2012 Fourth International Conference on Computational and Information Sciences

A Novel Method of Vessel Segmentation for X-ray Coronary Angiography Images

Yanli Li [1], Shoujun Zhou [1,2,3], Jianhuang Wu [1,2,3,*], Xin Ma [1], Kewen Peng [4]
[1]Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China
[2]The Chinese University of Hong Kong, Hongkong SAR, China
[3]Shenzhen Key Laboratory of Neuro-Psychiatric Modulation, Shenzhen, China
[4]Nanshan People's Hospital, Shenzhen, China
[*]jh.wu@siat.ac.cn

***Abstract*—This paper presents a new automatic region-growing method for vessel segmentation in two-dimensional X-ray coronary angiography images. The method consists of two parts: the feature map extraction based on a novel vesselness function; and the segmentation process which includes automatic seed-point selection, main branch segmentation and vessel detail repair. Both the greyscale and spatial information are extracted for segmentation based on region growing algorithm. The presented method is validated on several clinical X-ray coronary angiography images, and the experimental results show that the method can not only segment large vessels but also small vessels.**

Keywords-X-ray coronary angiography; vesselness function; vessel segmentation; region-growing

I. INTRODUCTION

X-ray has been widely used in clinical applications and X-ray coronary angiography technique is taken as "gold standard" for diagnosing coronary artery diseases. However, besides vessels, there may be bones, spines and soft tissues in the X-ray coronary angiogram. These defects, coupled with the uneven distribution of contrast agent and other factors, make the clinical observation and diagnosing procedure much more difficult. Therefore, it is essential to utilize image processing technique to aid clinical diagnosis. Vessel segmentation is one of the most common methods for assistance diagnosis.

In recent decades, a variety of vessel segmentation techniques are proposed, such as direct tracking [1, 2], active contours [3, 4], centerline optimization among points [5, 6], and Markov marked point processes [7]. For a comprehensive introduction to these techniques, we refer to the survey of Kirbas et al. [8] and Lesage et al. [9].

As a basic image segmentation method, region-growing method is widely used in medical image processing for its simplicity and efficiency. The basic idea of the region-growing method for extracting vessels is as follows： starting from seed-points or regions located inside a vessel, region-growing methods segment the vessel by incrementally recruiting pixels to a region based on certain inclusion criteria. There are two commonly segmentation criteria: grayscale similarity and spatial proximity [8]. Region-growing based on a simple grayscale threshold [10] is one of the most typical grayscale similarity models, which assumes that pixels having similar grayscale value are likely to belong to the same object. However, the optimal threshold is determined experimentally, and other drawbacks of this approach include sensitivity to noise and inhomogeneity of contrast agent, over-segmentation and high possibility of generating holes.

Wave propagation technique [11] with spatial coherent is a typical region-growing method of spatial proximity models. It can be seen as an ordered region-growing scheme, where candidate pixels for inclusion are ordered according to fitness criteria with local schemes to correct the geometry of the growing wave. A spatially coherent propagation makes the topology analysis easier. For example, the connectivity of the propagating interface can be exploited to detect bifurcations.

In this paper, a novel vessel segmentation method for X-ray coronary angiography images is presented. This method is similar to the region-growing methods based on grayscale similarity but more effective. In order to improve the contrast of the vessel and background, a multi-scale enhancement filter is used to obtain a feature map, with which, the region growing algorithm can easily segment most of the vessel regions. Then a vessel detail repairing process is applied to further improve the final segmentation results. The main contributions of this paper are twofold. Firstly, a new vesselness function based on multi-scale filtering is defined, which offers a good feature map for the subsequent region-growing algorithm. Secondly, after vessel segmentation based on the feature map, a vessel detail repairing process is used to obtain small vessels and fill the existing holes.

In the following sections, the details of our vessel segmentation method are described in section II. The experimental results and discussion are given in section III. Finally, conclusion remarks are included in section IV.

II. METHOD

A. Overview

The whole procedure of our method includes two parts: feature map extraction and vessel segmentation which consists of seed-point selection, main branch segmentation and vessel detail repairing.

