Segmentation of coronary arteries from CT angiography images

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ABSTRACT

We present an automated method for delineation of coronary arteries from Cardiac CT Angiography (CTA) images. Coronary arteries are narrow blood vessels and when imaged using CTA, appear as thin cylindrical structures of varying curvature. This appearance is often affected by heart motion and image reconstruction artifacts. Moreover, when an artery is diseased, it may appear as a non-continuous structure of widely varying width and image intensity. Defining the boundaries of the coronary arteries is an important and necessary step for further analysis and diagnosis of coronary disease. For this purpose, we developed a method using cylindrical structure modeling. For each vessel segment a best fitting cylindrical template is found. By applying this technique sequentially along the vessel, its entire volume can be reconstructed. The algorithm is seeded with a manually specified starting point at the most distal discernible portion of an artery and then it proceeds iteratively toward the aorta. The algorithm makes necessary corrections to account for CTA image artifacts and is able to perform in diseased arteries. It stops when it identifies the vessels junction with the aorta. Five cardiac 3D CT angiography studies were used for algorithm validation. For each study, the four longest visually discernible branches of the major coronary arteries were evaluated. Central axes obtained from our automated method were compared with ground truth markings made by an experienced radiologist. In 75% of the cases, our algorithm was able to extract the entire length of the artery from single initialization.

Keywords: coronary arteries, segmentation, computer-assisted diagnosis, CT angiography

1. INTRODUCTION

According to the American Heart Association, heart disease is the leading cause of death nationwide. Atherosclerosis, a condition in which one or more plaques form in the arteries, can cause partial or complete blockage of blood flow through the artery. Recent developments in CTA imaging techniques allow for the acquisition of three-dimensional volumetric images of the entire heart region. These images are vital in obtaining precise information about the structure of the coronary artery tree and additionally, help to make more accurate diagnosis.[1,2] In this work we focus on automated reconstruction of coronary arteries from CTA images. Defining the structure of the coronary artery is the first step toward the automated diagnosis of coronary artery disease.

Certain features of coronary arteries and cardiac CT imaging introduce difficulties and must be addressed in the design of an automated method. Coronary arteries are very narrow blood vessels and when imaged using CTA (Figure 1), are very sensitive to image noise artifacts, which make them harder to segment. Moreover, the profiles of the blood vessels on cardiac CT images are often affected by stairstep artifacts caused by limitations of modern CTA acquisition techniques;[3] currently cardiac CT images are taken by during several consecutive cardiac cycles. Spatial deviations of the heart position occur between the acquisition cycles and cause displacements as shown in Figure 2.

Figures 3 - 7 illustrate different issues with appearance of a coronary artery on a cardiac CTA image. Geometric sketches at the right side are supplemented with light shaded three-dimensional visualizations of example

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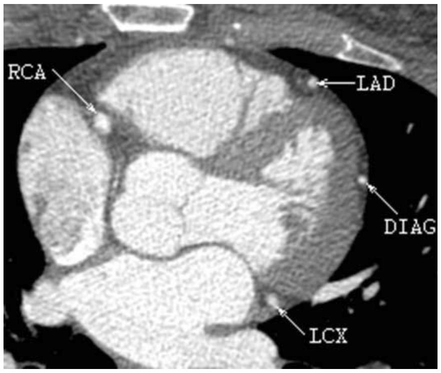

Figure 1. CTA image slice and four major branches: RCA - right coronary artery, LAD - left anterior descending artery, DIAG - its first diagonal branch, LCX - left circumflex artery.

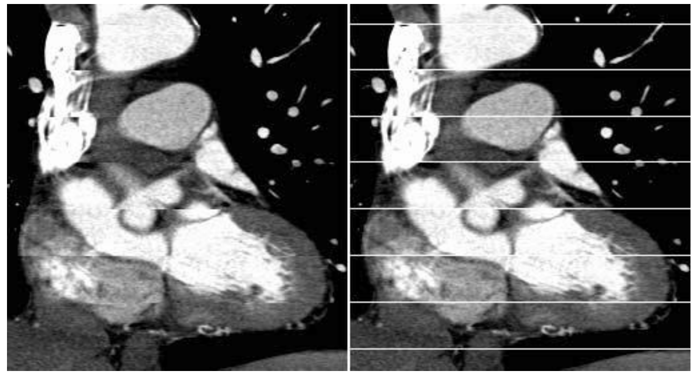

Figure 2. Coronal reconstructions of heart region shows stairstep artifacts. White lines on the right image denote borders between different cardiac cycles.

