An Enhanced Retinal Vessel Detection Algorithm

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***Abstract*- Retinal Vessel detection is one of the most studied fields of vessel detection. Study of retina is important as it can help to the diagnosis of many diseases. In this article a combinational algorithm which is based on Gabor wavelet and classification is modified. The modified algorithm gains more than 2% accuracy and outperforms the first algorithm.**

I. INTRODUCTION

Study of vascular and non-vascular tissues has been one of the main tools of diagnosis for many years. Study of retinal vasculature is important as it can help to the diagnosis of hypertension, diabetes, arteriosclerosis, cardiovascular disease and stroke. Computer aided disease diagnosis has spread as it eases the diagnosis, increase the accuracy and speeds up the whole process. Most of these techniques depend on algorithms realizing vessels from non-vessel parts of a tissue.

Different methods have been developed in case of vessel detection. These methods are grouped into three, Kernel based, trackers and classifier based methods[1]. In kernel based methods response of one or more kernels is used to detect the vessel. Most of kernel based algorithms require sort of post processing to enhance the kernel response and gain better accuracy. An algorithm that utilizes a tracker is the one which starts from one or more points and keeps tracks of features extracted by means of a model. The tracked features form the vessel. These methods mostly use a threshold to find the starting points that looks to be a vessel.

The classifier based methods extract a group of features that can be suitable for classifying the pixels of an image into vessel and non-vessel. The simplest form of these algorithms uses threshold based algorithms to detect the vessel.

Recently, enhanced algorithms are based on combination of these methods; a good example of these algorithms could be found in [2-5]. Combinational methods are center of attention because of their accuracy and optimum response. Combining kernel based methods and a supervised classification technique is the most well-known method of combinational group. In this case response of kernels is used as features of a classifier. There is always a triad off between accuracy and training time of the classifier. In this article we concentrate on a combinational method proposed by Soares et al[2] and it is shown that the result can be improved by modifying feature extraction part of the algorithm.

Next section will be an introduction to the Soares' method. In section III the improvement scheme is explained. Section IV contains the simulation results of the two algorithms and comparison of methods. The last part is dedicated to conclusion.

II. SOARES' METHOD

Gabor wavelet response as feature vector and using a supervised classifier to classify the pixels of retinal images into vessel and non-vessel is the main idea of Soares et al[2]. In this section the major parts of the algorithm, feature extraction by use of Gabor wavelet and the classification technique is explained.

A. Feature Extraction

Soares et al uses continuous form of wavelet defined by(1), where c_ψ, ψ, b, θ and a denote normalization constant, analyzing wavelet, displacement vector, rotation angle and scale.

$$T_\psi(b,\theta,a) = c_\psi^{-1/2} \langle \psi_{b,\theta,a} | f \rangle \tag{1}$$

Continuous wavelet can be implemented using Fourier transform described by(2).

$$T_\psi(b,\theta,a) = c_\psi^{-1/2} \int \exp(jkb)\hat{\psi}^*(ar_{-\theta}k)\hat{f}(k)d^2k \tag{2}$$

where $j=\sqrt{-1}, \hat{\psi}^*$ and $\hat{f}$ denote the Fourier transform. Soares et al used Gabor kernel to calculate the wavelet. Gabor is a directional kernel; this property makes it an excellent choice for vessel detection. Gabor wavelet is defined by(3).

$$\psi_G(x) = \exp(jk_0)\exp\left(-\frac{1}{2}|Ax|^2\right) \tag{3}$$

where $A = \mathrm{diag}\left[\varepsilon^{-1/2}, 1\right], \varepsilon \geq 1$ is a 2×2 diagonal matrix which contains the anisotropy of the filter and k_0 is a vector that defines the frequency of the complex exponential. Soares et al sets the ε parameter to 4 and $k=[0,3]$ to perform the calculations. They also used the maximum response of the wavelet over all possible orientations, which is calculated by(4).

$$M_{\psi(b,a)} = \max_\theta \left|T_\psi(b,\theta,a)\right| \tag{4}$$

Thus Gabor wavelet transform is computed for spanning from 0 up to 170° at steps of 10° and the maximum is taken.

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The maximum modulus of the wavelet transform over all angles is calculated for multiple scales are then taken as pixel features. Each image's extracted feature is normalized by its own mean and standard deviation by use of(5).

$$\hat{v}_i = \frac{v_i - \mu_i}{\sigma_i} \tag{5}$$

where $\hat{v}_i$ is the i_{th} normalized feature value, v_i is the i_{th} feature value, μ_i and σ_i are respectively mean and standard deviation of the i_{th} feature.

B. *Classification*

Classification can be performed by use of different tools. Histograms[6], threshold[7-10] and statistical classifiers[2, 3, 5, 11] are all methods of classification that has been used in case of retinal vessel detection.

