Segmentation Method of Degree-based 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 of degree is proposed. Firstly, the paper analyzes the characteristic of coronary angiograms. Secondly, 6 different Gaussian matched templates are used to enhance the coronary angiograms in order to remove the background. Finally, the coronary arteries are obtained with the method of degree-based transition region extraction. The experiments indicate that the proposed method outperforms the segmentation method based on not only top-hat but also Gaussian filter about the small vessels extraction, connectivity and effectiveness. The method is indeed valuable for diagnosis and the quantitative analysis of coronary arteries.**

Keywords- image segmentation; Gaussian filtering; graph theory; degree; 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 enhance the image and then extract the vessels.

There are many previous works on extracting blood vessels from coronary angiograms. 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 that of the vessel, [1], [2] and [3] enhance the vessels used morphological operator, then extracts the vessel using mean filter template. The segmentation method based on morphological 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. 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]. 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 the methods mentioned above.

This paper analyzes the characteristic of coronary angiograms, and then a new segmentation method based on transition region extraction of degree is proposed. At first, 6 different Gaussian matched filters are used to enhance the coronary arteries. Then the transition region is extracted by using the method of degree. Finally, obtain the vessels by using the segmentation threshold by histogram of transition region. The experiments indicate that the proposed method outperforms the other segmentation methods mentioned in the paper about the small vessels extraction and background elimination. In addition, the method is indeed valuable for diagnosis and 3-D reconstruction of the vessels.

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

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perpendicular to their length can be approximated by a Gaussian curve. Such a kernel may be mathematically expressed as

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

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. 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, the center is assumed to be about the origin [0, 0]. The rotation matrix is given by

$$r_i = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \quad (2)$$

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

$$\overline{p_i} = \left[u, v\right] = \overline{pr_i} \quad (3)$$

A Gaussian curve has infinitely long double side trails. The trails are truncated at $u = \pm 3\sigma$, $|v| \leq L/2$. Corresponding weights in the i^{th} kernel are given by

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

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

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

Thus the convolution mask used in this algorithm is give by

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

It must be noticed that a vessel may be oriented at any angle $\theta (0 \leq \theta \leq \pi)$. The matched filter will have its peak response only when it is aligned at an angle $\theta \pm \pi/2$. 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. Two such kernels for two different angles are giver in Fig. 1. A lot of experiments proved $\sigma = 1.5, L = 9$ could be matched well with a blood vessel for coronary angiogram. An original coronary angiogram is given in Fig. 2(a). The enhancement result is given in Fig. 2(b). The most of the background is eliminated from Fig. 2.

III. Vessel Extraction Method

A. Typical Transition Region Extraction Method

Typical transition region extraction method applies the average of gradient and clip transformation of grayscale. Let

0	0	0	0	0	0	0	0	4	0	0	0	0	0	0
0	0	0	0	0	0	4	4	4	0	0	0	0	0	0
0	0	0	0	4	4	4	3	3	2	0	0	0	0	0
0	0	4	4	4	3	3	2	1	0	0	0	0	0	0
0	4	4	3	3	2	1	0	–2	–3	–4	0	0	0	0
0	4	3	2	1	0	–1	–3	–4	–5	–6	–6	0	0	0
0	0	2	1	–1	–2	–4	–5	–6	–6	–5	–1	0	0	0
0	0	0	–2	–3	–5	–6	–6	–6	–5	–3	–2	0	0	0
0	0	0	–4	–5	–6	–6	–5	–4	–2	–1	1	0	0	0
0	0	0	–6	–6	–5	–4	–3	–1	0	1	2	3	4	0
0	0	0	0	–4	–3	–2	0	1	2	3	3	4	4	0
0	0	0	0	0	0	1	2	3	3	4	4	4	0	0
0	0	0	0	0	2	3	3	4	4	4	0	0	0	0
0	0	0	0	0	0	4	4	4	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

(a) Segments along 30° direction

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	3	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	4	3	2	1	–2	–5	–6	–5	–2	1	2	3	4	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

