Automated Coronary Tree Segmentation and Path line Detection in MSCT

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Abstract

This document describes a novel scheme for the automated extraction of the central lumen lines of coronary arteries from computed tomography angiography (CTA) data. The scheme first obtains a segmentation of the whole coronary tree and subsequently extracts the centerlines from this segmentation.

The first steps of the segmentation algorithm consist of the detection of the aorta and the entire heart region. Next, candidate coronary artery components are detected in the heart region after the masking of the cardiac blood pools. Based on their location and geometrical properties the structures representing the right and left arteries are selected from the candidate list. Starting from the aorta, connections between these structures are made resulting in a final segmentation of the whole coronary artery tree, A fast-marching level set method combined with a backtracking algorithm is employed to obtain the initial centerlines within this segmentation. For all vessels a curved multiplanar reformatted image (CMPR) is constructed and used to detect the lumen contours. The final centerline was then defined by determining the center of gravity of the detected lumen in the transversal CMPR slices.

Within the scope of the MICCAI Challenge 'Coronary Artery Tracking 2008', the coronary tree segmentation and centerline extraction scheme was used to automatically detect a set of centerlines in 24 datasets. For 8 data sets reference centerlines were available. This training data was used during the development and tuning of the algorithm. Sixteen other data sets were provided as testing data. Evaluation of the proposed methodology was performed through submission of the resulting centerlines to the MICCAI Challenge website[1].

Contents

[1]http://cat08.bigr.nl

1 Method

Figure 1 provides an overview of the components of the coronary tree segmentation steps within the proposed algorithm. The first step consists of the automatic detection of the ascending aorta in the CTA data (1). Next, a mask image containing the whole heart isolated from other structures in the thorax is obtained (2). Within the heart region a mask image containing large contrast filled structures is obtained using morphological filtering(3). Using these obtained mask images the region within the heart containing the coronary arteries is thresholded and all the connected components in the region are obtained(4). Subsequently, these connected components are sorted on the likelihood of being part of the coronary vessel tree. With all these pre-processing steps completed, a region growing technique is started in the ascending aorta and stopped when it has reached two coronary tree candidate components(5). From these two contact points a second region grower is started that iteratively tries to reconnect more candidate components(6).

