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HYPERTENSIVE RETINOPATHY DIAGNOSIS FROM FUNDUS IMAGES BY ESTIMATION OF AVR.

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Abstract

Hypertensive retinopathy is a disease that damages the retina of the eye and results in loss of vision and is closely associated with high blood pressure. Severe case of hypertensive retinopathy causes systematic aliments that may cause cardiovascular diseases, heart and renal failure, loss of vision and finally death. Thus the timely diagnosis and treatment of the disease is vital. Arteriovenous ratio is used to diagnose hypertensive retinopathy. In this paper we proposed an algorithm in which, the blood vessels are segmented out initially, from the pre processed retinal images. Gray level and moment based features are extracted to classify the detected pixels as belonging to the blood vessel class or not. Intensity variation and colour information is used to classify the vessel as arteries or veins. Vessel width estimation method is used to measure the arteriovenous ratio from which various stages of hypertensive retinopathy can be identified. Retinal images were obtained from the VICAVR database, along with images collected form Deepam eye hospital Chennai. From the images that were collected 25 were normal images and 76 images of hypertensive retinopathy.

Keywords: Hypertensive retinopathy; fundus image; arteriovenous ratio; classifier.

1. INTRODUCTION

Hypertensive retinopathy is the damage caused to the retina of the eye due to high blood pressure. Hypertensive retinopathy leads to systematic morbidity and mortality. Mild cases of hypertensive retinopathy is characterised by retinal arteriolar narrowing and nicking of arteries and veins and vascular diseases in some cases. Moderate case of the disease is associated with the presence of micro aneurysms, haemorrhages and soft exudates that may result in cardiovascular diseases and congestive heart failure. . This is characterised by the narrowing of blood vessels, fluids leakage from the vessels, swelling of macula and optic nerve and presence of hard and soft exudates. Hypertensive retinopathy is graded based on the severity and four grades of the disease are defined, grade 1 which is known as mild hypertensive retinopathy, grade 2 is moderate hypertensive retinopathy, grade 3 is a combination of grade 1 and grade

2 and finally grade 4 known as accelerated hypertensive retinopathy. A clear description of the various grades of hypertensive retinopathy and the associated systematic complications are given below in detail.

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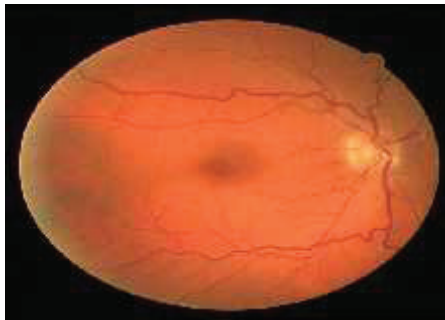*E-mail address*:.knr@ece.sastra.edu.

Figure 1: A normal fundus image.

Table 2: Stages of hypertensive retinopathy, indications and systematic association.

Retinopathy grade	Indications	Systematic association
Mild	Arteriolar narrowing, nicking of veins and arteries, opacity of arteriolar wall	Weakly associated with cardiovascular diseases.
Moderate	Haemorrhages, hard and soft exudates.	Heart failure, stroke and cardiovascular mortality.
Accelerated	Optic Disc swelling and vision loss.	Renal failure and mortality.

Moreover the disease can be diagnosed by certain changes in the retinal vessels namely arteriosclerosis which is the thickening of the retinal arteries and various changes in the arteriovenous crossings can also be observed. The changes observed are venous deflection also known as Salus sign, localised venous narrowing also known as Gunns sign, right-angled crossing by deflection of veins and Bonnets sign which is venous distal banking.

