

Hybrid Method for Retinal Image Segmentation and Identifying True Vessels

A. Prabin¹, J. Veerappan², M. C. John Wiselin³, S. Binu Sathiya⁴ and Parvathy R. Nair⁵

¹Assistant Professor, Immanuel Arasar JJ College of Engineering, Nattalam, Tamil Nadu, India

²Professor, Sethu Institute of Technology, Virudhunagar, Tamil Nadu, India

³Professor, Travancore Engineering College, Oyoor, Kerala, India

⁴Assistant Professor, NI University, Thuckalay, Tamil Nadu, India

⁵Cape Institute of Technology, Levinchipuram, Tamil Nadu, India

E-mail: wiselin16@yahoo.com

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Abstract - As digital imaging and computing power increasingly develop, so too does the potential to use these technologies in ophthalmology. Image processing, analysis and computer vision techniques are increasing in prominence in all fields of medical science, and are especially pertinent to modern ophthalmology, as it is heavily dependent on visually oriented signs. We describe a novel technique that utilizes the global information of the segmented vascular structure to correctly identify true vessels in a retinal image. The model segmented vascular structure as a vessel segment graph and transform the problem of identifying true vessels to that of finding an optimal forest in the graph. An objective function to score forests is designed based on directional information. Our proposed solution employs candidate generation and expert knowledge to prune the search space. Each vessel is tracked individually by repeatedly finding the next vessel point with a scoring function that considers the pixel intensity and orientation in the vicinity of the current point in the image. Bifurcations and crossovers are detected using some intensity profile. Tracking for the same vessel then continues along the most likely path. The importance of our proposed work disambiguate between vessels at bifurcations and crossovers, we need to figure out if linking a vessel segment to one vessel will lead to an adjacent vessel being wrongly identified .

Keywords: Principal Component Analysis, Watershed Transformation, Optic Disc segmentation, Region discrimination, Circular approximation

I. INTRODUCTION

DIABETIC retinopathy, hypertension, glaucoma, and macular degeneration are now-a-days some of the most common causes of visual impairment and blindness. Early diagnosis and appropriate referral for treatment of these diseases can prevent visual loss. Usually, more than 80% of global visual impairment is avoidable and in the case of diabetes by up to 98%. All of these diseases can be detected through a direct and regular ophthalmologic examination of the risk population. However, population growth, aging, physical inactivity and rising levels of obesity are contributing factors to increase of them, which causes the number of ophthalmologists needed for evaluation by direct examination is a limiting factor. So, a system for automatic recognition of the characteristic patterns of these pathological cases would provide a great benefit.

Regarding this aspect, optic disc (OD) segmentation is a key process in many algorithms designed for the lesions, and the identification of other fundus features. Change in the shape, color or depth of the OD is an indicator of various ophthalmic pathologies, especially glaucoma. Although the OD has well defined features and characteristics, localizing the OD automatically and in a robust manner is not a straightforward process, since the appearance of the OD may vary significantly due to retinal diseases and the size varies from one person to another. Detection is critical due to the geometric relationship that exists between the vasculature and the position of the OD in the retina. Locating the OD

is quite important for many reasons, since it may be easily confounded with large exudative lesions by image analysis techniques.

OD detection remains a problematic task due to the discontinuities along the boundary where blood vessels cross, dramatic hue changes within the OD boundary, with the most extreme being the intra-disc hemorrhage. OD segmentation is difficult since some parts of the disc boundary are not well defined and some parts are partly obscured by the blood vessels in the retinal image, which makes the disc shape more complicated. General purpose algorithms often fail to segment the OD due to fuzzy boundaries, inconsistent image contrast or missing edge features. Disc boundary detection should therefore be aimed to correctly segment the OD by detecting the boundary between the retina and the nerve head.



