Support System for the Automated Detection of Hypertensive Retinopathy using Fundus Images

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ABSTRACT
Fundus image analysis is playing an important role in the early detection of retinal eye diseases like diabetic retinopathy, glaucoma etc. Automated detection of hypertensive retinopathy (HR) is a recent development in this field. Segmentation of blood vessels, measurement of tortuosity, diameter measurement, finding the artery vein ratios (AVR) are few important measures for finding HR using digital fundus images. We propose a support system to assist the ophthalmologist in detecting HR in early stages. Segmentation of blood vessels is done using Radon transform, optic disk is detected by Hough transform and then the AVR is calculated. The proposed support system will help the ophthalmologist in the early detection of HR.

General Terms
Image processing, Algorithms, Radon Transform, Hough Transform.

Keywords
Fundus images, Hypertensive retinopathy, arteriovenous ratio.

1. INTRODUCTION
Hypertension is a worldwide problem that affects up to 50 million people in the United States and approximately one billion worldwide. Hypertensive retinopathy is the damage to the retina from high blood pressure which can damage the retinal blood vessels. Poorly controlled systemic hypertension causes damage to the retinal microcirculation, so that recognition of hypertensive retinopathy may be important in cardiovascular risk stratification of hypertensive patients. Most people with hypertensive retinopathy do not have symptoms until late in the disease; however some may report decreased vision or headaches. Retinal arterioles can be visualized easily and non-invasively. Several recent studies have shown that retinal micro vascular changes can be reliably documented by retinal photographs using a fundus camera. Their acquisition is cheap, non-invasive and easy to perform, and the most important lesions of HR are visible in this type of images. The other obvious advantages are the permanence of the record, facilities for discussion and observer control and opportunity for piece comparison of the fundal states at interval of time. This opportunity is valuable in the understanding of the natural development of the disease and in the assessment of treatment. Abramoff et al [1] defines fundus imaging as the process whereby a 2-D representation of the 3-D retinal semi-transparent tissues projected onto the imaging plane is obtained using reflected light. The fundus images acquired can be stored, processed and transmitted using image processing techniques.The retinal features related to HR can be roughly divided into two main groups.Those related to vascular morphological abnormalities, and those that are related to the alteration of the blood-retinal barrier or to more severe vascular damage, such as hemorrhages and ischemic events. One of the first changes in vessels morphology to occur is the increase in vessel tortuosity [2]. Tortuosity can be intuitively defined as a non smooth appearance of the vessel course. Traditionally the blood vessels have been examined due to their importance in clinical evaluation, and the vascular diameter [3] has been one of the most important characteristics for the diagnosis of hypertension. Hence health professionals have used the arteriovenous ratio (AVR) to establish the presence of high blood pressure because the arteries present a diminishment in their widths in hypertensive patients.

In this paper we propose a support system for the automated detection of hypertensive retinopathy .Segmentation of blood vessels is done using Radon transform. To find the AVR which is an indicator of presence of HR is done by detecting the optic disk and then marking the Region of interest. The segmented vessels are classified as arteries and veins in this region and finally AVR is calculated.

2. MATERIALS AND METHODS
The images used for the segmentation of blood vessels were obtained from publicly available DRIVE database. The database includes 40 retinal fundus images along with their manual segmentation result for blood vessels as a reference standard. For the detection of Hypertensive retinopathy we use the images from the data set acquired from the Department of Ophthalmology, Kasturba Medical College, Manipal, India. The images were taken in a TOPCON non-mydriatic retinal camera with model number TRC-NW200. The built-in CCD camera provides up to 3.1 megapixels of high quality imaging. The inbuilt imaging software is used to store the images in the JPEG format. The images were photo-graphed and certified by the doctors in the department. The images were taken in a resolution of 560×720. Figure 1 shows a typical input fundus image taken from the DRIVE database.