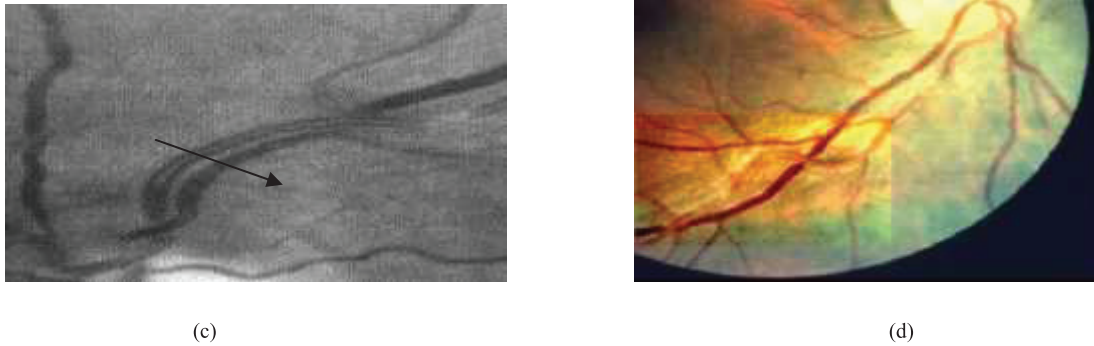(a)   (b)

(c)

(d)
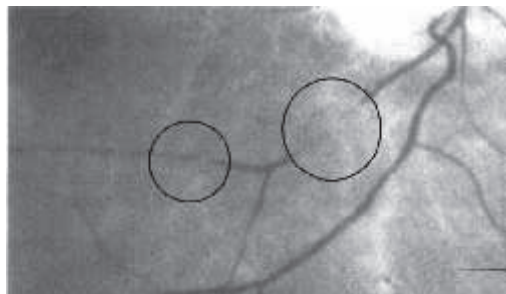
Figure 2. (a) Retinal image indicating the localised narrowing of vessels (b) Right angled crossing of vessels indicated by an arrow (c) Retinal image with arrow indicating Bonnets Sign (d) Retinal image with the presence of right angled vessel crossing and Bonnets sign.

The Arteriovenous ratio is calculated and this serves as a measure for detecting the stages of hypertensive retinopathy.

Table 2: A/V ratio for various stages of hypertensive retinopathy.

Degree of hypertensive retinopathy.	A/V ratio	A/V crossings
Normal	0.667-0.75	None
Grade 1	0.5	Mild compression of venules.
Grade 2	0.33	Compression or elevation of venules.
Grade 3	0.25	Right angled crossing of vessels, nicking.
Grade 4	Fine cords	All the above symptoms in addition to distal congestion.

2.   RELATED WORK

Subhasis Chaudiri et al [1] proposed a method for blood vessel detection using a two dimensional matched filter. Here a new operator is introduced for feature extraction which depends on the spatial and optical properties of the object to be identified .The matched filter is used to detect linear segments of blood vessels, 12 templates are used to detect the vessels in all directions.

James Lowell et al [2] proposed a method for measuring the retinal vessel width, wherein the vessel diameter is measured based on the two dimensional difference of Gaussian model. The performance of the algorithm is compared with Brinchmann -Hansen half height, Gregson's rectangular profile and Zhou's Gaussian model. The algorithm is 30% more precise than the existing algorithms.

Di Wu et al [3] proposed a method for adaptive detection of blood vessels in the retina which is based on contrast enhancement, feature extraction and tracing. Gabor filter responses are used for feature extraction. Forward detection, bifurcation identification and backward verification are used to trace the vessel segments. The true positive and false positive rate for normal and abnormal images are also analysed and is found to range between 80%-91% and 2.8%-5.5% for normal images and 73.8-86.5% and 2.1-5.3% for abnormal images.

Mohammed Al-Rawi et al [4] also proposed a method for detecting blood vessels in the retina employing matched filters and making use of the DRIVE database to evaluate the performance of the algorithm used.

P.Echevarria et al [5] presented a blood vessel segmentation method utilising a tracking based algorithm based on level set and fast marching methods. Here the images are filtered using two dimensional filters .Blood vessel walls are considered as linear ,the blood vessel are modelled as Gaussian .12 different kernels are defined with 15 degree spacing. And each kernel is convolved with the image and the region of maximum response is found and as a result the blood vessels are detected. Level set are used in addition to remove noise.

