A Review on Detection of Extra Blood Vessel Growth in Retinal Images Using Wavelet Based 2D-Gabor & Contourlet Transform

***Prof. S.V.Pattalwar*[1]*, Mr.L.S Kalkonde* [2]**

[#]*Department of Electronics and Telecommunication Engineering,*
Prof Ram Meghe Institute of Technology & Research, Badnera

Abstract— **Diabetes can cause the loss of vision when it starts affecting your retina. Retinopathy a disease of the retina that can result in loss of vision. Explicitly retinopathy involving damage to the small blood vessels in the retina; results from chronically high blood glucose levels in people with poorly controlled diabetes. Diabetic retinopathy, the most common diabetic eye disease, occurs when blood vessels in the retina change. Sometimes these vessels swell and leak fluid or even close off completely. In other cases, abnormal new blood vessels grow on the surface of the retina. In this paper we are comparing techniques for early detection of hetromorphic blood vessel growth in diabetic patient using 2D-gabor transform & wavelet based contourlet transform. The performance of these systems is evaluated on publicly available DRIVE and STARE databases of manually labelled images. Here we consider accuracy & standard deviation for comparison.**

***Index Terms— Diabetic retinopathy, blood vessel,* growth hetromorphic, leak, swell & vision.**

I. Introduction & Related Work

Diabetes kills with neither speed nor precision, but with stealth and the slow accumulation of insults. It can rob a person of the ability to see, feel, think, walk, and have sex [4]. Diabetes mellitus, or simply diabetes, is a group of metabolic diseases in which a person has high blood sugar, either because the pancreas does not produce enough insulin, or because cells do not respond to the insulin that is produced. This high blood sugar produces the classical symptoms of polyuria (frequent urination), polydipsia (increased thirst) and polyphagia (increased hunger). The cost of diabetes to an individual cannot be calculated, but for the United States an estimated $245 billion was spent in 2012 a 41% increase from $174 billion in 2007, according to new research released on care for chronic diabetes-related complications. Diabetic retinopathy is the most common diabetic eye disease [3].

Traditional methods for edge detection such as Sobel, Prewwit, Canney are lagging behind since we have to process fundus images where edges are not sharp. To overcome this some attempts have already been made to extract retinal vessels from fundus images such as matched filter approach [5],vessel tracking methods to obtain the vasculature structure. [6],watershed algorithm [7], probabilistic filters [8], Morphological Processing is widely used for extracting the diabetic retinopathy lesions [9].Discrete ripplet transform is used for enhancing the DRIVE database image [10]. It has been proved that due to certain characteristics of retinal images the vessel detection is more difficult, therefore by adopting enhancement technique before segmentation will provide additive advantage in segmentation process through morphological operators. Morphological reconstruction is done to the segmented image so as to get the connected components of the image thus getting the reconstructed image. Through mathematical morphology technique retinal blood vessel extraction is done, noise can be reduced & contrast can be improved by first enhancing retinal image [5].

In this paper, we are conferring about 2D Gabor wavelet transform & wavelet based contourlet transform.

The paper is organized in seven sections. In section II classification of diabetic retinopathy, section III will clarify actual problem with DR, image database is provided in section IV .Comparison and evaluation of the two techniques for automated vessel enhancement and segmentation is discussed in section V. Experimental results on the retinal images of the DRIVE and STARE databases and their analysis is given in Section VI followed by conclusion in section VII.

II. Classification of Diabetic Retinopathy

A. BDR-Background Diabetic Retinopathy

The earliest stage of diabetic retinopathy. With this condition, damaged blood vessels in the retina begin to leak extra fluid and small amounts of blood into the eye. Sometimes, deposits of cholesterol or other fats from the blood may leak into the retina.

B. PDR- Proliferative Diabetic Retinopathy

Mainly occurs when many of the blood vessels in the retina close, preventing enough blood flow.

