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Automated Glaucoma Screening using CDR from 2D Fundus Images

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Abstract:
Glaucoma is a chronic eye disease that leads to blindness. This disease cannot be cured but we can detect the disease in time. Current tests using intraocular pressure (IOP)measurement are not sensitive enough for population based glaucoma screening. Optic nerve head assessment in retinal fundus images is more promising and superior than current methods. This paper proposes segmentation of optic disc and optic cup using superpixel classification for glaucoma screening. In optic disc segmentation, clustering algorithms are used to classify each superpixel as disc or non-disc. For optic cup segmentation, in addition to the clustering algorithms, the Gabor filter and thresholding is used. . The segmented optic disc and optic cup are then used to compute the cup to disc ratio for glaucoma screening. The Cup to Disc Ratio (CDR) of retinal fundus camera image is the primary identifier to confirm glaucoma for a given patient.

Index terms: *Glaucoma Screening, Gabor Filter, Intraocular pressure, Optic cup segmentation, Optic disc segmentation, Thresholding, CDR.*

I. INTRODUCTION

Glaucoma is a chronic eye disease of the major nerve of vision, called the optic nerve which is progressively damaged. If glaucoma is not diagnosed and treated in time, it can progress to loss of vision and even blindness. Glaucoma usually causes no symptoms early,it can only be diagnosed by regular eye examinations. It is predicted to affect around 80 million people by 2020[1].

There are different methods to detect glaucoma: assessment of (1) raised intraocular pressure (IOP), (2) abnormal visual field,(3) damaged optic nerve head. The IOP measurement using non-contact tonometry is not sensitive enough for population based glaucoma screening. A functional test through vision loss requires special equipment only present in territory hospitals and therefore unsuitable for screening. Optic nerve head assessment can be done by a trained professional. However manual assessment is subjective, time consuming and expensive. Hence, automatic optic nerve head assessment would be very beneficial.

In the previous work on "Classifying glaucoma with image-based features from fundus photographs"[2], the features are normally computed at the image-level and we use image features for binary classification between glaucomatous and healthy subjects[3]. Many glaucoma risk factors are considered, such as vertical cup to disk ratio(CDR),disc diameter, peripapillary atrophy(PPA),etc.Among of these CDR is commonly used. A larger CDR indicates a higher risk of glaucoma. There has been some research into automatic CDR measurement from 3D images[4]. The 3D images are not easily available and high cost of obtaining 3D images makes it inappropriate for a large scale screening program. This paper proposes an automatic glaucoma screening using CDR from 2D fundus images.

II. Literature Survey

[1] 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[5] 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, 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 inpainted and the region of interest is normalized before feature extraction and subsequent classification.

[2] Locating the Optic Nerve in a Retinal Image Using the Fuzzy Convergence of the Blood Vessels

We describe an automated method to locate the optic nerve in images of the ocular fundus. Our method uses a novel algorithm we call fuzzy convergence to determine the origination of the blood vessel network[6]. We evaluate our method many images of healthy retinas and diseased retinas, containing such diverse symptoms as tortuous vessels, choroid revascularization, and hemorrhages that completely obscure the actual nerve. We also compare our method against three simpler methods, demonstrating the performance improvement. All our images and data are freely available for other researchers to use in evaluating related methods.

[3] Detection of Optic Disc in Retinal Images by Means of a Geometrical Model of Vessel Structure

We present here a new method to identify the position of the optic disc (OD) in retinal fundus images. The method is based on the preliminary detection of the main retinal vessels[7]. All retinal vessels originate from the OD and their path follows a similar directional pattern (parabolic course) in all images. To describe the general direction of retinal vessels at any given position in the image, a geometrical parametric model was proposed, where two of the model parameters are the coordinates of the OD center. Using as experimental data samples of vessel centerline points and corresponding vessel directions, provided by any vessel identification procedure, model parameters were identified by means of a simulated annealing optimization technique. These estimated values provide the coordinates of the center of OD**.**

[4] Detecting the Optic Disc Boundary in Digital Fundus Images Using Morphological, Edge Detection, and Feature Extraction Techniques.

Optic disc (OD) detection is an important step in developing systems for automated diagnosis of various serious ophthalmic pathologies. This paper presents a new template-based methodology for segmenting the OD from digital retinal images. This methodology uses morphological and edge detection techniques followed by the Circular Hough Transform to obtain a circular OD boundary approximation. It requires a pixel located within the OD as initial information. For this purpose, a location methodology based on a voting-type algorithm is also proposed. The algorithms were evaluated on many images and the results were fairly good.

