CHAPTER 3

LITERATURE SURVEY

3.1 FUNDUS IMAGE PREPROCESSING

Fundus image preprocessing for feature detection mainly aims at the correction of non-uniform luminosity. Improper scene illumination as well as non-ideal acquisition conditions due to for example, misadjusted imaging system can introduce severe distortions into the resulting image. These distortions are usually perceived as smooth intensity variations across the image. With such unevenness, the subsequent image processing operations like image registration, segmentation, or pattern recognition may be complicated; therefore, the correction of illumination inhomogeneities is highly desirable. The goal of illumination correction is to remove uneven illumination of the image caused by sensor defaults, non uniform illumination of the scene, or orientation of the surface. The known illumination correction methods in the literature can be categorized in the following groups: filtering, segmentation based, surface fitting, and other methods (Kubecka et al. 2010).

There are several methods in literature for solving the problem of non uniform illumination in fundus images. In Liu et al. (1997), Luo et al. (2001), Li et al. (2003), and Li et al. (2004), fundus images are divided into smaller sub-blocks, and the blocks are processed instead of the whole image. The idea in this method is that the illumination variation in a small block is lower than that in the whole image. However, there are some problems with this method. For example, adjacent pixels near to the border of two sub-blocks may have very different values in a result image depending on which block the pixels belong to. The problem is due to independently processed sub-blocks where distinct blocks do not take other blocks into account.

Specific methods of illumination correction were proposed in the frame work of retinal image processing and analysis. Simple and fast methods using large-kernel median filter to obtain low-pass correction coefficients were used by Niemann et al. (2006). Foracchia et al. (2005) model the background of a fundus image as a white Gaussian random field and use Mahalanobis distance for background pixel classification. Contrast normalization using high-pass filtering is used in Fleming et al. (2006) as one step of microaneurysm detection procedure. Additive model of non uniform illumination is used in Abdel Razik (2008), together with adaptive histogram equalization.

In Usher et al. (2003), Synthanayothin et al. (1999, 2003) and Osareh (2004), the local contrast enhancement method is used for equalizing uneven illumination in the intensity channel of fundus images. In Philips et al. (1993), Hsu et al. (2001), and Ege et al. (2000), a large mean filter, large median filter, or both are used for estimating the fundus background. Illumination variation in a fundus image can be eliminated by subtracting the background estimation from the original image or by dividing the original image by the background estimation. Few other methods are also presented in the literature. For example, in Wang et al. (2000), the intensity values in dark regions have been increased. Each illumination equalization method has its own advantages and disadvantages, but no technique was found that would completely solve the problem of uneven illumination.

Illumination correction based on background subtraction is one of the widely accepted methods in fundus image preprocessing. Uneven illumination in a fundus image can be corrected by subtracting the background estimation from the original image or by dividing the original image by an estimated background. In this work, the method of luminosity correction used is based on a segmentation of background pixels and subsequent computation of luminosity function is based only on the background image. The main advantage of this approach is that it does not produce any ringing effect.

3.2 OPTIC DISC DETECTION

Automatic detection and localization of optic disc is of paramount importance in all image processing applications with fundus images. Current optic disc detection methods available in the literature can be broadly classified in to intensity-based (Synthonyathin et al. 1999, 2002, Walter and Klein 2001), template-based (Li and Chutatape 2001, 2003, 2004, Lalonde 2001 and Osareh 2002, 2004), shape-based (Barrett et al. 2001 and Abdel Ghafar et al. 2004) and vessel-based (Hoover and Goldbaum 1998, 2003, Foracchia et al. 2004, Lowell et al. 2004, Tobin et al. 2006, Abramoff and Niemeijer 2006, Neiemeijer and Abramoff 2007 and Youssif et al. 2008) approaches. However most of the existing OD detection methods can be classified as given below.

