Automatic Segmentation of Retina Vessels by Using Zhang Method

Ehsan Saghapour, and Somayeh Zandian

Abstract—Image segmentation is an important step in image processing. Major developments in medical imaging allow physicians to use potent and non-invasive methods in order to evaluate structures, performance and to diagnose human diseases. In this study, an active contour was used to extract vessel networks from color retina images. Automatic analysis of retina vessels facilitates calculation of arterial index which is required to diagnose some certain retinopathies.

Keywords—Active contour, retinal vessel segmentation, image processing.

I. INTRODUCTION

SEGMENTATION of retina vessels has been exploited in order to measure morphological features of retina blood vessels retina such as length, width, curvature and bifurcation angle patterns which are used for diagnosing, screening, evaluating and treating cardiovascular diseases such as diabetes, hypertension, and arthrosclerosis. For example, Identification and automatic analysis of vessels can be useful in administering screen programs for diabetic retinopathy. It is also a valid way in estimation of infant retinopathy, low-diameter artery, diseases related to curvature of vessels, hypertension and macula. The mentioned way is also suitable for determining vessel diameter in the case of hypertension. Treatment with laser operation is also another acceptable method. Automatic retina mapping system is used to extract bifurcation points in order to record multi-functional images, combine retina images and identify discs and location of macula. The map of retina vessels is different from one person to another and it is compatible to use for determining biometrics. Manual segmentation of retina vessels is time consuming. This process also requires high expertise and long-period exercises. The mentioned method has been accepted in the medical society as the first step to develop computerized diagnosis of ophthalmic diseases. Conducted studies have been categorized according to the used image processing methodologies and algorithms. Retinal vessel segmentation algorithm has been divided into seven major parts:

(1) pattern recognition techniques, (2) matched filtering, (3) vessel tracking/tracing, (4) mathematical morphology, (5) multi scale approaches, (6) model based approaches and (7) parallel/hardware based approaches [1].

To extract blood vessels from retina images using deformable methods, Spona et al. [2] used classic snake combined with topological characteristics of blood vessels. In their next paper [3], in addition to adjusting parameters accurately, a morphologic operator is proposed to extract vessel edges. Al-diri and Honter [4] offered an active parametric contour called twin ribbon which included two coupled contours. With regard to Chan and Vese [5] model, Sum and Cheung [6] proposed to modify non-uniform brightness by incorporating local image contrast in active contour based on surface sets.

In this study, an active contour is exploited in order to extract retina vessels using local or global divisions. Images with the dimension of 584×565 which are available on DRIVE [7] public retina database are used here. In order to analyze data, MATLAB is a suitable software.

In this work, we first present an overview of zhang method. Then, we use it to extract blood vessels from retina images. Finally, this method will be compared with some other methods.

II. ZHANG METHOD

Zhang et al [8] proposed a new force by combining Chan-Vese model (C-V) and GAC model [9]. The mentioned force is able to find object edges better. Inner and outer boundaries can be identified using initial contour automatically. In this paper, Zhang et al method is used to extract retina vessels. Zhang et al contour model is summarized as follow:

For a given image, I(x), located in the domain Ω, we have equation (1) by minimizing energy function. Energy function can be calculated from:

$$E = \lambda_1 \int_{inside(c)} |I(x) - c_1|^2 dx + \lambda_2 \int_{outside(c)} |I(x) - c_2|^2 dx \qquad (1)$$

where c_1 and c_2 are the constants indicating average intensities of inner and outer parts of contour, respectively. It is given that:

$$\begin{cases} c = \{x\epsilon\Omega : \phi(x) = 0\} \\ inside(c) = \{x\epsilon\Omega : \phi(x) > 0\}, \\ outside(c) = \{x\epsilon\Omega : \phi(x) < 0\}. \end{cases} \qquad (2)$$

Minimizing energy function allows parameters c_1 and c_2 to be:

$$c_1(\phi) = \frac{\int_\Omega I(x).H(\phi)\,dx}{\int_\Omega H(\phi)\,dx}, \qquad (3)$$

Ehsan Saghapour is with Department of Medical Physics and Biomedical Engineering, Shiraz University of Medical Sciences, Shiraz, Iran (corresponding author to provide; e-mail: ehsan_s9573@yahoo.com).

