Retinal Vasculature Segmentation Using Wavelets and Supervised Classification

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Abstract. *Segmentation of the retinal vasculature is a first step towards automated screening for diabetic retinopathy, a leading cause of adult blindness, but which can be prevented if identified early enough. This paper summarizes the retinal vasculature segmentation approach developed combining the two-dimensional continuous wavelet transform and supervised pixel classification. The open source software developed for testing and demonstration is also described. Experimental evaluation using receiver operating characteristic (ROC) analysis on two public image databases yields areas under the ROC curves slightly superior to those presented by other state-of-the-art methods, while minimizing the need for user interaction and showing efficient computing times.*

1. Introduction

Diabetes and its associated complications have been identified as significant growing public health problems. The worldwide prevalence of diabetes was estimated to be 2.8% in 2000, projected to 4.4% in 2030. Diabetic retinopathy (DR) is a major complication of diabetes, which in Brazil is responsible for 7.5% of adult work incapacity causes and for 4.58% of visual impairment, while being the leading cause of new cases of adult blindness in the USA and other developed countries. Retinal vasculature segmentation is a primary step towards the automated analysis of the retina, to be applied in a screening tool for early detection of DR. Another major application is retinal image registration, of interest in change detection, mosaic synthesis and real-time spatial referencing. Retinal vessel segmentation has received an increasing amount of attention in the last 10 years. An overview of the various approaches devised and the state-of-the-art is available in the master's thesis summarized in this paper [Soares 2006].

The master's thesis presents the evolution of the two-dimensional (2-D) Gabor wavelet vessel segmentation approach, through the introduction of the supervised pixel classification framework (described in Section 2), which allows wavelet responses at various scales to be combined for detecting vessels of different widths. Within this framework, user interaction is not necessary, provided appropriate manual segmentations are available for classifier training. The Bayesian classifier using Gaussian mixture models to describe class likelihoods was evaluated, showing to provide a fast classification phase

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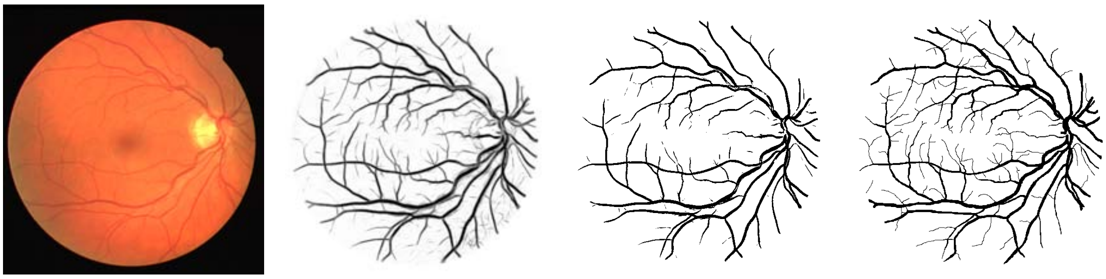

Figure 1. From left to right: original colored retinal image from the DRIVE database; posterior pixel probability estimates using the GMM classifier with $c = 20$ and $N = 10^6$; final automatic segmentation; manual segmentation.

while presenting good results. An open source software was developed in MATLAB for testing, including a graphical user interface, as described in Section 3. Experiments and ROC analysis of the method were performed on two public databases of retinal images, as presented in Section 4, corroborating the method's performance and allowing comparisons with other approaches. The approach adopted and the software developed have been tested for the characterization of the vasculature morphology in identifying the proliferative stage of DR [Jelinek et al. 2007] and represent an effort towards the creation of an automated tool for DR screening by non-specialist health workers. Finally, the advances made in the approach have been published [Cornforth et al. 2005, Jelinek et al. 2007, Soares et al. 2005, Soares et al. 2006, Soares and Cesar-Jr. 2007].

