Cup Segmentation by Gradient Method for the Assessment of Glaucoma from Retinal Image

Rupesh Ingle[#1], Pradeep Mishra[#2]

[#] *Authors are M. Tech. Students in Electrical Department, Veermaata Jijabai Technological Institute(VJTI)*

Mumbai University, Mumbai, India

Abstract— **Automatic analysis of retinal images is emerging as an important tool for early detection of eye diseases. Glaucoma is one of the main causes of blindness in recent times. Deformation of Optic Disk (OD) and the Cup (inside the Optic Disk) is important parameter for glaucoma detection. The detection of OD manually by experts is a standard procedure for this. There have been efforts for OD segmentation but very few methods for the cup segmentation. Finding the cup region helps in finding the cup-to-disk (CDR) which is also an important property for identifying the disease. In this paper, we present an automatic cup region segmentation method based on gradient method. The method has been evaluated on dataset of images taken from random images from different sources. The segmentation results obtained shows consistency on handling photometric and geometric variations found across the dataset. Overall, the obtained result show effectiveness in segmentation of the cup in the process of glaucoma assessment.**

Keywords— **Cup, glaucoma, gradient, optic disk(OD), retinal images.**

I. INTRODUCTION

Glaucoma is one of the common cause of blindness with about 79 million people in the world is likely to be affected by glaucoma by the year 2020 [1]. It is a complicated disease in which damage to the optic nerve leads to progressive, irreversible vision loss. It is symptomless in the early stages and since the loss cannot be restored its early detection and treatment is essential to prevent damage to the vision [2].

The OD is the location in the eye where ganglion cell axon exits the eye to form optic nerve and it represent the beginning of the optic nerve. The optic nerve head carries from 1 to 1.2 million neurons which carries visual information from eye towards the brain. The OD can be divided into two zones namely the cup and the neuroretinal rim. Cup is the central bright zone and peripheral region is called the neuroretinal rim. This structure is shown in figure 1. The loss in optic nerve fibres results in the cup region enlargement and thinning of neuroretinal rim called cupping. Cupping is the hallmark of glaucoma which is the visible manifestation of optic nerve head structure.

The OD can be imaged two-dimensionally either through indirect stereo biomicroscopy or with stereo colour fundus photography. The ratio of optic disc cup and neuroretinal rim
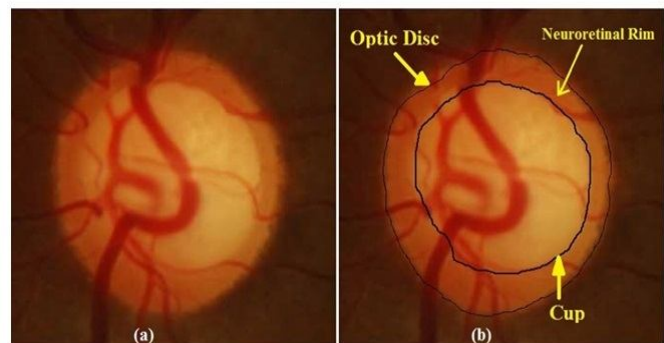

Fig. 1. (a) Original retinal image. (b) Optic Disc and Cup boundary.

surface area in these images, called Cup-to-disc (CDR). It is an important structural indicator for accessing the presence and progression of glaucoma. Various parameters are estimated and recorded to detect the glaucoma stage which include cup and OD diameter, area of OD and rim area etc. Efforts have been made to automatically detect glaucoma from 3-D images [3], [4], but high cost makes them not appropriate for large scale screening.

Colour fundus imaging (CFI) is one of the method that is used for glaucoma assessment. It has emerged as a preferred method for large-scale retinal disease screening [5] and is established for screening of large-scale diabetic retinopathy. The work published on automated detection can be divided in three main strategies: A) without disk parameterization. In this a set of features are computed from CFI and two-class classification is employed to find a image as normal or glaucomatous [6]-[9], [14]. These features are computed without performing OD and cup segmentation. B) with disk parameterisation with monocular CFI, and C) with disk parameterization using stereo CFI [10]-[12]. In these strategies which are based on disk parameterisation, OD and cup regions are segmented to estimate disk parameters. A stereo CFI gives better characterisation (by giving partial depth information inside the OD such as cup, neuroretinal rim) compared to monocular CFI.

