CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The eye is an important organ that allows human to observe, react
and adapt to surrounding environments. It also enables to interpret shapes,
colours and dimensions of objects visualized.

1.1.1 Anatomy of Human Eye

Eye contains three major layers, an outer layer sclera in continuous
with cornea, a vascular layer choroid and the neurosensory component retina.
The visible parts of the eye also include the coloured
(blue, green, brown or a mixture of these) iris, and an opening in the iris, the
normally black pupil. A ray of light, after passing through the cornea, which
partially focuses the image, passes through the anterior chamber, the pupil,
 lens, vitreous and is then focused on the retina. The retina is supported by
pigment epithelium, which is normally opaque (Goran and Alistair 2011).

1.1.2 Retina and its Structures

The retina is a unique site where the microcirculation can be
imaged non-invasively providing an opportunity to study the structure and
pathology of human blood circulation (Liew and Wang 2011). Embryologically, retina is part of the central nervous system, readily
accessible to examination and can be investigated with relative ease by both
scientists and clinicians. Moreover, an estimated 80% of all sensory information in human is thought to be of retinal origin, indicating the importance of retinal function for the ability to interact with the outside world (Hildebrand and Fielder 2011).

Light sensitive, multi-layered retina comprises of various significant anatomical structures such as optic disc, macula and blood vessels. Variations in these structures are found to be correlated with pathological changes and provide information on severity or state of various diseases. The retina is the only location where blood vessels can be directly captured non-invasively in vivo. Optic Disc (OD) is a structure in retina, which is seen as a pale, round or slightly vertical oval disc. A distinguishing feature of the OD is that, it is the region of convergence for the blood vessel network. The change in the shape, colour or depth of OD is an indicator of various ophthalmic pathologies (Patton et al 2006).

Macula appears on the fundus photograph as central dark region because of the presence of pigments and dense retinal nerve fibers without rod photoreceptors. The fovea is deep-red or red-brown in colour and lies at the centre of the macula. It is the part of the retina that is used for fine vision. It is at a distance of about two times the optic disc diameter temporal to the optic disc (Li and Chutatape 2004).

Retinal blood vessels are important structures in retinal images. The information obtained from the examination of retinal blood vessels offers many useful parameters for the diagnosis or evaluation of ocular or systemic diseases. The retinal vasculature is composed of arteries and veins that are visible within the retinal image. The vessels have less reflectance compared to other retinal surfaces and appear darker relative to the background (Abramoff et al 2010).
1.1.3 Retinal Abnormalities

The retinal vasculature is a unique site where the microcirculatory vessels are arrayed in a two-dimensional plane amenable to non-invasive high-resolution photography and subsequent in-depth analysis. The microcirculation represents the bulk of the circulatory system, and its role in vascular pathology is poorly understood. Recent population-based and epidemiological studies have documented the subtle retinal vascular changes that occur in metabolic disorders such as diabetes, hypertension, obesity and metabolic syndrome, providing new understanding of the microvascular involvement in these disorders. It has now become evident that these retinal vascular changes might be markers of early, pre-clinical stages of these metabolic disorders and may predict their clinical onset (Liew and Wang 2011).

The three entities namely neovascularisation, collateralization and shunt formation form the major anatomical change with blood vessels. Each has a different appearance, different aetiology and prognosis. In retinal neovascularisation, new vessels originate from the pre-existing retinal vascular bed. They are located either within or adjacent to the retina, in areas where vessels are not normally present. Retinal neovascularisation usually appears most often at the disc and near the larger retinal veins. But they may develop from any point in the retinal vascular bed, and grow either superficially towards the vitreous, or downwards beneath the retina. Early neovascularisation may appear as tufts of irregular or fine vessels on the retinal surface.

Retinal collaterals are vessels which develop within the framework of the existing retinal vascular network. Collaterals originate from the retinal capillary bed, join obstructed to non-obstructed adjacent vessels, or by-pass obstructions in a single vessel.
Vascular shunts are arteriovenous communications, congenital or developmental, in which blood passes directly from artery to vein without going through the normal capillary bed. Flow in these vessels is usually rapid, but may be slow if the shunt is fed by a vessel with a reduced flow (Abramoff et al 2010).