C. SDR- Severe Diabetic Retinopathy

Continuous abnormal vessel growth & scare tissue, which lead to retinal detachment & hence loss of vision.

D. Macular Edema

Diabetic macular edema may be asymptomatic at first. As the edema moves in to the fovea (the center of the macula) the patient will notice blurry central vision. The ability to read and recognize faces will be compromised.

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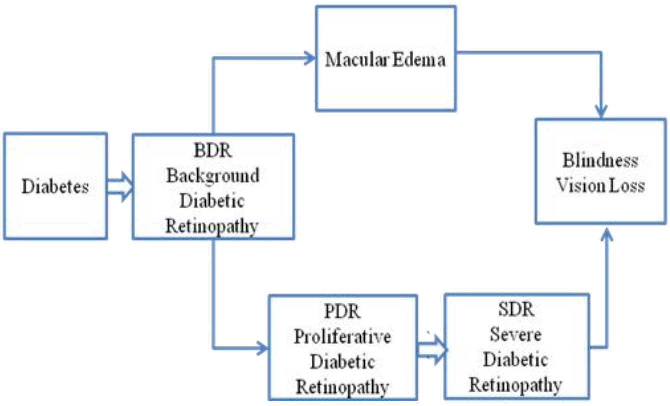

Fig 1 Classification of diabetic retinopathy

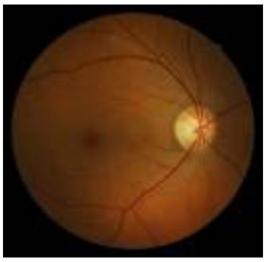

Fig 2 Healthy eye

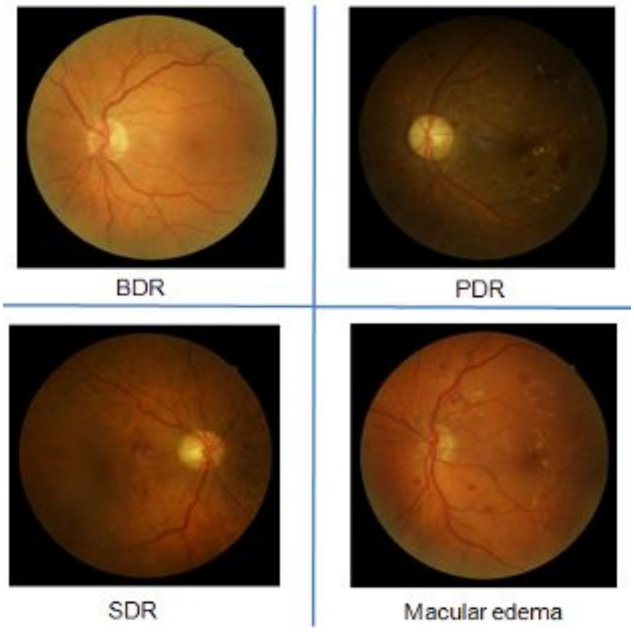

Fig 3 Unhealthy eye patterns

III. Actual Problem

With reference to recent data shared by WHO-World Health Organization, total number of people with diabetes is projected to rise from 171 million in 2000 to 400 million in 2030 [3][4]. People with diabetes are 25 times more likely to become blind than the general population**.** So it is essential to get acquainted with stages of the retinopathy to detect it in early stage. In the early stages, small fine blood clots develop on the retina accompanied with hazy white spots. At this stage, the retinopathy can be easily cured and reversed. In later stages, the vessels leak producing condition of macular edema when the vision starts to get affected. As the vessels continue leaking, fibrous fine bands like cobwebs develop on the retina and as they heal, the fibrous bands pull off the retina causing retinal detachment at multiple places leading to *"total loss of vision"*. Refer fig 4 & 5 for comparison of vision by normal eye & eye affected due to diabetic retinopathy.

