Glaucoma Screening Based On Super Pixel Classification and the Detection of Macula In Human Retinal Imagery

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Abstract - Glaucoma is a chronic eye disease that leads to vision loss. As it cannot be cured, detecting the disease in time is important. Current tests using intraocular pressure (IOP) are not sensitive enough for population based glaucoma screening. Optic nerve head assessment in retinal fundus images is both more promising and superior. This paper proposes optic disc and optic cup segmentation using super pixel classification for glaucoma screening. In optic disc segmentation, histograms and centre surround statistics are used to classify each super pixel as disc or non-disc The methods can be used for segmentation and glaucoma screening. The self assessment will be used as an indicator of cases with large errors and enhance the clinical deployment of the automatic segmentation and screening. Macula is the major landmark for retinal fundus image registration and is indispensible for the quick understanding of retinal images. For the detection and subsequent extraction of macula, we first perform bit plane decomposition to the preprocessed image. The bit plane 0 and bit plane 1 are found to carry vital information of the location and boundary of macula. Then we locate the exact boundary by means of mathematical morphology. The proposed algorithm is computationally simple and does not require a prior knowledge of other retinal image features like optic disc or vasculature.

***Keywords* - Optic disc segmentation, optic cup segmentation, glaucoma screening, macula, bit plane decomposition, mathematical morphology**

1. Introduction

Glaucoma is the term applied to a group of eye diseases that gradually result in loss of vision by permanently damaging the optic nerve, the nerve that transmits visual images to the brain. Glaucoma is the second leading cause of blindness worldwide. The retina is the innermost layer in the eye and the retinal nerve fibers transmit the visual signal from the photoreceptors in the eye to the brain via the bundle going out of the eye, known as the optic nerve. Glaucoma leads to continuous and speedy damage of the retinal nerve fiber layer and hence can lead to permanent blindness. Hence the diagnosis of glaucoma at an earlier stage is very important for its treatment. A major concern with glaucoma detection is that the disease has no particular set of physical causes or symptoms that doctors can recognize to detect the disease in an early stage. The main focus in glaucoma diagnosis is to detect changes in the visual functioning of the eye at early stages of the disease so that vision can be protected and preserved through medical treatment.

Glaucoma is a generic name for a group of diseases which causes progressive optic neuropathy and vision loss due to degeneration of the optic nerves. It is the second leading cause of blindness, and is predicted to affect around 80 million people by 2020.

2. Literature Survey

In India, it is estimated that Glaucoma affects 12 million people and by 2020, this is expected to be 16 million. Statistics say that one in eight persons above the age of 40 years in India is either suffering from Glaucoma or is at the risk of the disease [1]. Progression of the disease leads to loss of vision, which occurs gradually over a long period of time. As the symptoms only occur when the disease is quite advanced, glaucoma is called the silent thief of sight. Glaucoma cannot be cured, but its progression can be slowed down by treatment. Therefore, detecting glaucoma in time is critical.

In a system which detects features in ultrasound images of eye using fundus, there developed an algorithm to automatically identify clinical features in ultrasound images of the eyes using classification and segmentation techniques. They have used signal processing techniques to locate sclera spur. But the visual quality of the image degrades severely due to speckle noise. To reduce speckle noise they have used multi scale algorithm and tested the algorithm on various images of eye and have given comparative studies in tabular form for each image processed[2]. The algorithm worked well in 97% cases where features were correctly extracted in processed image. However, the designed algorithm failed for a few of images, where more noise was present [3].Then a new technique Automated system using fundus images introduced and is mainly affects the optic disc by increasing the cup size is proposed . The ratio of the optic cup to disc (CDR) in retinal fundus images is one of the primary physiological parameter for the diagnosis of glaucoma. The K means clustering technique is recursively applied to extract the optic disc and optic cup region and an elliptical fitting technique is applied to find the CDR values. The system mainly consists of three different stages. Three classifiers, KNN, SVM and Bayes classifier are used to analyze the performance. The drawbacks of the classifiers like misclassification, imbalance between numbers of training samples, poor choices of weights etc lead this system to fail [4]. There are different types of glaucoma. Some glaucoma occurs suddenly. So, detection of glaucoma is essential for minimizing the vision loss. Increased cup area to disc area ratio is the significant change during glaucoma. Optic disc (OD) is the visible portion of the optic nerve, from which the nerve fibres exit the eye. The OD is characterized by color, contour, and cup. The typical color of OD is orange-pink with a pale centre. Due to optic atrophy the orange pink color gradually disappears and appears pale [5]. So coloured fundus images are considered. The methods can also be combined for obtaining better accuracy. Blood vessels in the color fundus images are the limitation to segment the OD reliably and accurately for finding CDR. In other application such as automatic detection and determining the exact location of the apex point of the anterior chamber region for efficient angle calculation from the various live ultra sound images (USB),they have developed an algorithm based on active contours to calculate clinical parameters , new region classification and segmentation techniques. The paper focuses on the calculation of Angle Open Distance .They have discussed the various steps of algorithm, but the paper lacks the clinical parameters taken into consideration. The testing images have not been mentioned [6] .