Malfunction of the blood retinal barrier causes early diabetic retinopathy. Diabetic Retinopathy refers to an ocular manifestation of systemic disease, such as single microaneurysm, retinal haemorrhage, soft exudates, cotton-wool spots, venular beading and new vessel formation. Exudates are lipid and lipoprotein deposits that appear as white or yellow patches in retinal images. They are often seen as individual clusters or as large rings around leaking capillaries. The detection of exudates contributes significantly in the mass screening of diabetic retinopathy. There are complicated relationships found among retinopathy, hypertension, diabetes and obesity. Hypertension is a significant risk factor for retinal abnormalities. High blood pressure is found to be associated with retinal changes such as focal arteriolar narrowing, arteriovenous nicking and retinopathy. Most tissues are pervaded by blood vessels and lymphatic vessels.

Nutrition, respiration and other metabolic activities rely on proper local vascular supply. These arteries are affected by arteritis, an obstructive disease. Hypertensive sclerosis is associated with vascular hypertension which involves diminution of arterial blood supply. This leads to ischemia resulting in atrophy and degeneration. Such diseases affect the retina resulting in retinal arterial obstruction. Histopathological studies have demonstrated that these retinal signs reflect vascular damage from aging, hypertension, and other processes.

Pathological studies have further suggested that retinal signs are closely related to microvascular pathologies of other organs. In persons with
hypertension, the retinal arteriole narrows and its media thicken and develop sclerosis. Thus there are suggestive anatomical, physiological and pathological reasons to believe that changes in the retinal microvasculature may be useful indicators of the vascular structural pathologies of the coronary micro-circulation, and the non-invasive retinal assessment may assist heart diseases risk stratification.

Retinal vessel is explored in clinical settings as a risk stratification tool. The vessel appearance is an important indicator for many diagnoses, which includes diabetes, hypertension, and arteriosclerosis. Knowledge on blood vessel location can further be used to reduce the number of false positives in microaneurysm and haemorrhage detection. Artery–vein crossings and patterns of small vessels can also serve as diagnostic indicators. Veins and arteries have many observable features which includes the diameter, colour, tortuosity (relative curvature), and opacity (reflectivity). 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. Blood vessels are also used as landmarks for registration of retinal images of a same patient gathered from different sources (Hoover 2000).

1.2 IMAGE PROCESSING IN MEDICINE

Medical imaging is one of the fastest growing areas both in the clinical setting in hospitals and in research and development. It plays a central role in the global healthcare system as it contributes to improved patient outcome and cost-efficient healthcare in all major disease entities. More and better research in medical imaging is needed to increase knowledge about disease processes and therapy management with the long-term goal of improving the health. An increased research effort in medical imaging is used
for personalised medicine with individually tailored treatment, more evidence-based decision making within healthcare, less complications during and after surgery and better understanding of the effect of treatments on diseases. Increasing technology leading to the development of digital imaging systems over the past two decades has revolutionised medical imaging. Although digital imaging does not still have the resolution of conventional photography, modern digital imaging systems offer very high-resolution images that are sufficient for most clinical scenarios (Patton et al 2006). In addition, digital imaging provide the advantages of easier storage on media that do not deteriorate in quality with time, transmission over short distances throughout a clinic or over large distances using electronic transfer thereby allowing expert “at-a distance” opinion in large rural communities.

1.3 RETINAL IMAGING

Image processing, analysis and computer vision techniques are increasing in prominence in all fields of medical science. They are pertinent in modern ophthalmology, as it is heavily dependent on visually oriented signs. Over the past decade, the retinal image analyses are widely used in medical community for diagnosing and monitoring the progression of many diseases. As digital imaging and computing power are increasingly developing, the potential to use these technologies in ophthalmology also have improved.

Developments in image processing relevant to ophthalmology over the past fifteen years include the progress made towards developing automated diagnostic systems for conditions, such as diabetic retinopathy, age-related macular degeneration and retinopathy of prematurity. These diagnostic systems offer the potential to be used in large-scale screening programs, with the potential for significant resource savings, as well as being free from observer bias and fatigue (Patton et al 2006).
Retinal imaging is a foundation of clinical care and management of patients with retinal as well as systemic diseases. The ability to image the retina and develop techniques for analyzing the images is of great interest. As this requires the retina to see the outside world, the involved ocular structures have to be optically transparent for image formation. Thus, with proper techniques, the retina is made visible from the outside, making the retinal tissue, and thereby brain tissue, accessible for imaging noninvasively (Abramoff et al 2010).

