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A Survey on Retinal Blood Vessel Segmentation Algorithm for Diabetic Retinopathy using Wavelet

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***Abstract*— Blood vessel structure in retinal images have an important role in diagnosis of diabetic retinopathy. There are several method present for automatic retinal vessel segmentation. For developing retinal screening systems blood vessel segmentation is the basic foundation since vessels serve as one of the main retinal landmark features.**

The most common signs of diabetic retinopathy include haemorrhages, cotton wool spots, dilated retinal veins, and hard exudates. A patient with diabetic retinopathy disease has to undergo periodic screening of eye. For the diagnosis, doctors use colour retinal images of a patient required from digital fundus camera. The present study is aimed to develop an automatic system for the extraction of normal and abnormal features in colour retinal images. We present a method that uses morlet wavelet for vessel enhancement due to their ability to enhance directional structures and thresholding technique for accurate vessel segmentation.

***Index Terms*—Diabetic Retinopathy, Retinal Blood Vessels, Segmentation, Wavelet.**

I. INTRODUCTION

Retinal angiography images are mainly used in the diagnosis of diseases such as diabetic retinopathy and hypertension etc. In diabetic retinopathy structure of retinal blood vessels change that leads to adult blindness. To overcome this problem automatic biomedical diagnosis system is required. The diabetic retinopathy has 4 stages. Mild Non-proliferative Retinopathy is the earliest stage.in this micro aneurysms occur. They are small areas of balloon-like swelling in the retina's tiny blood vessels.The next stage is Moderate Non-proliferative Retinopathy. As the disease progresses, some blood vessels that nourish the retina are blocked.The third stage is Severe Non-proliferative Retinopathy. Many more blood vessels are blocked, depriving several areas of the retina with their blood supply. These areas of the retina send signals to the body to grow new blood vessels for nourishment.The advance stage is Proliferative Retinopathy. At this advanced stage, the signals sent by the retina for nourishment trigger the growth of new blood vessels.

This condition is called proliferative retinopathy. These new blood vessels are abnormal and fragile. They grow along the retina and along the surface of the clear, vitreous gel that fills the inside of the eye. By themselves, these blood vessels do not cause symptoms or vision loss. However, they have thin, fragile walls. If they leak blood, severe vision loss and even blindness can result.The main stage of diabetic retinopathy are Non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR)[4,1].

Eye care specialist can screen vessel abnormalities using an efficient and effective computer based approach to the automated segmentation of blood vessels in retinal images. Automated segmentation reduces the time required by a physician or a skilled technician for manual labeling. Thus a reliable method of vessel segmentation would be valuable for the early detection and characterization of changes due to such diseases [3,4,5]. This article presents the automated vessel enhancement and segmentation technique for colored retinal images. Segmentation of blood vessels from image is a difficult task due to thin vessels and low contrast between vessel edges and background. The proposed method enhances the vascular pattern using 2-D Morlet wavelet and then it uses thresholding technique to generate gray level segmented image.

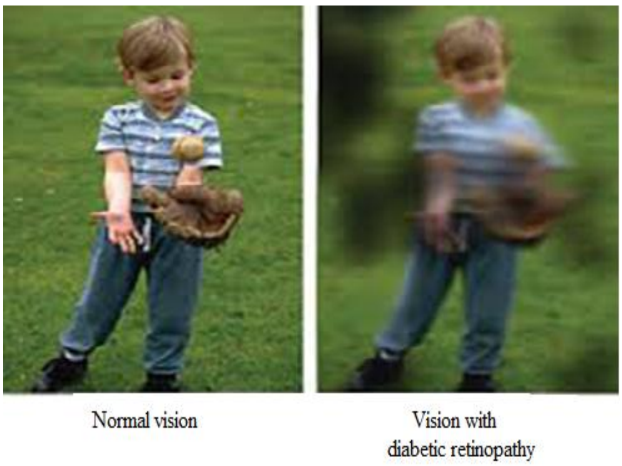

Figure -1(a)

