

Automated Feature Extraction of Retinal Images to Assist Early Sign of Diabetic Retinopathy

A Project Report

submitted by

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under the guidance of

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Bachelor of Technology and Master of Technology



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THESIS CERTIFICATE

This is to certify that the thesis titled **Automated Feature Extraction of Retinal Images to Assist Early Sign of Diabetic Retinopathy**, submitted by **Gagan Kumar Arora**, to the Indian Institute of Technology Madras, for the award of the degree of **Master of Technology**, is a bona fide record of the research work done by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

KEYWORDS: Medical Imaging; Image Processing; Data Mining; Diabetic Retinopathy; Exudates Identification; Optic Disc Localisation

Diabetic Retinopathy is a severe and widely spread eye disease which can be regarded as manifestation of diabetes on the retina. For the diagnosis of Diabetic Retinopathy, digital color fundus images are becoming increasingly important. This fact opens the possibility of applying image processing techniques in order to facilitate and improve diagnosis in different ways. Screening to detect retinopathy disease can lead to successful treatments in preventing visual loss. Intraretinal fatty (hard) exudates are a visible sign of diabetic retinopathy and also a marker for the presence of co-existent retinal oedema.

Detecting retinal exudate lesions in a large number of images generated by screening programmes, is very expensive in professional time and opens to human error. In this thesis I explore the benefits of developing an automated decision support system for the purpose of detecting and classifying exudate pathologies of diabetic retinopathy.

I presented new approaches to effectively extract optical disk ,soft exudates,Blood Vessels and haemorrhage. I also explored already existing Blood Vessel detection techniques and advanced it further to extract haemorrhage. Optical Disk detection acts as pre-requisite for finding soft exudates as they exist in almost same contrast, intensity and brightness. Also blood vessels detection helps us to define threshold to segment haemorrhage. With the algorithms developed, I made the diagnostic tools

that may play a major role in mass-screening and monitoring of Diabetic Retinopathy.

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CHAPTER 1

Introduction and Motivation

1.1 Introduction

In recent times, India, Malaysia, Thailand and other parts of the world have been faced with society related diseases like diabetes. According to recent survey (4), 4% of the population has been diagnosed of diabetes disease alone and it have been recognize and accepted as one of the main cause of blindness in the country if not properly treated and managed. Early detection and diagnosis have been identified as one of the way to achieve a reduction in the percentage of visual impairment caused by diabetes with more emphasis on routine medical check which the use of special facilities for detection and monitoring of the said disease (4). The effect of this on the medical personnel need not be over emphasized, it has lead to increase work load on the personnel and the facilities, increase in diabetes screening activities just to mention a few. A lot of approaches have been suggested and identified as means of reducing the stress caused by this constant check up and screening related activities among which is the use medical digital image signal processing for diagnosis of diabetes related disease like diabetic retinopathy using images of the retina. Diabetes is a disorder of metabolism. The energy required by the body is obtained from glucose which is produced as a result of food digestion. Digested food enters the body stream with the aid of a hormone called insulin which is produced by the pancreas, an organ that lies near the stomach. During eating, the pancreas automatically produces the correct amount of insulin needed for allowing glucose absorption from the blood into the cells. In individuals with diabetes, the pancreas either produces too little or no insulin or the cells do not react properly to the insulin that is produced.

The build up of glucose in the blood, overflows into the urine and then passes out of the body. Therefore, the body loses its main source of fuel even though the blood contains large amounts of glucose (7).

The effect of diabetes on the eye is called Diabetic Retinopathy (DR). It is known to damage the small blood vessel of the retina and this might lead to loss of vision. The disease is classified into three stages: Background Diabetic Retinopathy (BDR), Proliferate Diabetic Retinopathy (PDR) and Severe Diabetic Retinopathy (SDR). In BDR phase, the arteries in the retina become weakened and leak, forming small, dot like haemorrhages. These leaking vessels often lead to swelling or edema in the retina and decreased vision. In the PDR phase, circulation problems cause areas of the retina to become oxygen-deprived or ischemic. New fragile, vessels develop as the circulatory system attempts to maintain adequate oxygen levels within the retina. This phenomenon is called neovascularisation. Blood may leak into the retina and vitreous, causing spots or floaters, along with decreased vision. In the SDR phase of the disease, there is continued abnormal vessel growth and scar tissue, which may cause serious problems such as retinal detachment and glaucoma and gradual loss of vision.

This research work is one of the method of applying digital image processing to the field of medical diagnosis in order to lessen the time and stress undergone by the ophthalmologist and other members of the team in the screening, diagnosis and treatment of diabetic retinopathy. Current techniques of DR detection and assessment are mostly manual, expensive, potentially inconsistent, and require highly trained staff to facilitate the process by searching large numbers of retinal images. These images are usually interpreted visually by the ophthalmologists in order to diagnose DR. However, many of these captured images will be normal, but some will need further grading of abnormalities, so that a judgement can be made on whether treatment is required.

1.2 Aim and Objective

The application of digital imaging to ophthalmology has now provided the possibility of processing retinal images to assist clinical diagnosis and treatment. Fundus image analysis notably improves the diagnostic value of these images. In fact, with the advent of better and inexpensive ophthalmic imaging devices, along with the rapid growth of proper software for identifying those at risk of developing DR, as well as the reduction in costs and increase in computational power of computers, an advanced and cost-effective retinal image analysis system can be developed to assist ophthalmologists to make the diagnosis more efficiently. Such a system should be able to detect early signs of background retinopathy and provide objective diagnosis based on some criteria defined by the ophthalmologists. It is expected that the proposed system will not only extend ophthalmologists capability and productivity during examination but also provide an automatic tool for the mass screening of DR.

Intraretinal fatty exudates are a visible sign of DR and also a marker for the presence of coexistent retinal oedema. If present in the macular area, oedema and exudates are a major cause of visual loss in the non-proliferative forms of DR. Retinal oedema and exudates in the central area are the clinical signs most closely linked with treatable visual loss. Exudates are associated with patches of vascular damage with leakage and typically manifested as spatially random yellow patches of varying sizes and shapes. Indeed, the size and distribution of exudates may vary during the progress of the disease. In this thesis,I have concentrated on detecting exudates as the prime marker because it is likely that accumulating exudates is always associated with retinal oedema, and unlike oedema, exudates are more visible in colour retinal photographs. Detecting exudates in the retina in a large number of images generated by screening programmes, which need to be repeated at least annually, is very expensive in professional time and open to human error. The main objective of the investigation described in this work is to contribute novel methods to quantitatively

diagnose and classify exudate lesions in colour retinal images from non-proliferative DR screening programmes.

1.3 Thesis Structure

This thesis is structured as explained below

Chapter 2: Chapter starts with an eye anatomy and abnormalities associated with an eye. It also elaborate on how work started on Diabetic Retinopathy.

Chapter 3: Preprocessing of retinal image. It states various methods for preprocessing and its utility in getting good results.

Chapter 4: It states about the optical disk. It details the core characteristics explored and novel approach to extract optical disk. It also states about exudates and how they are responsible for Diabetic Retinopathy. We also discuss its detection algorithm in the chapter.

Chapter 5: Chapter 5 discusses about the blood vessel network. We discuss the approach of extracting the vascular tree from retinal image. It also elaborates about haemorrhages and its core characteristics. They are also very much responsible for Diabetic Retinopathy.

Chapter 6: Shows the results and conclusion.

Chapter 7: It presents the product development (DR toolbox).

CHAPTER 2

Retinal Image and Diabetic Retinopathy

2.1 The eye structure

The human eye functions very similarly to a camera. Light comes in through the cornea, pupil and lens at the front of the eye just as the lens of the camera lets in light to the film. The light is then focused on the retina like the film in a camera. This information will then be sent to the brain via the optic nerve, which connects the eye to the brain, and finally the image is perceived in the brain [3]. Figure 2.1 illustrates a cross section of the human eye and highlights the main components.

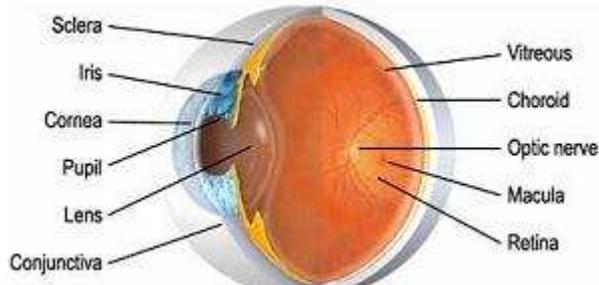


Fig. 2.1: A cross section of the human eye.

Among the various ocular structures, here we only explain the anatomical parts, which are more relevant to this research work. The retina is a thin multi-layered sensory tissue that covers the inside wall at the back of the eye. It is covered by millions of photo receptors (rods and cones). These photo receptors are responsible for receiving light beams, exchanging them into electrical impulses and then transmitting these impulses information to the brain where they are turned into images.

