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Segmentation Method Based on Transition Region Extraction for Coronary Angiograms

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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. Firstly, we construct 6 different Gaussian templates that are used to enhance the coronary angiograms. Then the transition region is extracted by using local entropy-based on transition region extraction method. Finally, determine the segmentation threshold and the vessels are obtained. The experiments indicate that the proposed method outperforms the method using morphological operator on the small vessels extraction, connectivity and effectiveness. In addition, the method is indeed valuable for diagnosis and the quantitative analysis of coronary arteries.**

Index Terms* – *Coronary angiogram, Image enhancement. Gaussian filtering, Local entropy, 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 artery 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 enhance the image and then extract the vessels.

At present, 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 the pixels of the vessel, [1], [2] and [3] enhance the vessels used morphological operator, then extracts the vessel using mean filter template. Although the method of Top-hat can eliminate the part of noise, but it can not eliminate the noise whose size is nearer or lower the size of vessel. The Gaussian filter is used to enhance the image by [4] and [5], 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] demonstrated the existence of transition region for the first time in 1988. Ref. [8] introduced the transition region into image segmentation. The effective average gradient and clip transformation is applied in this method. Gradient-based methods are widely used in image segmentation, but they have both advantages and limitations. The main disadvantage is that they are much sensitive to noise. The same drawbacks will happen in gradient-based transition region extraction methods, such as those methods mentioned above.

In the paper, aiming at the features of coronary angiograms, a new segmentation method based on transition region extraction is proposed. At first, 6 different Gaussian filters are used to enhance the coronary arteries. Then the transition region is extracted by using local entropy method. Finally, obtain the vessels using the segmentation threshold by histogram of transition region. The experiments indicate that the proposed method outperforms the morphological operator algorithm on the small vessels extraction, connectivity and effectiveness. In addition, the method is indeed valuable for diagnosis and the quantitative analysis of coronary arteries.

II. ENHANCE CORONARY ANGIOGRAM

A. Properties of the coronary arteries

Coronary arteries usually have the following properties:

1) Since the blood vessels usually have small curvatures, the anti-parallel pairs may be approximated by piecewise linear segments.

2) Since the vessels have lower reflectance compared to other body tissues surfaces, they appear darker relative to the background. The blood vessel gray-level profiles along directions perpendicular to their length may be approximated by a Gaussian curve, although the intensity profile varies by a small amount from vessel to vessel.

3) Although the width of a vessel decreases as it travels radially outward from the optic disk, such a change in vessel caliber is a gradual one. The widths of vessels are found to lie within a range of 2-10 pixels.

Now let us consider the detection of an arbitrary 1-D signal $s(t)$ in an additive Gaussian white noise. If the signal is passed through a filter with transfer function $H(f)$, the output signal $s_0(t)$ is given by

$$s_0(t) = \int H(f)\{S(f)+\eta(f)\}\exp(j2\pi ft)df \qquad (1)$$

where $S(f)$ is the Fourier transform of $s(t)$,and $\eta(t)$ is the noise spectrum. Using Schwartz's inequality, it can be proved that the filter $H(f)$ that maximizes the output signal-to-noise ratio is given by $H_{opt}(f) = S*(f)$. Since the input signal

$s(t)$ is real valued, $h_{opt}(t) = s(-t)$. This optimal filter with the impulse response $h(t)$ is commonly known as the matched filter for signal $s(t)$. In a typical communication system, if there are n different signals $s_i(t), i = 1, 2 \cdots, n$, the received signal is passed through a stack of n matched filters. If the response due to the i^{th} filter is the maximum, it is concluded that the signal $s_j(t)$ is transmitted.

Under the present context, it may be noted that the intensity profile can be assumed to be symmetrical about the straight line passing through the center of the vessel. Hence, $s(-t) = s(t)$. The optimal filter must have the same shape as the intensity profile itself. In other words, the optimal filter is given by $H_{opt}(d) = \exp(-d^2/(2\sigma^2))$. The negative signal indicates that the vessels are darker than the background. Also, note further that instead of n different types of objects having to be identified, the problem reduces to deciding whether or not a particular pixel belongs to a vessel. If the magnitude of the filtered output at a given pixel location exceeds a certain threshold, the pixel is labeled as a part of a vessel.

When the concept of matched filter is extended to two-dimensional images, it must be appreciated that a vessel may be oriented at any angle $\theta(0 \le \theta \le \pi)$. The matched filter $s(t)$ will have its peak response only when it is aligned at an angle $\theta \pm \pi/2$. Thus, the filter needs to be rotated for all possible angles, the corresponding responses are to be compared, and for each pixel only the maximum response is to be obtained.