Fig 4 Normal vision

Fig 5 Same scene viewed by a person with diabetic retinopathy

IV. Image Database

Images of retina captured using fundus camera are used for processing purpose, so that we able to diagnose the retinal diseases. In medical terms fundus is termed as bottom or baseline of anything. Fundus image consist *retina, optic disc, macula & posterior pole*.Image databases are very important because all image processing algorithms developed have to be tested and verified. An overview of all publicly available retinal image databases known to us is given in this section.

A. DRIVE (Digital Retinal Images for Vessel Extraction) Database

The database consist of 40 colour fundus photographs & their ground truth images. Each image is JPEG compressed. All images in DRIVE database are digitized using a Cannon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Each image is captured using 24-bits per pixel at the image size of 768×584. These images were labeled by hand, to produce ground truth vessel segmentation. Below figure shows a sample of the input image from this database [17].

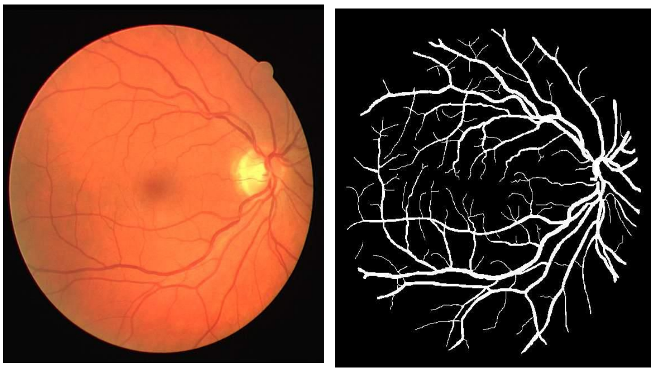

Fig 6 Retinal images from DRIVE database (left), hand labeled ground truth vessel segmentation

B. STARE (Structured Analysis of Retina) Database

Here there are twenty retinal fundus slides and their ground truth images. The images are digitized slides captured by a Top Con TRV-50 fundus camera with 35 degree FOV. Each slide was digitized to produce a 605 x 700 pixel image with 24-bits per pixel(RGB image). All the twenty images were carefully labeled by hand to produce ground truth vessel segmentation by an expert. Below figure shows a sample of the input image from this database [18].

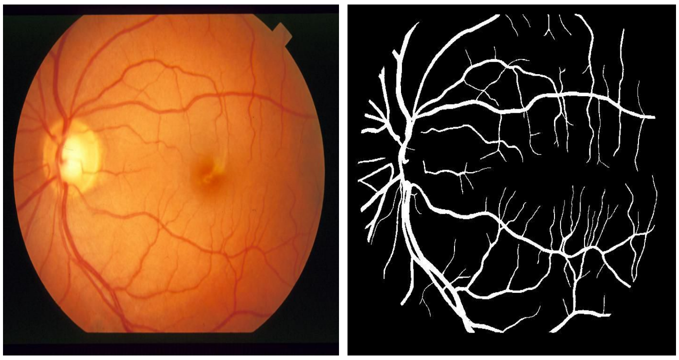

Fig 7 Retinal images from STARE database (left), hand labeled ground truth vessel segmentation

V. Comparative Analysis

Above said techniques are compared over here.

E. Technique Using 2D-Gabor Wavelet Transform

Refer flow chart for simulation steps in fig 8. We can summaries the simulation steps as first step is of preprocessing can ensure appropriate detection of abnormality by automatic screening system .In second step image enhancement is achieved through 2D gabor transform then finally we get segmented image.

i. Preprocessing

In automatic screening system pre processing of image got enormous importance since noise may introduce in image due to moment of subject (patient) & inadequate illumination may change optic disc darker than other areas of image as a pre-processing step of all retinal funds images only green band is extracted & all further processing are applied on green component, as it displays best contrast vessel to background & the greatest contrast between optic disk & retinal tissue, whereas the red & blue channels show low contrast and are very noisy hence we accentuate on green component of image.

