Measurement of Retinal Blood Vessel Caliber Using Two Different Segmentation Methods

Behdad Dashtbozorg[1,2]
Behdad.dashtbozorg@fe.up.pt

Ana Maria Mendonça[1,2]
amendon@fe.up.pt

Aurélio Campilho[1,2]
campilho@fe.up.pt

[1] Laboratório de Sinal e Imagem,
Instituto de Engenharia Biomédica,
Universidade do Porto

[2] Faculdade de Engenharia,
Universidade do Porto

Abstract

In this paper, we explore two different retinal vessel segmentation methods for the reliable estimation of vessels caliber in retinal images in order to assess vascular changes as an aid for the diagnosis of the ocular manifestations of several systemic diseases, namely diabetic retinopathy and hypertensive retinopathy.

1 Introduction

Retinal vessels can be affected by many diseases. In conditions such as diabetic retinopathy, the blood vessels often show abnormalities at early stages [1], [2]. Changes in retinal blood vessels are also associated with hypertension and other cardio-vascular conditions [3], [4]. Retinal vessel dilatation is a well-known phenomenon in diabetes and significant dilatation and elongation of arterioles, venules, and their macular branches occur in the development of diabetic macular edema that can be linked to hydrostatic pressure changes [5].

An automatic retinal image analysis could provide an immediate and objective classification of retinopathy. Within this context, the main challenges to the automatic analysis of blood vessel changes are to be able to accurately segment the blood vessels, to align the images (registration), to correct any global variations in illumination, to estimate vessel caliber and to find segments of blood vessels that have changed significantly.

In this paper, most of our intention is on comparing two different segmentation methods and using these algorithms for vessel calibre estimation. The first method segments retinal vessels based on centerline detection and morphological reconstruction [6]. The second method uses 2-D Gabor Wavelets and supervised classification for segmentation [7].

2 Segmentation Methodologies

Vessel segmentation algorithms are the critical components of circulatory blood vessel analysis systems. In this section, we review two different methods for segmenting retinal vessels. First we briefly review the method proposed by Mendonça and Campilho which is based on the combination of the detection of centerlines and morphological reconstruction [6]. After that we review the method proposed by Soares *et al.* which is based on classifying each pixel as vessel or non-vessel [7].

The first method in [6], follows a pixel processing-based approach. The initial step of vessel centerline detection combines local information, used for early pixel selection, with structural features, as the vessel length. Global intensity characteristics and local vessel width information are adaptively exploited in the subsequent vessel filling phase. This method has three phases. The first one, the pre-processing phase, the background is normalized by subtracting an estimation of the background obtained by filtering with a large arithmetic mean kernel and then thin vessels are enhanced.

The next phase is the detection of centerline segment candidates. The first operation aiming at extracting vessel centerline pixels is the application of a set of directional differential filters sensitive to the main vessel orientations. The particular kernels in this work are first-order derivative filters, known as difference of offset Gaussian filters (DoOG filters), with prevailing responses to horizontal (0°), vertical (90°), and diagonal (45°, 135°) directions. From each image containing the selected set of candidate points in one specific direction, an initial collection of centerline segments is generated by a region growing process. Each centerline candidate segment is validated by comparing its intensity and length features with image dependent reference values.

The third phase is vessel segmentation. For this purpose, a multi-scale approach is followed, where a set of morphological operators with increasing structuring element size is used for generating several enhanced representations of the vascular network.

In this method, the background normalized image is processed by a sequence of top-hat operators using circular structuring elements of increasing radius. The range of the radius of the structuring elements varies from 1 to 8 pixels, covering the overall range of vessel widths. The eight images at various scales are finally reduced to four, each one obtained as the average of the two responses of operators with consecutive radii. For each vessel enhanced image, a marker and mask images are obtained using threshold values derived from the intensity histogram of the non-null pixels; each one of these thresholds is defined as the highest intensity value such that the number of pixels with intensities above this limit is greater or equal to a predefined percentage.

The final image with the segmented vessels is obtained by iteratively combining the centerline image with the set of images that resulted from the vessel segments reconstruction. In the first iteration, vessel centerline pixels are used as seeds for a region growing algorithm, which breed these points by aggregating the pixels in the reconstructed image derived from the top-hat operator with the smallest structuring element size. The aggregation of points is, as usual, conditioned by the connectivity restriction. In each of the subsequent three iterations, the reconstructed images corresponding to the vessels with increasing width are in turn used for extending the output of the previous region growing step.