There has been some research into automatic CDR measurement from 3D images. Cup is the depressed area inside the optic disk, hence the 3-D depth is the primary feature of the cup boundary, for which the automated detection is a relatively new task and challenging work in fundus image processing. However, 3D images are not easily available, 2D colour fundus images are still referred to by most clinicians. Moreover, the high cost of obtaining 3D images make it inappropriate for a large-scale screening program [7].Pixel classification based methods use various features such as intensity, texture, etc. from each pixel and its surroundings to find the disc. While comparing the pixel classification based methods and the deformable model based methods, can conclude that their performances are similar. Currently used pixel classification based methods and deformable model based methods have some limitations, so a super pixel classification based method and combine it with the deformable model based method is introduced. Super pixels are local, coherent and provide a convenient primitive to compute local image features. They capture redundancy in the image and reduce the complexity of subsequent processing. To overcome the drawbacks of k-means clustering ,the simple linear iterative clustering algorithm (SLIC) is used 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. SLIC is also simple to use with only one parameter.Figure 1 represents the block diagram for detecting the severeness of glaucoma using super pixel classification method.Optic cup and disc segmentation is done by using SLIC .

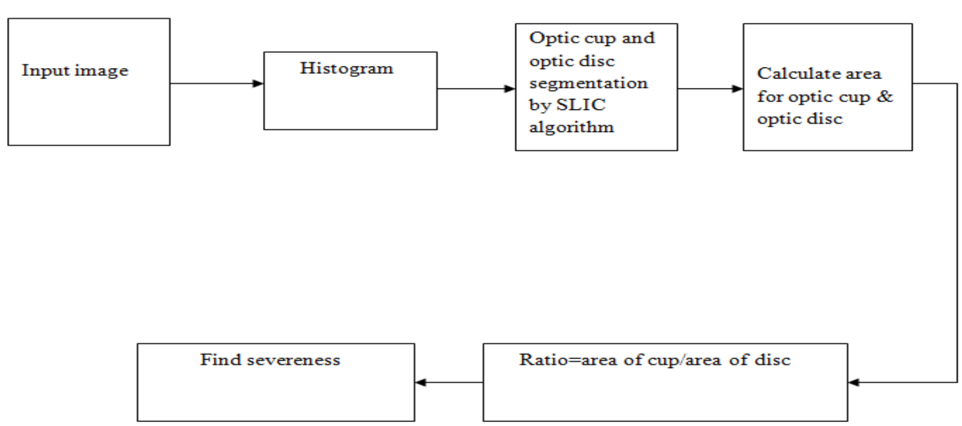

Figure 1 Block Diagram

Swelling in the macular region of retina which is also known asmacular edema, is a complication of the eye often leading to reduced capacity of vision. *Diabetic macular edema* (DME) caused due to diabetes is a high risk complication which can cause irreversible loss of vision. Early detection of even a minor sign of DME is essential as it may also appear without any external symptoms [8]. Once detected during retinal examination, it demands immediate treatment ranging from glycemic and blood pressure control, to laser surgery. DME is generally detected directly or indirectly. Direct ways are using stereoscopy (for manual examination) or optical computed tomography images. Indirect method is by detecting the presence of hard exudates (HE) in the retina. HE are formed due to secretion of plasma from capillaries resulting from the complications of retinal vasculature and could lead to retinal swelling. In color fundus images they appear as yellow–white deposits. Detecting the presence of hard exudates (HE) in different areas of retina is now considered a standard method to assess DME from color fundus images .The severity of the risk of edema is evaluated based on the proximity of HE to the macula, which is defined to be a circular region centered at fovea and with one optic disc (OD) diameter. The risk for DME increases when the HE locations approach the macula, with the risk being the highest when they are within the macula. This is an important factor in DME assessment for further referral of the patients to an expert.

Automatic detection of anatomical structures in retinal images using digital image processing has received considerable attention during the past two decades. We, human beings, have a unique capability to easily find imperfections in spatial structures. This visual mechanism works even when we do not know what the ideal pattern is and what the possible types of defects are. Just by looking at a relatively regular structure containing an imperfection, we can usually tell what is wrong there. When it comes to diagnosis, computer implementation using an algorithm becomes complex and is not 100% reliable. Hence all computers assisted methods of feature detection and diagnosis in retinal images needs a final opinion from an expert.

