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Sparse Dissimilarity-Constrained Coding For Glaucoma Screening

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ABSTRACT: Eye disease which damages the optic nerve that carries information from the eye to the brain is Glaucoma. It is the second foremost reason of blindness, detecting the disease in time is important because it cannot be cured. Many approaches are done in identifying Glaucoma; those are not enough for population based glaucoma screening. Optic nerve head assessment in retinal fundus images is both more promising and superior. This paper proposes image processing technique for the early detection of glaucoma. Glaucoma is one of the major causes which cause blindness but it was hard to diagnose it in early stages. In this paper, we propose a method for cup to disc ratio (CDR) assessment using 2-D retinal fundus images. In the proposed method, the optic disc is first segmented and reconstructed using a novel sparse dissimilarity constrained coding (SDC) approach which considers both the dissimilarity constraint and the scarcity constraint from a set of reference discs with known CDRs. Subsequently, the reconstruction coefficients from the SDC are used to compute the CDR for the testing disc. 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 the color retinal fundus camera image is the primary identifier to confirm Glaucoma for a given patient.

KEYWORDS- CDR, Sparse dissimilarity constrained coding (SDC).

I. INTRODUCTION

Glaucoma is an irreversible eye syndrome. According to reports in 2010, it is second primary reason of blindness in the world. Studies have been shown that increase in intraocular pressure (IOP) of the eye is one the cause for glaucoma. To maintain healthy vision, eye produces a small amount fluid called aqueous humour the same amount fluid will be thrown out of eye. This balance keeps the IOP in limit. If the balance is not maintained the IOP increase and damage the optic nerve head which make irreversible vision loss. So, the early precise detection and treatment of glaucoma will control the progression of the disease. Although glaucoma cannot be cured currently, it can be slowed down through treatment. This makes the screening of people at high risk of glaucoma for timely detection very meaningful. Currently, the air-puff intraocular pressure (IOP) measurement, visual field test, and optic nerve head (ONH) assessment are often used in glaucoma assessment. However, the IOP measurement provides low accuracy in glaucoma detection and a visual field examination requires special equipment only present in specialized hospitals. Therefore, they are unsuitable for screening in the population. ONH assessment is more promising for glaucoma screening. It can be done by a trained professional. However, manual assessment is subjective, time consuming, and expensive. In recent years, automated algorithms for ONH assessment have received much attention.

Digital image processing is the use of computer algorithms to perform image processing on digital images. The 2D continuous image is divided into N rows and M columns. The intersection of a row and a column is called a pixel. The image can also be a function other variables including depth, color, and time. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

This paper is for the automated CDR assessment from 2-D fundus images. This paper focuses on computing the CDR from the disc. In order to compute the CDR using the proposed SDC, it is important to locate and segment the disc. The disc localization focuses on finding an approximate location of the disc, very often the disc centre. In this paper, we

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segment the disc using the self-assessed disc segmentation method, which is a combination of three approaches (Super pixels Segmentation, Edge Detection and Circular Hough Transform).The disc normalization process which includes background removal and the Disc Uneven Illumination Correction is also to be done.

It has been shown that the self-assessed approach achieves more accurate disc segmentation than the individual methods. Motivated from the observation that similar discs often have very similar CDRs and the fact that many discs do not have obvious boundary between neuro-retinal rim and the optic cup, we propose a sparse dissimilarity-constrained coding (SDC) to estimate the CDR for a new disc image. The proposed method computes the dissimilarities between the testing disc images and the reference disc images from their overall intensity changes and uses them as the dissimilarity constraint in the SDC-based disc reconstruction. Several major factors that often affect the disc dissimilarity computation and the disc reconstruction have been considered, including BVs, uneven illumination within each disc image, and the illumination changes between different images. we segment the disc using the disc segmentation method in which first 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 for segmenting the Optic Cup. Based on the segmented disc and cup, CDR is computed for glaucoma screening.

II. RELATED WORK

H. A. Quigley et.al [1] has proposed a system on Glaucoma is a chronic eye disease. It is the leading cause of irreversible blindness, and is predicted to affect around 80 million people by 2020. As the disease progresses silently without easily noticeable visual symptoms especially in the early stages, 50–90% of patients are unaware of the disease until it has reached its advanced stages. Thus, glaucoma is also called the silent theft of sight. Although glaucoma cannot be cured currently, it can be slowed down through treatment. J. Meier et.al [2] has proposed a system on one strategy for automatic Optical Nerve Head (ONH) assessment is to use image level features for a binary classification between glaucomatous and healthy subjects. In these methods, selection of features and classification strategy is difficult and challenging. The other strategy is to follow clinical indicators. Cheng et.al [3] proposed super-pixel classification-based approach by including features from super-pixel level, which significantly improves the disc and cup detection. However, it has a bias of underestimating large cups and overestimating small cups due to the dominance of medium sized cups used to train the model. Very often, these methods rely on the contrast between the cup and the neuro-retinal rim to find the cup boundary for CDR computation and can be challenging to use effectively when the contrast is weak. M. D. Abramoff Et.al [4] proposed a system on automated segmentation of the cup and rim from spectral domain oct of the optic nerve head. In this there is some research into automated cup to disc ratio (CDR) assessment from 3-D images such as stereo images and optical coherence tomography images. However, the cost of obtaining 3-D images is still high, which makes it inappropriate for low-cost large-scale screening.