There have been few attempts for OD and cup segmentation from monocular images for structure segmentation and glaucoma detection [13], [15]. The methods proposed above are based on the condition of taking monocular images from same source and under a fixed protocol. Mostly images are taken centred on the OD. Our work is aimed at developing a pre-screening method to assist in glaucoma detection for large-scale screening programs on

the retinal images taken without any fixed protocol and from different sources. Method based on radial gradient is applied for the cup segmentation used for glaucoma assessment. This paper presents the partial work for glaucoma assessment by cup-to-optic disk area ratio by detection the cup region using gradient method.

II. GRADIENT IN IMAGES

A. Background

An image gradient is a directional change in the intensity or colour in an image. Image gradients may be used to extract information from images. In graphics software for digital image editing, the term gradient or colour gradient is used for a gradual blend of colour which can be considered as an even gradation from low to high values, as used from white to black in the images to the right. Gradient images are created from the original image (generally by convolving with a filter) for this purpose. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction. To get the full range of direction, gradient images in the x and y directions are computed.

Different lighting or camera properties can cause two images of the same scene to have drastically different pixel values. This can cause matching algorithms to fail to match very similar or identical features. One way to solve this is to compute texture or feature signatures based on gradient images computed from the original images. These gradients are less susceptible to lighting and camera changes, so matching errors are reduced.
The gradient of the image is given by the formula:

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial y}\hat{y}$$

A colour gradient (sometimes called a colour ramp or colour progression) specifies a range of position dependent colours. The gradient of a scalar field is a vector field that points in the direction of the greatest rate of increase of the scalar field, and whose magnitude is the rate of increase. In simple terms, the variation in space of any quantity can be represented (e.g. graphically) by a slope. The gradient represents the steepness and direction of that slope. The steepness of the slope at that point is given by the magnitude of the gradient vector.

The gradient (or gradient vector field) of a scalar function $f(x_1, x_2, x_3, ..., x_n)$ is denoted ∇f or where ∇ (the nabla symbol) denotes the vector differential operator, del. The notation "grad(f)" is also commonly used for the gradient. The gradient of f is defined as the unique vector field whose dot product with any vector $\mathbf{v}$ at each point x is the directional derivative of f along $\mathbf{v}$.
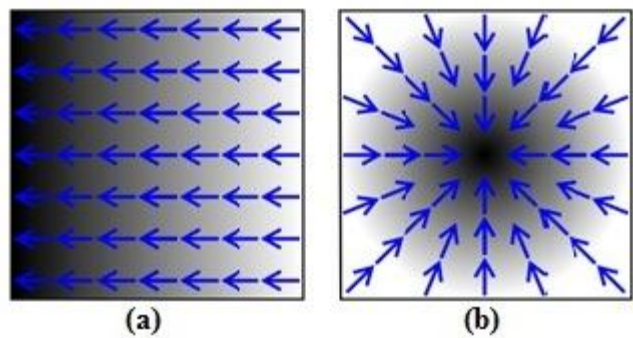

Fig. 2. (a) Linear gradient. (b). Radial gradient.

That is,

$$(\nabla f(x))\square v = D_v f(x)$$

Gradient can be found in two ways (a).Linear gradient and (b). Radial gradient. Linear colour gradient is specified by two points, and a colour at each point. The colours along the line through those points are calculated using linear interpolation, then extended perpendicular to that line. In digital imaging systems, colours are typically interpolated in an RGB colour space, often using gamma-compressed RGB colour values, as opposed to linear. On the other hand a radial gradient is specified as a circle that has one colour at the edge and another at the centre. Colours are calculated by linear interpolation based on distance from the center. Fig.2 shows linear and radial gradient.In our method as our area of interest is circular like region so we have used radial gradient to extract the region from the images.

