Segmentation of Coronary Arteries Based on Transition Region Extraction

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***Abstract*—Aiming at the complex background of coronary angiograms, weak contrast between the coronary arteries and the background, a new segmentation method based on transition region extraction is proposed. The paper analyzes the characteristic of coronary angiograms, and then 6 different Gaussian matched templates are used to enhance the coronary angiograms. Finally, the coronary arteries are obtained with local complexity method based on transition region extraction. The experiments indicate that the proposed method outperforms the segmentation method based on top-hat about the small vessels extraction, connectivity and effectiveness. The method is indeed valuable for diagnosis and the quantitative analysis of coronary arteries.**

***Index Terms*—coronary angiogram, Gaussian filtering, local complexity, transition region**

I. INTRODUCTION

The coronary angiography is an important examination for a diagnostic tool in cardiology. It is useful to precise diagnosis and treatment of patients to make an accurate analysis of vessel morphology on the angiogram. So it is necessary to extract vessels from the coronary angiogram. But usually there are several problems for extract vessels: weak contrast between the coronary arteries and the background, an apriority unknown and easily deformable shape of the vessel tree, sometimes overlapping strong shadows of bones and so on. Hence, it is important to extract the vessels.

There are many previous works on extracting blood vessels from coronary angiograms. The most of methods of vessel segmentation is based on gray-level feature. Utilizing the properties that the gray-level of the background is higher than that of the vessel, [1], [2] and [3] enhance the vessels used morphological operator, then extracts the vessel using mean filter template. The top-hat method can eliminate the part of noise, but it cannot eliminate the noise whose size is nearer or lower the size of vessel. In two-dimensional matched filter approach [4] and [5], the Gaussian filter is used to enhance the image, because the blood vessel gray-level profiles along directions perpendicular to their length can be approximated by a Gaussian curve [6]. But this method needs heavy computation, so its speed is slow. Transition region based on threshold is a newly developed segmentation method in recent years. Ref. [7] introduced transition region into image segmentation. The effective average gradient and clip transformation are applied in this method. In order to limit the affects of noise, the gradient operator is modified with Gaussian weight by [8]. But Gradient-based methods are much sensitive to noise.

This paper analyzes the characteristic of coronary angiograms, and then a new segmentation method based on transition region extraction is proposed. Firstly, Gaussian filters are used to enhance the arteries. Then the transition region is extracted used local complexity method. Finally, obtain the vessels used the segmentation threshold by histogram of transition region. The experiments indicate that the proposed method outperforms the top-hat method about the small vessels extraction and background elimination. In addition, the method is indeed valuable for diagnosis and the quantitative analysis of coronary arteries.

II. ENHANCE CORONARY ANGIOGRAM

The coronary arteries usually have the following properties:

- Since the blood vessels usually have small curvatures, the coronary arteries may be approximated by piecewise linear segments.
- Since the vessels have lower reflectance compared to other body tissues surfaces, they appear darker relative to the background. Hence, the gray-level of the vessel is lower than that of the background.
- Gray-level profiles of the cross section of coronary arteries have an intensity profile, which can be approximated by a Gaussian curve, although the intensity profile varies by a small amount from vessel to vessel.
- Although the width of a vessel decreases as it travels radially outward, such a change in vessel caliber is a gradual one. It will be assumed that all the blood vessels in the image are almost equal width.

The blood vessels may be considered as piecewise linear segments. The vessel gray-level profiles along directions perpendicular to their length can be approximated by a Gaussian curve. Such a kernel may be mathematically expressed as

$$K(x,y) = -\exp\left(-\left(x^2+y^2\right)/\left(2\sigma^2\right)\right) \quad |\, y \,|\leq L/2 \tag{1}$$

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where L is the length of the segment, which the vessel is assumed to have a fixed orientation. Here the direction of the vessel is assumed to be along the $y-$axis. For the vessels at different orientations, the kernel has to be rotated accordingly. Let $\overline{p}=[x,y]$ be a discrete point in the kernel and θ_i be the orientation of the i^{th} kernel matched to a vessel at an angle θ_i. In order to compute the weighting coefficients for the kernel, the center is assumed to be about the origin [0, 0]. The rotation matrix is given by

$$r_i=\begin{bmatrix}\cos\theta_i & -\sin\theta_i\\ \sin\theta_i & \cos\theta_i\end{bmatrix} \tag{2}$$

and the corresponding point in the rotated coordinate system is given by

$$\overline{p_i}=[u,v]=\overline{pr_i} \tag{3}$$

A Gaussian curve has infinitely long double side trails. The trail is truncated at $u=\pm3\sigma$, $|v|\le L/2$. The corresponding weights in the i^{th} kernel are given by

$$K_i(x,y)=-\exp\left(-\left(u^2+v^2\right)/\left(2\sigma^2\right)\right)\ \forall\overline{p_i}\in N \tag{4}$$

where $N=\{(u,v)\,\|\,u|\le 3\sigma,|v|\le L/2\}$ .If A denotes the number of points in N, the mean value of the kernel is determined as