(b) Segments along the vertical direction

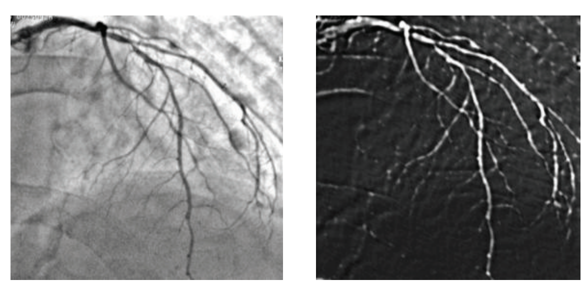
Figure 1. Two of the 6 different kernels

$f(i, j)$ 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, and then the EAG can be defined as

$$EAG = \frac{TG}{TP} \quad (7)$$

where

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



(a) Original image (b) Enhanced image

Figure 2. Enhanced image used Gaussian filter

is the total sum of the gradient and

$$TP = \sum_{g(i,j)\neq 0} 1 \quad (9)$$

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

The clip transformation function is defined as

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

$$f_{L}(i,j) = \begin{cases} f(i,j) & if\ f(i,j) > L \\ L & if\ f(i,j) \leq L \end{cases} \quad (11)$$

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.

Ref. [9] proved the existence of $L_{low} > L_{high}$ in EAG method on real images, in which condition the transition region cannot be extracted. Ref. [8] 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 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 of transition regions, degree-based transition region extraction method is proposed.

B. *Main Properties of Transition Regions*

The transition regions locate between the vessels and the background [10]. They usually have the following properties:

- They have certain width. There will sure exist transition regions near edges whether for step edge or for non-step edge. Transition regions around non-step edges have certain width of several pixels. Transition regions near the step edges have at least the width of one pixel. Generally in real images, for the error of sampling, even around the step edge there will be the width of several pixels.
- Transition regions cover around the vessels. Since edge is the boundary between object and background, the extracted transition region should cover around the coronary vessels.
- 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.

Fig. 3 shows two local neighborhoods. The number in both neighborhoods represents grayscale value. Comparing the two neighborhoods, it shows that the peak gradient of the right neighborhood is larger than the peak of the left, but the variety of the grayscale in the left neighborhood is more frequent than that in the right neighborhood. Transition region in image contains more frequent changes than large

2	3	5
4	6	4
7	4	3

(a)

2	4	8
2	8	4
8	4	2

(b)

Figure 3. Grayscale changes in different neighborhood

sudden changes. From the point of information theory, the left neighborhood contains more information than the right neighborhood does.

Aiming at the properties of the transition region, the parameter of degree is constructed and used to extract transition region. Thus, the transition region extraction and segmentation method based on degree is introduced.

C. *Similarity and degree*

An image can be converted into a weighted undiredted graph $G = (V, E)$. The pixels can be considered the nodes of the graph, V represents the node set of the graph, $N = |V|$ is the total sum of the nodes. E represents the edge set, an edge $e_{i,j}$ is formed between every pair of nodes, $e_{i,j} \in E$. In [11], the weight on each edge $w(i,j)$ is a function of the similarity between nodes i and j, and is defined as

$$w_{i,j} = \exp[-\frac{D(x_i - x_j)}{2\sigma^2}] \quad (12)$$

where $D(x_i - x_j)$ is Euclidean distance between two nodes i and j. For gray image, the similarity function can be defined as follow

$$w_{i,j} = \exp[-\beta c(i,j)] \quad (13)$$

where $c(i,j)$ is Euclidean distance of gray value between nodes i and j, β is the scale parameter.

The degree d_i of the node v_i is total sum of the edge weights. These edges connect with the node v_i. Such function is defined as follow

$$d_i = \sum_{j=1}^{k} w(i,j) \quad (14)$$

where $i, j \in \{1, 2, \cdots, N\}$, k is total sum of the edges which connects the node i .If $w(i,j) = 1$, $d_i = k$.

By analyzing (14), the properties of degree can be summarized as following

- The pixels have larger degree when they locate in the vessels and background. Because the gray values of the pixels are homogeneous, the weight by (13) and degree by (14) will be large.
- The pixels have smaller degree when they locate in the transition region. The transition regions locate between the vessels and the background, the grayscale of transition region changes frequently, so

the weight by (13) will be small, and degree by (14) also will be small.

- The independent noise will have small effect for degree of the graph, though it leads to sudden gray-level changes. Because the degree represents the difference of the gray gradation within the graph not the gradient amplitude, hence, the degree can be considered the filter that can eliminate independent noise.