The use of retinal digital image analysis has become increasingly common and offers sophisticated techniques to analyse different aspects of retinal vascular topography, such as the length and widths of retinal microvessels. Ophthalmologists conventionally imaged the eye using ophthalmoscopes in determining the health conditions of the retina. But abnormalities are often restrained and may be missed by visual observation or conventional retinal image inspection.

Fundus imaging is the most established way of retinal imaging. Until recently, fundus image analysis is the only source of quantitative indices reflecting retinal morphology. The various techniques of fundus imaging include fundus photography (including so-called red-free photography), colour fundus photography, stereo fundus photography, hyperspectral imaging, Scanning Laser Ophthalmoscopy (SLO), adaptive optics SLO, fluorescein angiography and indocyanine angiography (Abramoff et al 2010).

In fundus photography, the retinal images are acquired with a medical device called fundus camera, consisting of a powerful digital camera with a dedicated optics. A 2-D representation of the 3-D retinal semi-transparent tissues projected onto the imaging plane is obtained using reflected light of a specific waveband. The image intensities in this 2-D image represent the amount of reflected quantity of light.
Figure 1.1 (a) - (d) Representative normal retinal fundus images (DRIVE database, Neimeijer et al 2004)

In colour fundus photography, image intensities represent the amount of reflected red, green and blue wavebands as determined by the spectral sensitivity of the sensor. In stereo fundus photography, image intensities represent the amount of reflected light from two or more different view angles for depth resolution. In hyperspectral imaging, image intensities represent the amount of reflected light of multiple specific wavelength bands.
In SLO, image intensities represent the amount of reflected single wavelength laser light obtained in a time sequence. In adaptive optics SLO, image intensities represent the amount of reflected laser light optically corrected by modelling the aberrations in its wavefront. In fluorescein angiography and indocyanine angiography, image intensities represent the amounts of emitted photons from the fluorescein or indocyanine green fluorophore that is injected into the subject’s circulation (Abramoff et al 2010).

Figure 1.2  (a) - (d) Representative abnormal retinal fundus images
(Aria online)
Representative normal and abnormal retinal fundus images are shown in Figure 1.1 and Figure 1.2 respectively. Since the retina is normally not illuminated internally, external illumination projected into the eye as well as the light reflected by the retina must traverse the pupillary plane. Thus the size of the pupil, usually between 2 to 8 mm in diameter, has always been the primary technical challenge in fundus imaging. Fundus imaging is complicated by the fact that the illumination and imaging beams cannot overlap.

The careful clinical examination of the retinal vasculature provides information on hypertension-related tissue damage results in retinal arteriolar changes. These changes include microaneurysms, haemorrhages, soft exudates, cotton wool spots, focal arteriolar narrowing, arterio-venous nicking and generalized arteriolar narrowing. Grading the disease severity of diabetic retinopathy is currently in use for research purposes. The five stages are none, mild, moderate, severe and proliferative. Hence, analysis of healthy vasculature and their deformation due to different abnormal conditions play an important role in the detection and diagnosis of many eye diseases for ophthalmologists (Xu and Luo 2010).

1.4 AUTOMATIC DETECTION OF RETINAL STRUCTURES

Automatic detection of structures in retinal images is necessary and in particular the detection of blood vessels is most important. The characteristic features of retinal blood vessels are essential in automated diagnosis, quantification of the severity of disease and in the assessment of progression of therapy. The measurement of the retinal vessels is of primary interest in the diagnosis and treatment of a number of systemic and ophthalmologic conditions. The manual extraction and measurement is tedious and much more difficult since the blood vessels in a retinal image are complex and have low contrast. As a result, reliable and automatic methods for detection of vessels in retinal images are needed (Ben et al 2011).
Detection of the vessels leads to the identification of anatomy of interior of the eye by detecting optical nerves, the fovea, lesions, and any other existent anomalies. Sometimes, retinal blood vessel must be excluded for easy detection of pathological lesions like exudates or microaneurysms. Automatic detection and analysis of vasculature can also assist with repeatable quantification of vascular features, lesion detection, establishing links between retinal and cerebral vasculature, and modelling the variability of clinical judgement (Lupascu et al 2010).