The second method was proposed by Soares *et al.* in [7]. In this method, each pixel is represented by a feature vector including measurements at different scales taken from the two-dimensional (2-D) Gabor wavelet transform. The resulting feature space is used to classify each pixel as either a vessel or non-vessel pixel. This is done using a Bayesian classifier with class-conditional probability density functions (likelihoods) described as Gaussian mixtures, yielding a fast classification, while being able to model complex decision surfaces. The first phase in this algorithm is preprocessing. In order to reduce false detection of the border of the field of view (FOV) by the wavelet transform an iterative algorithm was developed to remove the strong contrast between the retinal fundus and the region outside of the FOV.

In the second phase, a set of features is extracted from the test images. For each pixel, five features are extracted. One is the green intensity and the others are four features obtained using 2-D Gabor wavelet at four different scales. The Gabor wavelet is capable of tuning to specific frequencies, thus allowing noise filtering and vessel enhancement in a single step.

The third phase in this method is the training of the classifier. In this method supervised classification has been applied to obtain the final segmentation, with the pixel classes defined as C_1={*vessel pixels*} and C_2={*non-vessel pixels*}. The authors used a Bayesian classifier in which each class-conditional probability density function (likelihood) is described as a linear combination of Gaussian functions which is called Gaussian mixture model (GMM) classifier. For each class, given the number k_i of Gaussians, the k_i Gaussian parameters and weights are estimated with the expectation- maximization (EM) algorithm. After defining the classifier, it is possible to segment vessels by classifying each pixel in the test images using the 5-feature vector.

3 Evaluation and vessel calibre measurement results

For evaluating these methods, the DRIVE database was selected. This database consists of 40 images (seven of which present pathology), along with manual segmentations of the vessels. The 40 images have been divided into training and test sets, each containing 20 images. The images in the training set were segmented by one observer, while images in the test set were segmented by two observer, resulting in sets A and B. The observers of sets A and B produced similar segmentations.

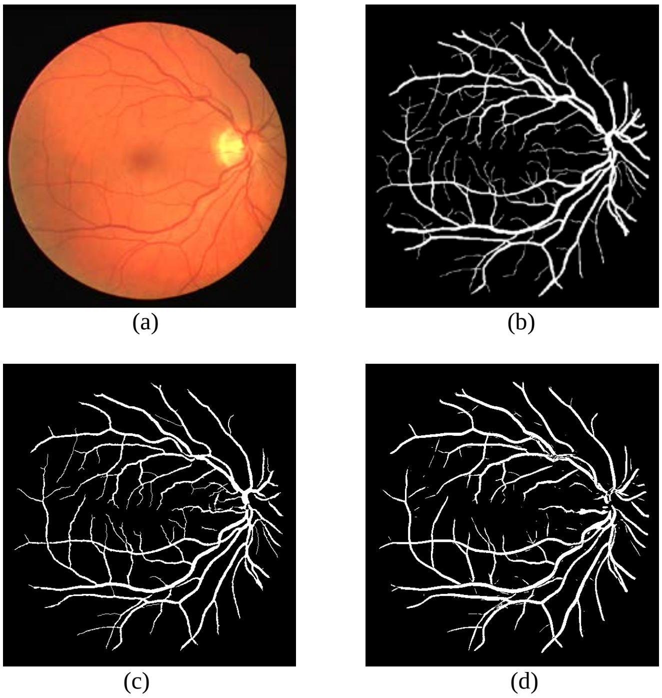

Figure 1: (a) Original color fundus image. (b) Manual segmentation by human observer. (d) Segmentation result by Mendonça method [6]. (d) Segmentation result by Soares method [7].

Performance is measured on the test set using the segmentations of set A as ground truth. The segmentations of set B are tested against those of A, serving as a human observer reference for performance comparison.

In the first phase of evaluation, we trained the Soares method with 20 images in the training set using the open source MATLAB scripts, which are available on their website [8]. The estimation of the GMM parameters for one million random vessel and non-vessel pixels as training samples for $k=20$ takes too much time and it also needs huge amount of memory. By reducing the number of samples to 300,000 and $k=5$, it takes 5 hours. The segmentation time for the test images in both methods was less than 1 minute but it should be mentioned that the method proposed by Mendonça and Campilho does not have a training phase.