3.2.1 Methods based on Intensity

Many techniques have been proposed in literature to detect the OD, mainly based on its specific round shape and relatively high brightness, as compared to the rest of the fundus image such as Goh et al. (2001), Li and Chutatape (2000, 2003 and 2004) and Walter et al. (2002). The optic disc normally is the brightest region in the retina. Thus, the intensity information can be used to detect the optic disc. Sinthanayothin et al. (1999, 2002) detected the optic disc by locating the region with the highest average intensity variation because normally many dark blood vessels converge at the bright optic disc.

A variance-based OD-detection method is given by Sinthanayothin et al. (1999). This method assumes the appearance of the optic disc as a yellowish region typically occupying approximately one seventh of the entire image. The intensity variance of the image should be at its highest within the optic disc because of relatively rapid variation in intensity values. The reason for this variation is the appearance of dark blood vessels besides bright nerve fibers. The variance-based OD-detection method can be divided into three different steps:

- Local contrast enhancement
- Determination of the variance within a running window
- Determination of the average variance within a running window

This method localizes the optic disc merely by means of its high grey level variation. However no method is suggested for the detection of the contours in this work.

The techniques reported so far, based on luminosity, however fail on images with severe pathologies. This works well, if there are no or only few pathologies like exudates that also appear very bright and are also well contrasted. It simply misses to locate the OD where the optic disc is obscured by hemorrhages or with a dark pigmentation. The present approach based on bitplane decomposition and mathematical morphology is an attempt to address the above problem.

3.2.2 Methods based on Template Matching

Template matching is a classical way to find the target object in an image (Gonzalez and Woods 1993). Li and Chutatape (2001-04) employed Principal Component Analysis(PCA) to extract features of the optic disc. They first manually cut sub-images around the optic disc region from the training images and then used PCA to obtain the “eigen-discs” that describes the “disc-space”. Using a template moving throughout a retinal image, the candidate sub-images were projected onto the disc-space and the candidate sub-image with the smallest reconstruction error was regarded as the optic disc. In their paper Osareh et al. (2002, 2004) proposed to locate the optic disc by using a template matching approach based on a normalized correlation coefficient. The normalization of the colour fundus image is performed by applying histogram specification as described in (Myler and Weeks 1993) on each colour plane (R,G and B).Then the optic disc region from 25 normalized images were averaged to produce a template. Finally they used the normalized correlation coefficient to find the most perfect match between the template and all the candidate sub-images. Lalonde et al. (2001) proposed a Hausdorff-based template matching. They estimate the OD contour using Hausdorff-based matching between detected edges and a circular template. In this the OD detection method is primarily based on pyramidal decomposition. First, a multiresolution processing was employed through pyramidal decomposition. Small bright lesions were eliminated at lower resolutions, which speed up the searching for the optic disc since it reduces the number of false candidates. A confidence value was calculated for all the candidate regions, and then the Canny edge detector (Canny 1986) was applied on the green channel image regions corresponding to the candidate regions to construct a binary edge map. Finally, the Hausdorff distance was used to match the edge map regions to a circular template of various different radii.

It has been reported that this method is not a robust one particularly in images with multiple pathologies and hemorrhages in the vicinity of optic disc.

3.2.3 Methods based on the Largest Object

Walter and Klein (2001) detected the optic disc as the largest and brightest object in the retina by assuming that all bright lesions are much smaller than the size of the optic disc. In this method of OD-localization a threshold is applied to obtain pixels with high intensity values and selects the center of the largest object as the OD-center. The detection of the optic disc is performed on the intensity component from the HSI space. In the intensity image, the optic disc is assumed to be the largest brightest part of the image. A simple threshold is applied to obtain a binary image containing parts of the optic disc and perhaps other bright appearing pathologies like exudates. The largest connected object within the thresholded image is expected to be a part of the optic disc. The center of this object is selected as the center of the optic disc. Here, an area threshold is used to localize the optic disc and the watershed transformation to find its contours. However, shape irregularities due to segmentation errors, particularly in the context of outgoing vessels or in low contrast could not have been eliminated. Also Walter and Klein (2002) uses a similar approach. But the algorithm fails when contrast is too low or when the red channel is saturated.