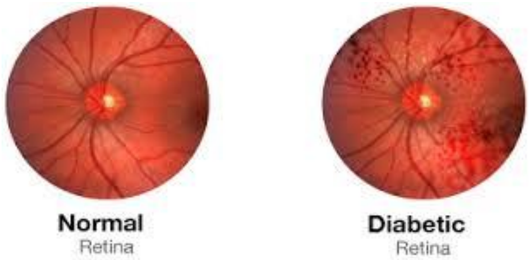

Figure-1(b)

Figure-1 shows the difference between the normal retinal image and diabetic retinal image.

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II. METHODOLOGY

1 Gabor Wavelet :

We present a method for automated segmentation of the vasculature in retinal images. The method produces segmentations by classifying each image pixel as vessel or non vessel, based on the pixel's feature vector. Feature vectors are composed of the pixels intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales. The Gabor wavelet is capable of tuning to specific frequencies, thus allowing noise filtering and vessel enhancement in a single step[4].

An automatic assessment for blood vessel anomalies of the optic fundus initially requires the segmentation of the vessels from the background, so that suitable feature extraction and processing may be performed. Several methods have been developed for vessel segmentation, but visual inspection and evaluation by receiver operating characteristic (ROC) analysis show that there is still room for improvement: human observers are significantly more accurate than the methods, which how flaws around the optic disk and in detection of the smallest vessels . In addition, it is important to have segmentation algorithms that are fast and do not critically depend on configuring several parameters, so that untrained community health workers may utilize this technology. This has motivated the use of the supervised classification framework described here, which only depends on manually segmented images and can be implemented efficiently.

A major difficulty in evaluating the results is the establishment of a reliable ground truth. Human observers are subjective and prone to errors, resulting in large variability between observations. Thus, it is desirable that multiple human-generated segmentations be combined to establish a ground truth, which was not the case in the analysis presented. The major errors are in false detection of noise and other artifacts. Another drawback of our approach is that it only takes into account information local to each pixel through image filters, ignoring useful information from shapes and structures present in the image. We intend to work on methods addressing this drawback in the near future. The results can be slightly improved through a post processing of the segmentations for removal of noise and inclusion of missing vessel pixels as in . An intermediate result of our method is the intensity image of posterior probabilities, which could possibly benefit from a threshold probing as in or region growing schemes.

B. Discrete Cosine Transform :

Support vector machine (SVM) has become an increasingly popular tool for machine learning tasks involving classification. In this paper, we present a simple and effective method of detect and classify hard exudates. Automatic detection of hard exudates from retinal images is worth-studying problem since hard exudates are associated with diabetic retinopathy and have been found to be one of the most prevalent earliest signs of retinopathy. The paper is organized as follows. Section 2 provides a related work on diabetic retinal exudates. The technique uses Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT) to create feature vector for retina images in Section 3, and diabetic retinal classification by color histogram clustering technique and SVM in Section 4. Finally, Section 5 presents the results and discussion of the experiments that have been conducted to compare the performance of the diabetic retinal exudates based on SVM and traditional methods. DCT with SVM is more efficient but the execution time is very high[16].

C. Morlet Wavelet :

The Morlet Wavelet transform is the kind of the Continuous Wavelet Transform, which is one class of the Wavelet transform.

There are three distinct classes about Wavelet transform in use today: Continuous Wavelet Transform (CWT), continuous Wavelet transform with discrete coefficients and Discrete Wavelet Transform. With respect to continuous/discrete in the input/output, we distinguish this three classes following. Table1. Shows the difference between these 3 classes with respect to there input and output.

