J Vis (2010) 13:263–270
DOI 10.1007/s12650-010-0037-y

REGULAR PAPER

Fabiola M. Villalobos-Castaldi · Edgardo M. Felipe-Riverón · Luis P. Sánchez-Fernández

A fast, efficient and automated method to extract vessels from fundus images

Received: 21 October 2009 / Accepted: 27 March 2010 / Published online: 5 May 2010

Abstract We present a fast, efficient, and automatic method for extracting vessels from retinal images. The proposed method is based on the second local entropy and on the gray-level co-occurrence matrix (GLCM). The algorithm is designed to have flexibility in the definition of the blood vessel contours. Using information from the GLCM, a statistic feature is calculated to act as a threshold value. The performance of the proposed approach was evaluated in terms of its sensitivity, specificity, and accuracy. The results obtained for these metrics were 0.9648, 0.9480, and 0.9759, respectively. These results show the high performance and accuracy that the proposed method offers. Another aspect evaluated in this method is the elapsed time to carry out the segmentation. The average time required by the proposed method is 3 s for images of size 565 × 584 pixels. To assess the ability and speed of the proposed method, the experimental results are compared with those obtained using other existing methods.

Keywords Retinal image analysis · Blood vessel network · Image segmentation · Fast automated analysis · Co-occurrence matrix · Entropy thresholding

1 Introduction

Retinal or fundus images provide information about the blood supply system to the retina. Accurate blood vessel segmentation is fundamental in the analysis of fundus images since further analysis usually depends on the accuracy of this segmentation (Chaudhuri et al. 1989). It is therefore desirable to provide ways of automating the process of the analysis of fundus images, using computerized image analysis, so as to provide at least preliminary screening information and also as an aid to diagnosis to assist the clinician in the analysis of difficult cases.

F. M. Villalobos-Castaldi · E. M. Felipe-Riverón (✉) · L. P. Sánchez-Fernández
Center for Computing Research, National Polytechnic Institute, Av. Juan de Dios Batiz and Miguel Othon de Mendizabal, Mexico, D.F. 07738, Mexico
E-mail: edgardo@cic.ipn.mx
Tel.: +52-5729-6000

F. M. Villalobos-Castaldi
e-mail: fvillalobosb07@sagitario.cic.ipn.mx

L. P. Sánchez-Fernández
e-mail: lsanchez@cic.ipn.mx

2 Retinal vessel segmentation

Visually, vessels in the fundus image appear as dark lines on a relatively uniform brighter background. Various methods are known for segmenting blood vessels in fundus images. The objective of retinal vessel segmentation is to decide which part of the image belongs to the foreground, which is of our interest for extracting features for recognition and identification, and which part belongs to the background, which is the noisy area around the boundary of the image (Chaohong 2007). Reliable vessel extraction is a prerequisite for subsequent retinal image analysis and processing because vessels are the predominant and most stable structures appearing in these images (Jung and Hong 2006). Accurate segmentation of retinal images influences directly the performance of minutiae extraction. If more background areas are included in the segmented retinal image, more false features are introduced; if some parts of the foreground are excluded, useful feature points may be missed.

Advances in vascular imaging technology have provided radiologists with non-invasive imaging modalities that can give accurate vascular information, which helps the physician to define the character and extent of a vascular disease, aiding diagnosis and prognosis (Kirbas and Quek 2004). As stated previously, accurate vascular extraction is the primary task in automated ophthalmic image analysis.

3 The proposed method

The proposed method described in this paper uses one of the basic approaches to edge detection: the enhancement/thresholding method to achieve a fast algorithm for automated detection of blood vessels in retinal images.

As depicted in Fig. 1, our method consists of five main steps: (1) Green color band selection; (2) automatic mask generation to avoid processing of the black border and corners present in images; (3) application of a matched filter to enhance the vessels edges; (4) computation of the co-occurrence matrix; and (5) automatic vessel network segmentation using the second order entropy.

