Classification of Fundus Photographs using Full Width Half Maximum Algorithm

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ABSTRACT
A computerized semiautomatic system has been presented for classification of fundus photographs. This classification is based on feature vectors obtained from twin Gaussian Intensity Distribution and full width half maximum algorithm for vasculature diameter measurement. Diagnostic performance with overall sensitivity of 75% and accuracy of 93% has been achieved using k-NN classifier and neural network both. The performance is evaluated using DRIVE database and fundus photographs from the hospital.

General Terms
Proliferative Diabetic Retinopathy, Retina.

Keywords
Gaussian Intensity Distribution, full width half maximum, fundus photographs, vasculature.

1. INTRODUCTION
In general blood vessels are not visible in vivo. But blood vessels on the retina can be directly captured noninvasively through pupil, in vivo. Retinal vessels provide useful information to clinical diagnosis and treatment. Hence segmentation and quantification of blood vessel topography is of central interest in a number of diseases, such as diabetic retinopathy (DR) which is primarily a retinal disorder, and others such as hypertensive retinopathy and stroke which are not primarily retinal but changes in the morphology of retinal vessels do occur [22]. Research into the clinical significance of various types of retinal lesions have shown that, the degree of venous beading is more powerful indicator of proliferative retinopathy than any other quantitative measurement of retinal abnormality [3]. Grading of the retinopathy is done based on features like microaneurysms, hard exudates haemorrhages, abnormal blood vessel width and venous beading (unusual variations in the diameter of vessel). This process requires a high degree of skill and experience.

The organization of this paper is as follows. Section 2 describes brief survey of existing literature. Section 3 gives materials used for the proposed method. In Section 4 we describe a methodology. The proposed method is composed of window selection, centerline plotting, profile data extraction using full width half maximum algorithm and then classification. Section 5 and section 6 describe results and conclusion.

2. BACKGROUND
Retinal vessels show variety of structural changes in different disease conditions; however in this paper we are exclusively concerned with changes in the diameter of vessels. Vasculature response to different physiological pathologies has been widely studied using variety of methods. The changes in the widths of the retinal vessels within the fundus are considered to be indicative of the risk level of diabetic retinopathy [22]. Generalized and focal retinal arteriolar narrowing have been shown to be strongly associated with current and past hypertension reflecting the transient and persistent structural effects of elevated blood pressure on the retinal vascular network [22] [23]. In all such cases it is not the absolute diameter of the vessel that is of interest, but variations in the diameter along a vessel. Segmentation of the vessels and measurement of the vascular diameter are two critical and challenging technical tasks in any system attempting automated diagnosis of vascular conditions. Fig.1 (a) shows normal fundus image and Fig.1 (b) shows DR image exhibiting blood vessels with structural changes.

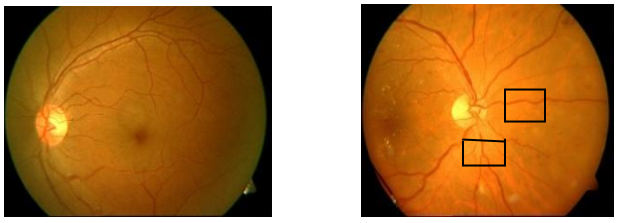

Fig 1: (a) Normal fundus image (b) Pathological (DR) fundus image exihibiting structual changes in vascular segments

There are many methods proposed for the detection of blood vessels in the fundus images. The various methods are edge detection method, model based approach, tracking approach and segmentation. Joes Stall et al. [8] presented a method for automated segmentation of blood vessels based on extraction of image ridges which coincide approximately with vessel centerlines. Frederic Zana et al. [12] described a method for segmentation of vessel like patterns using mathematical morphology and curvature evaluation. In order to separate out vessel like patterns Gaussian profile is considered. Chang Hua Wu et al [15] proposed a method for segmentation of small vessels particularly. They enhanced vessels using compound enhancement filter using eigen values of Hessian matrix and matched filters. Di Wu explained a method for the detection of blood vessels using Gabor filter responses [6]. Joao B Soares et al [7] presented a method for segmentation of retinal blood vessels based on Gabor wavelet transform responses taken at multiple scales. Sumeet Dua et al [17] explained a method for

