

ADABOOST-BASED DETECTION AND SEGMENTATION OF BIORESORBABLE VASCULAR SCAFFOLDS STRUTS IN IVOCT IMAGES

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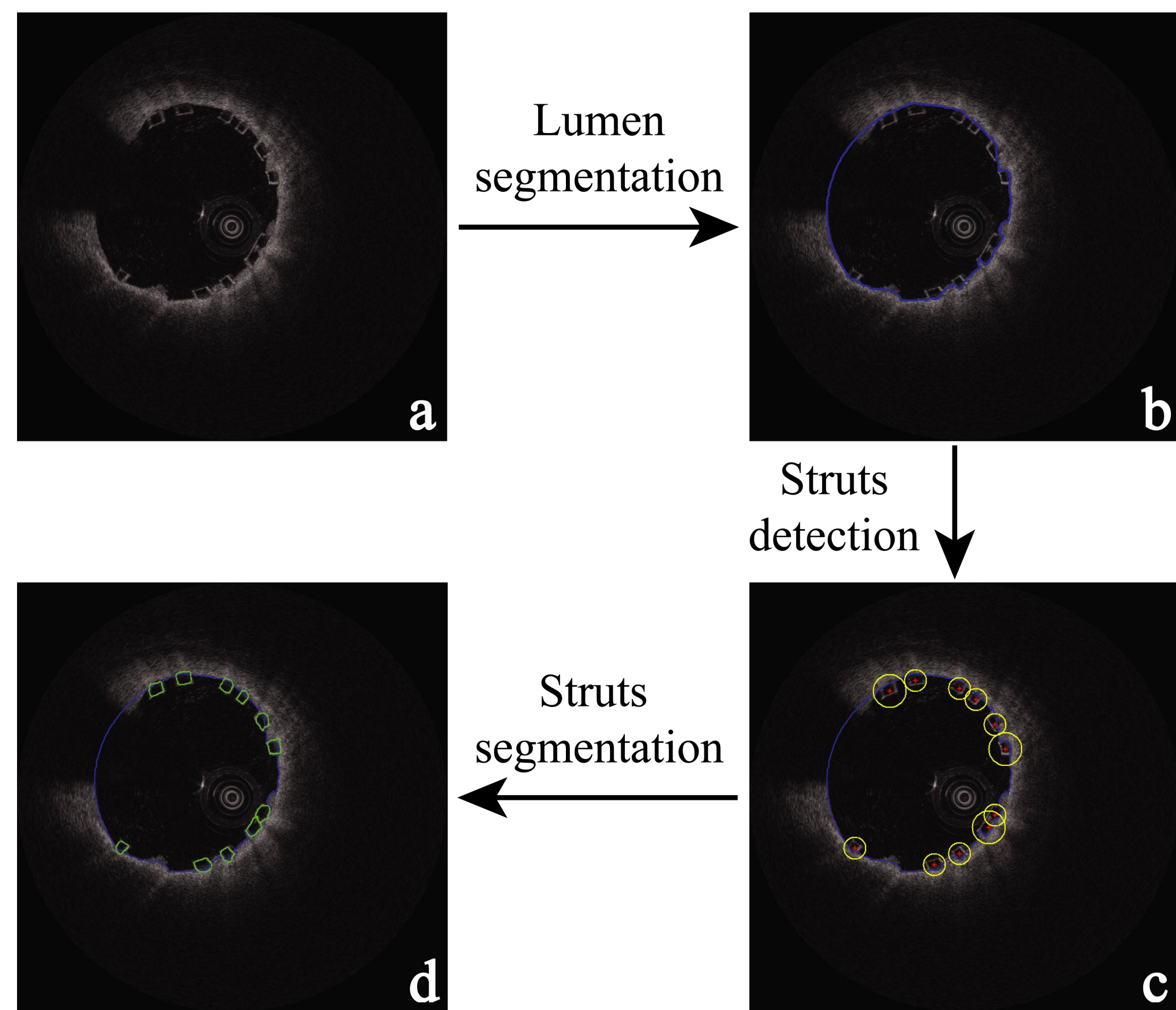


INTRODUCTION

- Bioresorbable Vascular Scaffolds (BVS) are the most promising type of stent in percutaneous coronary intervention.
- In clinical BVS stenting application, malapposition may happen and may lead to adverse cardiovascular events. It is therefore vital to detect malapposition immediately after stenting.
- Intravascular optical coherence tomography (IVOCT) is currently the state-of-the-art imaging modality.
- Manual analysis for struts malapposition in IVOCT images is time consuming and labor intensive.
- In this paper, an Adaboost-based detection and segmentation method is proposed to automatically evaluate struts malapposition in IVOCT images.