Unfortunately, most of the algorithms used today for retinal feature localization or detection are computationally intensive and are less accurate, particularly in the presence of a number of pathologies and varying levels of illumination. The proposed algorithm is simple, does not require any prior knowledge of other retinal features and is more efficient for implementation. There is no mathematical complexity involved as in other methods and hence there is a significant improvement in computational time also.

In an automatic screening method for detecting the development of glaucoma using multi- class support vector machine (Multi-class SVM). In this work, the data set is considered as 3 classes; non-glaucoma, glaucoma suspect, and glaucoma cases. Generally, the cup-to-disc ratio (CDRV) in vertical is the main indicator to analyze the development of glaucoma. When the CDRV is increased gradually, it also means that the size of the optic cup becomes larger. The experiment compares three different types of multi-class support vector machine; one is one-vs-the-rest technique, others are SVM with the decision tree. The results show that the performance of SVM together with the decision tree provides a good outcome. However, to obtain more reliable, the false negative rate should be the smallest number [9].There is some limitation of SVM. Normally, SVM achieves only for binary classes.

The other traditional techniques are added in order to increase the performance of SVM. An automatic disease detection system can significantly reduce the load of experts by limiting the referrals to those cases that require immediate attention. The reduction in time and effort will be significant where a majority of patients screened for diseases turn out to be normal. The ratio of normal patients to the ones showing disease symptoms can be as high as 9 to 1 in DR screening. Several attempts have been reported towards building an automated solution for DR detection, Motivated by these attempts, we aim to develop a solution for automatic assessment of DME from color fundus images. Such a solution will be a value addition to the existing infrastructure of DR screening. One strategy for automatic optic nerve head assessment is to use image features for a binary classification between glaucomatous and healthy subjects. These features are normally computed at the image-level. In these methods, selection of features and classification strategy is difficult and challenging.

The other strategy is to follow the clinical indicators. Many glaucoma risk factors are considered, such as the vertical cup to disc ratio (CDR), disc diameter, peripapillary atrophy (PPA), notching, ISNT rule 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. And here in proposed method, focuses on automatic glaucoma screening using CDR from 2D fundus images. Figure 2 shows how the objects are perceived by normal vision and a patient having glaucoma. The most reliable way of glaucoma diagnosis follows the investigation of the retina from the fundus image, which is taken by a special camera called fundus camera. A fundus camera or retinal camera is a specialized low power microscope with an attached camera designed to photograph the interior surface of the eye, including the retina, optic disc, macula, and posterior pole.