coronary artery segments obtained by clipping the surrounding region and applying intensity threshold. Figure 3 shows a typical segment that is without issues and is simple to track. Figure 4 shows the effect of the stairstep artifact that interrupts the continuity of a vessel image. The intensity of the vessel may change due to factors such as non-uniform distribution of contrast medium, internal calcification and soft plaque. With a change in intensity a segment of the artery may be below the threshold value and therefore not be detected. Figure 5 shows how intensity drop may cause the discontinuity. Occasionally, a coronary artery lies very close to another blood vessel or heart chamber of a similar intensity. Due to contrast medium noise, the artery may appear to have "leaked" into it as shown in Figure 6. Figure 7 shows a sharp turn of a coronary artery which is not peculiar to large blood vessels. Moreover, like any other blood vessels, coronary arteries have branching points that introduce a problem of choosing the correct path for a tracking-based method. Figure 8 shows an example of such a bifurcation point. An ideal algorithm should handle all the situations stated above.

An extensive overview of different vessel segmentation methods is presented in Kirbas et al,[4] however none of the methods addressed all the issues that are particular to the coronary arteries in cardiac CTA imaging. An approach that is based on statistical classification of heart regions and active contour models is presented by Yang et al;[5] preliminary experiments made on one case demonstrate promising results. The method proposed by Lavi et al[6] tracks the arteries using front-propagation technique and does the segmentation of the aortic root. The accuracy of the algorithm was assessed by the clinicians grades as a function of image quality. Boldak[7] employed a moment-based tracking approaches that use the local image information to determine vessel direction and includes sophisticated procedures for returning the algorithm to the correct path. Work of Wink et al[8] reports a general method for segmentation of contrast enhanced blood vessels. To navigate a path along the vessel it uses two-dimensional cross-section information. While it is sufficient for segmentation of relatively large blood vessels it may not be enough in case of small and noisy coronary arteries. Methods similar to one reported by Olabarriaga et al[9] and based on minimum-cost path and vessel-enhancement filters are gaining popularity. Though their experiments were done on conventional CT images, the same technique may be promising for CTA as well. However all these methods need to be validated carefully against cases with heart motion artifacts including discontinuities.

2. METHOD

An automated method for reconstruction of a vessel's central axis is presented. It is direct and does not require image pre-processing or pre-segmentation of any anatomical parts. It involves manual selection of seed points, iterative prediction of vessel behavior and search of best fitting cylindrical models to determine the next axis point. The algorithm starts from the most distal point of a specified artery and proceeds against the direction of blood flow until it locates the vessels junction with the aorta.

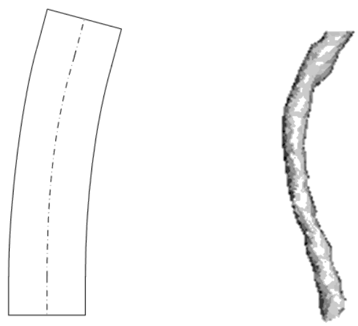

Figure 3. Typical segment of a coronary artery.

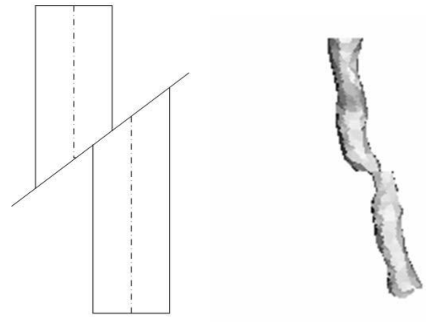

Figure 4. Vessel image affected by stairstep artifact is one of the major challenges.

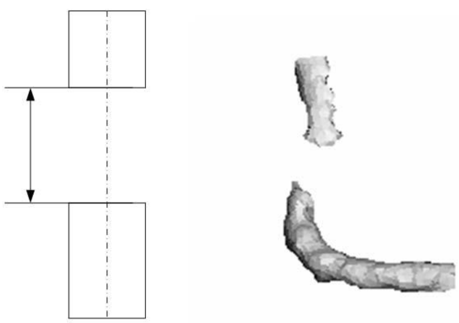

Figure 5. Gap caused by sudden drop of image intensity (threshold of 100 HU is applied before visualization). Partial template match and intensity threshold selection allow to overcome it.