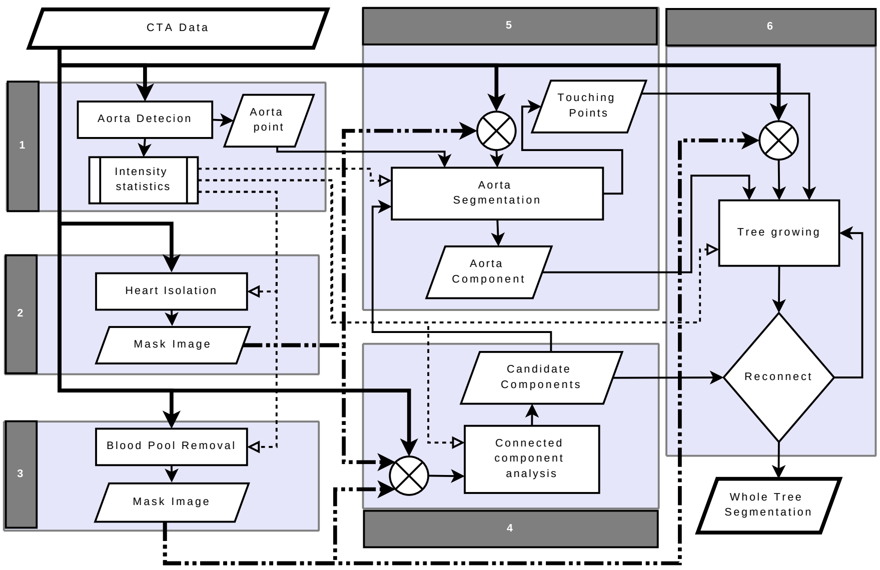


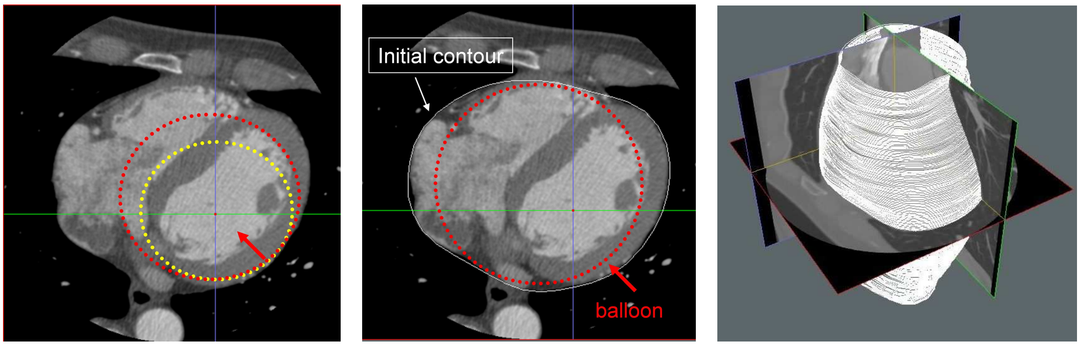
Figure 1: Coronary Tree Segmentation Overview. Flow chart of the segmentation scheme with various major components highlighted: (1) Aorta Detection, (2) Heart Isolation, (3) Blood Pool Removal, (4) Connected Component Analysis, (5) Aorta Segmentation, (6) Tree Growing

1.1 Aorta Detection

The detection of the ascending aorta is the first step in the segmentation of the coronary tree. Using a hough transform hyperintense circles are detected in one of the top slices of the dataset. Based on it's location the aortic cross section is selected. This initial circle is used to mark a region of interest for which in lower slices the aortic cross section can be detected. This continues until the detected circle deviates too much from the previous circle locations, or if no circle is detected. The center of the lowest detected circle is defined as the "'aorta point"' (see figure 1). The distribution of image intensities within the detected circles is recorded and later used in the definition of parameter settings for the remaining steps.

1.2 Heart Isolation

As an initialization method for the heart isolation we use a method derived from Funka-Lea et al.[1]. First, a point inside the heart is determined based on the center of gravity in the dataset weighted by the image intensities. At this point a 2D balloon model is inflated. When the virtual balloon touches the heart wall it will translate away from the wall (see figure 2(a)). This iterative process is stopped when the balloon has too many touching points with the wall to allow for significant translation. An optimal fit through gradient information along scanlines perpendicular to the edge of the virtual balloon, is used to obtain an initial contour (see figure 2(b)). This initial contour is copied to the neighboring slices as the starting contour for a similar fitting scheme. This procedure is repeated until all the slices are processed (see figure 2(c)). Based on the stack of resulting contours a mask image of the entire heart is constructed.



(a) (b) (c)

Figure 2: Heart Isolation Initialization. (a) Balloon inflation from the detected point inside the heart. (b) Scanline detection of the inital contour. (c) Final set of heart contours.

1.3 Blood Pool Masking

Following the approach of Cline et al.[2], the cardiac blood pools, in CTA characterized as hyperintense areas, are recognized and masked using binary morphological filters. An automatically determined threshold (based on the aorta intensities) is used to create a binary image of the contrast filled regions in the data. An erosion of the binary image is followed by a dilation, removing the smaller structures in the image. To include an additional border around the blood pools, the structuring element for dilation was chosen slightly bigger than the one for erosion (see figure 3(a) and 3(b)).