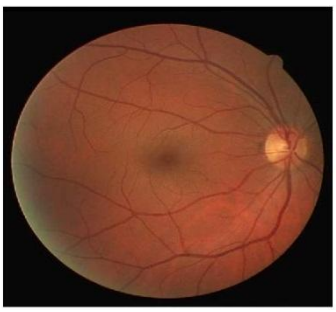

Figure 1. Normal Fundus Image

3. PREPROCESSING

Blood vessels appear most contrasted in the green channel compared to other channels in RGB image. So only the green channel of the image is used for further process. Since different images have different brightness and contrast, histogram specification is used to unify the input images with respect to the green channel of reference image. To spread the histogram of the image across the range of values, Adaptive histogram equalization (AHE) is performed on the input image as shown in Figure 2. The image is inverted for vessels to appear brighter than background. Also to get a uniform background, the image is filtered using median filter and is subtracted from the main image. Top-hat transform is then applied to eliminate the background to some extent as shown in Figure 3.

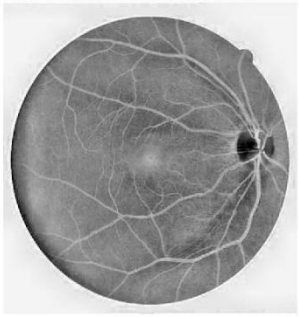

Figure 2. Histogram equalized image

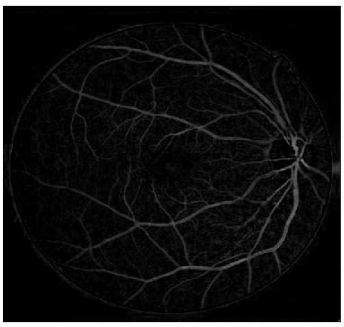

Figure 3. Background Elimination

4. SEGMENTATION OF BLOOD VESSELS

The segmentation of retinal blood vessels plays a prominent role in the detection of various diseases like Diabetes, cardiovascular diseases, retinopathy of prematurity and arteriosclerosis. Ophthalmologists can prevent vision loss if they identify changes in the blood vessel patterns. By Using the vasculature measure like vessel width, vessel branching coefficients and tortuosity, hypertensive retinopathy can be diagnosed in the early stages. The retinal vessel detection also finds the application in measuring the disease severity and the treatment effect can also be assessed.

2D-matched filter based approach was used for the vessel detection [4], [5]. The matched filter based approach achieves significant improvement over Sobel operator and morphological operators. It does give good results for normal fundus images, but with diseased fundus images it gives many false positives. To eliminate the OD and false positives a post processing step is required. Genetic algorithms were used for the matched filter optimization in the identification of retinal vessels. Literature also shows that the sensitivity of the matched filters can be optimized by new parameters using genetic algorithms [6] applied to different databases such as DRIVE etc. Images from Fluorescein angiograms were used to identify the vessels using mathematical morphology and curvature evaluation techniques which achieve significant improvement over matched filters and edge detection techniques [7]. A neural network based approach using PCA was used in [8]. The accuracy of the detection was high for major blood vessels, but less with smaller vessels. A 2-D Gabor wavelet based approach with supervised classification was used for the retinal segmentation. Based on the pixels feature vector the method classifies every pixel as blood vessel or non vessel and produces the required segmentations. A Bayesian classifier with class-conditional probability density functions described as Gaussian mixtures were used which yielded a fast classification [9].

In order to extract blood vessels, vessels must be segmented to some local windows and then orientation and width of segmented vessel must be detected in each local window. A sliding window is used to localize processing. By choosing an appropriate window size, all the vessel segments can be detected. The sliding window has an overlapping factor which means that the neighbour windows are not separated and are overlapped [10]. By defining the window size (n) and sliding factor (step), thin/thick vessels can be extracted. In this work a step size of 3 and a window size of 19 and 7 are used to detect wider and narrow vessels respectively. Figure 4 depicts the relation of step and window size (n).