2. Methods

The pixels of the retinal images [Figure 1] are viewed as objects represented by feature vectors, so that supervised classification may be applied for segmentation. In this case, the classes considered are *vessel* and *nonvessel* pixels. Training sets for the classifiers are derived from manual segmentations of training images, resulting in labeled feature vectors. The approach allows information from wavelet responses at various scales to be combined, accounting for vessels of different widths. It may be suitably applied to different retinal image modalities, such as colored and red-free images or fluorescein angiograms, provided the respective manual segmentations are available.

2.1. Wavelet Transform Features

Let $f, \psi \in L^2(\mathbb{R}^2)$ be, respectively, an image and the analyzing wavelet. The 2-D continuous wavelet transform (CWT) is defined in terms of the scalar product between f and translations, dilations and rotations of ψ:

$$T_\psi(\mathbf{b}, a, \theta) = a^{-1} \int \psi^*(a^{-1} r_{-\theta}(\mathbf{x} - \mathbf{b})) f(\mathbf{x})\, d^2\mathbf{x}, \tag{1}$$

where $\mathbf{b}$ indicates the position being analyzed, a is the scale or dilation parameter, r_θ denotes the usual 2-D rotation by θ and ψ^* denotes the complex conjugate of ψ. The transform represents a filter localized both in space and spatial frequencies and acts at a constant relative bandwidth, with higher frequency precision in large scales and higher spatial precision in small scales. This allows for analyzing localized properties and singularities, such as the blood vessels in the present case.

Among several available analyzing wavelets, the 2-D Gabor wavelet was chosen for the purposes of this work. The wavelet is defined as

$$\psi_G(\mathbf{x}) = \exp(i\mathbf{k}_0\mathbf{x}) \exp\left(-\frac{1}{2}(\mathbf{x}A\mathbf{x})\right) + \text{correction}, \tag{2}$$

where $i = \sqrt{-1}$ and $A = \text{diag}[\epsilon^{-1/2}, 1]$ is a 2×2 diagonal matrix that defines the anisotropy of the wavelet, i.e. its elongation in any desired direction. The Gabor wavelet is therefore simply an elongated Gaussian modulated by a complex exponential, with $\mathbf{k}_0$ defining the basic frequency vector. The wavelet is specially suited for detecting directional features and the parameters were adjusted as to enhance this property when applied to vessel detection. Additionally, the basic frequency and scales were chosen as to match the blood vessels, filtering out, at the same time, undesirable high frequency noise and low frequency background variations.

In order to detect vessels in any orientation, for each considered position and scale, the Gabor wavelet response with maximum modulus over all angles is kept, i.e. $M_\psi(\mathbf{b}, a) = \max_\theta |T_\psi(\mathbf{b}, a, \theta)|$. The features used for classification are thus the original green channel (for colored images) or gray channel (for monochromatic images and angiograms) and $M_\psi(\mathbf{b}, a)$ taken from the channel for different values of scale a, which are chosen as to span the possible widths of vessels. After feature generation, the normal transformation is applied to the feature space, so that each feature have an equivalent weight during distance calculation.

2.2. Gaussian Mixture Model Classifier

Good results were achieved using a Bayesian classifier in which each class-conditional probability density function (likelihood) is described as a linear combination of Gaussian functions, which will be referred to here as the *Gaussian mixture model* (GMM) classifier. GMMs represent a halfway between purely nonparametric and parametric models. They guarantee a fast classification phase that depends only on the number c of Gaussians used (i.e. independent of the number of training samples), while still allowing for modeling complex probability distributions.

3. Implementation and Graphical User Interface

The method's implementation for performing experiments originated a package of MATLAB scripts, that now also includes a graphical user interface (GUI) for preliminary testing. The package, named `mlvessel`, is available as open source code under the GNU General Public License (GPL) at the project's collaborative development website (`http://retina.iv.fapesp.br`) and currently counts with more than 280 downloads. The website also contains a collection of the method's results, allowing researchers to evaluate them in new and diverse manners.