1.4 Connected Component Analysis

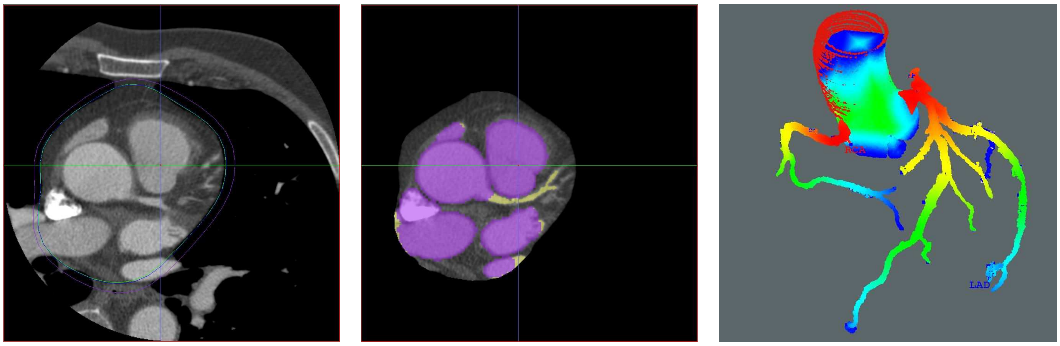
Using the obtained mask images of the heart and the blood pools, all remaining contrast filled structures within the heart can be extracted from the image. Again a threshold based on the aorta intensities is used to create the binary representations of these structures (see figure 3(b)). The various connected components within the structures are obtained using connected component labeling [3]. For the largest components a skeleton representation is created and used to distinguish between vessel-like structures and blob- or noise-like structures. This list of candidate coronary artery components is then sorted based on the probability of a structure being a vessel.

1.5 Aorta Segmentation

Starting from the'aorta point' that was found by the slice based Hough transform (section 1.1) a region growing process is started to segment the ascending aorta. This region grower is stopped when it reaches the top two components in the previously composed vessel candidate list. The boundary between the segmented aorta and these two components (known as the ”‘touching points”') represent the roots of the left and right coronary artery.

1.6 Tree Growing

Starting from the derived roots of the left and right coronary artery another region grower is initiated within the blood pool masked CTA data set. The output of the region grower is used to obtain the extremities of the currently grown tree. These extremities are subsequently used to find entries in the candidate components list that could be part of distally located segments in the coronary tree. If such components are found they are connected to the closest extremity point. This procedure is repeated until no more suitable candidate components can be found to reconnect to. The obtained aorta segmentation and the grown tree are finally merged together to form a complete segmentation of the whole coronary tree (see figure 3(c). This reconnection scheme is used to overcome problems with the loss of connectivity between the components due to lower intensities or the presence of a severe stenosis.



(a) (b) (c)

Figure 3: Coronary Tree Segmentation. (a) Heart isolation. (b) Masking of the blood pools in the heart (purple) and the detection of the candidate components (yellow). (c) Final tree segmentation with the aorta.

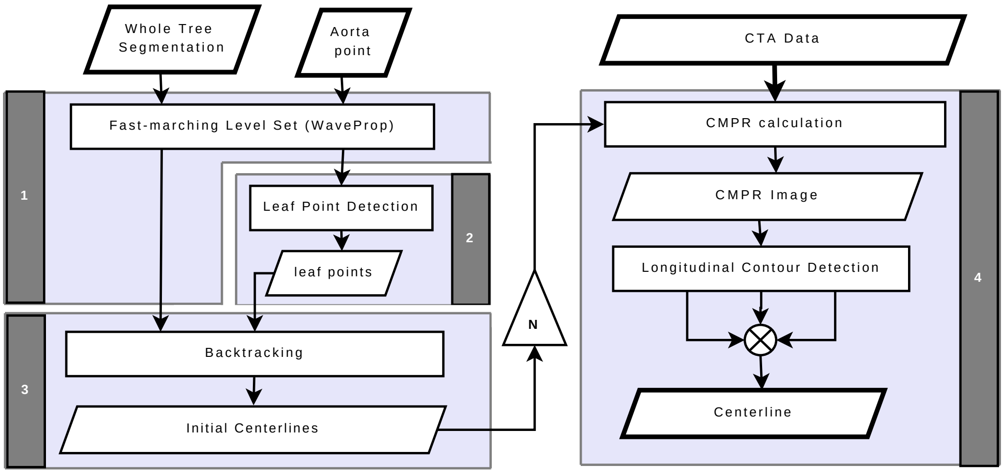


Figure 4: Centerline Extraction Overview. (1) WaveProp level set. (2) Detection of "'leaf points"' from the WaveProp output. (3) Initial centerlines though backtracking. (4) Refine each centerline using lumen contour detection.