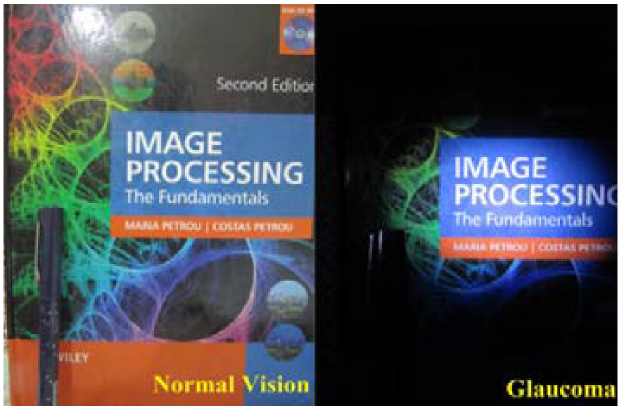

Figure 2 Normal vision vs. patient having glaucoma

The paper is organized as follows. In Section II, we introduce super pixel classification based OD segmentation including the generation of super pixels, the extraction of features from super pixels for the classification and the computation of the self-assessment reliability score. Section III introduces super pixel classification based cup segmentation, where the procedure is similar to that in disc segmentation. And to develop a solution for automatic DME assessment, first a decision module is required to validate the presence or absence of HE in a given color fundus image. Once their presence is confirmed, a second module has to assess the macular region for measuring the risk of exhibiting DME. Therefore, in this work, I propose a two-stage methodology for detection and assessment of DME. The next section provides an overview of the earlier work carried out for detecting the presence of HE followed by an outline of the proposed methodology. Discussions and conclusions are presented in final section.

3. Optic Disc Segmentation

Glaucoma is a term describing a group of ocular disorders with multi-factorial etiology united by a clinically characteristic intraocular pressure-associated optic neuropathy. This can permanently damage vision in the affected eye(s) and lead to blindness if left untreated. It is normally associated with increased fluid pressure in the eye (aqueous humors).The term "ocular hypertension" is used for people with consistently raised intraocular (IOP) without any associated optic nerve damage. Conversely, the term 'normal tension' or 'low tension' glaucoma is used for those with optic nerve damage and associated visual field loss, but normal or low IOP. Glaucoma can be roughly divided into two main categories, "open-angle" and "closed-angle" (or "angle closure") glaucoma. The angle refers to the area between the iris and cornea, through which fluid must flow to escape via the trabecular meshwork. Closed-angle glaucoma can appear suddenly and is often painful; visual loss can progress quickly, but the discomfort often leads patients to seek medical attention before permanent damage occurs. Open-angle, chronic glaucoma tends to progress at a slower rate and patients may not notice they have lost vision until the disease has progressed significantly.

Glaucoma has been called the "silent thief of sight" because the loss of vision often occurs gradually over a long period of time, and symptoms only occur when the disease is quite advanced. Once lost, vision cannot normally be recovered, so treatment is aimed at preventing further loss. Worldwide, glaucoma is the second-leading cause of blindness after cataracts.

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

Localization and segmentation of disc are very important in many computer aided diagnosis systems, including glaucoma screening. The localization focuses on finding an disc pixel very often the centre. Here the work focuses on the segmentation problem. The segmentation estimates the disc boundary, which is a challenging task due to blood vessel occlusions, pathological changes around disc, variable imaging conditions, etc. Here comes a super pixel classification based method and combine it with the deformable model based methods. Super pixels are local, coherent and provide a convenient primitive to compute local image features. They capture redundancy in the

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image and reduce the complexity of subsequent processing. In the proposed method, super pixel classification is used for an initialization of disc boundary and the deformable model is used to fine tune the disc boundary.

a) Super Pixel Generation:

Many algorithms have been proposed for super pixel classification. They have been proved to be useful in image segmentations in various images of scene, animal, human etc. 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. SLIC is also simple to use with only one parameter, i.e., the number of desired super pixels k.

b) Feature extraction:

Many features such as colour, appearance, gist, location and texture can be extracted from super pixels for classification. Since colour is one of the main differences between disc and non-disc region, colour histogram from super pixels is an intuitive choice. Motivated by the large contrast variation between images and the use of histogram equalization in biological neural networks, histogram equalization is applied to red r, green g, and blue b channels from RGB colour spaces individually to enhance the contrast. However, histogram equalization on r, g may yield dramatic changes in the image's colour balance.

