Retinal Vessel Segmentation Using Gabor Filter and Textons

Lei Zhang[1]
Lei.zhang@uea.ac.uk
Mark Fisher[1]
http://www2.cmp.uea.ac.uk/~mhf/
Wenjia Wang[1]
Wenjia.Wang@uea.ac.uk

[1] School of Computing Sciences, University of East Anglia, UK

Abstract

This paper presents a retinal vessel segmentation method that is inspired by the human visual system and uses a Gabor filter bank. Machine learning is used to optimize the filter parameters for retinal vessel extraction. The filter responses are represented as textons and this allows the corresponding membership functions to be used as the framework for learning vessel and non-vessel classes. Then, vessel texton memberships are used to generate segmentation results. We evaluate our method using the publicly available DRIVE database. It achieves competitive performance (sensitivity (TPF) =0.7673, specificity (1-FPF) =0.9602, accuracy=0.9430), and especially its considerably higher sensitivity means it is better in detecting vessels than the other methods. These figures are particularly interesting as our filter bank is quite generic and only includes Gabor responses.

1 Introduction

Retinal vessel segmentation is an important preliminary stage in automatic assessment of retinopathy as it enables the vascular tree to be constructed. The integrity of the vascular tree is a key factor in assessment of systematic disease such as diabetes, glaucoma etc. Conventionally, the assessment of the retina vessel anomalies is a skilled time consuming task [1], and as such it has been the focus of research into automatic assessment techniques. Many techniques for automatic retinal vessel segmentation have been proposed [17][18][21][22][23] but a significant number use filter-banks to identify vessel and non-vessel structures. The success of filter-based methods depends largely on the design of the filter bank used to extract vessel features. The work of Chaudhiri et al. [2] is a good example of a filter-bank approach that employs a classic matched filter (MF) and several authors have built on this idea. For instance, M. Al-Rawi et al. [3] improved the performance of the matched filter by optimizing the filter parameters. In [4], Gang et al. proposed an amplitude-modified second-order Gaussian filter. They optimized the parameters of the matcher filter via mathematical analysis and experimental simulation. Zhang et al. [5] proposed a novel extension of the MF approach named MF-FDOG to distinguish the vessels from non-vessel step edges. Wu et al. [6] used a compound filter-bank that combines Hessian-based filters, matched filters and incorporates edge constraints

in a vessel enhancement stage. Further development of compound filters followed due to Adjeroh and Kandaswamy, et al. [7] (RVF-20) and Zhang and Fisher [9] (MR11) for retinal vessel extraction. However these approaches that rely on special filters sometimes introduce pathological changes in the fundus image causing these anomalies to be segmented as vessels, whilst some tinny vessels are miss-segmented. Although a compound vessel enhanced filter set can address some of these limitations, it is computationally expensive since many filter kernels need to be applied on the image. This work investigates if we can balance this situation by decreasing the number of filters while maintaining or improving the segmentation performance. Our technique uses the Gabor filter to enhance retinal vessels. The Gabor filter was originally proposed by Dennis Gabor [20] and subsequently used by Daugman [10][11] to model specific frequencies and orientations of certain cells in the visual cortex of some mammals. Because of its characteristics, Gabor filters have been widely used in many applications of image processing, such as object recognition, edge detection, and texture classification. In this paper, we present a procedure for parameter selection based on the retinal vessel features, and use a further parameter λ to control the function's performance. Section 2.1 describes details of this procedure. We optimise the parameters within the framework of textons derived from vessel feature vectors. Texton-based approaches have been a significant branch of texture analysis processes since the term texton was first introduced by Julesz in the 1980's [13]. Psychophysical experiments have shown that these texture primitives (microstructures) discriminate differences among various textures and models a process used by humans to discriminate one texture from another. Leung and Malik [14] described an operational definition of textons which enables textons to be generated automatically from an image [8][12].

We evaluate our experimental approach by training and testing on the publicly available DRIVE database [17]. The DRIVE data set contains 40 TIFF formatted RGB retinal images with a size of 565*584 pixels. The database is divided into training and test sets, each set consists of 20 images. For the test set, two sets of manual segmentation are provided by two observers. In practice, the first set is used as ground truth whilst the other one can be used to calculate the differences with the first one thus provides the measurements of independent human segmentation. The sensitivity (TPF), specificity (1-FPF) and the overall accuracy are used as performance measures of the experiments. Our results are compared with other state of the art approaches.

