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Detecting the Optic Disc and Optic Cup Boundary for Glaucoma Screening: A Review

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Abstract**—**Glaucoma is the leading cause of irreversible blindness in the world. Assessment of damaged optic nerve head is both more promising, and superior to IOP measurement or visual field testing for glaucoma screening. This paper present here the automatic glaucoma screening using CDR from 2D fundus images using superpixel classification..We compute centre surround statistics from super pixels and unify them with histograms for disc and 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 for its disc segmentation result.

Index Terms—CDR, superpixel, Optic disc segmentation, Optic cup segmentation,2D fundus images.

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I. Introduction

Glaucoma is a diasease of the major nerve of vision, called the optic nerve and it is often associated with elevated intraocular pressure, in which damage to optic nerve can lead to loss of vision.

It is second most common cause of blindness worldwide [1]. As the symptoms only occurs when the disease is quite advanced, glaucoma is called the silent thief of sight. As it cannot be cured, detecting the disease in time is important.

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. 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 assessment is to use image features for a binary classification between glaucomatous and healthy subjects [2] These features are normally computed at the image-level.There are many glaucoma risk factors such as the vertical cup to disc ratio CDR[9],disc diameter,peripapillary atrophy, 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 in
automated segmentation of neural canal opening and. optic cup in 3-d spectral optical coherence tomography volumes of optic nerve head[3] but 3D images are not easily available and the high cost of obtaining 3D images make it inappropriate for a large-scale screening program.

II. Literature survey

1)."The number of people with glaucoma worldwide in 2010 and 2020"

To estimate the number of people with open angle (OAG) and angle closure glaucoma (ACG) in 2010 and 2020[1]. A review of published data with use of prevalence models. Data from population based studies of age specific prevalence of OAG and ACG that satisfied standard definitions were used to construct prevalence models for OAG and ACG by age, sex, and ethnicity, weighting data proportional to sample size of each study. Models were combined with UN world population projections for 2010 and 2020 to derive the estimated number with glaucoma. There will be 60.5 million people with OAG and ACG in 2010, increasing to 79.6 million by 2020, and of these, 74% will have OAG. Women will comprise 55% of OAG, 70% of ACG, and 59% of all glaucoma in 2010. Asians will represent 47% of those with glaucoma and 87% of those with ACG. Bilateral blindness will be present in 4.5 million people with OAG and 3.9 million people with ACG in 2010, rising to 5.9 and 5.3 million people in 2020, respectively. Glaucoma is the second leading cause of blindness worldwide, disproportionately affecting women and Asians.

2) "The prevalence and types of glaucoma in malay people: the Singapore Malay eye study"

To assess the prevalence and types of glaucoma in an Asian Malay population. The Singapore Malay Eye Study is a population-based, cross-sectional survey that examined 3280 (78.7% response) persons aged 40 to 80 years[4]. Participants underwent a standardized clinical examination including slit-lamp biomicroscopy, Goldman applanation tonometry, and dilated optic disc assessment. Participants who were suspected to have glaucoma also underwent visual field examination (24-2 SITA standard, Humphrey Visual Field Analyzer II), gonioscopy, and repeat applications tonometry. Glaucoma was defined according to International Society for Geographical and Epidemiologic Ophthalmology criteria.

Of the 3280 participants, 150 (4.6%) had diagnosed glaucoma, giving an age- and sex-standardized prevalence of 3.4% (95% confidence interval [CI], 3.3%-3.5%). The age- and sex-standardized prevalence of primary open-angle glaucoma was 2.5% (95% CI, 2.4%-2.6%), primary angle-closure glaucoma 0.12% (95% CI, 0.10%-0.14%), and secondary glaucoma 0.61% (95% CI, 0.59%-0.63%). Of the 150 glaucoma cases, only 12 (8%) had a previous known history of glaucoma. Twenty-seven (18%) eyes had low vision (based on best corrected visual acuity logarithm of the minimal angle of resolution [log MAR] >0.30 to <1.00 in the eye with glaucoma for unilateral cases; and based on the better eye for bilateral cases) and 15 (10%) were blind (log MAR, >/=1.00). The prevalence of glaucoma among Malay persons 40 years of age and older in Singapore is 3.4%, comparable to ethnic Chinese people in Singapore and other racial/ethnic groups in Asia. As in Chinese, Caucasians, and African people, primary open-angle glaucoma was the main form of glaucoma in this population. More than 90% of glaucoma cases were previously undetected**.**