978-0-7695-4789-3/12 $26.00 © 2012 IEEE
DOI 10.1109/ICCIS.2012.34

B. *Feature map extraction*

We assume that the two-dimensional (2D) vessel is a curved strip which is a familiar curvilinear structure. Since the coronary arteries have various sizes within a range, a multi-scale filtering is suitable for preprocessing. The convolution between the original image $I_o(x, y)$ and a Gaussian kernel $\mathrm{G(x, y;}\sigma)$ is used to represent the information at a certain scale:

$$I_\sigma(x, y;\sigma) = I_o(x, y) \otimes \mathrm{G(x, y;}\sigma) \tag{1}$$

where $\otimes$ indicates the convolution and G_σ is the 2D Gaussian kernel with the scale σ defined as:

$$\mathrm{G(x, y;}\sigma) = (1/\sqrt{2\pi\sigma^2})\exp(-(x^2 + y^2)/2\sigma^2) \tag{2}$$

The vascular local characteristics of a pixel p_0 are extracted by analysis of Hessian matrix. Hessian matrix is defined as:

$$H(p_0,\sigma) = \sigma^2 * \left\{-\partial^2 \mathrm{G(x, y;}\sigma)\right\} \otimes I_o \tag{3}$$

σ^2 is used to normalize the differentiation. Frangi *et al.* [12] introduced the corresponding relationship between Hessian matrix's eigenvalues and vessel morphology. According to this relationship, when vessels are imaged as dark curvilinear structures, we can regard the corresponding Hessian matrix with a large positive eigenvalue λ_2 and a small eigenvalue λ_1 ($|\lambda_2| >> |\lambda_1|$). Using this vessel characteristic, various vesselness functions have been presented in previous works [13, 14]. We define a similar vesselness function to extract the vessel feature map by thresholding the eigenvalue map using a threshold defined as follows:

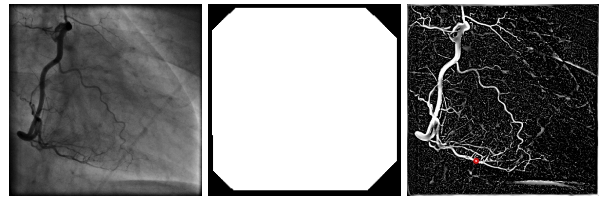
$$f(p_0,\sigma) = \begin{cases} \lambda_2 & if \quad \lambda_2 > \sigma^2/4 \\ 0 & else \end{cases} \tag{4}$$

$$f(p_0) = \max_{\sigma_{\min} \le \sigma \le \sigma_{\max}} f(p_0,\sigma)/\exp(\sqrt{2\sigma}) \tag{5}$$

$\sigma_{\min}$ and $\sigma_{\max}$ are the minimum and maximum scales which are fixed according to the approximate size of the smallest and largest vessel width to be detected in the image. $f(p_0)$ is named as vessel feature map.

C. *Region-growing*

Our region-growing process is based on three steps: automatic seed-point selection, main branch segmentation, and vessel detail repairing. In the following, we describe the details of these three steps.



(a) (b) (c)

Figure 1. (a) original image; (b) mask; (c) feature map with seed-point in red.

Step 1. Seed-Point Selection

The seed-points are obtained by analyzing the feature map. In experiments, we find that the point with maximum feature response will be classified as vessel point with high possibility. Sometimes features at the boundary position are close to the vascular space. Therefore, if we choose the point with maximum feature value as the seed-point, there may be an error that this point is located in the peripheral position. To solve this problem, considering there are no vessels in the peripheral region, a mask (See Fig.1 (b)) is offered to exclude the peripheral region. After the boundary region is excluded, the selection of the seed-points is much more robust. This automatic seed-point selection method works well for all the images used in this paper. Fig.1 (c) shows the feature map and the seed-point for Fig.1 (a).

Step 2. Main Branch Segmentation

Starting from the selected seed-point, region-growing process iteratively adds neighboring pixels to the segmentation with following conditions:

$$f(p_0) \ge T \tag{6}$$

In this work, Otsu threshold algorithm [15], which uses the zero and first order cumulative moments of the gray level histogram is used to select the optimal threshold T for the feature map. Then, the main branches of the vessels are extracted. Unfortunately, the small vessels cannot be extracted. In clinical diagnosis, lesions occasionally happen on small vessels. Thus, it is necessary to repair the segmented vessels to obtain small vessels.

