34–35, 2008.

[3]D. E. Singer, D. Nathan, H. A. Fogel, and A. P. Schachat, "Screening for diabetic retinopathy," Ann. Internal Med., vol. 116, pp. 660–671, 1992
.

[4]R. A. Abdel-Ghafar and T. Morris, "Progress towards automated detection and characterization of the optic disc in glaucoma and diabetic retinopathy," Informatics Health Social Care, vol. 32, no. 1, pp. 19–25, 2007.

[5] J. Meier, R. Bock,G.Michelson, L. G. Nyl, and J. Hornegger, "Effects of preprocessing eye fundus images on appearance based glaucoma classification," in Proc. 12th Int. Conf. Comput. Anal. Images Patterns, 2007, pp. 165–172.

[6] R. Bock, J. Meier, G. Michelson, L. G. Nyl, and J. Hornegger,"Classifying glaucoma with image-based features from fundus photographs,"Proc. 29th DAGM Conf. Pattern Recognit. , pp. 355–364, 2007.

[7] 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.

[8]J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B.Ginneken, "Ridge-based vessel segmentation in color images of the retina," IEEE Trans. Med. Imag., vol. 23, no. 4, pp. 501–509, Apr.2004.

[9]X. Zhu and R. M. Rangayyan, "Detection of the optic disc in images of the retina using the hough transform," in Int. Conf. IEEE Eng. Med.Biol. Soc., 2008, pp. 3546–3549.

[10] A. Aquino, M. Gegundez-Arias, and D. Marin, "Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques," IEEE Trans. Med. Imag., vol. 29, no. 11, pp. 1860–1869, Nov. 2010.

[11] J. Cheng, J. Liu, D. W. K. Wong, F. Yin, C. Cheung, M. Baskaran,T. Aung, and T. Y. Wong, "Automatic optic disc segmentation with peripapillary atrophy elimination," in Int. Conf. IEEE Eng. in Med.Biol. Soc., 2011, pp. 6624–6627..

First Author Ms.K.Kavitha
The author is currently a M.E Student in Computer Science and Engineering Department at Kalasalingam Institute of Technology. She had completed B.E from PSR Engineering College.

Second Author Mrs.M.Malathi
The author is an Assistant Professor in Computer Science Engineering Department at Kalasalingam Institute of Technology. He received his B.E from VPMM Engineering College; affiliated To Anna University, and M.Tech. Degree from Kalasalingam University. His Research interests are in the areas of Image Processing and Network security.