3.1 Green color band selection

A gray-level image is produced by extracting the green layer of the original RGB image. The green component of color image gives the blood vessels on a highly contrasted background (dark blood vessels on a bright background). Hence, the green channel of image is employed in the retinal vasculature detection (Srivastavas 2005).

3.2 Mask generation

Mask generation aims at labeling pixels belonging to the fundus Region of Interest (ROI) in the entire image (Siddalingaswamy and Prabhu 2007). Pixels outside that ROI are those belonging to the dark surrounding region in the image.

3.3 Image enhancement

In order to characterize the retinal features of interest, we need a preprocessing step to detect vessels. For this, we use a matched filter to detect piecewise linear segments of blood vessels in retinal images

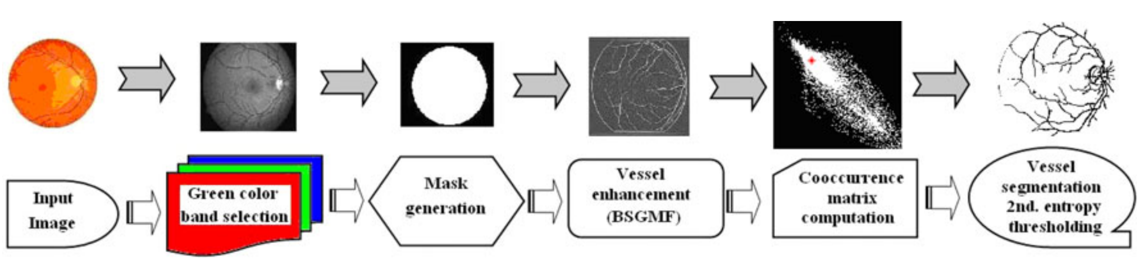

Fig. 1 Block diagram of the proposed method

(Yang et al. 2000). Twelve different templates were constructed to search for vessel segments along 12 possible directions at 15 degrees each.

$$f(x,y) = A\left[1 \pm K \exp\left(-\frac{d(x,y)^2}{2\sigma^2}\right)\right] \tag{1}$$

We have used $\sigma = 2$, which matched well with a blood vessel of medium caliber for the retinal images being considered. It may be noticed that, unlike some other edge detection methods or morphological operators where only the edges are detected, this enhancement method extracts the blood vessel as a whole (Chaudhuri et al. 1989). This procedure reduces the possibility of false detection of blood vessels in a non-ideal environment. Also, it suppresses the response due to the significant noise in the background where no blood vessels are present. The application of this method enhances individual vessels segments in the image. A proper thresholding scheme must be used to distinguish between enhanced vessel segments and the background.

3.4 Co-occurrence matrix computation

A co-occurrence matrix of an image is an $L \times L$ square matrix denoted by $W = [t_{ij}]_{L\times L}$ whose elements are specified by the numbers of transitions between all pairs of gray-levels in $G = \{0, 1,\ldots, L-1\}$ in a particular way (Yang et al. 2000; Srivastavas 2005). Consider the four neighboring locations of a pixel $f(m, n)$ at coordinates (m, n): $(m-1, n)$, $(m+1, n)$, $(m, n-1)$, $(m, n+1)$. Pixels at those locations are referred to as the 4-neighbors of $f(m, n)$ in Gonzalez and Woods (2008). The co-occurrence matrix developed by Haralick et al. (1973) is designed to dictate the gray-level changes by comparing its gray-level $f(m, n)$ to their corresponding gray-levels, $f(m-1, n)$, $f(m+1, n)$, $f(m, n-1)$, $f(m, n+1)$. Each entry in the matrix t_{ij} gives the number of times the pixel gray-level j follows the gray-level i in some pattern.

Let t be a value used to threshold an image. It partitions a co-occurrence matrix into four quadrants, namely, A, B, C, and D. These four quadrants can be further grouped into two classes, referred to as local quadrants and joint quadrants. We assume that pixels with gray-levels above the threshold are assigned to the foreground (corresponding to objects), and those equal to or below the threshold are assigned to the background. Then quadrants A and C correspond to local transitions within foreground and background, respectively, whereas quadrants B and D are joint quadrants which represent joint transitions across boundaries between background and foreground, respectively.