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

Since the texture feature from the PPA region is often involved in a large region, the features from neighboring super pixels are also considered in the classification of the current super pixel. The search for four neighboring super pixels for SPj and denote them as $SPj1$, $SPj2$, $SPj3$ and $SPj4$. $SPj1$ is determined as the first super pixel by moving out of the current super pixel horizontally to the left from its centre. Similarly, $SPj2$, $SPj3$ and $SPj4$ are determined by moving right, up and down, as shown in the figure 3

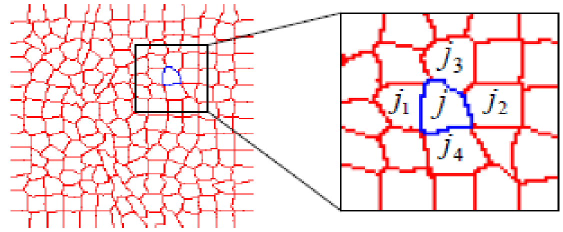

Figure 3 Illustration of neighboring super pixels

4. Optic Cup Segmentation

Detecting the cup boundary from 2D fundus images without depth information is a challenging task as depth is the primary indicator for the cup boundary. In 2D fundus images, one landmark to determine the cup region is the pallor, defined as the area of maximum colour contrast inside the disc. Another landmark is the vessel bends at the boundary of the cup. The main challenge in cup segmentation is to determine the cup boundary when the pallor is non-obvious or weak. In such scenarios, the lack landmarks, like intensity changes or edges to estimate the cup boundary reliably. Although vessel bends are potential landmarks, they can occur at many places within the disc region and only one sub-set of these points defines the cup boundary. Besides the challenges to obtain these points, it is also difficult to differentiate the vessel bends that mark the cup boundary from other vessel bends without obvious pallor information. Moreover, combining the vessel bends with pallor information is a challenging task that often requires a set of heuristic parameters, which raises the concern of the robustness of the method. So introducing a super pixel classification based method for cup segmentation that incorporates prior knowledge into the training of super pixel classification instead of relying on vessel bends and 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 cup segmentation. The histogram feature is computed similarly to that for disc segmentation, except that the histogram from the red channel is no longer used. This is because there is little information about the cup in the red channel.

b) Super pixel Classification for Optic Cup Estimation**:**

Randomly obtain the same number of super pixels from the cup and non-cup regions in the training step from a set of training images with manual cup boundary. The output value for each super pixel is used as the decision values for all pixels in the super pixel. 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 is computed as the cup boundary. The ellipse fitting here is beneficial for overcoming the noise introduced by vessels especially from the inferior and superior sector of the cup.

c) Cup to Disc Ratio:

In glaucoma affected eyes, the increase in blind area increases the cup size when disc size assumed to be constant. The cup to disc ratio increases in patients with glaucoma due to the enlargement of cup. Then follows the clinical convention to compute the CDR.CDR is an important indicator for glaucoma screening and is computed as

$$\text{Cup to Disc ratio } = \frac{Diameterof\ cup}{Diameter\ of\ disc} \tag{1}$$

Glaucoma breaks the nerves in the disk region, so that the area of optic cup increases. In order to find out the cup to disc ratio, first we extract the images of cup and disc separately. Then the vertical diameter of the two images is calculated and ratio is taken and also the obtained value is compared with the normal value. The cup to disc ratio of the person who got glaucoma will be higher than the normal value, and correspondingly Matlab will give the indication.

5. Preprocessing for Macula Detection

The *macula lutea* or macula is a yellow spot near the center of the retina, with a diameter of about 1.5 mm and is often defined as having two or more layers of ganglion cells. In retinal fundus images, the macula appears as a dark region nearby the centre of the image. Near the centre of the macula is the fovea, a tiny area responsible for our central, sharpest vision. Unlike the peripheral retina, it has no blood vessels; instead, it has a very high concentration of cones, allowing for the appreciation of colour. It is the darkest part in most fundus images; in some images it is not obvious to human eyes due to bright lighting or being covered by lesions. One important issue in fundus images is that retina is not a plane surface and therefore light does not have a uniform distribution, producing images with non-uniform illumination and consequently with different contrast areas. Vignetting is often an unintended and undesired effect caused by camera settings or lens limitations. The goal of illumination correction is to remove uneven illumination of the image caused by sensor defaults (vignetting), non uniform illumination of the scene, or orientation of the surface. Retinal image preprocessing consists of correction of non-uniform luminosity, color normalization and contrast enhancement. In this work we use a method of luminosity correction that is based on segmentation of background pixels and subsequent computation of luminosity function based only on the background image.