The main retinal components are as follows:

- 1- Superior temporal blood vessels
- 2- Superior nasal blood vessels
- 3- Fovea
- 4- Optic nerve head
- 5- Inferior temporal blood vessels
- 6- Inferior nasal blood vessels

2.2 Abnormalities associated with an eye

Abnormalities associated with the eye can be divided into two main classes, the first being disease of the eye, such as cataract, conjunctivitis, blepharitis and glaucoma. The second group is categorized as life style related disease such as hypertension, arteriosclerosis and diabetes.

When the retina is been affected as a result of diabetes, this type of disease is called Diabetic Retinopathy (DR), if not properly treated it might eventually lead to loss of vision. Ophthalmologists have come to agree that early detection and treatment is the best treatment for this disease (4). DR occurrence have been generally categorise into three main form viz, BDR, PDR, SDR. These were explained in chapter one of this report. These Three classes can occur in any of the form described below as:

Microaneurysms: These are the first clinical abnormality to be noticed in the eye. They may appear in isolation or in clusters as tiny, dark red spots or looking like tiny haemorrhages within the light sensitive retina. Their sizes ranges from 10-100 microns i.e. less than 1/12th the diameter of an average optics disc and are circular in shape, at this stage, the disease is not eye threatening.

Haemorrhages: Occurs in the deeper layers of the retina and are often called clot haemorrhages because of their round shape.

Hard exudates: These are one of the main characteristics of diabetic retinopathy and can vary in size from tiny specks to large patches with clear edges. As well as blood, fluid that is rich in fat and protein is contained in the eye and this is what leaks out to form the exudates. These can impair vision by preventing light from reaching the retina.

Soft exudates: These are often called cotton wool spots and are more often seen in advanced retinopathy.

2.3 How it started

There have been an increase in the use of digital image processing techniques for the screening of Diabetic Retinopathy after it was recommended as one of the method for screening Diabetic Retinopathy at the conference on DR held in Liverpool UK in 2005 (4). With this increase more work have been done to improve some of the existing screening method while new methods have also been introduced in order to really increase the sensitivity and the specificity of this method. Sensitivity refers to the percentage of abnormal fundus image classified as abnormal by the method while specificity can be defined as percentage of normal fundus image classify as normal. The higher these two factors the better the method. Most of the available work done can generally be categorised into screening of BDR and PDR while diagnosis of SDR have been left for the ophthalmologist. However only few work have really been done in the detection of microaneurysm and exudates, most work done are in vascular abnormalities detection using colour fundus images.

2.4 DR-Overview

Diabetic retinopathy is retinopathy (damage to the retina) caused by complications of diabetes mellitus, which could eventually lead to blindness. It is an ocular manifestation of systemic disease which affects up to 80% of all diabetics who have had diabetes for 10 years or more. Despite these intimidating statistics, research indicates that at least 90% of these new cases could be reduced if there was proper and vigilant treatment and monitoring of the eyes.

2.4.1 Signs and Symptoms

Diabetic retinopathy often has no early warning signs. Even macular edema, which may cause vision loss more rapidly, may not have any warning signs for some time. In general, however, a person with macular edema is likely to have blurred vision, making it hard to do things like read or drive. In some cases, the vision will get better or worse during the day.

As new blood vessels form at the back of the eye as a part of proliferative diabetic retinopathy (PDR), they can bleed (haemorrhage) and blur vision. The first time this happens, it may not be very severe. In most cases, it will leave just a few specks of blood, or spots, floating in a person's visual field, though the spots often go away after a few hours.

These spots are often followed within a few days or weeks by a much greater leakage of blood, which blurs vision. In extreme cases, a person will only be able to tell light from dark in that eye. It may take the blood anywhere from a few days to months or even years to clear from the inside of the eye, and in some cases the blood will not clear. These types of large hemorrhages tend to happen more than once, often during sleep.



(a) Vision of Normal Eye



(b) Vision of abnormal eye

Fig. 2.2: Comparison of Visions

2.4.2 Diabetic Retinopathy Prospective

Diabetes is an increasing health problem, both in India and the rest of the world. One of the most feared complications of diabetes is damage to the eye. It is estimated that people with diabetes have a 25 times greater risk of going blind than the non-diabetic population. Each year around 12% of patients in India who are registered blind have diabetic eye disease as a cause. DR is the leading cause of blindness in the population of working age in India and developed nations, and is of increasing importance in developing nations (6). Everyone who has diabetes is at risk for developing DR, but not everyone develops it. It is estimated that at any time around 10% of patients with diabetes will have DR requiring appropriate treatment (9). The great majority of DR complications can be prevented with proper examination and treatment.

The chemical changes caused by diabetes affect retinal capillaries (the smallest blood vessels linking arteries to veins). This progressive damage is called diabetic retinopathy (DR) and occurs due to a combination of micro-vascular leakage and micro-vascular occlusion. DR is conventionally classified according to the presence

of clinical lesions indicating leakage or occlusion, and their position in the eye. The three main forms are known as background retinopathy, maculopathy, and proliferative retinopathy.

The form of DR caused by micro-vascular leakage away from the macula is called background diabetic retinopathy (BDR) (3), and is shown by the presence of sacculations from the capillary walls (microaneurysms), blood (retinal haemorrhages), lipid exudates (hard exudates), and retinal oedema. This stage of the disease often has no obvious warning signs and patients are unaware that they suffer from the disease until it progresses into more severe levels (11). Detection at this stage - one of the purposes of this work - may allow treatment to prevent future complications. Sometimes, there are extensive areas of microvascular occlusion throughout the retina. The retinal tissue, which depends on those vessels for its nutrition, releases a vasoproliferative factor stimulating the growth of new abnormal blood vessels where the normal capillaries have already closed. This form of DR caused by closure of capillaries and growth of new vessels is named proliferative diabetic retinopathy. It may result in bleeding into the cavity of the eye and scarring with loss of vision. This work is not designed to detect this form of disease, which probably never occurs in the absence of background retinopathy or maculopathy. Figure 2.3 shows Diabetic Retinopathy effect on Vision.



Fig. 2.3: Diabetic Retinopathy effect on the vision. Without retinopathy (a), with retinopathy (b)

CHAPTER 3

Pre-Processing

3.1 Overview

We used Histogram equalization to perform preprocessing. This method usually increases the local 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 without affecting the global contrast. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. If the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal. Histogram equalization also seems to be used in biological neural networks so as to maximize the output firing rate of the neuron as a function of the input statistics.

The histogram in the context of image processing is the operation by which the occurrences of each intensity value in the image is shown. Normally, the histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit gray scale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those gray scale values. More about the histogram can be found in the [Histogram/Normalized Histogram Operation article](#).

Histogram equalization is the technique by which the dynamic range of the histogram of an image is increased. Histogram equalization assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. It improves contrast and the goal of histogram equalization is to obtain a uniform histogram. This technique can be used on a whole image or just on a part of an image. Histogram equalization redistributes intensity distributions. If the histogram of any image has many peaks and valleys, it will still have peaks and valley after equalization, but peaks and valley will be shifted. Because of this, "spreading" is a better term than "flattening" to describe histogram equalization. In histogram equalization, each pixel is assigned a new intensity value based on its previous intensity level.

3.2 Implementation

Pre-Processing improves the image data by suppressing unwanted distortions or enhancing some image features important for further processing. We used Histogram equalization (14) for preprocessing. Features like blood vessels, fovea, macula and microaneurysms are very dull in the retinal image, and processing such an image gives poor results. Firstly the original image's RGB space is transformed to HSI(Hue, Saturation and Intensity) space. HSI color space is more appropriate since the intensity component is separated from the other two components. Then we consider the probability distribution for every pixel using

$$P(x_i) = \frac{n_i}{n} \quad (3.1)$$

$i \in 0, \dots, L-1$ x_i represents pixel with pixel value equal to x_i . where n_i is number of pixels of value x_i and n is total number of pixels and $L = 256$. Let us also define C

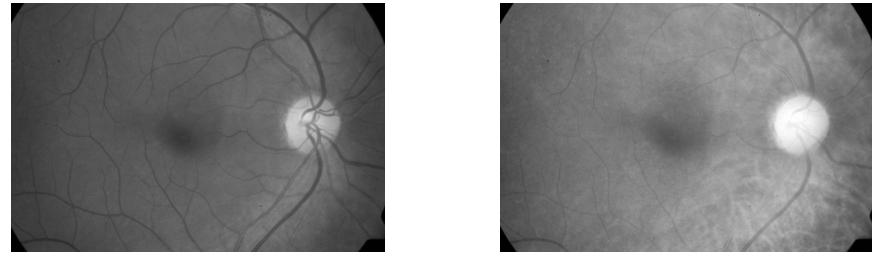
as the cumulative distribution function (CDF) corresponding to P as:

$$C(i) = \sum_{j=0}^i P(x_j) \quad (3.2)$$

also known as the image's accumulated normalized histogram. The general histogram equalization formula is:

$$CDF(v) = round\left(\frac{CDF(v) - CDF_{min}}{M \times N - CDF_{min}} \times (L - 1)\right) \quad (3.3)$$

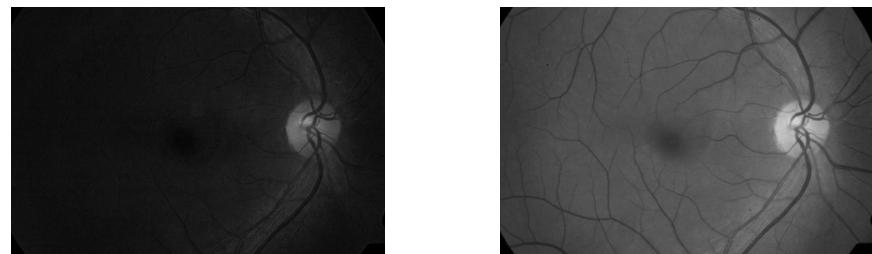
Figure 3.1 and 3.2 shows the red, blue, green and gray channel of image. Red channel is generally used to find optical disk as its contrasted over red channel. Green channel is used for blood vessels. Gray channel is generally used to compare the relative performance over various channels. Exudates and Optical Disk region normally show high intensity and thus contrast enhancement techniques assign them the highest values. Figure 3.3 shows the typical retinal cross section and its histogram. Figure 3.5 shows the effect of the transformation, which makes the brighter abnormalities much brighter and darker abnormalities much darker thereby easing the process of their extraction. Figure 3.7 shows the flow chart for the pre-processing of retinal image.



