Computer-aided detection of intracoronary stent in intravascular ultrasound sequences

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Purpose: An intraluminal coronary stent is a metal mesh tube deployed in a stenotic artery during percutaneous coronary intervention (PCI), in order to prevent acute vessel occlusion. The identification of struts location and the definition of the stent shape is relevant for PCI planning and for patient follow-up. The authors present a fully automatic framework for computer-aided detection (CAD) of intracoronary stents in intravascular ultrasound (IVUS) image sequences. The CAD system is able to detect stent struts and estimate the stent shape.

Methods: The proposed CAD uses machine learning to provide a comprehensive interpretation of the local structure of the vessel by means of semantic classification. The output of the classification stage is then used to detect struts and to estimate the stent shape. The proposed approach is validated using a multicentric data-set of 1,015 images from 107 IVUS sequences containing both metallic and bioabsorbable stents.

Results: The method was able to detect struts in both metallic stents with an overall F-measure of 77.7% and a mean distance of 0.15 mm from manually annotated struts, and in bioabsorbable stents with an overall F-measure of 77.4% and a mean distance of 0.09 mm from manually annotated struts.

Conclusions: The results are close to the interobserver variability and suggest that the system has the potential of being used as a method for aiding percutaneous interventions.

Key words: IVUS, Stent detection, coronary arteries

1. INTRODUCTION
An intraluminal coronary stent is a metal mesh tube deployed in a stenotic artery during percutaneous coronary intervention (PCI) in order to scaffold the arterial wall after balloon angioplasty and to restore the blood flow to prevent acute vessel occlusion. After x-ray guided stent placement, cases of underexpansion (stent is correctly apposed to the luminal wall but it is not completely expanded) or malapposition (the stent is not completely in contact with the luminal wall) may occur. The incomplete stent deployment due to underexpansion and malapposition may lead to restenosis and thrombosis in the follow-up. The identification of struts location and the definition of the stent shape, compared with the luminal border and the vessel border, allow physicians to assess stent placement in the vessel and the need for a further balloon postdilatation.

The image modality currently used as the reference for verifying the correct apposition of a stent is intravascular optical coherence tomography (OCT). However, intravascular ultrasound (IVUS), a catheter-based imaging technique that provides a sequence of tomographic images (pullback) of the internal vessel morphology [see Fig. 1(a)] represents a potential alternative. In an IVUS sequence the placement of a stent can be deduced by the position of its struts [see Fig. 1(b)]. The resolution in OCT images is ten-times higher than in IVUS images, but at the cost of lower penetration depth (1.5 mm in OCT compared with 5 mm in IVUS), which limits its ability to assess plaque burden and vessel remodeling. Moreover, guiding an OCT catheter requires the...
intubation of the coronary ostium in order to provide effective injection of contrast agent, which limits the analysis of ostial lesions. For these reasons IVUS represents a complementary imaging technique with respect to OCT, and in some cases it can be preferred to OCT to guide stenting procedures in the presence of complex lesions.3–5

Strut detection is a challenging task in IVUS images. Only a few struts are often visible, due to the inclination of the ultrasonic probe with respect to the longitudinal axis of the vessel and to the presence of calcifications or dense fibrosis in contact with the stent. On the other hand, several regions in the IVUS image may look similar to a strut, due to their local appearance. Clear examples of these regions are artifacts produced by the guide-wire, refractions of ultrasonic waves, reverberations or presence of small calcifications [see Figs. 1(c) and 1(d)]. Additionally, the strut texture and the thickness may vary significantly depending on the type of implanted stent, which can be either metallic or bio-absorbable.6,7

To date, several approaches for automatic stent analysis on optical coherence tomography (OCT) images have been presented.8–10 However, only a few approaches have been proposed in the field of IVUS image analysis,11–15 which address either the problem of stent modeling or strut detection.

The problem of stent modeling was tackled by Canero et al.,11 where two deformable cylinders corresponding to the luminal wall and the stent were used. The cylinders were adapted to image edges and ridges to obtain a three-dimensional reconstruction of the boundaries. A semiautomatic stent contour detection algorithm was presented by Dijkstra et al.12 The method performs a global modeling of struts by minimum cost algorithm, followed by refinement using local information on stent shape and image intensity gradient. Finally the user interaction is foreseen to correct the stent shape in 3D. Dijkstra et al.15 proposed an improved version of this method, where the stent shape is accurately reconstructed in images with good quality, but the algorithm requires at least three clearly visible struts.

On the other hand, the problem of strut detection was tackled by Rotger et al. and Hua et al.13,14 An automatic method, limited to bio-absorbable scaffolds, was proposed by Rotger et al.,13 using Haar-like features and a cascade of classifiers. A detection algorithm based on a two-stage classification framework for fully automatic stent detection has been presented by Hua et al.14 Despite the encouraging results, the number of false positives struts makes the method not suitable for clinical purposes.