3.2.4 Methods based on Hough Transform

Barrett et al. (2001) proposes to apply a Hough transform in order to locate the optic disc. The Hough transform technique is able to find geometric shapes in an image. Objects of geometric shapes may be detected by converting the equation of the object into a Hough space parameter equation. For example, a line and a circle can be represented in Hough space by:

$$line:\ xi\cos\theta + yi\sin\theta = \rho \tag{3.1}$$

$$circle:\ (xi - a)^2 + (yi - b)^2 = c^2 \tag{3.2}$$

The line has two parameters in Hough space, the angle θ and length ρ of the line. On the other hand the circle has three parameters in Hough space, the center (a, b) and the radius c of the circle. The optic disc has an approximately circular shape, therefore the Hough transform can be used to detect the optic disc. With the optic disc radius fixed in Hough parameter space, the search for a circular object becomes a two-dimensional problem.

This method finds the circular shape with fixed radius in a thresholded edge image of the fundus. To detect edges of all possible orientations at each pixel in an image compass edge detection with a Sobel kernel is applied. The maximal response of the Sobel kernel for each orientation is retained. On this edge map of the retinal surface a single threshold is applied to obtain a binary edge map. Finally the Hough transform technique is applied to the edge pixels in the edge map to accumulate evidence of circles with fixed radius c in the image. The circle with the highest magnitude of evidence is chosen as the optic disc.

The technique used in Pinz et al. (1998) is again a Hough transform based method to detect the contours of the optic disc. Obviously, some improvements have been made in this, but problems have been stated if the optic disc does not meet the shape conditions (e.g., if it lies on the border of the image) or if contrast is very low.

Tamura and Okamoto (1988) also approaches the problem of OD detection by using an area threshold to locate the optic disc. The contours are detected by means of the Hough transform, i.e., the gradient of the image is calculated, and the best fitting circle is determined. This approach is quite time consuming and it relies on conditions about the shape of the optic disc that are not always met.

Abdel-Ghafar et al. (2004) detected the optic disc using the circular Hough transform (CHT). First the retinal vessels were suppressed using a morphological closing operator. Then the Sobel operator was used to extract the edges in the image. Finally the CHT was applied to the edge map, and the optic disc was identified as the largest circle.

3.2.5 Methods based on the Retinal Vasculature

Since all vessels converge at the optic disc, it is also possible to identify the optic disc by vasculature features. Akita and Kuga (1982) addresses the optic disc localization problem by back tracing the vessels to their origin. This seems to be one of the most attractive ways to localize the optic disc, but it has to rely on vessel detection. It is desirable to separate segmentation tasks in order to avoid an accumulation of segmentation errors and to save computational time (note that the detection of the vascular tree is particularly time consuming). Hoover and Goldbaum (1998, 2003) proposed a fuzzy convergence technique for identifying the optic disc as the convergence point of the retinal vasculature. They describe a combination of two OD-detection methods. The first method calculates a fuzzy convergence image of the vasculature and then applies the hypothesis generation. The second method equalizes the illumination of the image's green plane and then applies the hypothesis generation. First, the retinal vessels were segmented using the matched filter (Chaudhuri et al. 1989) then each vessel branch was modeled using a fuzzy segment to form a convergence image. The intensity of each pixel on the convergence image is equal to how much of the fuzzy segment crossed that pixel. The strongest convergence point was regarded as the retinal vasculature convergence. Goldbaum et al. (1996) and Lowell et al. (2004) localizes the OD by using three optic disc features: (1) the blood vessels convergence at the optic disc; (2) the optic disc appears as a bright disc; (3) the large vessels entering the OD from above and below.