1.7 Centerline extraction

Using the whole tree segmentation all the centerlines of the coronary arteries are determined using a number of processing steps. An overview of this process is shown in figure 4. First, a fast-marching level set algorithm (WaveProp) is initiated within the segmentation from the center of the aorta (1). Using the arrival time information in the WaveProp output the "'leaf points"' of the coronary tree are determined (2). From these "'leaf points"' a back-tracking algorithm is initiated (3) to obtain a set of initial centerlines. Finally, these initial centerlines are used to construct curved multi planar reformatted (CMPR) images. Within these images the longitudinal lumen contours are automatically detected [4]. The final centerlines are now obtained by determining the center of gravity of the detected lumen in the transversal CMPR slices (4).

2 CAT08 MICCAI Challenge

The described method was applied to extract the coronary artery centerlines in 24 CTA data sets. The data sets were provided by the organizers of the "'Coronary Artery Tracking 2008"' challenge part of the "'3D Segmentation in the Clinic: A Grand Challenge II"' MICCAI workshop. For each data set 4 vessels had to be extracted. Four reference points were provided for each vessel: the start (S) and end (E) point of the vessel, a point approximately 3 cm distal to the start (B) and a fourth marker point to uniquely identify the vessel (A). For training and tuning of the algorithm, reference centerlines were provided for 8 data sets (training data). In this paper the results on the remaining 16 data sets (testing data) will be discussed. Within the challenge three categories were distinguished: "'automatic tracking"', "'tracking with minimal user interaction"' and "'interactive tracking"'.

To compete in the automatic tracking category point A or B could only be used for the selection of the centerline. Given the entire coronary tree that was extracted automatically, the vessel closest to one of these points was selected for analysis. In the majority of cases point A was found a suitable marker. Only in three cases (dataset 8 vessel 1, dataset 17 vessel 1 and dataset 18 vessel 2) point B was used.

For more details about the used measures within the challenge we would like to refere to the challenge description [5].

3 Results

The results of the comparison between the automatically extracted centerlines and the reference centerlines for the 16 testing data sets are shown in tables 1-3. In table 1 the average overlap measures and scores are shown. Table 2 shows the average accuracy measures and score and table 3 shows summary of all the measures and scores. The average processing time for a single data set was approximately 2 minutes on an Intel Duo Core 2.49 GHz, 3.50 GB RAM - Windows XP machine.

4 Conclusion & Discussion

A novel scheme was presented for the automatic segmentation of the whole coronary artery tree and the extraction of the artery centerlines from CTA data. The presented method was tested on 16 CTA data sets within the scope of the CAT08 MICCAI Challenge.

The results of the comparison of the extracted centerlines with the reference centerlines show that we score higher on the overlap measures compared to the accuracy measures. In our current research, the centerline detection is used as an initialization for further processing which has lower dependency on the exact position of the centerline. Its main purpose is to define a ROI within the dataset for other segmentation schemes (like lumen and plaque detection). For 76% of the analysed vessel the overlap in the clinical relevant part (OT) was more than 75%, making it relatively robust. Even with the presence of (severe) stenoses, the proposed algorithm was still capable of producing a centerline through the clinically relevant vessel segments. The method is also relatively fast and provides a number of intermediate results useful for other purposes, like the heart isolation for visualization.

For future work, we would like to improve the selection of the candidate components and work on the accuracy of the centerline extraction.

Acknowledgements
We would like to acknowledge Henk Marquering for his initial work on the coronary artery centerline and lumen detection.