1.A. Our contribution

We present a novel CAD system for fully automatic analysis of stents in IVUS image sequences. The overall layout of the methodology is depicted in Fig. 2. The proposed system allows: (1) the detection of stent struts and (2) provides an estimation of the stent shape, by contemporaneously considering the presence of struts and the vessel morphology. A curve approximating the stent shape is first estimated through a comprehensive interpretation of the vessel geometry. For this purpose, a semantic classification method is applied to each IVUS frame, with the aim of providing a robust and accurate labeling of regions of interest of the vessel in the IVUS frame. In the classification problem, the class strut is considered as one of the classes. For semantic classification purposes, we adopt the framework presented by

![Fig. 1. Example of IVUS pullback containing a stent (a). An example of IVUS frame belonging to the pullback in (a) is depicted in Cartesian (b) and polar (c) coordinates. In (d), details of the six regions highlighted in (c) are provided, for regions containing struts [(A)–(C)] and regions not containing struts [(D)–(F)], but visually similar to struts.](image-url)
Ciompi et al.,16 tailoring features used for classification to the problem at hand. As a result, an optimal descriptor of the local appearance of tissues in the IVUS frame is obtained, which represents one of the contributions. Successively, struts are detected based on both local appearance and stent model, which allows a reduction of false positives.

The contribution presented in this paper extends the formulation of a preliminary study presented by our group17,18 for strut detection and stent shape estimation. This paper describes the classification approach and the novel features introduced in depth. Additionally, in order to extensively validate the proposed CAD system, we collected a set of 107 IVUS sequences of in vivo arteries through an international multicentric collaboration across five centers. The method, preliminary tested on 589 images obtained by a single clinical center, has been now validated on a larger dataset of 1,015 IVUS images from the collected sequences, containing not only metallic stents as in Ciompi et al.18 but also bio-absorbable stents.

2. METHOD

The pipeline for the proposed CAD system for intracoronary stent analysis is depicted in Fig. 2. The three steps of the pipeline are detailed in Secs. 2.A–2.C.

2.A. Gating

Let us define an IVUS pullback as a sequence of frames $I = \{f_i\}$. In the proposed pipeline, we first preprocess the pullback by applying an image-based gating procedure. Gating is a necessary step in order to make the analysis robust to two kinds of artifacts generated by the heart beating: the swinging effect (repetitive oscillations of the catheter along the axis of the vessel) and the roto-pulsation effect (irregular displacement of the catheter along the direction perpendicular to the axis of the vessel). These two effects hinder the reliable identification of luminal area,19 which is an important factor for the analysis of stents inside the vessel. For this purpose, the method presented by Gatta et al.20 is applied to the IVUS pullback, which selects a sequence of gated frames $G = \{f_{g_j}\}$ that are processed by the proposed CAD system. It is worth noting that $G \subset I$ and that each index $g_j \approx 35i$ assumes a heart rate of approximately 60–80 bpm.

2.B. Semantic classification

In the proposed approach, the stent shape modeling is based on the definition of vessel morphology, assessed through a frame-wise analysis of the pullback. For this purpose, semantic classification that takes into account the relationships between regions of the IVUS frame is applied to each frame in $G$, in order to obtain a pixel-wise labeling of each gated frame. In Secs. 2.B.1–2.B.3 we define (1) the classes considered in the semantic frame labeling, (2) the pixel-wise descriptor of local IVUS frame appearance, and (3) the framework used for semantic classification.

2.B.1. Classes definition

We consider that the semantic interpretation of an IVUS frame in the context of stent analysis requires the definition of the following six areas [see Fig. 3(c)]: blood (B), plaque (P), calcium (C), guide-wire (G), strut (S), and tissue (T). It is important to stress that strut areas (S) indicate the pixels which are candidates for containing a strut. In order to define these regions of interest, we rely on manual annotations of the following contours in a set of training images [see Fig. 3(b)]: lumen border, vessel border, calcified plaques, stent struts, and guide-wire artifact, from which we derive the described areas of interest. For strut annotation purposes, we rely on a manually annotated set of points with coordinates $(x_i, y_i)$, which represent the center of struts, and consider the pixels belonging to a connected component area that includes the pixel in $(x_s, y_s)$ as belonging to the strut.

2.B.2. Pixel-wise descriptor

A descriptor of the local appearance in small neighborhoods of the IVUS frame is designed and associated to the central pixel of the neighborhood itself. Following a strategy proposed in several IVUS applications,16,21 the combination of different feature types is used. The operators used to design the pixel-wise descriptor are partially derived from the optimal set of features defined in Ciompi et al.,16 namely Gabor filters (GF), local binary patterns (LBP), Laplacian of Gaussian (LoG), normalized cross-correlation (NCC), shadow (SH), and matched filter response (MFR).

For Gabor filters, we adopted the set of parameters used in a previous paper,16 obtaining a bank of 20 filters. The feature maps obtained from the convolution of the IVUS frame and each of the 20 filters are used to define a pixel-wise feature vector $x_{GF} \in \mathbb{R}^{20}$. The contribution of local binary pattern to the pixel-wise IVUS descriptor consists of the output of four configurations of the texture descriptor, using the pairs of values $(R,P) = [(1,8),(2,16),(3,24),(4,32)]$. As a result, a feature vector $x_{LBP} \in \mathbb{R}^{4}$ is obtained.

Stent struts appear as rounded-like objects in IVUS images, which can be interpreted as bright blobs. For this reason, we consider the response of the convolution with the Laplacian of Gaussian (LoG) operator at scales $\{37.5, 56.3, 75, 93.7, 112\}$ μm, in order to cope with different strut sizes

Fig. 3. Example of IVUS image in Cartesian coordinates where struts are indicated (a). In (b), the polar view of the image is depicted, and the main areas of interest are annotated. In (c), the semantic classes are indicated (a). In (b), the strut filter manually annotated annotations in (c). In (d), the strut filter manually annotated is depicted.
and imaging parameter settings, obtaining a feature vector $x_{log} \in \mathbb{R}^5$.

