Indian Statistical Institute

Certificate of Approval

This is to certify that the thesis entitled "Automatic identification of the fovea region in fundus eye image" by Soumitra Samanta towards partial fulfillment for the degree of M.Tech. in Computer Science at Indian Statistical Institute, Kolkata, embodies the work done under my supervision.

(Prof. Bhabatosh Chanda)
Date: ECSU- Indian Statistical Institute
Kolkata.

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Abstract

Fovea is one of the main features of a fundus retinal image. The problem of automatically locating the Fovea, a spot located in the center of the macula and responsible for sharp central vision, on the retinal surface image is considered. Detection of Fovea region manually by ophthalmologists takes more time. Due to unavailability of trained ophthalmologists especially in developing countries like India automation is highly necessary. This report presents a technique for automatically locating the Fovea region with the help of Mathematical Morphology. The technique brought up here should find its advantage in real-time image-guided applications like a computer-assisted photocoagulation. The technique consists of two steps, first locate the Optic Disc and second locate the Blood Vessel. Then using some geometrical feature we locate the Fovea region.

Contents

Chapter 1

Introduction

Diabetic retinopathy is an eye disorder caused by diabetes, the primary cause of blindness. The International Diabetes Foundation reports that India has the largest share of this population with over 50 million people and growing rapidly (IDF 2009a). Health care costs motivated by diabetes are also increasing around the world. In the United States alone, projected costs of 376 billion are expected to rise to 490 billion by 2030 (Unwin et al. 2009). Given the gravity of the effects of retinopathy, early detection of the disease is absolutely essential in preventing un-necessary blindness. Unfortunately, there is no known cure for diabetic retinopathy and these treatments are management strategies at best. The number of ophthalmologists in a country like India is insufficient to support the growing diabetic population. Most rural regions in India do not have local ophthalmologists and rural populations do not typically travel to the closest city. Consequently, if an automated detection system could be developed, it would significantly improve the efficiency of ophthalmologists in this initiative and would extend basic retinopathy diagnosis to rural regions without the need for an expert. The main components of fundus retinal image are Fovea, Optic Disc and Blood Vessel. During last three decades people are trying to extract the above features automatically form fundus retinal image. Many research results on the analysis of color fundus image have been reported as reviewed in [18]. Some of the work tried to extract the anatomical structures such as Optic Disk, Fovea and Blood Vessels. Others attempted to detect lesions including cotton-wool spot, exudates and hemorrhages to help the diagnosis. While most of the effort is put on improving the detection algorithm, one thing less mentioned is the distribution of the lesions. In this report we concentrate only on the Fovea region. There are many methods in literature to detect the Fovea region. Here we describe a method to localize the Fovea region automatically.

1.1 Objective of the work

Diabetes is the most common cause of blindness in the working age group in the developed world. The patterns of disease that affect the fundus of the eye are varied and usually require identification by a trained clinical ophthalmologist. The employment of digital fundus imaging in ophthalmology provides us with digitized data that could be exploited for computerized detection of disease. Many investigators use computerized image analysis of the eye, under the direction of a clinical ophthalmologist [6–9]. The management of certain diseases would be greatly facilitated if a fully automated method was employed [10]. The obvious example is the care of diabetic retinopathy. Diabetic retinopathy is a critical eye disease which can be regarded as manifestation of diabetes on the retina. The screening of diabetic patients for the development of diabetic retinopathy can potentially reduce the risk of blindness in these patients by 50% and can provide considerable cost savings to public health systems. Most of the methods to identify the retinopathy are expensive, specifically by trained clinical ophthalmologist [11–14]. A wholly automated approach involving fundus image analysis by computer could provide an immediate classification of retinopathy without the need for specialist opinions and reduce the cost.

Manual semi-quantitative methods of image processing have been employed to provide faster and more accurate observation of the degree of macula oedema in fluorescein images [9]. Progress has been made towards the development of a fully automated system to detect microaneurysms in digitized fluorescein angiograms [7, 15]. Fluorescein angiogram images are good for observing some pathologies such as microaneurysms which are indicators of diabetic retinopathy. It is not an ideal method for an automatic screening system since it requires an injection of fluorescein into the body. This disadvantage makes the use of color fundus images, which do not require an injection of fluorescein, more suitable for automatic screening.

