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An Efficient Approach for the Segmentation of Retinal Blood Vessels

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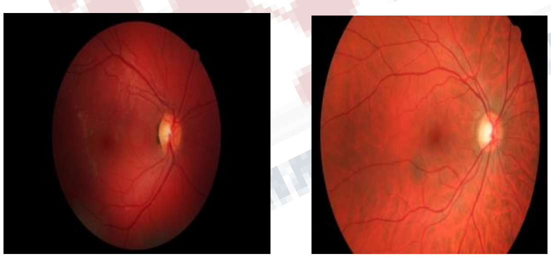
***Abstract:*-- The window to retinal vascular system is the eye. Retinal blood vessels play a vital role in the detection of eye diseases like diabetic retinopathy, hyper tension retinopathy and glaucoma. In this work, Gabor filter is used to enhance the blood vessel. The optimal threshold value is obtained for the gray scale images. Otsu based threshold technique is used to segment the retinal blood vessel. The vessel segmentation approach has been tested on the publically available DRIVE dataset. The extracted features are classified by K-Nearest Neighbor classifier. The performance of the system is proved by the experimental results.**

***Keywords:* Retinal blood vessel, Gabor filter, Otsu's threshold, Image Segmentation, K-Nearest Neighbor.**

I. INTRODUCTION

Human eye is an important part of the human body. The optics of the eye creates an image of the visual world on the innermost part of the eye called the retina (through the cornea and lens). Light that strikes the retina initiates a cascade of chemical and electrical events that trigger the nerve impulses. These are sent to the brain through the optic nerve. The retina can be photographed directly as the pupil is used as both an entrance and exit for the fundus camera's illuminating and imaging light rays. Retinal fundus image is used for to detect and analyze various types of diseases like diabetic retinopathy, hemorrhage and glaucoma. Diabetic retinopathy is a serious disease that affects the entire body [1].



(a) (b)

Fig. 1. Digital retinal images. a) a normal image b) an abnormal image

As manual segmentation and analysis of retinal images is tedious and costly, automated segmentation is important for an ophthalmologist to identify the disease [2]. Fig.1 shows the normal and abnormal retinal fundus images.

Several retinal blood vessel segmentation methods based on supervised and unsupervised approach have been proposed. Supervised methods find segmentation results with labeled images whereas unsupervised methods do not require labeled image. The four categories of unsupervised methods are matched filtering, vessel tracking, morphology processing, and model based algorithms.

II. METHODOLOGY

A. Two-Dimensional Gabor Filters

Gabor filters are simple and most powerful filters used for multi-scale /multi-directional analysis. These filters have specifically shown high performance as feature extractors for discrimination purposes [3,4,5]. Due to the detection of oriented features and specific frequencies to scale, these filters act as low-level oriented edge discriminators. Mathematically a two-dimensional (2D) Gabor function, g, is the product of a 2D Gaussian and an exponential function which can be given by:

$$g_{\theta,\lambda,\sigma 1,\sigma 2}(x,y) = \exp\{-1/2M(x,y)^T\}\exp\{j\pi/\lambda(x\cos\theta + y\sin\theta\} \quad (1)$$

Where M = diag(σ_1^{-2} , $\sigma^{-2}{}_2$). The parameters θ represents filter orientation, λ is the filter wavelength which modifies the sensitivity to high/low frequencies, and σ_1 and σ_2 characterize the filter standard derivations which represent scale value at orthogonal directions. When the Gaussian part is symmetric, we obtain the following isotropic Gabor function:

$$g_{\theta,\lambda,\sigma}(x,y) = \exp\{-x2(x,y)^T\}\exp\{j\pi/\lambda(x\cos\theta + y\sin\theta\} \quad (2)$$

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However, with this parameterization the Gabor function does not scale uniformly, when σ changes. Thus, it is preferable to use a new parameter γ= λ/ σ instead of λ so that a change in σ corresponds to a true scale change in the Gabor function. Also, it is convenient to apply a 90° counter clockwise rotation to Equation (2), such that θ expresses the orthogonal direction to the Gabor function edges. The following definition for the Gabor functions is used.

$$g_{\theta,\gamma,\sigma}(x, y) = \exp\{-(x^2+y^2)/2\sigma^2\}\exp\{j\pi/\lambda\ \sigma\ (x\sin\theta - y\cos\theta\}\quad (3)$$

By convolving a Gabor function with image patterns $f(x, y)$, we can evaluate their similarities. Here, we define the Gabor response at the point (x0, y0) as follows:

$$g_{\theta,\lambda,\sigma}(x_0,y_0) = (f * g_{\theta,\lambda,\sigma})\ (x_0,y_0) = \int f(x, y)g_{\theta,\lambda,\sigma}(x_0 - x,y_0 - y)dxdy \quad (4)$$

where * represent convolution. By selectively, changing each of the Gabor function parameters, the filter response (Equation (4)) can be tuned to particular patterns such as blood vessels arising in the images.