In previous papers,\textsuperscript{17,19} it has been shown that the normalized cross correlation (NCC) between patches of gated IVUS frames and adjacent frames in the pullback provides a low response in the presence of blood.\textsuperscript{10} Since the definition of the luminal area is an important factor in the analysis of stent, we adopt NCC as part of the pixel-wise descriptor. For this purpose, given a gated IVUS image $f_{gj}$ of the sequence, we consider the two adjacent (nongated) frames $f_{gj-1}$ and $f_{gj+1}$ (see Fig. 3). Three measures of NCC are computed over three pairs of frames considering regions of size $W \times W$, namely $\text{NCC}_{f_{gj-1}f_{gj+1}}^\text{NCC}$, $\text{NCC}_{f_{gj-1}f_{gj+1}}^\text{NCC}$, and the average of the three responses is used as feature. It is worth noting that this descriptor takes advantage of local contextual information along the IVUS pullback. We apply this operator varying $W$ from 0.1 to 0.2 mm with a step of 0.033 mm, and we also consider the average across all scales as an additional feature, obtaining a feature vector $x_{\text{NCC}} \in \mathbb{R}^5$.

The presence of shadows in the IVUS image is an indicator of presence of tissues or materials with high reflectance of ultrasonic waves, such as calcifications or stent struts. For this reason, we include in the descriptor two features named as shadow and relative shadow, extracted from the cumulative intensity of the ultrasound image along the radial direction,\textsuperscript{16} which form a feature vector $x_{\text{SH}} \in \mathbb{R}^5$.

The last feature used in the proposed descriptor is based on the response of the IVUS frame representation of the strut texture, which we call the strut filter. The texture of the strut filter is learned from training examples as follows. Given the set of annotated struts, we computed the filter by averaging the intensity of the gray level in a bounding box constructed around each position $(x_s, y_s)$. The size of the bounding box is defined as two times the diameter of the strut, estimated from the binary strut map obtained via Otsu thresholding of the gray levels of a sufficiently large region including struts in the training set. The obtained filter is depicted in Fig. 3(d).

The convolution of an IVUS frame and the strut filter gives high response in the presence of structures resembling struts. We use the pixel-wise value of the response as a feature of the descriptor, along with the pixel-wise product between the response and the IVUS image. In this way, we obtain a feature vector $x_{\text{SKR}} \in \mathbb{R}^2$.

Finally, the IVUS image as well as its smoothed version, computed by averaging the intensity in a $5 \times 5$ px neighbourhood, is included in the descriptor, obtaining a descriptor $x_{\text{IVUS}} \in \mathbb{R}^4$.

### 2.B.3. Semantic classification framework

The multiScale multiClass stacked sequential learning (M\textsuperscript{2}SSL) approach is used for the purpose of multiclass semantic classification of IVUS frames, since it has been shown to provide a robust interpretation of IVUS images.\textsuperscript{16,18} The M\textsuperscript{2}SSL is a classification architecture based on the stack of two classifiers, which we refer to as $H_1$ and $H_2$ [see Fig. 4(a)]. The classifier $H_1$ is fed with the feature vector $x_{\text{IVUS}}$ computed for each position $\vec{q}=(\rho, \theta)$ of the IVUS image in polar coordinates, and provides as output a vector $P \in \mathbb{R}^{N_c}$ of pseudo-likelihoods, where $N_c$ is the number of classes. The error-correcting output codes (ECOC) technique\textsuperscript{16} is used to deal with the multiclass problem and to compute the vector $P(\vec{q})$ at each location $\vec{q}$ in the image.

The classifier $H_2$ is fed with the combination of $x_{\text{IVUS}}$ with features of context $x_{C}$. The role of $x_{C}$ is to encode long-range interactions between regions in the image, in order to explicitly encode semantic relationships between tissues. This is done through a functional $J(P)$, which performs multiscale sampling of the likelihood map $P$ at $N_s$ scales [see Fig. 4(a)]. At each scale $s$, the map is smoothed with a Gaussian

![Fig. 4. Example of the architecture of the M\textsuperscript{2}SSL classification framework (a). An example of IVUS image in polar coordinates is depicted in (b), along with the corresponding classification maps for the stages classified by $H_1$ (c) and $H_2$ (d).](image-url)
kernel with standard deviation $\sigma_s = 2^{(s-1)}$ and then sampled in positions corresponding to the 8N neighborhood of each location $\hat{q}$, for each class [see Fig. 4(a)]. The central pixel is included as well. As a consequence, $|\mathbb{N}| = 9N_rN_s$. Finally, an extended feature vector $x_F = x_{\text{IVUS}} \cup x_C$ is provided to $H_2$, which assigns the label $Y$ pixel-wise. In this way, the classifier $H_2$ is trained using both information on the local tissue appearance and information on semantic relationships among regions in the IVUS image. The result of the semantic classification, i.e., the classification obtained after applying $H_2$, has less noise from a semantic point of view with respect to the result obtained only using $H_1$ [see Figs. 4(c) and 4(d)].

2.C. Stent modeling

In this section, we describe the procedure to assess the stent shape estimation and strut detection.