Fig. 1 A fundus photograph showing the macula as a spot to the left

The macula or macula lutea (from Latin macula, “spot” + lutea, “yellow”) is an oval-shaped highly pigmented yellow spot near the center of the retina of the human eye. It has a diameter of around 6 mm and is often histologically defined as having two or more layers of ganglion cells. Near its center is the fovea, a small pit that contains the largest concentration of cone cells in the eye and is responsible for central, high resolution vision. The macula also contains the para fovea and peri fovea. Because the macula is yellow in colour it absorbs excess blue and ultraviolet light that enter the eye, and acts as a natural sun block (analogous to sunglasses) for this area of the retina. The optic disc is the area on the right where blood vessels converge. The grey, more diffuse spot in the centre is a shadow artefact.

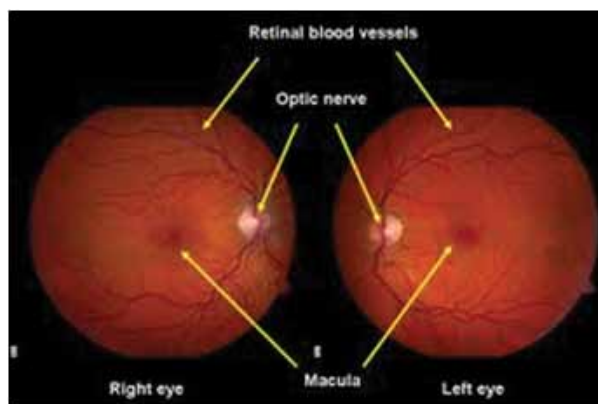


Fig. 2 Fundus Photography

Fundus photography is performed by a fundus camera, which basically consists of a specialized low power microscope with an attached camera. A fundus camera provides an upright, magnified view of the fundus. A typical camera views 30 to 50° of retinal area, with a magnification of 2.5x, and allows some modification of this relationship through zoom or auxiliary lenses from 15°, which provides 5x magnification, to 140° with a wide angle lens, which minifies the image by half. The OD location helps to avoid false positives in the detection of exudates associated with diabetic retinopathy, since both of them are spots with similar intensity. The OD margin can be used for establishing standard and concentric areas in which retinal vessel diameter measurements are performed by calculating some important diagnostic indexes for hypertensive retinopathy, such as central retinal artery equivalent (CRAE) and central retinal vein equivalent (CRVE). Moreover, the center, or even the border, of the OD also serves as initial point for vessel tracking algorithms due to the fact that all retinal vessels are originated from there.

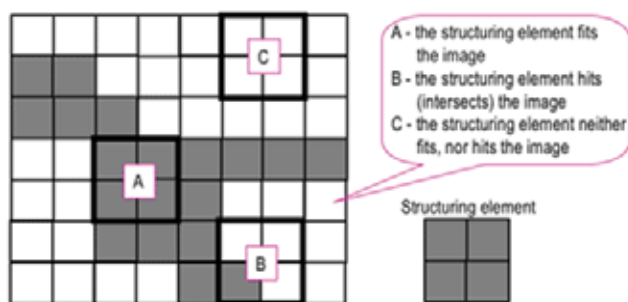


Fig.3 Probing of an image with a structuring element (white and grey pixels have zero and non-zero values, respectively).

Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element “fits” within the neighbourhood, while others test whether it “hits” or intersects the neighbourhood. A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image. The structuring element is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one. The matrix dimensions specify the size of the structuring element. The pattern of ones and zeros specifies the shape of the structuring element. An origin of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element. Morphological operators often take a binary image and a structuring element as input and combine them using a set operator (intersection, union, inclusion, complement). They process objects in the input image based on characteristics of its shape, which are encoded in the structuring element. The mathematical details are explained in Mathematical Morphology.

II. RELATED WORK

A KNN regressor is utilized to predict the distance in pixels in the image to the object of interest at any given location in the image based on a set of features measured at that location. The method combines cues measured directly in the image with cues derived from a segmentation of the retinal vasculature. The location of the fovea is estimated as the point of lowest matched filter response within a search area determined by the optic disc location. Second, optic disc segmentation is performed. Based on the detected optic disc location, a fast hybrid level-set algorithm which combines the region information and edge gradient to drive the curve evolution is used to segment the optic disc boundary.