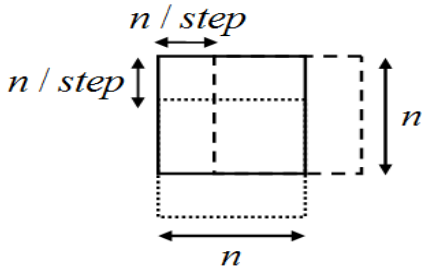

Figure 4. Overlapping parameters.

The Radon transform is used to detect features within a two-dimensional image. Radon transform computes the projection of an object in the image. Applying the Radon transform on an image g(x, y) for a given set of angles can be thought of as computing the projection of the image along the given angles [11]. The resulting projection is the sum of the intensities of the pixels in each direction, i.e. a line integral. The Radon transform is a mapping from the Cartesian rectangular coordinates to a distance and angle (ρ, θ), known as polar coordinates. Each point in (ρ, θ) domain corresponds to a line in the spatial domain (x, y) as shown is Figure 5.
The Radon transform of a function g(x, y) is given by

$$R(\rho,\theta) = \iint_{-\infty}^{\infty} g(x,y)\delta(\rho - x\cos\theta - y\sin\theta)\,dx\;dy$$

The above equation describes the integral along a line through the image, where ρ is the distance of the line from the origin and θ is the angle from the horizontal.

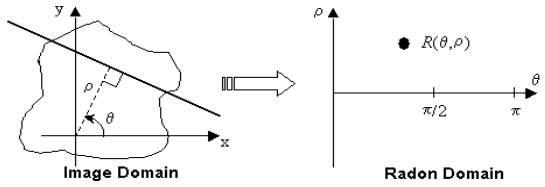

Figure 5. The Radon Transform

Before giving image to Radon transform, Circular mask is applied to local window to eliminate the diagonal effect since occurrence of peak value in diagonal directions is more probable than other orientations. By applying Radon transform for each specific angle θ produces a vector R containing the projection sum of image intensity at angle θ. The peak and the corresponding projection angle are detected. The profile in which biggest peak value occurs might contain vessel in its orientation angle α and projection peak value is further analyzed for validation of vessel. In vessel validation, existence of vessel in the local window is detected by comparing the peak amplitude with a predefined threshold. To use the same threshold value for windows with different size, the Projection peak value must be normalized by dividing profile's peak to the window size. If the peak amplitude is greater than threshold then a vessel is detected in the current local window and the vessel width is calculated. The width $W\rho$ in the direction α of a peak in a radon transform is determined by going left and right from peak offset in projection along angle α until reach a half-peak radon value, which is 50% of the peak radon value. It gives two values ρ1 and ρ2 which are vessel segment start and end positions. The width $W\rho$ is then calculated using the equation

$$W\rho = \rho 1 - \rho 2$$

Given the width, projection angle and window size, a mask is prepared which presents coarse vessels coverage area in the sub-image. So on a black *n* x *n* block, a white line is drawn which its angle equals projection angle and its position is determined by width. To improve the quality of extracted vessels, the local vessel mask is compared with binarized real vessels. Then refined vessels extracted from different local windows are then combined considering the overlapping ratio to make the mask. The final vessel map is achieved by morphological reconstruction and merging process which is done for each vessel width. Figure 6 shows the extracted blood vessels using Radon Transform.

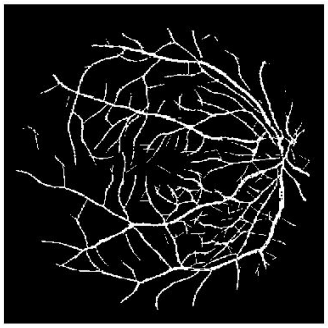

Figure 6. Segmented blood vessels

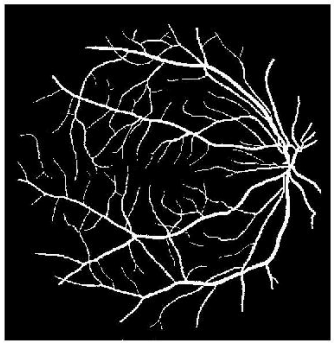

Figure 7. Manually segmented image

The performance of the method is evaluated using sensitivity and specificity at pixel level in comparison with manually segmented vessels shown in Figure 7. Sensitivity gives the percentage of pixels correctly classified as vessels by the method and specificity gives the percentage of non vessels pixels classified as non vessels. Table 1 shows the performance of the method on thirty images from the DRIVE database.

