

A novel methodology for detection of lumen, outer wall, plaques and stent struts in coronary arteries using optical coherence tomography.

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Abstract—In this work, we present a novel and accurate methodology for the segmentation of optical coherence tomography imaging (OCT) and detection of lumen and outer wall, plaque characterization and stent struts in stented arteries. In particular, the methodology starts with pre-processing and detection of the catheter artefact. Struts detection is based on the identification of the size of the shadow behind the struts. Our methodology can be applied to metal stents as well as to polymeric and bioresorbable vascular scaffold (BVS) stents. Lumen segmentation is based on Fuzzy clustering and Fast marching on the gradient image to find the shortest path. The outer wall is segmented using a methodology, which combines K-means and 3-dimensional (3D) surface fitting on the detected edges. K-means with 3 clusters is performed at the final step on the ROI between the lumen and outer border of adventitia to characterize the plaque type. The validation is achieved by comparing the algorithm's results with manual annotations provided by experts. The results demonstrate that our methodology is accurate in lumen ($R=0.99$) and outer wall segmentation ($R=0.77$) and struts detection ($R=0.82$). The average Hausdorff distance and the Dice Similarity for lumen segmentation is 0.097 mm and 0.96, respectively.

Keywords—OCT images, lumen segmentation, K-means, struts detection, plaque characterization.

I. INTRODUCTION

Coronary artery disease (CAD) still remains one of the most significant causes of death in developed countries [1]. The main phenotype of CAD is the thickening of the arterial wall and the subsequent lumen narrowing which causes the reduction of blood flow. Final stages of the atherosclerotic process are related with thrombus creation, myocardial infarction and death. At these cases or in the case of the patient having symptoms, catheterization is required for the patient especially for assessing the severity of the disease using x-ray angiography and potentially one endovascular imaging, such as intravascular ultrasound or optical coherence tomography (OCT). OCT is a light-based modality with resolution of 1 to 15 μm able to assess the lumen border, the plaque type, the stent struts and potentially the outer wall [2].

The main treatment strategy of severe stenosis is to perform percutaneous coronary intervention (PCI). In such case, a catheter is used for the positioning of an endovascular implant e.g. stent at the region of stenosis to restore the lumen diameter. Several types of stents are currently available in clinical practice, such as metallic stents, drug eluting stents and more recently bioresorbable vascular scaffolds (BVS).

The last years, several studies have been performed for OCT analysis and especially for struts detection. Wang *et al.* presented a machine learning approach to detect the stent struts and determine the depths of all struts using graph cut in OCT images [3]. This automated method achieved 0.91 recall and 0.84 precision. Another automatic method for the detection and assessment of struts apposition in OCT images was presented classifying the struts in 3 categories (covered, uncovered, malapposed) [4]. A four step algorithm was recently developed for preprocessing, lumen border detection, stent strut detection and 3D point cloud creation [5].

Zhou *et al.* performed automatic detection of plaques and classification of features based on textural features with accuracy over 80% [6]. A deep learning method was implemented by Gessert *et al.* that detected calcified, fibrous and lipid plaques with an overall accuracy 91.7%, sensitivity 90.9%, specificity 92.4% [7]. Finally, automatic characterization of the wall area using Convolutional NN was achieved by Athanasiou *et al.* to classify calcified, lipid tissue, fibrous tissue and mixed plaque with an overall accuracy 96% [8].

OCT automatic analysis has several challenges, which need to be overcome for the accurate detection of borders and plaque characterization: (i) the presence of catheter and blood artefacts typically interfere with segmentation results, (ii) the lumen and adventitia are typically over/under estimated in regions with shadow, (iii) high attenuation of the OCT signal in the media layer causes the adventitia border to not always be visible, especially in regions with plaque concentration, and, (iv) difficulty in discriminating between lipid and fibrous types of plaques. In this work, we present a novel and

validated methodology for the segmentation of OCT images and detection of struts. Preliminary results of plaque characterization are also presented.