D. Segmentation Method of Degree-based Transition Region Extraction

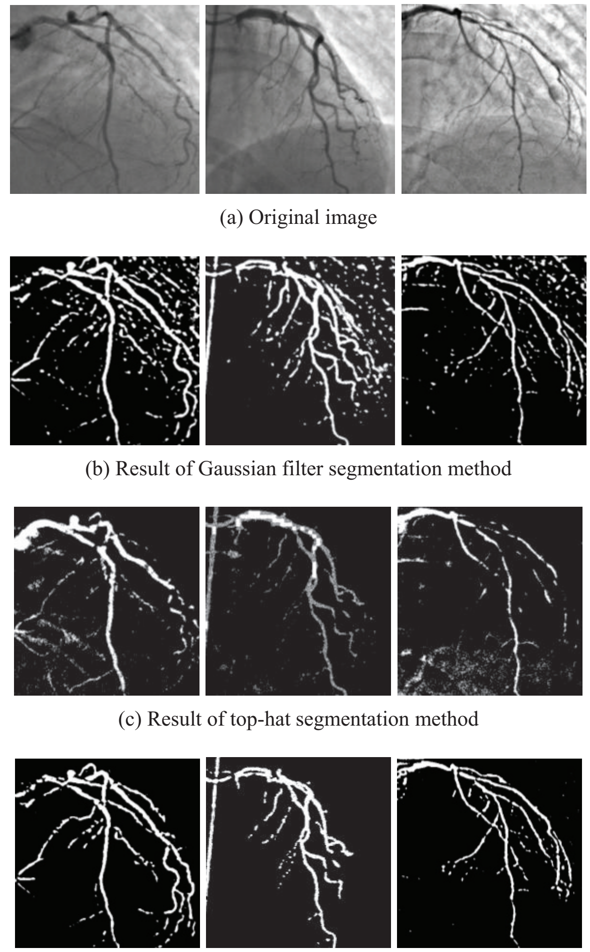
Under the present context, if an image is converted into a weighted undiredted graph, the degree as the parameter can be used to extract the transition region. The degree image is obtained by computing degree value of each pixel. In the degree image, the pixels in the transition region will have smaller degree value because their gray are heterogeneous, the pixels in the vessels or the background will have larger degree value because their grays are homogeneous. Some pixels whose degree value is lesser than certain threshold will be extracted. The transition region is made up of these pixels. The final segmentation threshold will be determined by the peak value or mean value of the histogram of the transition region.

In practical algorithm, all degree values will be ranged from small to large, and set a percentage p . p is the transition region pixels in all pixels of the whole image percentage. In general, p is between $5\% \sim 15\%$. The transition region will be made up of the pixels within this percentage p . The algorithm can be summarized as the following steps:

- Take the image as the graph, take the pixels as the nodes, and compute similarity value of each node in the graph by (13).
- Compute the degree value by (14).
- The degree value will be arranged from small to large, set a percentage p and the top p pixels will be extracted. Transition region will be made up of these pixels.
- Obtain the segmentation threshold by histogram of transition region.
- Extract vessels by threshold.

IV. Experimental Result and Discussion

In order to prove the efficiency of the proposed method, 50 coronary angiograms are segmented. The coronary angiograms come from China-Japan Union Hospital Jilin University. Three results of them are showed in Fig.4. A lot of experiments proved $\beta = 5, p = 10\%$ could be matched well with a blood vessel for coronary angiogram. The original images are given in Fig. 4(a), the result based on Gaussian filer method is given in Fig. 4(b), the result used morphological top-hat method is given in Fig. 4(c), and the result of the application of the proposed method is given in Fig. 4(d).



(a) Original image

(b) Result of Gaussian filter segmentation method

(c) Result of top-hat segmentation method

(d) Result used the proposed method

Figure 4. Segmentation result

When the result in Fig. 4(b), (c) and (d) are compared, it is easily seen that the method based on top-hat can eliminate the noise, but it also eliminate the small vessels whose size is nearer or lower the size of the background. The segmentation method based on Gaussian filter can preserve the small vessels, but simultaneously the background is preserved. It is obviously seen that the proposed method in the paper not only can eliminate the background but also can preserve the continuity of the small vessels in the image. The proposed method can perform effectively in detecting blood vessels even when the local contrast is quite low.