Fovea is the most essential part of the retina for human vision, protective mechanisms for avoiding bright light and especially ultraviolet irradiation damage are essential. For, if the delicate cones of our Fovea are destroyed we become blind. The Fovea is a small depression on the fundus image, which is indicated by a deep-red or red-brown color and a small brilliant reflex in the color fundus image. It is temporal to and slightly below the optic disk. The size of Fovea

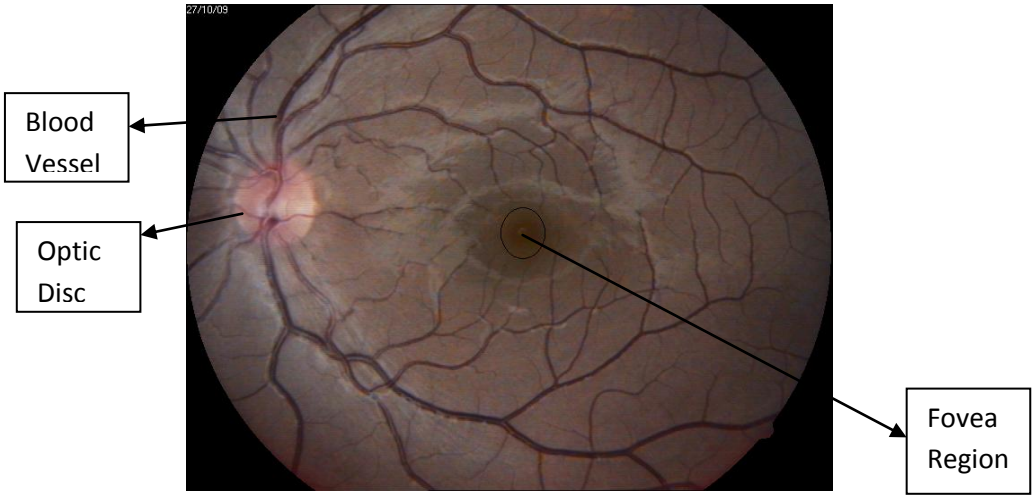

Fig. 1(a) Digital color fundus retina image

zone in the fundus eye image has a relation with various diseases which may lead to blindness. Usually the zone is approximated to a circle of radius 250 micron. If the said radius is smaller then we can conclude that there may be some deposition at the peripheral side, and that causes some infection or disease in eye, which may tends to retinopathy or blindness. Also if we measure the radius of the Fovea region, we can suggest the patient about his stages of retinopathy. If we collect and measure the same for a patient for a long time period at fixed interval, then we can draw an approximate conclusion on tendency of retinopathy of that patient.

1.2 Review of related work

Many research results on the analysis of color fundus image have been reported. Some of the works tried to extract the anatomical structures such as Optic Disc, Fovea and Blood Vessels. Others attempted to detect lesions including cotton-wool spot, exudates and hemorrhages to help the diagnosis. There are so many work related to Fovea region localization. In [1], they proposed a method based on Bayesian statistical methods that allow to incorporate the previous knowledge about the eye fundus in the model. The contour of the Fovea is modeled by means of a uni-dimensional Markov chain and the observed intensities are assumed Gaussian and statistically independent between pixels. In [2], they present a method based on the structure of blood vessels and with information on the optic disk. They used active shape model (ASM) algorithm to extract the main courses of blood vessels. The main courses of blood vessels were represented by thirty landmark points. In the training images these points on the main vessels were annotated manually. They try to fit a parabola on the main blood vessel and locate the Fovea region on the main axis of the parabola.

1.3 Organization of the report

The following chapters describe the total overview of the Fovea localization. Chapter 2 describes the Optic Disc localization method, chapter 3 describes the blood vessels detection method, chapter 4 we have presented the actual description of the Fovea region localization and in chapter 5 we have presented the experimental results.

Chapter 2

Optic Disc localization

The Optic Disc (OD) or Optic nerve head is the point in the eye where the optic nerve enters the retina. It appears in color fundus images as a bright yellowish or white region. Its shape is more or less circular, interrupted by the outgoing vessels. The size of the optic disk varies from patient to patient. Its diameter lies between 40 and 60 pixels in 640 × 480 color photographs [16]. Many techniques have been purposed for localization of optic disk. In [3] the Optic Disc is localized exploiting its high grey level variation. This approach has shown to work well, if there are no or only few pathologies like exudates, that also appear very bright and are also well contrasted. In [5] an area threshold is used to localize the Optic Disc. The contours are detected by means of the Hough transform. This approach is quite time consuming and it relies on conditions about the shape of the Optic Disc that are not always met. Here we use some morphological operator to localize the Optic Disc.