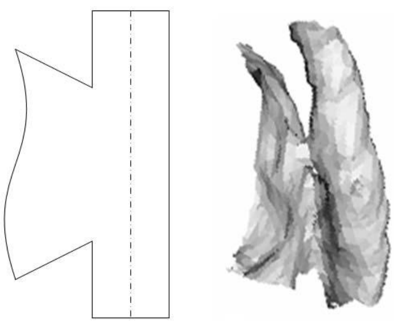

Figure 6. Adjacent structure of high intensity. Preserving direction of the previous segment helps to choose correct path.

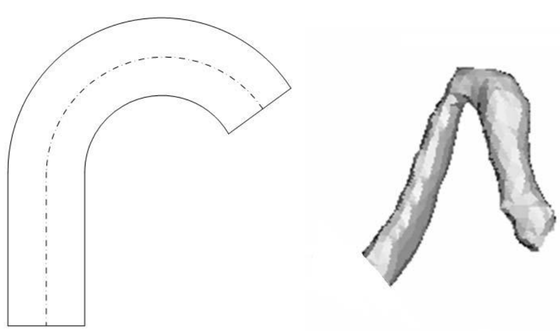

Figure 7. Sharp turn. Adjusting the size of the template and angle selection scheme allows to pass them with suitable precision.

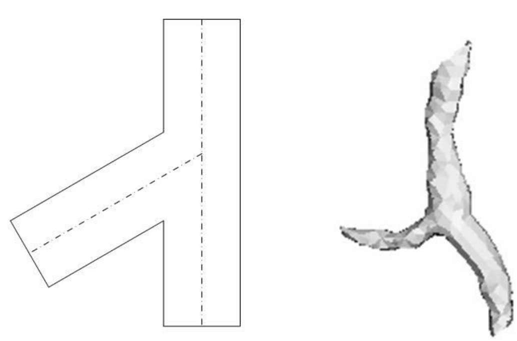

Figure 8. Vessel bifurcation point. Problem of choosing the correct path is solved by following the artery against blood flow direction.

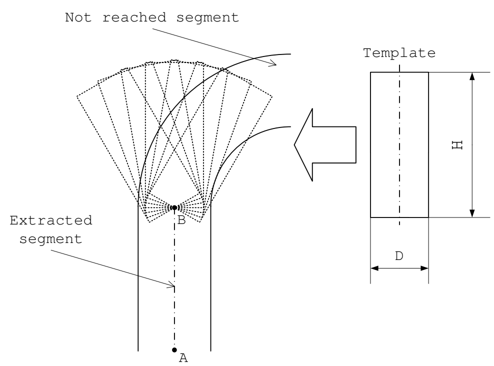

Figure 9. Search the template that best matches a segment of the artery. Initial template parameters are obtained from the previously extracted segment.

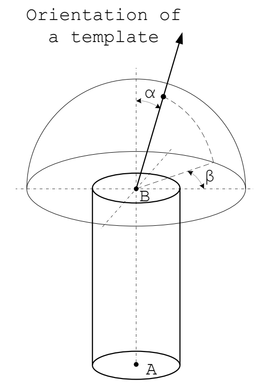

Figure 10. Specifying direction: α (zenith) and β (azimuth) determine the orientation of a template in space.

The cylindrical template matching model can tolerate a certain degree of image noise and heart motion artifacts. Usually, injected medium makes coronary arteries more contrast on a CT scan with respect to surrounding tissues, thus, in the general case, the tracing procedure should go in the direction of the highest intensity. To overcome the problem of changing intensity, a flexible local scheme that automatically selects the threshold for each coronary vessel segment was used. The problem with vessel bifurcations was avoided by forcing the algorithm to proceed against the direction of the blood flow. The algorithm preserves the direction of the already extracted central axis while looking for a template for the next segment. At the same time, it is able to trace the arteries making sharp turns. An angle search space selection procedure was included in the algorithm to account for ambiguous conditions.