3.5 Second-entropy thresholding segmentation

This thresholding method exploits the entropy of the distribution of the gray levels in the image. The maximization of the entropy (Eq. 2) of the thresholded image is interpreted as indicative of maximum information transfer (Pal and Pal 1989; Zhang and Zhang 2006).

$$t_{\mathrm{LRE}} = \arg\left\{\max_{t\in G=\{0,1,\ldots,L-1\}} J_{\mathrm{LRE}}(t)\right\} \tag{2}$$

4 Experimental results

In this paper we used the images included in the well-known DRIVE database to asses the performance of the proposed method (http://www.isi.uu.nl/Research/Databases). The DRIVE database contains 40 color retinal images of size 565×584 pixels. The images have been divided into two sets, a training set and a test set. Each one contains 20 color retina images. Each set also contains the corresponding segmented images, which were graded by two experts, resulting in sets A and B. In this paper, the performance is measured on the test set using as ground truth the segmentation of the set A. Figure 2 presents the segmentation results for various images that were analyzed in this work. In order to assess the performance of the proposed segmentation method, the binary images contained in the first labeled set have been used as the ground truth (G) to decide whether a vessel is truly present or absent, and the results of the proposed segmentation method (C) are used to decide whether a vessel has been detected or not (Kriston-Vizi et al. 2006). Based on this, it is possible to calculate four different values for performing a quantitative analysis of the algorithm's results (Zhang and Zhang 2006). These values are

1. A true positive (TP) value is a pixel marked as vessel in both G and C;
2. a true negative (TN) value is a pixel marked as non vessel in both G and C;
3. a false positive (FP) value is a pixel marked as vessel in C but as a non-vessel in G; and
4. a false negative (FN) value is a pixel marked as non-vessel in C but as a vessel in G.

The frequency of these cases provides data that can be used as an indication of an algorithm's performance. Several additional performance metrics are derived from the TP, TN, FP, and FN metrics. The true positive rate (TPR) is established by dividing the number of TP by the total number of vessels in G. The false positive rate (FPR) is computed by dividing the number of FP by the total number of non vessels in *G* (Niessen et al. 2000). Based on a total of 329,960 pixels contained in a fundus image of size 565 × 584 pixels, it is possible to obtain the TP, TN, FP, and FN quantities of the segmented image.

4.1 Sensitivity, specificity, and accuracy

Sensitivity, specificity, and accuracy are the most commonly terms associated to a binary classification test (vessel segmentation algorithms) that measure statistically the performance of the test. In binary classification a given data set is divided into two categories on the basis of a set of predefined common properties. Here, we are interested in classifying pixels either into the vessel or non-vessel class. From these two categories, in general, sensitivity indicates how well the test predicts one category (vessel pixels) and specificity measures how well the test predict the another category (non vessel pixels), whereas accuracy is expected to measure how well the test predicts both categories (vessel and non vessel pixels) (Hu et al. 2001). The accuracy (Acc) is dependent upon the number of FP and FN that occur. By definition, the sensitivity, specificity, and accuracy can be computed according to the next formulations (Eq. 3):

$$\begin{array}{ccc} \text{Sensitivity} & \text{Specificity} & \text{Accuracy} \\ = \frac{\text{TPs}}{(\text{TPs}+\text{FNs})} & = \frac{\text{TNs}}{(\text{TNs}+\text{FPs})} & = \frac{\text{TPs}+\text{TNs}}{(\text{TPs}+\text{TNs}+\text{FPs}+\text{FNs})} \end{array} \tag{3}$$

Figure 3 presents the results obtained from several state-of-the-art methods used to compare the performance of our segmentation method illustrated in the image 01_test.tif from the test set of the DRIVE image database. These methods are

- *Manual method:* It consists of the labeling of the vessels present in the image carried out manually by an observer trained by an ophthalmologist. The segmented images are used as the ground truth in the performance evaluation of the segmentation methods.