Somayeh Zandian is with Department of Electronic Engineering, Islamic Azad University of Fasa, Fasa, Iran (e-mail: ss_zandian@yahoo.com).

$$c_2(\phi) = \frac{\int_\Omega I(x).H(\phi)\,dx}{\int_\Omega (1-H(\phi))\,dx} \qquad (4)$$

By using the combination of area energy and length presented in equation (1) and minimizing them, a function for energy level changes is obtained:

$$\frac{\partial\phi}{\partial t} = \delta(\phi)\left[\mu\nabla\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - v - \lambda_1(I-c_1)^2 + \lambda_2(I-c_2)^2\right] \qquad (5)$$

where $\mu \gg 0$ and $v \gg 0$, λ_1 and λ_2 are constant parameters and μ controls zero surface stiffness. v is the contour speed. λ_1 and λ_2 control the power of data located inside and outside the contour. ∇ is gradient operator. $H(\phi)$ is Heaviside function and $\delta(\phi)$ presents Dirac function. Generally these two functions are expressed as :

$$\begin{cases} H_\varepsilon(Z) = \frac{1}{2}\left(1 + \frac{2}{\pi}arctan\left(\frac{z}{\varepsilon}\right)\right), \\ \delta_\varepsilon(Z) = \frac{1}{\pi}.\frac{\varepsilon}{\varepsilon^2+z^2}, \qquad Z\epsilon R \end{cases} \qquad (6)$$

Zhang et al. proposed a function called *spf* which adjusts the signs of inner and outer pressures such that when it is out of the object, contour will become smaller and if it is in the object, contour would extend. The equation is:

$$spf(I(x)) = \frac{I(x)-\frac{c_1+c_2}{2}}{Max\left(\left|I(x)-\frac{c_1+c_2}{2}\right|\right)}. \qquad (7)$$

where c_1 and c_2 are calculated using equation (3) and (4). Finally, the Zhang et al. active contour equation (8) is:

$$\frac{\partial\phi}{\partial t} = spf(I(x)).\alpha|\nabla\phi|, \qquad x\epsilon\,\Omega \qquad (8)$$
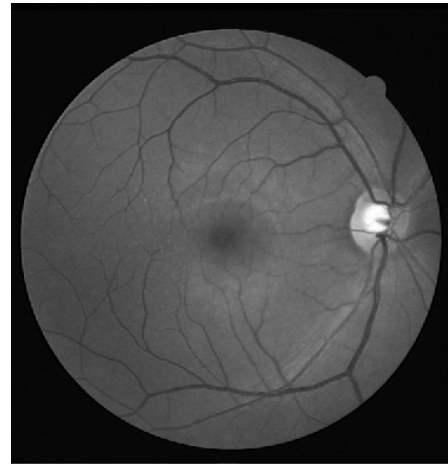
where α is a term of constant velocity.

III. Our Method

The images of DRIVE public database are color. At first, the green channel is extracted. The green channel is selected because it includes major data (see Fig. 1).

(a)

(b)

Fig. 1 a) RGB image, b) Extraction of Green Channel in image

In the next step, image is divided into 25×25 parts without overlapping. Then, a Gaussian filter is inserted on each part in order to flatten image and minimize noise. Additionally, contrast of each part improves (see Fig. 2).

DRIVE data base includes 40 images of which 20 ones are of training type and the remaining images are test ones. The best parameters for active contour are acquired by using training images. Consequently, the parts are put together. Now, output image is compared with the image used as Gold Standard in DRIVE database (see Figs. 3-4).