2.1 Algorithm

2.1.1 Preprocessing

The red, green and blue (RGB) space of the original image was transformed to Hue, saturation and intensity (HSI) space. Because In RGB spaces the color information is spread in three different components that is the color information are correlated. But HSI color space is more appropriate since it allows the intensity component to be separated from the other two color components that is the color information are uncorrelated. The intensity component is calculated according to the Eq. (1).A median filtering operation was then applied on I component to reduce the noise to get I_1 as a filtered image shown if Fig 2(a).

$$I = (R + G + B) / 3 \quad (1)$$

2.1.2 Morphological Operation

Apply a grayscale Morphological Closing operator on the intensity component I_1 will help to eliminate the Blood Vessels which may remain in the Optic Disc region (because the neighborhood pixels of the Blood Vessels are high contrast). A flat disc-shaped structuring element with a fixed radius of eight was used (as in general width of the blood vessels is less than eight pixels). Fig 2(b) shows a result after Closing operator was applied.

The Optic Disc is characterized by the largest high contrast of size 80×80 pixels in general [3]. We take the threshold T_1 such that 2.5% pixels are greater than T_1. The resulting Closing image was binarized by thresholding (T_1 as a threshold), shown in Fig 2(c). After that we use the binary closing operator to reduce the noise and identify the exact optic disk location, shown in Fig 2(d).

Now our aim is to fit a circle around the Optic Disc. To do that find the center of gravity (G say) of the Optic Disc which is considered as the center of the Optic Disc. Find the distance between G and all the contour points of the Optic Disc. Calculate the average of all the distances.

Take the average distance as a radius of the Optic Disc and fit a circle which cover the Optic Disc, shown if Fig 2(e).

2.1.3 Concise Algorithm

Step 1: Convert the image from RGB space to HSI space.

Step 2: Take intensity component (I) and apply median filtering operation on it and I_1 is the filtered image.

Step 3: Apply a grayscale Closing operator on I_1 with a flat disc-shaped Structuring element of radius eight and I_2 as a final image.

Step 4: Binarize the image I_2 by thresholding and I_3 as a binary image.

Step 5: Apply the Closing operator on I_3 with a flat disc-shaped structuring of radius twenty.

Step 6: End

2.2 Optic Disc localization results

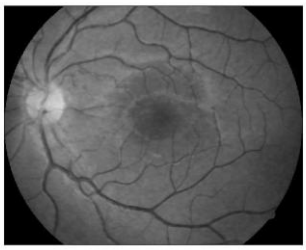

Fig. 2(a)

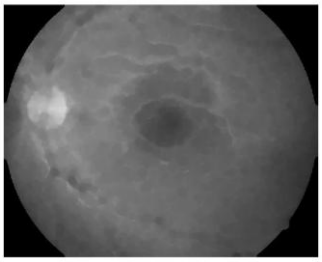

Fig. 2(b)

Fig. 2(c)

Fig. 2(d)

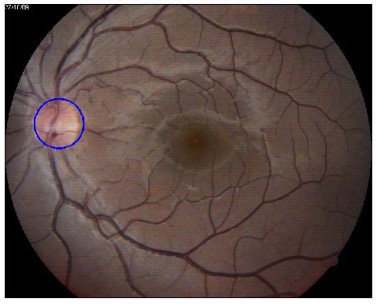

Fig. 2(e)

Fig. 2 Optic Disc detection: 2(a) Intensity component, 2(b) Morphological Closed image, 2(c) Binary image, 2(d) Morphological Closing on 2(c), and 2(d) Optic Disc location.

Chapter 3

Blood vessel detection

Blood vessels appeared as networks of either deep red or orange-red filaments that originated within the Optic Disc and were of progressively diminishing width. Vessels and arteries have many observable features, including diameter, color, tortuosity (relative curvature). Artery-vein crossings and patterns of small vessels can also serve as diagnostic indicators. An accurate delineation of the boundaries of blood vessels makes precise measurements of these features possible. These measurements may then be applied to a variety of tasks, including diagnosis, treatment evaluation, and clinical study. Here we are not interesting about the above features diagnosis. There are many methods in literature to localize the blood vessels. In [4], the cross section of a vessel in a retinal image was modeled by a Gaussian shaped curve, and then detected using rotated matched filters. In [5], they proposed a neural network approach with two class problem. Each pixel of the fundus image was classified as vessel or non-vessel. We proposed the method based on mathematical morphology.

3.1 Algorithm

3.1.1 Preprocessing

Before apply the morphological operator first we convert the color fundus image into grayscale image. Because in RGB space the color information are correlated. We transform the original (RGB) image into HSI and take the intensity component I (according to Eq. (1)) which represent a grayscale image of the original color image.