METHODOLOGY

Overview of Architecture



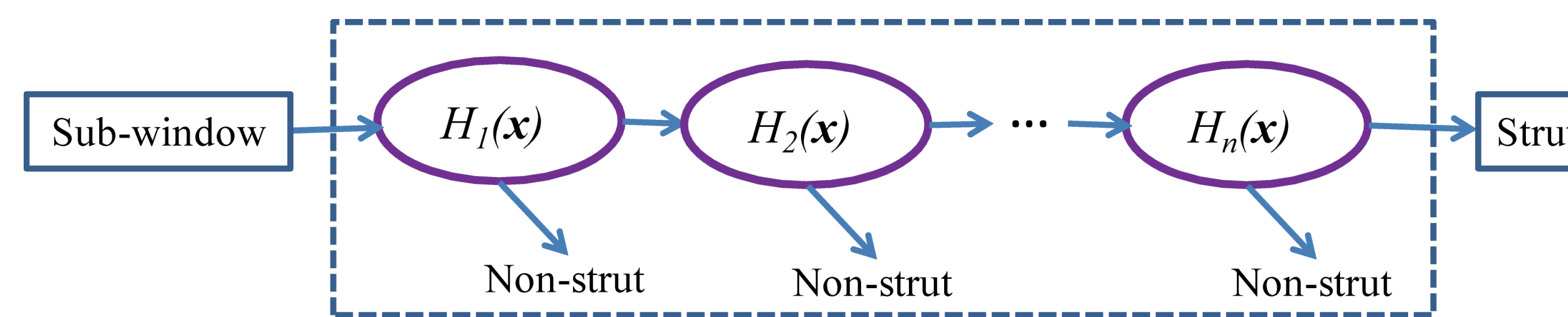
Adaboost-based detection

By combining a group of weak classifiers $h_j(\mathbf{x})$, a strong classifier $H(\mathbf{x})$ is obtained:

$$H(\mathbf{x}) = \begin{cases} 1, & \text{if } \sum_{j=1}^J h_j(\mathbf{x}) - t > 0 \\ 0, & \text{else} \end{cases}$$

where J is the number of weak classifiers and t is a manually-set threshold.

The final classifier is constructed by a cascade of strong classifiers. The structure is shown as follows.



