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

Stenting 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, and then to later monitor how it becomes covered by the neointima. One modality used for this is intravascular optical coherence tomography (IVOCT). While the identification and assessment of stent struts in IVOCT images is routinely done in clinical practice, manual analysis remains laborious and time-consuming. To address this, automated algorithms for stent segmentation have recently been developed. However, these are mainly used for stents without thick tissue coverage. This study proposes a new computer-aided method to automate the 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 then classifying objects.

The algorithm has been validated on 606 cross-sections chosen randomly from 34 cases containing pullbacks: at baseline and at 3-36-month follow-up. 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 keeps the arterial lumen from narrowing or thrombosing. Once the stent is implanted, endothelial tissue starts to grow over it as part of the natural healing process. The stent is fully enclosed by tissue in 3-12 months, depending on whether it has a coating (drug-eluting stents, DES) or not (base metal stents, BMS) [1,2]. Once complete, stent struts should be covered by a properly-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).

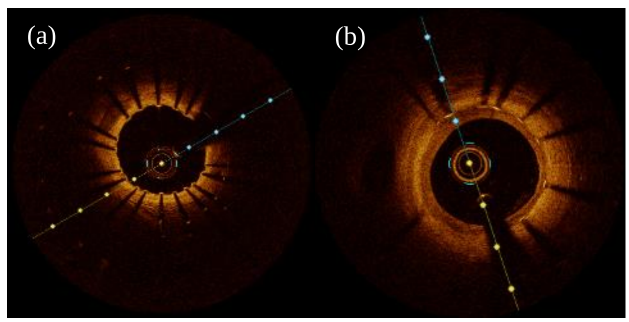

Figure 1. Cross-sections in OCT right after stenting (a) and during the follow-up procedure with visible neointimal hyperplasia (NIH) (b).

Optical coherence tomography (OCT) enables high-resolution visualization of the vessel wall and is particularly useful in assessing vessel healing, strut coverage, and stent apposition following implantation and on follow-up (Figure 1). It is crucial to monitor the behavior of the stent during the healing process. An automated algorithm was therefore developed and applied to quantitatively detect struts of implanted DES.

1.2. State of the art

An 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, various automated methods for stent assessment have been 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

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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 characteristically 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 strut segmentation algorithms described in the literature usually follow a scheme consisting of three main steps:

1. Identify “candidates”, i.e., areas containing a possible stent strut.
2. Extract features.
3. Classify step 1 candidates based on parameters determined in step 2 to accurately distinguish stent struts from incorrectly segmented areas.

Following this scheme, different approaches have been attempted. The initial selection of potential strut locations 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 follow this sequence. 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, artifacts such as inaccurately diluted blood, or vessels with irregular lumen.

The purpose of this study is to showcase a new fully automated method for detecting metal stent struts on follow-up.

The paper is organized in five sections: Section 1 presents the motivation behind our work and a review of the current state of stent strut detection. Section 2 provides an overview of the implemented algorithm, including OCT image preprocessing, lumen segmentation, and stent strut detection. Section 3 describes the statistical analysis performed and its results. Section 4 contains a discussion, and Section 5 closes the paper with a conclusion and highlights regarding 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 in Katowice, Poland (22 cases) and from the Regional Specialist Hospital in Wroclaw, Poland (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 contained pullbacks: at baseline and at 3-36-month follow-up. The obtained images are of varying quality and contain artifacts, thrombi, bifurcations, in-stent restenosis 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 detecting stent struts is likewise based on the scheme presented in Section 1.2. The algorithm consists of several key 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 1.53c), the algorithm was implemented in Python 3.7.

