

# Automatic Coronary Arteries Stenoses Detection in 3D CT angiography

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**Abstract.** Cardiovascular lesions are the world's leading cause of mortality. Early detection of these diseases using less invasive techniques provides better therapeutic outcome, as well as reduces costs and risks, compared to an interventionist approach. In this work we propose a two-step severe cardiac stenoses detection approach. First we used the geometric model of the stenosis to detect suspicious areas and then we applied a false positives (FPs) removal step, based on lesions appearance properties. The algorithm was tested, in the context of the MICCAI challenge, on a 42 3D cardiac CT angiography database provided by the organizers. For the detection, a sensitivity of 47% and a PPV of 14% is obtained as compared to QCA, while a sensitivity of 35% and a PPV of 8% is achieved as compared to CTA.

**Keywords:** CT angiography, Coronary arteries diseases, Stenosis detection

## 1 Introduction

Cardiovascular diseases (CVD) are the world's deadliest, claiming 17.1 million lives annually<sup>3</sup>. As a result of a built up of fatty materials on the inner vessel wall, *atheromatous plaque* is formed. Consequently, growth of the atheroma inward the vessel leads to a gradual narrowing of the lumen (*Stenosis*). This causes flow limitation or potentially a total occlusion of the vessel. Early detection of such lesions with a reliable localisation and quantification of the stenosis severity is very important to evaluate the related risk for the patient. Conventional invasive angiography has been the standard routine for vessel investigation and lesion detection. However, its invasive nature leads to a high risk for the patient's health and a related important cost for the intervention, specially when the patient shows some symptoms but doesn't exhibit a high likelihood for coronary stenosis. Recent studies [1] showed that X-ray computed tomography (CT) may be used as an alternative to accurately locate and grade heart lesions in a non invasive way. The reader may refer to [2] for a review of several clinical studies comparing

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<sup>3</sup> Source: The World Health Organisation

the performances of cardiac CTA with conventional invasive angiography for coronaries stenosis identification. In fact, cardiac CT has become a standard technique to inspect coronaries and rule out significant lesions. For cardiologists, this represents a valuable tool for diagnosis and necessary intervention planning with minimal related risk and costs.

However, analysis of cardiac CT exam for coronaries lesions inspection remains a tedious and time consuming task, as it is based on the manual analysis of the vessel cross sections. High accuracy is required, and thus only highly experienced clinicians are able to analyse and interpret the data for diagnosis. Consequently, conventional invasive angiography is still the standard procedure for CVD diagnosis. Computerized tools are critical to reduce processing time and ensure quality of diagnostics. An automatic coronaries analysis tool would help in non-invasive CT angiography examination, allowing pathologists to efficiently diagnose and evaluate risks associated with CVDs, and to raise the quality of the assessment from a qualitative level to a quantitative level.

## 2 State of the Art

Several recent research works have been devoted to the development of clinical diagnosis and follow-up tools based on medical images processing. Those dedicated to cardiovascular lesion detection have mainly focused on detecting and grading calcified plaques. In fact, in CT angiography this type of lesions can be easily highlighted as small bright regions inside the vessel [3]. Wesarg *et al.* presented an approach for automatically detecting calcified regions that combines diameter information and gray value analysis [4]. Toumoulin *et al.* presented a level set based approach to refine the delineation of the vascular inner wall and the calcified contours for quantification purposes [5]. In [6], a rotation invariant sampling pattern was designed to extract calcified lesion on coronaries. Trained classifiers were also used to distinguish calcified lesions among other lesion candidates in non contrasted CT angiography [7, 8].

These previous works have not been designed to identify fibrous (soft) plaque. Indeed, soft plaque is harder to characterise with high confidence and has been mainly detected by inspecting the difference volume between the vessel lumen and the vascular wall. Renard *et al.* [9] proposed a method to automatically detect soft plaques using contours models and vessel diameter estimation. In [10], the authors used a shape-based segmentation approach to extract the inner and outer vessel surfaces and then analyse the deviation between the two volumes. The method may need additional user interaction to accurately compute plaque volumes.