2.C.1. Stent shape estimation

Estimating the stent shape consists of finding a curve that simultaneously fulfills three criteria:

(i) The shape should cross as many struts as possible.
(ii) The shape should fulfill morphological constraints with respect to the vessel structure (e.g., no struts inside a calcified region).
(iii) Given the rigidity of the stent meshes, the shape should be as regular as possible.

Considering (iii), we assume the ellipse as a model for the stent shape, which has more degrees of freedom than the circular shape.15 In polar coordinates, the points of an ellipse are defined by the function $\rho(\theta)$, where $\rho$ is the distance from the ultrasound transducer and $\theta$ is the angle from the initial position of the transducer in the IVUS probe. The function can be written in a compact form as $\rho(\theta) = P(\theta) + Q(\theta)/R(\theta)$, with

\[
\begin{align*}
P(\theta) &= \rho_0[(b^2-a^2)\cos(\theta+\theta_0)-2\phi]+(a^2+b^2)\cos(\theta-\theta_0), \\
Q(\theta) &= \sqrt{2}ab\sqrt{R(\theta)-2\rho_0^2\sin^2(\theta-\theta_0)}, \\
R(\theta) &= (b^2-a^2)\cos(\theta-\theta_0)+a^2+b^2,
\end{align*}
\]

(1)

where the set of parameters $\mathcal{E} = \{a,b,\phi,\rho_0,\theta_0\}$ indicates, in order, the major ($a$) and minor ($b$) axes, the orientation ($\phi$), and the coordinates ($\rho_0,\theta_0$) of the center of the ellipse. Following the criteria (i) and (ii), a robust estimation of stent shape is obtained through a comprehensive interpretation of the curve position with respect to the vessel morphology. For this purpose, we take advantage of the output of the semantic classification16 by designing a functional $\Psi(\mathcal{E})$ that encodes the dependencies between parameters of stent curve and vessel morphology

\[
\Psi(\mathcal{E}) = \sum_{i=1}^{\lceil \mathcal{E} \rceil} w_i \mathcal{f}(\mathcal{E})_i^+ - \sum_{j=1}^{\lceil \mathcal{E} \rceil} w_j \mathcal{f}(\mathcal{E})_j^-.
\]

(2)

Based on the classification output $\hat{r}^+ = \{t(\mathcal{E})^+_i\}$ and $\hat{r}^- = \{t(\mathcal{E})^-_j\}$ are the regions of the image positively or negatively contributing to the correct curve placement. Based on the nomenclature defined in Sec. 2.B.1, we define $\hat{r}^+ = \{B_rP_rC_r,B_1P_1C_1\ldots\}$ and $\hat{r}^- = \{C_rS_rT_rS_1\ldots\}$, where the arrows indicate a region placed above ($\uparrow$), below ($\downarrow$), or crossed ($\leftarrow\rightarrow$) by the curve. The shape is initialized by approximating the border of the convex hull containing the blood area of the IVUS image with an elliptical shape.

2.C.2. Strut detection

Once the stent shape is estimated, the positions $s_A = (\rho_A,\theta_A)$ representative for struts are automatically detected by considering three conditions. First, the appearance of a strut is accounted by considering a likelihood map $L_\text{strut}(\rho,\theta)$, obtained through the normalized cross correlation between the IVUS image and the filter $K_S$ described in Sec. 2.B.2 [Fig. 3(d)]. A local maximum of $L_\text{strut}$ identifies a potential strut position. Strut detection is then subject to two additional conditions: (1) $s_A$ must belong to a region classified as strut $Q_\text{strut} = \{\hat{q}\}\cap\{\rho=\text{strut}\}$; (2) $s_A$ must be proximal with respect to the estimated stent shape. The coordinates of struts are then obtained as

\[
\begin{align*}
\{\tilde{\rho}_\text{strut},\tilde{\theta}_\text{strut}\} &= \arg\max_{\rho,\theta}(\\n\{\tilde{\rho}_\text{strut},\tilde{\theta}_\text{strut}\}) \cap Q_\text{strut}, \\
\text{s.t.} \\
\text{dist}(\tilde{\rho}_\text{strut},\tilde{\theta}_\text{strut}),(\rho_\text{sten},\theta_\text{sten}) &\leq d_\text{strut}.
\end{align*}
\]

(3)

We used the value $d_\text{strut} = 0.2$ mm, which is the distance used in clinical practice to assess malapposition. As a result, a set of coordinates $S_A(f) = \{s_A\}$ is obtained for each frame $f$, representing the positions of the centre of the detected struts.

3. VALIDATION

3.A. Material

A set of 107 sequences of IVUS images was collected through a multicenter study, containing both metallic (met) and bio-absorbable (abs) stents. Data acquisition protocol was approved by the IRB of each clinical centre. The IVUS sequences were acquired using iLab echograph (Boston Scientific, Fremont, CA) with a 40 MHz catheter (Atlantis SR Pro, Boston Scientific); no standardization of the echograph parameters was applied during the acquisitions. The pullback speed was 0.5 mm/s. The models of the metallic and bio-absorbable stents were “Promus Coronary Stent, Boston Scientific, MN” and “Absorb Bioresorbable Vascular Scaffold (BVS), Abbott, IL,” respectively.