(a) Typical Retinal Image

(b) Red Channel

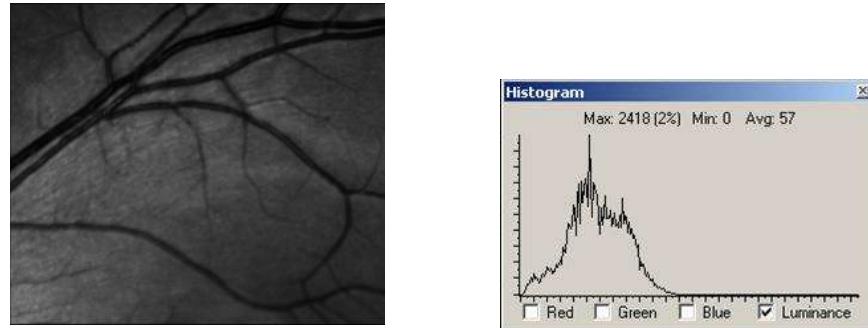
Fig. 3.1: Retinal Image and its Red Channel



(a) Its Blue Channel

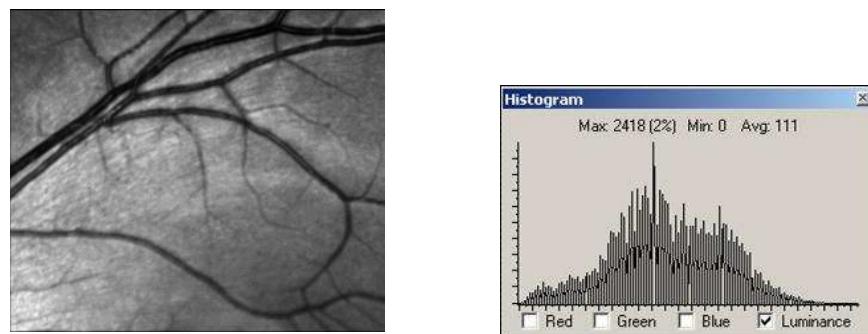
(b) Its Green Channel

Fig. 3.2: Retinal Image and its Green and Blue Channel



(a) Typical Retinal cross sectional Image (b) Histogram without Transformation

Fig. 3.3: Retinal Image and its Histogram before Preprocessing



(a) Retinal Cross sectional Image after transformation (b) Histogram after applying Transformation

Fig. 3.4: Retinal Image and its Histogram after Preprocessing

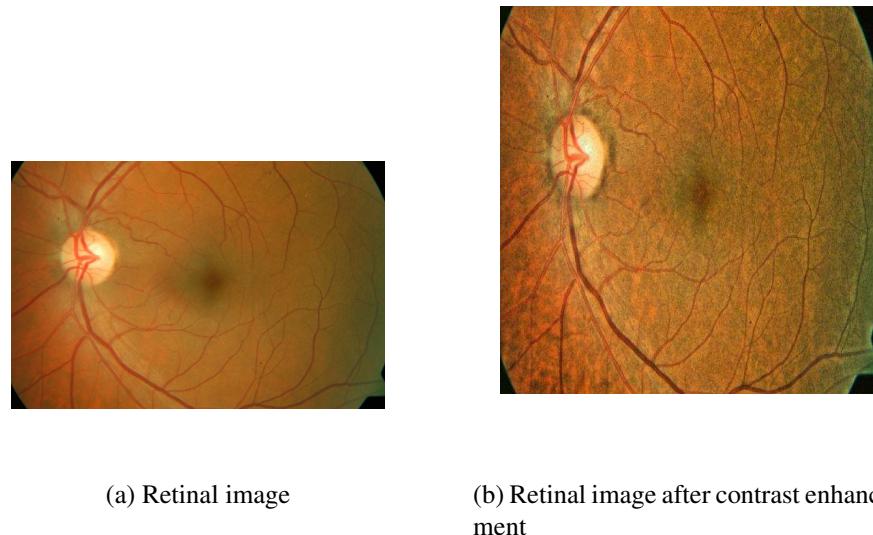


Fig. 3.5: Results of Contrast Enhancement

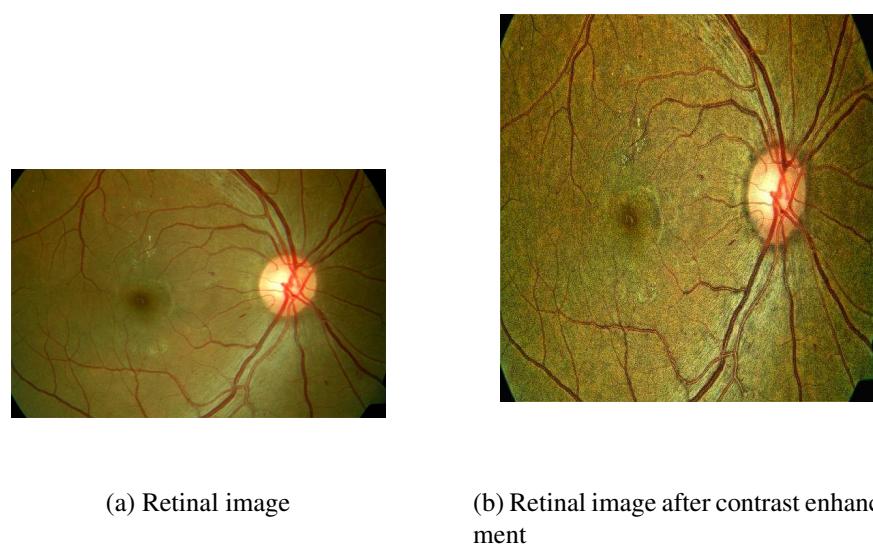


Fig. 3.6: Results of Contrast Enhancement

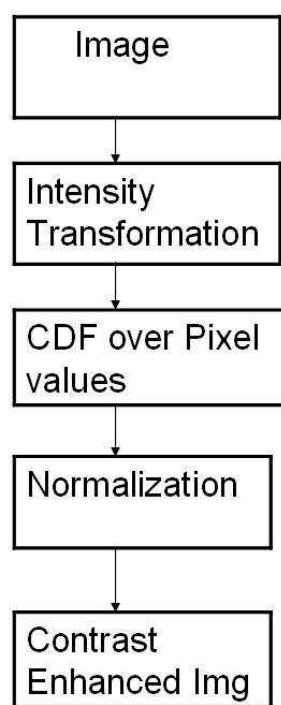


Fig. 3.7: Flow chart showing the pre processing algorithm

CHAPTER 4

Optical Disk and Exudates

4.1 Optical Disk

Optic disc localisation is necessary as a prerequisite stage in most algorithms applied for identification of the retinal anatomical structures and lesions. These are summarised as follows:

- Blood vessel tracking approaches: where blood vessels positioned in the neighbourhood of the optic disc provide seeds for vessel tracking.
- Macula localisation: where the approximately constant distance between the optic disc and the macula can be used as a priori knowledge for locating the macula.
- Retinopathy lesions identification: to improve the lesion diagnosis performance by masking or removing the false positive optic disc regions from the other required pathologies.

Optic disc localisation is indispensable in our automatic exudates identification approach, since it illustrates similar attributes to the exudates in terms of colour, brightness and contrast. By detecting it we can remove it from the exudate classification process. In fact, the results reported in coming chapters were all obtained after the removal of the optic disc using the work described in this chapter. Despite its importance, an accurate localisation is not an easy task as some parts of the boundary are not well defined in some images and several parts are obscured by the crossing blood vessels. Some of these difficulties which are experienced in optic disc localisation are apparent in Figure 4.1. As shown, the optic disc boundary is not always sharp and, more importantly. it is obscured in some places by blood vessels. Since

the optic disc region is broken up by the blood vessels, classical segmentation algorithms based exclusively on edge detection are not enough to accurately localise the optic disc as they do not incorporate the edge smoothness and continuity properties. In contrast, As the blood vessels reach the optic disc they turn and exit through the disc. However, there is often a brighter central region (the cup), which indicates the absence of nerve fibres and blood vessels. Also in severely affected eye optical disk loose its circular shape too. In such images its very difficult to find the boundary of optical disk. Our algorithm gives a good result on such images also.