The optic disc location algorithm is designed based on the characteristics of the different channels in digital colour fundus images. The method is used to detect the optic disc contour based on mathematical morphology along with principal component analysis. In the past KNN regressor is used mainly focused on locating the optic disc center. Principal component analysis is applied on the RGB

fundus image in order to obtain a gray image in which the different structures of the retina such as vessels and OD are differentiated more clearly to get an accurate detection of the OD. Next a variant of the watershed transformation, the stochastic transformation, followed to a stratified transformation are implemented on a region of the original image. The algorithm is fully automatic, so the process is speeded up and also the user intervention is avoided. The goal of this proposed method is to make easier the early detection of diseases related to the fundus and reduce the consultation time. Stochastic Watershed Transformation is used here. It is a segmentation technique for gray-scale images.

This algorithm is a powerful segmentation tool whenever the minima of the image represent the objects of interest and the maxima are the separation boundaries between objects. Due to this the input image of this method is usually a gradient image. The watershed transformation produces a segmentation which can be viewed as a set of closed contours of segmented regions. This transformation uses random markers to build a probability density function of contours, which is then segmented by volumic watershed for defining the most significant regions.

III. PRELIMINARIES

The first step of the pre processing stage consists of PCA to transform the input image to grey scale. This technique combines the most significant information of the three components RGB in a single image so that it is a more appropriate input to the segmentation method. Principal Component Analysis (PCA). The central idea of PCA is to reduce the dimensionality of a data set consisting of a number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the principal components (PCs), which are uncorrelated, and ordered. This technique maximizes the separation of the different objects that compose an image so that the structures of the retina are better appreciated. Inpainting technique is the next step used. Retinal vessels are originated from the OD therefore there are numerous vessels crossing its border which makes its discrimination difficult. So vessel removal of the enhanced image is implemented by the inpainting technique.

The main aim is to obtain the OD-boundary more precisely and to reduce the existing borders within the OD which increase the risk of sub-segmentation. Inpainting algorithms are used in diverse applications, from the restoration of damaged photographs to the removal or replacement of selected objects. In OD- Segmentation Stochastic Watershed Transformation is used. It is a segmentation technique for gray-scale images. This algorithm is a powerful segmentation tool whenever the minima of the image represent the objects of interest and the maxima are the separation boundaries between objects. Due to this the input image of this method is usually a gradient image.

The watershed transformation produces a segmentation which can be viewed as a set of closed contours of segmented regions. This transformation uses random markers to build a probability density function of contours, which is then segmented by volumic watershed for defining the most significant regions. Region Discrimination is the discrimination between the significant and non significant regions is based on the average intensity of the region. The value of each region will be equal to:

$$\mu \sum_{x \in \pi} z(x) \pi = \frac{1}{N}$$

Being N is the number of pixels of the corresponding region π . The regions belonging to the optic disc will be light regions around darker regions therefore the residue of a close-hole operator is calculated on $\mu\pi$ to obtain the regions. Afterwards, a threshold is applied on the resulting image to select the valid regions.

In Post Processing step, the region of interest has been obtained, the result must be fitted to eliminate false contours, which are detected due to the blood vessels that pass through the OD. The technique was performed to remove most of them, as previously mentioned, however some irregularities can still be appreciated in the final region contour. In this work, the OD-contour has been estimated as a circle in the same way that in although a elliptical shape could also have been chosen. The main reason for fitting the OD by a circle is because is algorithm will later be used to establish a zone of the retina.

The method is used to detect the optic disc contour based on mathematical morphology along with principal component analysis. In the past KNN regressor is used mainly focused on locating the optic disc center. Principal component analysis is applied on the RGB fundus image in order to obtain a gray image in which the different structures of the retina such as vessels and OD are differentiated more clearly to get a accurate detection of the OD. Next a variant of the watershed transformation, the stochastic transformation, followed to a stratified transformation are implemented on a region of the original image. The algorithm is fully automatic, so process is speeded up and also the user intervention is avoided. The goal of this proposed method is to make easier the early detection of diseases related to the fundus and reduces the consultation time. Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark.