3.1.2 Morphological Operation

Let I_1 be the transformed grayscale image, shown in Fig 3(a). Now we apply the grayscale Morphological Opening operator on I_1 with a flat disc-shaped structuring element of fixed radius three to get the final image I_2 (say). After that we apply the grayscale Morphological Closing operator on I_2 with the above structuring element of fixed radius eight and get I_3 as a final image, shown in Fig 3(b). The Closing operator will help us to eliminate the blood vessels.

Then we use the Morphological Top-Hat transformation (Eq. (2)) on I_3 we get the image I_4 (say), shown in Fig 3(c).Because the Top-Hat transformation is the difference between the closed image I_3 (which does not contains the blood vessels) and the grayscale image I_1 (which contains blood vessels as well as the information in I_3). So the Top-Hat transformation gives two types of information, one is Blood vessels (high contrast) and another one is totally dark region.

$$I_4 = I_3 - I_1 \quad (2)$$

We binarize the image I_4 by thresholding. Here we use zero as a threshold value. If the pixel value is greater than zero then we consider as Blood Vessels otherwise consider as a

background. Let I_5 be the binary image which gives the location of the blood vessels. There is some noise in I_5. To reduce the noise we use the component labeling on I_5 and thresholding on small area, get I_6 as a final image which gives the actual blood vessels location of the fundus image, shown in Fig 3(d).

3.1.3 Concise Algorithm

Step 1: Input I ($m \times n \times 3$) as a color image matrix.

Step 2: Convert RGB image to HSI.

Step 3: Apply Morphological Opening-Closing on I component.

Step 4: Use Top-Hat transformation.

Step 5: Binarized by thresholding.

Step 6: Component labeling.

Step 7: Thresholding on Area and get A as a resultant image matrix.

Step 8: End

3.2 Blood Vessel detection results

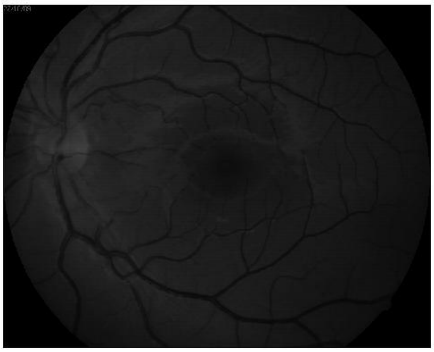

Fig. 3(a)

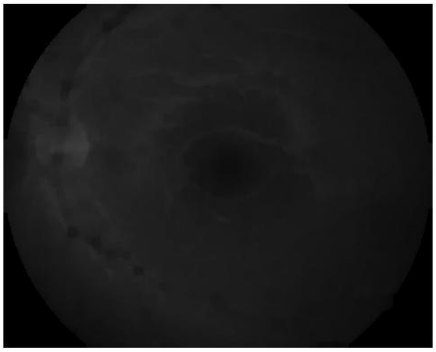

Fig. 3(b)

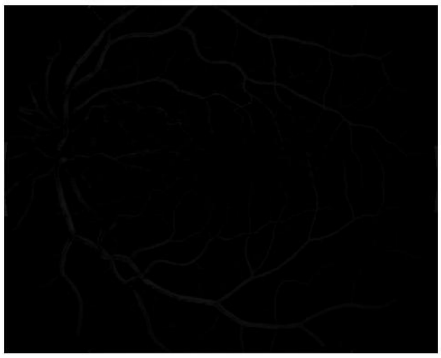

Fig. 3(c)

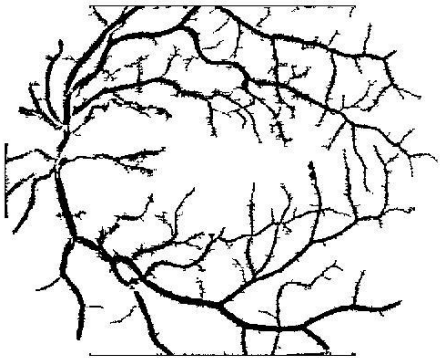

Fig. 3(d)

Fig. 3 Blood vessels detection: 3(a) Transformed grayscale image, 3(b) Morphological opening closing image, 3(c) Morphological Top-Hat transformed image, 3(d) Blood vessels location

Chapter 4

Fovea region localization

The Fovea is a small depression on the fundus, which is indicated by a deep-red or red-brown color and a small brilliant reflex in the color fundus. It is temporal to and slightly below the optic disk. In most of the fundus images the Fovea is the darkest part in the image. It is not obvious to human eyes in some images due to high illumination or being covered by the lesions. Its geometrical relation to other structures is employed in this section to locate the Fovea region robustly.