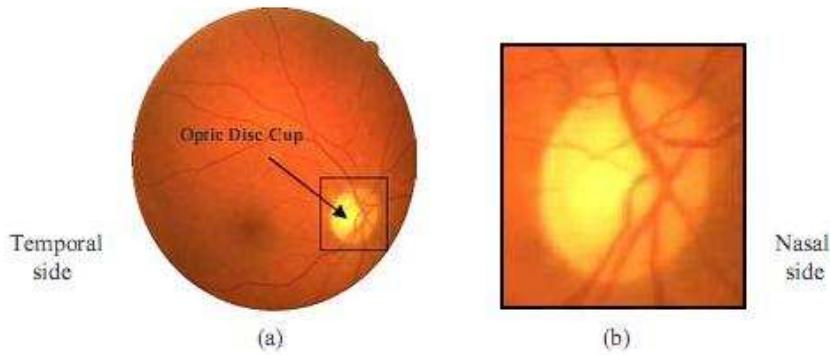


Fig. 4.1: A typical retinal image and the temporal and nasal side directions. The original image (a),optic disc close-up view (b).

The optic disc size and shape may vary significantly. The disc diameter is about 70-105 pixels in our retinal images. The optic disc part located on the nasal side is usually less bright than the temporal side portion and occasionally not visible at all. Sometimes the whole optic disk is brighter than the surrounding area, thus it can be seen as a disc; in others it can appear as a hollow ring. In either case the cup appears as a smaller, brighter region within the optic disc. Whereas locating the optic disc is an apparently simple task for an expert to trace the boundary, interpolating where necessary, traditional general-purpose boundary detection algorithms have not fully succeeded in segmenting the optic disc due to fuzzy boundaries, inconsistent image contrast, variability in appearance or missing edge features. Therefore, a reliable

optic disc localization is surprisingly difficult.

4.2 Method for Optical Disk Detection

Presently there are many approaches like Hough transformation, clustering, Morphological operations (13) used to find optical disk. Hough transformation is computationally expensive but gives decent level of efficiency. Clustering is less expensive but is also less efficient.

There are two important characteristics of optical disk in every retinal image(11). Firstly the intersection of core blood vessels lies in the optical disk. Moreover pre-processing enhances it further. Secondly, there is sharp jump in the contrast value as we move from the inside boundary of optical disk to the region outside retinal image. Pre-processing also enhance this jump. We used these two characteristics to locate the optical disk. Figure 4.2 shows these two characteristics.

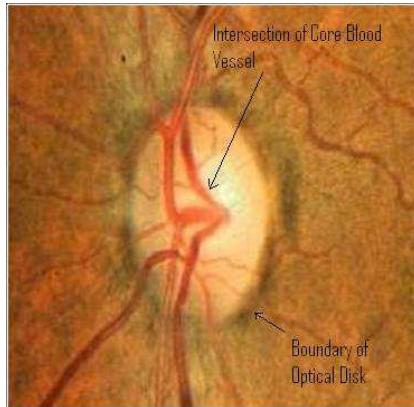


Fig. 4.2: Typical Optical Disk Region.

We normalized all retinal images to the standard size $M \times N$. Then we considered the sub image of size $(2\alpha + 1)$ by $(2\beta + 1)$, where α and β are taken as one eighth of

M , and calculated the average sub image's response for every pixel using:

$$I_{avg}(x, y) = \frac{\sum_{i=-\alpha}^{i=+\alpha} \sum_{j=-\beta}^{j=+\beta} I_o(x + i, y + j)}{(2\alpha + 1)(2\beta + 1)} \quad (4.1)$$

The variance image is then calculated using:

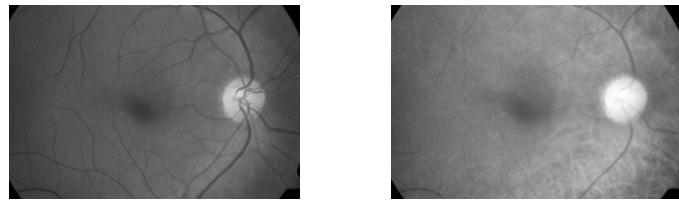
$$I_{var}(x, y) = (I_o(x, y) - I_{avg}(x, y))^2 \quad (4.2)$$

Variance is very high over optical disk region because of the two core characteristics discussed above. We also attempted to find optical disk just by locating the coordinates belonging to highest variance value. But this technique didn't give us good results. This approach miss locates the optical disk wherever exudates are of the same size as the optical disk. So we calculate window response for every pixel of variance image. Window response will be very high over the optical disk region. Pixel with the highest window response is defined as optical centre.

$$I_{Sum_Var}(x, y) = \sum_{i=-\alpha}^{i=+\alpha} \sum_{j=-\beta}^{j=+\beta} I_{var}(x + i, y + j) \quad (4.3)$$

$$I_{od}(x_{od}, y_{od}) = \text{Max}(I_{Sum_Var}(x, y)) \quad (4.4)$$

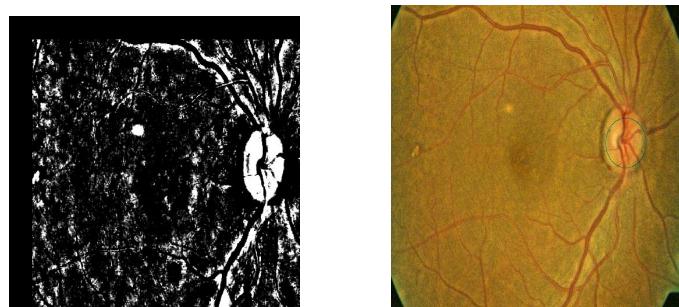
Figures 4.3,4.4 shows how image transformed in intermediate steps of algorithm. Figure 4.5 shows the result of optical disk recognition using above mentioned algorithm. Figure 4.6 shows the flow chart for the optical disk detection algorithm



(a) Retinal image

(b) Red Channel

Fig. 4.3: Retinal image and its red channel



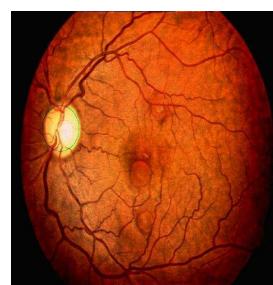
(a) variance Retinal image

(b) Optical disk detection,
marked with ellipse

Fig. 4.4: Variance image and the result of optical disk detection



(a)



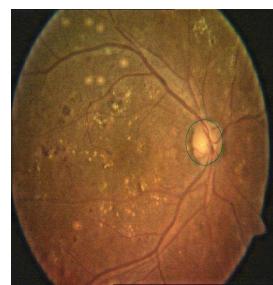
(b)



(c)



(d)



(e)



(f)

Fig. 4.5: Results of Optical Disk Recognition

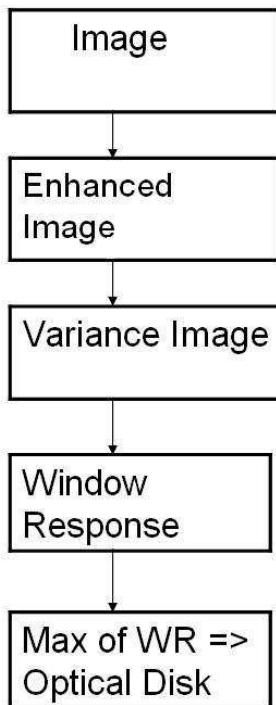


Fig. 4.6: Flow chart for the optical disk detection algorithm

4.3 Exudates

Exudates are the primary signs of diabetic retinopathy which are mainly cause of blindness and could be prevented with an early screening process. Pupil dilation is required in the normal screening process but this affects patients' vision. Proteins and lipids leaking from the blood into the retina via damaged blood vessels is the main cause of exudates. They can be identified on the ophthalmoscope as areas with hard white or yellowish colours and varying sizes, shapes and locations, near the leaking capillaries within the retina. Exudates represent accumulations of lipid and protein. They are typically bright, reflective, white or cream colored lesions seen on the retina. They indicate increased vessel permeability and an associated risk of

retinal edema (swelling). If this occurs on the macula (macular edema) vision may be lost.

Although not sight threatening in themselves they are a marker of fluid accumulation in the retina and if they are seen close to the macula center are considered sight threatening lesions. They are commonly seen in association with microaneurysms which themselves have increased leakage such that the classical lesion is a circular ring of exudates with several microaneurysms at its center. Focal laser treatment to the microaneurysms may prevent worsening of retinal swelling. Figure 4.7 shows the retinal image having exudate.