In Tobin et al. (2006), Abramoff and Niemeijer (2006) and Neiemeijer and Abramoff (2007), the optic disc was located using vasculature-related features: (1) probability distributions describing the luminance across the retina; (2) the density of the vasculature; (3) average thickness of the vasculature; (4) average orientation of the vasculature. Tobin et al. (2006) located the optic disc using a Bayesian classifier (Duda et al. 2001) trained using fifty images. Abràmoff and Niemeijer (2006, 2007) used the KNN regression (Duda et al. 2001) trained using hundreds of images. In Foracchia et al. (2004) and Youssif et al. (2008) the optic disc was located based on the fact that the retinal vasculature originates from the optic disc following a similar directional pattern in all retinal images. Foracchia et al. (2004) located the optic disc using a geometrical model of the retinal vessels structure. First, the main vessels originating from the optic disc were geometrically modeled using two parabolas, enabling the center of the optic disc to be located as the common vertex of the two parabolas. In Youssif et al. (2008) the optic disc is located using a proposed vessel direction matched filter. First, the retinal vessels were segmented using a 2-D Gaussian matched filter. Then the same segmentation algorithm was used to obtain a map of the directions of the vessels of the segmented retinal vessels. The segmented vessels were then thinned to represent the candidate centers of the optic discs. They then measured the difference between the proposed vessel direction matched filter and the directions of vessels at the surrounding area of each of the candidate center of the optic disc. The center of the optic disc center is the candidate with the minimum difference.

3.2.6 Miscellaneous Methods

The approach in Mendels et al. (1999) uses morphological filtering techniques and active contours are used to find the boundary of the optic disc. Shijian Lu et al. (2010) demonstrates that optic disc can be detected by a *Savitzky-Golay* smoothing procedure followed by the global thresholding of the difference between the retinal image and the estimated background surface. Although an average detection accuracy of 96.91% is claimed by the proposed method , it is computationally intensive and suffers from a number of limitations. First, it cannot handle retinal images with a relatively dark OD. Second, it extracts the OD through global thresholding where the OD may be completely separated into several components by the retinal blood vessels. Third, it cannot differentiate the OD and some circular bright retinal lesions. Finally, the 84.37% segmentation accuracy is too low for a robust method.

Frank ter Har (2005) describes some novel methods of optic disc detection.

A method based on the binary vasculature with the Hough transform is proposed. The optic disc is often a bright circular shape at the convergence of the vasculature. This method assumes that the OD-center lies close to a vessel of the vasculature. The Hough transform is used to determine the size and location of the optic disc. However, here the Hough transform is only applied on and close to the vasculature. In order to determine the potential OD-locations the segmentation of the vasculature is required. On the vessel probability map of Niemeijer et al. (2004) a threshold ($t = 0.5$) is applied to obtain a binary vessel segmentation. Since there is not a vessel exactly at the center of the optic disc the vasculature is dilated with a square shaped 5×5 kernel. Note that the dilation increases the amount of potential OD locations. The Hough transform probes for strong intensity changes. However, the intensity changes from vessel to retinal background are often larger than the intensity changes from optic disc to retinal background. Placing a circle between vessels can result in a higher Hough transform output, than placing the same circle around the actual optic disc. To ensure the Hough transform not to fit on vessels, the intensity changes of the dilated vasculature pixels are not taken into account.

Another method based on fuzzy convergence with the Hough transform is proposed by the same author. The optic disc is often a bright circular shape at the convergence of the vasculature. The result of fuzzy convergence often results in an image in which the optic disc is one of the highest convergence regions. However the hypothesis generation assumes that the largest region is the optic disc or draws no conclusion about the location of the optic disc. In this method the brightest p percent ($p = 0.35$) of the convergence image is selected. Dilation with a square structuring element of 6 × 6 is performed on these brightest pixels to overcome gaps created by small vessels. The resulting pixels are used as potential OD-centers. On these potential OD-centers the Hough transform is applied with different radii. This way a discrimination of smaller regions of convergence from larger regions of convergence is avoided. This method takes the following retina properties into account: The Hough transform looks for a circle on edges for which the intensity increases toward the circle's center, while the fuzzy convergence method takes the vesselness into account.

Few other schemes for OD detection by Frank ter Har (2005) are also described in the literature. These methods are based on pyramidal decomposition of the vasculature and the green plane, the branch with the most vessels, path convergence with the Hough transform and vasculature fitting on a directional model. He observed that the method which performs best is the vasculature fitting on a directional model. This method is found to be better than all other evaluated methods.