II. MATERIALS AND METHODS

We developed a novel methodology for the arterial segmentation and characterization of various types of plaques from OCT images. The process involves the following steps.

A. Pre-processing

The OCT pullback frames in cartesian coordinates are firstly converted to polar space. Then, the polar frames are passed through a bilateral filter to remove noise and blood artefacts from each frame [9].

B. Catheter artefact removal

To define the catheter artefact, the shadow regions on each polar frame are detected. However, the presence of shadows might be either due to the catheter or due to the existence of struts. Therefore, the candidate catheter pixels on each frame are stacked next to each other and the pixels corresponding to the catheter form a continuous path along the whole pullback. These pixels are then removed from each frame for the next steps of the process [10].

C. Strut detection

As described in step B, the slope and the size of the shadows on each polar frame are used as detection criteria for metallic struts. For the detection of BVS struts, a binary threshold of each polar frame is firstly obtained, and then the areas that transit from class 1 to class 0 and then to class 1 within a specified distance are extracted [11]. These areas correspond to BVS struts. An example of the strut and catheter detection of a stented artery is shown in Figure 1.

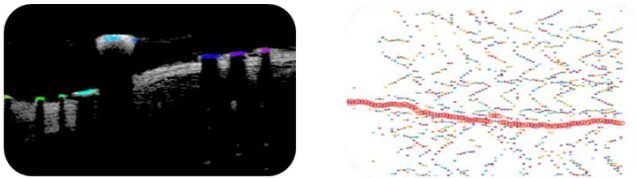


Fig. 1. Strut detection in a stented artery.

D. Lumen border detection

Each polar frame is clustered using a fuzzy clustering scheme (Fuzzy c-means). Then, by combining the gradient of the polar frame and the clustering information, the fast marching algorithm is used to find the shortest path from the left to the right edge of the frame. This path corresponds to the lumen border and is converted to cartesian coordinates.

E. Outer border of Adventitia detection

Each polar frame is convolved with a specially designed kernel to enhance the light-dark-light edges. Then, K-means clustering is performed to find the visible parts of the detected edges. Next, a 3D surface is fitted around the detected edges of each frame of the pullback to interpolate the missing information on the areas where the outer border is not visible [12]. The borders are finally converted to cartesian coordinates and are used to initialize an active contours model to extract the final outer border of the adventitia tissue.

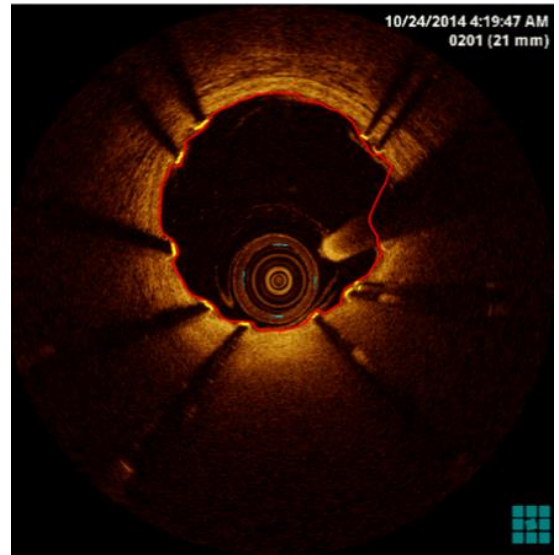


Fig. 2. Lumen and struts detection results. Red: detected lumen border. Yellow: detected struts

F. Calcified plaques segmentation and non-calcified plaques characterization

3 cluster K-Means is performed on the ROI between the lumen and outer border of adventitia. Then, closed shapes enclosed by the cluster representing Media are detected and hysteresis thresholding is performed to enhance the outer border of the calcific tissue [13]. Finally, a series of morphological operations to clear out noise and enhance calcifications are performed. Regarding the characterization of non-calcified types of plaques, K-means clustering is used to group the rest of the pixels of the ROI into 3 clusters: Lipid Tissue, the Fibrous Tissue and Mixed Tissue [14]. In OCT images, Lipid Tissue is represented by dark homogeneous regions with high attenuation, Fibrous Tissue is represented by bright homogeneous regions with low attenuation and the rest of the pixels are the Mixed Tissue.