To the authors' knowledge, few published works aim at automatically localizing, classifying and grading all plaque types with high confidence. Because of their different nature, it is hard to find a single method allowing the characterization of both of lesion types. In [11], a boosting-based classifier is trained using multi-scale features to automatically detect both calcified and non calcified lesions. However, this approach does not quantify the stenosis grade and thus

reports several clinically irrelevant lesions. Recently, Kelm et al. [12] presented a fully automated system that detects, grade and classify severe stenosis based on lumen radii analysis. This approach is highly dependant on the lumen quantification quality. Besides, the overall processing time was not reported.

In this work we propose an algorithm to automatically localize coronary lesions in contrast CT angiography. The total process is divided in three main steps: 1) Automatic centerlines extraction and arteries tree construction. 2) Vessel cross-section area quantification. 3) Lesions identification.

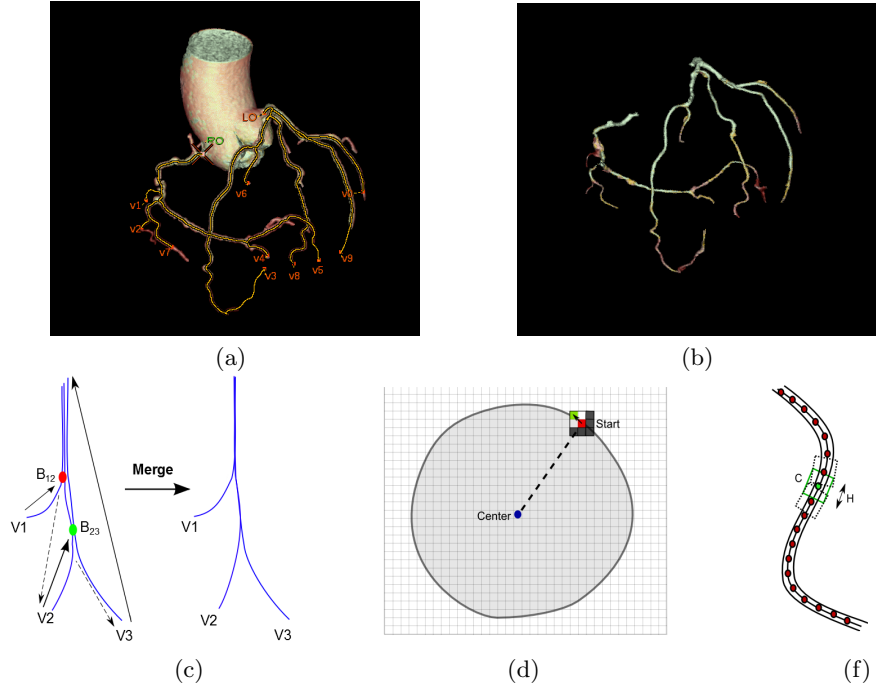
### 3 Artery Coronaries Tree construction

We used the centerlines automatically extracted by the Rcadia Team as input to our algorithm. The details of the extraction scheme are provided in [13]. For each exam we construct the right and left subtree of the coronaries using the provided centerlines. The two ostia are defined respectively as the barycenter of left and right centerlines' starting points. Then we detect all the bifurcation points as the first intersection points of the different centerlines starting from the leafs. An intersection is detected if two centerlines points are separated by a distance lower than a threshold  $T$  (we set  $T$  to 1 mm). Figure 1(c) shows an example of merging three centerlines. Starting from the first vessel ( $V1$ ), we identify the first vessel it intersects ( $V2$ ). Then we check if  $V2$  intersects an other vessel before intersecting  $V1$  (in this case  $V3$ ). We repeat the same process on  $V3$ . Here we see that  $V3$  does not intersect any other vessel, so we start by merging the two vessels  $V2$  and  $V3$  by setting the common segment of the two vessels (above  $B_{23}$ ) to the mean of the two vessels centerlines. Then we merge this resulting segment with  $V1$ . Furthermore, we apply a hamming filter, with a window size of  $w = 5$ , to smooth the centerlines and avoid discontinuity around junctions. Thus, the final coronaries tree is organised in a set of disjoint segments. The whole tree analysis is performed by segment traversing starting from each leaf and stopping if a bifurcation with a longer branch is reached.