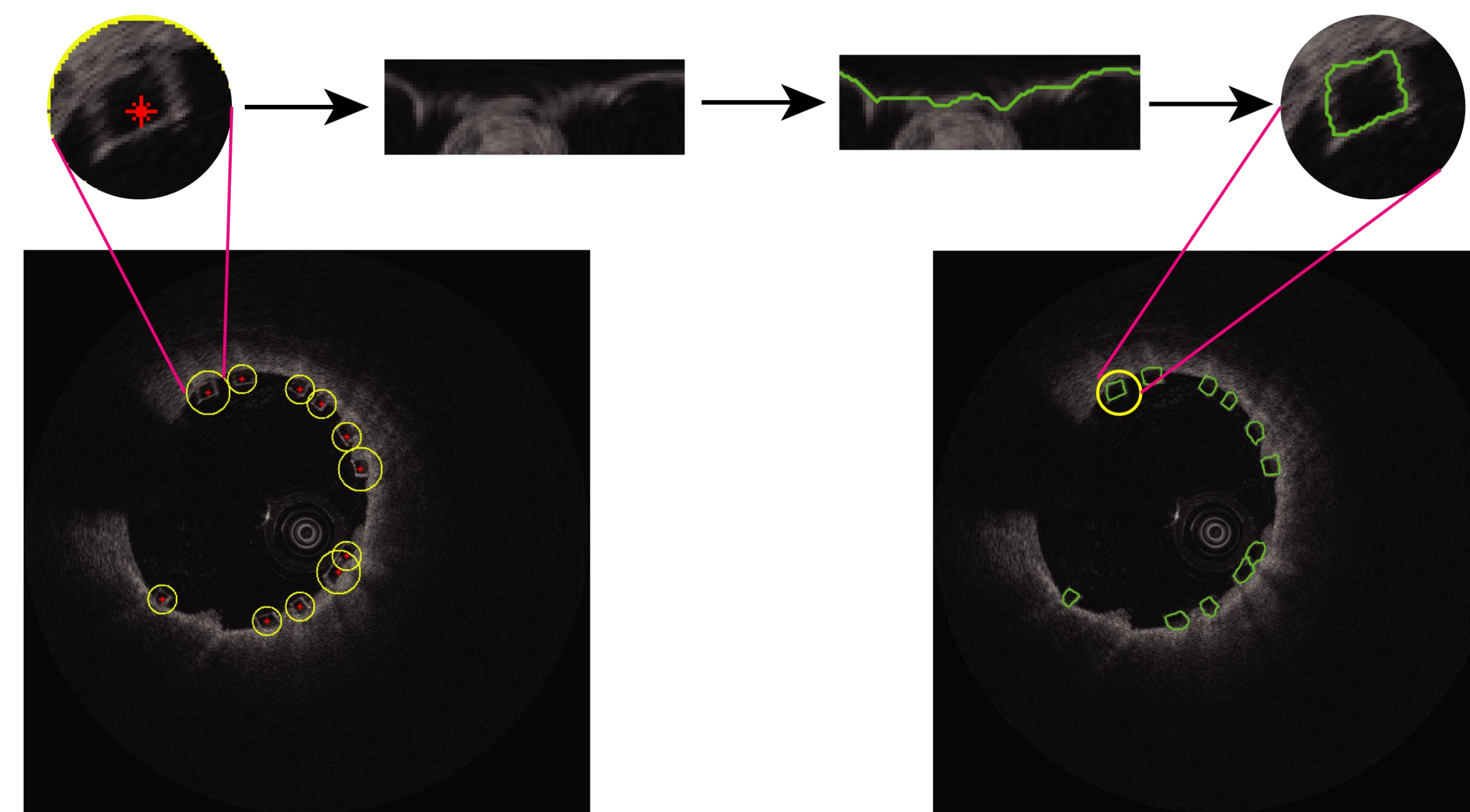
Dynamic programming-based segmentation

After detection, each ROI is transformed into polar coordinate system. The goal of struts boundary segmentation can be defined as searching for a path from column 1 to column M (M is the length of the polar image) with the optimal cost C . This problem can be broken into a series of sub-problems as:

$$C(\gamma, d) = E(\gamma, d), \quad \gamma = 1$$

$$C(\gamma, d) = \min C(\gamma - 1, d^*) + E(\gamma, d), \quad 1 < \gamma \leq M$$

The procedure of struts segmentation is shown as follows.