6. Bitplane Decomposition

The grey level of each pixel in a digital image is stored as one or more bytes in the computer. When the grey level is represented as a single byte, it is called an 8 bit image, representing grey level values in the range 0 to 255. Decomposing a digital image into its bit planes is useful for analyzing the relative importance played by each bit of the image. Instead of highlighting gray level images, highlighting the contribution made to total image appearance by specific bits is examined here. In a representative 8 bit gray level image, each pixel in an image is represented by 8 bits. The image is composed of 8, 1-bit planes ranging from bit plane 0 (LSB) to bit plane 7 (MSB). In terms of 8-bits, plane 0 contains all the lowest order bits in the bytes comprising the pixels in the image and plane 7 contains all the higher order bits. Thus bit plane decomposition of an 8 bit image yields eight binary images.

Binary images are best suited for performing morphological operations. The images obtained after bit plane decomposition are binary images, which are thus suitable for performing morphological operations. Dilation is an operation in which the binary image is expanded from its original shape. The degree of expansion is controlled by the structuring element. The dilation process is similar to convolution, in which the structuring element is reflected and shifted from left to right and then from top to bottom. In this process, any overlapping pixels under the centre position of the structuring element are assigned with 1 or black values. If X is the reference image and B is the structuring element, the dilation of X by B is represented as

$$X \oplus B = Z\ B\ z \cap X \subseteq X$$

where B is the image B rotated about the origin. When an image X is dilated by a structuring element B, the outcome element Z would be that there will be at least one element in B that intersects with an element in X. Erosion operator is a thinning operator that shrinks an image. The amount by which the shrinking takes place is determined by the structuring element. Here, if there is a complete overlapping with the structuring element, the pixel is set white or 0. The erosion of X by B is given as

$$X \ominus B = Z\ B\ z \subseteq X$$

In erosion, the outcome element Z is considered only when the structuring element is a subset or equal to the binary image X. Opening is done by first performing erosion, followed by dilation. Opening smoothens the inside of object contours, breaks narrow strips and eliminate thin portions of the image. It is mathematically represented as

$$X \circ B = (X \ominus B) \oplus B$$

Closing operation does the opposite of opening. It is dilation followed by erosion. Closing fills small gaps and holes in a single pixel object. The closing process is represented by

$$X \bullet B = (X \oplus B) \ominus B$$

Closing operation protects coarse structures, closes small gaps and rounds off concave corners.

7. The Methodology

The RGB image obtained from the fundus camera after pre-processing is separated in to its component images. Red, Green and Blue channels. On separating the RGB image in to its components, the green channel is found to exhibit a better contrast level. So only the green channel is selected for further processing. The contrast of the green channel is further increased by adding the image to the top-hat filtered image, and then subtracting the bottom hat filtered image from the same. This contrast enhanced image of the green channel is shown in Figure 4. This image is then converted in to a gray scale image and its histogram is computed. Later on, histogram equalization is performed on this image.

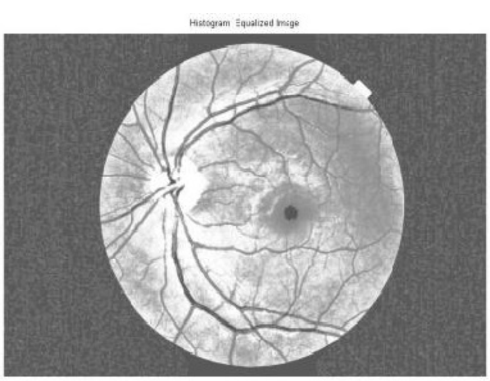

Figure 4 Histogram Equalized image

Now bit plane slicing is done on the image to decompose it into its bit planes. The lower order bit planes are preserved for further processing and the higher order ones are discarded. Bit plane 0 is now opened by a suitable disc shaped structuring element to obtain a clear dark region corresponding to the macula. This image is then complemented to take advantage of a white region corresponding to the macular region. Again an opening operation is performed with a disk shaped structuring element to obtain an image. A suitably processed bit plane 1 can be used to compensate for errors, if any, in the previous operation. The most severe errors in this stage are found to occur at the crossing of main blood vessels in the retina in certain images.