The vasculature fitting on a directional model is described by Frank ter Har (2005) as follows. This OD-detection method uses the orientation of the vasculature, which can be extracted from a fundus image to locate the optic disk. The idea to use vessel orientations to locate the optic disc was first introduced by Ruggeri et al. (2003). They used a mathematical model that described the expected vessel orientation for each point in an image with respect to the optic disc. Then the sum of squared differences was used to compare the orientations of a new vasculature with the mathematical model, resulting in the OD-location.

Starting at the optic disc, the vessels follow more or less the same divergence pattern in all retinal images. Four or five main vessels move in a vertical direction out of the optic nerve. Two of these main vessels curve away towards the macula and make sure that that part of the retina is supplied with blood, while the other main vessels diverge toward other parts of the retina. Branches of the main vessels are spread around the entire retina. Branches coming out of the two main vessels near the macula converge toward the macula. The automatic OD-detection method here captures these properties in a directional model.

Some of the algorithms discussed above will locate only the centre of optic disc, while another category of algorithms will locate it and encircle the area corresponding to optic disc. Very few algorithms are available in the literature for both localization and extraction of the optic disc pixels. The algorithms used today for optic disc localization and extraction are either computationally intensive or less accurate, particularly in the presence of anomalies like exudates in the human retina. Moreover the methods currently available for OD detection largely depends on a prior knowledge of other retinal features like vasculature for the accurate detection of OD. In an attempt to address the above issues, an optic disc localization and extraction based on bitplane decomposition and mathematical morphology is proposed in this research.

3.3 DETECTION OF MACULA AND FOVEA

Macula is the major landmark for retinal fundus image registration and is indispensible for the quick understanding of retinal images. Macula is a highly sensitive region of the retina responsible for the detailed central vision. The fovea is the macula center, which is the retina central zone (about 2mm of diameter). Macula and fovea segmentations are relatively less studied.There are two groups of macula segmentation/detection schemes: (1) template-based (Sinthonyathin et al. 1999, 2002) and (2) vasculature-based (Li and Chutatape 2003, 2004 and Niemeijer et al. 2007).

3.3.1 Template based Methods

The fovea appears as a large dark disc and is centered at the image approximately 2.5 times the optic disc diameter from the optic disc. This motivated Sinthanayothin et al. (1999, 2002) to detect the macular centre by using a template matching approach. The template was defined as 2D Gaussian to approximate a typical fovea. Equation 3.3 describes this template.

$$g(i,j) = 128\left[1 - exp\left(\frac{-(\mathrm{i}^2 + \mathrm{j}^2)}{2\sigma^2}\right)\right] \tag{3.3}$$

The location with the maximum correlation coefficient between the template and the image was chosen as the location of the fovea, restricted to the condition that it should be at an acceptable distance from the optic disc. They reported an accuracy of 80.4% on 100 images.

3.3.2 Vasculature based Methods

The fovea are supposed to be in the middle of the two large vessel trunks emanating from the optic disc and it can be detected using vasculature-related features (Li and Chutatape 2003, 2004 and Niemeijer et al. 2007). In Li and Chutatape (2003, 2004), the main courses of the blood vessels are extracted using a modified Active Shape Model (ASM). The ASM (Cootes et al 1995) consists of building a point distribution model (PDM) from a training set and an iterative searching procedure to locate instances of shapes in a new image. The main courses of blood vessels were described using 30 landmark points. They used eight landmark sets to train the PDM then the fovea was located by fitting the main courses on a parabola. Niemeijer and Abràmoff (2007) proposed a PDM to detect the optic disc, vessel arch, and the fovea together. This PDM was defined by 16 points. This PDM was derived from a set of 500 training cases.

Vidyasagar et al. (2007) reported that macula can be detected simply by masking out the vessel pixels using the result of blood vessel detection and finding the darkest cluster of pixels near the optic disc. However this requires a prior knowledge of optic disc and blood vessels in the retina.

