Automatic detection of coronary artery stenosis in CTA based on vessel intensity and geometric features

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Abstract. In this paper, we present a fast and fully automatic learning based system that is capable of detecting coronary stenoses in Computed Tomography Angiography (CTA) caused by all types of plaques, e.g. soft, mixed, and calcified. We extract geometrical and intensity based features that can capture the characteristic properties of the coronary vessels. We evaluated our method on the Rotterdam Coronary Artery Stenoses Detection and Quantification Evaluation Framework on 42 datasets. On the 24 testing datasets, a sensitivity of 57% and a PPV of 18% is achieved as compared to QCA, while a sensitivity of 57% and a PPV of 32% is achieved as compared to CTA. This clearly indicates that our method is good at ruling out disease (low false negative detection value), but has limited performance to detect significant stenoses ($> 50\%$ luminal diameter reduction; high false positive rate).

Keywords: stenoses detection, tractography, tensor, coronary arteries, CTA, calcifications, soft plaque, mixed plaque

1 Introduction

In the last decade, Coronary Artery Disease (CAD) has been the leading cause of death worldwide [1]. Extraction of arteries is a crucial step for accurate visualization, quantification, and tracking of pathologies. Especially, early detection and quantification of plaques is of high interest. However, interpreting and detecting the plaques requires substantial experience. It can take several hours for the physicians to do manual plaque segmentation for a single CTA dataset. An automated and fast system that can identify the severe and moderate stenoses could be an alternative to the physicians in the emergency cases.

For the automatic detection of plaques, delineation of coronary arteries is important. Creating a robust fully automatic vessel extraction algorithm is one of the most challenging and ongoing problems in the literature. A comprehensive treatment of the vessel segmentation methods can be found in [2] and [3] surveys.

A variety of algorithms have been proposed in the literature for detection of the plaques in CTA images. However, most of them focus on calcifications, and require substantial user involvement [4]. A few learning based fully-automatic methods have also been proposed in literature [5, 6]. However, they still focus on the calcified coronary lesions. Cylindrical sampling patterns, which can capture the characteristics of the vessel more sufficiently, are introduced by [5, 7] for feature extraction. The most recent works [8, 9] detect and identify all types of severe stenoses by analyzing the lumen thickness profile of the vessel.

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In this work, we propose a learning based method to automatically detect three types of plaques (calcified, soft, and mixed). We first extract the coronary vessel branches by the method we proposed [10], which generates the centerline coordinates as well as the lumen thickness information at each centerline coordinate (Section 2.1). Then, the longitudinal views of the vessel branches are created to extract rotation invariant features (Section 2.2). A cylindrical sampling pattern with varying radii, length and position is utilized to extract intensity based features. Moreover, since lesions affect the lumen thickness, the energy of the vessel radius profile, which aids detection of soft plaques [9], is utilized as a geometrical feature. Features are used to train a random forest (RF) classifier [11] with four-classes (no plaque, three plaque types).

2 Methods

Given a CTA image volume, the proposed method can automatically detect all types of coronary stenoses using the following four-step approach: (1) The coronary vessels are extracted around the provided centerline coordinates (LUMC/Medis team (Leiden, Netherlans) [12]) by the "Vessel Tractography" we presented in [10], (2) For each branch, longitudinal vessel volumes are generated to provide rotation invariance, (3) Features depending on the cylinder structure of the vessel are extracted along the centerline of the vessel, (4) Based on the extracted features, a random forest based classifier is utilized to detect the stenosis coordinates along the vessel.

2.1 Vessel Extraction

In our vessel extraction method [10], we view the vessel segmentation problem from a tensor estimation and tractography perspective as in Diffusion Tensor Imaging (DTI). Our original idea involves estimation of a tensor from multiple intensity measurements or potentials that are constructed by a cylindrical model added on top of the 4D curves model of Li and Yezzi [13]. This cylindrical component introduces directionality into the model, thus facilitates a tensor fit to the tubular structure. The estimated anisotropic tensor inside the vessel drives the segmentation analogously to a tractography approach in DTI starting from a seed point used as initialization. In addition, we developed a branch detection and unsupervised branch clustering method, which can automatically locate multiple branchings on complex tree structures. Therefore, starting from a seed point, an entire vessel tree can be captured by our technique, which provides the vessel orientation, its centerline (central lumen line) and its thickness (vessel lumen diameter). The method was tested on the Rotterdam Coronary Artery Centerline Extraction Framework, and it ranks the first among the semi-automatic vessel centerline extraction algorithms (See [14] for more details of the comparison).