the detection of blood vessels based on quad tree decomposition. Giribabu Kande et al [11] presented an algorithm for the segmentation of vessel like patterns using spatially weighted fuzzy c-means clustering. A cellular neural network with virtual template expansion technique was introduced by Renzo Perfetti et al for segmentation of blood vessel patterns [9]. Lili Xu, Shuqian Luo presented a method to segment retinal blood vessels based on adaptive local thresholding. They used support vector machines to classify residual fragments in binary image and then tracking algorithm is applied to get the whole vascular network [18]. O. Chutatape, Liu Zheng designed a second order derivative Gaussian matched filter and used it to locate centre point and width of a vessel in its cross-sectional profile[26]. Two main groups of algorithms were employed for this task i.e. scanning and tracking. According to the known blood vessel features, was designed and. To check the bifurcation of the network a simple branching detection strategy is implemented during tracking. James Lowell et al. presented an algorithm to measure the vessel diameter based on two dimensional Gaussian model [1]. Divyanjali Satyarthi et al. [2] proposed a method of detection of diabetic retinopathy using Gaussian intensity feature input and a vector quantizer classifier. They extracted the features pertaining to the blood vessels which are present only in Diabetic Retinopathy. With these features average diagnostic performance was found to be 90%. A piecewise Gaussian model for profiling and differentiating retinal vessels was described by Huiqi Li, Wynne Hsu. The characteristic of central reflex was specially considered in this approach [5]. S.Jerald, Jeba Kumar et al [16] described a method to calculate the prominent features that reveal information on the state of disease that are reflected in the form of measurable abnormalities in thickness and color using pre-processing techniques and vessel segmentation algorithm. In this work first the captured image was binarized and skeletonised to get the overall structure of all the terminal and branching nodes of the blood vessels. From the vessel structure they identified the terminal node and branching points automatically and then the main and branching blood vessel thickness was calculated.

3. MATERIAL

Two databases with images are used. The first one is obtained from a screening programme in the Netherlands. This database is known as the DRIVE (Digital Retinal Images for Vessel Extraction) database with 40 images, which is publically available. 33 photographs do not show any sign of diabetic retinopathy and 7 show signs of diabetic retinopathy. Each image has been JPEG compressed. The images were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels. The set of 40 images has been divided into training and a test set, both containing 20 images. Another database used has 14 fundus images both normal and pathological, captured by a Sony mydriatic fundus camera, with a 50° field of view, at Minto Regional Eye Hospital, Bangalore. The images were stored in JPEG image format files (.jpg). The image size is 576 × 768 at 24 bits, true color images.

4. METHODOLOGY

4.1 Blood vessel model

In the literature, various mathematical models have been proposed for the blood vessel. These models are based on the specific intensity profile of the blood vessel that is visible across the cross section. Gaussian intensity distribution model of the blood vessel consists of a series of oriented Gaussian curves and small number of parameters controls the size and the shape of the model. Often in high resolution retinal images a streak of light is clearly visible along the centre of the vessel termed as the central light reflex by clinicians and is believed to be due to the reflection of incident light from the surface of the blood vessel wall and or the column of blood [25]. Fig.2 (a) and (b) show retinal image cross sections without light reflex and with light reflex. A single Gaussian function is unsatisfactory to describe the intensity profile across a blood vessel. A variation to the basic model can be achieved by combining Gaussian model without light reflex and with light reflex. Gaussian intensity distribution model can be derived from the variations in pixel intensities across the blood vessel. It is seen that at the centre of the blood vessel the intensity is minimum and it increases gradually as we move towards the edges. Different blood vessels have different widths and different intensity profiles. Hence blood vessels can be modelled using twin Gaussian function (without light reflex and with light reflex conditions) and the specific intensity profile of the blood vessel that is visible across the cross section.

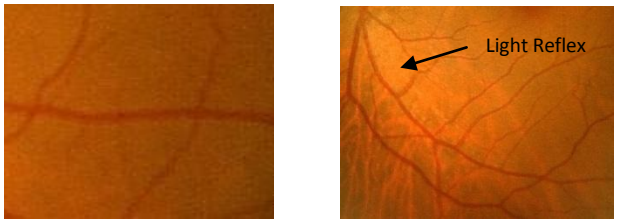

Fig 2: (a) Retinal Image segment without light reflex
(b) Retinal segment with light reflex