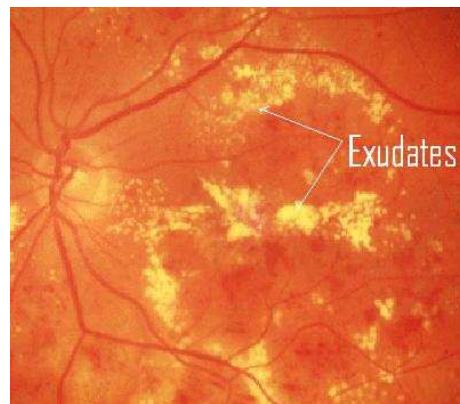


Fig. 4.7: Retinal Image showing Exudates

Exudates represent leak from surrounding capillaries and microaneurysms within the retina. Exudates are typically manifested as random yellowish/white patches of varying size, shapes and locations. These are either seen as individual spots, clusters, or are found in large rings around leaking capillaries. Exudates appear as bright lesions in Retinopathy images. They can vary a lot in color, intensity and illumination but have sharp edges or high contrast with background. They are responsible for the early sign of DR. They appear in the similar contrast and color as the optical disk does. Presently various morphological approaches and thresholding approaches are

used to detect them (8). It's very difficult to find the structuring element in morphological technique as exudates vary in size and shape. Our approach is as follows, Step 1: We produce three binary images on the red, green, and blue channels respectively with different thresholds for each. AND-ing these images produces a single binary image with pixels of high contrast. Clusters of such pixels typically indicate the presence of exudates. Step 2: Then for every highest cluster value (calculated in step 1), we search in its neighborhood for the pixels which are greater than 0.9 times the highest cluster value to mark the exudates. Since optical disk also appears in same contrast and intensity algorithm also captures the optical disk as exudates so finally in step 3, we subtract optical disk to get the exudates. Our approach is as follows, Step 1: We produce three binary images on the red, green, and blue channels respectively with different thresholds for each. AND-ing these images produces a single binary image with pixels of high contrast. Clusters of such pixels typically indicate the presence of exudates. Step 2: Then for every highest cluster value (calculated in step 1), we search in its neighborhood for the pixels which are greater than 0.9 times the highest cluster value to mark the exudates. Since optical disk also appears in same contrast and intensity algorithm also captures the optical disk as exudates so finally in step 3, we subtract optical disk to get the exudates.

Figure 4.8 shows the result of exudate detection. Exudates are marked with white color. Figure 4.9 shows the flow chart showing exudates detection algorithm.

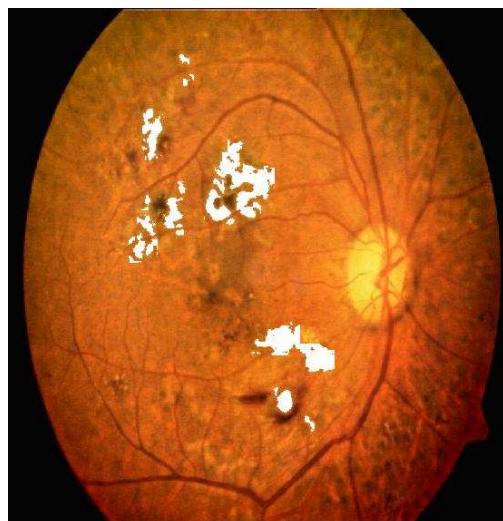


Fig. 4.8: Exudates detection

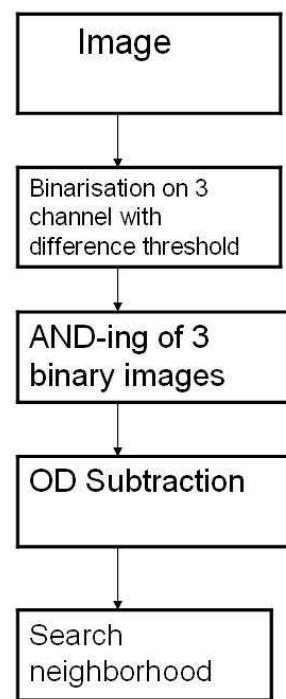


Fig. 4.9: Flow chart showing the exudates detection algorithm

CHAPTER 5

Blood Vessel and Haemorrhages

5.1 Blood Vessel

The automatic detection of blood vessels in the retinal images can help physicians for the purposes of diagnosing ocular diseases, patient screening, and clinical study, etc. Information about blood vessels in retinal images can be used in grading disease severity or as part of the process of automated diagnosis of diseases. Blood vessel appearance can provide information on pathological changes caused by some diseases including diabetes, hypertension, and arteriosclerosis. The most effective treatment for many eyerelated diseases is the early detection through regular screenings. Furthermore, a segmentation of the vascular tree seems to be the most appropriate representation for the image registration applications due to three following reasons:

- It maps the whole retina
- It does not move except in few diseases
- It contains enough information for the localization of some anchor points.

There are many previous works on extracting blood vessels in retinal images. In edge detection-based method (12), since local gradient maxima occur at the boundary of the vessels, the significant edges along these boundaries are extracted. The grouping process searches a partner for each edge which satisfies certain criteria like opposite gradient direction and spatial proximity. In tracking-based method each vessel segment is defined by three attributes. direction, width, and center point. The

density distribution of cross section of a blood vessel can be estimated using Gaussian shaped function. Individual segments are identified using a search procedure which keeps track of the center of the vessel and makes some decisions about the future path of the vessel based on certain vessel properties. An efficient piecewise threshold probing technique was proposed in (5) where the matched-filter-response (MFR) image is used for mapping the vascular tree. A set of criteria is tested to determine the threshold of the probe region, and ultimately to decide if the area being probed is a blood vessel. Since the MFR image is probed in a spatially adaptive way, different thresholds can be applied throughout the image for mapping blood vessels.

As new blood vessels form at the back of the eye as a part of proliferative diabetic retinopathy (PDR), they can bleed (haemorrhage) and blur vision. The first time this happens, it may not be very severe. In most cases, it will leave just a few specks of blood, or spots, floating in a person's visual field, though the spots often go away after a few hours. These spots are often followed within a few days or weeks by a much greater leakage of blood, which blurs vision. In extreme cases, a person will only be able to tell light from dark in that eye. It may take the blood anywhere from a few days to months or even years to clear from the inside of the eye, and in some cases the blood will not clear. These types of large hemorrhages tend to happen more than once, often during sleep.

5.2 Method for Blood Vessel Detection

Information about blood vessels can be used in grading disease severity or as part of the process of automated diagnosis of diseases with ocular manifestations. Blood vessels can act as landmarks for localizing the optic nerve, the fovea (central vision area), and lesions. As a result of systemic or local ocular disease, the blood vessels can have measurable abnormalities in diameter, color, and tortuosity. For example,

central retinal artery occlusion usually causes generalized constriction of retial arteries, hypertension may result in focal constriction of retinal arteries, central retinal vein occlusion typically produces dilated tortuous veins, arteriosclerosis can cause the arteries to acquire a copper or silver color, and diabetes can generate new blood vessels (neovascularization). Thus, a reliable method of vessel detection is needed, which preserves various vessel measurements.

The proposed algorithm (1) is composed of three steps. Since blood vessels usually have lower reflectance compared with the background, we apply the matched filter to enhance blood vessels with the generation of a MFR image. Secondly, an entropy-based thresholding scheme can be used to distinguish between vessel segments and the background in the MFR image. A length filtering technique is used to remove misclassified pixels.

5.2.1 Matched Filter

In (2). the gray-level profile of the cross section of a blood vessel can be approximated by a Gaussian shaped curve. The concept of matched filter detection is used to detect piecewise linear segments of blood vessels in retinal images. Blood vessels usually have poor local contrast. The two-dimensional matched filter kernel is designed to convolve with the original image in order to enhance the blood vessels. A prototype matched filter kernel is expressed as

$$f(x,y) = -\exp\left(\frac{-x^2}{2\sigma^2}\right), \text{ for } |y| < L/2 \quad (5.1)$$

Where L is fixed parameter. Background pixels are assumed to be of constant zero mean, Gaussian white noise. Secondly, the MFR image is processed by a proper

thresholding scheme in order to extract the vessel segments from the back-ground. An efficient entropy-based thresholding algorithm, which takes into account the spatial distribution of gray levels, is used because an image pixel intensities are not independent of each other. Specifically, we implement a local entropy thresholding technique (10) which can well preserve the spatial structures in the binarized/thresholded image. Then we used eight connected pixel labeling to remove the misclassified pixels. So for eight connected pixel labeling, we convolve the 3 by 3 square matrix over foreground pixels if the window response equals eight then we do not change the foreground pixel but if the window response is less than 8 we flip the foreground pixel to background pixel.