Ana Maria Mendonca et al [6] work was on extracting vessel center lines and are used for the next filling phase .The output obtained from four directional differential operators are processed to select connected sets of vessels and vessel derived features are used to classify points as center pixels. Iterative region growing is the next step and the result is integrated with images obtained from morphological filters. The algorithm performance is analysed using two publically available databases and the sensitivity and specificity are analysed.

Yannis A et al [7] proposed a method to detect ocular vessels based on fuzzy clustering. This method overcomes the problem faced by other methods namely initialisation and vessel profile modelling and classifies fundus vessels as vessel and non vessel. Here the starting and termination point of the vessels are described. The center points, vessel directions and edge points and additional variables are introduced are used for tracing the blood vessels and all the variables are used for fuzzy vessel tracing. Faraz Oloumi et al proposed a method for blood vessel detection where in directionally sensitive Gabor filters are used.

O.Chutatape et al [8] utilised a matched second-order derivative Gaussian filter which is designed to locate the center points and width of a vessel in its cross sectional profile. Kalman filter are used to estimate the next possible location of blood vessel segments by observation of its pattern changing process. A simple branching detection strategy is used to track the blood vessel.

Frederic Zana et al [9] work was based on employing mathematical morphology as it tree like geometry can be used for registration of images .A cross curvature evaluation is performed to differentiate vessels from background. The algorithm is based on noise reduction, Gaussian profile improvement, curvature evaluation and linear filtering.

Adam Hoover et al [10] proposed an automated method to locate and outline retinal vessels in the ocular fundus .Here the local and global features are used to segment the vessels .A Gaussian function is used for the matched filtering. As vessels occur in various orientations a filter bank consisting of2D segment profile is used. A threshold probing is carried out to decide whether the region is a blood vessel.

Elisa Ricci et al [11] work was based on the retinal blood vessel segmentation using line operators and support vector classification .This is based on estimating the average grey level along fixed length lines passing through the target pixel. A line detector with thresholded output was used for an unsupervised classification. The two orthogonal line detectors were used whose outputs were used to form the feature vector for supervised classification. The effectives of both methods were analysed using ROC characteristic curve.

3. MATERIALS AND METOHDS

3.1. MATERIALS

Colour fundus images with resolution of 96x96 dpi and 768 X 576 pixels were obtained from Deepam eye hospital, Chennai. A Topcon fundus camera model TRC50X was used to capture the retinal images. 25 images were normal and 76 images were abnormal from the images that were collected and a database was formed. The guidance of an ophthalmologist was used to mark the type and location of abnormalities in the database and this is used as the ground truth for the classification stage.

3.2 PROPOSED METHOD

For the detection of blood vessels the features are extracted from the pre processed image. The extracted features are fed to a classifier in order to label the pixel as vessel or non vessel.

3.2.1. PRE PROCESSING

The green band of the image is separated to obtain a monochrome image. This is because green channel has the best vessel contrast in comparison to red channel, whereas blue channel has low dynamic range. The intensity variation in the background is less in the green plane of the image.
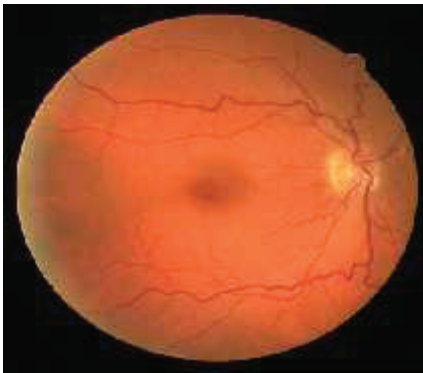

(a)   (b)

Figure 3. (a) Original fundus image, (b) Green plane image.