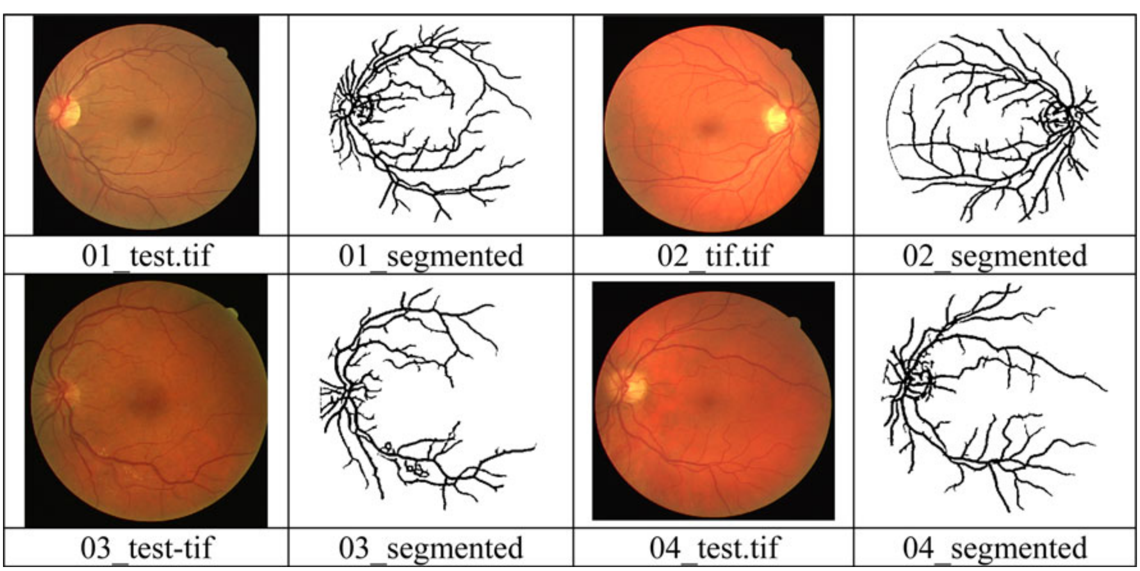

Fig. 2 Segmentation results of several images contained in the test set of the DRIVE database