Table 1 Performance of retinal blood vessels segmentation method

Database	No. of Images	Sensitivity (%)	Specificity (%)	Accuracy (%)
DRIVE	30	82.2±4	97.4±0.8	92±4

5. OPTIC DISK DETECTION FOR THE MARKING OF REGION OF INTEREST

Identification of the OD is very significant in locating the region of interest (ROI) which is a standard region for measuring the blood vessels to find the AVR. In the fundus image OD appears as an orange or pink region measures about 1.5mm in diameter. It is also the entry and exist point for nerves entering and leaving the retina to and from the brain. The size, location and appearance of the OD vary in fundus images. It looks mostly circular but may look elliptical in some fundus images because of negligible angle between object and image planes. The detection of OD becomes challenging in the presence of bright lesions like exudates as both appear very bright. Over the last 25 years many researchers have detected the OD in fundus using different techniques. Lee et al. [12] detected the OD using their high pixel intensity with a high grey scale value. The method fails when there are lesions with similar high grey scale values [13]. A method based on PCA (Principle component analysis), where the clustered brightest pixels are used as candidate optic disc regions [14].PCA was applied and centre of the OD was marked by finding the smallest distance between the fundus image and its projection. By applying the intensity variance between the OD and the adjacent retinal vessels Sinthanayothin et al. [15] detected the optic disk. This technique fails in the presence of white lesions and choroidal vessels. In recent years to detect the OD contour model based approaches [16], geometric parametric model [17] and Fuzzy convergence [18] based methods were used. The detection of

the Optic disk is performed in red component because blood vessels do not appear in the red component, but they may interfere in the green component. Its Histogram is taken and the candidate area with highest 4% gray level is selected. Only these pixels are highlighted, because the exudates are also having the same intensity as that of optic disk, some of the exudates may also get highlighted. The centre of the optic disk and its periphery is found by applying Circular Hough Transform for which a suitable radius is the input (Here we have used R=40) and then the edge points and centre of the optic disk is highlighted. Once we identify the centre of optic disk ROI is set as twice the radius of the optic disc, to three times the radius of the optic disc, giving a concentric area centered in the middle of the optic disc as shown in Figure 8.

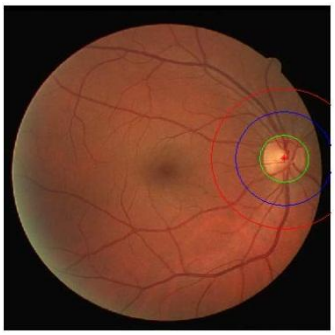

Figure 8. Detected OD and ROI

6. AVR CLASSIFICATION

The Japanese guidelines used for reading retinal fundus images for hypertension states that the A/V ratio should be measured on vessels in the region from quarter-disc to one disc diameter from the optic disc margin. The arteriovenous ratio (AVR) is an important indicator to establish the presence of high blood pressure which causes the diminishment in the arteries width [19]. If the AVR is about 2/3 then it is considered to be normal. If the AVR is less than 2/3 the fundus image is considered as hypertensive. The consequences caused by the hypertension such as heart attack, brain stroke and renal failure can be prevented if we identify the presence of hypertension early. Ophthalmologists distinguish arteries and veins on the basis of the color and width of the vessels. So the color information is used for the classification of arteries and veins. The ROI provides a mask for vessel classification within the region. Arteries have a higher level of intensity than the veins in the red channel of the RGB image. The mean intensity of all the pixels are calculated and compared with individual components. The component with a mean greater than the mean of all the pixels is classified as an artery and the mean with lower value is classified as a vein. Every part of the vessel in the ROI is divided into different components. Each connected component is then taken at a time and the numbers of white pixels are counted. Now the components having maximum and minimum values are determined for both arteries and veins and AVR is calculated.

