Adaptive Segmentation of Vessels from Coronary Angiograms Using Multi-scale Filtering

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***Abstract*—In this paper, we propose a novel automatic and effective method for the vessel segmentation based on Hessian matrix. First, to obtain vessel structure more reliably, we select 25 frames of well-contrast angiograms automatically for further vessel segmentation. Second, we define an adaptive feature transform function using the gray value and the scale to improve the feature response. First, we enhance the original image contrast by reducing the gray level of vessels, and then adjust the eigenvalues by taking the enhanced gray level as a rectification factor to better differentiate between the vessel points and the background ones. We also use the scale as a weighting factor. In the way, vessel and background can result in different feature responses. Next, Hessian with Gaussian derivatives at multi-scales was computed due to different vessel widths, and the maximum response is selected as the vessel candidate. Finally, we use a connected components labeling method to detect the largest connected component as our segmentation result. In our experiments, 14 angiogram sequences are used to evaluate the accuracy. The accuracy of well-contrasted angiograms is 95.66%. For the result of segmentation, 40 angiograms are used to compare with other methods. After inspecting by a cardiologist, the experimental results show that our method works well for the enhancement and segmentation of vessels.**

Keywords-vessel segmentation; coronary angiograms; feature transform; Hessian matrix

I. INTRODUCTION

Cardiovascular disease is one of the most common causes of death in the world. Coronary angiography is the most important evaluation and operation tool in the diagnosis and treatment of the cardiovascular disease. Accurate segmentation of coronary artery from X-ray angiograms is an important step for the diagnosis. However, in a complex background, the segmentation of vessels from spines and soft tissues in the X-ray angiograms is difficult due to intensity variations, low contrast or various shapes of vessels.

Blood vessels segmentation can be used not only to locate the position of vessel stenosis but also measure blood vessel diameters. The methods for the segmentation of angiograms could be categorized into three categories: pattern recognition [1, 2, 3, 4], tracking based [5, 6] and model based [7, 8, 9, 10, 11]. Patter recognition methods automatically detect objects via vessel features. Hern´andez-Vela et al. [1] proposed a method based on multi-scale edgeness measure. Multi-scale edges and geodesic paths are combined to customize the Graph cuts model to the segmentation of vessel structures. Ashoorirad and Baghbani [2] used fuzzy inference system and morphology filters for vessel segmentation. These methods are difficult to deal with edge noises and bifurcations vessels. In contrast, tracking based methods apply local operators on a region to estimate next vessel points. Zhou et al. [4] presented a tracking method that utilizes vessel features to segment the vessel tree based on probabilistic tracking and fuzzy inferring. The tracking algorithm cannot effectively track vessels in complex background and mostly rely on the manual setting. Model-based methods such as deformable splines and snake models use a set of parametric curves to segment. Sun et al. [10] proposed an active contour model using local morphology fitting for automatic vascular segmentation. The model based methods are hard to set model parameters and affect the computational cost for each frame of angiograms. Multi-scale Hessian matrix has been proposed to enhance and segment vessel structures [1, 3, 4, 6, 12]. For the enhancement of vessels, Frangi et al. [3] presented a multi-scale method based on Hessian matrix. The local feature of the vessel which is based on the eigenvalues of the Hessian matrix is obtained. The eigenvalues can differentiate a pattern as tubular structure, plate-like structure and blob-like structure. This method can enhance vessels effectively. By contrast, Tagizaheh et al. [11] presented an approach to vessel segmentation by combining multi-scale Hessian matrix and active contour model. Li et al. [4] combined multi-scale Hessian matrix with region growing to resolve the vessel structure and intensity variations. However, these methods are unable to suppress background noise and achieve accurate segmentation. In this paper, we proposed a novel automatic and effective method for the vessel segmentation based on multi-scale Hessian matrix. The remaining of this paper is organized as follows: In section II, we describe our method that contains well-contrast angiogram selection and vessel segmentation. In section III, experiments and analysis are reported. Finally, conclusion is included in section IV.