B. Design of Gaussian filter

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

$$K(x,y) = -\exp\left(-\left(x^2+y^2\right)/\left(2\sigma^2\right)\right) \quad |\, y \,| \le L/2 \qquad (2)$$

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 aligned along $y-$axis. For the vessels at different orientations, the kernel has to be rotated accordingly. The two-dimensional matched filter kernel in a discrete grid is designed as follows. 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 computer the weighting coefficients for the kernel, it is assumed to be centered about the origin [0, 0]. The rotation matrix is given by

$$r_i = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \qquad (3)$$

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

$$\overline{p_i} = [u, v] = \overline{pr_i} \qquad (4)$$

Assuming an angular resolution of 30°, we need 6 different kernels to span all possible orientations. A Gaussian curve has infinitely long double sided trails. We truncate the trail at $u = \pm 3\sigma$. A neighborhood N is defined such that $N = \{(u,v) \,||\, u \,|\le 3\sigma, |\, v \,|\le L/2\}$. The corresponding weights in the i^{th} kernel are given by

$$K_i(x,y) = -\exp\left(-\left(u^2+v^2\right)/\left(2\sigma^2\right)\right) \quad \forall \overline{p_i} \in N \qquad (5)$$

If A denotes the number of points in N, the mean value of the kernel is determined as

$$m_i = \sum_{\overline{p_i} \in N} K_i(x,y)/A \qquad (6)$$

Thus the convolution mask used in this algorithm is give by

$$K_i'(x,y) = K_i(x,y) - m_i \quad \forall \overline{p_i} \in N \qquad (7)$$

Because of the hardware design of the image processing system, the weighting coefficients in the kernel need to be integers in the range (-128,128). The coefficients are each multiplied by a scale factor of 10 and truncated to their nearest integer.

An original coronary angiogram is given in Fig. 1, the result of Top-hat method is given in Fig.2 and the result of the application of this filter is given in Fig. 3.

Fig. 1 The original coronary angiogram

Fig. 2 The result of the application of Top-hat

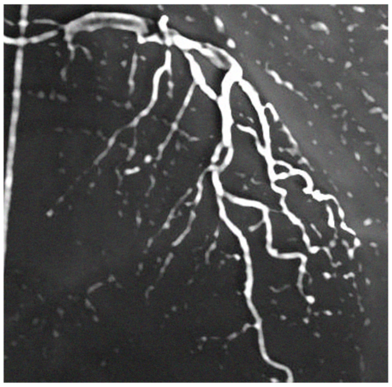

Fig. 3 The result of the application of Gaussian filter

The coronary angiograms are provided by China-Japan Union Hospital Jilin University. For this case, we choose $\sigma = 1.5$, $L = 9$. A lot of experiments prove that $\sigma = 1.5$ can be matched well with a blood vessel for coronary angiogram. When the result in Figs 2 and 3 are compared, it is readily seen that the coronary arteries are enhanced in the image used proposed algorithm more than in the image used Top-hat method.

III. Vessel Extraction Method

A. Gradient-based transition region extraction methods (G-TREM)

Typical G-TREM applied 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 represent the integer set of spatial coordinates of the pixels. Let $g(i,j)$ be the gradient of the image, then the EAG can be defined as

$$EAG = \frac{TG}{TP} \tag{8}$$

where

$$TG = \sum_{i,j \in S} g(i,j) \tag{9}$$

is the total sum of the gradient and

$$TP = \sum_{g(i,j) \neq 0} 1 \tag{10}$$

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

The clip transformation function is defined as

$$f^{L}(i,j) = \begin{cases} L & \text{if } f(i,j) \geq L \\ f(i,j) & \text{if } f(i,j) < L \end{cases} \tag{11}$$

$$f_{L}(i,j) = \begin{cases} f(i,j) & \text{if } f(i,j) > L \\ L & \text{if } f(i,j) \leq L \end{cases} \tag{12}$$

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.

Ref. [9] proved the existence of $L_{low} > L_{high}$ (in which condition the transition region can not be extracted) in EAG method on real images. Ref. [10] improved EAG method and proposed Gaussian weighted EAG to limit the affects of noise.

Methods mentioned above are all essentially based on gradient. Gradient-based on 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 segmentation.

In fact, gradient–based methods cannot completely describe the properties of the transition region. By analysing the properties of transition regions, local entropy-based on transition region extraction method is proposed.

B. The main properties of transition regions

Transition regions locate between the vessels and the background [11]. They usually have the following properties:

1) They have certain width. Whether for step edge or for non-step edge there will sure exist transition regions near edges. Transition regions around non-step edges have certain width of several pixels. Generally in real images, for the error sampling, even around the step edge there will be width of several pixels.

