(IJITR) INTERNATIONAL JOURNAL OF INNOVATIVE TECHNOLOGY AND RESEARCH
Volume No.4, Issue No.6, October – November 2016, 5237-5241.

Diagnosis Of Glaucoma Using Superpixel Classification Method

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Abstract: **Glaucoma is a global health problem expected to affect millions of people in world wide. Glaucoma is a chronic eye disease of the optic nerve and a leading cause of blindness and vision loss in worldwide. If glaucoma is not diagnosed and indulgence in time, it can steps forward to loss of vision and even blindness. Now a days several methods is used to detect and assessment of glaucoma such as intraocular pressure (IOP), abnormal visual field and assessment of damaged optic nerve head. The intraocular pressure measurement is performed using non-contact tonometry, but it is not sensitive for population based glaucoma screening. The assessment of abnormal visual field is performed by functional test through special equipment, but it is only present in territory hospitals and therefore unsuitable for screening. The Optic nerve head assessment can be done by a trained professional. So to avoid these problems a new method is proposed for screening glaucoma using super pixel classification.**

The proposed system performs optic disc and optic cup segmentation. It uses the 2D fundus images. In optic disc segmentation, clustering algorithms are used to sort each superpixel as disc or non-disc, where as in optic cup segmentation the apart the clustering algorithms, gabor filter is also incorporated into the feature space to enhance the performance. The proposed method have been assessed based on the area of the optic disc and optic cup. 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. A larger CDR indicates a higher risk of glaucoma. The proposed work is to be carried out using Matlab technical computing language

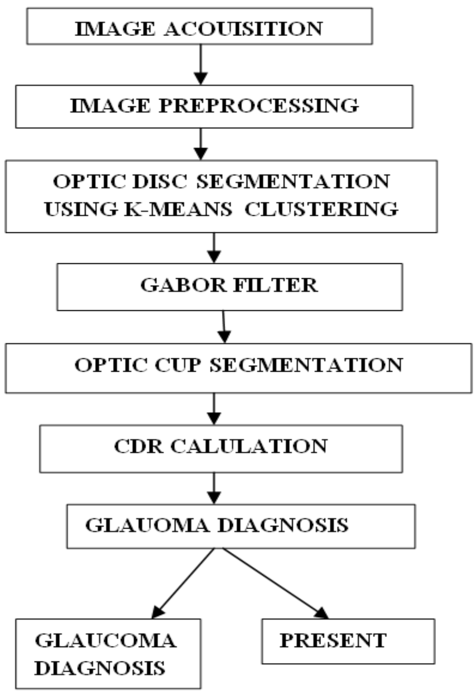
I. INTRODUCTION

Glaucoma is a major eye disease in the world. Glaucoma is a disease 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. Progression of the disease leads to loss of vision, which occurs gradually over a long period of time. It is second most common cause of blindness worldwide. As the symptoms only occurs when the disease is quite advanced, glaucoma is called the silent thief of sight. However, several glaucoma patients are not known of the disease until it has reached its final stage. Glaucoma cannot be cured, but its progression can be slowed down by treatment. Therefore, detecting glaucoma in time is critical. 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 noncontact tonometry is neither specific nor sensitive enough to be an effective screening tool because glaucoma can be present with or without increased iop. In tonometry normal inner pressure range is 12-22 mmhg. In tonometer the value exceeds the normal pressure range we can confirmedas glaucoma is present. High IOP is the strongest known risk factor for glaucoma but it is neither necessary nor sufficient to induce the neuropathy. 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 tonometry or perimetry for glaucoma screening. Optic nerve head assessment can be done by a trained professional. However, manual assessment is subjective, time consuming and high cost. Therefore, automatic optic nerve head assessment would be very usefull. One strategy for automatic optic nerve head assessment is to use image features for a binary classification between glaucomatous and healthy subjects. There are many glaucoma risk factors such as the vertical cup to disc ratio CDR, disc diameter. 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 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. IMPLEMENTED METHOD