Finding the best fitting model for each artery segment is an optimization problem. At step n, among all cylindrical templates $\{t_i(n)\}$ with orientation α, β, diameter d, height h, and intensity threshold I_{th}, we search for the one $t_{best}(n)$, that best matches image region S:

$$t_{best}(n) = \arg\max_{t_i(n)}\{R(t_i(n), S)\}, \quad t_i(n) = f[\alpha, \beta, d, h, I_{th}, t_{best}(n-1)],$$

where $R(t_i(n), S)$ is the template-image matching metric which computes the fraction of volume within the image region enclosed in the template that has an intensity above I_{th}. Certain constrains of intensity threshold, orientation and size of the template are applied based on anticipated vessel behavior.

2.1. Formal algorithm description

Algorithm 1 was implemented as a solution to the optimization problem stated above. The first step for the algorithm is manual initialization. A user specifies two seed points A and B denoting placement and direction of the starting artery segment. Seed point A is the first visually discernible point belonging to the central axis. Seed point B is selected at a distance approximately equal to two diameters from the point A. Part AB of the vessel must be chosen at an approximately straight segment of the vessel.

Once the segment AB has been extracted, we need to find the next segment of the artery. We start to search for a cylindrical template originating at point B that best matches the real image region as shown in Figure 9. This template should have the direction close to AB but is allowed to deviate to accommodate vessel turns. Deviations in space from the direction AB can be specified by two angles: α (zenith) and β (azimuth) as shown at Figure 10. Selection of a proper search range for α is very important. While too small a range of α prevents the algorithm from following the sharp vessel turns, too large a range may cause the algorithm to turn in the wrong direction.

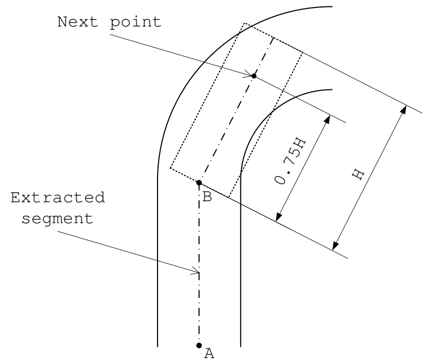

Figure 11. Next axis point is located at the distance equal to three quarters of the best matching template to prevent the algorithm from going "off road".

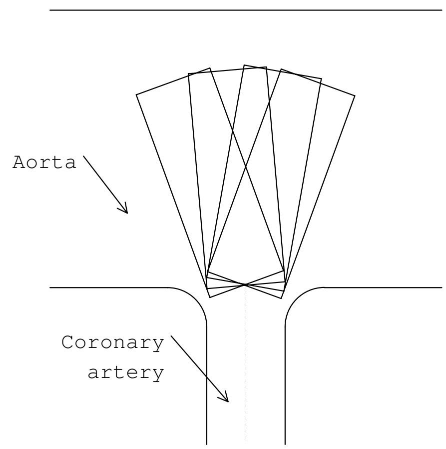

Figure 12. Too many matching templates is a good indication that the aorta has been reached.

Initially we set the diameter D of the templates to be less than the diameter of the previously extracted segment in order to account for possible vessel narrowing. The height of the template is always chosen to maintain a constant template aspect ratio: $H = r_{aspect}D$.

While searching for best fitting template we compute the ratio $R(t) = M(t)/V(t)$ of the template region volume $M(t)$ having intensity above a certain threshold I_{th} to the volume $V(t)$ of the template. Since the coronary arteries usually have image intensity higher than surrounding tissues, higher values of $R(t)$ would favor the true vessel direction on the image.

If there are too many templates with high value of $R(t)$, this means that the vessel diameter has increased and the same search procedure is repeated for a template with a slightly increased diameter. If the diameter increases more than σ_{max} times relative to the diameter of the previous segment, the algorithm terminates. A significant jump in the diameter value usually means that the coronary artery joined with the aorta as shown in Figure 12.

In contrast, if we find only templates with a low ratio $R(t)$, this may be caused by either an intensity drop or a sharp turn. Therefore, first the search procedure is repeated with a smaller intensity threshold I_{th}, second it is repeated with an extended α search range. Such adjustments are made until the template with high enough value of $R(t)$ is found. If the intensity drop is too much relative to the average intensity of the 27-voxel neighborhood of point B, the algorithm terminates. If the template is not found even within the extended search range, the algorithm also terminates. Usually, these situations happen in case of a severe vessel discontinuity.