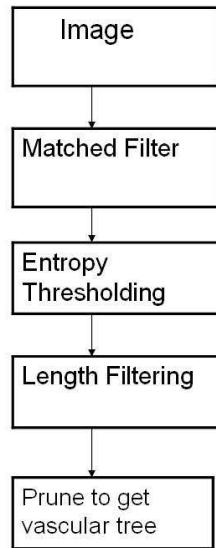
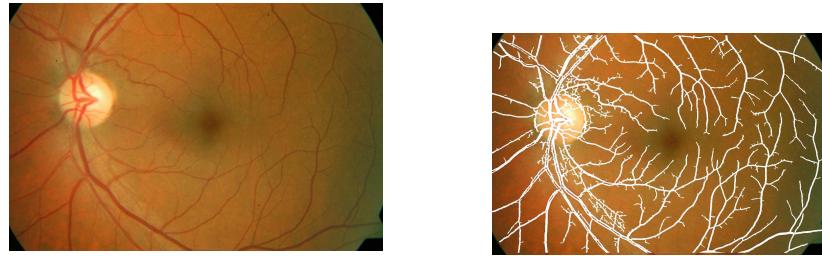


Fig. 5.1: Flow chart showing the blood vessel detection algorithm

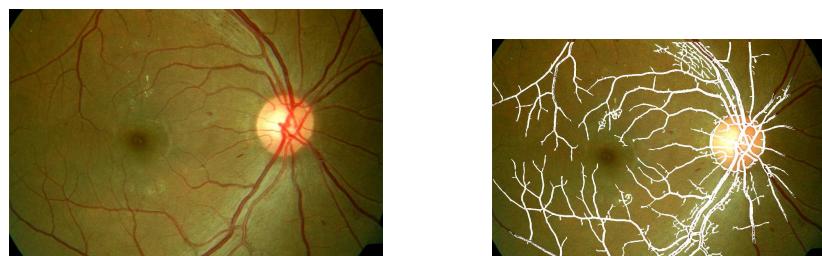
Figure 5.2 and 5.3 shows the Retinal image and the result of overlapped blood vessel network after its detection. Figure 5.1 shows the flow chart for the blood vessel detection algorithm.



(a) Typical Retinal image

(b) Typical Retinal image showing overlapped blood vessels

Fig. 5.2: Blood Vessel Detection.



(a) Typical Retinal image

(b) Typical Retinal image showing overlapped blood vessels

Fig. 5.3: Blood Vessel Detection.

5.3 Haemorrhages

Retinal haemorrhage is a disorder of the eye in which bleeding occurs into the retina. The retina is a thin disc-shaped layer of light-sensitive tissue on the back wall of the eye. Its job is to translate what we see into neural impulses and send them to the brain via the optic nerve. A retinal haemorrhage can be caused by hypertension, retinal vein occlusion (a blockage of a retinal vein), or diabetes mellitus (which causes small fragile blood vessels to form, which are easily damaged). Retinal haemorrhages can also occur due to shaking, particularly in young infants (shaken baby syndrome) or from severe blows to the head. Retinal haemorrhages that take place outside of the macula can go undetected for many years, and may sometimes only be picked up when the eye is examined in detail with an ophthalmoscope. However, some retinal haemorrhages can cause severe impairment of vision.

5.4 Method for Haemorrhage Detection

Haemorrhages are dark red spots which occur due to the leakage of blood from blood vessels. Their presence reflects the early sign of DR. Thitiporn Chanwimaluang presented a very efficient algorithm for detecting blood vessel network from retinal image [13]. The Core characteristics of haemorrhages are that they occur in almost same range of intensity as blood vessels. Vascular tree is the most prominent anatomical structure in the retinal image. Vascular tree is considered as the most appropriate representation of the retinal image as it maps the whole retina. It also contain the enough information for the localization of many anchor points.

In our algorithm we first segment the retinal image using the threshold obtained from plotting histogram of vascular tree's skeleton (Morphological thinned vascular tree) of blood vessels and then subtract the vascular tree to get haemorrhages. We then plot the histogram with a bin value of 26 and then take that value which has the

highest frequency as α . Then we segment the retinal image using 0.95 times α as lower threshold and 1.05 times α as upper threshold. After some experimentation with a range of threshold values, we picked 0.95 - 1.05. This gives us the image with haemorrhages along with blood vessels. Finally we subtract the vascular tree to get the haemorrhages. We also explored the algorithm to extract blood clots which occur because of the breaking of the blood vessels. However clotting is the very late sign of DR. Clotting detection can also be obtained by changing the threshold values

5.4.1 Morphological Thinning

Thinning is a morphological operation that is used to remove selected foreground pixels from binary images, somewhat like erosion or opening. It can be used for several applications, but is particularly useful for skeletonization. In this mode it is commonly used to tidy up the output of edge detectors by reducing all lines to single pixel thickness. Thinning is normally only applied to binary images, and produces another binary image as output.

The thinning operation is calculated by translating the origin of the structuring element to each possible pixel position in the image, and at each such position comparing it with the underlying image pixels. If the foreground and background pixels in the structuring element exactly match foreground and background pixels in the image, then the image pixel underneath the origin of the structuring element is set to background (zero). Otherwise it is left unchanged. Note that the structuring element must always have a one or a blank at its origin if it is to have any effect. The choice of structuring element determines under what situations a foreground pixel will be set to background, and hence it determines the application for the thinning operation. Digital skeletons, generated by thinning algorithms, are used in the characterization and analysis of the shape of objects in binary images

Thitiporn Chanwimaluang suggested the method of vascular tree extraction using

matched filter and local entropy thresholding (10). Firstly it rotates the Gaussian filter every 15 degree to get the maximum response and marked it as blood vessel network then it pruned the network using Local Entropy Thresholding. Now the resultant vascular tree contains the blood vessels also the boundary of haemorrhages. In order to get the appropriate threshold for haemorrhages we need to remove the blood vessels which are straight. So we apply the morphological thinning operation using the straight line as structuring element. We put vascular tree as the main binary image and straight line of 8 pixels as the structuring element. In order to trace the direction, we rotate the structuring element (straight line) at 0 degree, 45 degree and 90 degree to prune the straight blood vessels.

5.4.2 Thresholding and Vascular tree subtraction

After getting the skeleton of vascular tree, we plot the histogram of it with bin value of 26. Then we define α as intensity value corresponding to the highest frequency. Pixels are labeled using 0.9 times α as lower threshold and 1.05 times α as upper threshold. Now label points contain blood vessels, boundary of haemorrhages and inside of haemorrhages. Now we subtract the vascular tree obtained from (1) to get the haemorrhages. We also looked over the blood clots detection where α value is not decided by intensity of maximum frequency but by the average intensity of vascular tree. Then upper threshold and lower threshold is decided accordingly.

Figure 5.4 shows the result of Haemorrhages Detection algorithm. Haemorrhages are marked with red color. Figure 5.5 shows flow chart for haemorrhages detection algorithm.



(a) Retinal image

(b) Retinal image after Haemorrhages
Detection

Fig. 5.4: Result of Haemorrhages Detection

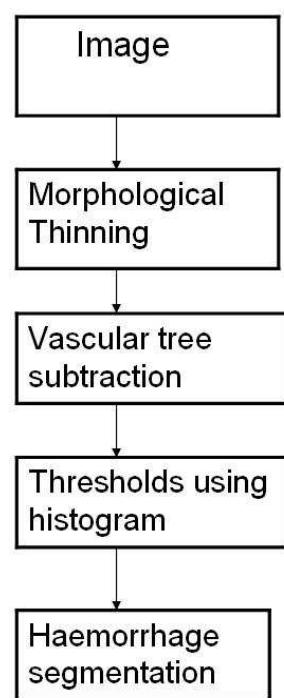


Fig. 5.5: Flow chart showing haemorrhages detection algorithm

CHAPTER 6

Results and Conclusion

6.1 Optical Disk

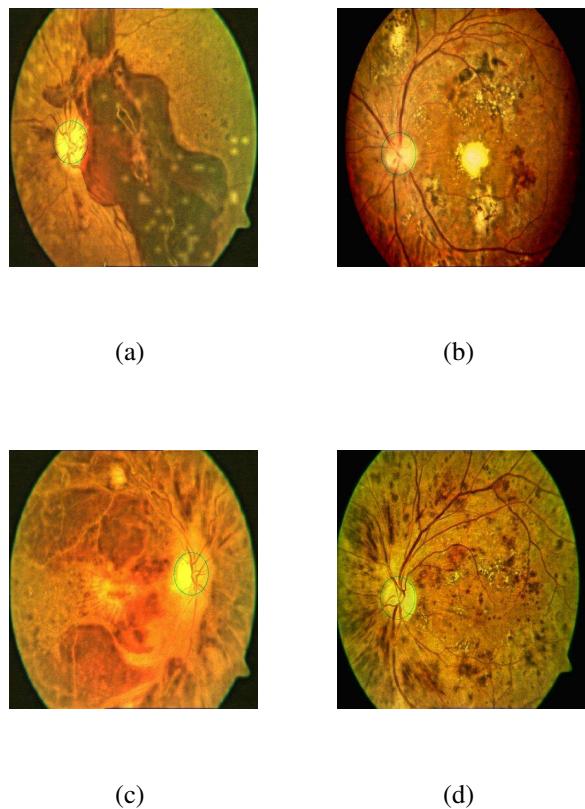


Fig. 6.1: Results of Optical Disk Recognition, ellipse represents optical disk.