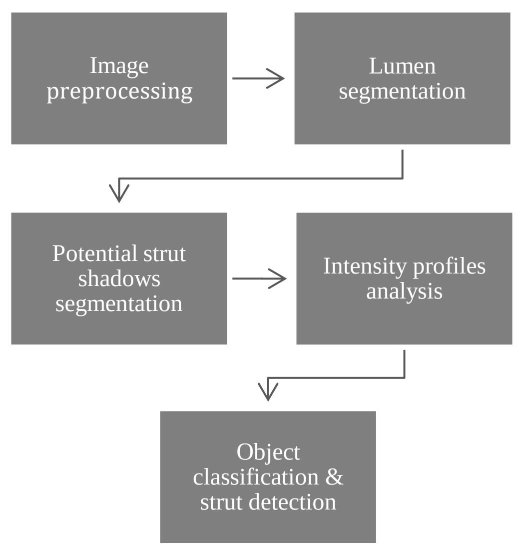

Figure 2. Flowchart of the proposed algorithm.

The purpose of preprocessing is to prepare the image for further analysis, where unnecessary information that may disturb the algorithm is removed. In study, 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 vessel lumen segmentation via an algorithm based on binarization and active contour model. 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.

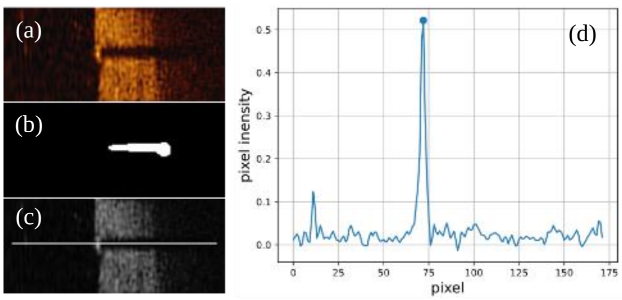

Figure 3. Fragment of the original image in polar coordinates (a), segmentation of the strut shadow (b), and intensity profile passing through the shadow (c, d).

Afterward, the image intensity profiles passing through each object are determined. Every profile is analyzed and, if it meets certain conditions, e.g., a peak exceeding a height threshold followed by a clear decrease in intensity, the object is considered a shadow of a 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 determining 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:

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

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

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

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 demonstrated that the proposed 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 demonstrated similar results. However, the majority of those articles focused on stent analysis immediately after implantation and did not account for the proliferation of neointima or ISR, excluded cases with artifacts, or validated their algorithms on a poorly differentiated population.

Although the efficacy of the algorithm is satisfactory, there are some characteristics to the images that continue to pose a challenge. Figure 4 shows the results of a sample stent strut detection obtained using the proposed method. In addition to points where a strut was successfully detected, there are also cases where 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 a ghost strut. i.e., an artifact where the strut is multiplied in the shadow region. It also 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 difficulties manually evaluating a stent.

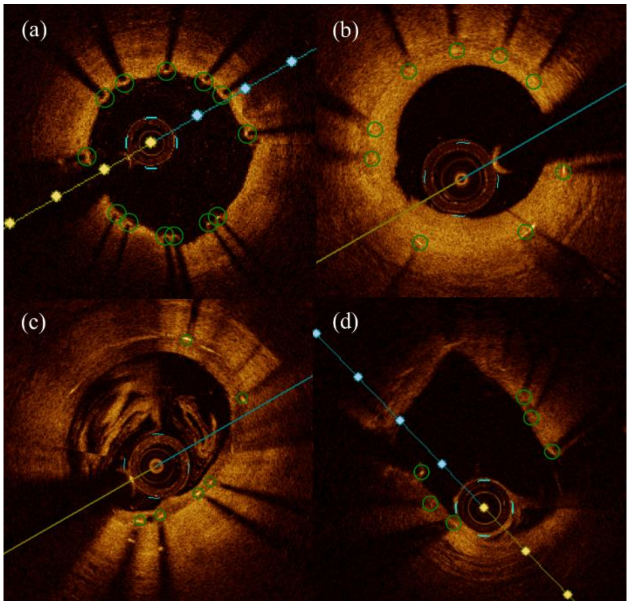

Figure 4. Sample results of stent strut detected by the proposed algorithm. Images (a) and (b) show successful detection, while images (c) and (d) show partially failed detection.

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 especially relevant 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 especially useful in investigating the causes of accelerated intimal hyperplasia, e.g., malapposition or strut rupture. Moreover, it enables the assessment 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. The next step in our study will be to refine the algorithm in order to increase its performance in cases that remain challenging, as described above.

Acknowledgments

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