Use of classification is based on the basis of classifying pixels into vessel and non-vessel groups. The classifier used by Soares et al is Gaussian Mixture Model. *G.M.M* is kind of Bayesian classifier which uses a linear combination of Gaussian functions as class-conditional probability density function[12]. Decision making is done using Bayesian rules defined by(6).

$$\begin{aligned} &\textit{decide}\ \text{vessel}\ \textit{if}\ P(v \mid \text{vessel}).P(\text{vessel}) > \\ &\qquad P(v \mid \text{nonvessel}).P(\text{nonvessel}) \\ &\qquad \textit{else decide}\ \ \text{nonvessel} \end{aligned} \tag{6}$$

Number of Gaussians is an important factor in this method which results in different accuracy. Besides, it affects the time of training, more Gaussians takes more time to train.

III. Enhancement

Kernel-based methods have been used for vessel detection for a long time. Different kernels have been used in literature. One of the most famous kernels that have been used is Gabor kernel. This kernel sometimes is used indirectly, for example Vermeer et al[1] used a modified Laplace kernel which results in a Gabor Kernel. Definition of Gabor kernel given by (2) can be extended and written as(7).

$$\begin{aligned} &\psi_G = \exp\left\{-\left(\frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2}\right)\right\}\cos\left(2\pi x'/\lambda\right) \\ &\text{where } \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \end{aligned} \tag{7}$$

Zhang et al[7] used the above definition and studied the best possible parameters of the kernel, their studies shows for extracting a vessel with the width of *d*, while using window size of *h,* it is best to select $\lambda = 1.5h$, $\sigma_x = \sigma_y = 0.5\lambda$ and $0.5\lambda \geq d$. So by selecting the above definition and the suggested values of parameters, it is expected to get a better vessel realization. Beside the tuned Gabor kernel Zhang et al[7] suggests variance of responses over all possible orientations as defined by (8).

$$V_{\psi(b,a)} = \operatorname{var}_{\theta}\left|T_\psi\left(b,\theta,a\right)\right| \tag{8}$$

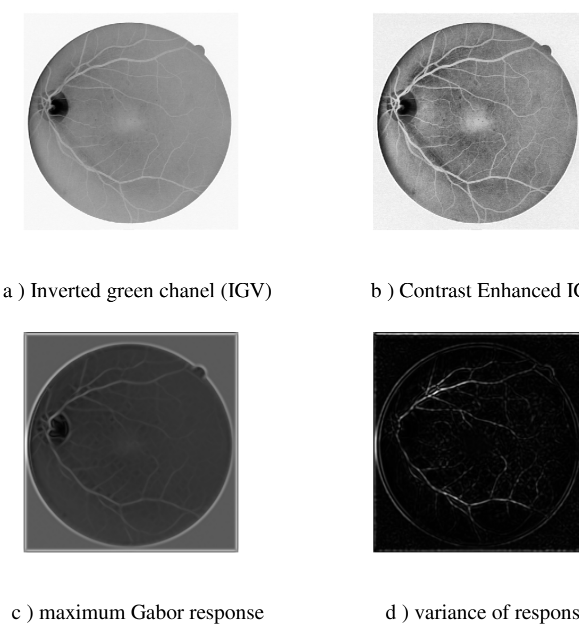
As Fig. 1 shows variance of responses results in a noise insensitive response in comparison to the maximum response. But it needs a preprocessing, such as adaptive contrast enhancement[13] to generate an acceptable response in which vessels can be fully realized.

So it is suggested to let the parameters be adaptive with the width of vessels instead of using a fixed set of values. Also using the variance of responses instead of maximum response is preferred. Using these suggestions the original algorithm was modified and tested on a dataset.

IV. Results

The two algorithms were implemented and tested on the DERIVE dataset. Four different scales of Gabor response plus the inverted green channel of the image were used as feature vector. One million random samples used to train the classification. The implementation was done by using Matlab 7, on a system with 2.4Ghz CPU and 1Gb of RAM. Fig. 2 shows the result of segmentation of the enhanced algorithm for a sample retinal image.

Table I, summarizes result of simulation for the two algorithms, as it is shown the enhanced algorithm that utilizes adaptive Gabor kernel and variance of response outperforms the other algorithm.



a) Inverted green chanel (IGV) b) Contrast Enhanced IGV

c) maximum Gabor response d) variance of response

Fig. 1. Response of Gabor over all orientations, comparison of maximum and variance of response

V. CONCLUSION

In this article it was shown by using the adaptive Gabor kernel and variance of response, instead of maximum response and fixed Gabor kernel in a combinational algorithm, the accuracy increases. In this case a gain of 2.36% is reached.

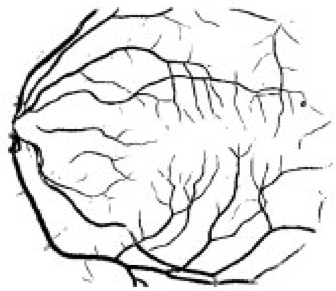


Fig. 2. Sample of vessel detection using the enhanced algorithm

TABLE I
ACCURACY EVALUATION OF ALGORITHMS
USING DERIVE DATA SET

Algorithm	Accuracy
Soares (K^*=2)	91.04%
Proposed algorithm (K^*=2)	93.40%

**K* is the number of Gaussians used in *G.M.M.*

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