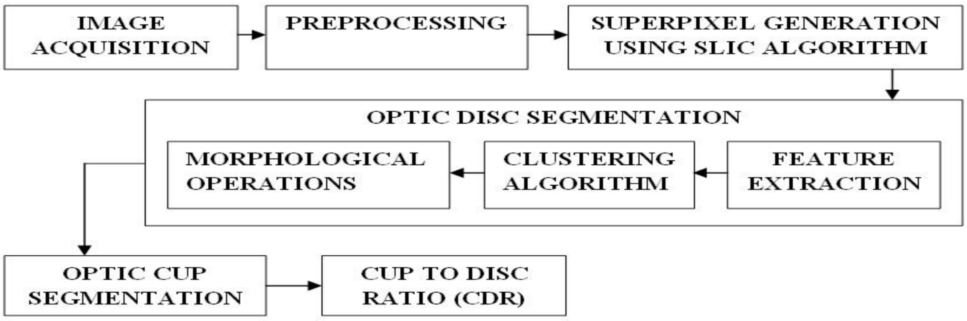
[5] Optic Nerve Head Segmentation

Reliable and efficient optic disk localization and segmentation are important tasks in automated retinal screening. General-purpose edge detection algorithms often fail to segment the optic disk due to fuzzy boundaries, inconsistent image contrast or missing edge features. This paper presents an algorithm for the localization and segmentation of the optic nerve head boundary in low-resolution images (about 20 /pixel). Optic disk localization is achieved using specialized template matching and segmentation by a deformable contour model. The latter uses a global elliptical model and a local deformable model with variable edge-strength dependent stiffness. The algorithm is evaluated against randomly selected images from a diabetic screening program. Ten images were classified as unusable; the others were of variable quality. The localization algorithm succeeded on all bar one usable image.

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. 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



4.1. Image acquisition:

The retina can be observed and recorded using several methods including Fluorescein Angiograms (FA), Transient Visual Evoked Potential (TVEP) or fundus camera. FA is a medical estimation tool that injects fluorescein into the body before image capture so vessel features (arteries, capillaries and veins) can standout and be photographed

4.1.Image Preprocessing:

First, we need to enhance the image that we are going to use. We can either apply basic filter techniques or we can use histogram equalization techniques for the process of histogram equalization.We also found some techniques to generate too noisy images for glaucoma detection (histogram equalization adaptive histogram equalization or color normalization. Thus, we have selected methods which are well-known in medical image processing and preserve image characteristics. Naturally, the proposed system can be improved in the future with adding new methods. In detecting abnormalities associated with fundus image, the images have to be preprocessed in order to correct the problems of uneven illumination problem, nonsufficient contrast between exudates and image background pixels and presence of noise in the input fundus image. Aside from aforementioned problems, this section is also responsible for color space conversion and image size standardization for the system.

One of the problems associated with fundus images is uneven Illumination. Some areas of the fundus images appear to be brighter than the other. Areas at the centre of the image are always well illuminated, hence appears very bright while the sides at the edges or far away are poorly illuminated and appears to be very dark. In fact the illumination decreases as distance form the centre of the image increase. Many methods were tried in resolving this problem of un-even illumination, among which are the use of Naka Rushton method and Adaptive Histogram Equalization Method (AHEM). AHEM gives better performance, higher processing speed and work well for all images of different sizes, hence the reason for it being used as method of correcting un-even illumination.

4.2.Superpixel Generation:

They have been proved to be useful in image segmentations in various images of scene, animal, human etc.

Slic Algorithm:

This paper uses the simple linear iterative clustering algorithm (SLIC) to aggregate nearby pixels into superpixels in retinal fundus images[8]. Compared with other superpixel 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 superpixels. We introduce a new superpixel algorithm, simple linear iterative clustering (SLIC), which adapts a k-means clustering approach to efficiently generate superpixels. Despite its simplicity, SLIC adheres to boundaries as well as or better than previous methods. At the same time, it is faster and more memory efficient, improves segmentation performance, and is straightforward to extend to superpixel generation. SLIC is simple to use and understand.

By default, the only parameter of the algorithm is k, the desired number of approximately equally-sized superpixels. For color images in the CIELAB color space, the clustering procedure begins with an initialization step where k initial cluster centers = li,ai,bi,xi,yi T are sampled on a regular grid spaced S pixels apart. To produce roughly equally sized superpixels, the grid interval is S= N/k . The centers are moved to seed locations corresponding to the lowest gradient position in a 3 ∗3 neighborhood. This is done to avoid centering a superpixel on an edge, and to reduce the chance of seeding a superpixel with a noisy pixel.