For investigations and monitoring the progression of many diseases, proper segmentation of retinal blood vessels is crucial. Combined efforts from information technology and medicine community produce different methods for the detection and segmentation of retinal blood vessels and enhance the potential for automated diagnosis (Amin 2011).

1.5 PRE-PROCESSING OF RETINAL IMAGES

Retinal images acquired with a digital fundus camera captures the illumination reflected from the retinal surface. Despite controlled conditions, many images suffer from non-uniform illumination due to several factors which include the curved surface of the retina, pupil dilation (highly variable among patients) and presence of diseases. The curved retinal surface and the geometrical configuration of the light source and camera lead to a poorly illuminated peripheral part of the retina with respect to the central part. Other factors which affect the image quality include patient movement, poor focus, bad positioning, reflections, disease opacity and inadequate illumination. These factors and artifacts will cause a significant proportion of images to be of such poor quality so as to interfere with analysis. Approximately, 10% of retinal images artifacts are significant enough to impede human grading (Teng et al 2002).
Image can be expressed in terms of its illumination and reflectance components. Most image processing algorithms presume that the illumination variation is uniform or lighting is controlled. The illumination component of an image varies a great deal, often more than the reflectance component. The edges of objects in the image will be blurred and detection rates commonly drop quickly under this condition. So corrections for uneven illumination are very important for image processing. Collectively these operations are termed image pre-processing. Pre-processing of the fundus data either removes or flags the aforementioned interferences.

The process of compensating for illumination changes requires not only the primary visual cortex, but also the participation of higher level visual areas. So illumination compensation is a very difficult problem. A common approach to overcoming image variations because of changes in the illumination conditions is to use image representations. They are relatively insensitive to these variations such as the edge map of the image, the image filtered with 2D Gabor filters, the first and second derivatives of the gray level image, and nonlinear transform. They compensate changes of illumination to certain degree (Hong Liu 2002).

Contrast enhancement techniques are used widely in image processing. They determine an optimal transformation function relating original gray level and the displayed intensity such that contrast between adjacent structures in an image is manually portrayed. One of the most popular automatic procedures is Histogram Equalization. The histogram of an image represents the relative frequency of occurrence of gray levels within an image. Histogram modelling techniques modify an image so that its histogram has a desired shape. In this technique, the goal is to obtain a uniform histogram for the output image, so that an optimal overall contrast is perceived. However, this introduces undesirable artifacts and noise and is less
effective when the contrast characteristics vary across the image. Adaptive Histogram Equalization (AHE) overcomes this drawback by generating the mapping for each pixel from the histogram in a surrounding window. AHE computes the histogram of a local window created at a given pixel and determines the mapping of that pixel. This provides a local contrast enhancement (Jin et al 2001). AHE does not allow the degree of contrast enhancement to be regulated (Stark 2000).

In image enhancement problems, the conventional linear techniques prove to be inadequate as they cannot cope with the nonlinearities of the image formation model. In addition, they do not take into account the nonlinear nature of the human visual system. Linear filtering techniques tend to blur edges and degrade other fine image details. Filters having good edge and image detail preservation properties are highly desirable for image filtering. Noise smoothing and edge enhancement are inherently conflicting processes. Filtering algorithm should ideally vary from pixel to pixel depending upon the local context. The local conditions are evaluated vaguely in some portions of an image. It is extremely difficult to set the conditions under which a certain filter should be selected. Thus a single filter may not be suitable for filtering of different parts of an image. Therefore, a filtering system should possess the capability of reasoning with unclear and uncertain information. This suggests the use of fuzzy logic for image filtering.

The application of fuzzy techniques in image processing is a promising research field. Fuzzy techniques have already been applied in several domains of image processing (e.g., filtering, interpolation, and morphology), and have numerous practical industrial and medical image processing applications (Verma et al 2011).

Most of the available fuzzy filtering techniques can be divided in two broad categories namely fuzzy-rule-based techniques and adaptive fuzzy
techniques. In fuzzy-rule-based methods, human knowledge expressed in linguistic terms is used. In the second category, many adaptive fuzzy systems are available.