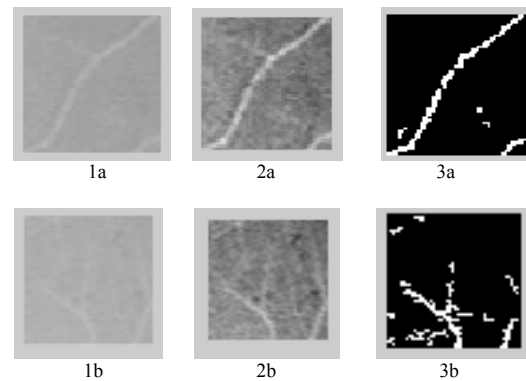The Gold Standard image is drawn by expert of medicine in manual hand.

Fig. 2 1a) a part of image, 2a) inducing Gaussian filter and improving contrast, 3a) inducing active contour, 1b) a part of image, 2b) inducing Gaussian filter and improving contrast, 3b) inducing active contour

After administration of the mentioned program, statistical methods including sensitivity, specificity and accuracy are used. Comparison with the related works is conducted here. Sensitivity and specificity are two indices for evaluating the result of dual classification in statistics. If it is possible to divide data into positive and negative groups, then this method is used to compare the difference of processing techniques. Sensitivity is defined as a ratio of positive values

which are labeled as positive correctly in experiments. Specificity is a ratio of negative values which are signed correctly in experiments.

$$Specificity = \frac{TN}{FP+TN}, \qquad (9)$$

$$Sensitivity = \frac{TP}{TP+FN}, \qquad (10)$$

$$Accuracy = \frac{TP+TN}{P+N}, \qquad (11)$$

TP: True Positive, TN: True Negative,
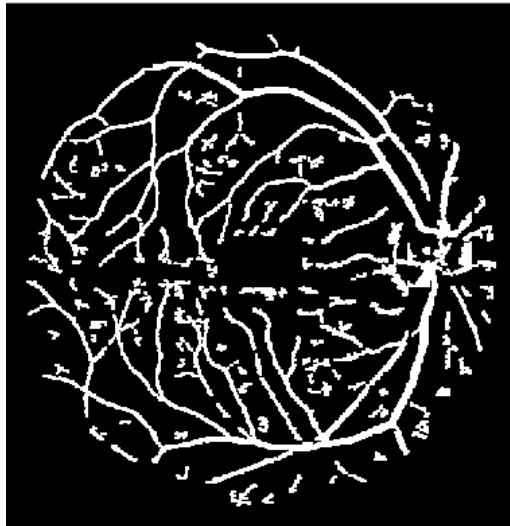
FN: False Negative, FP: False Positive
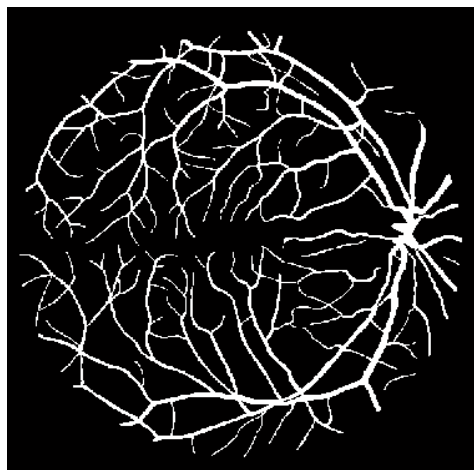

Fig. 3 Image generated by the proposed method

Fig. 4 Gold Standard

IV. RESULTS AND DISCUSSION

Sensitivity, specificity and accuracy along with processing time are 74.53%, 94.81%, 93.80% and 112s respectively. The techniques compared in Table I use active contour in order to extract retina vessels. Each technique has its own unique innovation. The method used in this paper is better than Al-Diri et al. [10] method and Spona et al. [2 and 3] method with regard to sensitivity and accuracy.

In comparison, with regard to speed, according to Table II, it is obvious that just the speed of Spona model is higher than the speed of our model. Without optimization of MATLAB code, image processing in the DRIVE database on a PC with Dual CPU 1.83 and 2.0 GB RAM requires 112 seconds.