G. Validation strategy

Fig. 3 Validation dataset for our methodology.

For the validation of lumen and outer wall borders we have used **xxxx** manually annotated by experts frames from ten human patients (**xxxxxxxx**). Dice coefficient and Hausdorff distance are the validation metrics, while the correlation was also examined using regression analysis and Bland-Altman plots.

The validation of the strut detection was based on 280 OCT frames acquired from stented arteries with different stent types (eight different models of stents). Comparison was made again with manual annotations and we have calculated the sensitivity of the methodology, the positive predictive value and the F1 score.

III. RESULTS

Validation of our methodology for the lumen area and diameter presents very satisfactory results. The Hausdorff distance is 0.0698 mm and the Dice coefficient **xxxx**. The correlation coefficient for lumen area is **xxxx**, while for lumen diameter is also **xxxx**.

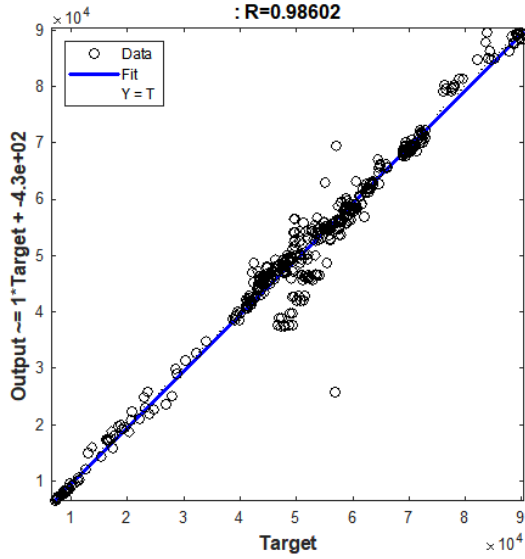


Fig. 4. Regression plot of manually annotated lumen area with algorithm's results.

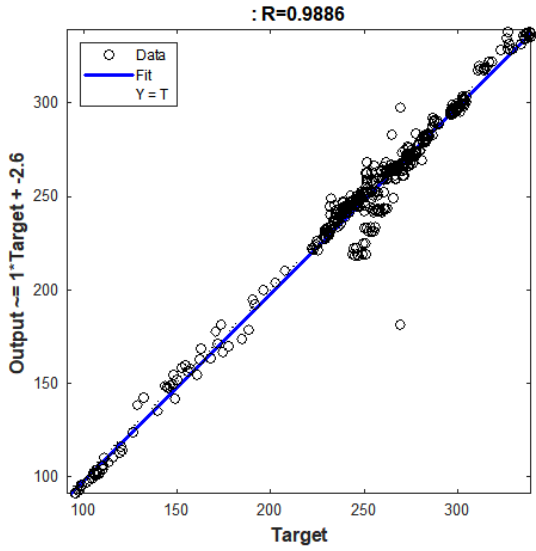


Fig. 5. Regression plot of manually annotated lumen diameter with algorithm's results.

Regarding the detection of the outer border of adventitia, the correlation coefficient between the detected and annotated adventitia areas is 0.77, while for the diameter it is 0.78. From the regression plots in Fig. 6 and Fig. 7, it can be determined that the algorithm overestimates the stenotic areas of the vessel where the outer border of the adventitia is not visible due to the presence of plaques.