In order to further prove the efficiency of the proposed method, the quantitative analysis among the different methods is given in Tab. 1. Coronary artery stenosis is the most common reason that leads to coronary heart disease, so the average diameter of the left anterior descending artery (LAD) is an important parameter. In Tab. 1, d is the average diameter of LAD, $\sum L$ is the total length of the extracted vessels, ∇L is the difference between the extracted vessels length and the true length of the vessels. The data of the first line is the true value of the vessels. The data from the second line to the fourth line are respectively obtained

TABLE I. ANALYZING OF EXTRACTING EFFECT AMONG DIFFERENT METHODS

	Image No.1			Image No.2			Image No.3		
	$\sum L$	∇L	d	$\sum L$	∇L	d	$\sum L$	∇L	d
True value	3268	0	2.73	2952	0	2.75	2606	0	2.68
Method No. 1	2762	506	2.69	2143	809	2.70	2058	548	2.64
Method No. 2	1562	1706	2.68	1378	1574	2.69	1286	1320	2.60
Method in the paper	2945	323	2.72	2543	409	2.73	2256	350	2.69

from Fig. 4(b) to (d). From Tab. 1, it is obviously seen that the data obtained by the proposed method is the closest to the true value of the vessels among the different methods. It further proved that the proposed method outperforms the other methods mentioned in the paper on the small vessels extraction, connectivity and effectiveness.

V. Conclusion

The paper present a novel segmentation method of transition region extraction based on degree. Gaussian filters are used to enhance the coronary angiograms at first. Then the transition region is extracted by using degree-based transition region extraction. At the end, the segmentation threshold is obtained by histogram of transition region and the vessels are obtained. The experiments indicate that the proposed method outperforms not only the morphological top-hat method but also the Gaussian filtering method on the small vessels extraction, connectivity and effectiveness. In addition, the method is indeed valuable for diagnosis, the quantitative analysis of coronary arteries and 3-D reconstruction of the vessels.

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REFERENCES

[1] Eiho. S, and Qian. Y, “Detection of coronary artery tree using morphological operator,” Computers in Cardiology, pp. 525-528, 1997.

[2] Z.W. Tang, H. Zhang, and G.S. Hu, “Morphological multiscale vessel enhancement for coronary angiograms,” J Tsinghua Univ (Sci & Tech), vol. 46, no. 3, pp. 418-420, 2006.

[3] Y.H. Yu, et. al, “Study of coronary artery segmentation from coronary digital angiography,” Shandong Journal of Biomedical Engineering, vol. 21, pp. 5-10, 2002.

[4] Z. Xu, et. al, “Heat vessels extraction from angiogram,” Chinese Journal of Biomedical Engineering, vol. 22, no. 1, pp. 6-11, February 2003.

[5] G. Chen, H. Yi, and Z.H. Ni, “Automatic vessel boundary extraction and stenosis quantification method based on Laplacian-of- Gaussian algorithm using DSA images,” Chinese Journal of Scientific Instrument, vol. 27, no. 12, pp. 1641-1646, December 2006.

[6] Chaudhuri. S, and Chatterjee. S, “Detection of blood vessels in retinal images using two-dimensional matched filters,” IEEE Trans on Medical Imaging, vol. 8, no. 3, pp. 263-269, 1989.

[7] Y.J. Zhang, and J.J. Gerbrands, “Transition region determination based thresholding,” Pattern Recognition Letters, vol.12, no. 1, pp. 13-23, 1991.

[8] X.J. Liang, N. Le, Transition region algorithm based on weighted gradient operator. Image Recognition Automat, pp. 4-7, China, 2001.

[9] Groenewald. A.M, Barnard, E, Botha, E.C, “Related approaches to gradient-based thresholding,” Pattern Recognition Letters, vol. 14, pp.567-572, 1993.

[10] C. Yao, H.J. Chen, and J.P. Li, “Segmentation of retinal blood based on transition region extraction,” Acta Electronica Sinica, vol. 36, no. 5, pp. 974-978, 2008.

[11] Shi J, and Malik J, “Normalized cuts and image segmentation,” IEEE Trans, vol.22, no. 8, pp. 888-905, 2000.