ii. Adaptive Histogram Equalization

In the adaptive algorithms each pixel is modified based on the pixels that are in a region surrounding that pixel. This region is called *contextual region*. The adaptive histogram equalization is computationally intense, locally adaptive, and usually produces superior images and for this reason we are implementing this step to increase the speed of the basic non-adaptive method. If we have an image of n x n pixels, with k intensity levels and the size of contextual region is m x m, then time required is calculated as

$$\text{Computation Time} = o(n^2(m+k)) \qquad (1)$$

iii. 2D Gabor Wavelet Transform

The Gabor wavelet transform has some impressive mathematical and biological properties .we have learned that the wavelet transform could perform multi-resolution & multi-orientation time-frequency analysis. It consists of a group of Gabor filters at different frequencies and directions. Gabor wavelets were produced by a Gabor kernel that is a product of an elliptical Gaussian and a complex plane wave [12].

The Gabor kernel is defined as:

$$\psi_G(x) = \exp(jk_0 x)\exp(-1/2|Ax|^2) \qquad (2)$$

where A is a 2 x 2 diagonal matrix that defines the anisotropy of the filter and k_0 is a vector that defines the regularity of the complex exponential.The response with highest modulus over all ranging from 0° up to 170° is calculated for each pixel location using .

$$M_\psi(b,a) = \max_\theta |T_\psi(b,\theta,a)| \qquad (3)$$

Gabor wavelet has good characteristics in space frequency, space position and direction selectivity.

iv. Segmentation for Enhanced Image

Thresholding [1] techniques produce segments having pixels with similar intensities. Generally we have gray-level based segmentation method using global thresholding.

In global thresholding, a threshold value of θ is chosen and the following condition is imposed

$$f(m,n) = 1 \;\; if \;\; f(m,n) \geq \theta$$
$$= 0 \;\; elsewhere \qquad (4)$$

Above equation is a binarisation algorithm; it contains no indication on how to select the value of threshold parameter θ & it is to be selected in optimal manner.

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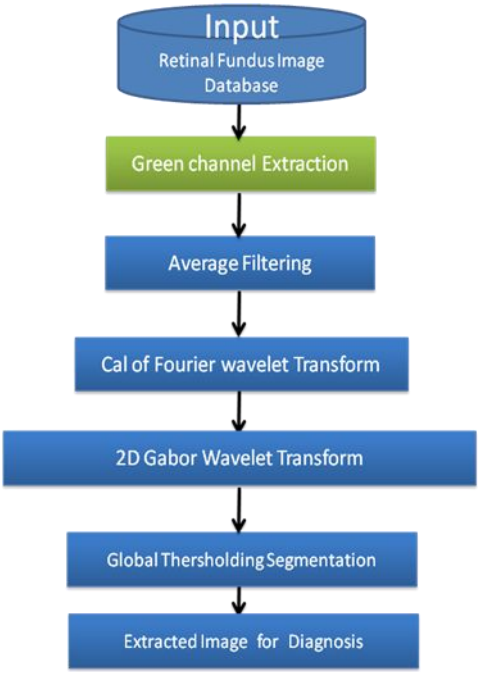

Fig 8 Flow chart for Gabor Wavelet

F. Technique Using WBCT - Wavelet Based Contourlet Transform

Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique is employed while histogram equalization works on the entire image, CLAHE operates on small regions in the image, called tiles.

Although the wavelet transform is proved powerful in many signal and image processing applications such as compression, noise removal, image edge enhancement, and feature extraction.

It has been observed that wavelet transforms are not capable of reconstructing curved images perfectly; hence we switch over concept, called contourlet Transform, proposed by Do and Vetterli [15]. It is a multi-resolution and directional decomposition of a signal using a combination of Laplacian Pyramid (LP) and a Directional Filter Bank (DFB). As shown in figure 9 & 10, the first stage provides sub band decomposition through laplacian pyramid & the second stage of the WBCT is a directional filter bank (DFB), which provides angular decomposition. Since the wavelet filters are not perfect in splitting the frequency space to the low pass and high pass components, that is, not all of the directions in the HL image are vertical and in the LH image are horizontal, we use fully decomposed DFB on each band.