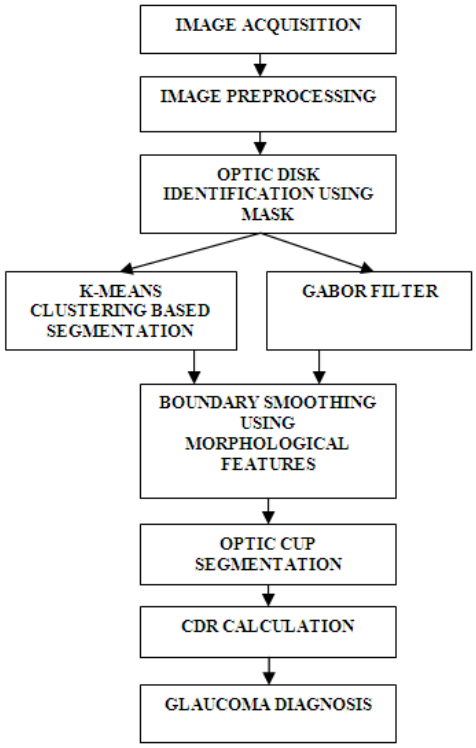
3)"Effects of preprocessing eye fundus images on appearance based glaucoma classification,"

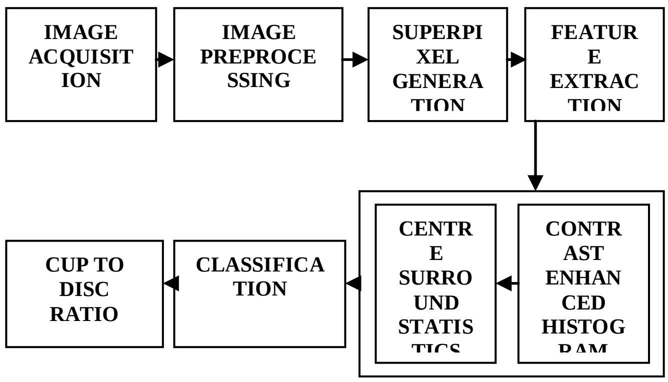
Early detection of glaucoma is essential for preventing one of the most common causes of blindness. Our research is focused on a novel automated classification system based on image features from fundus photographs which does not depend on structure segmentation or prior expert knowledge. Our new data driven approach that needs no manual assistance achieves an accuracy of detecting glaucomatous retina fundus images comparable to human experts. In this paper[5], we study image preprocessing methods to provide better input for more reliable automated glaucoma detection. We reduce disease independent variations without removing information that discriminates between images of healthy and glaucomatous eyes. In particular, nonuniform illumination is corrected, blood vessels are in painted and the region of interest is normalized before feature extraction and subsequent classification. The effect of these steps was evaluated using principal component analysis for dimension reduction and support vector machine as classifier.

III.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.

IV. PROPOSED SYSTEM BLOCK DIAGRAM





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 [6] to model the disc boundary because of its computational efficiency.

In addition, we also present a superpixel classification based approach using histogram [7] 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.

A.Superpixel generation

This paper uses the simple linear iterative clustering algorithm [8] (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 colour, appearance, gist, location and texture can be extracted from superpixels for classification [9]. Since colour is one of the main differences between disc and non-disc region, colour histogram from super pixels is an intuitive choice [7]. 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. However, histogram equalization on *r, g, b* may yield dramatic changes in the image's colour balance. Thus, hue *h* and saturation *s* from HSV colour 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 $256 \times 5 = 1280$ dimensional feature $HIST_j = [\_{j}(HE(r))\ \_{j}(HE(g))\ \_{j}(HE(b))\ \_{j}(h)\ \_{j}(s)]$ is computed for the j_{th} superpixel SP_j , where $HE(\cdot)$ denotes the function of histogram equalization and $\_{j}(\cdot)$ the function compute histogram from SP_j

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 colours. Inspired by these observations, we propose centre surround statistics (CSS) from super pixels as a texture feature. To compute CSS,nine spatial scale dyadic Gaussian pyramids are generated with a ratio of 1:1 (level 0) to 1:256 (level 8).

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 [10] is computed as the fitted estimation. The active shape model employed in [11] is used to fine tune the disc boundary. Compared with [11], the proposed method can also be treated as an active shape model based approach with initial contour obtained by superpixel classification.

D. Self-assessment reliability score

A self-assessment reliability score is computed to evaluate the quality of the automated optic disc segmentation. Define the set of points from the raw estimation as X and the set of points from the fitted estimation as $Y = f(X)$, e.g., the red and white lines in respectively. For each point x in X, we find its nearest point in Y and their distance is computed as

$$d_f(x) = \inf \{d(x, y) \mid y \in Y\}$$

Where inf represents the infimum and $d(x, y)$ the Euclidean distance between x and y. Then, the self-assessment reliability score is computed as the ratio of the number of x with $d_f(x) < T$ to the total number of x, i.e.,

$$r(X) = Card(\{x \mid d_f(x) < T, x \in X\})/Card(X)$$

Where $Card(Z)$ is the cardinality of the set Z, and T is a threshold empirically set as five pixels in this paper for our images with average disc diameter around 350 pixels.

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.

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 $HISTc_j$ to be differentiated from that for disc segmentation. Similarly, the centre surround statistics $\_CSSc_j$ 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 [12] is computed as the cup boundary.

C. Cup to Disc Ratio

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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.

V. CONCLUSIONS

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 [65] will be used for enahancement.The accuracy of the proposed method is much better than the airpuff IOP measurement and previous CDR based methods.

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