International Journal of Engineering and Techniques - Volume 1 Issue 3, May - June 2015

RESEARCH ARTICLE OPEN ACCESS

Glaucoma Screening Based On Super pixel Classification

Sushma G.Thorat[1], Prof.Savita Raut[2]
1(Department of electronics and telecommunication, Siddhant college of engineering, pune university)
2 (Department of electronics and telecommunication, Siddhant college of enginnering, pune university)

Abstract:

Glaucoma is a chronic eye disease in which the optic nerve head is progressively damaged which leads to loss of vision. Early diagnosis and treatment is the key to preserving sight in people with glaucoma. Current tests using intraocular pressure (IOP) are not sensitive enough for population based glaucoma screening. Assessment of the damaged optic nerve head is both more promising, and superior to IOP measurement or visual field testing. This paper presents superpixel classification based optic disc and optic cup segmentation for glaucoma screening. In optic disc segmentation, histograms and centre surround statistics are used to classify each superpixel as disc or non-disc. For optic cup segmentation, in addition to the histograms and centre surround statistics, the location information is also included into the feature space to boost the performance. The segmented optic disc and optic cup are used to compute the CDR for glaucoma screening. The Cup to Disc Ratio (CDR) of the color retinal fundus camera image is the primary identifier to confirm Glaucoma given patient.

Keywords — IOP measurement, optic cup segmentation, optic disc segmentation, CDR.

I. INTRODUCTION

Glaucoma is a chronic eye disease of the major nerve of vision, called the optic nerve which is progressively damaged. Glaucoma is characterized by a particular pattern of progressive damage to the optic nerve that generally begins with a subtle loss of side vision. If glaucoma is not diagnosed and treated, it can progress to loss of central vision and blindness. Glaucoma usually causes no symptoms early in its course, at which time it can only be diagnosed by regular eye examinations (screenings with the frequency of examination based on age and the presence of other risk factors).It is predicted to affect around 80 million people by 2020[1].

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 "air puff test") is neither specific nor sensitive enough to be an effective screening tool because glaucoma can be present with or without increased IOP.

measurement using non-contact tonometry (also known as the "air puff test") is neither specific nor sensitive enough to be an effective screening tool because glaucoma can be present with or without increased IOP. A functional test through vision loss requires special equipments Only present in territory hospitals and therefore unsuitable for Screening. Assessment of the damaged optic nerve head is both more promising, and superior to IOP measurement or visual field testing for glaucoma screening. Optic nerve head assessment can be done by a trained professional. However, manual assessment is subjective, time consuming and expensive. Therefore, automatic optic nerve head assessment would be beneficial.

One strategy for automatic optic nerve head assessments to use image features for a binary classification between glaucomatous and healthy subjects [2] which are normally computed at the image-level. In these methods, selection of features and classification strategy is difficult and challenging There are many glaucoma risk factors such as the vertical cup to disc ratio (CDR),peripapillary atrophy (PPA),notching etc. . 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. There has been some research into automatic CDR measurement from 3D images [3].However, because 3D images are not easily available, 2D color fundus images are still referred to by most clinicians.

II. PROPOSED SYSTEM

This paper focuses on automatic glaucoma screening using CDR from 2D fundus images. This paper proposes superpixel classification based disc and cup segmentations for glaucoma screening. We compute centre surround statistics from super pixels and unify them with histograms for disc and cup segmentation In this proposed approach, preprocessing such as image filtration, color contrast enhancement are performed which is followed by a combined approach for image segmentation and classification using texture, thresholding and morphological operation. Multimodalities including K-Means clustering, Gabor wavelet transformations are also used to obtain accurate boundary delineation. We incorporate prior knowledge of the cup by including location information for cup segmentation. Based on the segmented disc and cup, CDR is computed for glaucoma screening.

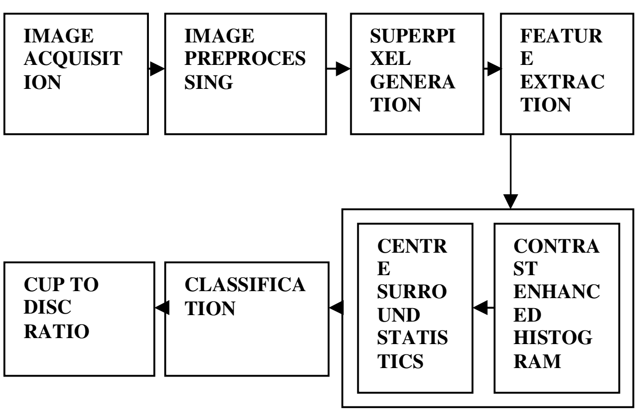

Fig. 1 Block diagram of proposed system

Optic Disc Segmentation

Optic disc detection is an important step in developing systems for automated diagnosis of various serious ophthalmic pathologies. Optic disc segmentation is not an easy matter. Besides the variations in OD shape, size, and color pointed out, there are some additional complications to take into account. Some approaches have been proposed for disc segmentation but we use Circular Hough Transform [4] to model the disc boundary because of its computational efficiency.