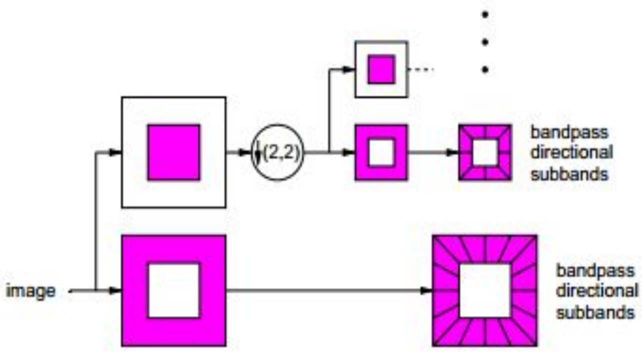

Fig 9 A flow graph of the contourlet transform

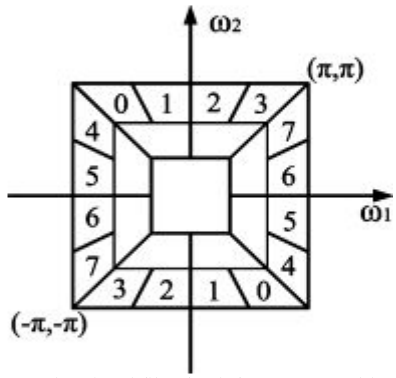

Fig 10 Directional filter bank frequency partitioning

The contourlet transform has good approximation properties for smooth 2D functions and finds a direct discrete-space construction, and is therefore computationally efficient. Also it is a non-redundant version of the contourlet transform. WBCT has good characteristics features in multi-scale edge enhancement. Let us define wavelet based contourlet packets as [19]

$$\eta_{j_i,k,n}^{p_i,q_i,(l_d)} = \sum_{m\in Z^2} g_k^{(l_d)}[m - S_k^{(l_d)} n]\,\psi_{j_i,m}^{p_i,q_i} \qquad (5)$$

Where,

j_i, p_i, q_i are the indices of the terminal node of wavelet packet tree which specify the scale, direction, and location, respectively.

For l - level DFB

$$\sum_{m\in Z^2} g_k^{(l_d)}[m - S_k^{(l_d)} n] \ , \ 0 \le k \le 2^{l_d} \ , m \in Z^2$$

is directional basis for $l^2(Z^2)$, $g_k^{(l_d)}$ is the impulse response of the synthesis filter, l_d directional level.

Finally $\eta_{j_i,k,n}^{p_i,q_i,(l_d)}$ forms a orthonormal basis for $V_L^2 = W_j^{0,0}$ leaf node.

Objective of segmentation is to extract various features of the image in order analyze it. So here we discuses multilayered thresholding for blood vessel segmentation which takes enhanced image by WBCT as an input. Multilayered thresholding performs well for large variations in illumination and even for capturing the thinnest vessels. With reference to fundus image blood vessels have high response at center and low on edges. So it is very difficult to find one optimal threshold value for accurate blood vessel segmentation without any supervised algorithm. In multi layer -red thresholding technique, we apply different thresholds values iteratively and keep track of vessels in successive layers. If we compare multilayered thresholding (MT) with global thresholding (GT) then we find MT provides better results than GT.