2) Transition regions cover around the coronary vessels. Since edge is the boundary between object and background, the extracted transition region should cover around the coronary vessels.

3) The grayscale in transition region changes of 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.

Fig. 4 shows two image neighborhoods. The number in both neighborhoods represents grayscale value. Comparing the two neighborhoods, it shows that though the peak gradient of the right neighborhood is larger than that of the left, but the grade changes of the grayscale in 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 neighborhood does.

Entropy can best represent the information containing in the image. Local entropy can best describe the properties of the transition region. Thus local entropy into transition region extraction is introduced.

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

Fig. 4 Grayscale changes in different neighborhood

C. Local entropy regions

Ref. [12] defined the entropy of image as

$$E = -\sum_{i=0}^{L-1} P_i \log P_i \tag{13}$$

where

$$P_i = \frac{n_i}{M \times N} \tag{14}$$

is the probability of grayscale i appears in the image, L is the maximal grayscale, n_i is the number of pixels with grayscale i, $M * N$ is the image size. If we define a small neighborhood Ω_k by window size $M_k * N_k$ within the image, then the entropy of Ω_k can be given by

$$E(\Omega_k) = -\sum_{j=0}^{L-1} P_j \log P_j \tag{15}$$

where

$$P_j = \frac{n_j}{M_k \times N_k} \tag{16}$$

is the probability of grayscale j appears in the neighborhood Ω_k, n_j is the number of pixels with grayscale j in the neighborhood. $E(\Omega_k)$ is the local entropy of neighborhood Ω_k.

D. Local entropy-based transition region extraction

Local entropy is related to the variance of grayscale in the neighborhood. From (14) we can see that the local entropy is larger for a heterogeneous region but smaller for a homogeneous neighborhood. Hence, the transition region will have large local entropy values than those are not in transition regions of image. We may define an appropriate neighborhood window Ω and compute its local entropy. When we move the neighbor window pixel by pixel within the image from left to right and top to bottom, we will obtain the local entropy value of each pixel. In other words we obtain an entropy image. By appropriate entropy threshold the transition region will then be extracted. 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:

1) Given certain neighbor window size and appropriate entropy threshold.

2) Compute the local entropy by (15).

3) Extract transition region.

4) Obtain the segmentation threshold by histogram of transition region.

5) Extract vessels by threshold.

A too small window size will result in imprecise estimate of local entropy because of the lack of sampling, while a too large window loses localization. A lot of experiments suggest that 11×11 window size be appropriate for the coronary angiograms

The threshold entropy can be determined by the following definition

$$E_T = \alpha E(\Omega_k)_{\max} \tag{17}$$

where $E(\Omega_k)_{\max}$ is the maximal entropy of the entropy 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. By this way, (17) should be compute in step2.

The original coronary angiogram is given in Fig. 1, and the result of the application of this method is given in Fig. 6. The morphological Top-hat is also applied to the same image, and the result is given in Fig.5. When the result in Figs 5 and 6 are compared, it is readily seen that the proposed algorithm preserves the continuity of the vessels in the image. Also, we have found the algorithm to perform effectively in detecting blood vessels even when the local contrast is quite low.

IV. CONCLUSION

The paper present a novel segmentation method of transition region extraction based on Gaussian matched filters. Aiming at the properties of coronary angiograms, we use 6 different Gaussian filters to enhance the coronary angiograms at first. Then the transition region is extracted by using local

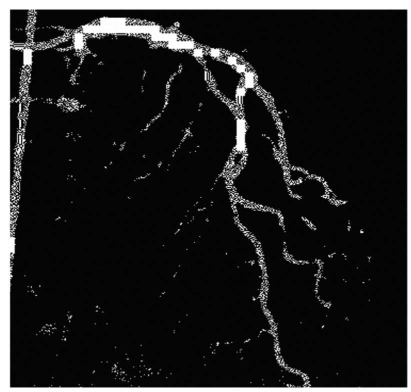

Fig. 5 The result using morphological Top-hat

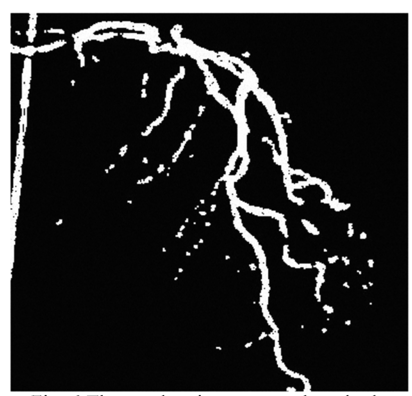

Fig. 6 The result using proposed method

entropy-based on transition region extraction method. 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, the quantitative analysis of coronary arteries.

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