Next, in the assignment step, each pixel *i* is associated with the nearest cluster center whose search region overlaps its location. This is the key to speeding up our algorithm because limiting the size of the search region significantly reduces the number of distance calculations, and results in a significant speed advantage over conventional *k*- means clustering where each pixel must be compared with all cluster centers. This is only possible through the introduction of a distance measure *D*, which determines the nearest cluster center for each pixel.

4.3. Optic Disc Segmentation:

4.3.1. Background:

The segmentation estimates the disc boundary, which is a challenging task due to blood vessel occlusions, pathological changes around disc, variable imaging conditions, etc. Feature Extraction techniques like clustering algorithm and morphological operations are used for optic disc segmentation[9]. Circular Hough transform is also used to model the disc boundary because of its computational efficiency.

K-means clustering algorithm:

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them.

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The points are clustered around centroids μiAi = 1…k which are obtained by minimizing the objective

$$\sum_{j=1}^{K} \sum_{i=1}^{X} \left\| x_i^{(j)} - c_j \right\|^2$$

where $xi\ j\ {-cj}$ 2is a chosen distance measure between a data point $xi\ j$ and the cluster centre cj , 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
- Repeat the following steps until the cluster labels of the image do not change anymore.
- 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.

$$c^{(i)} := \arg\min_j ||x^{(i)} - \mu_j||^2$$

- 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 the all the intensities, j iterates over all the centroids and μi are the centroid intensities.

4.3.2. Feature extraction:

Gabor Filter:

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex. Jones and Palmer showed that the real part of the complex Gabor function is a good fit to the receptive field weight functions found in simple cells in a cat's striate cortex.The Gabor space is very useful in image processing applications such as optical character recognition, iris recognition and fingerprint recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation.Among various wavelet bases, Gabor functions provide the optimal resolution in both the time (spatial) and frequency domains, and the Gabor wavelet transform seems to be the optimal basis to extract local features for several reasons. The problem with cup and disc segmentation is that the visibility of boundary is usually not good especially due to blood vessels. Gabor wavelets can be tuned for specific frequencies and orientations which is useful for blood vessels. They act as low level oriented edge discriminators and also filter out the background noise of the image. Since vessels have directional pattern so 2-D Gabor wavelet is best option due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies

4.4 Optic Cup Segmentation:

We can use thresholding or binarization for Optic Cup segmentation Process. This process will convert the given image into a thresholded or binarized image where we can easily get our Optic Cup. Binary images are produced from color images by segmentation. Segmentation is the process of assigning each pixel in the source image to two or more classes. If there are more than two classes then the usual result is several binary images.

The simplest form of segmentation is probably Otsu thresholding which assigns pixels to foreground or background based on grayscale intensity. Another method is the watershed algorithm. Edge detection also often creates a binary image with some pixels assigned to edge pixels, and is also a first step in further segmentation.

4.4.1. Binarization:

Binarization is a process where each pixel in an image is converted into one bit and you assign the value as '1' or '0' depending upon the mean value of all the pixel. If greater then mean value then its '1' otherwise its '0'.

4.4.2 Thresholding:

Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images.

During the thresholding process, individual pixels in an image are marked as "object" pixels if their value is greater than some threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. This convention is known as threshold above. Variants include threshold below, which is opposite of threshold above; threshold inside, where a pixel is labeled "object" if its value is between two thresholds; and threshold outside, which is the opposite of threshold inside .Typically, an object pixel is given a value of “1” while a background pixel is given a value of “0.” Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's labels.

Threshold selection:

The key parameter in the thresholding process is the choice of the threshold value (or values, as mentioned earlier). Several different methods for choosing a threshold exist; users can manually choose a threshold value, or a thresholding algorithm can compute a value automatically, which is known as automatic thresholding

A simple method would be to choose the mean or median value, the rationale being that if the object pixels are brighter than the background, they should also be brighter than the average. In a noiseless image with uniform background and object values, the mean or median will work well as the threshold, however, this will generally not be the case. A more sophisticated approach might be to create a histogram of the image pixel intensities and use the valley point as the threshold.

The histogram approach assumes that there is some average values for both the background and object pixels, but that the actual pixel values have some variation around these average values. However, this may be computationally expensive, and image histograms may not have clearly defined valley points, often making the selection of an accurate threshold difficult. In such cases a unimodal threshold selection algorithm may be more appropriate.

Morphological operation:

The disc and cup boundary detected from the segmentation methods may not represent the actual shape of the disc and cup since the boundaries can be affected by a large number of blood vessels entering the disc. Therefore the morphological operations are employed to reshape the obtained disc and cup boundary. Then CDR is calculated by taking the ratio of the area of cup to OD.