4.1 Geometrical feature

To find the Fovea region we use some geometrical features of the fundus image**.** If we observe carefully all the blood vessels of the fundus image they converge to the Fovea region. If we extract only the blood vessel from the fundus image then we can observe maximum white region around the Fovea region. According to the trained ophthalmologist the centre of the Fovea was usually located at a distance of approximately 2.5 times the diameter of the Optic Disc, from the centre of the Optic Disc.

4.2 Algorithm

4.2.1 Algorithm Description

The inputs for this algorithm are a grayscale image I_1 and an image which contains only blood vessels of I_2.

Using the above described geometrical information we locate a point (P) on the image I_2, which contains the blood vessels only horizontally form the center (G) of the Optic Disc at a distance 2.5 times the diameter of the Optic Disc which is nearer to the Fovea region.

Now we draw a vertical strip of width 9 pixels through the point P (take P as middle of the strip and 4 pixels left and right side of P) perpendicular to the line GP, shown in Fig. 4(a). Traverse the vertical strip by a (9×9) window from point P in upward and down ward direction. Count the number of black pixels in each window. Let M and N are the two Arrays containing the number of black pixels in each (9×9) window in upward and downward direction respectively. Find the first occurrence of zeros in each array denote it by S_1, S_2 and E_1, E_2 be the last consecutive zero occurrence of each Arrays (M and N respectively). Let d_1 and d_2 be the distance between S_1, E_1 and S_2, E_2 respectively. Say the starting (S) and ending (E) position of the maximum distance of d_1 andd_2. Find the middle point D (say) of S and E.

Now our goal is to find the candidate region. To do that, consider a binary image I_3 of same size of the input image with only a black pixel at position D. Take a flat disc with radius DS as a structuring element apply the binary Morphological Dilation operation on image I_3 to

get the candidate region R (say). The darkest part of the region on image I_1 corresponding to the region R gives the Fovea region.

We binarize the region on image I_1 corresponding to the region R by gray label thresholding, shown in Fig. 4(c). Let R_1 be the resultant region. Then to remove the noise we use Morphological Closing Opening operation on R_1 and get R_2 as a final region.

Our aim is to fit a circle around the Fovea region. To do that find the center of gravity (G_1) of the region R_2 which is considered as the center of the Fovea region. Find the distance between G_1 and all the contour points of the region R_2. Take the average distance as a radius of the Fovea region and fit a circle which covers the Fovea region, shown in Fig. 4(d).

4.2.2 Concise algorithm

Inputs: A grayscale image (I_1) of given color image, an image (I_2) which contains only blood vessels, center and diameter of the Optic Disc.

Step 1: locate a point (P) at a distance 2.5 times the diameter of the Optic Disc from the center of the Optic Disc on the image I_2.

Step 2: Consider a vertical strip of width 9 pixels around the point P. Count the number of black pixels in a (9 × 9) window with in the vertical strip.

Step 3: Let A and B are the two Arrays containing the number of black pixels in each (9 × 9) window in upward and downward direction respectively.

Step 4: Find the first occurrence of zeros in each array denotes it by S_1, S_2 and E_1, E_2 be the last consecutive zero occurrence of each Arrays(A and B respectively).

Step 5: Let d_1 andd_2 be the distance between S_1, E_1 and S_2, E_2 respectively. Let the starting (S) and ending (E) position of the maximum distance of d_1 and d_2.

Step 6: Find the middle point D (say) of S and E. Consider a binary image I3 of same size of the input image with only a black pixel at position D.

Step 7: Apply the binary morphological dilation operation with flat disc shaped structuring element of radius DS and get the region R which contain the Fovea region.

Step 8: Now consider the pixels of the input grayscale fundus image with in the region R. The darkest region of the region R gives the Fovea region which is extracted by the binarization of the pixels of R by thresholding.

Step 9: To remove the noise apply the binary closing followed by opening operator with a flat Disc shaped structuring element.

Step 10: End

4.3 Fovea region localization results

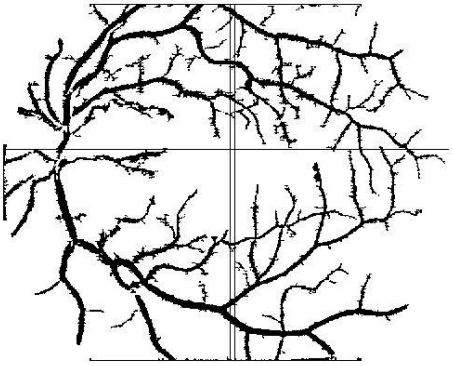

Fig. 4(a)