II. METHOD

This section describes an automatic segmentation of vessels from X-ray angiograms. The method contains two main stages: (1) Well-contrast angiograms selection. (2) Vessels segmentation from the well-contrast angiograms.

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A. Well-contrast angiograms selection

Since different tissues within the body have different degrees of the X-ray beam attenuation, the coronary angiography requires contrast agent to better visualize blood vessels inside the body. In the clinical angiography, the sequence of the angiogram contains 25 frames per second. The film-taking continues 4~10 seconds according to the doctors' habit. The response of the injected contrast agent in angiograms can be classified into five types: (1) Contrast-agent is not injected yet. (2) Contrast-agent is not distributed in vessels. (3) Contrast-agent is distributed in vessels. (4) Contrast-agent is attenuated gradually. (5) All contrasts have been attenuated. Fig. 1 shows the response of the injected contrast agent in angiograms. In each angiogram sequences, only the frames of the type 3 are valuable the medical examination. These images are called well-contrast frames which have approximately 25 frames.

Angiograms are affected by heartbeat and responses of injected contrast agent over time. We cannot observe a complete vessel structure in a single angiogram of the input sequence. To obtain vessel structure more reliably, we select the well-contrast angiograms section automatically by the following method. Since the gray value shows abrupt difference on vessel boundaries, vessel candidates can be detected from the intensity distribution of cross-sections. We select five horizontal and five vertical scan lines to examine the gray value changes among nearby pixels in Fig. 2. Vessel candidates are defined as following: The gray value must have large changes and it would find other point which has large changes in a limited width. We count the number of vessel candidates in each frame and select 25 frames with the highest vessel candidates in an angiogram sequence.

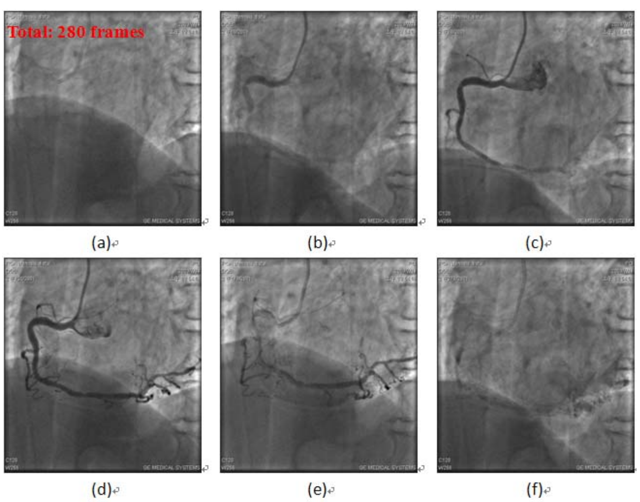

Figure 1. The response of the injected contrast agent, (a) Contrasted-agent is not injected yet, (b) and (c) contrast-agent not distributed in vessels, (d) contrast-agent distributed into vessels completely, (e) contrast-agent is attenuated, and some vessels are missing, (f) all contrasts have been attenuated.

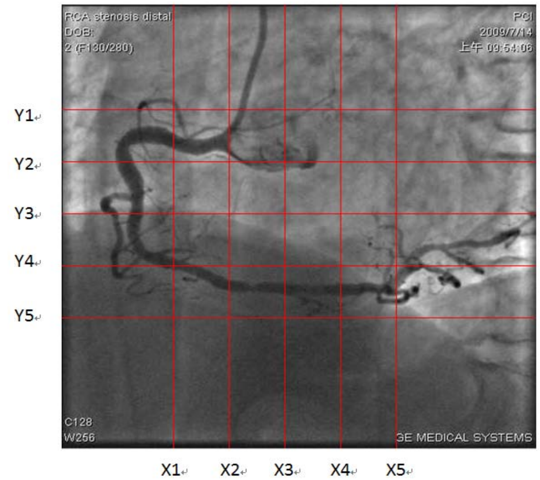

Figure 2. Five horizontal and five vertical scan lines of each frame are selected to examine gray value changes.