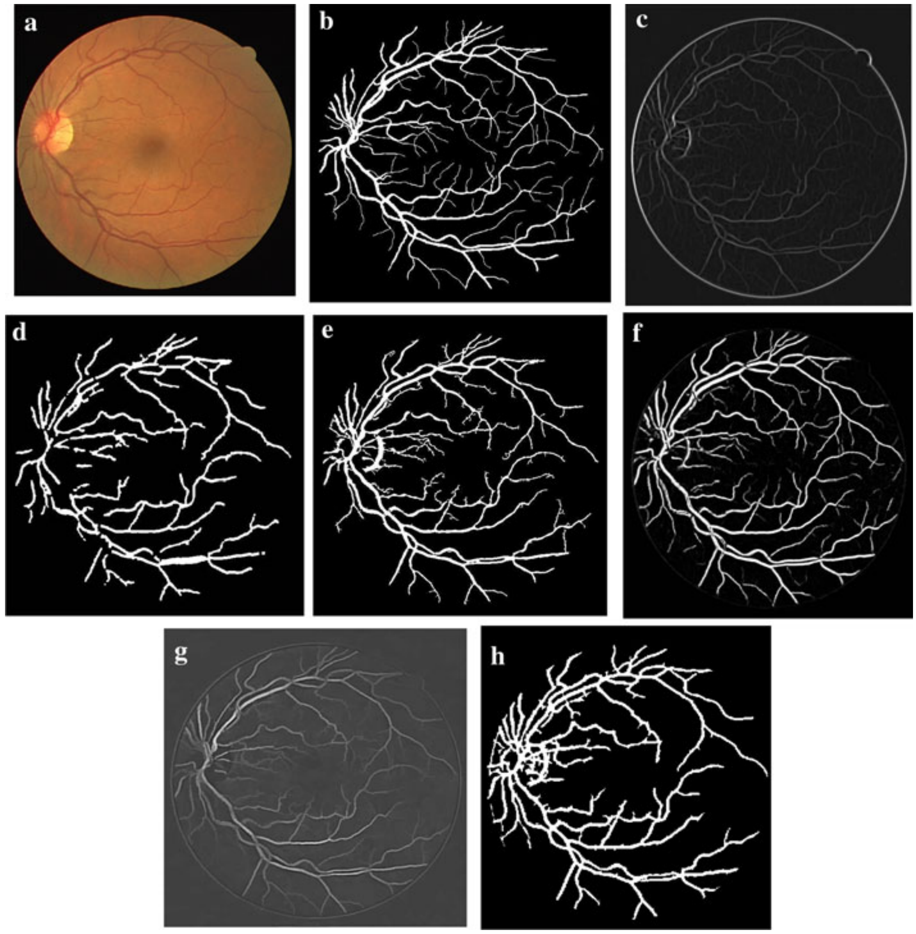

Fig. 3 Segmentation results from several methods used to compare the performance of the proposed segmentation method with the image 01_test.tif from the test set of the DRIVE database **a** original test image, **b** manual segmentation result, **c** Chaudhuri et al. (1989) method, **d** Jiang and Mojon method (2003), **e** Martinez-Perez et al. multi-scale method (1999), **f** Staal et al. method (2004), **g** Zana et al. method (1977), **h** result of the proposed method (2009)

- *Chaudhuri et al.* (1989)*:* The authors address the problem of detecting blood vessels in retinal images that usually have poor local contrast. The principal goal is to design an operator which is nearly optimal for the recognition of certain special objects in the image, particularly for the detection of blood vessels in retinal fundus images. The gray-level profile of the cross section of a blood vessel is approximated by a Gaussian shaped curve. 12 different templates were constructed to search for vessel segments along all possible directions.
- *Jiang and Mojon* (2003)*:* They proposed a general framework of adaptive local thresholding based on a verification-based multi-threshold probing scheme. This approach is regarded as knowledge-guided adaptive thresholding. The framework is applied to detect vessels in retinal images. For all the probed thresholds, the binary objects in the image are extracted. Using a classification scheme to these objects, only those having vessels features will be classified.
- *Martinez-Perez et al.* (1999)*:* The authors use a combination of scale space analysis and region growing to segment the vasculature. The histograms of both features are used in the final region-growing step, in which the images pixels are divided into two classes, “vessel” and “non-vessel”. This is accomplished by alternating the vessel and background region, growing and lowering the feature thresholds. This continues until no new pixels are added to either of the two classes. Two features are used to characterize the blood vessels, the gradient magnitude of the image intensity, and the ridge strength both at different scales.
- *Staal et al.* (2004)*:* In this paper is presented a simple vessel segmentation method based on pixel classification from the extraction of image ridges, which coincide approximately with vessel centerlines.

For each pixel in the image, a feature vector is constructed and a classifier is trained with these feature vectors. Performance of the kNN-classifier was superior for all experiments, so this classifier was selected. This resulted in a probability map in which for each pixel in the image is indicated the probability that it is a vessel pixel. By thresholding the probability map a binary image of the vasculature can be obtained.

- *Zana and Klein* (*2001*)*:* This paper presents an algorithm based on mathematical morphology and linear processing for vessel recognition in a noisy retinal angiography. In order to separate the vessels from their environment, a geometrical model of undesirable patterns is defined. First, bright round peaks are extracted. Next, linear structures are extracted using mathematical morphology, and using a Laplacian filter several differential properties are computed. Finally, vessels are extracted using curvature differentiation.