In this problem, first, the provided centerline coordinates of the vessels (LUMC/Medis team) [12]) are interpolated to generate denser coordinates, and the radius is estimated for each coordinate. Missing branches are found by the tractography approach by considering the provided points as seeds (See Figure 1).

2.2 Stenoses Detection

After the vessel extraction step, centerline is interpolated to obtain denser coordinates. Then, the longitudinal views of each vessel are formed to extract intensity based rotation

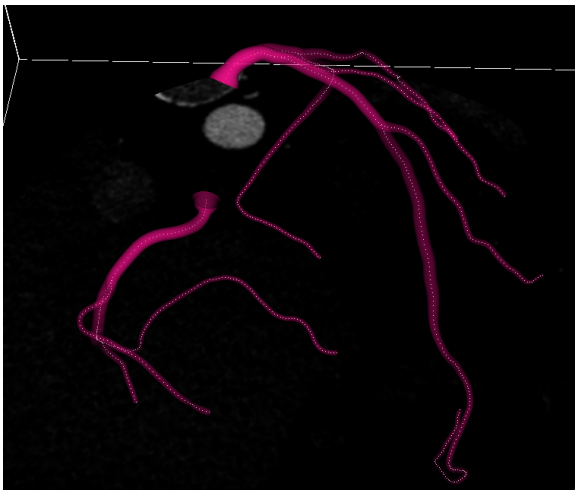


Fig. 1. Extracted coronary vessels from dataset 25.

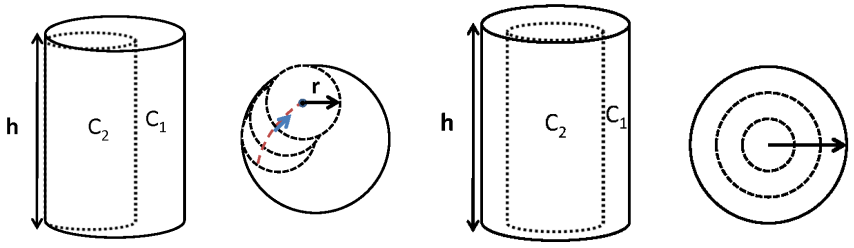
invariant features along the centerline of the vessel. Longitudinal views are created by taking the consecutive image cuts normal to the vessel by considering the thickness of the vessel. Normal vector of the plane is represented by the vessel direction vector ($\boldsymbol{v_3}$) and the image cuts along each centerline coordinate are formed by projecting the original image I to the projected image I_{prj} in a $(r+d)\times(r+d)$ disk region. r represents the vessel lumen radius, d is the necessary padding to ensure to include the pathology surrounding the lumen. Then, longitudinal images are created by taking the envelope of the image cuts. Mathematically, the image cut is expressed as follows:

$$I_{prj}(i,j) = I(\boldsymbol{c}\,(u_{n-1}) + (i - x_c)\boldsymbol{v}_1 + (j - y_c)\boldsymbol{v}_2), \tag{1}$$

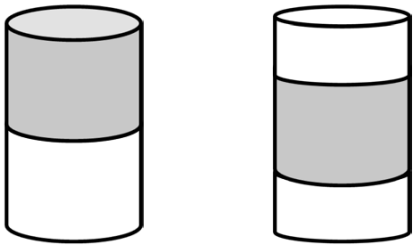
where x_c, y_c are the coordinate centers of the I_{prj}. $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$ are the vectors that orthogonally span the image plane, x_c, y_c are the coordinate centers of the I_{prj}. (See Figure 2 for an example of the longitudinal view of a vessel branch.)

Fig. 2. Longitudinal view of a coronary vessel branch.

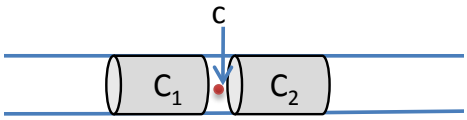
For any supervised learning algorithm to work effectively, the selected features should sufficiently capture the characteristic properties of the underlying classes of the data. Coronary lesions have no specific shape, size or location along the centerline. As the vessels have cylindrical structures, it seems quite reasonable to choose a cylindrical pattern elongated through the vessel with varying center, radius and height. We consider a fixed cylinder C_1 axis aligned along the centerline with the $r+d$ radius and varying height, and also a



(a) C_2 is stucked on the boundary of the C_1. (b) C_2 is alongated through the centerline.