### 4 Vessel Wall Quantification

Anatomically a stenosis corresponds to the narrowing of a vessel lumen. Therefore, investigating the inner vessel diameter variation is relevant to detect stenotic region candidates. First, vessel structures are identified using a watershed process based on gray-level gradients and markers proposed in [14]. The centerline points are used as vessel markers to initialise the watershed process. The resulting volume is used as a 3D binary input, yielding the vessel lumen estimation. For each point of the centerline, we compute the vectorial contour of the cross section from the previously segmented object (fig. 1(d)). Finally we derive a subvoxel contour to provide better accuracy and avoid blocky contours at voxel level. The median voxel value, on the previously extracted contour, is used as a threshold density  $d_T$  to compute a sub-pixel iso-densities curve, using linear interpolation between voxel grey values to refine the curves position. Thus for each contour

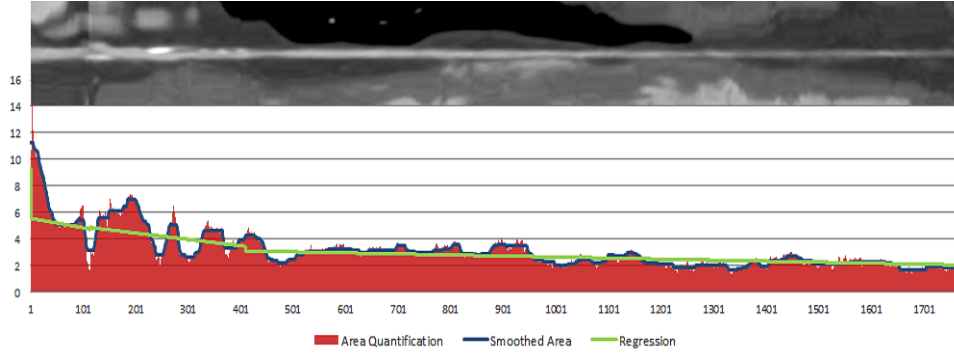
point, with a grey level  $d_c$ , we detect the neighbouring point having a grey value  $d_n$  such as  $d_T$  is lying between  $d_c$  and  $d_n$ . Then a displacement  $u = \frac{d_T - d_c}{d_n - d_c}$  is computed to refine the contour point. Once the vessel lumen quantification is processed, the section area is measured. To improve robustness against erroneous section quantification, we slide a 3D box of height  $H$  (typically 10 voxels) along the centerline and we set the active vessel section area to the median value of all the sections included inside the box (fig. 1(c)). Figure 2 shows an example of obtained profiles.



**Fig. 1.** Coronary tree construction and Vessel lumen Quantification: (a) Resulting coronary tree for the dataset 09. (b) Lumen volume form the watershed process. (c) Merging example of 3 centerlines. (d) Lumen contour extraction: For each vessel cross section a 2D ray casting is used to find the starting point of the section contour, i.e. the first point outside the watershed volume. Then, we look for the next contour point in a restricted neighbourhood of the current point. The process stops when the starting point is reached for the second time. (e) Vessel Area quantification: for each center point the correspondent section area is set to the median value of all the section area inside the box of height  $H$ .