Gaussian model (without light reflex) of the blood vessel has the equation,

$$f(z) = h_1 e^{-s_1 \alpha} \qquad (1)$$

where $\propto = (x.\sin\theta - y.\cos\theta - \mu - cf.y^{2)})^2$

x and y maps the profile data range , h_1 is the height and s_1 is the width of the Gaussian G_1. μ is the Gaussian offset and cf represents the curve factor, θ controls orientation of the model. The offset compensates the model if the centreline is not entirely central. The two dimensional Gaussian model with light reflex shares the same base parameters as its non light reflex counterpart. This is due to the main body of the model staying unaltered.The light reflex variation to the core standard consists of a gaussian curve G_2, approximately half the size of G_1 and is subtracted from G_1. Additional parameters are added to control the shape and size of the light reflex. These parameters h_2 and s_2 are the height and width of the gaussian G_2 respectively making the light reflex section of the model as adjustable as the main. With the additional parameters the two dimensional model with light reflex can be given by equation,

$$f(z) = h_1 e^{-s_1 \alpha} - h_2 e^{-s_2 \alpha} \qquad (2)$$

Fig.3 shows one dimensional representation of Gaussian model without light reflex and Fig.4 gives one dimensional representation of Gaussian model with light reflex.

4.2 Profile data extraction

The intensity distribution of blood vessel is investigated in the green component. The green plane exhibits the best contrast between the vessels and background while the red component could be saturated and blue component is usually very dark. Average blood column width being between 8-10 pixels, green component of the fundus photograph is divided in segments with average profile length 10 x 10 pixels, so as to record intensity of only desired segment and not the background intensity. This size is also adequate to locate vessel centre and then to fix points, so as to draw vessel centreline. Orientation of the blood vessel is taken from 0-π. Japanese guideline for reading retinal fundus images states that artery to vein ratio (A/V ratio) should measured on vessels in the region from quarter disc to one disc diameter from the optic nerve head margin[4]. In addition major vessels used for the A/V ratio measurement usually run from the optic nerve head to upper and lower temporal regions. Hence blood vessels which are considered for feature extraction are these measure blood vessels in upper and lower temporal regions of retina. Thus from temporal regions of green plane of the fundus image, 25 vasculature segments are obtained. For each segment vessel centre 'c' is obtained first then two points (p_1 and p_2) are marked on either side of the vessel centre so as to plot vessel centreline. The procedure is as shown in the Fig.5. Gaussian intensity distribution along the vascular centreline is then obtained.Several previous authors have presented algorithms for measuring vasulature diameters. Binchmann-Hansen et al measured widths of the retinal vessels using microdensitometry and observed the importance of the central light reflex[1] [24] [25]. They presented an algorithm which is called full width half maximum (FWHM). This approach calculates a half height point on the left and right sides of the initial estimated midpoint of the profile. On each side, the minimum and maximum intensity levels are calculated and the half height point is located where the profile crosses the midpoint in intensity between minimum and maximum. The FWHM estimate of the profile width is then the distance between these half height points. This approach is also called as half height at full width (HHFW). Fig.6 and Fig.7 show Gaussian intensity distribution obtained for a blood vasculature segment without light reflex and with light reflex conditions respectively. For every vasculature segment feature input vector is obtained from twin Gaussian intensity distribution. Fig.8 shows distribution of features for normal and pathological fundus images. The gaussian profile heights (h_1, h_2) and widths (s_1, s_2) change drastically in case of any pathology occurring in the image. Blood vessel with increased diameter show greater values of these four parameters than the healthy blood vessel.

4.3 Feature set and Classification

The aim of this work is to classify each image as either normal or proliferative diabetic retinopathy image based on diameters of blood vessels running in the upper and lower temporal regionsof the retina. For this purpose labeled example features and classifier is needed. The feature set used in this work is created by applying FWHM algorithm to measure blood vessel width from the intensity profile orthogonal to a retinal vessel. With this minimum and maximum intensities are identified on either side of without light reflex and with light reflex profiles. From these values heights of G_1 and G_2 can be obtained. Profile width is the distance between half maximums as shown in Fig.4. Thus each input feature vector to classifier has four characteristic features h_1, s_1 h_2 and s_2. In this experiment two classifiers are used. K-nearest neighbor (k-NN), a linear classifier and a feed-forward neural network with backpropogation algorithm, a nonlinear classifier. k-NN is more or less trivial to tune and can be good baseline in judging features whereas a neural network is a parallel system**,** capable of resolving paradigms that linear computing cannot. The training set consisted of 34 images. From each image 25 segments are carefully selected which are consisted of only blood vessel segment and not other information. Profile data is extracted for each segment which form feature input vector to classifier. The classifier is also provided with a target input vector which has two classes normal and diabetic retinopathy. The testing data consists of 14 images. This data has not been trained to classify.