TABLE I . DIFFERENT CLASSES OF WAVELET TRANSFORM

Class	***Input***	***Output***
Continuous wavelet transform	Continuous	Continuous
continuous Wavelet transform with discrete coefficients	Continuous	Discrete
Discrete Wavelet Transform	Discrete	Discrete

The Morlet wavelet has a form very similar to the Gabor transform. The important difference is that the window function dose also be scaled by the scaling parameter, while the size of window in Gabor transform is fixed.

There are several types of wavelets, such as 2-D Mexican hat and the optical wavelet but 2-D Morlet wavelet is chosen. This type of wavelet is suitable for our purpose since it has the capability of detecting oriented features and tuning to specific frequencies. Since it can adjust to the frequency, background noise can be removed.

The Morlet wavelet is the most popular complex wavelet used in practice, which mother wavelet is defined as

$$\psi_m(x) = \exp(jk_0 x)\exp(-\frac{1}{2}|Ax^2|) \quad (1)$$

diagonal matrix that defines the anisotropy of the filter

Where $j = \sqrt{-1}$ and $A = diag[\varepsilon^{\frac{-1}{2}}, 1], \varepsilon \geq 1$ is a 2*2.

2 The Morlet wavelet is a complex exponential modulated Gaussian function.
3 The aim is to find maximum modulus in all scales and over all orientations.
4 Different scales of Morlet transform allow us to detect vessels with various thicknesses.
5 The flexible window size with scaling parameter and makes it possible to segment vessels of different orientations.

In our project classification is based on the pixels. Each pixel is categorized as vessel or non-vessel. Two widely known measurements are used for evaluation of his method :sensitivity and selectivity. The true positive fraction (TPF), also called sensitivity, is determined by dividing the number of pixels correctly classified as vessel pixels (TP) by the total number of vessel pixels in the ground truth.

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

Specificity is determined by dividing the number of pixels correctly classified as background pixels (TN) by the total number of background pixels in ground truth.

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

Where false negative (FN) appears when a pixel in a vessel is segmented in the non-vessel area, and a false positive (FP) when a non vessel pixe4l is segmented as a vessel pixel. True positive (TP) and true negative (TN) when a pixel is correctly segmented as a vessel or non vessel.

The accuracy of the binary classification is defined by

$$Accuracy = \frac{TP + TN}{P + N} \tag{4}$$

Where P and N represent the total number of vessel and non-vessel pixels in the segmentation process. The accuracy shows the degree of conformity between the output and the manual of original image. Thus, the accuracy is strongly related to the segmentation property and shows how proper are the segmentation method. For this reason it is used to evaluate and compare different methods.

Morlet wavelet is more accuracy from the other vessel detection method.The Morlet transform enhance the vessel contrast and filter out the noise. It is used in different scales and makes it possible to segment vessels of different orientations. Using manual for learning allows the approach to be trained for different type of images.

The Morlet transform enhance the vessel contrast and filter out the noise. It is used in different scales and makes it possible to segment vessels of different orientations. These characteristics will make it suitable for our work, and Wavelet transform can be seen a powerful tool in time-frequency analysis. conventional wavelet transform is based on real-valued wavelet function and scaling function, but the Morlet Wavelet transform is actually a complex Wavelet transform.

III. RESULTS AND CONCLUSION

In this paper ,a retinal blood vessel segmentation algorithm is proposed. The morlet wavelet is efficient in enhancing vessel contrast, while filtering out noise. Morlet is the flexible window size with scaling parameter. 2-D Morlet wavelet is chosen, because it has the capability of detecting oriented features and tuning to specific frequencies. Since it can adjust to the frequency, background noise can be removed.The proposed technique can be used in both normal and abnormal retinal blood vessels segmentation.

In gabor wavelet window size is fixed[4], so that morlet wavelet is selected for this framework One of the most important differences that encourage us using Morlet is the flexible window size with scaling parameter while the size of window in Gabor transform is fixed.DCT with SVM is more efficient but the execution time is very high[16]. So that we use morphological operation and thresholding in our project, it reduces execution time.

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