Figure 6.1 shows that we are able to find optical disk in unhealthy eyes. In figure 6.1-b we successfully find the optical disk where exudates are of same size and contrast as optical disk. In Figure 6.1-c optical disk and background are of

same contrast but still variance approach is able to find optical disk. Figure 6.1-d is unhealthy image having haemorrhages.

6.2 Exudates

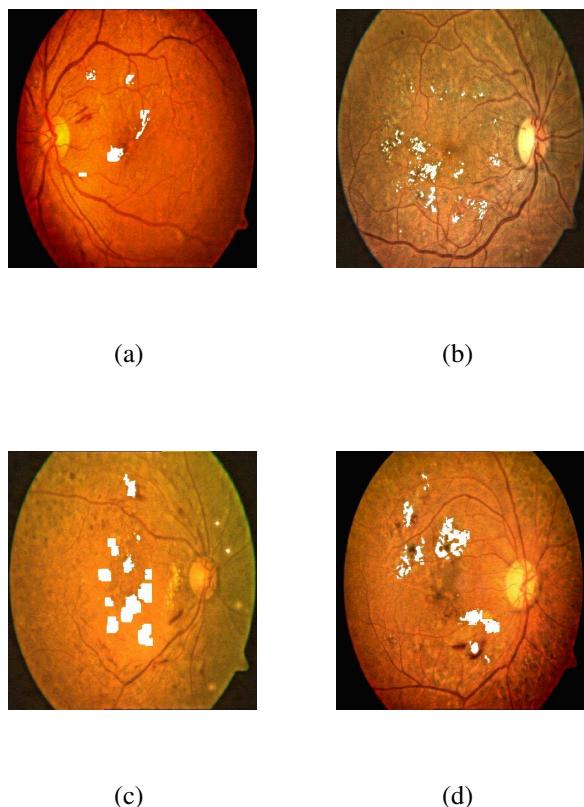


Fig. 6.2: Results of Exudates Recognition, white patch represents Exudates.

Figure 6.2 shows that we are able to find exudates in unhealthy eyes. Figure 6.2-a is saturated retinal image and we are successful in finding the exudates. In figure 6.2-b exudates detection shows that, they occur in tiny clusters. In figure 6.2-c and Figure 6.2-d our algorithm successfully detects the exudates.

6.3 Blood Vessels

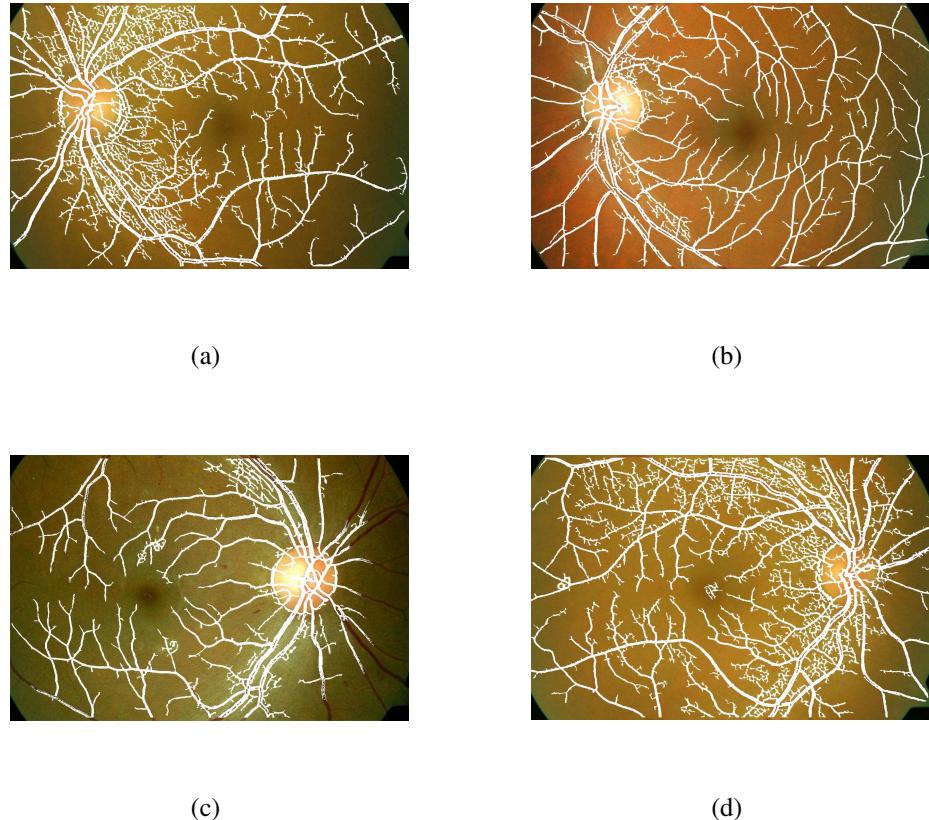


Fig. 6.3: Results of Blood Vessel Recognition, they are shown as overlapped blood vessels

Figure 6.3 shows the overlapped blood vessel retinal image. In figure 6.3-a,b,d algorithm perfectly detects the blood vessel as vascular tree. Blood vessel are marked with white color.

6.4 Haemorrhages

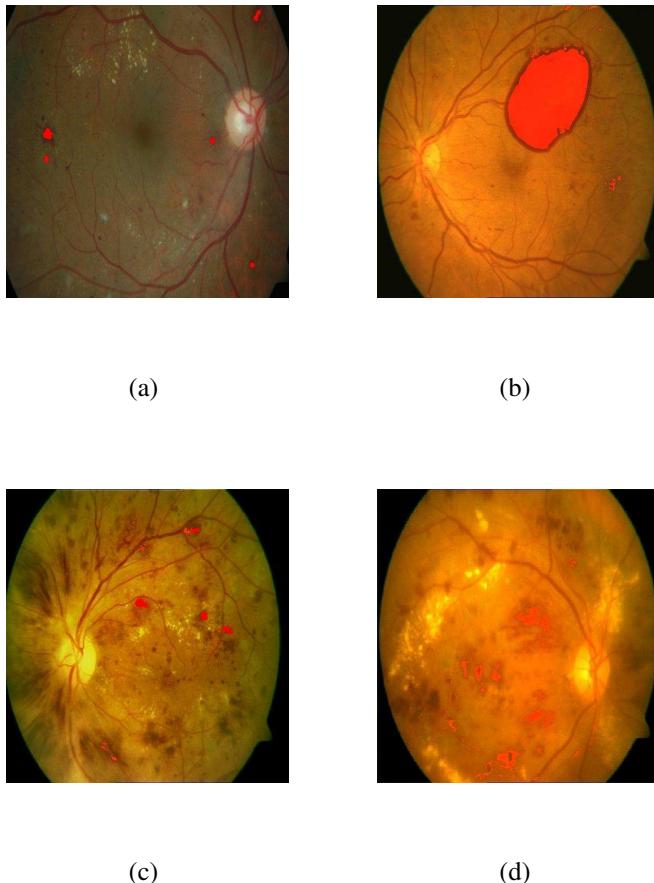


Fig. 6.4: Results of Haemorrhages Recognition, dark patch represents haemorrhages.

Figure 6.4 shows the haemorrhages recognition. In figure 6.4-a haemorrhages occur in tiny clusters and our algorithm is able to capture tiny clusters also. In Figure 6.4-b haemorrhages occur in single cluster as blood clot. In unhealthy retinal images (Figure 6.4-c and 6.4-d) our algorithm perfectly detects the haemorrhages.

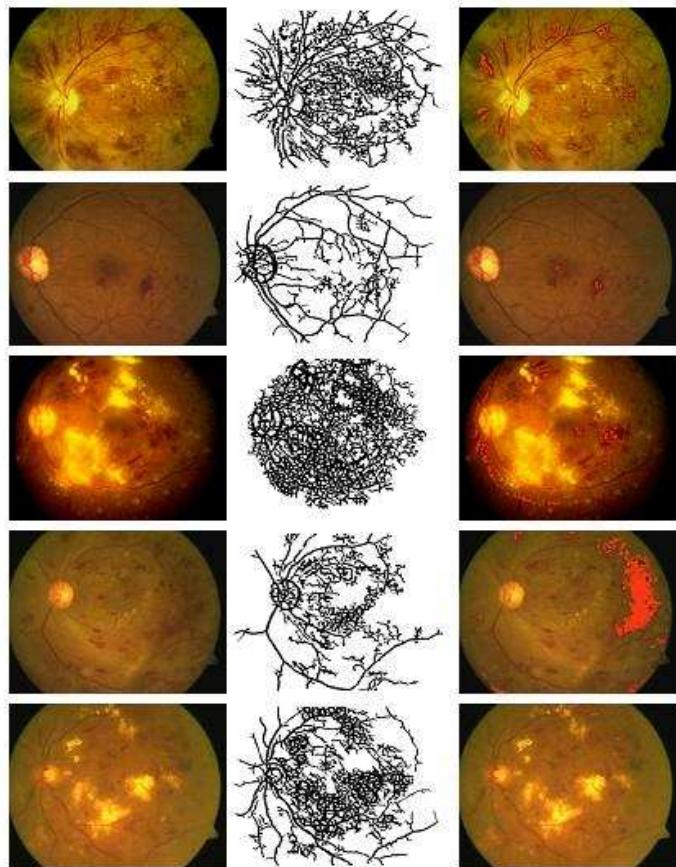


Fig. 6.5: Results of vascular tree and haemorrhages

6.5 About Results

Figure 6.4 shows the results of haemorrhages detection and Figure 6.2 shows the results of exudates detection. We performed optical disk detection on 90 images, including healthy and unhealthy images, out of which it correctly marked optical disk on 85 images with a success rate of 94.5 %. Figure 6.1 shows the results of optical