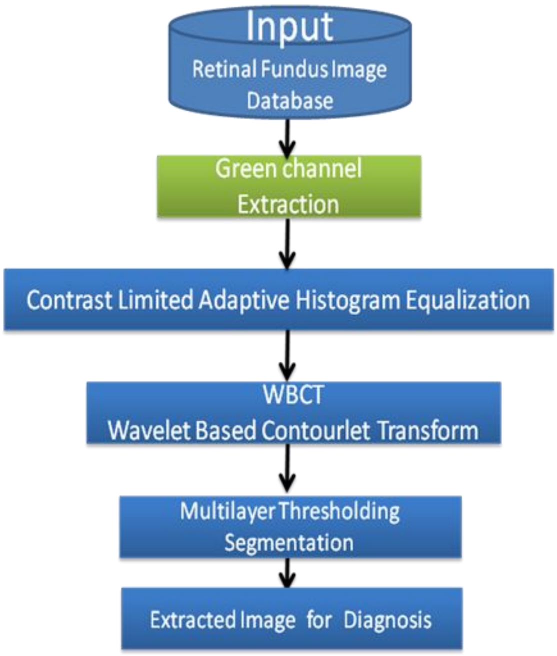

Fig 11 Flow chart for wavelet based contourlet transform

VI. BENCHMARKING PARAMETERS

In medical diagnosis, the medical input data is usually classified into two classes, where the disease is either present or absent. The classification accuracy of the diagnosis is assessed using the sensitivity and specificity measures. Following the practices in the medical research, the fundus images related to the diabetic retinopathy are evaluated by using sensitivity and specificity per image basis. Sensitivity is the percentage of abnormal fundus classified as abnormal, and specificity is the percentage of normal fundus classified as normal by the screening. The higher the sensitivity and specificity values, the better the diagnosis. Sensitivity and specificity can be computed as

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

$$Accuracy = \frac{(TP + TN)}{TP + FN + TN + FP} \quad (8)$$

Here TP denotes true positive, FP denotes false positive, FN is false positive & TN is true negative. True Positive refers to the correctly identified vessel pixels, True Negative refers to the wrongly identified vessel pixels, False Positive refers to the correctly identified background pixels and False Negative refers to the wrongly identified background pixels.

We compare above two transforms using average accuracy & standard deviation.

TABLE I: VESSEL SEGMENTATION RESULTS (DRIVE DATASET)

Sr No.	Technique	Average Accuracy	Standard Deviation
1	Chaudhari et al	0.9103	0.0048
2	Staal et. al.	0.9441	0.0079
3	Jiang et. al.	0.9466	0.0055
4	2-D Gabor Wavelet	0.95	0.0050
5	WBCT	0.9740	

TABLE II: VESSEL SEGMENTATION RESULTS (STARE DATASET)

Sr No.	Technique	Average Accuracy	Standard Deviation
1	2nd Observer	0.9351	0.0171
2	Staal et. al.	0.9516	0.0329
3	Soares et. al.	0.9480	0.0298
4	2-D Gabor Wavelet	0.9588	0.0333
5	WBCT	0.98	

VII. CONCLUDING REMARKS

An image database, ground truth and evaluation methodology was proposed for evaluating and comparing methods for automatic detection of diabetic retinopathy. Best promising result will be provided by WBCT in terms of Accuracy. Still we can compare other parameters such as PSNR, selectivity & specificity.

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AUTHORS

[1] **Prof.S.V.Pattalwar** received master's degree in 1998 in Electronics Engineering from SGBAU, Amravati University, India. He has ▼23 years of teaching experience & currently working as Associate Professor in Department of Electronics & Telecommunication at Prof Ram Meghe Institute of Technology & Research, Badnera-Amravati (India). His main research interests include Electromagnetic, Microwave Communication, and Parallel Computing. He is a fellow of IETE & IEI also member of ISTE. He has published 26▼▼▼▼▼▼ papers in National &International Journal & Conferences.

[2] Laxmikant S. Kalkonde is presently pursing master's Degree in Digital Electronics from SGBAU, Amravati University, India. He Worked as RF Engineer in Metro Wireless Engineering (India) Pvt. Ltd. Mumbai. He has 5 years of working experience.. His Areas Of interest are Digital Signal Processing, Wireless Communication and Image processing. He is associate member of IETE. HE has published 1 paper in International Conference.