Step 3. Vessel detail repairing

In order to repair the details of vessels, the first directional derivatives which describe the variation of image grayscale in the neighborhood of a point is used in this step. Under a multi-scale framework, the magnitude of the gradient $|\nabla I_\sigma|$ represents the slope of the image grayscale for a particular value of the scale parameter σ. The final result is calculated as following:

$$\partial I_\sigma(x, y;\sigma) = I(x, y) \otimes \sigma * \partial G(x, y;\sigma) \tag{7}$$

$$|\nabla I_\sigma| = \sqrt{(\partial_x I_\sigma)^2 + (\partial_y I_\sigma)^2} \tag{8}$$

Figure 2. $\underset{\sigma_{\min}<\sigma<\sigma_{\max}}{Max}(|\nabla I_\sigma|)$ for Fig.1 (a)

$$g(p_0) = \max_{\sigma_{\min}<\sigma<\sigma_{\max}} (|\nabla I_\sigma|) \tag{9}$$

Fig. 2 illustrates the $g(p_0)$ calculated from Fig. 1(a). The vessel detail repairing process is mainly based upon $g(p_0)$. Similar to previous procedure, the region-growing process is used for further segmentation. All the vessel points obtained from main branch segmentation are planted as seed-points. The classification of eight-neighboring pixels as vessels is based primarily upon following conditions:

$$g(p_0) \le mean(g(p_0)) \text{ AND } f(p_0) \ge T - \delta_v \tag{10}$$

δ_v is the standard deviation of $f(p_0)$ for all the vessel pixels obtained by previous step. This procedure is relied on the fact that $g(p_0)$ gives the boundary information of the vessels in X-ray coronary angiography images. With the region-growing process, it is possible to extend the main branches until reaching the boundary.

III. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the results of the presented method for vessel segmentation are demonstrated and compared to other vessel extraction techniques. Fig.3 shows the comparison results obtained by Frangi *et al.* 's vesselness function [12] and ours. It can be seen that Frangi *et al.*'s function can only generate large vessel, while our function can yield both large vessel and small vessel. On the other hand, Frangi *et al.*'s function contains several parameters which are difficult to control. Usually a small variation of one of the parameter's values will result in a significant change in the final results. In contrast, our function has only one parameter and the result is more robust. Moreover, Frangi *et al.*'s feature map gives higher response for large vessel segments, but in our feature map, large vessels and small vessels have similar grayscale value, which gives better characteristic for the subsequent process of region-growing than the Frangi *et al.'s* feature map (see Fig. 4).

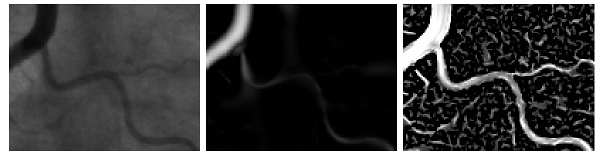
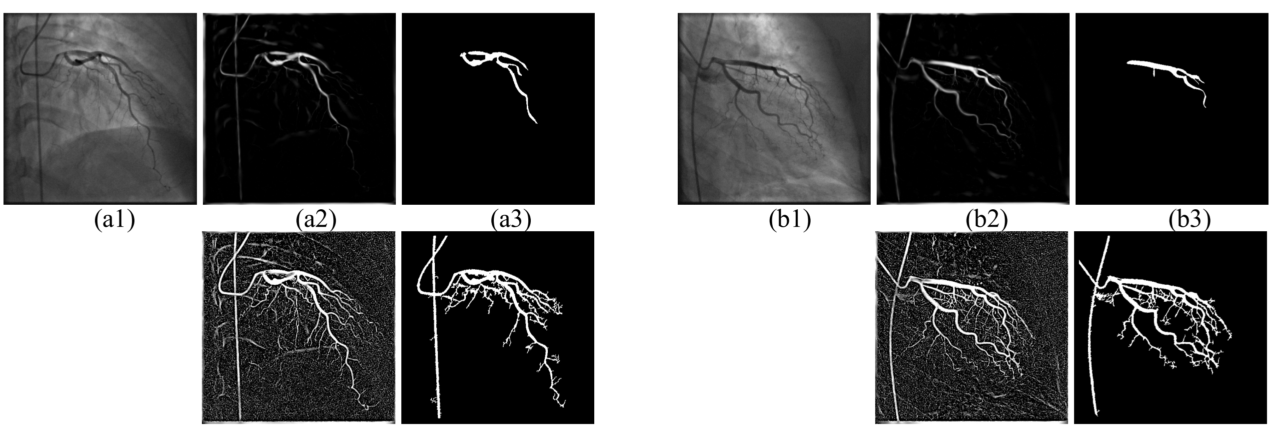