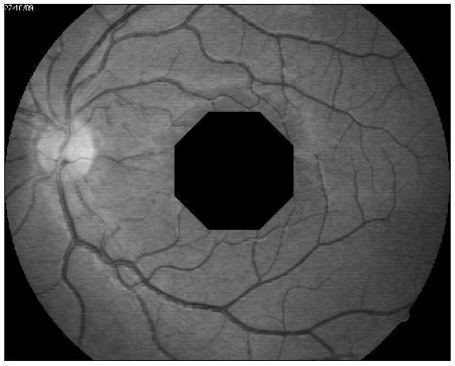

Fig. 4(b)

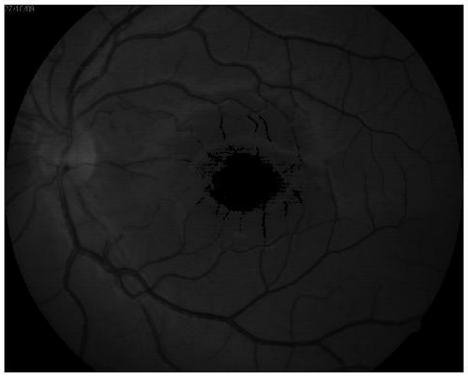

Fig. 4(c)

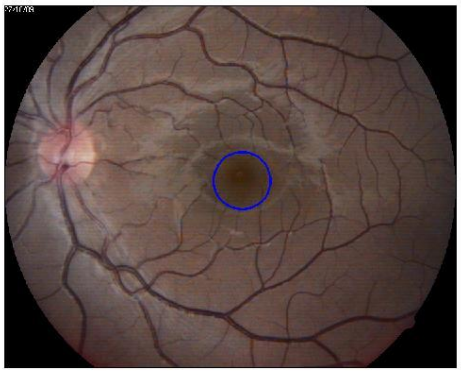

Fig. 4(d)

Fig. 4 Fovea region localization: 4(a) Vertical strip around the point P, 4(b) Rough region(R) containing the Fovea , 4(c) Binarization of region R , 4(d) Fovea region location.

Chapter 5

Experimental results

The performance of our Fovea localization system is verified on some patient's retina fundus image. We have verified on 10 different patients retina images. The images were stored in Bitmap format files (.bmp). The image size is 720 × 576 pixels at 24 bits per pixel. We have used the system with following hardware specification to run our algorithm:

Processor: Intel(R) Core(TM) 2 Duo CPU T6400 @ 2.00GHz 2.00 GHz

Memory (RAM): 1.00GB

System type: 32-bit Operating System.

We have used the MATLAB7 software tools with Windows operating system to implement our algorithm. The execution time of the algorithm on the above specified system is around 7 seconds.

5.1 Given RGB images

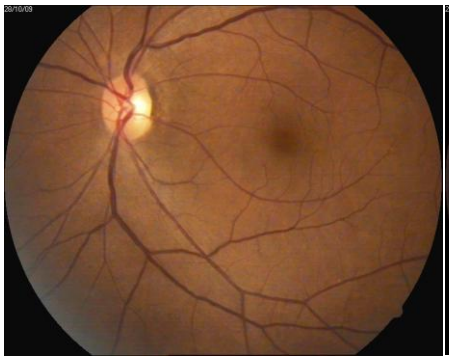

Fig. 5.1(a)

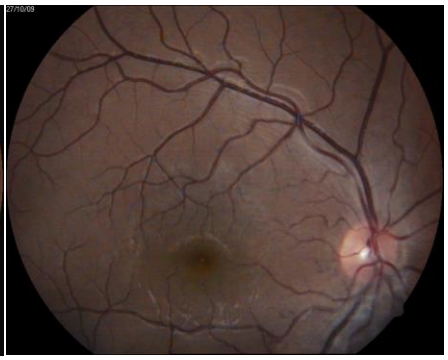

Fig. 5.1(b)

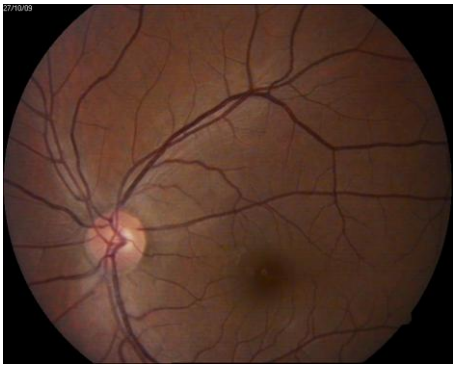

Fig. 5.1(c)