In histogram equalization we are trying to maximize the image contrast by applying a gray level transform which tries to flatten the resulting histogram. It turns out that the gray level transform that we are seeking is simply a scaled version of the original image's cumulative histogram. That is, the gray level transform T is given by $T[i] = (G-1)c(i)$, where G is the number of gray levels and $c(i)$ is the normalized cumulative histogram of the original image.

When we want to specify a non-flat resulting histogram, we can use the following steps:

1. Specify the desired histogram $g(z)$
2. Obtain the transform which would equalize the specified histogram, T_g , and its inverse T_g^{-1}
3. Get the transform which would histogram equalize the original image, $s=T[i]$

4. Apply the inverse transform Tg^{-1} on the equalized image, that is $z=Tg^{-1}[s]$

Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images that user would apply false-colour to. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low colour depth.

Watershed Transformation is the transformation used here. A watershed is a basin-like landform defined by highpoints and ridgelines that descend into lower elevations and stream valleys. In image processing, different watershed lines may be computed. In graphs, some may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges. Watersheds may also be defined in the continuous domain.

There are also many different algorithms to computer watersheds. For a segmentation purpose, the gradient magnitude (i.e., the length of the gradient vectors) is interpreted as elevation information.

Different approaches may be employed to use the watershed principle for image segmentation.

- Local minima of the gradient of the image may be chosen as markers, in this case an over-segmentation is produced and a second step involves region merging.
- Marker based watershed transformation make use of specific marker positions which have been either explicitly defined by the user or determined automatically with morphological operators or other ways.

IV. OPTIC DISC SEGMENTATION

A. Pre-processing

The first step of the pre processing stage consists of PCA to transform the input image to grey scale. This technique combines the most significant information of the three components RGB in a single image so that it is a more appropriate input to the segmentation method.

B. Principal Compound Analysis

The central idea of PCA is to reduce the dimensionality of a data set consisting of a number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the principal components(PCs), which are uncorrelated, and ordered. This technique maximizes the separation of the different objects that compose a image so that the structures of the retina are better appreciated.

C. Inpainting

Retinal vessels are originated from the OD therefore there are numerous vessels crossing its border which makes its discrimination difficult. So vessel removal of the enhanced image is implemented by the inpainting technique. The main aim is to obtain the OD-boundary more precisely and to reduce the existing borders within the OD which increase the risk of sub-segmentation. Inpainting algorithms are used in diverse applications, from the restoration of damaged photographs to the removal or replacement of selected objects.

D. OD- Segmentation

1. Stochastic Watershed Transformation

It is a segmentation technique for gray-scale images. This algorithm is a powerful segmentation tool whenever the minima of the image represent the objects of interest and the maxima are the separation boundaries between objects. Due to this the input image of this method is usually a gradient image. The watershed transformation produces a segmentation which can be viewed as a set of closed contours of segmented regions. This transformation uses random markers to build a probability density function of contours, which is then segmented by volumic watershed for defining the most significant regions.

E. Region Discrimination

The discrimination between the significant and non significant regions is based on the average intensity of the region. The value of each region will be equal to:

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F. Post Processing

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V. EXPERIMENTAL RESULT

This frame work consisting overall project layout of getting original input fundus image and enhancement image as well as inpainting of vessel mask .The final interface gives the optic disc segmentation.

A. Original Fundus Image

Variability between fundus images in color, intensity, size, presence of artefacts, etc., makes each state-of-the-art method uses a different input image. The validation of the method has been carried out using different optic disk images.

B. Enhanced Image

Enhancement analysis maximizes the separation of the different objects that compose a image so that the structures of the retina are better appreciated. In addition, it is much less sensitive to the existing variability in a fundus image regarding colour, intensity, etc.