Table 1 reports the comparison of the computed performance metrics for our proposed segmentation algorithm against the state-of-the-art results obtained by the methods described above (Niemeijer et al. 2004). The experimental results show that the proposed method performs better in extracting vessels, achieving the highest score amongst all the methods with which it was compared.

The proposed segmentation method was also compared with another state-of-the-art method, which has some similarities with our method. In the HongQing (2004) approach the author proposed a novel method to segment blood vessels. This algorithm is composed of two steps: an image enhancement step by using a matched filter and the entropy-based thresholding stage, which is an automatic technique for thresholding digital images, based on the gray level-gradient co-occurrence matrix and on the maximum entropy principle. This thresholding scheme is different from our proposed segmentation method and from others 2-D entropies segmentation approaches (Pal and Pal 1989; Yang et al. 2000; Zhang and Zhang 2006; Chanwimaluang and Fan 2003) because it uses the information contained in the gray level-gradient co-occurrence matrix to evaluate the 2-D entropies.

Figure 4 presents the results obtained from this thresholding scheme compared with the corresponding results of the proposed segmentation method described in this paper. As it can be seen in resulting images, the difference between both methods is evident. Some differences between both procedures are pointed out now.

1. In HongQing (2004) the author uses the gray level-gradient co-occurrence matrix obtained from a normalized gray-level image and of a normalized gradient image. However, we use the co-occurrence matrix including the information about the relation of the gray levels between adjacent pixels to obtain structural information of the image.
2. In HongQing (2004) the quadrants A and D of the co-occurrence matrix are used as the object class and the background class, respectively. On the other hand, we use the quadrants A and C as the corresponding classes because of the gray level the vessels and the background have in the original image.
3. Similarly, in HongQing (2004) the quadrants B and C, corresponding to the local transitions between vessel and background, are used to maximize the total second-order entropy to find a threshold vector. In our method we use the quadrant A (objects) and the quadrant C (background) to maximize the second-order local entropy to obtain the threshold value for the object-background segmentation.

It is possible to observe from the segmented images (Fig. 4b, e) that the method proposed by HongQing (2004) results in broken small vessels and capillaries. His method segments also as blood vessels the border of the optic disk, the borders of the image itself, and the macula, all resulting in a high false positive rate. Then, the author proposes a post-processing step in order to eliminate those non-vessel objects whose edges

Table 1 Comparison of our method with other state-of-the-art methods

Fig. 3	Method	Se	Sp	Acc
b	Manual	0.7482	0.9757	0.9473
c	Chaudhuri et al. (1989)	0.2663	0.9901	0.8773
d	Jiang and Mojon (2003)	0.6363	0.9662	0.9212
e	Martinez-Perez et al. (1999)	0.7508	0.9582	0.9181
f	Staal et al. (2004)	0.7047	0.9796	0.9442
g	Zana and Klein (1977)	0.6585	0.978	0.9377
h	Our proposal (2009)	0.964855	0.948025	0.975905

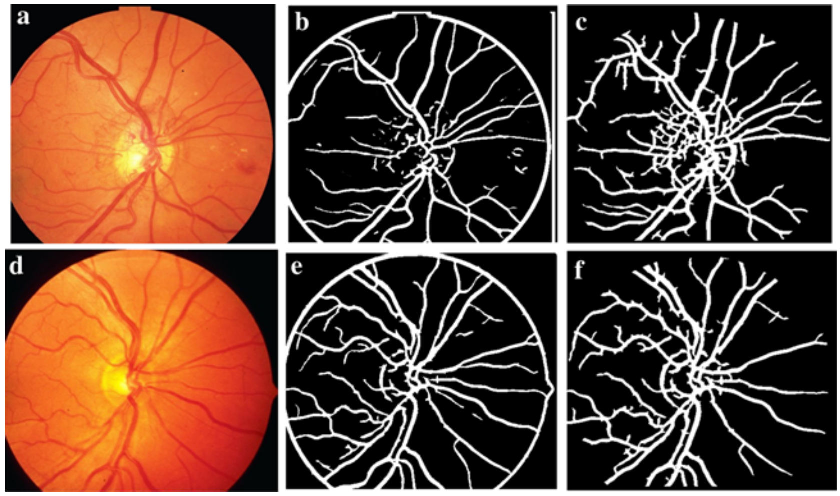

Fig. 4 Experimental results of the proposed segmentation method compared with those obtained by a state-of-the-art thresholding scheme that seems to have some similarities with our 2-D entropy thresholding method, **a** and **d** original images, **b** and **e** experimental results of the method presented in HongQing (2004), and **c** and **f** results of our proposal