III. PROPOSED SYSTEM

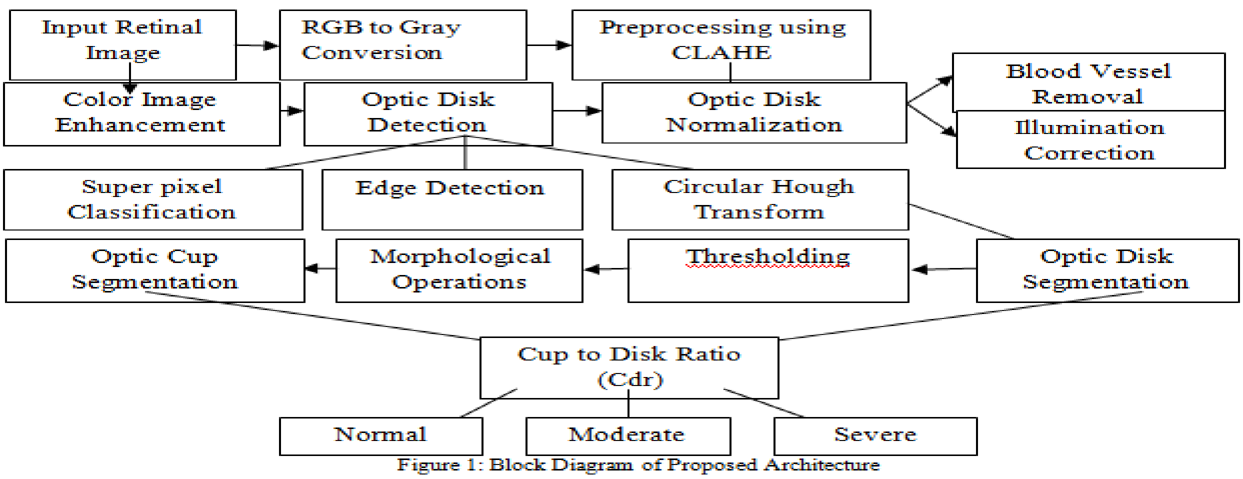

Figure 1: Block Diagram of Proposed Architecture

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Figure 1 represents the overall proposed architecture. Firstly we have to consider retinal image of an patient as input image, this image is subjected to pre-processing in that retinal image is converted into gray scale image and for image enhancement will make use of CLAHE pre-processing algorithm, from the enhanced image we are going for optic disk detection and optic disk normalization by calculating the blood vessel content and will remove those vessels for better image quality. Next, will go for super pixel classification by using SLIC algorithm and edge detection by using canny edge detection algorithm and by keeping the standard threshold value as a reference one will apply circular hough transform technique to find out the status of the disease. Next, by calculating cup to disk ratio and comparing it with the standard threshold value will decide the affected area and also result will be based on the CDR ratio and threshold value.

A. CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

Contrast limited adaptive histogram equalization (CLAHE)
is a popular technique in biomedical image processing, since it is very effective in making the usually interesting salient parts more visible. The image is split into disjoint regions, and in each region local histogram equalization is applied. Then, the boundaries between the regions are eliminated with a bilinear interpolation. The main objective of this method is to define a point transformation within a local fairly large window with the assumption that the intensity value within it is a stoical representation of local distribution of intensity value of the whole image. The local window is assumed to be unaffected by the gradual variation of intensity between the image centers and edges. The point transformation distribution is localized around the mean intensity of the window and it covers the entire intensity range of the image.

Consider a running sub image W of N X N pixels centered on a pixel P (i,j) , the image is filtered to produced another sub image P of (N X N) pixels according to the equation below

$$p_n = 255 . \left(\frac{[\emptyset_w(p) - \emptyset_w(\mathrm{Min})]}{[\emptyset_w(\mathrm{Max}) - \emptyset_w(\mathrm{Min})]} \right) \qquad (1)$$

Where

$$\emptyset_w(p) = \left[1 + \exp\left(\frac{\mu_w - p}{\sigma_w} \right) \right]^{-1} \qquad (2)$$

And Max and Min are the maximum and minimum intensity values in the whole image, while μ_w and σ_w indicate the local window mean and standard deviation which are defined as:

$$\mu_w = \frac{1}{N^2} \sum_{(i,j)\in(k,l)} p(i,j) \qquad (3)$$

$$\sigma_w = \sqrt{\frac{1}{N^2} \sum_{(i,j)\in(k,l)} (p(i,j) - \mu_w)^2} \qquad (4)$$

As a result of this adaptive histogram equalization, the dark area in the input image that was badly illuminated has become brighter in the output image while the side that was highly illuminated remains or reduces so that the whole illumination of the image is same.