To facilitate the comparison between these two retinal vessel segmentation algorithms, we have selected the segmentation accuracy as performance measure. The accuracy is estimated by the ratio of the total number of correctly classified pixels (sum of true positives and true negatives) by the number of pixels in the image FOV. Other important measures are sensitivity and specificity, which are indicators of the number of properly classified pixels, respectively in the true positive and true negative classes. Sensitivity is also known as true positive fraction, while the true negative fraction, which stands for the fraction of pixels erroneously classified as vessel points, is associated with specificity. Table 1 shows the result of this comparison. As we can see in this table the method proposed by Mendonça and Campilho has better accuracy when compared with the other method. The segmentation results of these methods can be seen in Figure 1.

In the second phase of evaluation, we selected 100 coordinates inside the vessels (5 points in each test image) and determined the vessels caliber on the segmentation results (the corresponding binary images) of both methods.

In order to obtain an estimation of vessel caliber, we calculate the distance transform of binary results of the vessel segmentation methods. This transform computes the Euclidean distance transform of the binary images and labels each pixel of images with the distance between that pixel and the nearest non-vessel pixel. After that, for each coordinate, we find the value of distance transform. The vessel diameter value is calculated by duplicating the result of the distance transform minus one.

Table 2 shows the average of relative error of vessel caliber measurement based on first human observer. For more comparison and better accuracy, we also calculate the relative error in different cases: 1) in all of selected points, 2) only in points where the difference between vessel caliber for the two human observers is less than two pixels 3) the difference is less than one pixel, 4) equal caliber in both human observer results. As we can see in table 2, the method proposed by Mendonça has a smaller relative error when compared with the Soares method.

Table 1: Performance of vessel segmentation methods

Method	*Average Accuracy*	*True positive fraction*	*False positive fraction*
2nd Human observer	0,947	0,776	0,027
Mendonça [6]	0,945	0,744	0,025
Soares [7]	0,940	0,752	0,031

Table 2: Relative error of vessel calibre measurement

Method	*Case 1*	*Case 2*	*Case 3*	*Case 4*
Number of points	100	66	52	39
2nd Human observer	33%	9%	5%	0
Mendonça [6]	32%	26%	29%	28%
Soares [7]	40%	32%	37%	39%

4 Conclusion

We provided a review of two retinal vessel segmentation methods and compared their performance. One of the methods follows a pixel processing-based approach and the other one is based on supervised classification. As a result of an overall comparison, the method proposed by Mendonça and Campilho has better performance in measuring the retinal vessel caliber and also in the detection and segmentation of thin vessels. As can be seen in Figure 1, most of the thin vessels in Soares method are not segmented. Also Soares method needs training and it takes a lot of time for training the classifier.

Acknowledgements

This work is being supported by FCT (Fundação para a Ciência e Tecnologia) under research grant SFRH /BD/73376/2010.

References

[1] T. T. Nguyen and T. Y. Wong, Retinal vascular changes and diabetic retinopathy, *Current Diabetes Reports*, vol. 9, no. 4, pp. 277-283, 2009.

[2] T. T. Nguyen, J. Jin Wang and T. Y. Wong, Retinal vascular changes in pre-diabetes and Pre-hypertension, *Diabetes Care*, vol. 30, no. 10, pp. 2708-2715, Oct. 2007.

[3] T. Y. Wong, A. Kamineni, R. Klein, A. R. Sharrett, B. E. Klein, D. S. Siscovick, M. Cushman and B. B. Duncan, Quantitative retinal venular caliber and risk of cardiovascular disease in older persons, *Arch Intern Med*, Vol. 166, pp. 2388-2394, Nov. 2006.

[4] A. S. Neubauer, M. Ludtke, C. Haritoglou, S. Priglinger and A. Kampik, Retinal vessel analysis reproducibility in assessing cardiovascular disease, *Optometry and Vision Science*, vol. 85, no. 4, pp. E247–E254, Apr. 2008.

[5] Guan, K. Hudson, C. Wong, T. Kisilevsky, M. Nrusimhadevara, R. K. Lam, W. C. Mandelcorn, M. Devenyi, R. G. Flanagan, J. G., Retinal hemodynamics in early diabetic macular edema, *Diabetes New York*, Vol. 55; no. 3, pp. 813, 2006.

[6] A.M. Mendonça and A. Campilho, Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction, *IEEE Trans. Med. Imag.*, vol. 25, pp. 1200-13, Sep. 2006.

[7] V. J. Soares, J. J. Leandro, R. M. J. Cesar, F. H. Jelinek, and M. J. Cree, Retinal vessel segmentation using the 2-d gabor wavelet and supervised classification, *IEEE Trans. Med. Imag.*, vol. 25, no. 9, pp. 1214–1222, Sep. 2006.

[8] http://sourceforge.net/projects/retinal/files/mlvessel/