This endeavor spotlights on customized glaucoma screening using CDR from 2D fondues pictures. This endeavor executed super pixel plan based plate and holder divisions for glaucoma screening. In this proposed procedure, preprocessing, for instance, picture filtration, shading intricacy change are performed which is trailed by a joined technique for picture division and portrayal using surface, thresholding and morphological operation. Multimodalities including K-Means gathering, Gabor wavelet changes are in like manner used to get exact utmost diagram. We join previous learning of the glass by including range information for compartment division. In perspective of the separated circle and compartment, CDR is prepared for glaucoma screening. This errand mainly focuses on customized glaucoma screening using CDR from 2d

III. BLOCK DIAGRAM



Block diagram of Implemented method

Optic Disc Segmentation :

Dependable and effective optic circle limitation and division are essential undertakings in mechanized retinal screening. Broadly useful edge identification calculations frequently neglect to section the optic plate because of fluffy limits, conflicting picture complexity or missing edge highlights. This paper introduces a calculation for the limitation and division of the optic nerve head limit in low-determination pictures (around 20/pixel). Optic plate confinement is attained to utilizing particular layout coordinating and division by a deformable shape model. The last uses a worldwide circular model and a neighborhood deformable model with variable edge-quality ward solidness. The calculation is assessed against haphazardly chosen pictures from a diabetic screening project. Ten pictures were delegated unusable; the others were of variable quality. The limitation calculation succeeded on all bar one usable picture.

Superpixel generation:

This undertaking uses the straightforward direct iterative grouping calculation (SLIC) to total adjacent pixels into superpixels in retinal fundus pictures. Contrasted and other superpixel techniques, SLIC is quick, memory productive and has astounding limit adherence. SLIC is likewise easy to use with one and only parameter, i.e., the quantity of coveted superpixels. We present another superpixel calculation, straightforward straight iterative grouping (SLIC), which adjusts a k-means bunching way to deal with productively superpixels. Notwithstanding its effortlessness, SLIC sticks to limits and also or better than past techniques. In the meantime, it is speedier and more memory effective, enhances division execution, and is direct to stretch out to superpixel era. SLIC is easy to utilize and get it.

GABOR FILTER

Gabor filter is a linear filter used to detect the edge. It is used to reduce noise. Gabor filter can be tuned for specific frequencies and orientations which are useful edge detection. They act as low level oriented edge discriminators and also filter out the background noise of the image. Since that have directional pattern so 2-D Gabor filter is best option due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies.

B. K-Means Clustering Algorithm:

K-Means calculation is an unsupervised bunching calculation that groups the data information focuses into various classes in view of their characteristic separation from one another. The calculation expect that the information highlights frame a vector space and tries to discover regular bunching in them.

K-Means calculation is an unsupervised bunching calculation that groups the data information focuses into various classes in view of their characteristic separation from one another. The calculation expect that the information highlights frame a vector space and tries to discover regular bunching in them. The focuses are grouped around centroids µiAi = 1… k which are acquired by minimizing the tar

$$\sum_{J=1}^{K}\sum_{I=1}^{X} ||X_i^{(j)} - c_j||^2$$

Where|| $X_i^{(j)}$-c_j||^{2}is a chosen distance measure between a data point xij 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

IV. OPTIC CUP SEGMENTATION

The optic cup is the white cup, area in the center of the optic disc. During embryonic development of the eye, the outer wall of the bulb of the optic vesicles becomes thickened and invaginated, and the bulb is thus converted into a cup, the optic cup consisting of two strata of cells. These two strata are continuous with each other at the cup margin, which ultimately overlaps the front of the lens and reaches as far forward as the future aperture of the pupil. In cup segmentation,when the pallor is weak or non-visible it is difficult to estimate the cup boundary. In cup segmentation, use thresholding or binarization for optic cup segmentation process. This process will convert the image into a B/W (Black & White) image where it can easily segment the optic cup from disc region. We present a superpixel classification based method for cup segmentation. The procedure for the cup

Feature Extraction

After obtaining the disc, the minimum bounding box of the disc is used for the cup segmentation. The histogram 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 CSS cj can be computed.