1.6 PROCESSING OF RETINAL IMAGES

Automated segmentation of the vessels (arterioles and venules) within digital images of the fundus is the next step in the analysis of retinal vascular system. It is further used to study the correlation between the microvascular system and health. There are various approaches to segment blood vessels that have been identified. These approaches are based on edge detection, matched filter, thresholding, tracking, mathematical morphology and classifier techniques (Hoover et al 2000, Cemil and Francis 2003, Vijayakumari and Suriyanarayanan 2012).

The segmentation is a challenging task due to the poor contrast and widely varying range of vessel widths. A variety of structures, such as the retina boundary, macula, OD and pathologies produce stronger responses at the boundaries. There is also a bright strip running down the centre of some vessels called the central reflex causing a complicated intensity cross-section, which makes it harder to distinguish vessels. This enables the requirement of thresholding methods.

Thresholding is a popular method for image segmentation. It is widely used in many image processing applications such as optical character recognition, infrared gait recognition, automatic target recognition, detection of video changes and medical image applications (Seyyed 2012). From a grayscale image, bi-level thresholding can be used to create binary images, while multi-level thresholding determines multiple thresholds which divide the pixels into multiple groups.
The bi-level and multi-level thresholding methods can be classified into parametric and nonparametric approaches. A great number of thresholding methods belonging to parametric and non-parametric approaches have been proposed in order to perform bi-level thresholding (Sezgin and Sankur 2004; Lievers and Pilkey 2004; Chu et al 2004; Gonzales-Baron and Butler 2006). For parametric approaches, the gray level distribution of each group is assumed to obey a Gaussian distribution. Then, these approaches attempt to find an estimate of the parameters following Gaussian distribution that best fits the histogram. Non-parametric approaches find the thresholds that separate the gray level regions of an image based on some discriminating criteria optimizing an objective function such as the between-class variance (Otsu 1979) and entropy using Kapur’s function (Kapur et al 1985).

Kapur and Otsu methods are the two popular methods commonly employed in thresholding techniques. Otsu’s method is one of the best threshold based methods and its basic principle is to split the image’s pixels into two classes, and confirms the best threshold value through the variance maximum value between the two classes. This method has proved to be one of the best thresholding techniques for uniformity and shape measures. However, the computation time grows exponentially with the number of thresholds due to its exhaustive searching strategy, which would limit the multi-level thresholding applications (Wang and Zhen 2006).

Recent developments of statistical mechanics based on a concept of non-extensive entropy, also called Tsallis entropy, have intensified the interest of investigating a possible extension of Shannon’s entropy to information theory. This interest appears mainly due to similarities between Shannon and Boltzmann entropy functions. The Tsallis entropy is a new proposal in order to generalize the Boltzmann traditional entropy to non-
extensive physical systems (Satya and Kayalvizhi 2010). Simple threshold methods have limitations, as it is confounded by pathology and unequal illumination. The variability is countered by enhancing the pixels on a regional basis.

1.6.1 Multi-Level Thresholding

Multi-level thresholding is one of the most important image segmentation techniques, which converts the gray-scale image to an indexed image by decreasing the number of intensity levels (Marwan and Eswaran 2012). Multi-level thresholding divides the pixels into several classes. The pixels belonging to the same class have gray levels within a specific range defined by more than two thresholds. Otsu’s criterion selects optimal thresholds by maximizing the between class variance. However, inefficient formulation of between class variance makes the method quite time-consuming in multi-level thresholds selection. The computation time increases sharply when the number of thresholds increases, so the traditional exhaustive method do not hold good. Therefore, use of intelligence optimization methods to find the best thresholds quickly is essential (Zhang et al 2011).

Tsallis entropy is non-extensive in such a way that for a statistical dependent system. It is extended to the fields of image processing, because of the presence of the correlation between pixels of the same object in a given image. The correlations can be regarded as the long-range correlations that present pixels strongly correlated in luminance levels and space fulfilling (Zhang et al 2011).
1.6.2 Optimization Based Analysis

Recently, evolutionary algorithms such as Genetic Algorithm (GA), Differential Evolutions, Tabu Search, Particle Swarm Optimization (PSO) and ant colony optimization have found wide spread applications in all the fields.