We collected 1,015 frames from the 107 pullbacks. An expert manually annotated the beginning and the end of the stent in each sequence; more than one annotation per pullback was allowed when several stents were implanted in subsequent segments of the same artery. We split the dataset
into two subsets, one used for training and one used for testing purpose. The training set consisted of 13 pullbacks, from which we randomly selected 180 frames. All IVUS frames of the training set contained only one guide wire. For each frame in the training set an expert manually annotated the contour of the six areas defined in Sec. 2.B.1 from which we randomly selected 180 frames. All IVUS sequences, 835 frames were randomly selected, 709 containing metallic stents (testmet) and 126 containing bio-absorbable stents (testabs). In each dataset, the proportion of frames with and without stent was roughly 1:1, with the exception of the test set provided by hospital #1, which only contained stent frames (see Table I). In each frame, two observers were asked to independently annotate the locations of stent struts in Cartesian coordinates, which we converted into polar coordinates \((\rho^i, \theta^i)\). It is worth noting that the definitions that were used for the training and test sets permit evaluation of the performance of the method without the need for cross-validation techniques. Table I describes the data-sets used in the evaluation process.

### 3.B. Experiments on stent modeling

The detection of struts and modeling of the stent shape are based on the semantic classification of IVUS frames. In order to train \(H_1\) and \(H_2\) with different data, \(train\) was split into two balanced subsets \(train_{H_1}\) and \(train_{H_2}\), containing 90 frames each. In our experiments, adaptive boosting was used for training both \(H_1\) and \(H_2\) classifiers. The multiclass problem was handled using the error-correcting

### Table I. Detailed description of the data-sets used in this study.

| Data-set type | Hospital Number | Stent deployment | Pullbacks | Label | N frames | % of stent frames | Training | Test |
|---------------|-----------------|-----------------|-----------|-------|----------|------------------|----------|------|
| Metallic      | #1 13           | Deployed        | 90        | Roughly 50 | \(train_{H_1}\) |
| #2 3          | Deployed        | 45              | Roughly 50 | \(test_{abs}\) |
| #3 1          | Deployed        | 21              | Roughly 50 | \(test_{abs}\) |
| Bio-abs.      | #4 4            | Deployed        | 84        | Roughly 50 | \(test_{abs}\) |
| #5 1          | Deployed        | 21              | Roughly 50 | \(test_{abs}\) |

### Table II. Quantitative results (average and standard deviation) reporting the performance of the algorithm over the dataset \(test_{meta}\) containing metallic struts. The results are separated according to the following categories: all the frames (All), presence of bifurcations (Bifurcation), calcification (Calcium), small-large vessel (Small-large), and absence of previous cases (Normal). The mean and standard deviation (in parenthesis) distances between automatic and manual struts \((d_{SS})\), and between manual struts and stent curve \((d_{SC})\) are indicated.

| Pullbacks | Label | Precision (P) | Recall (R) | F-measure (F) | Strut to strut distance \((d_{SS})\) | Strut to curve distance \((d_{SC})\) |
|-----------|-------|---------------|------------|---------------|---------------------------------|---------------------------------|
|           |       | Mean% (std%)  | Mean% (std%) | Mean% (std%) | Mean (mm) [std (mm)]              | Mean (mm) [std (mm)]              |
| All       | auto vs obs-1 | 76.4 (27.5)  | 89.9 (19.6)  | 77.7 (24.2) | 0.10 (0.04) | 0.15 (0.12) |
|           | auto vs obs-2 | 78.4 (28.6)  | 84.8 (22.7)  | 75.7 (25.7) | 0.09 (0.04) | 0.14 (0.11) |
|           | obs-1 vs obs-2 | 86.6 (20.8)  | 93.3 (17.1)  | 86.9 (19.0) | 0.07 (0.05) | 0.17 (0.12) |
| Bifurcation| auto vs obs-1 | 63.3 (32.9)  | 88.9 (20.6)  | 66.3 (28.9) | 0.11 (0.04) | 0.17 (0.12) |
|           | auto vs obs-2 | 62.9 (33.6)  | 80.0 (25.4)  | 62.5 (29.6) | 0.09 (0.04) | 0.18 (0.14) |
|           | obs-1 vs obs-2 | 80.0 (26.7)  | 92.8 (16.5)  | 82.0 (23.6) | 0.07 (0.06) | 0.17 (0.13) |
| Calcium   | auto vs obs-1 | 69.2 (29.3)  | 89.7 (21.1)  | 71.9 (26.3) | 0.10 (0.04) | 0.17 (0.13) |
|           | auto vs obs-2 | 73.0 (29.8)  | 80.0 (26.1)  | 68.4 (25.3) | 0.10 (0.04) | 0.17 (0.13) |
|           | obs-1 vs obs-2 | 82.1 (23.5)  | 93.5 (16.4)  | 84.0 (19.5) | 0.07 (0.06) | 0.21 (0.15) |
| Small-large| auto vs obs-1 | 54.0 (36.2)  | 86.7 (23.2)  | 57.3 (31.2) | 0.11 (0.04) | 0.23 (0.15) |
|           | auto vs obs-2 | 55.5 (32.5)  | 82.6 (27.1)  | 60.6 (30.0) | 0.10 (0.04) | 0.21 (0.15) |
|           | obs-1 vs obs-2 | 85.0 (23.1)  | 85.8 (27.0)  | 79.2 (24.1) | 0.07 (0.05) | 0.23 (0.15) |
| Normal    | auto vs obs-1 | 77.4 (26.6)  | 91.1 (18.7)  | 79.4 (21.8) | 0.10 (0.04) | 0.15 (0.12) |
|           | auto vs obs-2 | 79.6 (27.3)  | 86.7 (21.9)  | 78.2 (22.9) | 0.09 (0.04) | 0.14 (0.11) |
|           | obs-1 vs obs-2 | 87.6 (20.4)  | 94.0 (16.3)  | 88.1 (18.2) | 0.07 (0.05) | 0.14 (0.11) |
Table III. Quantitative results (average and standard deviation) reporting the performance of the algorithm over the dataset testabs containing metallic struts. The results are separated into two categories: all frames (All) and frames containing struts (Stent-only). The mean and standard deviation distances between automatic and manual struts ($d_{SS}$), and between manual struts and stent curve ($d_{SC}$) are indicated.