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 get the 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 is used as the cup boundary.

Binarization and Thresholding:

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 coming from the color images by applying segmentation process. 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 thresholdingwhich 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.

Binarization:

In a binary image, each pixel assumes one of only two discrete values: 1 or 0. A binary image is stored as a logical array. By convention, this documentation uses the variable name BW to refer to binary images.

Thresholding:

Thresholding is very simple technique for 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 otherwise mark as the "background" pixels. 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

Volume No.4, Issue No.6, October – November 2016, 5237-5241.

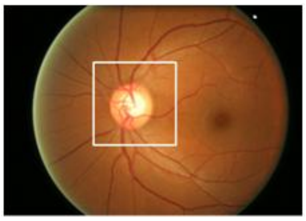
coloring each pixel white or black, depending on a pixel's labels.

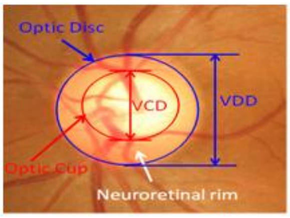
CDR Calculation and Diagnosis

After obtaining the disc and cup, various features can be computed. The cup to disc ratio (CDR) compares the diameter of the cup portion of the optic disc with the total diameter of the optic disc. The hole represents the cup and the surrounding area the disc. Based on the segmented disc and cup boundary, we can calculate the disc area diameter (VDD) and cup area diameter (VCD). Then the cup to disc ratio (CDR) is computed as

CDR = Area of Cup (VCD)/Area of Disc (VDD)

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. Generally, the normal cup to disc ratio (CDR) is 0.3. The cup to disc ratio is above 0.3, then it suggests glaucomatous, otherwise normal.





Major structures of the optic disc: The region enclosed by the blue line is the optic disc; the central bright zone enclosed by the red line is the optic cup; and the region between the red and blue lines is the neuroretinal rim.

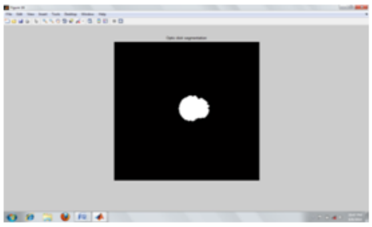
Reference values of CDR

REFERENCE VALUES	
Normal	Normal
Moderate	Moderate
Severe	Severe

Simulation Results:

The input image was actually acquired using canon CR5 non mydriatic camera with a 45 degree field of view. In this proposed approach, preprocessing such as, image filtration, contrast enhancement and histogram equalization are performed.

Fig(a) Original Image



Fig(b) Optic Disc

Fig(c) Histogram equalized Image

Fig(d) K-Means clustering

Fig (e) Gray scale Image

Fig (f) Segmented optic disc

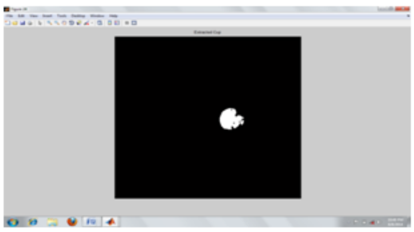


Fig (g) Segmented optic cup

V. CONCLUSION

In this paper presented glaucoma screening using super pixel classification. This paper is presented and evaluated for glaucoma detection in patients using multimodalities including simple linear iterative clustering (SLIC) algorithm, K-means clustering and gabor filter of the color fundus camera image to obtain accurate boundary delineation. Using structural features like CDR the ratio value exceeds 0.3, we can classify as the glaucoma is present. This shall help in patients worldwide by protecting further deterioration through timely medical intervention. We can increase the number of patients and analyze the performance

VI. REFERENCES

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