B. Cup Segmentation

Deformation of OD and the Cup is important parameter for glaucoma detection. The cup region is not necessarily being circular, its shape varies in the eye and with glaucoma. The CDR is an important method in glaucoma detection, where the area of cup to disk is found. This causes a need to find the cup region. In proposed method the approximate cup region has been found from data set. The data set is random and obtained from different sources. The region of interest varies widely in images by images. In some images the region of interest is small and large in others. So the first thing needed to bring them in some fixed size so as to apply same code to all of them. But still size of OD in images differs even if images are brought in same size. The gradient will give change in the colour intensity in the targeted region with the neighbouring area. But this property is also observed to vary in RGB colour channels of these images. It needed to find a threshold that will work on different images and give satisfactory region. So after lot of iterations threshold are set which performed consistently well on our dataset.Having compared R, G and B colour channels, we found the cup region appears continuous (except major blood vessels). Blood vessels in images results in the discontinuity of the cup region obtained from images. For further processing we took
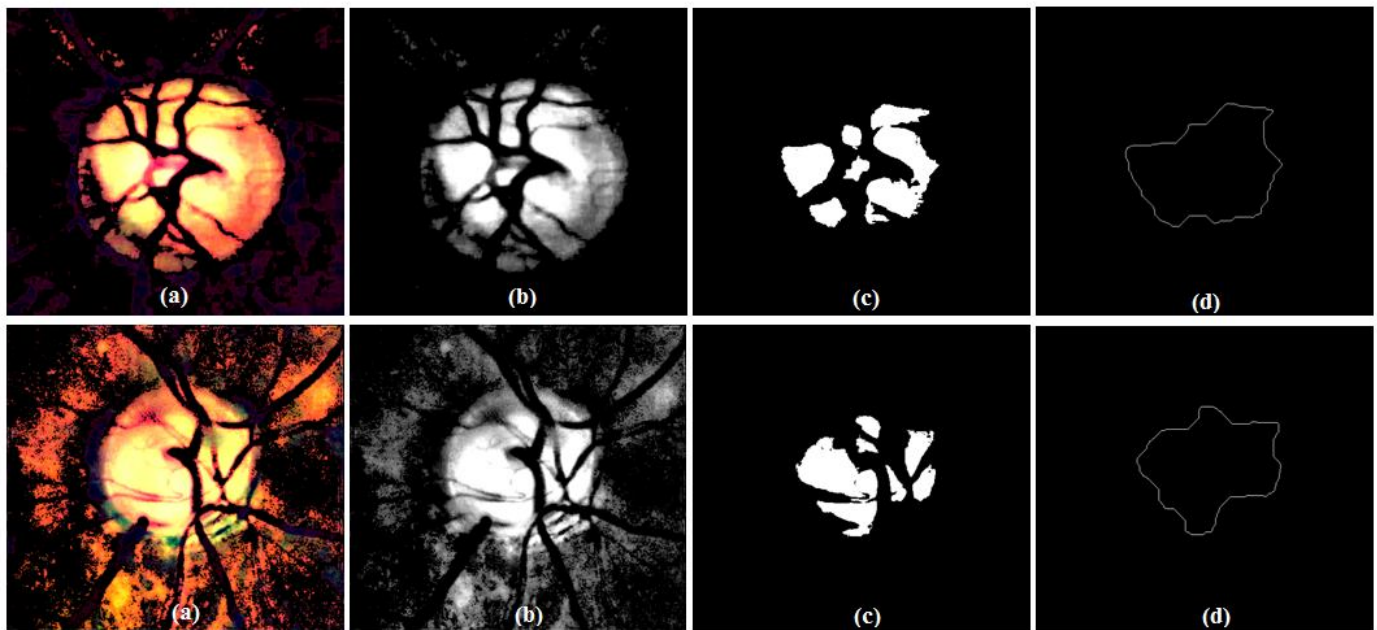
Fig.3. (a) Image after RGB thresholding, (b) G colour channel image after RGB thresholding, (c) Region obtained with gaps due to blood vessels and (d) Perimeter of region derived from (c).

G colour channel which gives better region segmentation. These openings of blood vessels are then filled with circular structural elements to get continuous region.

III. CUP DETECTION

Glaucoma assessment is based on the CDR where diameter measured in the vertical direction. One another parameter is the cup and disk areas. The area ratio is selected to access the overall accuracy obtained in all directions unlike the CDR which accuracy in one direction only. Both CDR and area ratios can be computed by finding areas of OD and Cup region which is obtained by their segmentation. The OD segmentation is a part of our future work, our paper present here the crucial cup region segmentation. The method was tested on dataset of different random sources with large variations in size of images and features. The images are brought to some fixed dimension for applying the same strategy to all of them.

The contrast of all images are improved for R, G and B channels by transforming the values using contrast limited adaptive histogram equalization (CLAHE)[16]. CLAHE operates on small regions in the image called tiles, rather than entire image. Each tiles contrast is enhanced so that the histogram of the output region approximately matches the histogram specified by the flat histogram parameter. The neighbouring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast especially in homogenous areas, are limited to avoid amplifying any noise that might be present in the image.