In addition, we also present a superpixel classification based approach using histogram [5] to improve the initialization of the disc for deformable methods. The flow chart of the proposed disc segmentation method is summarized in figure1. The segmentation comprises: a superpixel generation step to divide the image into super pixels; a feature extraction step to compute features from each superpixel; a classification step to determine each superpixel as a disc or non-disc superpixel to estimate the boundary; a deformation step using deformable models to fine tune the disc boundary.

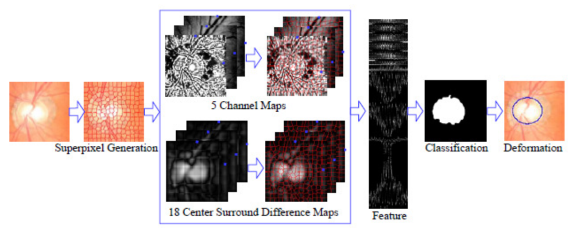

Fig.2 Superpixel based optic disc segmentation

A. *Superpixel generation*

This paper uses the simple linear iterative clustering algorithm [6] (SLIC) to aggregate nearby pixels into super pixels in retinal fundus images. Compared wit other methods, SLIC is fast, memory efficient and has excellent boundary adherence.

B. Feature Extraction

1) Contrast Enhanced Histogram:

Many features such as color, appearance, gist, location and texture can be extracted from super pixels for classification [7]. Since color is one of the main differences between disc and non- disc region, color histogram from super pixels is an intuitive choice [5]. Histogram equalization is applied to red *r*, green *g*, and blue *b* channels from RGB color spaces individually to enhance the contrast for easier analysis. However, histogram equalization on *r, g, b* may yield dramatic changes in the image's color balance. Thus, hue *h* and saturation *s* from HSV color space are also included to form five channel maps The histogram of each superpixel is computed from all the five channels: the histogram equalized *r, g, b* as well as the original *h, s*. The histogram computation uses 256 bins and 256 × 5 = 1280 dimensional feature *HISTj* = [_j(*HE*(*r*)) _j(*HE*(*g*)) _j(*HE*(*b*)) _j(*h*) _j(*s*)] is computed for the *jth* superpixel *SPj* , where *HE*(•) denotes the function of histogram equalization and _j(•) the function compute histogram from *SPj.*

2) Centre surround statistics:

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 superpixel does not work well as the texture variation in the PPA region is often from a larger area than the superpixel because the superpixel often consists of a group of pixels with similar colors. Inspired by these observations, we propose centre surround statistics (CSS) from super pixels as a texture feature.

C. *Initialization and Deformation*:

The LIBSVM with linear kernel is used as the classifier in our experiments. The output value for each superpixel is used as the decision values for all pixels in the superpixel. In our implementation, the mean filter is used as a smoothing filter to achieve the smoothed values. The smoothed decision values are then used to obtain the binary decisions for all pixels with a threshold. In our project, we assign +1 and -1 to positive (disc) and negative (non-disc) samples and the threshold is the average of them is 0.Now we 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 best fitted ellipse using elliptical Hough transform [8] is computed as the fitted estimation. The active shape model employed in is used to fine tune the disc boundary. Compared with [9], the proposed method can also be treated as an active shape model based approach with initial contour obtained by superpixel classification.

Optic cup segmentation

The main challenge in cup segmentation is to determine the cup boundary when the pallor is non-obvious or weak. We present a superpixel classification based method for cup segmentation. The procedure for the cup segmentation is similar to that for disc segmentation with some minor modifications

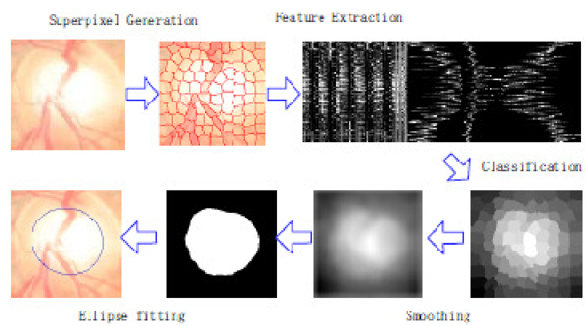

Fig.3. Superpixel based optic cup segmentation

A. Feature Extraction

After obtaining the disc, the minimum bounding box of the disc is used for the cup segmentation. The histogram feature is computed similarly to that for disc segmentation, except that the histogram from red channel is no longer is used. We denote it as $HIST_{c\,j}$ to be differentiated from that for disc segmentation. Similarly, the centre surround statistics $\_CSS_{c\,j}$ can be computed

B. Superpixel Classification for Optic Cup Estimation

We randomly obtain the same number of super pixels from the cup and non-cup regions from a set of images with manual cup boundary. The LIBSVM with linear kernel is used again in our experiment for classification. The output value for each superpixel is used as the decision values for all pixels in the superpixel. A mean filter is applied on the decision values to compute smoothed decision values. Then the smoothed decision values are used to obtain the binary decisions for all pixels. The largest connected object is obtained and its boundary is used as the raw estimation. The best fitted ellipse [10] is computed as the cup boundary.

