A New Computer-Aided Solution for the Automatic Detection of Metal Stent Struts in Follow-up Evaluation in OCT Images

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Abstract

Stent implantation is commonly used in the treatment of coronary artery disease. To optimize the results of the procedure, it is crucial to evaluate the stent immediately after its implantation, as well as to later monitor the coverage of the stent by the neointima. One of the modalities used for this purpose is intravascular optical coherence tomography (IVOCT). Identification and assessment of stent struts in IVOCT images is a common procedure in clinical practice, however, manual analysis is laborious and time-consuming. Therefore, automated algorithms for stent segmentation have been developed in recent years, but these mainly concern stents without thick tissue coverage. This study proposes a new computer-aided method for automatic detection of both covered and uncovered metal stent struts in OCT images. In general, the algorithm involves segmenting potential stent strut shadows, analyzing the distribution of pixel intensities in detected areas, and classifying objects.

The algorithm has been validated on 606 cross-sections chosen randomly from 34 cases containing pullbacks: at baseline and at a 3-36-month follow-up. Thus, the presented algorithm achieves sensitivity of 88% and precision of 90% including in-stent restenosis cases.

1. Introduction

1.1. Background and clinical importance

Percutaneous coronary intervention (PCI) with stent implantation is the most common procedure for treating coronary artery disease. A stent is a tiny, expandable metal mesh coil that helps to prevent the artery from narrowing or reclosing. Once the stent is implanted, tissue begins to grow over it as part of the vessel healing process. The stent should be fully lined with tissue within 3 to 12 months, depending on whether it has a drug coating (drug-eluting stents, DES) or not (base metal stents, BMS) [1,2]. After this time, the stent struts should be covered by a well-functioning neoendothelium. Unfortunately, this is not always the case. There are many factors that interfere with the healing process, resulting in late stent thrombosis or in-stent restenosis (ISR).

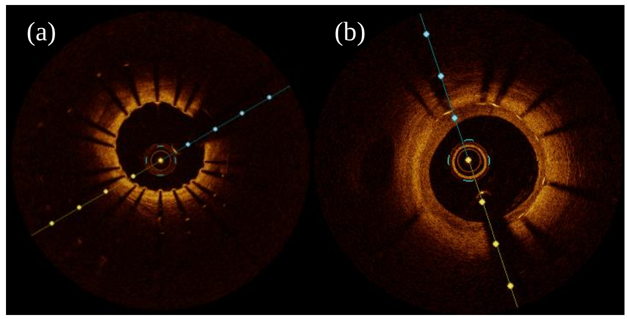

Figure 1. Cross-sections in OCT right after stenting (a) and during the follow-up procedure with visible neointimal hyperplasia (NIH) (b).

Optical coherence tomography (OCT) allows high-resolution assessment of the vessel wall and is particularly useful to assess vessel healing, strut coverage and stent apposition after implantation, as well as in follow-up (Figure 1). It is very important to monitor the behavior of the stent during the healing process. In order to quantitatively assess these aspects, an automated algorithm was developed and applied to detect struts of implanted DES stents.

1.2. State of the art

A pullback of the intravascular OCT image sequence for a single patient usually contains hundreds of cross-sections depicting thousands of stent struts. It is time-consuming to perform a quantitative analysis of every scan manually. Therefore, automated methods for stent assessment have been highly developed over the past two decades. To date, several different strategies for stent struts detection have been proposed. Most methods are based on the observation that metal stent struts completely reflect light during the examination and, as a result, are represented in the OCT image as a group of high-intensity pixels followed by an elongated group of low-intensity pixels, called the strut shadow. Hence, for most articles, the analysis involves looking for areas of characteristic high intensity (struts) or low intensity (shadows).

IVOCT image analysis is usually performed on two-dimensional cross sections of the vessel in polar or Cartesian coordinates. Stent struts segmentation algorithms described in the literature usually follow a scheme consisting of three main steps:

1. Determination of 'candidates', that is, areas of potential stent struts location.
2. Feature extraction.
3. Classification of candidates from step 1. based on parameters determined in step 2. into actual stent struts locations and incorrectly segmented areas.

Basing on the above scheme, different methods can be distinguished as it is possible to perform these steps in different ways. The initial selection of potential locations of the struts is often done by looking for local extremes of intensity or gradient [3-6]. Other methods used at this stage include the continuous wavelet transform [7] or the eigendecomposition of the Hessian matrix [8]. Feature extraction of prespecified areas of interest usually involves determining the statistical parameters of the local intensity or gradient or analyzing the location of struts on previous cross sections. The final step, which consists of classifying candidates in terms of the actual occurrence of struts, is usually performed by thresholding or using neural networks, among others [5,7]. However, not all methods proposed in the literature are based on the described pattern. For example, there are some studies in which stent struts were segmented directly by neural networks such as YOLO, R-FCN [9] or other deep convolutional models [10]. Although more than one method has been proposed, there are still unresolved issues in the area under discussion. Most of the described algorithms were unable to deal with struts covered by a thick layer of neointima, and artifacts such as inaccurately diluted blood or vessels with irregular lumen.