PSO is an evolutionary computation technique developed by Kennedy and Eberhart (1995) which is based on bird flocking and fish schooling. PSO is a meta–heuristic technique as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. PSO has been proved to be one of the most promising algorithms for many intricate problems in engineering and sciences. Its simplicity and faster convergence make it an attractive algorithm to employ. The population is called swarm and the individuals are termed as particles. The word ‘swarm’ is inspired from jagged movement of particles in the problem region. The particles are assumed to be mass-less and volume-less (Baijal et al 2011). A novel bacterial-derivative based algorithm that exploits the foraging behaviour of bacteria to collectively detect edges in an image has developed (Passino 2002, Liu and Passino 2002).

Bacterial Foraging Optimization (BFO) Algorithm proposed by Passino (2002) belongs to the family of nature – inspired optimization algorithms. Applying a group foraging strategy with swarms using Escherichia. Coli (E. Coli) bacteria in multi-optimal function is the key idea of this algorithm. Bacteria search for nutrients in a manner to maximize energy obtained per unit time. Nutrients in this algorithm correspond to the edge pixels. Bacteria move by either tumbling or swimming. In the classical approach, the direction of movement is decided randomly while tumbling and every direction is equally preferred (Verma et al 2011). The process, in which a bacterium moves by taking small steps while searching for nutrients, is
called chemotaxis and key idea for BFO is mimicking chemotactic movement of virtual bacteria in the problem search space (Das et al 2009). Individual bacterium also communicates with others by sending signals. A bacterium takes foraging decisions after considering two previous factors. Bacterial foraging optimization algorithm has already been applied in the optimal control engineering, transmission loss reduction (Tripathy et al 2007), machine learning (Kim and Cho 2005), active power filter design (Mishra and Bhende 2007) and colour image enhancement (Hanmandlu et al 2009). A comparative study on the performance various meta-heuristic techniques for multi-level thresholding problem has been recently attempted (Kamal et al 2010).

1.7 FEATURE EXTRACTION OF RETINAL IMAGES

Feature extraction methodologies analyze objects and images to extract the most prominent features that are representative of the various classes of objects (Vasantha et al 2010). The effectiveness of the segmentation process directly influences the reliability of the features extracted to represent the vessels. The features are the descriptors which capture different details from the region of interest to represent and distinguish a unique class of images. The features are classified as statistical, geometrical, textural and structural based out of which texture based features are more commonly used. Texture is a property that represents the surface and structure of an image. Texture can be defined as a regular repetition of an element or pattern on a surface. Image textures are complex visual patterns composed of entities or regions with sub-patterns with the characteristics of brightness, colour, shape and size. An image region has a constant texture if a set of its characteristics are constant, slowly changing or approximately periodic. Texture can be regarded as a similarity grouping in an image (Srinivasan and Shobha 2008).
Texture has qualities such as periodicity and scale; it can be described in terms of direction, coarseness, contrast and so on. Different approaches are used to compute texture features. A statistical approach is used in the form of co-occurrence matrices. The Gray level co-occurrence matrix method is one of the most known texture analysis method that estimates image properties related to second-order statistics. The following six textural features coarseness, contrast, directionality, linelikeness, regularity and roughness which correspond to human visual perception and compared them with psychological measurements for human subjects (Tamura et al 1978, Howarth and Stefan 2004).

1.8 SIMILARITY MEASURES

Feature selection is the process of identifying and removing the irrelevant and redundant information. Feature selection prior to learning is useful artificial intelligence methods have been extensively used in medical engineering to primarily perform classification of images and data. These techniques include expert systems, artificial neural networks, genetic algorithms, fuzzy logic and hybrid systems. Validating the performance of vessel segmentation algorithms is not straightforward, primarily due to the difficulty in identifying the ground truth and, establishing what exactly computer segmentation is expected to produce. A secondary issue is the fact that, based on the application, the degree or amount of error that is acceptable varies and a way to quantify the error needs to be developed. For example, topological applications for studies of the vasculature may place a high emphasis on detection of all vascular segments or precision in determining the vessel boundaries, possibly to sub-pixel accuracy.

Similarity measure, which serves to evaluate the spatial correspondence of images, plays a crucial role in this process. Selection of appropriate similarity measure depends on domain of transformation,
modalities involved, and optimization method used in the images. This becomes even more important when matching involves deformations. The size of an image region is used for similarity determination which also influences rigidity of the model. As the region size increases the elasticity of model decreases, and it is more difficult to detect and correct small local differences.