Li et al. (2004) presented a model based approach in which a snake was used to extract the vascular tree based on the location of the optic disk. Then, the information from the snake was used to find the macula center. Mari˜no et al. (2008) have introduced an approach to detect macula and fovea. But unfortunately, like most of the existing methods, this also requires a prior knowledge of optic disc and the retinal vasculature and hence it is computationally complex and time consuming. The approach by Tobin et al. (2007) for macula localization also relies on the segmented retinal blood vessels and hence the computational load is high.

Unfortunately most of the algorithms used today for macula localization or fovea detection are computationally intensive, requires prior information on retinal vasculature or OD, and are less accurate, particularly in the presence of pathologies in the human retina. In order to address the above draw backs, a novel approach based on bitplane slicing and morphological image processing for macula detection and extraction is proposed in this work.

3.4 SEGMENTATION OF RETINAL BLOOD VESSELS

Retinal blood vessel segmentation is the key in automatic screening systems for retinal abnormalities. Several studies were carried out on the segmentation of blood vessels in general, however only a small number of them were associated with retinal blood vessels. Tramontan et al. (2011) describe a semi-automated system that measures the arteries to veins ratio (AVR) which seems to be a very early indication of the likelihood of developing retinopathy. Also, the tortuosity of the vessels is correlated with the abnormal blood pressure which appears to be an early index of various other retinopathies (Stanton et al. 1995, Grisan et al. 2008).

Some of the methods typically utilize classical edge detectors such as Sobel, Gaussian and Laplacian of Gaussian (Gang et al. 2002, Lei et al. 2001, Quek et al. 2002, Zana and Klein 2001 and Zhou et al. 1994). However, these edge detectors are not able to detect the vessel structures accurately since vessels in retinal fundus images usually have poor local contrast where the edges are rarely sharp and distinct enough to be readily identified. Vessel segmentation is a specific line detection problem and hence many vessel extraction algorithms originated from the line detection techniques. There are two steps in vessel segmentation: vessel enhancement and vessel classification. Automated segmentation of vasculature is a difficult task particularly due to the fact that the width of retinal vessels can vary from very large to very small and the local intensity contrast of vessels may be weak and unstable.

In the process of vessel enhancement, vessel contrasts are enhanced and noise is suppressed. Vessel enhancement is usually implemented locally by using a window centered at the pixel to be enhanced. This class of techniques originated from the classical image processing problem: finding parallel edges and ridges in an image. Line detectors include high-pass filters, band-pass filters, and mathematical morphology filters. There are two basic line models, the bar-shaped model that is used to find parallel edges and the Gaussian-shaped model used to find ridges. After vessel enhancement, the pixels are classified as vessel pixels and non-vessel pixels. Methods for classification can be summarized as supervised methods and un-supervised methods. Unsupervised methods are much more popular in vessel segmentation. The easiest way for vessel segmentation is to find an optimal threshold to classify the pixels according to their intensities. The classification results can be improved at a price of more computation. However, current vessel segmentation methods fall under the following categories:

3.4.1 Pixel based Methods

The simplest methods of segmenting the vasculature of the eye rely on the observation that when the retina is photographed, and the green channel extracted from that image, the blood vessels appear to be darker than their surrounds. Simply stating that any pixel darker than some threshold is part of a blood vessel is the naive first approach, which will detect some blood vessels, but on the overall will perform extremely weak. To improve this approach, the threshold is not based on some fixed global value, but the average brightness across the image is taken, and those pixels whose intensity is greater than the threshold from the overall average image intensity are deemed to be vessel. This method again performs poorly, as light levels and contrast will vary across the image due to initial lighting conditions, pathologies within the eye and artifacts related to the technique used to take the photograph, as well as the skill of the camera operator. Using some local intensity average based on a neighborhood of pixels surrounding the one in question and then performing the thresholding operation on that pixel can give better results, but these are still less than ideal. However, when combined with further filtering and line detection to extract only features that have the characteristics of vessels, very good results can be obtained. Jiang and Mojon (2003) managed up to 92.12% accuracy for certain metrics according to a study by Niemeijer et al. (2004).