C. Segmented Image

The discrimination between the significant and non significant regions is based on the average intensity of the reg. the final segmentation, providing robustness and reliability.

D. Morphological Post Processing Image

Short segments between two junctions are not necessary. Hence we propose to use morphological post processing image.

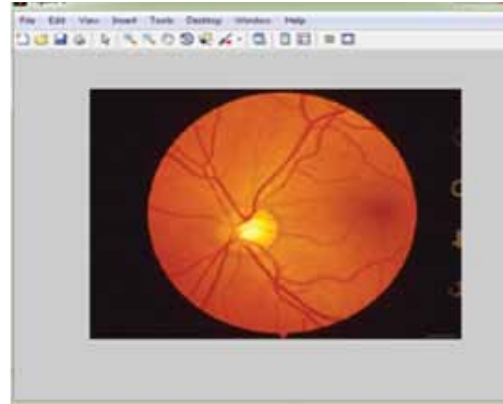


Fig. 4(a) Input Image

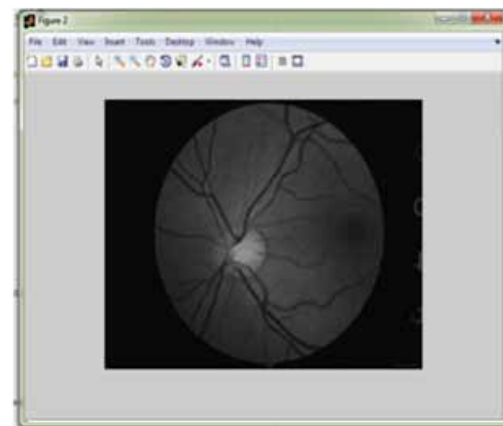


Fig.4 (b) Enhanced Image

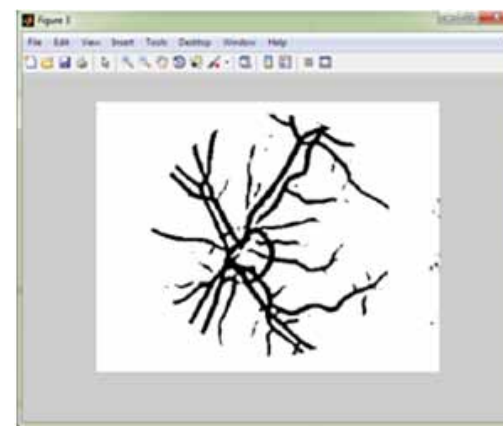


Fig. 4(c) Segmented Image

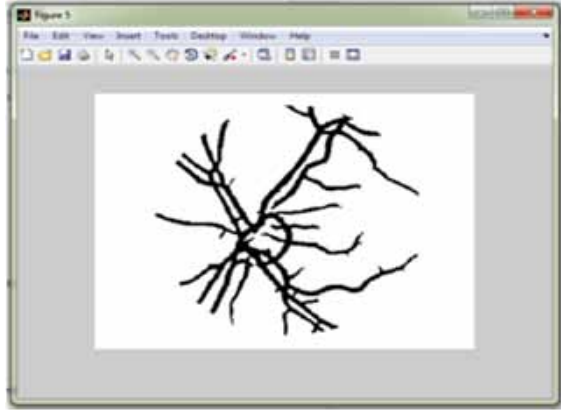


Fig. 4 (d) Result of segmented true vessels

VI. CONCLUSION

The algorithm has been validated on five different public databases obtaining promising results and improving the results of other methods of the literature. The final goal of the proposed method is to make easier the early detection of diseases related to the fundus. Its main advantage is the full automation of the algorithm since it does not require any intervention by clinicians, which releases necessary resources (specialists) and reduces the consultation time, hence its use in primary care is facilitated. As for future lines, the optic disc will also be detected with the goal of measuring the cup-to-disc ratio. A high C/D ratio will indicate that a fundus is suspicious of glaucoma.

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