Once the best fitting template is found it is put on top of the already extracted segment as shown in Figure 11. The next axis point is placed at a distance of $0.75H$ from point B to ensure that the axis lies within the vessel. Then the entire procedure of the search is repeated for the next segment of the artery.

To evaluate the quality of the algorithm, its output was compared with manual markings made by an experienced radiologist. Five cardiac 3D CT angiography image sets (64-slice CT scanner GE LightSpeed VCT, slice thickness: 0.625 mm, in-plane resolution: $0.48 \ldots 0.52$ mm) were used in the experiment. For each study, the four longest visually discernible branches of the major coronary arteries imaged at the most relaxed temporal stage of the heart cycle were considered.

3. RESULTS

The results of the artery delineation can be represented as a chain of best fitting cylindrical templates stitched together as shown in Figure 13. Automatically and manually extracted central axes for one of the cases are shown in Figure 14. Black circles represent the markings created by our automatic method and gray circles

Algorithm 1 Coronary artery reconstruction

A, B	points of initial segment
d	initial diameter
I_{max}	maximum intensity threshold
I_{drop}	allowed intensity drop relatively to previous segment
I_{step}	intensity iteration step
$\delta_{min},\ \delta_{max}$	starting and ending diameter coefficients
δ_{st}	diameter iteration step
$\alpha_{st},\ \alpha_{range}$	step and range for zenith search
α_{ext}	extended value of starting zenith
$\beta_{st},\ \beta_{range}$	step and range for azimuth search
r_{aspect}	template height to diameter aspect ratio
r_{match}	template match ratio
t_{tmm}	too many matches ratio
t_{step}	next axis point distance coefficient

1:	$\alpha_{start} \leftarrow 0$	initialize lower bound of zenith search range
2:	$I_{th} \leftarrow I_{max}$	set intensity threshold
3:	**for** $\delta = \delta_{min}$ to δ_{max} step δ_{st} **do**	iterate diameter coefficients
4:	$D \leftarrow \delta \cdot d$	obtain diameter for the template
5:	$H \leftarrow r_{aspect} \cdot D$	calculate template height
6:	$T \leftarrow \emptyset$	initialize set of templates
7:	**for** $\alpha = \alpha_{start}$ to $\alpha_{start} + \alpha_{range}$ step α_{st} **do**	iterate through possible zeniths
8:	**for** $\beta = 0$ to β_{range} step β_{st} **do**	iterate through azimuths
9:	$T \leftarrow T \cup t(A, B, \alpha, \beta, D, H)$	add template to the set
10:	$V(t) \leftarrow \{v \in t \cap S\}$	establish the set of voxels within the template
11:	$M(t) \leftarrow \{v \in t \cap S : I(v) > I_{th}\}$	find the subset of high intensity voxels
12:	$R(t) \leftarrow \lvert M(t)\rvert / \lvert V(t)\rvert$	calculate matching metrics
13:	**end for**	
14:	**end for**	
15:	$T_{fit} \leftarrow \{t \in T : R(t) > r_{match}\}$	find subset of best fitting templates
16:	**if** $T_{fit} = \emptyset$ **then**	if no fitting templates found
17:	$I_{th} \leftarrow I_{th} - I_{step}$	first, decrease threshold intensity
18:	**if** $I_{th} > I_{27}(B) - I_{drop}$ **then**	if intensity is not too low
19:	**go to** 3	reinitialize diameter and restart the search
20:	**end if**	
21:	**if** $\alpha_{start} = 0$ **then**	
22:	$\alpha_{start} \leftarrow \alpha_{ext}$	second, extend zenith search space
23:	**go to** 2	reinitialize intensity, diameter and restart the search
24:	**end if**	
25:	**stop**	no matches (discontinuity)
26:	**end if**	
27:	**if** $\lvert T_{fit}\rvert < t_{tmm} \cdot \lvert T\rvert$ **then**	if not too many matching templates
28:	$t_{best} \leftarrow \arg\max_{t \in T_{fit}} \{R(t)\}$	get the best match
29:	$A \leftarrow B$	mark the segment as extracted
30:	$B \leftarrow B + t_{step} \cdot vector(t_{best})$	get next axis point
31:	$d \leftarrow D$	remember diameter
32:	**go to** 1	process next segment
33:	**end if**	
34:	**end for**	
35:	**stop**	too many matches (reached aorta)