To obtain more precise measurements of the vessels caliber, the Parr - Hubbar formulas are used. Those formulas provide more reliable measurements [20] and are defined as follows. The Central Retinal Artery Equivalent (CRAE) is calculated as

$$CRAE = \sqrt{(0.87Wa^2 + 1.01Wb^2 - 0.22WaWb - 10.73)}$$

And the Central Retinal Vein Equivalent is calculated as

$$CRVE = \sqrt{(0.72Wa^2 + 0.91Wb^2 + 450.02)}$$

where Wa is the caliber of the smaller branch arteriole/vein and Wb is the caliber of the larger branch arteriole/vein.

Then the AVR can be calculated as

$$AVR = \frac{CRAE}{CRVE}$$

The veins and arteries that have been classified are detected with blue and red colors respectively on the RGB image as displayed in the Graphic User Interface (GUI) of Figure 9. The GUI was made to guide the health professional through the measurement process. The system is built as an executable program that allows users to load retinal images and perform the measurements of the AVR. At the end of the process, the system displays the status if the retinal image is normal or not based on the AVR measurement. The GUI shows the input image to be normal because the AVR value is more than 0.6.

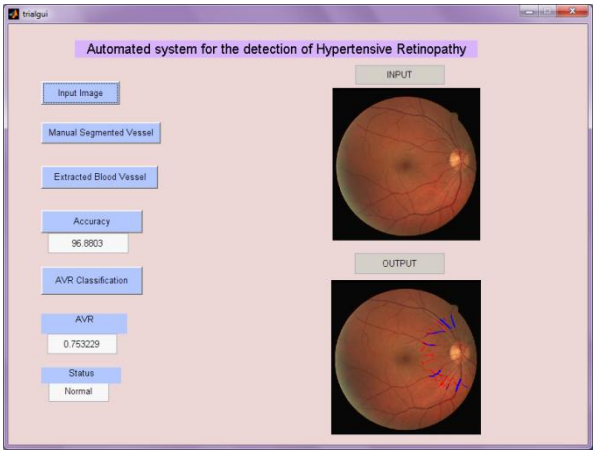

Figure 9 AVR for the input image

7. RESULTS AND DISCUSSION

The drive image database was used as the database for this work. The images are preprocessed first to make the database uniform. To find the AVR we must get the segmented blood vessels from the fundus image. Radon transform is applied to the fundus images to obtain the vessels segmentation which shows an accuracy of 92% in segmenting the blood vessels. The Radon transform makes algorithm more robust and is less sensitive to noise in the image than other line detectors, because the intensity fluctuations due to noise tend to be cancelled out by the process of integration. To find the ROI which is an area used to measure AVR, we must detect the optic disk. Hough transform based approach is used here for the detection of optic disk. The Hough transform is preferred over other methods because it can detect hardly visible circles and also in noisy environments. The segmented blood vessels inside the region of interest were classified as arteries and

veins depending on the mean intensity of the each vessel. Once they are classified as arteries and veins, the AVR ratio was calculated which will determine the presence of the hypertension in the patient. A set of 30 images were taken from the KMC hospital Manipal. They were classified as normal and hypertensive depending on the AVR ratio by an expert ophthalmologist. Out of 30 images we could classify 25 images as hypertensive, 5 images as normal.

8. CONCLUSION

The fundus images analysis for the detection of hypertension is a recent development. We have presented a preliminary system for the detection of hypertensive retinopathy. The AVR ratio can change drastically if the classification of AVR is not done carefully. The system works well provided the AVR classification is proper. We have used a small set of images, hence it needs to be tested on a large database which the authors are intended to do in the near future. This technique of identifying the hypertensive retinopathy with fundus image analysis will help the ophthalmologist in the decision support as well as in the mass screening of hypertensive retinopathy.

9. ACKNOWLEDGMENTS

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