(c)



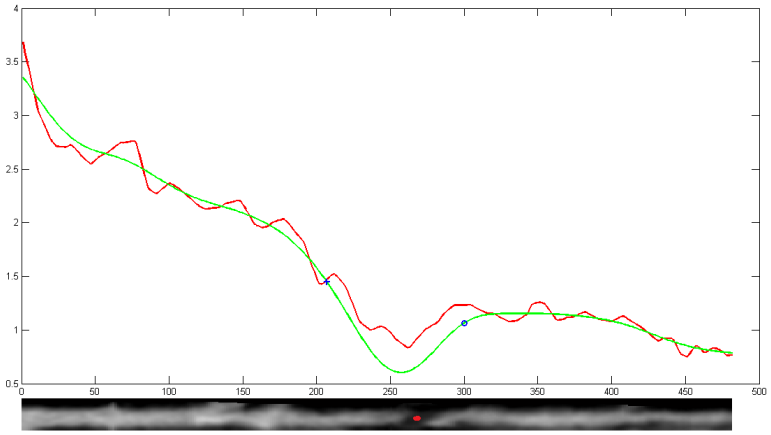
(d)

Fig. 3. (a,b) Illustration of the C_1 and C_2 from the alongated and top view; (c) Haar-like patterns; (d) Illustration of the cylindrical gradient.

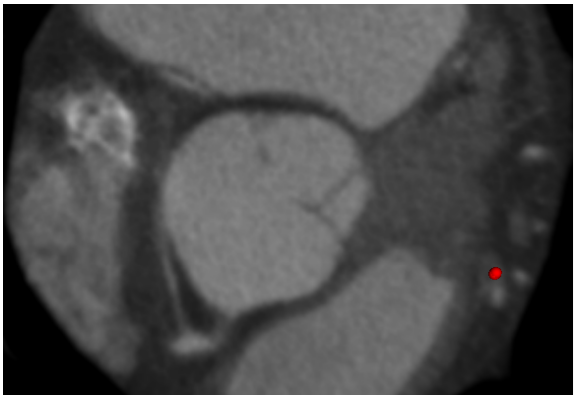
rotating cylinder, C_2, around the vessel direction, inside C_1, with varying radii, height (h) and center (c) (See Figures 3(a) and 3(b) for the possible cylindrical patterns). Although a similar sampling pattern was also used in [5, 7], Mittal et al. [5] only considered the calcified lesions. Tessmann et al. [7] proposed a multi-scale cylindrical pattern, where they extracted sample positions on a cylinder for feature extraction, whereas, in our method, we extract the region-based features. Experimentally, the height range is selected between $3 \leq h \leq 11$, and radii are chosen as $R/2$ and R. The differences of the average intensity regions, $C_1 - C_2$ and C_2, are calculated as features. As shown in Figure 3(c), the differences of the sum of intensities between the gray and white regions are also calculated as features. These features behave as Haar-like features, which are the most well-known features in Object Recognition [15]. However, the features from the cylindrical patterns rather than rectangular patterns in original Haar filters, capture the structure of the vessels more sufficiently.

We calculate the cylindrical gradient at a centerline coordinate (c) as our second type intensity based feature. The cylindrical gradient is calculated by taking the central difference of the average of intensities inside the cylinders (C_1 and C_2) with same height and radius. (See Figure 3(d) for the illustration).

We also analyze the estimated radius profile to detect possible stenosis regions on arteries as in [9]. In order to locate stenotic regions, first, the estimated radius curve is smoothed by Gaussian filtering. Then, we look at the energy profile of the derivative of the radius curve to detect the start and end points of the stenosis. In the last step, each centerline coordinate is binary labeled (stenotic and non-stenotic), and the binary label is used as another stenosis feature. An example for the geometric features are shown in Figure 4.



(a) At the top plot, Red: Original Radii Profile, Green: Smoothed Radii Profile, The valley between blue (+,o) pairs: Stenotic region. At the bottom figure, longitudinal view of the corresponding coronary branch is depicted, stenotic region is shown by red.



(b) Estimated stenosis is depicted by red on the CTA volume.

Fig. 4. An example for the geometric features.

3 Results

In total, 163 features are extracted, and classified using the Random Forests algorithm. The random forests classifier [11] is an ensemble of many decision trees. It outputs the class that is the mode of the classes' output by the individual trees. Each individual decision tree in the forest is grown by picking 17 input variables at random out of the total 163. A total of 250 trees are grown.

We evaluated our method on the Rotterdam Coronary Artery Stenoses Detection and Quantification Evaluation Framework. The framework includes 18 training and 24 testing datasets, where the training datasets include the annotated stenotic coordinates. The results on the testing dataset are shown in Table 1 and 2. Table 1 shows the P.P.V. and sensitivity score for each Calcium category CCS. Our average QCA sensitivity score is 0.57%, and CTA sensitivity score is 0.57%. Additionally, we obtained 0.18% QCA P.P.V (Positive Predictive Value) score and 0.32% CTA P.P.V. score. The comparison of our method with the results of observers are tabulated in Table 2. The results on the 42 datasets (training+testing) are shown in Table 3.