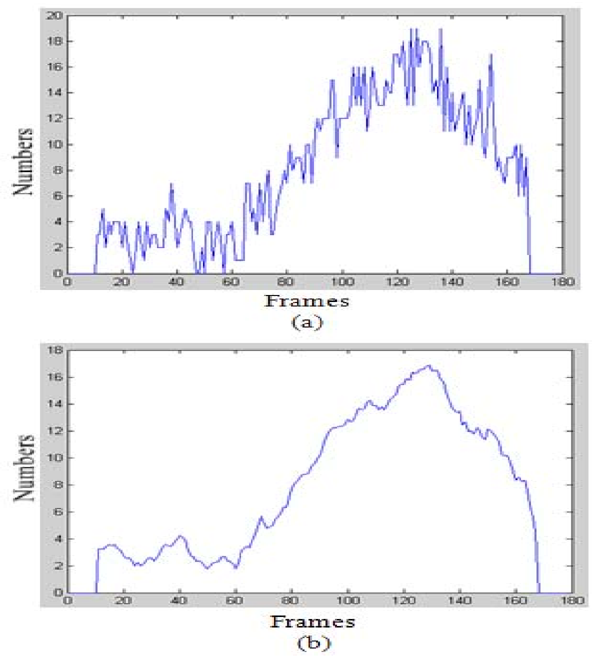

Figure 3. Counts of vessel candidates, (a) the count of an angiogram sequence, (b) the smoothed counts.

Candidate vessels can be found incorrectly due to the existence of result involves: (1) bones, (2) the leaking of contrast-agent, (3) the contours of overlapped organs, (4) blood vessels being parallel to scan line.

Since background of each frame is different, the above confounding factors do not exist consistently in background. To avoid the influence of these outliers, the count of the frame *f(i)* is smoothed by those of nearby eight frames, *f(i-4) ~ f(i+4)*. Fig. 3(b) shows the smoothed results of an angiogram sequence. We select the frame with the highest number of the vessel candidates as the best well-contrast frame and then chose previous 12 and next 12 frames as the well-contrasted angiogram section. The smoothed process can avoid the error detection of vessel candidates. Thus, 25 frames of well-contrast angiograms are used for further vessel segmentation.

B. Vessels segmentation

Since the distribution of gray values of the vessels may be similar to those of backgrounds, the accuracy of the vessel segmentation may be affected. In this study, we propose an adaptive feature transform function to detect vessels based on the eigenvalues of the multi-scales Hessian matrix. The Hessian matrix is defined as the second-order partial derivatives of the local intensity at each point of a 2D image. For each point of an image, the Hessian matrix is defined as follows:

$$H(x,y;\sigma)=\begin{pmatrix} I_{xx}(x,y;\sigma) & I_{xy}(x,y;\sigma) \\ I_{yx}(x,y;\sigma) & I_{yy}(x,y;\sigma) \end{pmatrix}, \tag{1}$$

where I_{xx}, I_{xy}, I_{yx} and I_{yy} denote second derivatives of image point $I(x,y)$,

$$I_{xx}(x,y;\sigma)=\frac{\partial^2}{\partial x^2}G(\sigma)*I(x,y), \tag{2}$$

where $G(\sigma)$ is a Gaussian distribution function with scale σ and * denotes a convolution operator.

Hessian matrix is used to obtain vessel features from eigenvalues and eigenvectors. Frangi et al. [3] defined a vesselness measure based on eigenvalue analysis of Hessian matrix. In our study, the dark vessel structure in a bright background has a large positive eigenvalue λ_2 and a small eigenvalue λ_1 ($|\lambda_2| > |\lambda_1|$). We obtain the large positive eigenvalue λ_2 as our vessel feature.

The eigenvalue of the local vessel and those of the background may be very similar, so it is hard to distinguish between the vessel and the background. We define an adaptive transform function including the gray value and the scale to improve the vessel feature response.

First, we enhance the original image contrast by reducing the gray level of vessels. The enhancement function is given by:

$$I_e(x,y)=\begin{cases} I(x,y)+30, & \text{if } I(x,y)>T, \\ I(x,y)-30, & \text{else}, \end{cases} \tag{3}$$

where $I(x,y)$ is a pixel gray value, and T is a threshold value. In our experiments, the threshold value is set as 130.