4.4 Performance Measurement

Performance of the classifier is verified by calculating True Positives (TP), false negatives (FN), false positives (FP) and true negatives (TN). From these quantities Recall Rate (RR), True Negative Rate (TNR) and Positive Predictive Value (PPV) and Accuracy are chosen as measurements of accuracy of the algorithm, calculated using equations (3), (4), (5) and (6).

$$\text{Recall Rate} = \frac{TP}{TP + FN} \quad (3)$$

$$TNR = \frac{TN}{TN + FP} \quad (4)$$

$$PPV = \frac{TP}{TP + FP} \quad (5)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

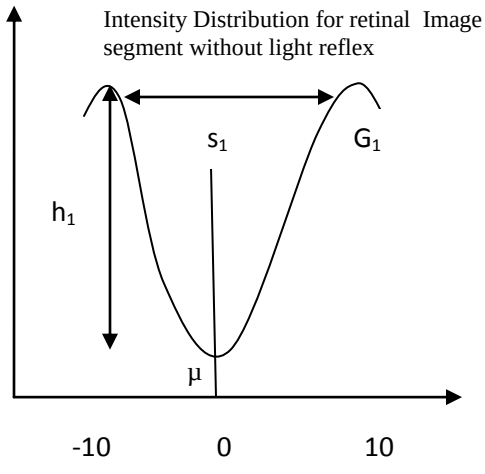

Fig 3: One Dimensional Representation of Gaussian Model without light reflex

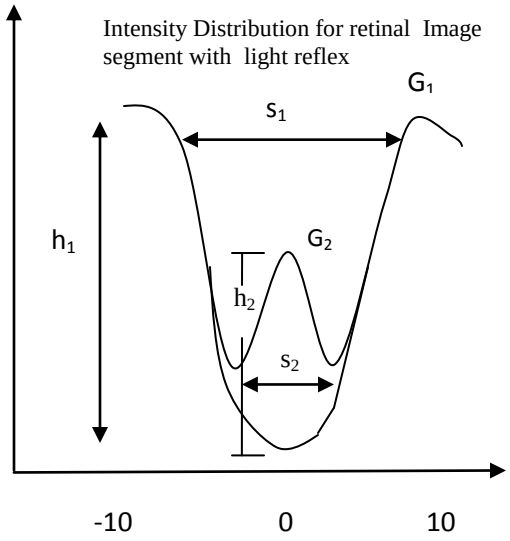

Fig 4: One Dimensional Representation of Gaussian Model witht light reflex

5. Results

We have proposed a computational paradigm for the detection of diabetic retinopathy, particularly proliferative diabetic retinopathy. This approach is based on Gaussian intensity distribution and measurement of blood vessel width. In Table I overview of the performance of k-NN classifier and neural network is given. These results have been presented and discussed with expert ophthalmologist. Both the classifiers have shown the same performance with Recall Rate (RR) 75 %, True negative Rate (TNR) 98.97%, Positive Predictive Value (PPV) 95% and Accuracy 92.85%.

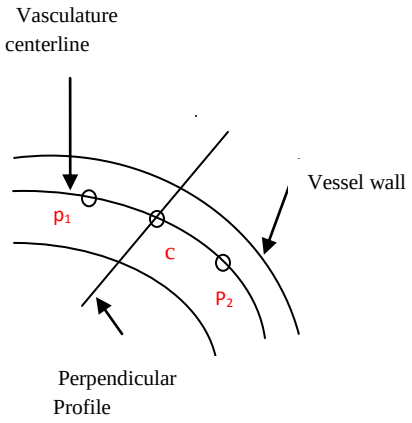

Fig 5: Intensity distribution along the vasculature centreline

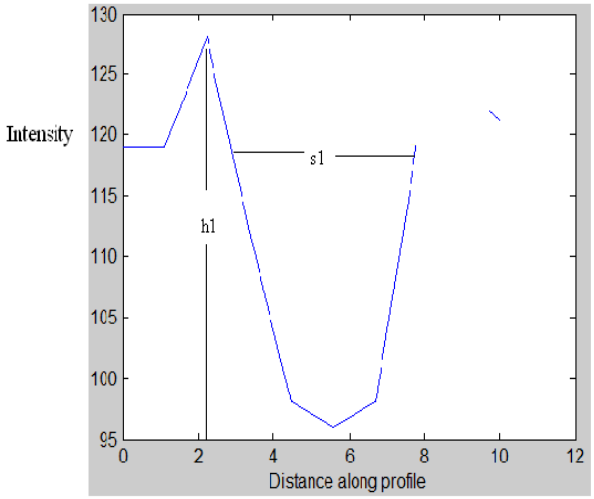

Fig 6 : Gaussian Intensity Distribution for vasulature segment without light reflex