3.3.2.1.1. Removal of central light reflex in the blood vessel and background homogenisation

Retinal vessels have low reflectance compared to the background retinal surfaces and as a result the vessels have a light streak that lies in the central region [12]. Morphological opening is applied to the image, with a disc shaped structuring element with three pixel diameter. The structuring element is selected in such a way that it does not cause the merging of vessels that lie close to each other [13].
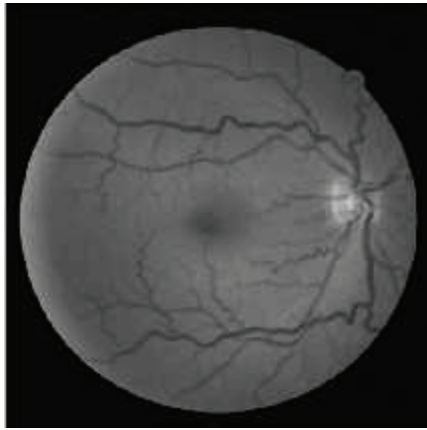
(a)   (b)
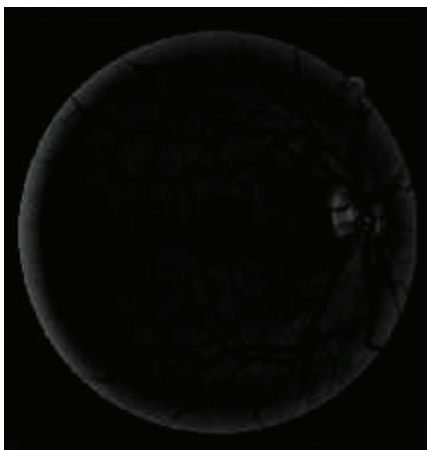
(c)   (d)

Figure 4(a) Morphologically opened image, (b) Background image, (c) Shade corrected image, (d) Complementary homogenised image.

A mean filter is utilised to smoothen the image and reduce the salt and pepper noise. [14] The image is smoothened further employing a Gaussian kernel. A background image is got by applying a mean filter. The difference image is got either by subtracting or dividing the background image from the green plane image, thus a shade corrected image is obtained   [15].The background pixels constitutes the darkest pixel in the image and have different intensity within an image. Shade corrected image reduces the intensity variation of the background pixels [16]. A homogenised image is then obtained in order to reduce the

intensity variation between images this is brought about by modifying pixel intensities in accordance to a global transformation function. Utilising the global transformation function the maximum pixel intensity value corresponding to the background pixels are standardised and as a result the background intensity variation is reduced.

$$p_0 = \begin{cases} 0, p < 0 \\ 255, p > 0 \\ p, \text{otherwise} \end{cases}$$ (1)

$$p = pi + 128 - pi\_max$$ (2)

Where pi and p_0 are the input and output pixel values.

3.2.1.2. Vessel enhancement

The final vessel enhanced image is obtained by initially generating the complement of the homogenised image, followed by a top-hat transformation of the complementary image. The top-hat transformation is carried out by utilising a disc structuring element of 8 pixel radius. The darker features remain in the image where as the brighter lesions namely the exudates are removed.
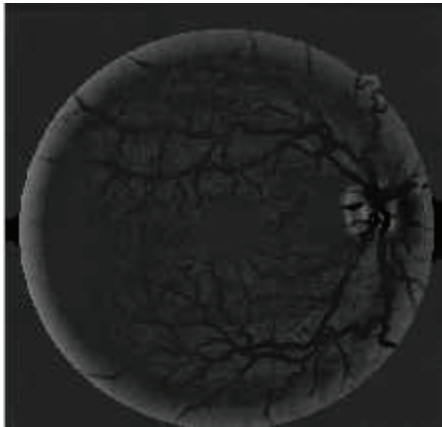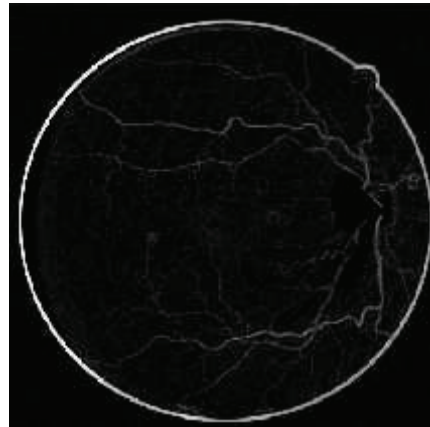
(a)   (b)
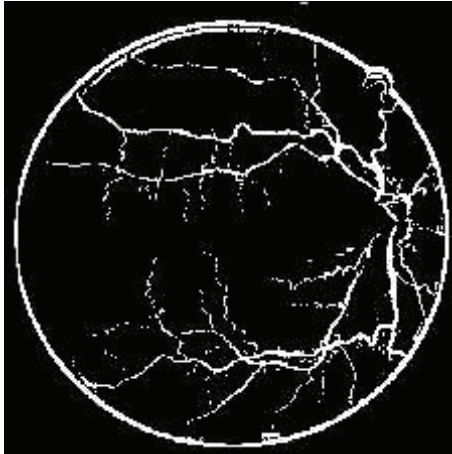
(c)