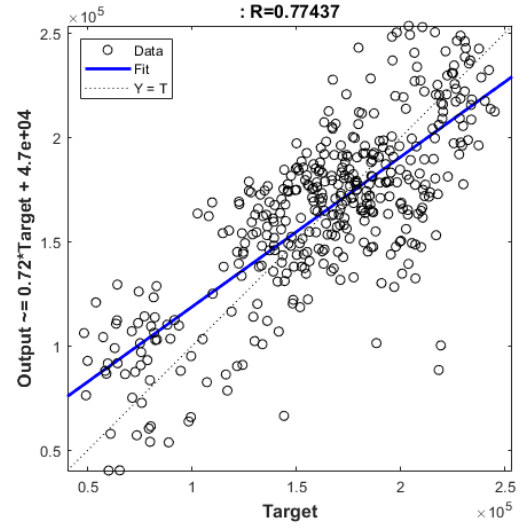


Fig. 6. Regression plot of manually annotated adventitia area with algorithm's results.

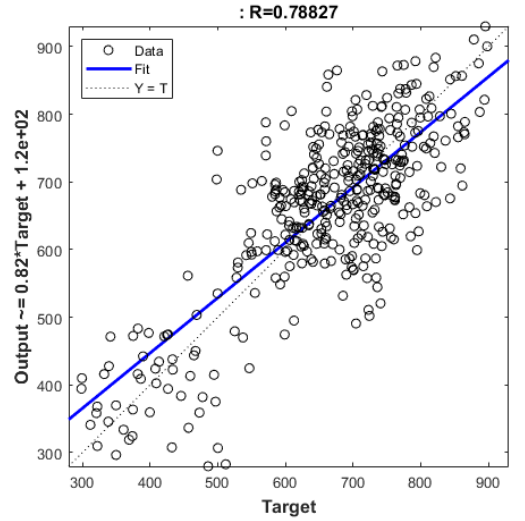


Fig. 7. Regression plot of manually annotated adventitia diameter with algorithm's results.

Fig. 8 presents the detected struts in 3D space. This is also visualized in Fig. 9 on top of the 3D reconstructed lumen surface using the lumen segmentation methodology presented earlier.

The regression coefficient (R) between the manual annotations and the automatic detection of the stent struts using the proposed methodology is 0.82, as shown in Fig. . Finally, Table I presents the sensitivity, positive predictive value and F1 score for the strut detection comparing our developed methodology with the provided manual annotations.

TABLE I. VALIDATION RESULTS FOR STRUTS DETECTION.

<i>Metric</i>	<i>Type</i>	<i>Result</i>
Recall/Sensitivity	TP / (TP + FN)	xxxx
Precision/PPV	TP / (TP + FP)	xxx
F1 Score		xxx

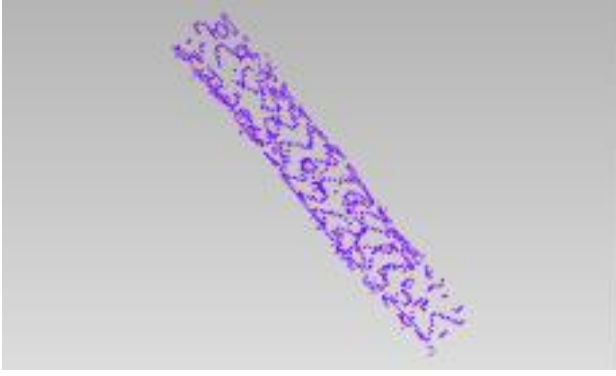


Fig. 8. Case example of detected struts from OCT pullback.

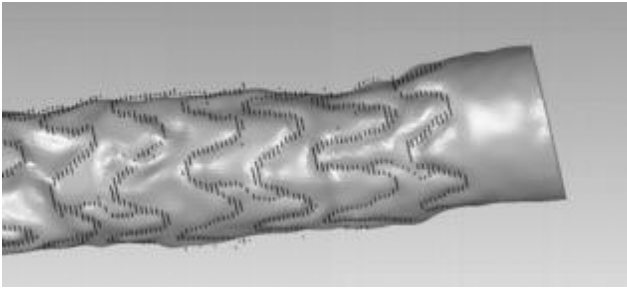


Fig. 9. Detected struts positioned on the 3D arterial lumen.