DATA & EVALUATION

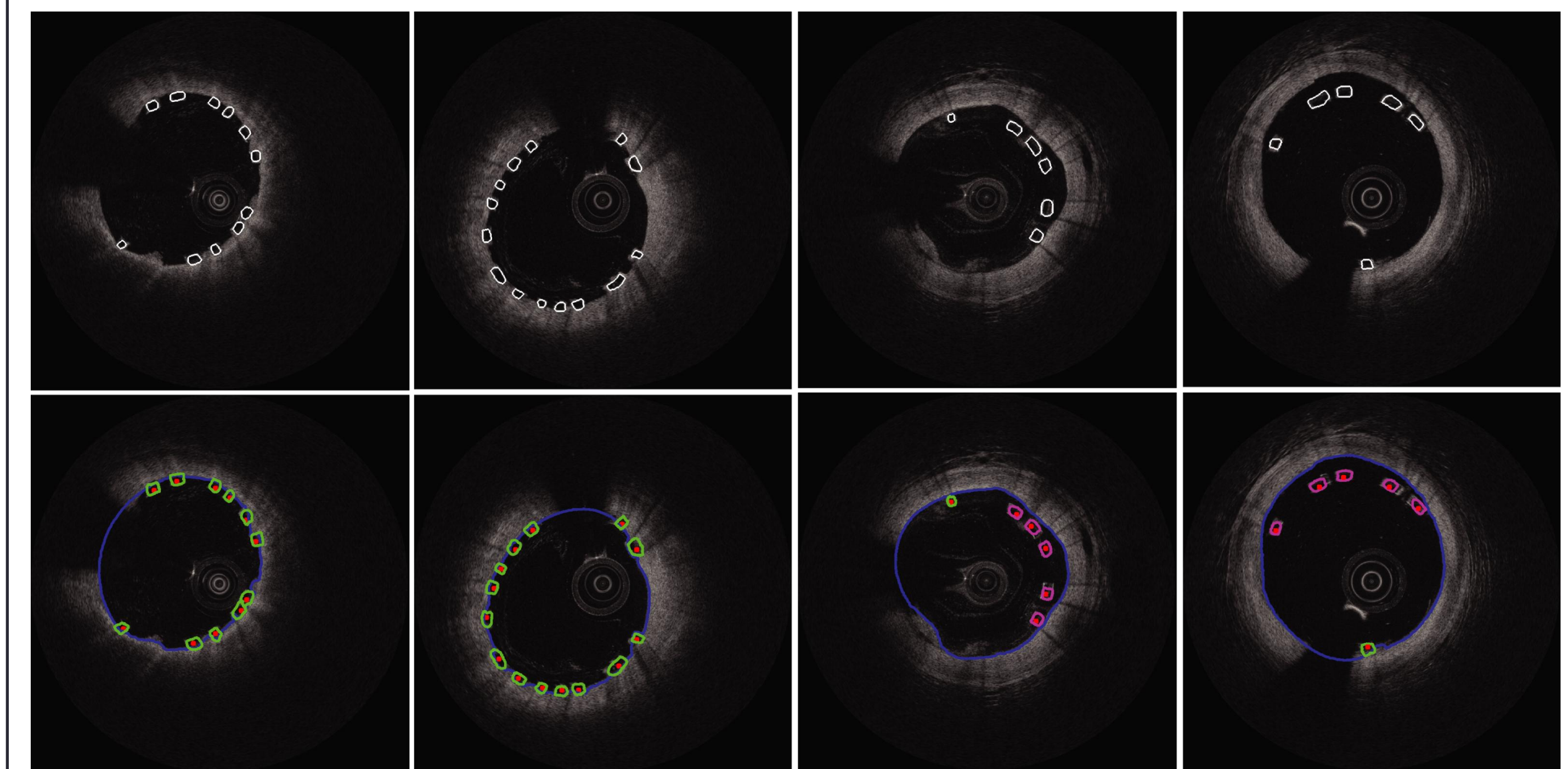
Training sets: 1500 positive samples and 4500 negative samples for each strong classifier.

Testing sets: a total of 4029 BVS struts from 480 IVOCT images.

Evaluation: True positive rate (TPR), false positive rate (FPR), F-measure, center position error (CPE), and Dice coefficient are computed for evaluation.

RESULTS

Qualitative results



The first row is the images of ground truth marked by white curves. The second row is the segmentation results, where the green and purple curves represent apposed and malapposed struts respectively.

Quantitative results

Data set	No.F	No.GT	Struts Detection				Struts Segmentation			
			TPR(%)	FPR(%)	F-measure	CPE(μm)	TPR(%)	FPR(%)	F-measure	Dice
1	81	691	94.2	14.1	0.90	28.9	93.2	15.0	0.89	0.79
2	119	928	88.8	18.3	0.85	32.4	86.3	20.6	0.83	0.79
3	86	635	83.6	18.0	0.83	28.4	82.2	19.4	0.81	0.76
4	76	603	91.9	20.5	0.85	34.4	90.0	22.1	0.84	0.79
5	118	1172	87.9	15.0	0.86	22.4	86.9	16.0	0.85	0.79
Average	-	-	89.3	17.2	0.86	29.3	87.7	18.6	0.84	0.78

CONCLUSIONS

In this paper, we presented an automatic method for BVS struts detection and segmentation in IVOCT images based on Adaboost algorithm and dynamic programming. The qualitative and quantitative evaluation shows that our method is effective and robust for BVS struts detection and segmentation, and is capable of malapposition analysis.