## 5 Stenosis Detection

Stenosis detection is performed in two steps. In the first step, for each segment, we reconstruct a *synthetic* area profile to be used as a “healthy lumen” reference for this segment. To achieve this, we apply robust regression on the segment



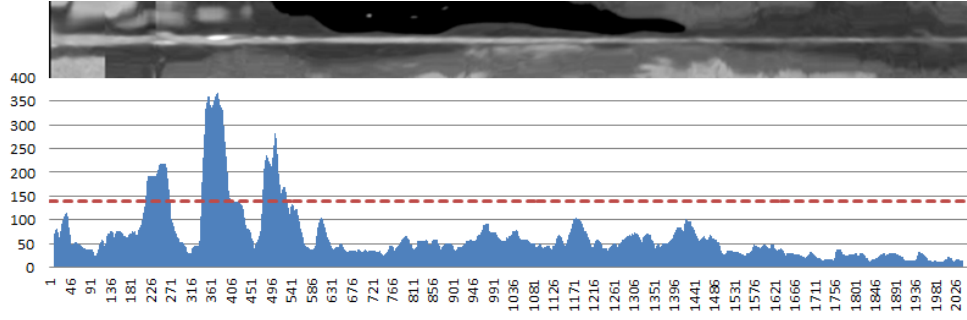
**Fig. 2.** Vessel Area Profile: (Top) Lumen view of a diseased vessel. (Bottom) Original and smoothed vessel area profile per 2D section. The vessel theoretic profile is constructed using a robust linear regression

area profile by removing the outliers from the set of the observed data before the regression step. Then for each center point we compare the real section area to the synthetic/expected value and we mark the point if it falls outside a fixed range around the expected value. The width of this range depends on the severity of the stenosis we want to rule out. For this work, we extract all points presenting a deviation higher than  $S = 50\%$  of the expected value. Once we have computed this first set of stenotic area, we propagate the flagged points to extract the whole lesion area by detecting the start and end point of the lesions. Those extremity points are detected if the real value crosses the expected value. The center of the stenosis is set to the center of the section with the smallest area. At the end of this first step we have computed a set of stenosis candidates, however likely to contain false positives.

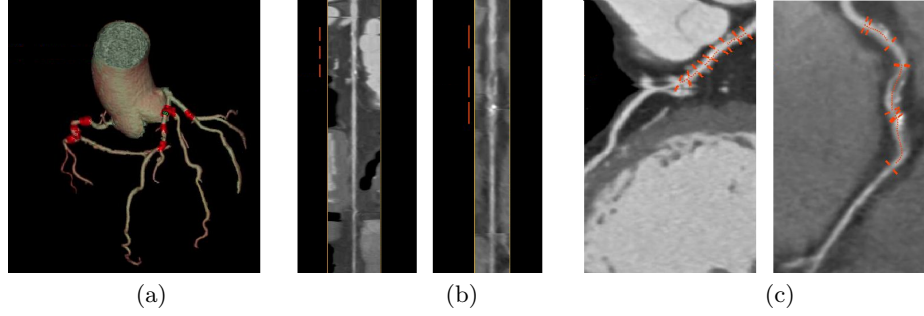
In addition to the analysis of the vessel section area, we propose to use additional vessel statistics in order to improve the accuracy of lesion detection. Indeed, cardiovascular lesions are characterised by their appearance in CT angiography. Thus, for each centerline point and for 10 sections around this point, we dilate the vessel 2D cross section by  $\delta = 3 \text{ voxels}$  and we compute the difference between the maximum ( $max$ ) and minimum ( $min$ ) grey level value inside this local dilated 3D volume. Besides, this variation is weighted based on the distance of each point from the starting point of the corresponding vessel branch. This allows us to avoid considering irrelevant high variations at vessel distal parts (see figure 3). Furthermore, we compute the standard deviation ( $STDev$ ) of the grey level along the whole vessel branch. Then for every flagged lesion in step one, we keep the points such as  $(max - min) > \alpha * STDev$  ( $\alpha = 1.5$ ).

## 6 Evaluation for MICCAI 2012 coronary artery stenosis detection challenge

We have tested our algorithm on the 42 multi-vendor CTA datasets of typical patients provided by the MICCAI Stenosis detection/quantification and lumen



**Fig. 3.** Difference variation between the max and min value along the vessel branch inside the 3D sliding box.



**Fig. 4.** Stenosis detection for dataset 09: (a) 3D rendering of the coronary tree with detected stenosis highlighted in red. (b) Lumen views of the left anterior descending artery and the right artery coronary (c) Curved view of the left anterior artery and the right. Detected stenotic areas are marked in between two red segments. For each lesion the minimum area section is also reported.

segmentation challenge. The database is composed of 18 training datasets, with QCA and CTA reference standards, and 24 other testing datasets. The mean overall processing time of our method is 1 minute, including the lesion detection process that takes 10 seconds on a 4-core Intel(R) Xeon(R) CPU 5160 at 3.00GHz computer, with 4.00 GB (RAM).