B.Otsu's method

Otsu's threshold based method contain two classes of pixels or bi-modal histogram ie., foreground and background then obtain the optimum threshold divide those two classes so that their combined spread (intra-class variance) is minimal[6]. The extension of the original method to multi-level threshold is referred to as the Multi Otsu method.

In Otsu's method exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \quad (5)$$

Weights ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2 variances of these classes.

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_1(t)\omega_2(t)\left[\mu_1(t) - \mu_2(t)\right]^2 (6)$$

Which expressed in terms of class probabilities ω_i and class means μ_i.

The class probability $\omega_1(t)$ is computed from the histogram as t:

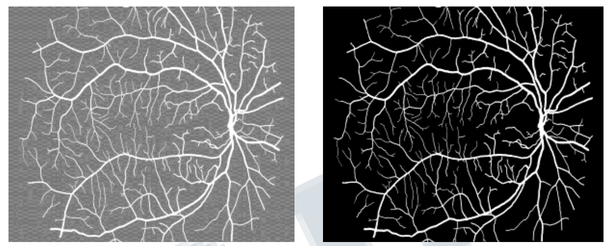
$$\omega_1(t) = \Sigma_0^t p(i) (7)$$

While the class mean $\mu_1(t)$ is:

$$\mu_1(t) = \left[\Sigma_0^t p(i)\,x(i)\right]/\omega_1 \quad (8)$$

Where, $x(i)$ is the value at the center of the i^{th} histogram bin.

Similarly, $\omega_2(t)$ and μ_t on the right-hand side of the histogram for bins greater than t can be computed.



(a) (b)

Fig. 2. a) Thresholded Gray image b) Thresholded image - Otsu's Method

C. K-Nearest Neighbor classifier

Each pixel of the image is constructed as feature vector [9]. This method is very simple because it stores only feature vectors and labels of the training images, and calculates the distance between the feature vector and the training image database. In the classification process, the unlabeled query value is assigned to label of its K nearest neighbors. The classification is based on the label of its K-nearest neighbor by majority value. The main advantage of the KNN is suitable for multi – modal classes, because the decision is done by small neighborhood of same object. This method is the accurate and efficient approach to perform the multi-modal target class [10].

III. PROPOSED METHOD

This paper presents segmentation of retinal blood vessel based on Gabor filter and Otsu's method. The frequency and orientation values are used to extract the Gabor magnitude. The optimal threshold value based on the Otsu's technique is used to segment the retinal blood vessel. The K-Nearest Neighbor classifier is a simple and powerful method to select the pixels randomly from the training set. The extracted features are classified and finally, the accuracy, sensitivity and specificity measurements are evaluated. The performance of the system is evaluated based on the experimental results.

IV. EXPERIMENTAL RESULTS

The performance of the system is estimated from the images on the publically available DRIVE dataset. As pixels are classified as vessel and non-vessel, four possibility values achieved True Positive (TP), True Negative (TN), False Positive (FS) and False Negative (FN). Blood Vessels correctly detected are classified as True Positive, and wrongly detected vessels are True Negative. Correctly and wrongly detected non-blood vessels are false positive [8, 9]. The performance is analyzed by the following parameters:

i)Sensitivity

In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease (true positive rate).
Sensitivity (Se) = TP / (TP+FN)

ii)Specificity

Test specificity is the ability of the test to correctly identify those without the disease (true negative rate).
Specificity (Sp) = TN / (TN+FP)

iii)Accuracy

Given a set of data points from a series of measurements, the set can be said to be accurate if the values are close to the true value of the quantity being measured.
Accuracy (Acc) = (TP+TN) / (TP+FN+TN+FP)

Table1 shows the performance calculated using the proposed method and obtained the accuracy is 96.5%, sensitivity is 71.2% and specificity is 97.2%.

Table 1. Performance Table

Image	Se	Sp	Acc
1	0.691	0.975	0.981
2	0.725	0.962	0.965
3	0.687	0.974	0.967
4	0.726	0.989	0.963
5	0.647	0.982	0.967
6	0.719	0.975	0.958
7	0.723	0.983	0.943
8	0.762	0.981	0.971
9	0.659	0.949	0.971
10	0.683	0.957	0.963
Average	0.712	0.972	0.965

V. CONCLUSION

The retinal blood vessel segmentation plays an important role in the identification of various pathological disorders. In this paper, an automatic segmentation of retinal blood vessel based on Gabor filter is presented. The Extracted features are analyzed and classified by the K-Nearest Neighbor classifier. Experimental result shows that the proposed method is efficient, effective and can be easily implemented to segment fundus images.

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