$$m_i=\sum_{\overline{p_i}\in N}K_i(x,y)/A \tag{5}$$

Thus the convolution mask is give by

$$K_i'(x,y)=K_i(x,y)-m_i \quad \forall\overline{p_i}\in N \tag{6}$$

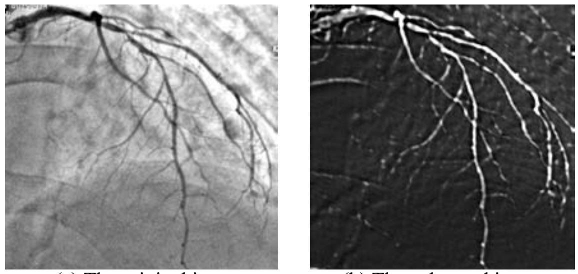
It must be noticed that a vessel may be oriented at any angle $\theta(0\le\theta\le\pi)$. In the paper, assuming an angular resolution of 30°, 6 different kernels are needed to span all possible orientations. So the corresponding responses are to be compared, and for each pixel only the maximum response is to be obtained. A lot of experiments prove that $\sigma=1.5$ and $L=9$ can be matched well with a blood vessel for coronary angiogram. An original coronary angiogram is given in Fig. 1(a). The enhancement result is given in Fig. 1(b). The most of the background is eliminated from Fig. (1).

III. Vessel Extraction Method

A. *Typical Transition Region Extraction*

Typical transition region extraction method applies the average of gradient and clip transformation of grayscale. Let $f(i,j)$ be an image function defined on $M\times N$ image size, $(i,j)\in S$, S represents the integer set of spatial coordinates of the pixels. Let $g(i,j)$ be the gradient of the image, then EAG can be defined as

$$EAG=TG/TP \tag{7}$$



(a) The original image (b) The enhanced image

Figure 1. The enhanced image used Gaussian filter

$$TG=\sum_{i,j\in S}g(i,j) \tag{8}$$

is the total sum of the gradient and

$$TP=\sum_{g(i,j)\neq0}1 \tag{9}$$

is the total sum number of pixels with non-zero gradient values in the image.

The clip transformation function is defined as

$$f^L(i,j)=\begin{cases}L & if\ \ f(i,j)\ge L\\ f(i,j) & if\ \ f(i,j)<L\end{cases} \tag{10}$$

$$f_L(i,j)=\begin{cases}f(i,j) & if\ \ f(i,j)>L\\ L & if\ \ f(i,j)\le L\end{cases} \tag{11}$$

Two $EAG(L)\sim L$ curves can be obtained by computing EAG of the clipped image. From these two curves the value of L_{low} and L_{high} confining the transition region will be determined. It is proved in [9] that the existence of $L_{low}>L_{high}$ in EAG method on real images, in which condition the transition region cannot be extracted. EAG method is improved in [8] and proposed Gaussian weighted EAG to limit the affects of noise. Methods mentioned above are all essentially based on gradient. Gradient-based methods are sensitive to noise and will result in $L_{low}>L_{high}$ or incorrect L_{low} and L_{high}, thus will finally result in bad quality of segmentation. In fact, gradient–based methods cannot completely describe the properties of the transition region. By analyzing the properties, transition region extraction method based on local complexity is proposed.

B. *Local Complexity*

Transition regions usually have the following properties [10]: they have certain width; they locate between the vessels and the background; the grayscale of transition region changes frequently. The frequent changes of grayscale bring abundant information to transition regions. Gradient is good for sudden grayscale changes, but not the best measure for frequent grayscale changes. See the following example: Fig. 2 shows two local neighborhoods. The number in both neighborhoods represents grayscale value. Comparing two neighborhoods, it shows that the peak gradient of the right neighborhood is larger than that of the left, but the grade changes of the grayscale in

2	3	5		2	4	8
. 4	6	4		2	8	4
7	4	3		8	4	2
	(a)				(b)	

Figure 2. Grayscale changes in different neighborhood

the left neighborhood is more frequent than that in the right neighborhood. Transition region in images especially in medical images contains more frequent changes than large sudden changes. From the point of information theory, the left neighborhood contains more information than the right does.

From above analyzing, the parameter of local complexity is constructed and used to extract transition region. Let $f(i,j)$ be gray distributed function defined on $M \times N$ image size, $(i,j) \in S$, S represents the integer set of spatial coordinates of the pixels. If the image has 256 gray-levels, the histogram of the image will be expressed by

$$h(l) = \sum_{i=1}^{M} \sum_{j=1}^{N} \delta(l - f(i,j)) \tag{12}$$

where $l \in \{0,1,\cdots,255\}$ is the gradation of gray, $\delta(\cdot)$ is unit impulse function. In order to avoid repeating count for the same gray-level pixels, the function is defined by

$$s_l(h(l)) = \begin{cases} 1 & h(l) \neq 0 \\ 0 & h(l) = 0 \end{cases} \tag{13}$$

where compute $h(l)$ by (12). The gray complexity is

$$C = \sum_{l=0}^{255} s_l \tag{14}$$

The gray complexity by (14) actually is a statistic of the gray gradation changes within the image. The definition is not significant for the total image. It is usually used to the local neighborhood as the statistic of the gray gradation changes. If a small neighborhood Ω_k is defined by window size $M_k \times N_k$ within the image, k is the center pixel, the local complexity of Ω_k can be given by

$$C_k(\Omega_k) = \sum_{l=0}^{255} s_l \tag{15}$$

By analyzing (15), the properties of local complexity can be summarized as following:

- The more gray gradation Ω_k contains, the larger $C_k(\Omega_k)$ will be. The less gray gradation Ω_k contains, the smaller $C_k(\Omega_k)$ will be.
- The local complexity is larger for a heterogeneous region but smaller for a homogeneous region from (15). Hence, the transition region will have large local complexity value than those are not in transition regions of image.
- The independent noise will have small effect for the local complexity, though it leads to sudden gray-level changes. Because the local complexity represents the difference of the gray gradation within Ω_k not the gradient amplitude, hence, the local complexity can be considered the filter can eliminate independent noise.

C. Transition Region Extraction and Vessels Segmentation

Under the present context, an appropriate neighborhood window Ω_k ($M_k = N_k$) may be defined, and compute its local complexity. Then the local complexity value is given the center pixel k . When the neighborhood window is moved pixel by pixel within the image from left to right and top to bottom, the local complexity value of each pixel can be obtained. In other words a local complexity image is obtained. In the local complexity image, the pixels in the transition region will have large local complexity value because their gradients are heterogeneous, the pixels in the vessels or the background will have smaller local complexity value because their gradients are homogeneous. Thus the transition region will be extracted by appropriate local complexity threshold. The final segmentation threshold will be determined by the peak or mean of the histogram of the transition region. The algorithm can be summarized as the following steps:

- Given certain neighborhood window size and appropriate local complexity threshold.
- Compute the local complexity by (15).
- Extract transition region.
- Obtain the segmentation threshold by histogram of transition region.
- Extract vessels by threshold.

The neighborhood window size will be not only too large but also too small. If the window size is too small, the pixels in the window will be lack that cannot reflect the change of the local complexity. If the window size is too large, it will lose localization. A lot of experiments suggest that 11×11 window size be appropriate for the coronary angiograms in the paper.

The local complexity threshold can be determined by

$$E_T = \alpha C_k(\Omega_k)_{\max} \tag{16}$$

where $C_k(\Omega_k)_{\max}$ is the maximal local complexity of the local complexity image, α is a coefficient between 0 and 1. In order to extract sufficient pixels for transition region α is a coefficient between 0.6 and 1. A lot of experiments suggest that $\alpha = 0.9$ be appropriate for the coronary angiograms in the paper.

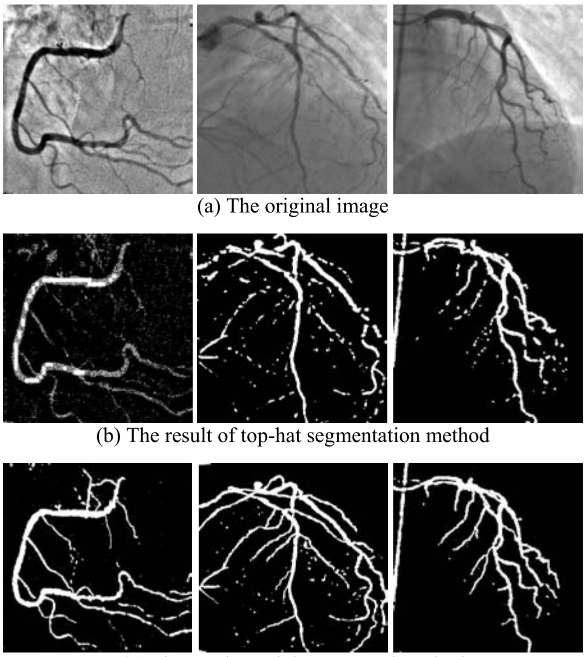
IV. EXPERIMENTAL RESULT AND DISCUSSION

50 coronary angiograms are segmented, which come from China-Japan Union Hospital Jilin University. Three results of

them are showed in Fig.3. The original images are given in Fig. 3(a), the result used morphological top-hat method is given in Fig.3 (b), and the result of the application of the proposed method is given in Fig.3(c). When the result in Fig. 3(b) and (c) are compared, it is easily seen that the method of top-hat can eliminate the part of noise, but it also eliminate the small vessels whose size is nearer or lower the size of the background. It is also seen that the proposed algorithm preserves the continuity and effectiveness of the small vessels in the image, and perform effectively in detecting blood vessels even when the local contrast is quite low.

V. CONCLUSION

The paper present a novely segmentation method of transition region extraction based on local complexity. Aiming at the properties of coronary angiograms, 6 different Gaussian filters are used to enhance the coronary angiograms at first. Then the transition region is extracted by using local complexity method based on transition region extraction. At the end, the vessels are obtained. The experiments indicate that the proposed method outperforms the morphological top-hat on the small vessels extraction, connectivity and effectiveness. In addition, the method is indeed valuable for diagnosis and the quantitative analysis of coronary arteries.



(a) The original image

(b) The result of top-hat segmentation method

(c) The result used the proposed method

Figure 3. The segmentation result

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