The purpose of this study is to demonstrate a new fully automated detection of metal stent struts in the follow-up evaluation.

The paper is organized in five sections as follows: Section 1 presents the motivation of our work and the review of the state of the art in the area of stent struts detection. Section 2 specifies the overview of the implemented algorithm, including OCT image preprocessing, lumen segmentation, and stent struts detection. Section 3 describes the statistical analysis tests performed and their results. Section 4 contains a discussion, and Section 5 closes the paper with conclusions, and it highlights future directions.

2. Materials and methods

2.1. Dataset

For validating the algorithm, 34 IVOCT pullbacks (32 different patients) were used. The data were acquired from the Department of Cardiology and Structural Heart Diseases at the Medical University of Silesia (22 cases) and from the Regional Specialist Hospital in Wroclaw (12 scans) with a commercially available C-7 system using a 0.019-inch ImageWire (LightLab Imaging, Westford, MA). All scans presented a coronary artery fragment with an implanted metal stent. The analyzed dataset contains both pullbacks: at baseline and at a 3-36-month follow-up. The obtained images are of varying quality and contain artifacts, thrombi, bifurcations, in-stent restenosis (ISR) and malapposed struts. The scans were stored in DICOM and AVI format. The proposed algorithm was tested using 606 cross sections randomly selected from all the 34 pullbacks.

2.2. Proposed algorithm

The proposed method for the detection of stent struts is also based on the scheme presented in Section 1.2. The algorithm consists of several major steps: preprocessing, segmentation of the vessel lumen, segmentation of potential stent strut shadows, and candidates analysis and classification. Except for lumen segmentation, which was realized as a macro in the ImageJ software (version 1.53 c), the algorithm was implemented in Python 3.7.

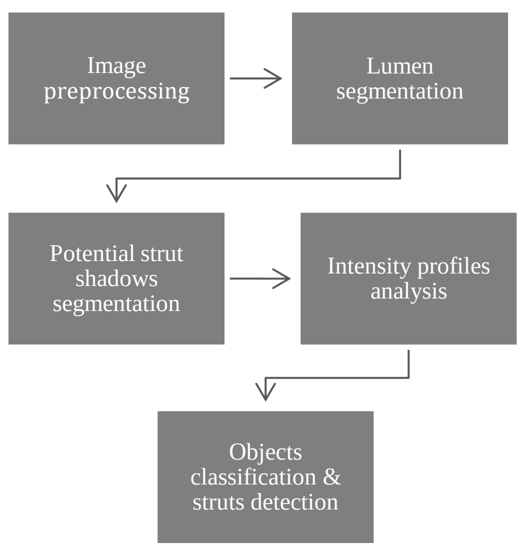

Figure 2. Flowchart of the proposed algorithm.

The purpose of preprocessing is to prepare the image for further analysis, so in this step unnecessary information that could disturb the algorithm is removed. In the case of the proposed method, preprocessing includes cropping the image and removing the probe and markers that come from the OCT data acquisition software. All these operations are performed automatically.

The next step is segmentation of the vessel lumen. For this purpose, an algorithm based on binarization and active contour model was used. This method is described in detail in [11].

The determined vessel lumen boundary is then used to create a ring-shaped mask that covers the vessel wall tissue. The thickness of the mask is adaptively determined based on the distribution of pixel intensity. Then, adaptive thresholding is performed in the red component of the image within the created mask to segment the shadows of the stent struts. To denoise the image and to smooth the objects, a series of morphological operations is performed on the image.

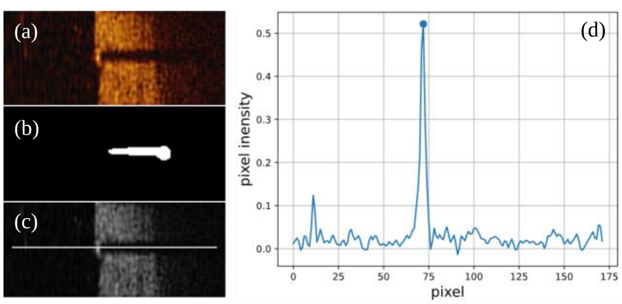

Figure 3. Fragment of the original image in polar coordinates (a), segmentation of the strut shadow (b), and intensity profile passing through the shadow (c, d).

