Quantitative Measurement of Coronary Artery Stenosis in CCTA Images Using a 2D Parametric Intensity Model

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***Abstract*—In this paper, we propose an approach based on 2D vessel model to segment the vessel lumen in three-dimensional coronary computed tomographic angiography (CCTA) images. The 2D parametric intensity model is introduced first to simulate the intensity distribution of vessel lumen with different size in the longitudinal images. Then the Levenberg–Marquardt method is applied to fit the model within a series of region-of interests defined in the longitudinal image. The estimated parameters of the model are employed to define the boundary points of vessel lumen. The detected boundary points of vessel lumen in six longitudinal images are transformed to the cross-sectional planes in order to calculate the degree of stenosis according to the luminal areas. Our proposed method was evaluated in ten CCTA images with ten reported non-calcified stenosis. The degree of each stenosis was computed according to the luminal area and compared with the standard reference given by radiologists. Experimental results show that our method can estimate the degree of stenosis with a high accuracy.**

I. INTRODUCTION

Cardiovascular disease is a major cause of death in the world. Coronary computed tomographic angiography(CCTA) as a non-invasive imaging modality is increasingly applied to the early diagnosis of coronary heart disease. Clinical research demonstrated that the luminal narrowing on the coronary arteries can be displayed in the CCTA datasets [1]. Thus, an accurate analysis of vessel morphology should be performed to measure the degree of stenosis quantitatively for the diagnosis and treatment planning. However, delineation of lumen contours manually is a time consuming work and may introduce additional bias which could lead to inaccurate quantification. Therefore, it is necessary to implement a segmentation method for stenosis quantification in CCTA images.

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Many previous works have been done for vessel lumen segmentation [2]. However, the segmentation of coronary lumen from CCTA images is a challenge task because of the low contrast of coronary arteries, image noise, motion artifacts and the influence of surrounding tissues. Recently, several approaches have been developed for coronary artery stenosis detection, stenosis quantification and lumen segmentation in CCTA images and evaluated by a standardized evaluation framework named Rotterdam Coronary Artery Algorithm (RCAA) evaluation framework [3]. In RCAA evaluation framework, the ability of stenosis detection and quantification for the whole coronary tree is evaluated. However, the evaluation results showed that the discrimination between non-significant and significant stenosis ($\geq$ 50% luminal narrowing) and quantitative measurement of stenosis remained challenge tasks for the methods evaluated in RCAA evaluation framework.

In this paper, we develop an algorithm for quantitative measurement of stenosis in CCTA images using a 2D parametric vessel intensity model. This 2D model is deduced from a 3D tubular model presented by Wörz [4]. In the 3D model presented by Wörz, the cross-section of a vessel is assumed to be a circle, which may lead to inaccurate measurement of luminal area. Thus, a 2D model is derived from Wörz's model in our algorithm to improve the accuracy of quantification. The 2D vessel model is fitted to the vessel lumen in the longitudinal images reconstructed from different angles. Then the detected boundary points of vessel lumen from longitudinal images are mapped into the cross-sectional planes to measure the luminal areas. In our preliminary study, ten non-calcified stenoses reported in the CCTA images were used to evaluate the performance of our method. The experimental results show that our method can estimate the degree of the stenosis with a high accuracy by comparing with the reference standard measured by radiologists.

II. TWO-DIMENSIONAL PARAMETRIC INTENSITY MODEL

Straight longitudinal image is a practical tool to display the morphology of a tortuous vessel extracted from 3D image. In the straight longitudinal images, the change of luminal diameter can be observed. In Fig.1, three straight longitudinal images of a LAD artery reconstructed from 0°, 60° and 120° are displayed respectively. The centerline of longitudinal image along x direction corresponds to the extracted centerline of vessel. From these images, a luminal narrowing can be found, especially in the images of 0° and 120°. In Fig.2, two plots display the image intensities of the 1D profiles at two different positions in the longitudinal images (positions A and B in Fig.1). The positions A and B are located at the proximal part and distal part of LAD respectively. As the plots shown in

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Fig. 2, the Gaussian function is suitable to model the intensity structure of the distal part obviously, but generally not the case for the proximal part because the 1D profile in the proximal part is plateau-like. To more accurately model the vessel of both small and large widths, a 2D intensity model is introduced first in this paper for detecting the boundary points of vessel lumen in the longitudinal images.