3.4.2 Edge Detection based Methods

A step up from pixel methods based solely on the intensity at a given point is edge detection algorithms. These use standard image-processing techniques such as the Canny, Sobel and Laplacian operators to extract lines from within the image. While they are appropriate for many applications in computer vision, generic edge detection operators are less appropriate for the task of retinal vessel segmentation due to the fact that most vessels have boundaries that are blurred or indistinct, and very fine vessels are often only two or three pixels wide, which are not picked up, instead being seen as part of the background.

In addition to this, the edge detection operations do not distinguish between vasculature and pathologies within the eye. They can falsely classify the optic disc as the border of a blood vessel due to the contrast between the optic disc and the remainder of the retina, and will pick up on lesions, haemorrages and any other areas of contrast within the image. This makes them unsuited to direct vessel extraction, however the Sobel operator is used to refine the results of the adaptive localized thresholding approach used by Jiang and Mojon (2003). Can et al. (1999) also use custom-made templates which resemble Prewitt operators to detect vessel boundaries and guide their exploratory algorithm. All the exploratory algorithms require some form of guidance, and a form of edge detection can provide one way of guiding the tracing of the vessel, so edge detection can play a part in an effective method of image segmentation despite the fact that in isolation they are not adequate for the entire task at hand.

3.4.3 Exploratory Algorithms

Can et al. (1999) presented a tracking-based method to trace retinal vasculature in live retinal video angiograms and extract features such as intersections and crossovers. Exploratory algorithms, as demonstrated by Can et al. in 1999 and later by Grisan et al. in 2004 begin by sampling a large number of points within the image at regular intervals. Can et al. (1999) presented a tracking-based method to trace retinal vasculature in live retinal video angiograms and extract features such as intersections and crossovers. They then perform operations on these sampled points to determine the likelihood that these pixels are within a blood vessel.

Once some candidate seed points have been determined to be blood vessels, directional edge detection filters are used to trace out the path of the blood vessel across the surface of the retina. Having acquired some candidate points that are likely to be vessels, antiparallel edges are searched for using directional templates similar to the edge detection templates of Sobel and Prewitt. Antiparallel edges are those that are in opposing directions on either side of the candidate vessel, of sufficient strength to indicate the presence of a legitimate edge. Once strong directional edges are detected, they must be filtered to determine the actual location of the blood vessel relative to the edges. Part of the filtering of the detected edges is that they are oriented at 180 degrees, ±22.5 degrees, in the case of (Can et al. 1999). This prevents edges that clearly belong to different vessels being grouped together as only those edges sufficiently parallel to belong to the same vessel are recorded as being potential edges to the section of vessel being traced. This has the advantage, as explained by Lin et al. (2004), of substantially reducing the processing required relative to pixel-based methods, as in the initial stage only some small number or pixels need be processed to determine whether or not they are likely to be vessel, and from this starting point only vessel pixels and a small boundary around them are processed. Pixels that represent vessels in an image consist of between 10% and 15% of the field of view, as has been shown in papers by Niemeijer et al. (2004), and Stall et al. (2004), and verified in the course of our experiments. Because of this, exploratory algorithms can significantly cut down on the processing required per image. This is particularly relevant where vessel identification is being used to guide computer-controlled surgical equipment, as new images are typically provided to be processed at 30 or more frames per second from video equipment, and processing must be done in real time to provide feedback and guidance to surgical tools.

3.4.4 Ridge based Methods

Ridge detection is based on the observation that the vessels can be modelled as ridges, where for each pixel a gradient is determined, based on the intensity of that pixel and surrounding pixels. Once a gradient is determined for each pixel the direction of maximum curvature can be determined along a line covering several pixels, and the peak of the ridge is that point at which the gradient is zero. When the ridges have been highlighted, further processing is done to link ridges and classifies pixels based on their gradients and that of neighboring vessel pixels. The effectiveness of one implementation of such an approach is shown in the paper published by Staal et al. (2004). In this study, the method was shown to perform fairly well, achieving a false positive rate of 1.9%, but a corresponding low true positive rate of only 69.7%.