TABLE I
COMPARISON OF THIS STUDY TECHNIQUE AND OTHER METHODS WITH REGARD TO SPECIFICITY, SENSITIVITY AND ACCURACY

Methods	Sensitivity	Specificity	Accuracy
Non-Expert Human	0.776330	0.972314	0.947046
Li et al. [11]	0.780	0.978	---
Espona et al. [2]	0.6634	0.9682	0.9316
Espona et al. [3]	0.7436	0.9615	0.9352
Al-Diri et al. [10]	0.7282	0.9551	---
Our Method	**0.7453**	**0.9481**	**0.9380**

TABLE II
RUNNING TIMES FOR DIFFERENT SEGMENTATION METHODS

Methods	Time (Seconds)
Espona et al. [3]	32.1
Espona et al. [2]	38.4
Staal et al. [12]	900
Mendonca and Campilho [13]	150
Soares et al. [14]	180
Human Observer	7200
Our Method	**112**

V. CONCLUSION

Segmentation of retina blood vessels has attracted many researchers' attention recently. Extraction of retinal vascular tree leads to a backbone of many automatic computerized systems for screening and diagnosing cardiovascular and ophthalmologic diseases. In this study, a suitable algorithm is proposed for automatic blood vessel segmentation and vessel diameter evaluation. The mentioned technique is based on an active contour having selective local or global segmentation. Average sensitivity, specificity and accuracy of the vessel segmentation on DRIVE database images are 74.53%, 94.81% and 93.80%, respectively.

REFERENCES

[1] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka, C. G. Owen, and S. A. Barman, "Blood vessel segmentation methodologies in retinal images – A survey," Computer methods and programs in biomedicine, vol. 108, pp. 407-433, 2012.
[2] L. Espona, M. J. Carreira, M. Ortega, and M. G. Penedo, "A snake for retinal vessel segmentation," Pattern Recognition and Image Analysis, vol. 4478, Lecture Notes Comput. Sci., pp. 178–185, 2007.
[3] L. Espona, M. Carreira, M. Penedo, and M. Ortega, "Retinal vessel tree segmentation using a deformable contour model," 19th International Conference on Pattern Recognition, pp. 1–4, 2008.

[4] B. Al-Diri and A. Hunter, "A ribbon of twins for extracting vessel boundaries," IFMBE Proc. 3rd European Medical and Biological Engineering Conference EMBEC'05, vol. 11, no. 1, 2005.

[5] T. F. Chan and L. A. Vese, "Active contours without edges," IEEE Transactions on Image Processing, vol. 10, pp. 266-277, 2001.

[6] K. Sum and P. Y. S. Cheung, "Vessel extraction under non-uniform illumination: A level set approach," IEEE Transactions on Biomedical Engineering, vol. 55, pp. 358-360, 2008.

[7] Drive: "Digital Retinal Images for Vessel Extraction," 2007 (available from: http://www.isi.uu.nl/Research/Databases/DRIVE/).

[8] Y. Zhang, W. Hsu, and M. L. Lee, "Detection of Retinal Blood Vessels Based on Nonlinear Projections," Journal of Signal Processing Systems, vol. 55, pp. 103-112, 2009.

[9] V. Caselles, R. Kimmel, and G. Sapiro, "Geodesic active contours," International journal of computer vision, vol. 22, pp. 61-79, 1997.

[10] B. Al-Diri, A. Hunter, and D. Steel, "An active contour model for segmenting and measuring retinal vessels," IEEE Transactions on Medical Imaging, vol. 28, pp. 1488-1497, 2009.

[11] L. Wang, A. Bhalerao, and R. Wilson, "Analysis of retinal vasculature using a multiresolution hermite model," IEEE Transactions on Medical Imaging, vol. 26, pp. 137-152, 2007.

[12] J. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. Van Ginneken, "Ridge-based vessel segmentation in color images of the retina," IEEE Transactions on Medical Imaging, vol. 23, pp. 501-509, 2004.

[13] A. M. Mendonca and A. Campilho, "Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction," IEEE Transactions on Medical Imaging, vol. 25, pp. 1200-1213, 2006.

[14] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree, "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," IEEE Transactions on Medical Imaging, vol. 25, pp. 1214-1222, 2006.