4.5. CDR Calcilation and Diagnosis:

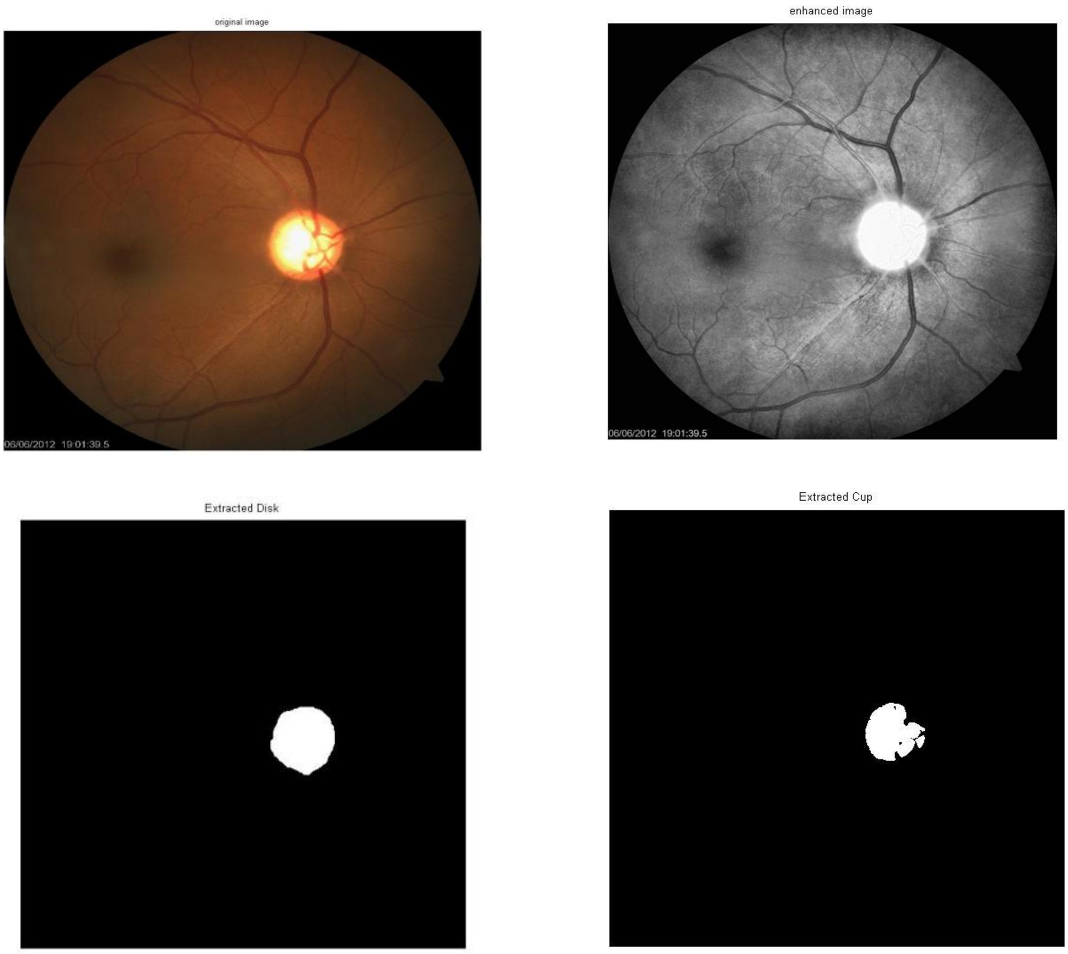
After obtaining the disc and cup, various features can be computed. We follow the clinical convention to compute the CDR. As mentioned in the introduction, CDR is an important
indicator for glaucoma screening computed as

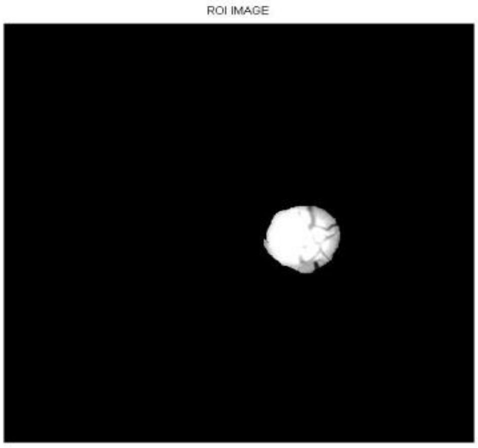
CDR = Area of Cup/Area of Disc

The computed CDR is used for glaucoma screening. When CDR is greater than a threshold, it is glaucomatous, otherwise it will be considered as a healthy one.

V. EXPERIMENTAL RESULT

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.





VI. 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 Hough 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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