Figure 3. Comparison results using different vesselness function. The images from left to right are the input image, Frangi *et al* 's feature map and our feature map, respectively.

In Fig. 5, the comparison of the segmentation results for Fig. 1(a) before and after vessel details repairing is shown. It is obvious that the repairing process can fill the holes in the main vessel branch (see position 1) and extend the original main vessel branches and repair the small missing vessels (see position 2 and 3, respectively.). Compared to the conventional region growing method without detail repairing process, our method further utilizes the edge information of the original X-ray coronary angiography image, which keeps the boundary of the vessels. Another example of our method is illustrated in Fig. 6, the results once again show that our additional process avoid the problem of high possibility of generating holes and missing vessel details. However, although most of the vessel regions are extracted successfully, over-segmentation exists in areas with complex background noise.



(a1) (a2) (a3) (b1) (b2) (b3)

(a4) (a5) (b4) (b5)

Figure 4. Comparison result of vessel enhancement: (a1) and (b1) the original images; (a2) and (b2) Frangi et al.'s feature maps; (a3) and (b3) vessel segmentation via region-growing with (a2) and (b2) respectively; (a4) and (b4) our feature maps; (a5) and (b5) vessel segmentation via region-growing with (a4) and (b4) respectively.

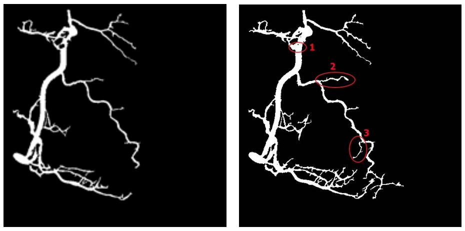
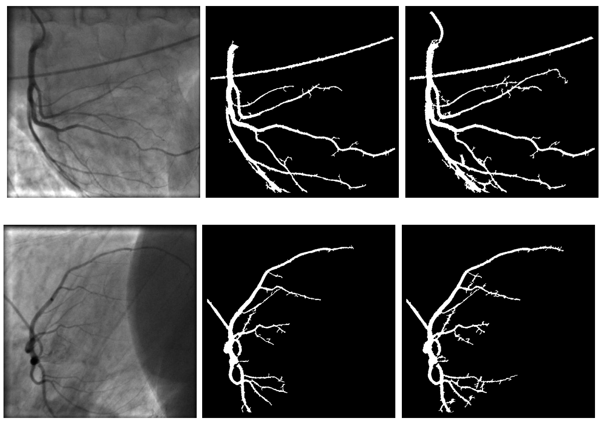


Figure 5. Left is the main branch of vessel using region-growing; Right is the repaired image and the vessels in red circle are the repaired details.



(a) (b) (c)

Figure 6. Comparison of vessel region-growing: (a) original images; (b) main branch segmentation; (c) vessel detail repairing.

IV. CONCLUSION

In this paper we have presented an automatic region-growing method for vessel segmentation which is based on the feature map of the input image. In the preprocess step, a new vesselness function is defined to extract the feature map. Compared to Frangi *et al.'* s function, our function has only a parameter, which makes it easier to control. The obtained feature map has similar grayscale value which simplifies the segmentation process based on region-growing. In order to automatically and correctly select the seed-point located in the vessel region, a mask is introduced to exclude the boundary region. A repairing procedure is employed to refine the segmented vessels for those missing details. Experiments show that our algorithm can segment large vessels and small vessels, though the final result may be over-segmented in some areas with complex background noise. In our future works, more prior knowledge of the vessel may be utilized to make the segmentation algorithm more robust and less sensitive to the high noise.