|                  | Precision ($P$) | Recall ($R$) | F-measure ($F$) | Strut to strut distance ($d_{SS}$) | Strut to curve distance ($d_{SC}$) |
|------------------|-----------------|--------------|----------------|----------------------------------|----------------------------------|
|                  | Mean% (std%)    | Mean% (std%) | Mean% (std%)   | Mean (mm) [std (mm)]             | Mean (mm) [std (mm)]             |
| auto vs obs-1    | 87.0 (22.8)     | 80.4 (24.5)  | 78.8 (22.8)    | 0.09 (0.04)                      | 0.09 (0.07)                      |
| auto vs obs-2    | 80.9 (27.6)     | 76.1 (22.4)  | 73.3 (23.3)    | 0.10 (0.04)                      | 0.11 (0.08)                      |
| obs-1 vs obs-2   | 88.6 (18.5)     | 85.2 (22.5)  | 83.7 (17.5)    | 0.09 (0.04)                      |                                  |

output codes$^{23}$ (ECOC) framework with one-versus-one strategy to train binary dichotomies. As a result, $H_1$ and $H_2$ consisted of 15 binary classifiers each. The number of scales in M$^2$SSL was $N_s = 6$, which allows the encoding of long-range interactions that cover up to half of the image size. The training of the weights $w = \{w_i, w_j\}$ was

Fig. 5. Examples of cases of strut detection. Frames are grouped according to the following categories: normal small and large vessel (A and B columns), bifurcation (C and D columns), calcium (E and F columns). In each image annotations from two observers are depicted (in green squares and yellow star markers) as well as the results of the automatic method (represented with red circle markers). The stent shape automatically computed is outlined using a blue solid line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article). (See color online version.)
done in cross-validation by approximating manual struts annotations with an elliptic model and then averaging the normalized amount of tissues for each frame of the training set.

The struts were detected in position \((\rho^i_A, \theta^i_A)\) and the stent modeled as detailed in Secs. 2.C.1 and 2.C.2. First, we compared the automatic detection with the manual annotation \((\rho^i_M, \theta^i_M)\) and computed true positives (TP), false positives (FP), and false negatives (FN). For evaluating the detection, we considered a strut detected at \((\rho^i_A, \theta^i_A)\) as being inside a circular region \(N\) of radius \(\Phi\) around each \((\rho^i_M, \theta^i_M)\):

- if \((\rho^i_A, \theta^i_A) \in N\) \(\Rightarrow\) TP,
- if \((\rho^i_A, \theta^i_A) \notin N\) \(\Rightarrow\) FP,
- if \(N \cap \{(\rho^i_A, \theta^i_A)\} = \emptyset\) \(\Rightarrow\) FN.

Based on these criteria, parameters of Precision (P), Recall (R), and F-Measure (F) were computed.

Second, we evaluated the quality of the information provided by the detected strut to estimate the stent shape. For this purpose, we considered the distance between the automatically computed curve to the manual struts. The performance was assessed in terms of both (a) radial distance \(d_{sc}\) between the strut points \((\rho^i_M, \theta^i_M)\) and the stent curve \((\rho^i_{stent}, \theta^i_{stent})\) and (b) radial distance \(d_{ss}\) between \((\rho^i_M, \theta^i_M)\) and \((\rho^i_A, \theta^i_A)\). The results in terms of both detection performance and distance are shown in Table II for metallic stents and in Table III for bio-absorbable stents. Visual results are depicted in Fig. 5 for metallic stents, where results are grouped by categories of frames containing: Small-large vessels (columns A and B, rows 4 and 5), frames containing a Bifurcation (columns C and D), and frames containing Calcium plaques (columns E and F). Frames not belonging to the previous categories (columns A–B, rows 1–3) were labelled as Normal.

In Fig. 6, visual results for cases of bio-absorbable stent are depicted. In this case, due to the smaller number of examples, solely the two categories (All) and (Stent-only) were considered.

4. RESULTS AND DISCUSSION

4.1. Metallic stents

When frames containing metallic stents are processed, an average performance of \(F_{obs-1} = 77.7\%\) and \(F_{obs-2} = 75.7\%\) on All frames) is reached. The quantitative results of this study outperform methods based on similar approaches (F-measure of 71\% in Ciompi et al., 17 F 66\% in Hua et al., 14) although the comparison is not straightforward since the performances reported in the other papers were obtained on different datasets. The method performs well in the presence of normal frames as well as in the presence of bifurcations and calcified plaques (Table II). This represents an interesting result, since in terms of manual annotations, a high interobserver variability score is obtained in the category bifurcation as well as in frames containing calcium where the two observers, in some cases, placed the struts in different locations of the plaque. Lower performance is obtained on frames with small and large vessels, mainly due to a suboptimal initialization of the stent shape.