Divyanjali Satyarthi et al.[2] proposed a method of detection of diabetic retinopathy using Gaussian intensity feature input and vector quantizer considering single gaussian profile (h_1 and s_1). And average diagnostic performance was found to be 90%.Gaussian intensity distribution must be considerd with light reflex as the light reflex is understood to run across the surface of the plasma zone and the blood column of erythrocytes and is believed to be generatedfrom a rough reflecting surfaces.Hence in our method we consider twin gaussian intensity distribution without light reflex and with light reflex.With this improved performance of 93% has been achieved.

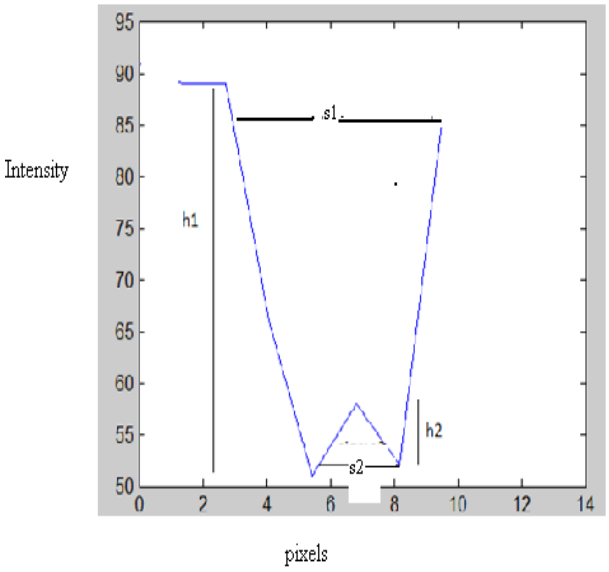

Fig 7: Gaussian Intensity Distribution forvasulature segment without light reflex

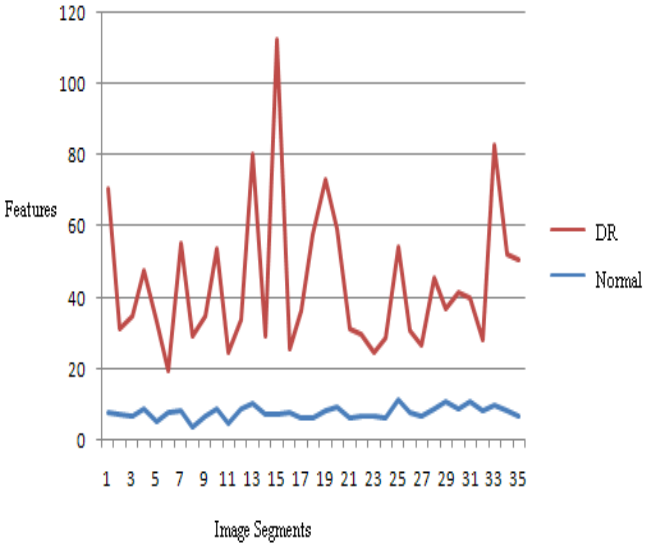

Fig 8: Distribution of features for normal and pathological fundus images

6. CONCLUSIONS

This paper proposed a method for classification fundus photographs into two classes, normal and diabetic retinopathy. The overall process consisted of obtaining Gaussian intensity distribution and using FWHM algorithm for measuring width of vasculature segments in the temporal region of the retina. As the typical vessel is only few pixels wide, obtaining precise measurements of vascular widths is a critical and demanding process in automated retinal image analysis. The proposed method considers intensity distribution with light reflex and without light reflex and gives improved performance in detecting diabetic retinopathy from fundus photographs. In this work we have considered only changes in the vessel width but along with this other characteristic features of DR like microaneurysms, exudates haemorrhages and blood vessels features like like tortuosity, tortuosity density could also be considered in grading retinopathy. Also the results obtained are on the few samples hence it is necessory to validate the results on more samples. Nonavailabilty of common database with large number of samples restricts comparative analysis of this approach with other methods.

Table I Performance of the classifiers (k-NN and Neural network)

Sl.No	Parameter	Performance (%)
1	Recall Rate	75
2	TNR	98.97
3	PPV	95
4	Accuracy	92.85

RR-Recall Rate, TNR-True Negative Rate, PPV-Positive Predictive Value

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