8. Results and Discussions

I have presented super pixel classification based methods for disc and cup segmentations for glaucoma screening and an approach to the rapid detection and extraction of macula from the images of human retina. It has been demonstrated that CSS is beneficial for both disc and cup segmentation. In disc segmentation, HIST and CSS complement each other. CSS responds to blobs and provides better differentiation between PPA and discs compared with histograms. Histograms with the contrast enhancement overcome the limitation of CSS due to contrast variations. Reliability score is an important indicator of the automated results. From our experience, disc segmentations with $r \geq 0.85$ is likely to indicate good cases. For lower ones, it is likely that the results are inaccurate, even though the deformation in the last step might still find a good result in some situations. It is important to have a good disc segmentation because the CDR computed from a wrong disc is not very meaningful for doctors. In cup segmentation, the benefit of CSS is even larger than that in disc segmentation, because the colour change from cup to neuroretinal rim is much smaller. Therefore, the uneven illumination becomes a large noise affecting the cup segmentation. The CSS computed from the centre surround difference is less sensitive. and thereby improves the result. It is important to point out that the proposed superpixel classification is used as an initialization for deformable models.

Macula segmentation is of paramount importance in developing automated diagnosis expert system for DR. Any impairment in the macula can immediately affect vision. Macula segmentation is a key step in almost all algorithms used to identify fundus features automatically. Furthermore macula detection is important for automatic diagnosis of other ophthalmic pathologies also. Given the fixed position relationship between optic disc (OD) and macular center, OD position can be used as a reference to locate macular area. Most of the algorithms available

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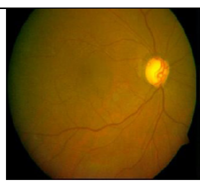
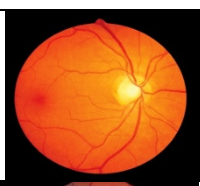
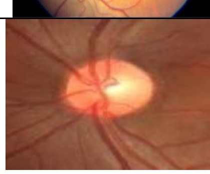
today depends on this feature and thus requires a prior knowledge and segmentation of OD. Due to similar color tone to some other lesions and abnormalities such as hemorrhages, accurate macula identification can be valuable to reduce the false positive rate of algorithms designed to detect those lesions. Unfortunately most of the algorithms used today for macula localization or detection are computationally intensive, requires prior information on OD and retinal vasculature, and are less accurate, particularly in the presence of pathologies in the human retina. There are large influences of human errors and subjectivity on the results of inspection by a human expert also. Presence of other factors such as noise, non-uniform illumination and variety of defect types in retinal imagery make the detection of features and pathologies in fundus images a challenging problem.

The main attraction of the proposed method is its simplicity, accuracy and saving in computational time. Moreover this algorithm does not require a prior knowledge of other retinal features for the detection of macula. This algorithm demonstrates its strong ability to differentiate macula from other regions in the image. The method works pretty well even when the input image is a low-contrast one. The experimental results demonstrate that the proposed

algorithm is fast and robust. Results for some eye images are given in the table 1.

Table 1:Shows severeness of glaucoma and macula condition

Images	Cup ratio	Disc ratio	CDR	Severeness	Macula condition
	428	1166	.36707	Abnormal	Normal
	960	12169	.078889	Moderate risk	Normal
	98	3054	.032089	normal	Abnormal retina, severe risk
	293	25096	.011675	normal	Abnormal retina, moderate risk
	320	8833	.039228	normal	normal

9. Conclusion

Optic cup and disc segmentation based on super pixel classification and a novel macula localization and extraction algorithm is proposed in this paper. The algorithm is superior to the existing algorithms in terms of computational time and accuracy.

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