It can be noted that in the presence of normal and small-large vessels [Figs. 5(A) and 5(B)], most of the struts selected by the observers are identified by the automatic method (rows 1–3) and the estimated stent curve fits well all the manually labelled struts. However, when the vessel is narrow (stenotic) or large (Fig. 5, rows 4 and 5), we observed an underestimation of the lumen area, which affects the estimation of the stent shape.

In the presence of bifurcations [Figs. 5(C) and 5(D)], we can notice disagreement between the two observers (rows 4 and 5). Nevertheless, automatic detection of the proposed CAD system matches the annotation of at least one of the two observers. In Fig. 5 (D,5), two concentric stents are present in the vessel, the first one which is covered by plaque, and the second one deployed in the inner lumen area. As a result, the automatic stent contour fits the struts closer to the catheter.

In the presence of calcifications [Figs. 5(E) and 5(F)], the method is able to correctly detect struts even if located close to calcified plaques (rows 1–3). However, in other cases the close
contact with a calcified plaque hampers the correct detection of struts (rows 4–5). As a consequence, the estimated stent shape does not follow the vessel boundary. In the IVUS frame in Fig. 5 (F5), most of the struts are identified, however, in the top area the catheter shadow partially occupies the lumen area, preventing the stent shape to fit all the detected struts.

4.B. Bio-absorbable stents

In the presence of bio-absorbable stents, the performance of the strut detection method (Table III) is comparable with the result obtained on metallic frames (F\textsubscript{stru–1} = 78.8% and F\textsubscript{stru–2} = 73.3%). The performance reported in this paper is comparable with the numerical results of Rotger et al.\textsuperscript{13} (F-Measure of 71% and 75%), although the comparison is not straightforward, since they were assessed on a different dataset. This result is interesting, since the algorithm for strut detection was only trained with the local appearance of the metallic stent, demonstrating that the method is flexible and can be applied to IVUS images containing a more heterogeneous variety of stent types.

Most of the struts selected by the observers are identified by the proposed automatic method (see Fig. 6). It is interesting to note that a reasonable estimation of the stent shape is obtained even if few struts are present in the image [Fig. 6(a), bottom]. In Fig. 6(b), bottom, the stent shape is slightly overestimated and the stent contour crosses the vessel border in the bottom part of the image. In Figs. 6(c), top and 6(c), bottom cases of false positive and false negative detection are shown, respectively. In particular, in Fig. 6(c), top, it is interesting to note that a strut at the bottom of the image is correctly identified even if located close to the guide shadow reverberations. Finally, the two cases in which the detection performance of the algorithm is low are depicted in Fig. 6 column (d). In Fig. 6(d), top, the agreement between the observers is low, and the algorithm detects struts identified by one of the two observers. In Fig. 6(d), bottom, the algorithm incorrectly identifies bright scatterers on the vessel border as struts.

The image-base gating procedure is aimed at identifying the most stable frames of the sequence, which correspond to the end-diastolic phase. Such procedure allows for an efficient computation of the normalized cross-correlation (NCC) feature along adjacent frames (not gated frames) as shown in Balocco et al.\textsuperscript{19} However, the gating procedure does not guarantee that successive gating frames (and consequently the struts contained in the image) are aligned, which makes tracking of individual struts impossible. This additional feature can be obtained by applying the method developed by Gatta et al.\textsuperscript{24} and it is foreseen as future research.

Both training and validation data used in this study come from IVUS equipments working at 40 MHz. As a consequence, in order to apply the trained method to IVUS sequences acquired at different frequencies and from different echograph producers, the semantic classifier and the strut kernel should be retrained. Although this may seem a limitation for the current approach, it is worth noting that a similar procedure was followed in the “Lumen + External Elastic Laminae Border Detection in IVUS” challenge,\textsuperscript{25} where we retrained our method developed with 40 MHz data using 20 MHz data from a different vendor, and we achieved the top performance among fully automatic methods for the detection of the media-adventitia at 20 MHz. Since the classification approach used in this paper relies on the same classification framework used in the challenge,\textsuperscript{16} we expect our system for stent analysis to perform on other types of sequence with comparable performance.

It might be noticed that the algorithm has been trained using frames containing only one guide wire. Therefore, in cases where two or more guide wires are present and their shadow is visible in the IVUS image, the shadow having a lower response would be likely classified as a calcification or as a strut.

The method has been implemented in MATLAB (The MathWorks, Natick, MA, USA, 2011) and the computation time is 0.33 s/frame, using an Intel i7 quad-core processor. Although the numerical performance obtained in this study outperforms the qualitative results reported in previous approaches, a fair comparison of several methods over the same dataset would only be possible by competing in a challenge, similar to the one presented in Balocco et al.\textsuperscript{25}

5. CONCLUSION

We have presented a framework for CAD of intracoronary stents in IVUS image sequences, able to detect struts and provide an estimation of the stent shape. The results obtained on a heterogeneous dataset containing both metallic and bioabsorbable stents collected through a multicentric collaboration are close to the interobserver variability and suggest that the system has the potential to be used during percutaneous interventions.