Each pixel of the image has different feature responses. Larger variations in gray values have larger eigenvalue; on the other hand, smaller eigenvalues will have few variations. Therefore, we adjust the eigenvalue at each point of a 2D image by taking the enhanced gray level as a rectification factor to better differentiate between the vessel points and the background ones. A wider vessel has darker gray values than the small one, and it has larger feature responses. But above method cannot deal with the vessel width. Therefore, we set a weighting factor in our experiments from 1 to 15. The adaptive feature transform function is given as follows:

$$V(x,y;\sigma)=\begin{cases} 1-\exp(-\frac{S^2}{c}), & \text{if } \lambda_2(x,y;\sigma)>0 \\ 0 & \text{else}, \end{cases}, \tag{4}$$

where c is a constant and λ_2 is eigenvalue.

$$S^2=\left(\frac{1}{w^2\times I_e(x,y)}\right)^2\times\lambda_2^{\,2}(x,y;\sigma), \tag{5}$$

where I_e is the enhanced gray value and w is a weighting factor.

In the way, vessel and background can result in different feature responses. To detect different vessel widths, Hessian matrix with Gaussian derivatives at multi-scales is computed, and the maximum response is selected as the vessel candidates. The final vessel filter response is given by:

$$V_c(x,y)=\max(V(x,y;\sigma)),\ \sigma=\sigma_1,\ldots,\sigma_n \tag{6}$$

where σ_1 and σ_n are minimum and maximum scales. Fig. 4(b) shows the vesselness map of our method.

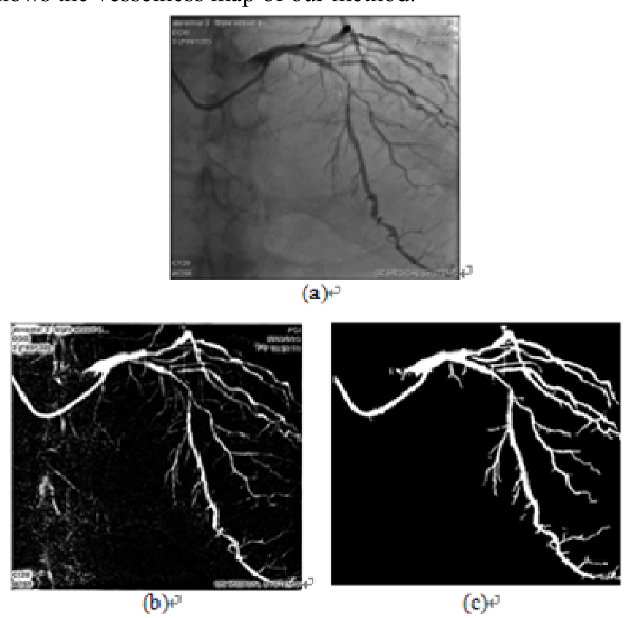

Figure 4. (a) the original images, (b) our method's vessel map, (c) segmentation result of our method

The vessel candidates are thresholded as a vessel map. The map will contain vascular structures and other components such as bones and noises. Vessels are large and long structures. We can remove other components whose size is small. Connected-component analysis is used to detect connected regions in binary images. In this study, we use a recursive method of eight-connected component labeling. Finally, we obtain the largest connected component as our segmentation result in Fig. 4(c).

III. Experimental Results

The size of a single X-ray image is 512 * 512 pixels with 8-bit gray-scale.

A. Well-contrast angiograms evaluation

To evaluate the efficiency of the algorithm, we sample 14 angiogram sequences, with each sequences consisting of 70-280 images. Three error measures are used to evaluate the accuracy of the proposed method: true positive rate (TPR), false positive rate (FPR) and accuracy (ACC). The well-contrast angiograms from each angiogram sequence are compared with manual selection by a cardiologic expert. The average accuracy of well-contrasted angiograms is 95.66%. The evaluation results are shown in Table 1.