Experiments can be executed through function calls, with results presented as images and tables organized in HTML pages. Most of the package's functionality is also accessible through the GUI, which currently comprehends visualizing pixel features; creating and training classifiers; and applying them for image segmentation. A new implementation of the software developed in C++ will soon be available, which should be faster, have better usability and be independent of MATLAB, allowing wider reach.

Table 1. A_z and accuracies for different segmentation methods and also a second human observer. A_z indicates the area under the ROC curve, while the accuracy is the fraction of correctly classified pixels.

Segmentation method	Database			
	DRIVE		STARE	
	A_z	Accuracy	A_z	Accuracy
GMM, $c = 20$, $N = 10^6$	**0.9614**	**0.9466**	**0.9671**	**0.9480**
$M_\psi(\mathbf{b}, 4)$	0.9312		0.9351	
[Chaudhuri et al. 1989]	0.9103		0.8987	
[Jiang and Mojon 2003]	0.9327	0.8911	0.9298	0.9009
[Staal et al. 2004]	0.9520	0.9441	0.9614	0.9516
Second observer		0.9473		0.9349

4. Experimental Evaluation and Results

The method was evaluated on the DRIVE and STARE public databases of colored retinal images and corresponding manual segmentations (as illustrated in Figure 1), previously used for evaluation in several works. Besides corroborating the method's performance, this allows for comparisons between different approaches. The performances are measured using receiver operating characteristic (ROC) curves. ROC curves are plots of ordered pairs of true positive and false positives rates for varying thresholds on pixel posterior probability estimates or filter responses. Ground truths for evaluation are derived from manual segmentations. The areas under the ROC curves (A_z) may then be used as single numerical measures of the overall performance of each method.

Different segmentation methods are compared in Table 1, that presents A_z and accuracies for the following: GMM classifier with $c = 20$ Gaussians and $N = 10^6$ training samples; filtering using a single Gabor wavelet scale ($M_\psi(\mathbf{b}, 4)$); our implementation of the matched filter of Chaudhuri et al. (1989); and the methods of Jiang and Mojon (2003) and Staal et al. (2004), as published by the latter. Accuracies are also presented for second sets of manual segmentations tested against those used as ground truth. After the master's thesis was defended, new methods have been published with results that suggest they perform equivalently or better those presented in Table 1, though A_z values or complete ROC curves were not presented. ROC analysis allows for an objective comparison and is the most widespread technique for retinal vessel segmentation evaluation. However, it is not sufficient for a complete evaluation, as wide vessels have an exaggerated importance and characteristics such as the presence of gaps are not taken into account and other quantitative measures have been proposed. Visual analysis is thus very important, and shows some typical difficulties of the method that should be solved in future work, such as false detection of pathologies and failure to detect the thinnest vessels.

Fixing the dimension of the feature space, classification of an image's pixels using the GMM classifier takes time $O(cP)$, where P is the total of pixels in the image. The process of feature generation is basically the calculation of the wavelet coefficients, which is done by a series of correlations. By using the fast Fourier transform and the Fourier definition of the CWT, these are done in $O(P \log_2 P)$. Tests were performed using a kNN classifier, which showed similar A_z and accuracies, but with much larger computation times, while a linear classifier also tested showed worse results.

5. Conclusion

The method introduced in the master's thesis yields an area under the ROC curve slightly superior to that of other state-of-the-art methods, while the Gabor wavelet shows itself efficient for vessel detection, outperforming the filter of Chaudhuri et al. (1989). The supervised classification framework minimizes the need for user interaction, with method adjustment being done using manual segmentations. Results are obtained in reasonable time and an open source prototype implementation was developed, representing an effort towards automated DR screening. Visual inspection reveals some flaws of the method, which works only locally to each pixel and could benefit from a posterior global detection phase. Finally, given its conceptual simplicity, the method could be applied to the segmentation of other oriented structures, such as neurons or roads in aerial photography.

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