ACKNOWLEDGEMENTS

This work was supported by Guangdong Natural Science Foundation (No.S2011010001820), Introduced Innovative R&D Team of Guangdong Province "Robot and Intelligent Information Technology", and the National Science Foundation of China (No.61179020). We would like to thank Chen Mingyang and Wang Sen for their helpful comments.

REFERENCES

[1] M. Schaap, R. Manniesing, I. Smal, T. V. Walsum, A. V. D. Lugt, and W. J. Niessen, "Bayesian Tracking of Tubular Structures and Its Application to Carotid Arteries in CTA," Medical Image Computing and Computer-Assisted Intervention, pp. 562-570, 2007.

[2] Y. Yin, M. Adel, and S. Bourennane, "Retinal Vessel Segmentation using a Probabilistic Tracking Method," Pattern Recognition, vol. 45, pp. 1235-1244, 2012.

[3] C. Li, C.-Y. Kao, J. C. Gore, and Z. Ding, "Implicit Active Contours Driven by Local Binary Fitting Energy," 2007 IEEE Conference on Computer Vision and Pattern Recognition, pp.1-7, 2007.

[4] Y. Shang, R. Deklerck, E. Nyssen, A. Markova, J. d. Mey, X. Yang, and K. Sun, "Vascular Active Contour for Vessel Tree Segmentation," IEEE Transactions on Biomedical Engineering, vol. 58, no. 4, pp. 1023-32, 2011.

[5] F. Benmansour, L. D. Cohen, M. W. K. Law, and A. C. S. Chung, "Tubular Anisotropy for 2D Vessel Segmentation," 2009 IEEE Conference on Computer Vision and Pattern Recognition, vol. 1-4, pp. 2286-2293, 2009.

[6] M. Pechaud, R. Keriven, and G. Peyre, "Extraction of Tubular Structures over an Orientation Domain," 2009 IEEE Conference on Computer Vision and Pattern Recognition, vol. 1-4, pp. 336-342, 2009.

[7] C. Lacoste, G. Finet, and I. E. Magnin, "Coronary Tree Extraction from X-ray Angiograms using Marked Point Processes," 2006 IEEE International Symposium on Biomedical Imaging: Macro to Nano, vol. 1-3, pp. 157-160, 2006.

[8] C. Kirbas and F. Quek, "A Review of Vessel Extraction Techniques and Algorithms," ACM Computing Surveys, vol. 36, no. 2, pp. 81-121, 2004.

[9] D. Lesage, E. D. Angelini, I. Bloch, and G. Funka-Lea, "A Review of 3D Vessel Lumen Segmentation Techniques: Models, Features and Extraction Schemes," Medical Image Analysis, vol. 13, no. 6, pp. 819-45, 2009.

[10] T. Boskamp, D. Rinck, F. Link, B. Kummerlen, G. Stamm, and P. Mildenberger, "New Vessel Analysis Tool for Morphometric Quantification and Visualization of Vessels in CT and MR Imaging Data Sets," Radiographics, vol. 24, no. 1, pp. 287-297, 2004.

[11] F. K. Quek and C. Kirbas, "Vessel Extraction in Medical Images by Wave-propagation and Traceback," IEEE Transactions on Medical Imaging, vol. 20, no. 2, pp. 117-31, 2001.

[12] A. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale Vessel Enhancement Filtering," Medical Image Computing and Computer-Assisted Intervention, vol. 1496/1998, pp. 130-137, 1998.

[13] M. E. Martinez-Perez, A. D. Hughes, S. A. Thom, A. A. Bharath, and K. H. Parker, "Segmentation of Blood Vessels from Red-free and Fluorescein Retinal Images," Medical Image Analysis, vol. 11, no. 1, pp. 47-61, 2007.

[14] S. J. Zhou, J. Yang, Y. T. Wang, and W. F. Chen, "Automatic Segmentation of Coronary Angiograms based on Fuzzy Inferring and Probabilistic Tracking," BioMedical Engineering OnLine, vol. 9, no. 1, pp. 21-40, 2010.

[15] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms," IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62-66, 1979.