2 Method

In this experiment we choose a Gabor filter kernel to extract features of retinal vessels as the function encodes information about specific frequencies and orientations. The Gabor filter was originally introduced by Dennis Gabor [20] and defined as

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} e^{j\omega_0 x} \quad \text{(Eqn. 1)}$$

where $\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$ represents a Gaussian envelope and $e^{j\omega_0 x}$ is a complex sinusoid. Daugman [11] extended the concept to two dimensions

$$g(x,y) = \bar{g}(x,y) e^{j[u_0(x-x_0)+v_0(y-y_0)]}$$
$$\text{where} \quad \bar{g}(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\frac{1}{2}\left(\frac{x^2}{\sigma_x}+\frac{y^2}{\sigma_y}\right)} \quad \text{(Eqn. 2)}$$

where σ_x, σ_y determine the spread of the Gaussian envelope and x_0, y_0 the origin in the spatial domain. If the terms x_0, y_0 are set to 0, this Equation can also be written

$$G_{\lambda,\theta,\varphi,\sigma,\gamma}(x,y) = e^{\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)} \cos\left(2\pi\frac{x'}{\lambda}+\varphi\right) \quad \text{(Eqn. 3)}$$

where $x' = x\cos\theta + y\sin\theta$, $y' = -x\sin\theta + y\cos\theta$ and λ is the wave length (hence $1/\lambda$ is the spatial frequency) of the Gabor filter kernel. The angle parameter $\theta \in [0, \pi)$ determines the filter direction and specifies the orientation of normal parallel stripes of a Gabor function. The spatial aspect ratio γ determines the ellipticity of Gabor kernel (if γ equals 1, the kernel is circular) and σ is the standard deviation of Gaussian envelope.

2.1 Optimization of Gabor filter parameters

Because the vessel boundaries are normally presented and form (approximately) parallel edges, we model the vessel as an even symmetric function with $\varphi = 0$ and $\varphi = \pi$ corresponding to *center-on* and *centre-off* responses (Fig 1-c and 1-d). Since retinal vessels appear darker compared with their background (e.g. Fig.1-a) we choose $\varphi = \pi$ for our kernel model. Neurophysiological research shows that the parameter λ and σ are not independent [16]. Petkov and Kruizinga [15] reported that the ratio σ/λ is related to the half-response spatial frequency bandwidth *b* and can be set as follows.

$$\frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{\ln 2}{2}}\cdot\frac{2^b+1}{2^b-1} \quad \text{(Eqn. 4)}$$

In practice, the bandwidth *b* controls the number of visible parallel excitatory and inhibitory stripe zones. Three zones, one inhibitory and two excitatory are visible in the retinal vessel structure (Fig.1-a) so we determined *b*=3 in our experiment. We set the spatial aspect ratio γ as 0.85 as our previous work suggests this ratio to be optimal. Since σ and λ are correlated, only one of them (λ) is considered a free parameter. Hence, we can write

$$G_{\lambda,\theta}(x,y) = e^{\left(-\frac{x'^2+0.72y'^2}{0.12\cdot\lambda^2}\right)} \cos\left(2\pi\frac{x'}{\lambda}+\pi\right) \quad \text{(Eqn. 5)}$$

Orientation of the retinal vessels is another significant structural characteristic since vessels are neither vertical nor horizontal precisely. Hence, the Gabor filter kernels are designed to cover 12 different orientations in 15° increments. An optimized kernel size is obtained by considering the value of σ. This plays a significant role in determining the width of vessels that will be detected. We choose λ by plotting a family of ROC curves for a range of filter responses obtained from on a training set of images. Typical results are plotted in Figure 2 and from this analysis we chose the λ =13 (Fig. 1-e). Using Eqn. 4 we find σ is 3.12 and hence a suitable kernel size is 9×9.

2.2 Generating the Texton

A texton is an element (e.g. line segment, elongated blobs, cross and terminator) that is defined to represent the basic micro geometric textural structure in image [13]. The training procedure includes two stages. We trained vessel and non-vessel textons. In the vessel texton training stage our Gabor filter bank was applied to obtain filter response and the background was removed.

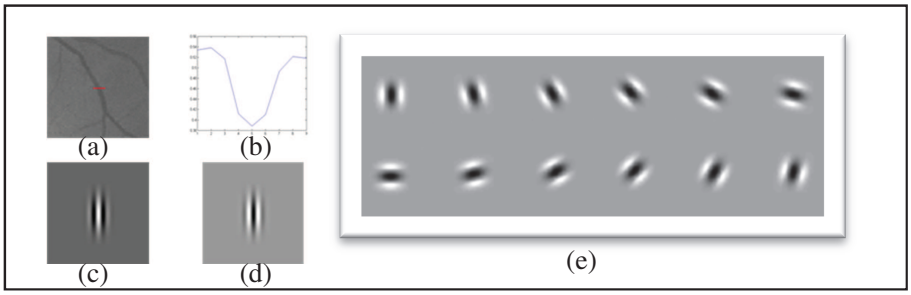

Figure 1: Showing the characteristics of vessel boundaries, the symmetric Gabor kernel and the Gabor filter bank. (a) is a panel cropped from a gray-level retinal image; (b) a gray level profile from the red line crossing the vessel in (a); (c) Gabor kernel with parameter φ=0; (d) Gabor kernel with parameter φ= π; (e) is optimized Gabor filter bank for retinal vessel feature extraction.