After a lot of then iterations initial threshold is set for R, G and B channels of images to extract only those regions whose R channel pixel values less than 60 and G+B pixel values greater than 100. Other pixels are neglected by equating making their values zero. The images then observed to be giving more detail of interested region and neglecting outer areas. Then the radial gradient is found in images in all 8 directions by doing convolution 2 times with [-1 0 0; -1 8 -1; -1 0 0] in x-direction and with [1 0 0; -1 8 -1; 1 0 0] in y-direction. Magnitude of the intensities are calculated and then, we linearly transformed intensities values to the range of [0-1] and extract pixels using a threshold to select pixels only with value greater than 0.4. We get the numbers of disconnected elements of the images with gaps due the interruption of large blood vessels. The elements of 2D images are labelled with pixels labelled as 0 are background. The pixels labelled 1 make up one object; the pixels labelled 2 make up a second object, and so on. The objects falling in cup regions are large in size as compared to the objects falling outside the cup region which may appear in some images due to diversity in the contrast of the different images. This possibility is eliminated by selecting a threshold length of 800 of the objects. These gives region falling inside the OD and on the cup area is as shown in fig 3(c). The gaps and holes in the objects are then filled by using structuring element, a circular disk of radius 30. Consequently, as seen in fig 3(d) a perimeter or region is derived which is then superimposed on the original image to indicate the cup boundary.

IV. RESULTS

This method was tested on dataset of retinal images including normal and the images with glaucoma from different sources. The images are observed in all 3 RGB channels. After lot of iterations it was observed that the G and
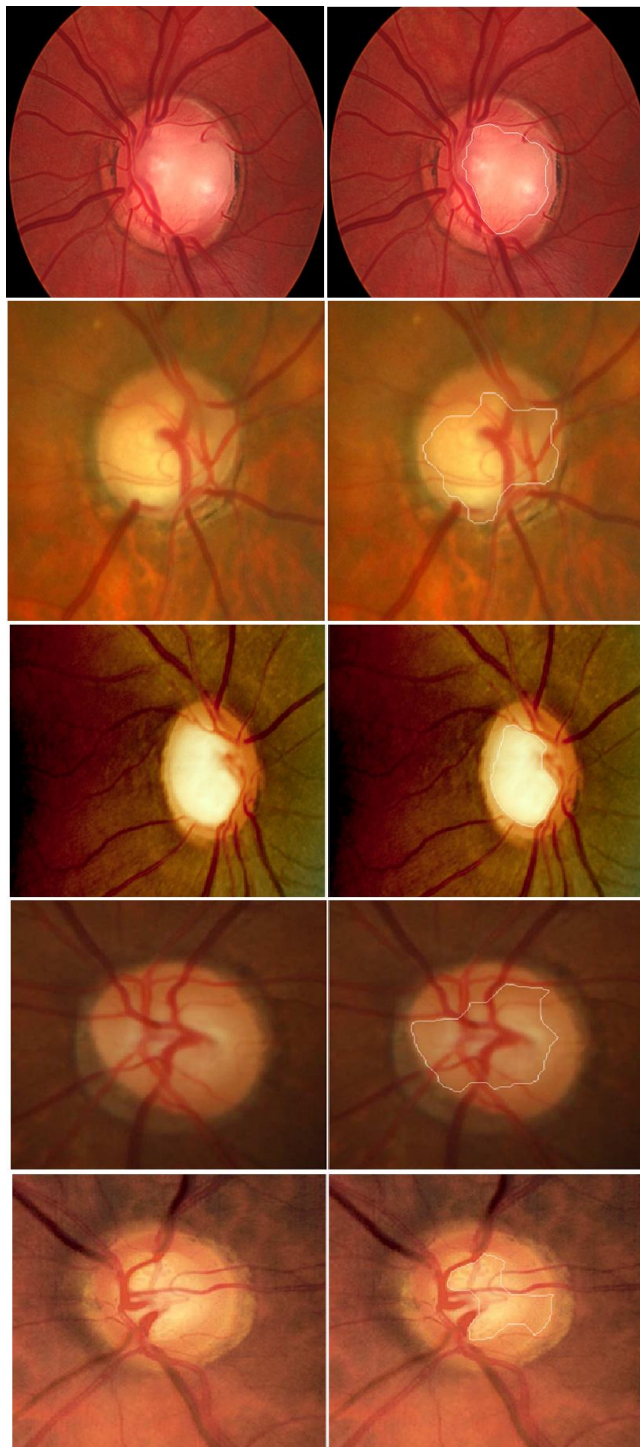
Fig. 4. Source images with their Gradient estimated Glaucoma region.

B channels were more informative about the cup region. The coordinates have been set a threshold of less than 60 (for R channel), and greater than 100(for G+B channel). Other pixels are equated to zero making them background. The average gradient has been in all directions by convolving with [-1 0 0;-1 8 -1;-1 0 0] in x direction and with [1 0 0;-1 8 -1; 1 0 0] in y direction. The fig 4 shows the images with the figure of detected cup region using gradient method. As CDR and the area ratios are important indicator used for glaucoma detection, this method was kept in mind so in the first stage we found the cup region. In general, the cup deformation is not uniform so various iterations has been carried out for its estimation. The OD region can

be found by same method which will be used to get relative ratios for detection of glaucoma.