TABLE I. THE ACCURACY OF WELL-CONTRAST ANGIOGRAMS

	Average-TPR	Average-FPR	Average-ACC
The performance of the well-contrast angiograms	87.71%	2.7%	95.66%

B. Segmentation evaluation

In this paper, we present an adaptive feature transform function to segment vessels. Fig. 5 shows results of feature different responses. Hessian matrix and Frangi et al.'s [3] function can only determine vessel's approximate position in Figs. 5(b) and 5(c). On the other hand, Hessian matrix and Frangi et al.'s feature responses are hard to detect vessel edge. Fig. 5(d) shows our method's feature response. Compared with other methods, our method can obtain better feature responses. Fig. 5(e) shows comparison result of feature response. Hessian matrix and Frangi et al.'s method unable deal with the similar gray value. Our method can differentiate between the vessel points and the background ones.

For the result of the segmentation, we test 40 angiograms from 14 patients. The processing of a single X-ray image of size 512× 512 pixels takes approximately 6 sec in average on an Intel Core 2 Duo 2.19 GHz. Figs. 6 and 7 show the comparison results of the vessel feature responses. It shows that Frangi et al.'s and Zhou et al.'s [4] cannot detect vessels in complex background. Fig. 8 shows the result of segmentation can remove other components such as bones and noises. After inspecting by a cardiologic expert, the experimental results show that our method works well for the enhancement and segmentation of vessels.

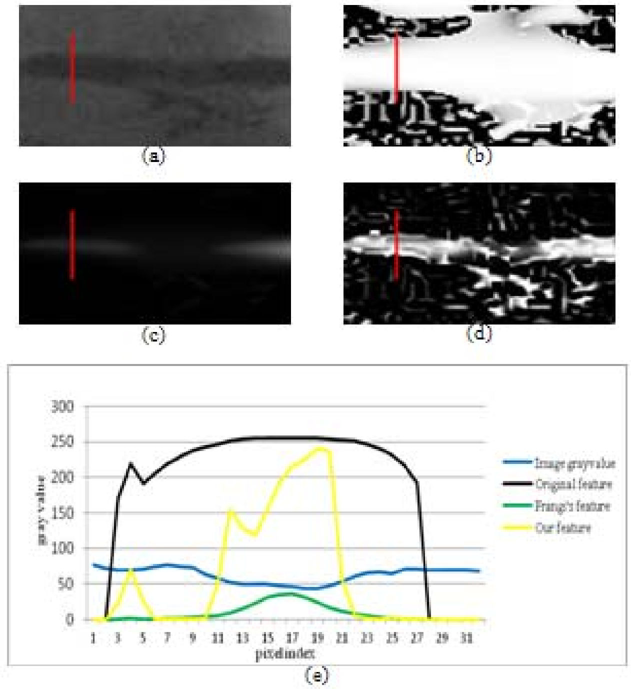

Figure 5. The result of feature response, (a) original image, (b) original feature response by Hessian matrix, (c) Frangi's feature response, (d) Our method's feature response, (e) compare the feature response on the red line in Figure (a)-(d); black: original feature response; in green: Frangi's; in yellow: our method.

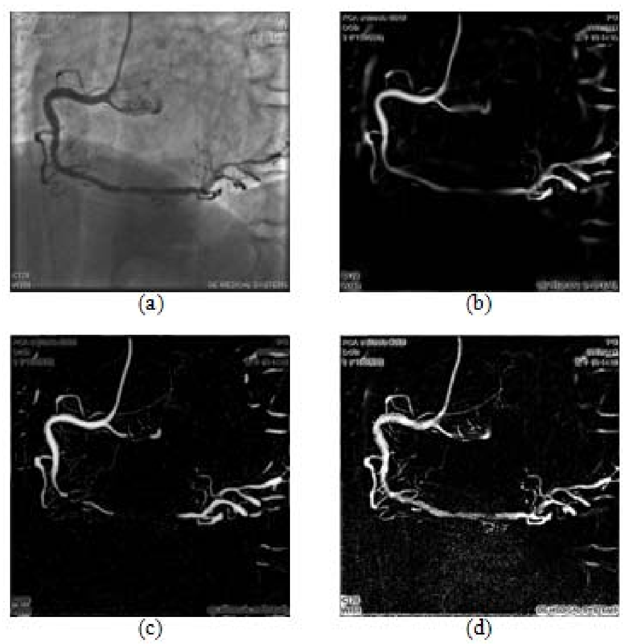

Figure 6. Comparison result of vessel enhancement, (a) the original images, (b) Frangi et al.'s vesselenss feature map, (c) Zhou et al.'s vesselness feature map, (d) our vesselness feature maps.