C. Cup to Disc Ratio

Based on the segmented disc and cup boundary, the cup to disc ratio (CDR) is computed as

$$CDR=VCD/VDD$$

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

III. EXPERIMENTAL RESULTS

A. Data sets

Our experiments uses 2326 images from 2326 different subject eyes including 650 from the Singapore Malay Eye study (SiMES) and 1676 from Singapore Chinese Eye Study (SCES). We evaluate the proposed disc segmentation and cup segmentation method using the manual boundary as "ground truth" Among the 2326 eyes, 168 SiMES and 46 SCES eyes are diagnosed as glaucomatous by ophthalmologists.

B. Optic Disc Segmentation

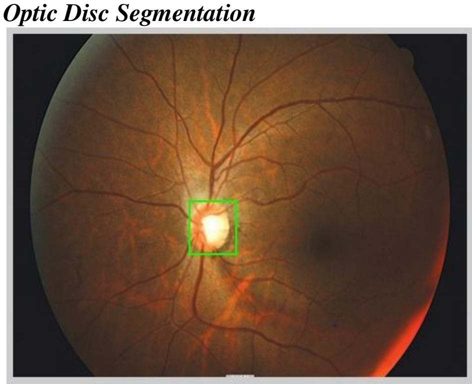

Fig.4. optic cup segmentation

From the fig, the disc boundary can be obtained by taking the decision values from the super pixel. The raw and fitted estimation is also performed for the initialization of disc boundary. The decision values from the support vector machine are used for segmentation. Output of each super pixel is used as the decision values. Each image is divided into super pixels. The features are used to classify each super pixel as cup or non- cup. The decision values from the SVM output are smoothed to determine the cup boundary. The cup can be located at the centre section of the disc.

IV. CONCLUSION

In this paper, I present superpixel classification based methods for disc and cup segmentation for glaucoma screening. It has been demonstrated that CSS is beneficial for both disc and cup segmentation. In disc segmentation, HIST and CSS complement each other as CSS responds to blobs and provides better differentiation between PPA and discs compared with histograms. Reliability score is an important indicator of the automated results. I have demonstrated that, by replacing circular Haugh transform based initialization with the proposed one for active shape model; I am able to improve the disc segmentation. In future work, multiple kernel learning will be used for enahancement.The accuracy of the proposed method is much better than the air puff IOP measurement and previous CDR based methods.

REFERENCES

[1] H. A. Quigley and A. T. Broman, "The number of people with glaucoma worldwide in 2010 and 2020," Br. J.Ophthalmol., vol. 90(3), pp. 262– 267, 2006.

[2] R. Bock, J. Meier, G.Michelson, L. G. Nyl, and J. ornegger, "Classifying glaucoma with image-based features from fundus photographs," Proc. of DAGM, pp. 355–364, 2007.

[3] Z. Hu, M. D. Abramoff, Y. H. Kwon, K. Lee, and M. K. Garvin, "Automated segmentation of neural canal opening and optic cup in 3-d spectral optical coherence tomography volumes of the optic nerve head," Inv Ophthalmol Vis Sci., vol. 51, pp. 5708–5717, 2010

[4] 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, pp. 1860–1869, 2010.

[5] J. Cheng, J. Liu, Y. Xu, D. W. K. Wong, B. H. Lee, C. Cheung, T. Aung, and T. Y. Wong, "Superpixel classification for initialization in model based optic disc segmentation," Int. Conf. of IEEE Eng. in Med. And Bio. Soc., pp. 1450–1453, 2012.

[6] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk, "Slic superpixels compared to state-of-the-art superpixel methods," IEEE Trans. Pattern Anal. and Mach. Intell., vol. 34, pp. 2274–2281, 2012

[6] J. Tighe and S. Lazebnik, "Superparsing: Scalable nonparametric image parsing with superpixels," European Conf. on Computer Vision, vol. 5, pp. 352–365, 2010.

[7] 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," Int. Conf. of IEEE Eng. in Med. And Bio. Soc., pp. 6624–6627, 2011

[8] F. Yin, J. Liu, S. H. Ong, Y. Sun, D. W. K. Wong, N. M. Tan, C. Cheung, M. Baskaran, T. Aung, and T. Y. Wong, "Model-based optic nerve head segmentation on retinal fundus images," Int. Conf. of IEEE Eng. in Med. and Bio. Soc., pp. 2626–2629, 2011.

[9] Z. Zhang, F. Yin, J. Liu, W. K. Wong, N. M. Tan, B. H. Lee, J. Cheng, and T. Y. Wong, "Origa-light: An online retinal fundus image database for glaucoma analysis and research," Int. Conf. of IEEE Eng. in Med. and Bio. Soc., pp. 3065–3068, 2010.

[10] L. Duan, I. W. Tsang, and D. Xu, "Domain transfer multiple kernel learning," IEEE Trans. Pattern Anal. and Mach. Intell., vol. 34, pp. 465–479, 2012.