Figure 5 shows sample detected stenosis regions by the proposed algorithm (depicted by red lines) over the related CTA cross-section images on the data #28, 36 and 33 from the Rotterdam challenge.

Table 1. Summary of Rotterdam Test Results

Calc. cat.	**QCA Sens. %**	**QCA P.P.V %**	**CTA Sens. %**	**CTA P.P.V. %**
0	0.00	0.00	0.33	0.29
1	1.00	0.17	0.75	0.50
2	0.67	0.31	0.60	0.40
3	0.78	0.21	0.56	0.23
4	0.67	0.25	1.00	0.20
All	**0.57**	**0.18**	**0.57**	**0.32**

Table 2. Comparison of the Testing Results

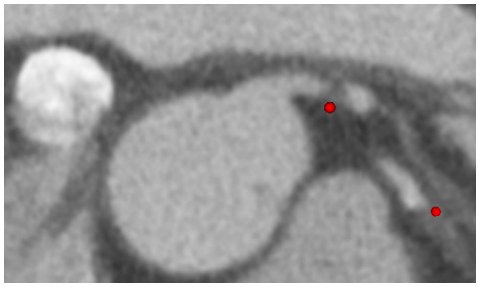
Method	**Cat.**	**QCA Sens.**		**QCA P.P.V**		**CTA Sens.**		**CTA P.P.V.**		**Avg. rank**
		%	**rank**	**%**	**rank**	**%**	**rank**	**%**	**rank**	
Observer1	Min. User	0.88	1.0	0.40	2.2	0.79	1.2	0.58	2.2	1.7
Observer2	Min. User	0.70	2.3	0.49	1.2	0.64	3.1	0.72	1.5	2.0
Observer3	Min. User	0.68	2.6	0.45	2.3	0.68	2.4	0.62	2.1	2.4
Our Method	**Min. User**	**0.57**	**3.1**	**0.18**	**4.2**	**0.57**	**3.7**	**0.32**	**4.0**	**3.8**

4 Conclusion

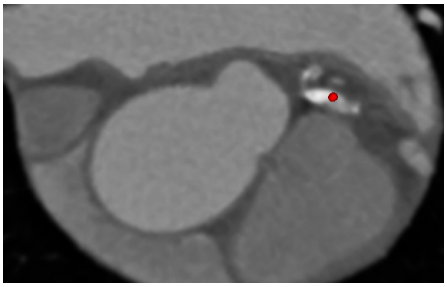
Learning based automatic method for the detection of stenotic lesions in coronary computed tomography angiography is proposed. Suggested cylindrical and geometrical features can capture the characteristics of a vessel. The method is evaluated on the Rotterdam

Table 3. Comparison of the Training+Testing Results

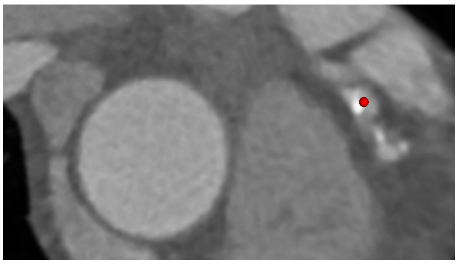
Method	Cat.	QCA Sens.		QCA P.P.V		CTA Sens.		CTA P.P.V.		Avg. rank
		%	rank	%	rank	%	rank	%	rank	
Observer1	Min. User	0.78	1.2	0.42	2.4	0.84	1.1	0.56	2.4	1.8
Observer2	Min. User	0.67	2.0	0.52	1.5	0.69	3.2	0.73	1.5	2.1
Observer3	Min. User	0.54	3.9	0.49	2.0	0.66	3.5	0.64	2.0	2.8
Our Method	**Min. User**	**0.53**	**3.1**	**0.26**	**4.1**	**0.66**	**2.8**	**0.41**	**4.0**	**3.5**



(a) Dataset 28: soft plaque example.



(b) Dataset 36: calcified plaque example.



(c) Dataset 33: mixed plaque example.

Fig. 5. Illustrations of the stenotic regions on sample CTA volumes.

Coronary Artery Stenoses Detection and Quantification Evaluation Framework. On the 24 testing datasets, a sensitivity of 57% and a PPV of 18% is achieved as compared to QCA, while a sensitivity of 57% and a PPV of 32% is achieved as compared to CTA. This clearly indicates that our method is good at ruling out disease (low false negative detection value), but has limited performance to detect significant stenoses ($> 50\%$ luminal diameter reduction; high false positive rate).

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