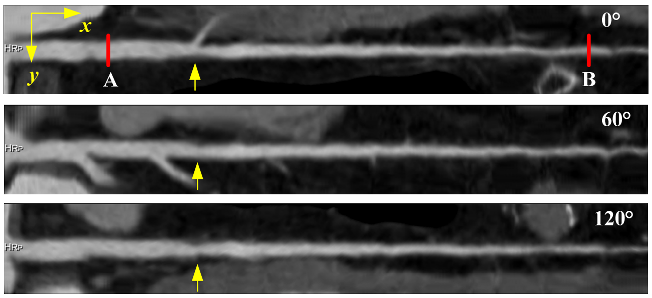

Figure 1. Straight longitudinal images of a LAD artery reconstructed from 0°, 60° and 120°. A stenosis (marked by yellow arrows) can be observed.

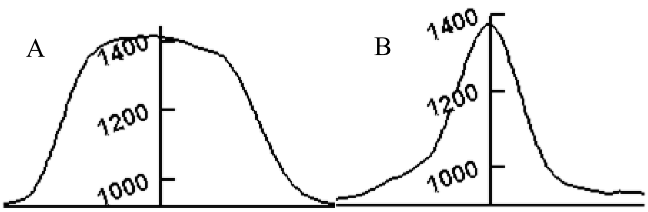

Figure 2. The profile of image intensity at two positions A and B marked in the longitudinal image of 0° in Fig.1. Positions A and B are located at the proximal part and the distal part of LAD respectively.

The 2D parametric vessel intensity model is defined mainly based on a function $g_{\text{Profile}}(\mathbf{x})$ which describes the image intensity distribution in 1D profile. The $g_{\text{Profile}}(\mathbf{x})$ can be written as

$$g_{\text{Profile}}(\mathbf{x}) = g_{Disk<}(y,R,\sigma)\left(1-\Phi_{\sigma_\Phi}\left(\frac{R}{\sigma}-T_\Phi\right)\right) + g_{Disk>}(y,R,\sigma)\Phi_{\sigma_\Phi}\left(\frac{R}{\sigma}-T_\Phi\right) \quad (1)$$

where $\mathbf{x}=(x,y)^T$, R is the radius of vessel and σ is a Gaussian image smoothing parameter. $\Phi(y)=\int_{-\infty}^{y}(2\pi)^{-1/2}e^{-\xi^2/2}d\xi$, $\Phi_\sigma(y)=\Phi(y/\sigma)$. Two thresholds T_Φ and σ_Φ are set to be 1.72 and 1.0 respectively as employed in [4]. $g_{Disk<}(y,R,\sigma)$ and $g_{Disk>}(y,R,\sigma)$ are defined as

$$g_{Disk<}(y,R,\sigma) = \frac{2R^2}{4\sigma^2+R^2}e^{-\frac{2y^2}{4\sigma^2+R^2}} \quad (2)$$

$$g_{Disk>}(y,R,\sigma) = \Phi\left(\frac{c_2-1}{c_1}+c_1\right) \quad (3)$$

in which $c_1=\frac{2}{3}\sigma\frac{\sqrt{\sigma^2+y^2}}{2\sigma^2+y^2}$, $c_2=\left(\frac{R^2}{2\sigma^2+y^2}\right)^{1/3}$. Fig.3 shows 1D profile function $g_{\text{Profile}}(\mathbf{x})$ with different ratios R/σ. When the ratio R/σ changes, the model can be applied to simulate the intensity distribution of the vessel with different sizes. The 1D profile function $g_{\text{Profile}}(\mathbf{x})$ is swept along the y direction to generate the 2D parametric vessel intensity model.

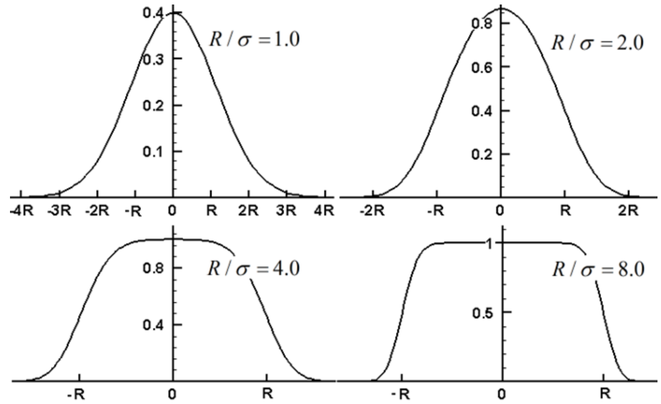

Figure 3. Function $g_{\text{Profile}}(\mathbf{x})$ with different ratios R/σ.