Figure 13. Modeled segment of LAD (20% of full length): cylinders of different shades represent best matching templates stitched together

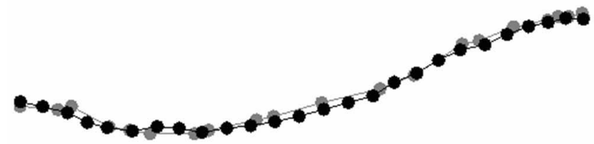

Figure 14. Same segment of the artery: comparison of automatically (black) and manually (gray) marked axis (diameter of each circle is 1mm)

Figure 15. Volume rendering of the heart region with automatically extracted RCA and LAD (marked white)

represent the manual marks. The diameter of each circle is 1 mm. The algorithm result displayed with respect to the heart is shown in Figure 15.

The average distance between the segments along the entire artery length was measured. In all cases the algorithm was able to reconstruct the central axis within the distance of 1 mm from the marked ground truth location. In 15 out of 20 vessels, the algorithm identified the entire length of the artery with a single manual initialization. In the remaining five it could extract only a portion of the artery. However, the algorithm could be manually reseeded from the point where it stopped, and when this was done, it was able to complete the delineation procedure. Ratios of extracted segment to visually discernible artery lengths are shown in Table 1.

Table 1. Portions of artery branches extracted from a single manual initialization.

CASE	CX0001	CX0017	CX0018	CX0019	CX0020
LAD	1.0*	1.0*	1.0	1.0	1.0
RCA	1.0	0.3	1.0	1.0	1.0
LCX	0.3	0.2	1.0	1.0	0.9
DIAG	1.0	1.0	1.0	1.0	0.6

* - cases used for selection of the algorithm parameters

In four out of five cases of premature completion, the algorithm stopped at a point of discontinuity caused by cardiac motion, an example of which is shown in Figure 16. In the remaining case, the algorithm incorrectly identified the tangent boundary of the heart as the junction point with the aorta as shown in Figure 17.

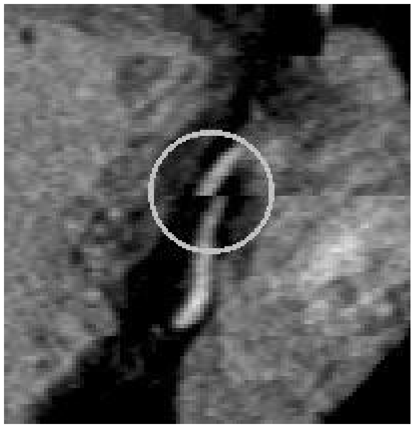

Figure 16. RCA: Example of premature completion due to significant discontinuity caused by stairstep artifact.

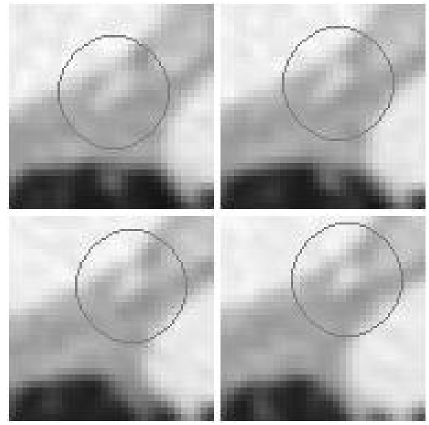

Figure 17. LCX: Significant drop of image intensity nearby one of the heart chambers. Algorithm erroneously decides that aorta is reached.

4. CONCLUSION

We designed an automated method that can extract the central axes of the coronary arteries from CTA images. Preliminary results obtained in this work indicate that our method can be used to approach this goal. The algorithm was specifically designed to handle coronary arteries that can be affected by disease, noise, heart motion and image reconstruction artifacts. The cylinder modeling approach allows us to extract very thin segments barely seen on a CT scan. Because of the flexibility and adaptive nature of the algorithm, it was able to track arteries of different sizes and curvatures, containing calcifications, soft plaque and surgical stent implants. The template matching scheme could even tolerate certain degree of stairstep artifacts by preserving the orientation of the vessel in the same direction. However, additional work needs to be done to develop a more robust system that overcomes the challenges of complex cases due to either complex anatomy or technical issues.

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