To train non-vessel textons vessel pixels were removed in order to obtain non-vessel influences background responses. The textons were generated by employing a *k*-means clustering algorithm on the filter responses. As representations of texture, the textons were aggregated based on the properties of distances calculated from memberships to clustering centres. This procedure is an iterative process.

Initially, K random points were selected as the means (centroids) of K clusters. Corresponding memberships were selected based on differences of Euclidean distance between means and centre bins. New means of those memberships were calculated again which were new clustering centroids. The process runs iteratively until it converges. Both vessel textons and background textons were stored in a texton dictionary and subsequently used in test stage. In test stage, the trained textons were assigned depending on responses of filter bank and corresponding memberships are calculated. The vessel texton relative memberships generate texton maps and the final segmentation results are obtained by combining various vessel texton relative maps. At textons training stage, various values of parameter K (no. of cluster centres) were chosen (K= 2,…,20). The corresponding accuracies were calculated by evaluating with respect to ground truth. The appropriate K=12 can be selected since the corresponding accuracy reaches maximum.

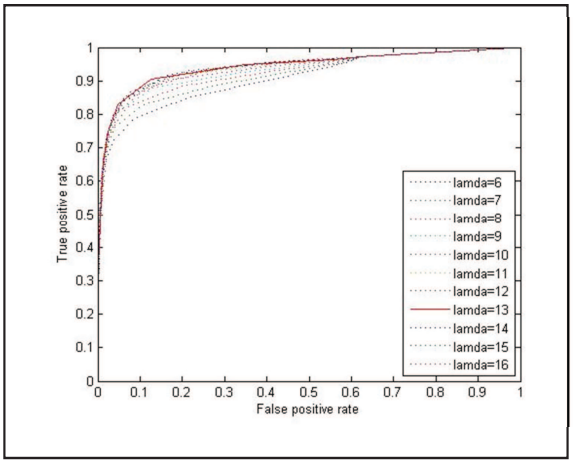

Figure 2: the ROC curves obtained by different lambda values.

3 Experiment results

The proposed method was tested and evaluated on DRIVE data sets. In order to quantify the performance of proposed approach, the resulting segmentation is compared to its corresponding ground truth. The ground truth is defined by a binary vessel mask in which all vessel pixels are set to one and all non-vessel pixels are set to zero. Our algorithm was evaluated in terms of sensitivity, specificity and accuracy for each sample of test images. The sensitivity (TPF) represents the true positive rate of segmentation and a significant factor in evaluating the performance of the method. The specificity (1-FPF) indicates the correct classification rate for segmentation of non-vessel pixels. The accuracy refers the overall segmentation performance. As shown in Table 1, for the DRIVE dataset, average specificity reaches 0.9602 with 0.7673 sensitivity, the average accuracy is 0.9430. To verify the performance of our proposed methods, we compare results with other state-of-the art approaches for retinal vessel segmentation. Table 1 presents corresponding results. The relative terms of measurement are average obtained from all of the test images. The experimental results show that our proposed method has produced a much better sensitivity, whilst maintaining almost the same overall accuracy, compared with the best other methods. In practice, it's difficult to balance the sensitivity and specificity. Normally, with increasing sensitivity, the value of specificity might reduce and this, in turn changes the overall accuracy. In our experiment, we find the sensitivity increase more than 5% however the specificity just reduce 1% compare with other methods. This verifies the robustness of our method in detecting retinal vessels.

Method	**Performance Results**			
	database	***Sensitivity***	***Specificity***	***Accuracy***
2nd observer	DRIVE	0.7761	0.9725	0.9473
Our method	DRIVE	**0.7673**	**0.9602**	**0.9430**
Mendonca [19]	DRIVE	0.7344	0.9764	0.9452
Zana[18]	DRIVE	0.6696	0.9769	0.9377
Staal [17]	DRIVE	0.7194	0.9773	0.9441
Zhang [5]	DRIVE	0.7120	0.9724	0.9382
Soares [22]	DRIVE	0.7283	0.9788	0.9466
Fraz[23]	DRIVE	0.7525	0.9722	**0.9476**

Table 1: comparative results on DRIVE database

4 Conclusion

We proposed a novel method for retinal vessel segmentation by using both Gabor filter and texton. A new filter bank for retinal vessel network enhancement was designed based on the human visual system and the corresponding parameters of the Gabor filter were optimized using a ROC analysis of the filter performance on training data. Our experimental results demonstrated that our method significantly enhances the true positive rate while maintaining a level of specificity that is comparable with other approaches. The overall performance accuracy (0.943) is better than most of state-of-the-art retinal vessel segmentation methods proposed by other authors. Although the performance of our method in terms of sensitivity, specificity, and accuracy is good, we can find some limitations and weaknesses from our method. Visually, some false positive pixels are evident in our segmentation results, especially in an area around the optic disc (OD). This is because the area surrounding the OD exhibits strong contrast and so there are significant gradient changes on its boundary. We intend to address these limitations in our further work.

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