Besides parameters R and σ, four parameters are included in our model, which are the surrounding tissue intensity levels a_0, the vessel intensity levels a_1 and 2D rigid transformation $T(\mathbf{x})$ with the translation parameter y_0 in the direction y perpendicular to the centerline of the vessel and the rotation parameter α. The expression of 2D parametric intensity model for longitudinal vessel images is written as

$$\begin{aligned} g_{\text{L,Profile}}(\mathbf{x},\mathbf{p}) &= a_0+(a_1-a_0)g_{\text{Profile}}(T(\mathbf{x})) \\ \mathbf{p} &= (R,\sigma,a_0,a_1,y_0,\alpha) \end{aligned} \quad (4)$$

III. Quantification of Vessel Lumen

In our method, the boundary points of vessel lumen are detected in 6 longitudinal images reconstructed with a 30-degree interval, as shown in Fig.4. We utilize an incremental segmentation strategy to segment the boundary of lumen in the longitudinal images between given start and end points on the vessel. The parametric intensity model $g_{\text{L,Profile}}(\mathbf{x},\mathbf{p})$ in (4) fits to the image intensities $g(\mathbf{x})$ within a series of small rectangular region-of-interests (ROIs) defined along the vessel centerline as displayed in Fig.4. In each ROI, the optimal parameters of the model can be obtained by minimizing the objective function

$$\arg\min_{\mathbf{p}} \sum_{\mathbf{x}\in\text{ROI}} \left(g_{\text{L,Profile}}(\mathbf{x},\mathbf{p})-g(\mathbf{x})\right)^2 \quad (6)$$

The Levenberg–Marquardt method [5] is employed to minimize this objective function. In the iterative fitting process, some constraints are used to ensure the objective function converge to the expected local minimal, i.e., the value of R, σ, a_0 and a_1 should be the positive, a_1 should be larger than a_0, the translation parameter y_0 should be less than half of the height h of the ROI. The termination criterion is that the difference between two successive values of the objective function is less than a threshold value of 10^{-4}. The maximum iterations time is set to be 400.

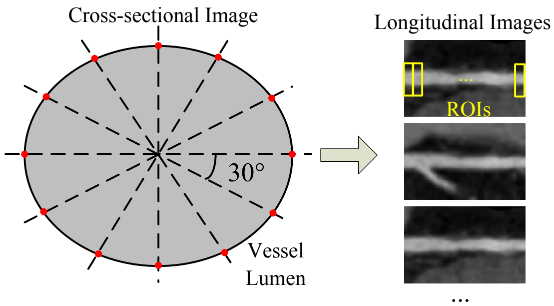

Figure 4. Boundary detection of vessel lumen in 6 longitudinal images. The longitudinal images are reconstructed from 6 different directions (dot-lines) with a 30-degree interval.

The size of ROI is an important parameter in our segmentation algorithm. The width w of the ROI is set to be a small value to ensure the 1D profiles of vessel at different positions in x direction within the ROI are similar. The height h of the ROI should be adapted to the size of vessel to avoid the influence of surrounding tissues. In this paper, w is fixed at 1.5mm and h is set to be 2.5R (R is the radius of vessel estimated in the previous ROI). The incremental step to generate the ROIs along the centerline is set to be 0.5mm. Thus, there is 1.0mm overlap between two consecutive ROIs. As adopted in [4], the parameters estimated in the previous ROI are used to initialize the parameters for the model fitting in current ROI. The coordinates of two boundary points $\mathbf{b}_t$ and $\mathbf{b}_b$ in the ROI can be defined as

$$\mathbf{b} = \begin{bmatrix} \cos(\alpha) & \sin(\alpha) \\ -\sin(\alpha) & \cos(\alpha) \end{bmatrix} \cdot \mathbf{r} + \begin{bmatrix} 0 \\ y_0 \end{bmatrix} \quad (7)$$

in which $\mathbf{r}$ is set to be $(0, -R)^T$ and $(0, R)^T$ to compute $\mathbf{b}_t$ and $\mathbf{b}_b$ respectively. R, α and y_0 are the estimated parameters by the Levenberg–Marquardt method. The introduction of parameter α allows that the boundary of lumen cannot be parallel to the centerline of vessel.