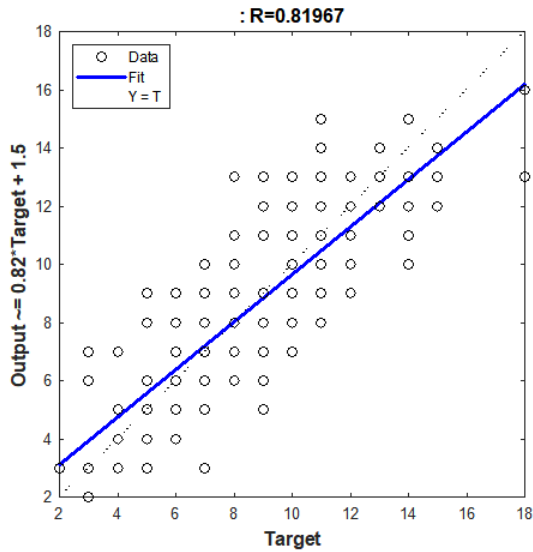


Fig. 10. Regression plot between the manually annotated struts with the proposed methodology.

Preliminary results of plaque detection are also in very good agreement with the manual annotation as it is shown in Fig. 61. In particular, two annotated frames with calcified plaques and the respective identified borders of the same plaque by the algorithm are presented. Calcifications identified by an expert are depicted with the white border while the algorithm results are shown in magenta. Validation of the plaque characterization algorithm will be presented in a future work.

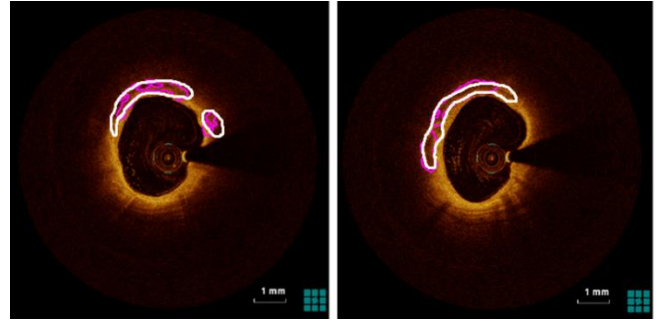


Fig. 61. Comparison of manual annotation for calcified plaque detection and automatic segmentation.

IV. DISCUSSION

In this work, we implemented a novel methodology for the OCT assessment and specifically, for the segmentation of the lumen and outer wall borders, the detection of struts in case of stented pullbacks and the plaque characterization. Validation of the implemented algorithms is achieved using manual annotations from expert observers. Lumen detection has 0.99 correlation with the manual annotation, while the outer border of adventitia has 0.77 correlation with the experts' annotations. The PPV value to detect the struts of the stent is 0.78, meaning that most struts are correctly identified by our algorithm.

The abovementioned algorithms have been implemented as a tool and the analysis takes about 15-20 minutes to extract lumen, adventitia and struts point clouds depending on pullback size. Plaque characterization takes ca. 1 – 1.5 second per frame. Additionally, quantitative measures are extracted for vessel evaluation e.g. plaque burden, vessel length, cross-sectional area and perimeter. Quantitative stent evaluation measures are also extracted such as: overall number of struts, strut width, stented segment length, number of malapposed struts.

The main novelty of our methodology is that it provides fully automated segmentation of the arterial lumen, struts (both BVS and metallic), outer adventitia border and plaque characterization. Validation was achieved using manual annotations from human patients, having data from different time periods (pre- and post- stenting, and follow up examination). Moreover, we validated the strut detection algorithm on 8 different types of BVS stents. This is important because the struts of the various stents have usually different representation on the OCT frames and using our methodology the struts can be identified providing the opportunity to assess the result of the stent deployment in terms of malapposition independently of the type of stent.

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