3.4.5 Methods based on Mathematical Morphology

The use of morphological operations in image segmentation typically uses combinations of the opening and closing operations to select for features, which may not necessarily be entire objects but components of the object being sought. These opening and closing operators are operations that can repeatedly enlarge and reduce the size of features, allowing the elimination of noise and smaller details by shrinking them to such a point that they are removed from the image, while simultaneously retaining and potentially emphasizing the larger elements. These openings and closings are built up from erosions and dilations, which are conceptually straightforward filters applied to an image that contract or expand the borders of regions, restricting their actions to those that are above or below some threshold of intensity or other criteria.

Zana and Klein (2001) introduced a mathematical morphology-based method using curvature evaluation to detect vessel-like patterns in noisy color fundus images . The potential of mathematical morphology is demonstrated by Zana and Klein (2001) for vessel detection compared to other current image segmentation techniques by Niemeijer et al. in (2004) and against a wavelet-based image segmentation technique implemented by Leandro et al. (2001). Leandro et al. (2001) explained that the morphological approach could extract fine details more reliably than the wavelet approach that they used, but both approaches required post-processing with region-growing. Sobel edge detectors or adaptive thresholding is used to produce the final image. Even after following this processing, the resulting outputs suffered from noise due to pathologies within the eye and had inability to pick up very fine capillaries. However the work done by Zana et al. was one of the best performing techniques tested by Niemeijer et al. (2008).

The above mentioned methods are principal approaches in vessel segmentation but because of a wide variety of problems as well as different kinds of fundus images involved, a variation/ combination of the above mentioned approaches can also be found in the literature. The method presented by Chaudhari et al. (1989) is primarily based on 2-D matched filter. Here, the concept of matched filter algorithm is employed for the detection of piecewise linear segment of retinal blood vessels. Hoover et al. (2000) improved the methodology by Choudhary et al. (1989) by threshold probing technique. Kande et al. (2008) also uses matched filter in Choudhary et al. (1989) to detect vessel tree. The improvised result is achieved by using thresholding algorithm based on the Spatially Weighted Fuzzy C-Means (SWFCM) clustering. Staal et al. (2004) proposed an automated segmentation of vessels in two-dimensional color images of the retina. Akram et al. (2009) and Oloumi et al. (2007) detected the vascular pattern and thin vessels by using 2-D Gabor wavelet. Sofka and Stewart (2005) made an improvement in blood vessel detection in the context of low-contrast and detected even the narrow vessels by multi-scale matched filters. A supervised approach based on artificial neural network (ANN) was proposed for blood vessel extraction in (Sinthanayothin et al. 1999, 2002). The sensitivity and specificity achieved by this method are quite high, however post-processing was required to do away with the misclassified vessels.

Gang et al. (2002) introduced a matched filter-based method using an amplitude-modified second-order Gaussian filter to detect and measure retinal vessels in color fundus images. Hoover et al. (2000) proposed a thresholding-based method to locate and outline blood vessels using a piecewise threshold obtained from local and global vessel features cooperatively. Staal et al. (2004) proposed a classification-based method to segment blood vessels in color images of the retina. Image ridges coinciding approximately with vessel centerlines were used as feature vectors. Xu et al. (2008) presented a hybrid algorithm using a matched filter, mathematical morphology, contrast enhancement and threshold probing for segmentation of the retinal vessels in scanning laser ophthalmoscopy (SLO) images. Niemeijer et al. (2008) proposed a supervised pixel classification-based vessel segmentation approach in OCT projection images .

Automatic retinal blood vessel segmentation is a complicated affair because of the fact that retinal images are often noisy, poorly contrasted, and there is a wide variation in vessel widths. Most of the methods mentioned above work well to detect the main parts of the vessel tree. However, it does not perform well to extract the narrow vessels. Since the vessels have a wide range of width and the area of small width usually has very low contrast, it simply misses to identify it as a vessel. Keeping the above problems in mind and as an attempt to address it, a vessel extraction algorithm based on contrast limited adaptive histogram equalization and mathematical morphology is proposed in this research.