V. Conclusion and Future Scope

This work on detection of cup region was applied on the image dataset and the region was detected with fair accuracy. An essential piece of writing of this paper is that considering the radial gradient method and its implementation discussions

has the best chance of finally leading to a prototype formation for glaucoma detection. Extension of this work will be in finding the OD region for detection of glaucoma. As a future work, the method can be extended to help in differentiating the glaucomatous images from different retinal images. And this can be further extended for early detection of the glaucoma disease.

References

[1] World health organization programme for the prevention of blindness and deafness - global initiative for the elimination of avoidable blindness World health organization, Geneva, Switzerland, WHO/PBL/97.61 Rev.1, 1997.

[2] G. Michelson, S. Wrntges, J. Hornegger, and B. Lausen, "The papilla as screening parameter for early diagnosis of glaucoma," Deutsches Aerzteblatt Int., vol. 105, pp. 34–35, 2008.

[3] P. L. Rosin, D. Marshall, and J. E. Morgan, "Multimodal retinal imaging: New strategies for the detection of glaucoma," in Proc. ICIP, 2002.

[4] M.-L. Huang, H.-Y. Chen, and J.-J. Huang, "Glaucoma detection using adaptive neuro-fuzzy inference system," Expert Syst. Appl., vol. 32, no. 2, pp. 458–468, 2007.

[5] D. E. Singer, D. Nathan, H. A. Fogel, and A. P. Schachat, "Screening for diabetic retinopathy," Ann. Internal Med., vol. 116, pp. 660–671,1992.

[6] J. Meier, R. Bock, G. Michelson, L. G. Nyl, and J. Hornegger, "Effects of preprocessing eye fundus images on appearance based glaucoma classification," in Proc. CAIP, 2007, pp. 165–172.

[7] R. Bock, J. Meier, G. Michelson, L. G. Nyl, and J. Hornegger, "Classifying glaucoma with image-based features from fundus photographs," in Proc. DAGM, 2007, pp. 355–364.

[8] L. G. Nyl, "Retinal image analysis for automated glaucoma risk evaluation," SPIE: Med. Imag., vol. 7497, pp. 74971C1–9, 2009.

[9] J. Yu, S. S. R. Abidi, P. H. Artes, and A. Mcintyre, "Automated optic nerve analysis for diagnostic support in glaucoma," in Proc. IEEE Symp. Computer-Based Med. Syst., 2005, pp. 97–102.

[10] C. Muramatsu, T. Nakagawa, A. Sawada, Y. Hatanaka, T. Hara, T. Yamamoto, and H. Fujita, "Determination of cup and disc ratio of optical nerve head for diagnosis of glaucoma on stereo retinal fundus image pairs," in Proc. SPIE. Med. Imag., 2009, pp. 72 603L–2.

[11] J. Xu, O. Chutatape, E. Sung, C. Zheng, and P. Chew, "Optic disk feature extraction via modified deformable model technique for glaucoma analysis," Pattern Recognit., vol. 40, no. 7, pp. 2063–2076, 2007.

[12] A. Guesalag, P. Irarrzabal, M. Guarini, and R. lvarez, Measurement of the glaucomatous cup using sequentially acquired stereoscopic images," Measurement, vol. 34, no. 3, pp. 207–213, 2003.

[13] J. Liu, D. Wong, J. Lim, H. Li, N. Tan, and T. Wong, "Argali—An automatic cup-to-disc ratio measurement system for glaucoma detection and analysis framework," in Proc. SPIE Med. Imag., 2009, pp. 72 603K–8.

[14] R. Bock, J. Meier, L. G. Nyl, and G. Michelson, "Glaucoma risk index: Automated glaucoma detection from color fundus images," Med. Image Anal., vol. 14, no. 3, pp. 471–481, 2010.

[15] D. Wong, J. Liu, J. H. Lim, H. Li, X. Jia, F. Yin, and T. Wong, "Automated detection of kinks from blood vessels for optic cup segmentation in retinal images," in Proc. SPIE Med. Imag., 2009, p. 72601J.

[16] Zuiderveld, Karel. "Contrast Limited Adaptive Histogram Equalization." Graphic Gems IV. San Diego: Academic Press Professional, 1994. 494-485.