Table 2 Comparison of the execution times

Method	Execution time
Manual	2 h
Wang and Bhalerao (2003)	7.0 min
Soares et al. (2006)	3.0 min
Chanwimaluang and Fan (2003)	2.5 min
Chaudhuri et al. (1989)	1.0 min
Our proposal (2009)	3 s

are well matched to the shape of the kernels. In our method, according to the results obtained, we do not need any post-processing step.

The author in HongQing (2004) does not present some analysis of the performance of the segmentation method; thus it is not possible to compare the segmentation results based on a performance metric as our method does.

Finally, we focus the analyses on the time that the proposed algorithm takes out to accomplish the whole process for blood vessel segmentation. On a Pentium (R) Dual-Core T4200 @ 2 GHz and 4 GB of internal memory, and with a MATLAB 7.4.0 (R2007a) implementation, it takes as average 3 s to segment out the vessels. Table 2 shows the elapsed time comparison amongst our method with some state-of-the-art results obtained from Wang and Bhalerao (2003), Soares et al. (2006), Chanwimaluang and Fan (2003) and Chaudhuri et al. (1989).

5 Conclusions

In this paper a fast, efficient, and automatic algorithm for segmenting the blood vessels from retinal fundus images is presented. The proposed segmentation method is based on the second local entropy that acts as a threshold value and on the gray-level co-occurrence matrix. The algorithm is designed to have flexibility in the definition of the blood vessel contours. There are several parameters of algorithms that have effects in the performance of the vessel segmentation methods. The most significant parameter is the thresholding value. This method gives a powerful tool to obtain an automatic threshold value to segment the vessel depending only on the information contained in the analyzed image. Because the proposed segmentation method computes this value automatically for each image, it is not necessary to specify a threshold value.

Choosing a good criterion to measure the performance of vessel segmentation algorithms is not a trivial task. This is because it depends on some factors such as the low contrast between the vessels and the background, the variability that exists in the vessel width in the entire vasculature, the optic disk edge can be wrongly interpreted as a blood vessel, and the fact that it is not possible to establish the same algorithm conditions for all the situations that can be presented in the application of the algorithm. The effectiveness of the proposed method was measured and resulted in a higher Selectivity, specificity and accuracy than those obtained by others methods with which they were compared. The results obtained demonstrated that the proposed algorithm can be considered in medical applications as a medical image analysis method or a retinal vessel measurement procedure for retina disease diagnosis.

Acknowledgments The authors of this paper wish to thank the National Polytechnic Institute, Center for Computing Research and Postgraduate and Research Secretary, Mexico, for their support under the research grant number SIP 20082213.

References

Chanwimaluang T, Fan G (2003) An efficient blood vessel detection algorithm for retinal images using local entropy thresholding, vol 5. In: Proceedings of the International Symposium on Circuits and Systems, 2003. ISCAS '03. V-21–V-24

Chaohong W (2007) Advanced feature extraction algorithms for automatic fingerprint recognition systems. PhD dissertation, Faculty of the Graduate School of State University, Buffalo, New York

Chaudhuri S, Chatterjee S, Katz N, Nelson N, Goldbaum M (1989) Detection of blood vessels in retinal images using two-dimensional matched filters. IEEE Trans Med Imaging 8(3):263–269

Gonzalez R, Woods J (2008) Digital image processing, 3rd edn. Prentice Hall, New Jersey