Figure 4. (a) Top-hat transformed image (b) Vessel enhanced image (c) Final vessel enhanced image

3.2.2 Feature extraction

In order to decide whether the pixels detected are blood vessels or not, a feature vector is created which is then used for the classification stage. The feature vectors are created based on the gray level and the variation in moments.

3.2.2.1. Feature extraction based on gray level

The blood vessels are darker when compared to the surrounding retinal structures [17]. The gray level variation between the pixels belonging to the blood vessels and the surrounding regions considering a small region centred at a (x,y) is found out. The five descriptors for defining the gray level features are given by,

$$P_1(a,b) = I_g(a,b) - \min_{(s,t) \in S^9_{a,b}} \{I_g(s,t)\} \tag{3}$$

$$P_2(a,b) = \max_{(s,t) \in S^9_{a,b}} \{I_g(a,b)\} - I_g(a,b) \tag{4}$$

$$P_3(a,b) = I_g(a,b) - \underset{(s,t) \in S^9_{a,b}}{mean} \{I_g(s,t) \tag{5}$$

$$P_4(a,b) = \underset{(s,t) \in S^9_{a,b}}{std} \{I_g(s,t)\} \tag{6}$$

$$P5(a,b) = I_g(a,b) \tag{7}$$

3.2.2.2. Feature extraction based on moments

As the blood vessels are piecewise linear and occur as line segments descriptors that do not vary based on the rotation, translation and changes in scale can serve as a feature vector to detect the blood vessels. For a given pixel (x, y) of the final image with vessel enhanced, a window is defined around the region which is centred on a wide vessel and a sub image is generated.

Seven values were compute by [Hu 1962] which was got by normalising third order central moments, these values are invariant to the scale, orientation and position of the object under test. The seven moments are given as,

$$M1 = (\eta20 + \eta02), \tag{8}$$

$$M2 = (\eta20 - \eta02)^2 + 4\eta11^2, \tag{9}$$

$$M3 = (\eta30 - 3\eta12)^2 + (3\eta21 - \eta03)^2, \tag{10}$$

$$M4 = (\eta30 + \eta12)^2 + (\eta21 + \eta03)^2, \tag{11}$$

$$M5 = (\eta30 - 3\eta12)(\eta30 + \eta12)[(\eta30 + \eta12)^2 - 3(\eta21 + \eta03)^2] \tag{12}$$

$$+ (3\eta21 - \eta03)(\eta21 + \eta03)[3(\eta30 + \eta12)^2 - (\eta21 + \eta03)^2], \tag{13}$$

$$M6 = (\eta20 - \eta02)[(\eta30 + \eta12)^2 - (\eta21 + \eta03)^2] \tag{}$$

$$+ 4\eta11(\eta30 + \eta12)(\eta21 + \eta03), \tag{14}$$

$$M7 = (3\eta21 - \eta03)(\eta30 + \eta12)[(\eta30 + \eta12)^2 - 3(\eta21 + \eta03)^2] \tag{}$$

$$- (\eta30 + 3\eta12)(\eta21 + \eta03)[3(\eta30 + \eta12)^2 - (\eta21 + \eta03)^2]. \tag{15}$$

Of the seven moments defined the first two moments are taken into consideration as they provide better accuracy. The other moments were not considered as it decreases the performance of the classification stage. Two pixels were defined for each vessel that was detected, namely one pixel lying inside the vessel and one lying outside the vessel. The moments calculated for these pixels completely characterise the blood vessel independent of the width and orientation of the vessel. But the drawback of the above mentioned method is that the center pixel of the sub image cannot be used to categorise between a vessel and non vessel. To overcome this issue the moments are calculated by multiplying the moments initially computed by a Gaussian matrix with zero mean and variance 1.7.The moments M1 and M2 increase when the pixels under consideration are pixels belonging to the vessel regions and decrease otherwise.