B. SUPER-PIXEL CLASSIFICATION USING SLIC ALGORITHM

This paper uses 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. The number of desired super pixels is the main parameter why we used SLIC and it is simple also only because of this parameter. We adopted a new super pixel algorithm, simple linear iterative clustering (SLIC), which uses a k-means clustering approach for proper generation of super pixels. This algorithm is best when compared to other conventional methods. Along that, it is faster and more memory efficient, improves segmentation performance, and is straightforward to extend to super pixel 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 super pixels. To produce roughly equally sized super pixels, the grid interval is S= N/k.

For color images in the CIELAB color space, the clustering procedure begins with an initialization step where k initial cluster $\mathrm{centres} = li, ai, bi, xi, yi$ T is sampled on a regular grid spaced S pixels apart. The centres are moved to seed locations corresponding to the lowest gradient position in a neighborhood. This is done to avoid centering a super pixel on an edge, and to reduce the chance of seeding a super pixel with a noisy pixel. Next, in the assignment step, each pixel “i” is associated with the nearest cluster centre whose search region overlaps its location. This is the key to

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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 centered for each pixel.

C. EDGE DETECTION USING CANNY EDGE DETECTOR

The standard edge detection algorithm in the industry is Canny edge detector. There are several steps are to be fallowed in the canny edge detector, Initially we have to smoothen the retinal image with a two dimension Gaussian, next take the gradient of an considered image, then suppression is done through non-maximal, then edge threshold is calculated. The next step is to extract moving edges from sequential video frames and process the resulting edge information to obtain quantitative geometric measurements of passing vehicles. We are comparing and calculating vehicle density by using these two different edge techniques. The edges are detected by the canny edge algorithm. Using the gradient kernel approach image gradient magnitude is calculated in horizontal direction. Gx and vertical direction Gy for each pixel. And the direction of the pixel is measured by

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{4}$$

Threshold values such at the higher threshold value (HIV) and lower threshold value (LTV) are selected from the histogram of the image in order to detect the edges.

D. CIRCULAR HOUGH-TRANSFORMATION

We established an approach based on the In order to detect small circular spots in the image, will implement an approach called Circular Hough Transformation. Images are obtained by detecting circles on the images using circular Hough transformation. With this technique, from the image a set of circular objects can be extracted. Circle shape of the optic disk is computed using circle equation given below

$$r^2 = (x-a)^2 + (y-b)^2 \tag{5}$$

Where "r" represents the radius of the circle and (a, b) represents coordinates, which is the center of the circular object. To find out a circular disk in the image it is required to collect votes in three dimensional spaces (a, b, r). CHT transforms the image coordinate parameters into set of collected votes in the constraint space. Followed by every dot in the votes are calculated and accumulated in the group for all combination. Highest voting point will be considered the center of the circle and the coordinate points are

$$x = a + r * \cos(\theta) \tag{6}$$

$$y = b + r * \sin(\theta) \tag{7}$$

E. OPTIC CUP SEGMENTATION

For Optic Cup segmentation Process we can using thresholding method. This process will convert the given image into a thresholded image where we can easily get our Optic Cup. By segmentation process binary images are obtained from color images. 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 may be Otsu thresholding which assigns pixels to foreground or background based on gray scale intensity. Edge detection also often creates a binary image with some pixels assigned to edge pixels, and is also a first step in further segmentation.

F. THRESHOLDING

There are many methods are available in image segmentation among those thresholding is the simplest method. From a gray scale 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 and as "background" pixels otherwise. This phenomenon is known as threshold above. Values of pixels 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.

G. MORPHOLOGICAL OPERATIONS

Actual shape of the disc and cup will not represent the disc and cup boundaries which are detected from the segmentation methods, because the boundaries can be affected by a large number of blood vessels entering the disc. So the morphological operations are implemented to reshape the obtained disc and cup boundary. Then CDR is calculated by taking the ratio of the area of cup to area of disc. For accurate measurement of optic disc and the cup areas we are

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removing blood vessels from the image. Morphological operation such as erosion, dilation, opening and closing are implemented on the image. The Morphological erosion operation erodes away the regions of foreground pixels and for dilation was to gradually enlarge the regions of the foreground pixel, therefore this techniques help to remove unwanted bright spots or boundaries present in the image. A disc shaped structuring element of size 15 was created and a closing and opening operation was performed on both the red and green component images. A value of 1 (white) was obtain for the region that contains the optic disc and cup, whereas a value of 0 (black) for the background.