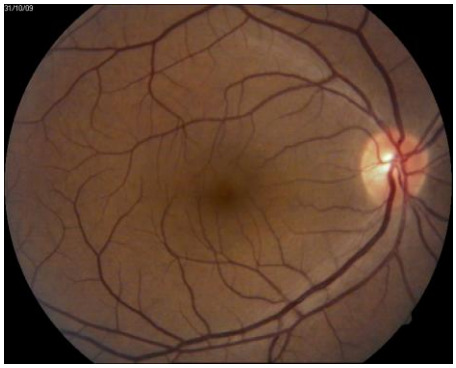

Fig. 5.1(d)

The above shown figures are the input images

5.2 Results of Optic Disc localization

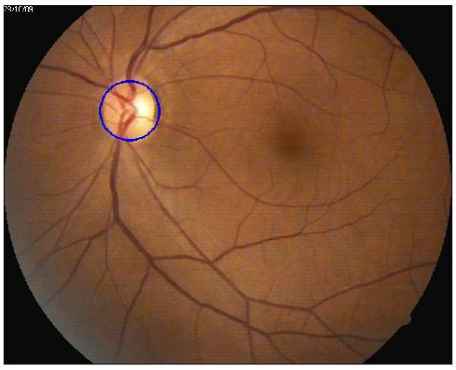

Fig. 5.2(a)

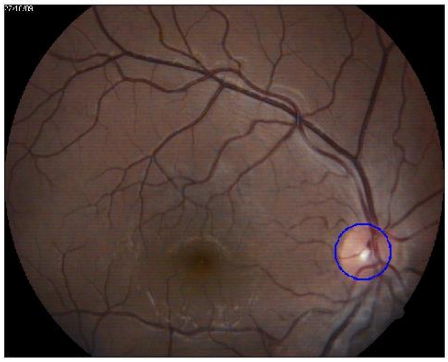

Fig. 5.2(b)

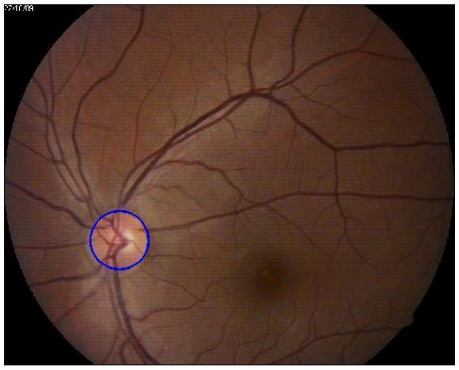

Fig. 5.2(c)

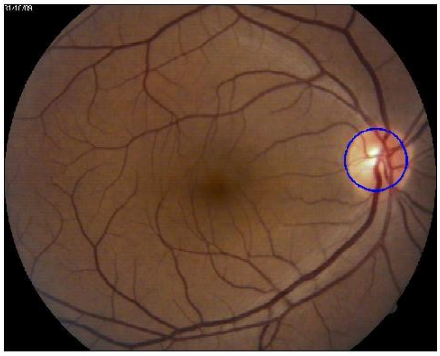

Fig. 5.2(d)

Fig. 5.2 Optic Disc localization: 5.2(a), 5.2(b), 5.2(c) and 5.2(d) shows the Optic Disc localization of the input images 5.1(a), 5.1(b), 5.1(c) and 5.1(d) respectively.

5.3 Results of blood vessel localization

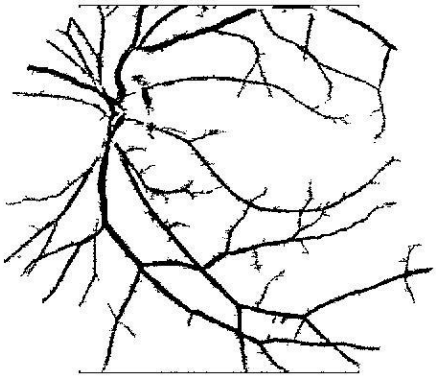

Fig. 5.3(a)

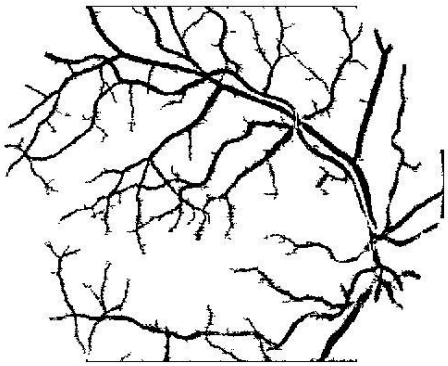

Fig. 5.3(b)