The following feature vectors were also considered in addition to the five feature vectors previously defined.

$$F6(x,y) = \log(M1) \tag{16}$$

$$F7(x,y) = \log(M2) \tag{17}$$

3.2.3Classification

Seven feature vectors are defined for each pixel in the retinal image. Two classes are defined namely vessel or non vessel. The distribution of training set data is analysed in feature space based on this the suitable classifier is used. As the probability of linear separation between two classes is low a non linear classifier is utilised. SVM classifier was found to be most suitable non linear classifier.

SVM is a supervised learning algorithm where a hyper plane is defined for the separation of classes. The hyper plane can also be defined for non linear classification problems.SVM supports both regression and classification and is designed to handle continuous variables. The linear hyper plane is given by,

$$w^T a + x = 0 \tag{18}$$

Where a is the feature vector and w is the weight and x is the bias. Margin is defined as the distance between the separating hyper plane and the points that lie closest to it. The maximum margin of separation between the hyper planes is defined as the optimal separating hyper plane in SVM. For the nonlinear case SVM is defined as follows by including the slack variable,

$$\frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \tag{19}$$

Provided,

$$b_i(w^T a_i + x) \geq 1 - \xi_i, \qquad i = 1, \dots, N. \tag{20}$$

$$\xi_i \geq 0, \qquad i = 1, \dots, N. \tag{21}$$

The margin of separation is defined as soft. Here C' is a user defined variable and it controls the trade off between minimising the classification error and maximising the maximising the margin of separation. The most important task is to distinguish between the false positive and false negative and this is estimated from the sensitivity and specificity. The error terms are weighed in order to reduce the classification error and is given as,

$$\frac{1}{2} w^T w + C^+ \sum_{i|b_i=+1} \xi_i + C^- \sum_{i|b_i=-1} \xi_i \tag{22}$$

Subjected to the constraints,

$$b_i(w^T a_i + x) > 1 - \xi_i, \qquad i = 1, \dots, N. \tag{23}$$

The collected retinal images are trained and a training set is formed with the feature vectors and the classification results are found. The retinal images were collected from VICAVR database and in addition to these 76 images of patients suffering from hypertensive retinopathy were also collected .The classifier was initially trained on the training set and then tested using the test set. To measure the performance of the classifier and ROC analysis is carried out.

3.3.2 Estimation of AVR ratio

The retinal vessels are segmented and classified, from the output obtained by the above method an ROI is defined .The ROI in this case is the optic disc, and the ROI is set to be four times the radius of the optic disc. The retinal vessels within the optic disc has to then be classified into arteries and veins [18]. The intensity associated with arteries is high in comparison with veins this serves as a criterion to distinguish between arteries and veins. This is done by calculating the mean of intensities and the pixels having intensities greater than the mean value are classified as arteries and others belong to the class veins.

The retinal vessels can also be classified based on the colour variations. Copper wiring which is a condition is caused by increase in light reflex due to thickening of the vessel wall. As this condition worsens it leads to silver wiring where the arteries appear white in colour due to narrowing of the vessels.