Similarity measures quantify the similarity between segmentations with respect to different criteria and validate the accuracy of segmentation. The image processing literature shows different sets of measures out of which overlap, geometrical and figure of merit measures are often used (Frounchi et al 2011). Overlap measures calculate some kind of overlap between the two segmentations. The intersecting and non-intersecting regions of the two segmentations are identified and different fractions are defined, each measure placing more emphasis on the extent of agreement of some regions of interest. Geometrical measures compare the segmentations in terms of their shape differences capturing variations such as the distance between the boundary pixels of the two segmentations. Pratt’s figure of merit helps in understanding how each edge contributes to the overall quality of the image. It is used to compare the edge detector output and balances the errors that can produce erroneous edge maps, missing valid edge points, failure to localize edge points and classification of noise fluctuations as edge points (Panetta et al 2008).

1.9 PERFORMANCE MEASURES

Segmentation performance can be measured in various ways such as accuracy, sensitivity and specificity (Ginnekena and Romeny 2000). The standard performance measures were computed using validation set which includes True Negative (TN), False positive (FP), True positive (TP) and False Negative (FN). TN corresponds to normal subjects identified as normal
whereas TP corresponds to abnormal subjects identified as abnormal. Similarly FN corresponds to abnormal subjects identified as normal and FP corresponds to normal as abnormal.

Accuracy is the representation of classifier performance in global sense. Sensitivity and specificity are the proportions of abnormal data classified as abnormal, normal data classified as normal respectively. The positive predictive value is the proportion of true positives out of all positive results.

Another important performance metric is the Receiver Operating Characteristic (ROC) analysis (Centor 1991). In medicine, ROC analysis has been extensively used in the evaluation of diagnostic tests. The ROC curve displays diagnostic accuracy expressed in terms of True Positive Rate (TPR) against False Positive Rate (FPR) at all possible threshold values. It is also known as a relative operating characteristic curve, as it compares the two operating characteristics which are TPR and FPR.

1.10 DATABASE

Images from two different publicly available databases are considered for this research which includes Digital Retinal Images for Vessel Extraction (DRIVE) and Aria databases.

The DRIVE consists of 40 colour fundus photographs. The photographs are obtained from a diabetic retinopathy screening program in the Netherlands. Of the 40 images in the database, 7 contain pathology, namely exudates, haemorrhages and pigment epithelium changes (Niemeijer et al 2004).
Aria database was created in 2006, in research collaboration between St. Paul’s Eye Unit, Royal Liverpool University Hospital Trust, Liverpool, UK and the Department of Ophthalmology, Clinical Sciences, University of Liverpool, Liverpool, UK. The database consists of three groups; one has 92 images with age-related macular degeneration, the second group has 59 images with diabetes and a control group consists of 61 images. The ground truth of blood vessels, the optic disc and fovea location is marked by two image analysis experts as the reference standard (Aria online 2006).

1.11 OBJECTIVES OF THE THESIS

The main objective of the thesis is to characterise retinal images as normal and abnormal based on segmented vasculature content, using multilevel threshold and optimization methods. The specific objectives of the thesis are:

- To perform appropriate pre-processing operations on uniform sized retinal images to compensate non uniform illumination,
- To perform contrast enhancement to preserve all useful edge information,
- To extract vascular networks in normal and abnormal retinal images,
- To enhance the performance of multi-level thresholding using optimization based methods,
- To validate segmentation using similarity measures and to extract features and
- To classify the images into normal and abnormal.
1.12 ORGANISATION OF THE THESIS

The work reported in the thesis is organized into 5 Chapters: Chapter 2 discusses a brief review of the literature on pre-processing methods namely Otsu and Tsallis multi-level thresholding methods of detection of blood vessels. Further, Optimization based methods namely PSO and BFO algorithms are used to obtain relevant vasculature information. In addition, various textural features which are used for classifying normal and abnormal images are also discussed. Similarity measures which are used for validations of segmented images are also presented in detail. Chapter 3 describes the methods and protocols explain the detection subjecting to various pre-processing techniques, multithreshold methods, and optimization methods. Texture and Tamura features with similarity measures are also explained. Chapter 4 focuses on the results obtained through the analysis and the conclusions drawn from the analysis are presented in Chapter 5. The scope of future work is discussed in Chapter 6.