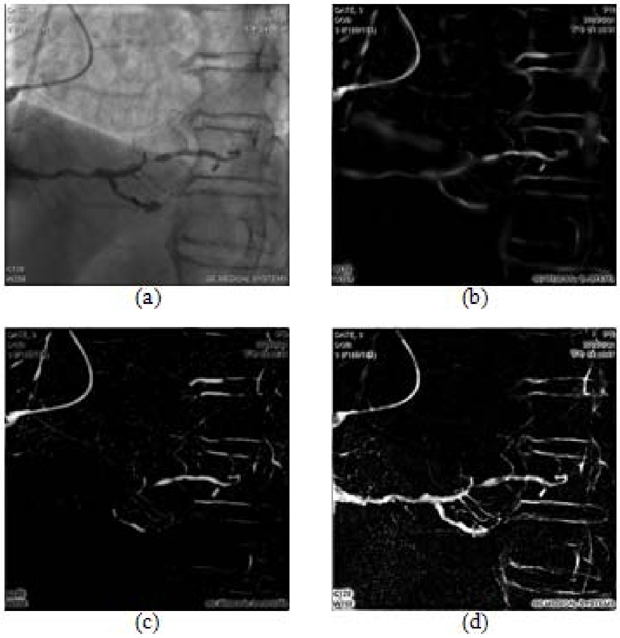

Figure 7. Other results of vessel enhancement, (a) the original images, (b) Frangi et al.'s vesselenss feature map, (c) Zhou et al.'s vesselness feature map, (d) our vesselness feature maps.

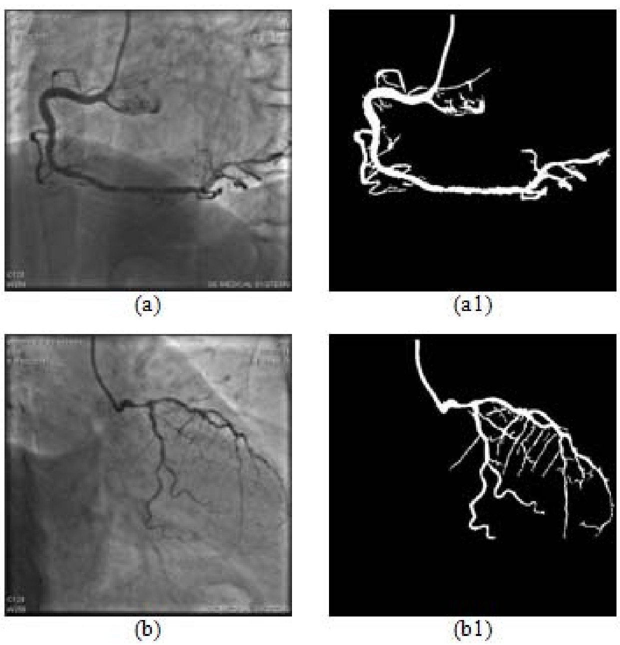

Figure 8. Result of vessel segmentation, (a) and (b) the original images, (a1) and (b1) Our method.

IV. CONCLUSION

This paper proposes a new method to segment vessel based on multi-scale Hessian matrix. In the part of defining well-contrast angiograms, it can obtain more information on vessel structure for diagnosis. In the part of the segmentation, a new adaptive vessel feature function is defined to extract the vesselness feature map. Compared to other methods, our function is easier to control and more robust in complex background. In our future, we will obtain more vessel characteristics such as vessel branch and vessel width, and analyze 3D vessel structure.

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