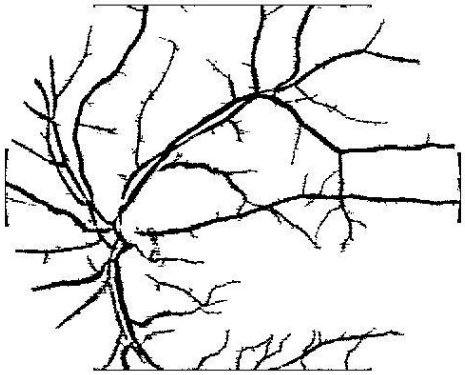

Fig. 5.3(c)

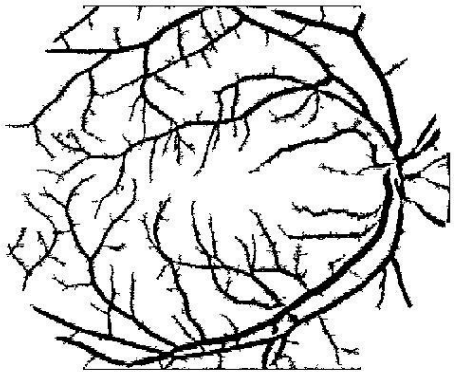

Fig. 5.3(d)

Fig. 5.3 Blood vessels detection: 5.3(a), 5.3(b), 5.3(c) and 5.3(d) showing the blood vessels of the input images 5.1(a), 5.1(b), 5.1(c) and 5.1(d) respectively.

5.4 Results of Fovea region localization

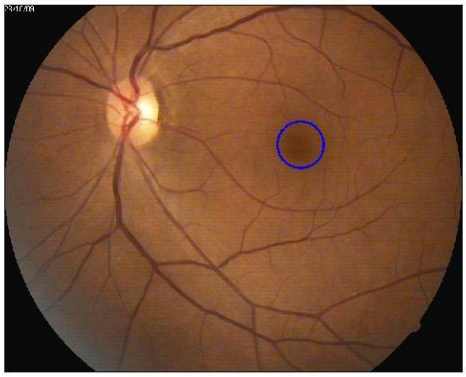

Fig. 5.4(a)

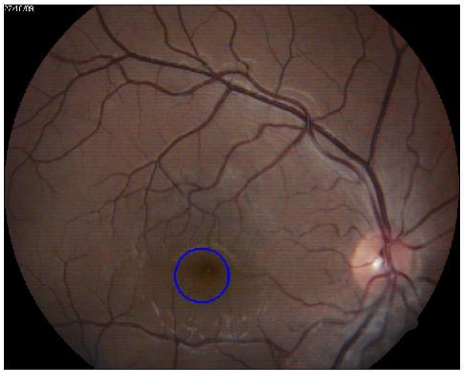

Fig. 5.4(b)

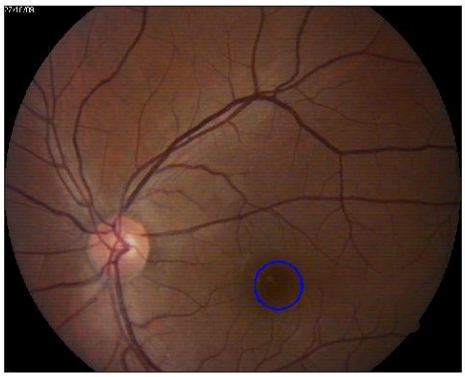

Fig. 5.4(c)

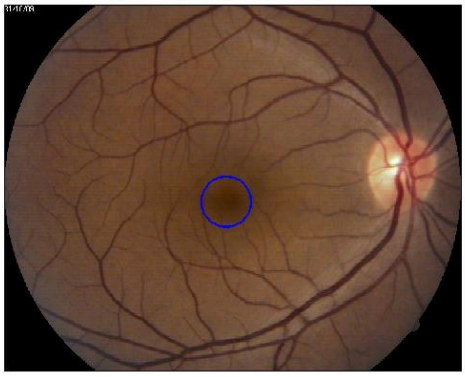

Fig. 5.4(d)

Fig. 5.4 Fovea region localization: 5.4(a), 5.4(b), 5.4(c) and 5.4(d) shows the Fovea region localization of the input images 5.1(a), 5.1(b), 5.1(c) and 5.1(d) respectively.

Chapter 6

Conclusion

In this report we have described a new efficient method to localize the Fovea in fundus image. We have used some morphological operators and geometrical features to localize the Fovea region. Our proposed method does not require any manual input parameters as an advantage over the previous proposed methods [2]. Also our algorithm takes very less amount of time to identify the Fovea region. Disadvantage of our proposed method is during the localization of Fovea region in the fundus image. That is due to the abnormal structure of blood vessels of a patient the considered strip may contain the Fovea region on the other side of our search region.

We are hopeful that the detection of the Fovea region will aid examination of fundus disorders.

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