In order to improve the accuracy of lumen quantification, a pre-processing step is applied. As shown by the box in the top image of Fig.5, when a side-branch is included in the ROI, the model fitting cannot estimate the parameters correctly. Since the centerlines of coronary artery tree have been extracted first, a morphological operator is performed to mask all the extracted side-branches of the interested vessel in the 3D image before lumen quantification. In Fig. 5, the regions of side-branches pointed by arrows are filled with a value of the intensity of background image.

After the lumen segmentation in all the longitudinal images, the detected boundary points from the longitudinal images can be transformed to the cross-sectional planes to estimate the luminal area of the vessel.

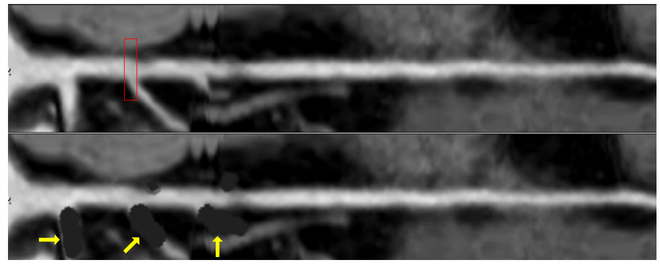

Figure 5. Longitudinal image of an artery with side-branches (top) and with side-branches masked by a morphological operator in the 3D image (bottom). The region of side-branches is filled with a value set to the intensity of image background.

IV. Experimental Results

We first performed 2D model fitting in two ROIs located at poistions A and B in Fig. 1. The model fitting results are demonstrated in Fig. 6 with the intialization of the model before the model fitting. The curves of real image intensity almost coincide with the curves of the fitted 2D intensity model. It means that the 2D intensity model used in our approach can describe the image intensity distribution of the vessel in the longitudinal images both for the large and the small vessels.

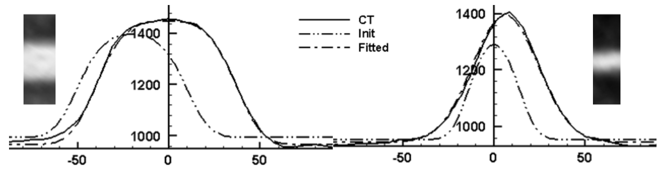

Figure 6. Model fitting results in two ROIs (positions A and B in Fig.1) are displayed in 1D profiles. The curves of real image intensity, intialized model and fitted model are drawn respectively.

To validate the performance of our approach, we used ten CCTA images acquired by Siemens dual-source 64-slice CT scanner. The axial image size is 512×512 and the average axial resolution is about 0.33mm. The distance between two axial slices is 0.5mm. In these CCTA images, ten non-calcified stenoses were reported by radiologists. The grades of stenosis were measured by the radiologists with the software of Siemens syngo CT Coronary Analysis. The grade of stenosis S_a is defined as

$$S_a = 100\% \times (1 - \frac{a_m}{a_r}) \quad (8)$$

where a_m is the minimal cross-sectional luminal area of a stenosis and a_r is the average cross-sectional luminal area at the begin and the end points of narrowing.

Before quantification, the centerlines of coronary artery tree in the experimental CCTA datasets were extracted automatically by the method proposed in [6]. The voxel size of longitudinal images was interpolated to 0.05×0.05mm^2. Two points were given manually by radiologists to define the segment of stenosis for lumen quantification. The lumen boundaries of 10 reported stenoses were detected by our proposed method in 6 longitudinal images with 30 degree interval and transformed into cross-sectional images finally. The initial parameters $\mathbf{p}_0$ and height for the first ROI are set to be $\mathbf{p}_0$ = (35, 15, 1000, 1400, 0, 0) and 5mm. The detected lumen boundaries in 3 longitudinal and 3 cross-sectional images are displayed in Fig.7 and Fig.8 respectively. The accuracy of segmentation results can be verified first by visual checking both in longitudinal and cross-sectional images. As the results shown in Fig.7, the detected boundaries coincide with the boundaries of vessel lumen in the real CCTA images. The pre-processing step can alleviate the influence of side-braches as shown in the right column of Fig.7.