Method	Cat.	QCA Sens.		QCA P.P.V.		CTA Sens.		CTA P.P.V.		Avg. rank
		%	rank	%	rank	%	rank	%	rank	
<b>A3SI_148</b>	Automatic	0.47	3.6	0.11	4.0	0.34	3.8	0.10	4.0	3.9
<b>Observer1</b>	Min.User	0.88	1.0	0.40	2.2	0.79	1.2	0.58	2.2	1.7
<b>Observer2</b>	Min.User	0.70	2.0	0.49	1.2	0.64	2.3	0.72	1.5	1.8
<b>Observer3</b>	Min.User	0.68	2.0	0.45	2.3	0.68	2.0	0.62	2.1	2.1

**Fig. 5.** Our Method vs Observers

Algorithm Step	QCA Sensitivity	QCA P.P.V	CTA Sensitivity	CTA P.P.V
Fisrt Step	0.56	0.12	0.38	0.05
Second Step	0.48	0.17	0.40	0.08

**Table 1.** Evaluation of the first and second step results on the training datasets

The evaluation is performed compared to the CTA and QCA references separately. The metrics considered are the sensitivity, which assesses the proportion of actual severe stenoses which are correctly identified, and the PPV, corresponding to the proportion of positive detection results that are true positives (TPs). Table 1 shows the evaluation results for the training dataset after each step of the stenoses detection algorithm. For the first step, we obtained a sensitivity of 56% as compared to QCA references and 38% as compared to CTA. However the obtained PPV for the CTA and QCA based evaluation was of 5% and 12% respectively. Those scores are related to the high amount of FPs reported by our section area analysis (i.e. first step). With the two steps detection approach, we were able to reduce the amount of the FP from 228 to 143 overall the training database which allows for better PPVs (8% compared to CTA and 17% w.r.t QCA).

Fig. 5 shows the obtained results for the testing database: the sensitivity is 47% compared to QCA references and 34% compared to CTA. These low scores are due to our vessel section area quantification step. In fact, we have noticed that the contours were erroneous for some lesions which lead to a false negative (FN) detection of the related stenosis. This is explained by the fact that for some cases the centerline was not really centred inside the vessel lumen, which biases the watershed final result. A more robust contour extraction approach should improve the detection accuracy. The PPV is of 11% and 10% per segment and per lesion respectively. This is explained by the number of FPs that are still remaining after the final step. Besides the erroneous detections related to the bad quantification quality or the erroneous centerlines, the FPs amount is also related to the way the TPs/TNs are classified. To evaluate the results, the software sets as FP any lesion we detect with our algorithm that have a reference degree lower than 50%. In fact, on the training dataset, the amount of the FPs per lesion moves from 143 to 96 per lesion and from 62 to 48 per segment if we remove this threshold of 50% for the lesion TP/TN classification (i.e. if we consider all the lesions reported in the reference standard).

## 7 Conclusion and Future Work

In this work we presented a fully automatic algorithm to rule out stenotic area in coronary arteries using 3D cardiac CT angiography. The algorithm allows for a coherent detection of diseased segments and severe stenoses. Thus it could be used as a first reader to indicate segments with high likelihood of severe stenosis. As future work, we will concentrate on improving the lumen delineation step in order to improve the lesion detection accuracy by using an approach to separately quantify the vessel lumen and outer wall. This should allow for a better detection of stenotic area as an important volume lying between the inner and the outer

vessel wall. Moreover, we would like to work on the stenosis grade quantification to improve the quality of the information provided to the clinician.

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