Afterward, the image intensity profiles passing through each object are determined. Every profile is analyzed and, if it meets conditions such as the presence of a peak exceeding a height threshold followed by a clear decrease in intensity, the object is considered a shadow of the stent strut and the peak in the profile is considered a point belonging to this strut (Figure 3).

3. Results

The algorithm was manually evaluated by an expert. The results validation included determination of the number of correctly detected struts (true positive, TP), the number of undetected struts (false negative, FN), and the number of places incorrectly marked as struts (false positive, FP) for each cross section individually. Then, based on the calculated values, sensitivity (S), precision (P), and Dice index were determined according to the following formulas:

$$S = \frac{TP}{TP + FN}$$

$$P = \frac{TP}{TP + FP}$$

$$Dice = \frac{(2 \cdot TP)}{2 \cdot TP \cdot FN \cdot FP}$$

where:

TP - number of true positives.
FP - number of false positives.
FN - number of false negatives.

After calculating the above metrics for each image separately, the median, first (Q1) and third quartile (Q3) values were determined. The final validation results are shown in Table 1.

Table 1. Automatic detection efficiency.

	Median (Q1-Q3)
Dice index	0.87 (0.77-0.94)
Sensitivity	0.88 (0.75-1.00)
Precision	0.90 (0.80-1.00)

4. Discussion

This study showed that the developed algorithm was 88% successful in detecting metal stent struts in OCT pullback taken just after implantation and at long-term follow-up, including cases with thick intimal hyperplasia.

Most studies presented in the literature review obtained results at a comparable or slightly higher level. However, the majority of these articles present the results of the stent analysis immediately after implantation and do not address the proliferation of neointima or ISR, exclude cases with artifacts, or validate their algorithms in a poorly differentiated population.

Although the efficiency of the algorithm can be considered satisfactory, there are still some features of the images or stents that interfere with the detection process. Figure 4 shows some sample stent struts detection results obtained using the proposed method. In addition to examples in which detection was successful, the figure also shows cases in which the measurement was disturbed by residual blood artifacts or by too little contrast between the vessel wall tissue and the shadow. Detection can also be affected by ghost strut (i.e., an artifact in which the strut is multiplied in the shadow region) or, in general, it fails in cases where the strut or its shadow is not visible in the image. However, it should be noted that in such cases even experts have sometimes difficulties with the manual evaluation of the stent.

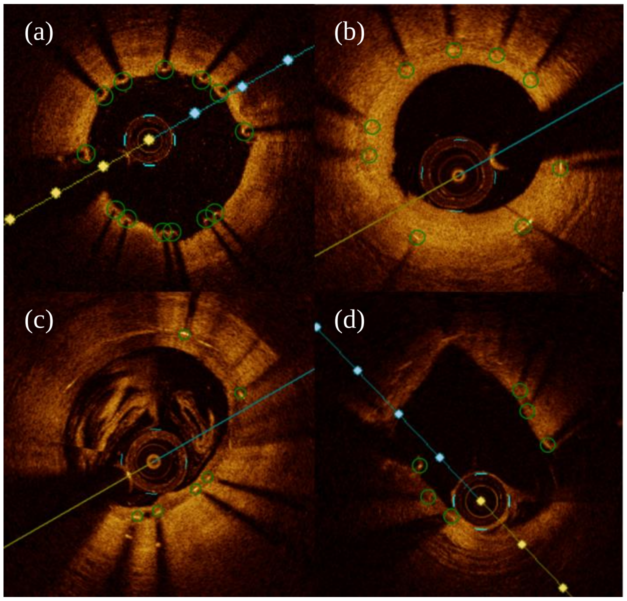

Figure 4. Sample results of stent struts detection by the proposed algorithm. Images (a) and (b) show fully successful detection, whereas in images (c) and (d) the detection was disrupted.

5. Conclusions

The presented algorithm is effective in detecting stent struts in IVOCT scans obtained immediately after implantation, as well as in long-term follow-up, including in-stent restenosis, which is still of interest to interventional cardiologists. This study focuses on DES and DES-ISR, which is more difficult to treat than BMS-ISR due to its different morphology. OCT is useful especially in such cases to investigate the causes of accelerated intimal hyperplasia, which could be, for instance, malapposition, strut rupture. Moreover, it enables to assess the distribution of neoatherosclerosis in the stent.

There have been many recent studies on algorithms to support the quantitative and qualitative analysis of stent healing. However, there is still a need to develop better and more accurate methods to support the diagnostic process, so the next step in the further development of our study will be to refine the algorithm in order to increase its performance in cases that remain challenging.

Acknowledgments

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