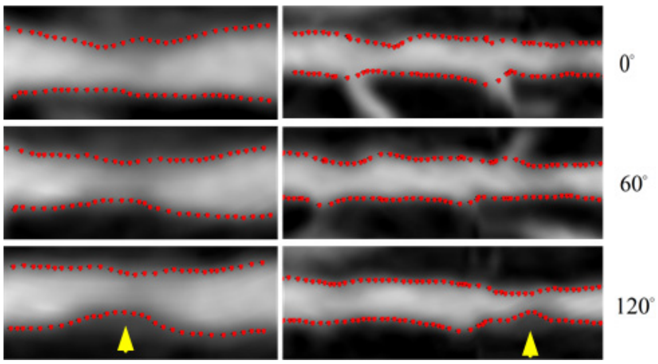

Figure 7. Segmentation results displayed in three longitudinal images of two stenoses (left and right columns).

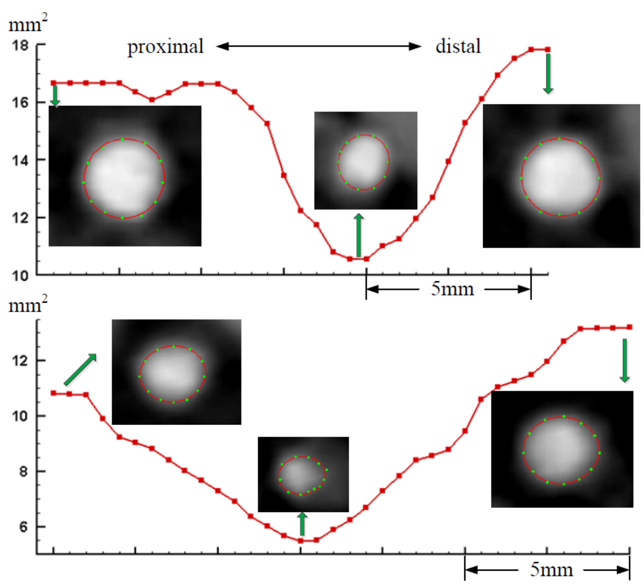

Figure 8. The estimated luminal area of No.2 (top) and No.6 (bottom) stenoses along the vessel. The ellipse contours (in red) of vessel lumen are estimated on the cross-sectional planes based on the boundary points of lumen (in green) detected by our proposed method .

In order to evaluate our method quantitatively, we used luminal area to compute the degree of stenosis. An additional step by fitting the extracted boundary points to an ellipse [7] was performed to approximate the luminal area in the cross-sectional images. In Fig.8, the curves of luminal area of two stenoses (No.2 and No.6) are displayed respectively. Three ellipse contours used to calculate the degree of stenosis are also shown in the cross-sectional planes in Fig.8. The severity degrees of 10 reported stenoses obtained by our method are summarized in Table I by comparing with the reference degrees of stenoses given by the radiologists. The average difference between estimated degrees and reference degrees of stenoses is 4.47% and the difference larger than 10% is only in one stenosis.

V. CONCLUSION

In this paper, we propose an approach based on 2D vessel model to segment the vessel lumen in 3D CCTA images. The 2D parametric intensity model is introduced first to simulate the intensity distribution of vessel lumen in the longitudinal images. Then the boundary points of vessel lumen in six longitudinal images of different angles are estimated by fitting the model in a series of ROIs. The detected boundary points are mapped back to the cross-sectional planes finally to estimate the luminal area along the vessel. Experimental results show that our method can measure the degree of stenosis accurately. Future work relates to validate our method with the calcified stenosis and evaluate our method by RCAA evaluation framework presented in [3].

TABLE I The comparison between the esimated degrees of stenoses and the reference degrees.

No.	a_m (mm^2)	a_r (mm^2)	Estimated degree (%)	Reference degree (%)	Difference (%)
1	4.43	9.26	52.2	60	7.8
2	10.55	17.26	38.9	35	3.9
3	3.86	8.48	54.5	55	0.5
4	6.52	13.68	52.3	55	2.7
5	10.35	18.83	45.0	40	5.0
6	5.46	12.69	57.0	60	3.0
7	4.43	9.53	53.2	50	3.2
8	3.99	10.13	60.6	65	4.4
9	5.31	7.34	27.6	40	12.4
10	7.01	11.35	38.2	40	1.8

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