Table 1: Average overlap per dataset

Dataset nr.	OV %	OV score	OV rank	OF %	OF score	OF rank	OT %	OT score	OT rank	Avg. rank
8	49.1	27.5	–	39.9	29.7	–	53.4	26.7	–	–
9	85.4	44.2	–	77.9	42.1	–	86.5	43.3	–	–
10	82.7	42.6	–	41.7	21.2	–	85.6	42.8	–	–
11	84.5	43.1	–	50.5	35.7	–	84.5	43.1	–	–
12	88.5	45.7	–	33.2	18.7	–	92.7	46.7	–	–
13	83.2	54.5	–	75.0	54.8	–	85.1	67.6	–	–
14	91.0	46.7	–	72.6	51.9	–	91.8	58.4	–	–
15	75.6	50.9	–	73.7	50.0	–	76.9	51.0	–	–
16	82.6	42.6	–	56.0	29.4	–	87.6	43.8	–	–
17	43.2	22.1	–	18.1	10.1	–	43.2	21.7	–	–
18	74.3	37.7	–	65.5	39.2	–	74.3	37.3	–	–
19	80.0	41.4	–	68.0	37.5	–	80.0	40.0	–	–
20	83.4	53.8	–	45.0	26.9	–	83.7	42.0	–	–
21	81.6	51.4	–	43.0	34.5	–	85.2	55.6	–	–
22	96.8	50.5	–	95.0	72.5	–	98.0	74.0	–	–
23	85.2	43.0	–	59.9	42.9	–	87.3	56.1	–	–
Avg.	**79.2**	**43.6**	**–**	**57.2**	**37.3**	**–**	**81.0**	**46.9**	**–**	**–**

Table 2: Average accuracy per dataset

Dataset nr.	AD mm	AD score	AD rank	AI mm	AI score	AI rank	AT mm	AT score	AT rank	Avg. rank
8	14.52	23.6	–	0.57	43.9	–	13.58	25.7	–	–
9	3.26	32.5	–	0.24	38.2	–	3.13	32.9	–	–
10	2.84	33.7	–	0.24	40.6	–	2.02	34.4	–	–
11	2.81	35.3	–	0.35	39.5	–	2.81	35.3	–	–
12	1.44	33.4	–	0.27	37.4	–	0.79	35.1	–	–
13	4.45	36.6	–	0.26	43.8	–	3.96	37.3	–	–
14	1.27	39.8	–	0.33	43.2	–	1.08	40.1	–	–
15	7.21	30.0	–	0.28	39.2	–	6.07	30.5	–	–
16	3.30	27.6	–	0.29	33.0	–	1.84	29.3	–	–
17	18.93	20.4	–	0.19	19.3	–	15.65	22.5	–	–
18	9.03	31.1	–	0.25	41.0	–	9.03	31.1	–	–
19	5.78	33.0	–	0.42	41.3	–	5.78	33.0	–	–
20	4.54	33.6	–	0.35	40.0	–	4.50	33.7	–	–
21	4.14	29.5	–	0.29	33.9	–	2.90	30.7	–	–
22	0.54	34.0	–	0.31	35.0	–	0.48	34.3	–	–
23	2.13	34.6	–	0.30	40.0	–	1.81	35.2	–	–
Avg.	**5.39**	**31.8**	**–**	**0.31**	**38.1**	**–**	**4.71**	**32.6**	**–**	**–**

Table 3: Summary

Measure	% / mm min.	% / mm max.	% / mm avg.	score min.	score max.	score avg.	rank min.	rank max.	rank avg.
OV	0.0%	100.0%	79.2%	0.0	100.0	43.6	–	–	–
OF	0.0%	100.0%	57.2%	0.0	100.0	37.3	–	–	–
OT	0.0%	100.0%	81.0%	0.0	100.0	46.9	–	–	–
AD	0.23 mm	47.13 mm	5.39 mm	1.3	47.5	31.8	–	–	–
AI	0.00 mm	1.13 mm	0.31 mm	0.0	53.5	38.1	–	–	–
AT	0.23 mm	47.13 mm	4.71 mm	1.3	47.6	32.6	–	–	–
Total							**–**	**–**	**–**

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