3.3.3. Measurement of vessel width

An edge image of the retinal vessels is obtained, the centreline pixel is then approximately found from the edge image. A mask is then defined in such a manner that the centre line pixel coincides with the centre of the mask. The edge pixels lying on either side of the center line pixels is computed using the mask. The number of pixels in the mask is calculated .The gray scale value of the pixel is checked to make sure that the pixel is an edge pixel or not. Once the edge pixel is found the edge pixel on the other side of the center line pixel is found out by shifting an angle of 180 degrees and the distance is incremented from an initial value one to the maximum size of the mask. Consider that (a, b) is the center line pixel position=1, 2, 3,... (mask size)/2 and Θ=0,...180°.Then (a1, b1) is given as,

$$a1 = a + u * \cos(\Theta) \tag{18}$$

$$b1 = b + u * \sin(\Theta) \tag{19}$$

(a)   (b)
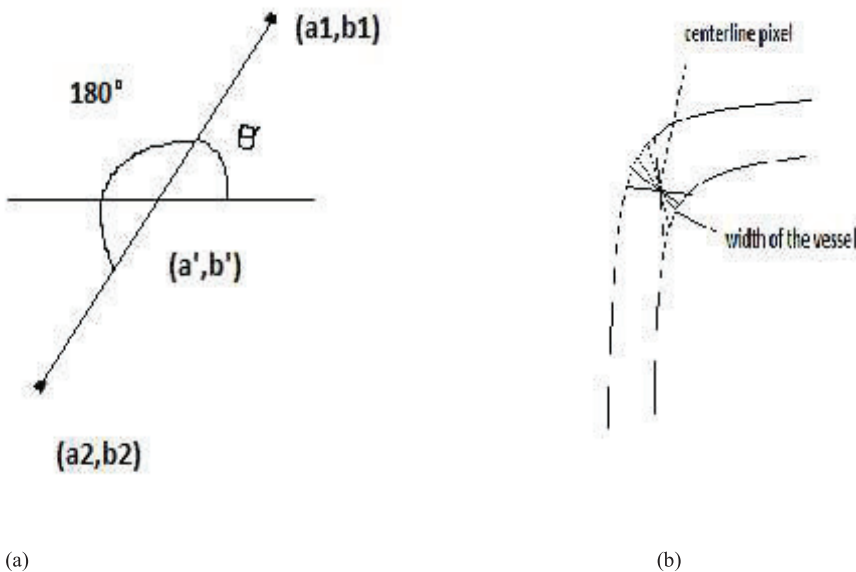
Figure5 (a) Determining the mirror pixel (b) Width of the vessel.

If the gray scale value of an edge pixel is 255 then the corresponding pixel value of the edge pixel on the opposite edge (a2, b2) is got by varying the value of u and $\Theta=\Theta+180$.The width of the cross section is

got by considering an imaginary line between two edge pixels passing through the center line pixel and computing the Euclidean distance between the edge pixels. The Euclidean distance is given as,

$$\sqrt{(a1 - a2)^2 + (b1 - b2)^2}$$ (20)

Alternatively, the edge pixels pairs are found and the number of pixels that lie between the two pixel points is approximated as the width of the vessel.

4. Experimental results

The width of the arteries and veins are computed and from this the arterious- venous (A/V) ratio is calculated. The change in vessel diameters serves to determine the presence of hypertensive retinopathy, arteriosclerosis and diabetes mellitus. The A/V ratio and its significance in determining the presence of hypertensive retinopathy and grading its severity is summarised in table 2.

The A/V ratio obtained by the above mentioned algorithm is obtained as 0.24-0.49 in the case of patients suffering from hypertensive retinopathy and 0.6-0.7 in normal cases. The various stages of hypertensive retinopathy can also be graded based on the data summarised in the table 2.Using the above algorithm 22 images out of the 25 normal images were detected as normal and 72 images out of the 76 abnormal images detected the presence of hypertensive retinopathy.

5.Conclusion

Blood vessels are detected by initially extracting the moment invariant features that are invariant to rotation, translation, scale change and the gray level features. A set of 7 features are found to be most suitable for the classification process from the twelve features that are obtained. The detected blood vessels are then identified as arteries and veins based on the intensity and colour features. The vessel width is determined by a vessel width estimation method which is discussed in the above work. The arteriovenous ratio serves to determine the changes in vessel diameter and to grade the various stages of hypertensive retinopathy, in addition to this it can also be used to detect the presence of arteriosclerosis and diabetes mellitus. There is a problem of false identification of the disease in certain rare cases .The classification rate can be improved further by introducing methods to effectively detect the localised narrowing and the right angled crossing of retinal vessels.

6.References

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