disk detection. Our algorithm detected the optical disk even in totally unhealthy image (Figure 6.1). Our algorithm is also strong enough to find optical disk in the cases where exudates occur in same size and contrast(Figure 6.2) because of the intersection of blood vessels in optical disk. Table 1 illustrate the confusion matrix for Exudate detection and haemorrhages. We run our algorithm on 90 images and confusion matrix is showing true positive (TP), true negative(TN), false positive(FP) and false negative(FN) at image level. We make the assumption that an image is a TP if our algorithm is able to capture at least one exudate (likewise one haemorraghe cluster) and the image truly had some exudates (likewise haemorrhages). Our assumption is fair enough as on an image level, all exudates occur in almost same contrast and intensity, as do all haemorrhage clusters. Figure 6.4 shows all the unhealthy images and we are able to capture all TP cases. Table 6.1 shows the Confusion matrix along with sensitivity and precision of the algorithm.

Exudates	TP=73	FN=3	FP=3	TN=11	Precision=79%	Sensitivity=96%
Haemorrhages	TP=32	FN=12	FP=3	TN=43	Precision=94%	Sensitivity=73%

Table 6.1: Confusion Matrix for Exudates and Haemorrhages detection, its sensitivity and Precision

6.6 Conclusion

In this work I present algorithms for detecting Optical disk, Exudates and Haemorrhages. We I showed that [1] can be used successfully for detecting blood vessels, which we advanced further to detect haemorrhages. As part of future work we are looking to improve the accuracy of detecting haemorrhages and also looking at working with images formed by a montage of 30 degree views. The main challenge in the automated early detection of Diabetic Retinopathy is to robustly detect exudates

and haemorrhages. In conclusion, this progress work presents good results in identification of important features of retinal image. Further investigation is required to validate the system ability to discriminate the presence or absence of diabetic retinopathy. In the end great thanks to Shakar Netralaya.

CHAPTER 7

Product Development

7.1 Graphical User Interface (GUI)

A graphical user interface (GUI) can be described as a graphical display that contains devices, or components, that enable a user to perform interactive tasks without creating a script or type commands at the command line [14]. These components can be push buttons, menus, toggle buttons, toolbars, checkboxes, radio buttons and sliders etc. Data can also be displayed in graphical form or plots or groups. The user need not know the details of the task. A simple GUI supported by MATLAB with its rich sets of tools is as shown in Figure 11-1.

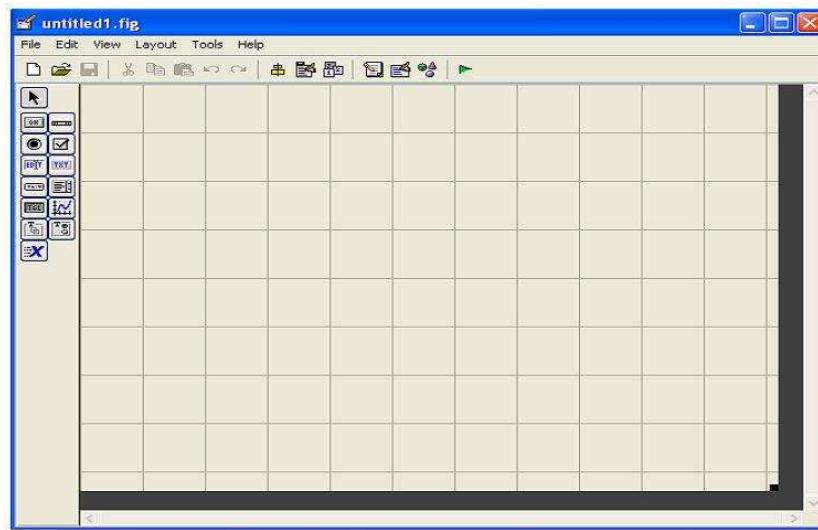


Fig. 7.1: GUI Supported by MATLAB

Creating a GUI using MATLAB Graphical User Interface Development Environment (GUIDE) is divided into two relatively managed and independent tasks, viz:

- 1) GUI Component layout
- 2) GUI Programming

In GUI component layout, the GUIDE enables the user to layout the GUI as required. It involves clicking and dragging of the components from the components palette to the layout area. These components can be aligned, resized, set tab order etc by using other tools accessible from the Layout Editor. Saving this GUI layout generates an M-Files (MATLAB) file which helps to control how the GUI works. This and subsequent activities constitute the GUI Programming tasks. The generated M- file provides code to initialize the GUI when launched and contains a framework for the GUI callbacks; the routines that execute in response to user-generated events such as a mouse click. Adding codes to the callbacks function using the M-file editor enable the GUI perform intended operations. Code design for the software is shown in the figure 11.2.

During my project work I made the software toolbox for the doctors to extract all such features with single click of mouse. I made it in matlab. GUI is shown in figure 11.3.

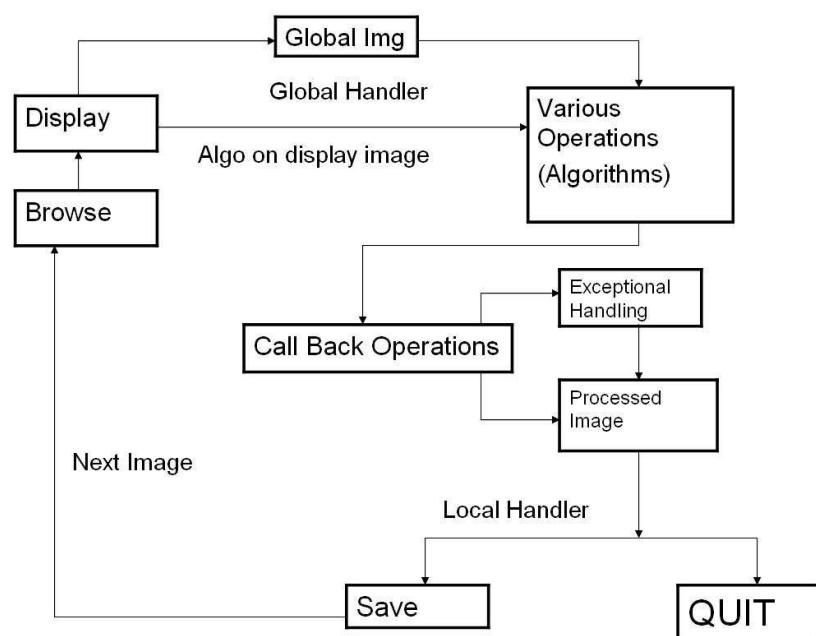


Fig. 7.2: Code design for the toolbox

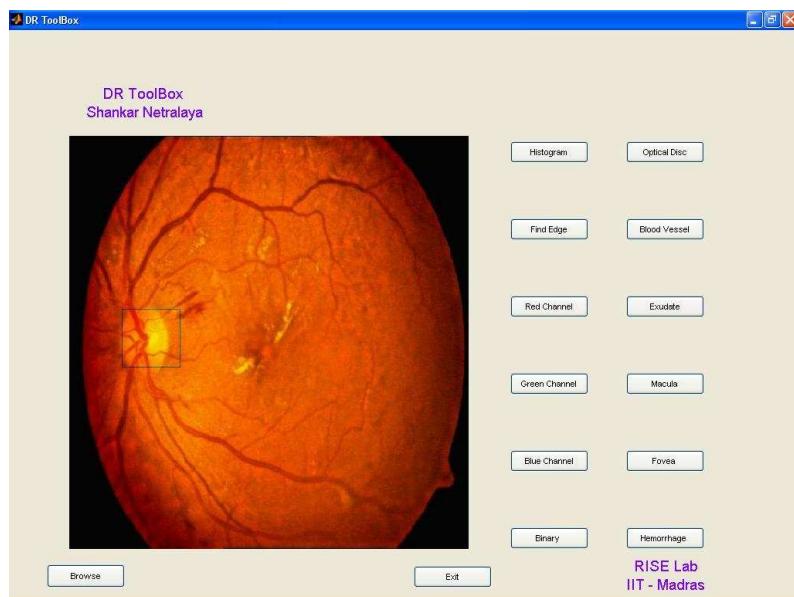


Fig. 7.3: GUI for software DR tool box

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LIST OF PAPERS BASED ON THESIS

Paper Submitted to:

1. Dr B. Ravindran and Gagan Kumar Arora. "Automated Feature Extraction of Retinal Images to Assist in Early Detection of Diabetic Retinopathy." *British Machine Vision Conference 2008*,