Haralick RM, Shanmugam K, Dinstein I (1973) Textural features for image segmentation. IEEE Trans Syst Man Cybern, SMC-3, (6):610–621

HongQing Z (2004) Segmentation of blood vessels in retinal images using 2D entropies of gray level-gradient co-occurrence matrix, vol 3, issue 17–21. In: IEEE international conference acoustics, speech, and signal processing (ICASSP), pp 509–512

Hu J, Kahsi R, Lopresti D, Nagy G, Wilfong G (2001) Why table ground-truthing is hard. In: Proceedings of the sixth international conference on document analysis and recognition, ICDAR-01, pp 129-133

Jiang X, Mojon D (2003) Adaptive local thresholding by verification-based multi-threshold probing with application to vessel detection in retinal images. IEEE Trans Pattern Recogn Anal Mach Intell 25:131–137

Jung E, Hong K (2006) Automatic retinal vasculature structure tracing and vascular landmark extraction from human eye image. In: Proceedings of the international conference on hybrid information technology, ICHIT, IEEE Computer Society, pp 161–167

Kirbas C, Quek F (2004) A review of vessel extraction techniques and algorithms, ACM Computing Surveys, 36(2):81–121

Kriston-Vizi J, Chinta R, Puah WC, Tiehua D, Wasser M (2006) An ImageJ plugin for the benchmarking of 3D segmentation algorithms and the specification of ground truth dataset. Imaging Informatics Division, Bioinformatics Institute Agency for Science, Technology and Research (A*STAR), Singapore

Martinez-Perez M, Hughes A, Stanton A, Thom S, Bharath A, Parker K (1999) Scale-space analysis for the characterization of retinal blood vessels. In: Taylor C, Colchester A (eds) Medical image computing and computer-assisted intervention-MICCAI'99, pp 90–97

Niemeijer M, Staal JJ, van Ginneken B, Loog M, Abramoff MD (2004) Comparative study of retinal vessel segmentation methods on a new publicly available database. In: Michael Fitzpatrick J, Sonka M (eds) Proceedings of SPIE on SPIE medical imaging, vol 5370, 648, pp 648–656

Niessen W, Bouma C, Vincken K, Viergever M (2000) Error metrics for quantitative evaluation of medical image segmentation. In: Klette R, Stiehl H, Viergever M, Vincken K (eds) Performance characterization in computer vision. Kluwer, The Netherlands, pp 275–284

Pal NR, Pal SK (1989) Entropic thresholding. Signal Process 16:97–10

Siddalingaswamy PC, Prabhu GK (2007) Automated detection of anatomical structures in retinal images. In: International conference on computational intelligence and multimedia applications, vol 3, pp 164–168

Soares JVB, Leandro JJG, Cesar RM, Jelinek HF, Cree MJ (2006) Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification. IEEE Trans Med Imaging 25:1214–1222

Srivastavas V (2005) Performance of micro-calcification detection algorithms, Master thesis, Department of Electrical and Computer Engineering, North Carolina State University, Raleigh, NC, USA

Staal J, Abramoff M, Niemeijer M, Viergever M, van Ginneken B (2004) Ridge-based Vessel segmentation in color images of the retina. IEEE Trans Med Imaging 23:501–509

Wang L, Bhalerao A (2003) Model based segmentation for retinal fundus images. In: Proceedings of Scandinavian conference on image analysis (SCIA)

Yang CW, Dye M, Shuenn C, Chuin W, Chia W, Chien L, Pau C, Chein C (2000) Computer-aided diagnostic detection system of venous beading in retinal images. Society of photo-optical instrumentation engineers. Opt Eng, 39(1293):1293–1303

Zana F, Klein JC (1977) Robust segmentation of vessels from retinal angiography. In: International conference on digital signal processing. Santorini, Greece, pp 1087–1091

Zhang YF, Zhang Y (2006) Another method of building 2D entropy to realize automatic segmentation. International Symposium on Instrumentation Science and Technology. J Phys: Conf Ser 48:303–307