H. OPTIC CUP TO DISK RATIO CALCULATION (CDR)

In CDR calculation the area of optic disk and optic cup are the primary values. By using CHT will mark optical disk. CHT provides the radius r after circle detection as explained in equation 5. CDR is calculated using the equation (8). Whenever there is progression of glaucoma the cup region will increase. The size of mask was determined empirically by calculation the area of the cup for 380 retinal fundus images. Various features can be computed after getting the disc and cup area. To compute the CDR will use clinical convention. CDR is an important indicator for glaucoma screening and it is calculated as

$$\text{CDR} = \text{Area of Cup} / \text{Area of Disc} \tag{8}$$

The calculated CDR is used for glaucoma screening. If CDR is greater than a threshold, then it is concluded as Glaucomatous, if not it is considered as a healthy one.

IV. EXPERIMENTAL RESULTS

The experimental result for the above discussed methodology is discussed in this section. Figure 2 represents the overall experimental results. Figure 2 (a) represents input image this image is preprocessed and enhanced by using histogram equalization technique shown in Figure 2(b). Next will apply CLAHE algorithm as shown in Figure 2(c) for de-noising, after de-noising will go for segmentation and enhancement by applying contrast enhancement method as shown in Figure 2(d) and 2(e) after enhancement will get clear picture of retinal image as shown in Figure 2(f) and next by comparing it with original image as shown in figure 2(g) we are going to determine whether Glaucoma is present or not for particular patient as shown in figure 2(h).

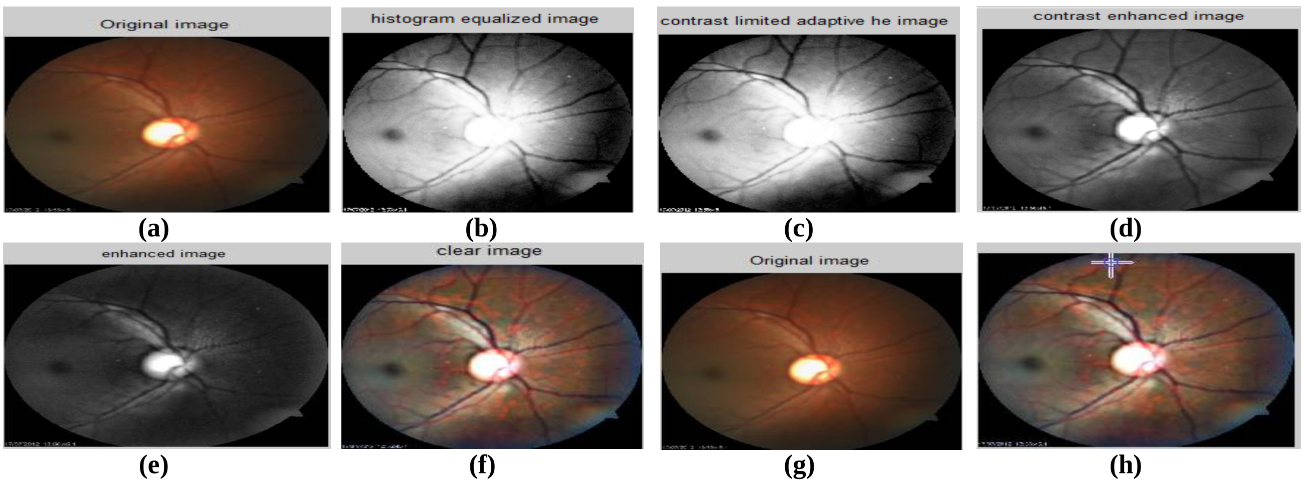

Fig.2: (a) Input original image; (b) Histogram Equalization Image; (c)CLAHE Image; (d) Contrast Enhanced Image; (e) Enhanced Image; (f) Clear Image; (g) Original Image; (h) Output Image

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V. CONCLUSION

In this approach, we propose the SDC for CDR assessment. The proposed SDC method achieves and combines the pixel wise CDR computation and glaucoma detection accuracy comparable with manual CDR assessment by experts. The time-consuming and expensive manual CDR assessment can be replaced by SDC for CDR assessment method. So we can assure that, the proposed method has great potential for low-cost glaucoma screening in polyclinics, eye centers, and especially in optical shops, according to discussions with clinicians and ophthalmologists. This method can be applied for other applications, though the computation of the d might need to be specially defined based on actual data. The limitation is that the method may not capture local cup deformation. It is also interesting to note that by using average CDRs from the two sets of manual CDRs as reference and ground truth, the proposed method achieves smaller CDR error and higher correlation. Future work will explore the integration of other factors to improve diagnostic outcomes toward a more reliable and efficient glaucoma screening system.

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