The method achieved performance of strut detection with an overall F-measure of 77.7% and a mean distance of 0.15 mm from the manually annotated struts in the case of a metallic stent, while for bio-absorbable stents an overall F-measure of 77.4% was obtained, with a mean distance of 0.09 mm from the manually annotated struts.

The system has been validated using cases of both metallic and bio-absorbable stents. It is worth noting that the system was solely trained using data from cases with metallic stents. Bio-absorbable stents are used less often during PCIs, therefore finding a large set of examples to train a new system is not a trivial task. However, good performance can be observed also in the presence of bio-absorbable stents, showing the capability of the system to generalize well to detection of unseen examples, including other types of stent.

The implicit analysis of cases of malapposition and underexpansion is out of the scope for this paper and represents part of our future research. Such analysis could be performed by combining the CAD framework described in this paper with existing systems for IVUS image analysis.\textsuperscript{19}
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CONFICT OF INTEREST DISCLOSURE

The authors have no COI to report.

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D. Trabattoni and A. L. Bartorelli, “IVUS in bifurcation stenting: What have we learned?,” EuroIntervention 6(Suppl J), 388–393 (2010).

H.-I. Yoon and S.-H. Hur, “Optimization of stent deployment by intravascular ultrasound,” Korean J. Intern. Med. 27, 30–38 (2012).

J. Waggoner, “How do OCT and IVUS differ? A comparison and assessment of these modern imaging modalities,” Card. Interventions Today 1, 46–52 (2011); available at http://citoiday.com/pdfs/cit0511_F3_feldman.pdf.

J. H. Reiber, S. Tu, J. C. Tuinenburg, G. Koning, J. P. Janssen, and J. Dijkstra, “QCA, IVUS and OCT in interventional cardiology in 2011,” Cardiovasc. Diagn. Ther. 1, 57–70 (2011).

R. Waksman, H. Kitabata, F. Prati, M. Albertucci, and G. S. Mintz, “Intravascular ultrasound versus optical coherence tomography guidance,” J. Am. Coll. Cardiol. 62, S32–S40 (2013).

B. D. Gogas, V. Farooq, Y. Onuma, and P. W. Serruys, “The absorb biore sorbable vascular scaffold: An evolution or revolution in interventional cardiology?,” Hell. J. Cardiol. 53(4), 301–309 (2012); available at http://www.ncbi.nlm.nih.gov/pubmed/22796817.

Y. Onuma and P. W. Serruys, “Biodegradable scaffold: The advent of a new era in percutaneous coronary and peripheral revascularization?,” Circulation 123, 779–797 (2011).

Z. Wang, M. Jenkins, G. Linderman, H. Bezzera, Y. Fujino, M. Costa, D. Wilson, and A. Rollins, “3-D stent detection in intravascular OCT using a bayesian network and graph search,” IEEE Trans. Med. Imaging 34, 1549–1561 (2015).

H. Lu et al., “Automatic stent strut detection in intravascular OCT images using image processing and classification technique,” Proc. SPIE 8670, 867015 (2013).

A. Wang, J. Eggemont, N. Dekker, H. M. Garcia-Garcia, R. Pawar, J. H. Reiber, and J. Dijkstra, “Automatic stent strut detection in intravascular optical coherence tomographic pullback runs,” Int. J. Cardiovasc. Imaging 29(1), 29–38 (2013).

C. Canero, O. Pujol, P. Radeva, R. Toledo, J. Saludes, D. Gil, J. Villanueva, J. Mauri, B. Garcia, and J. Gomez, “Optimal stent implantation: Three-dimensional evaluation of the mutual position of stent and vessel via intracoronary echocardiography,” in Computers in Cardiology (1999), pp. 261–264; available at http://ieeexplore.ieee.org/document/825956/which was published in the conference http://www.cinc.org/.

J. Dijkstra, G. Koning, J. Tuinenburg, P. Oemrawsingh, and J. Reiber, “Automatic stent detection in intravascular ultrasound images for quantitative measurements of the vessel, lumen and stent parameters,” in Computers in Cardiology 2001, Vol. 28 (Cat. No.01CH37287) (2001), Vol. 1230, pp. 25–28.

D. Rotger, P. Radeva, and N. Bruining, “Automatic detection of biodegradable coronary stents in IVUS images using a cascade of classifiers,” IEEE Trans. Inf. Technol. Biomed. 14, 535–537 (2010).

R. Hua, O. Pujol, F. Ciompi, S. Balocco, M. Alberti, F. Mauri, and P. Radeva, “Stent strut detection by classifying a wide set of IVUS features,” in MICCAI Workshop on Computer Assisted Stenting (2012), pp. 130–137; available at http://campar.in.tum.de/wikit/pub/STENT2012/ WebHome/STENT2012Proceedings.pdf.

J. Dijkstra, G. Koning, J. C. Tuinenburg, P. V. Oemrawsingh, and J. H. Reiber, “Automatic stent border detection in intravascular ultrasound images,” Int. Congr. Ser. 1256, 1111–1116 (2003).

F. Ciompi, O. Pujol, C. Gatta, M. Alberti, S. Balocco, X. Carrillo, J. Mauri-Ferre, and P. Radeva, “Holimab: A holistic approach for media-adventitia border detection in intravascular ultrasound,” Med. Image Anal. 16, 1085–1100 (2012).

F. Ciompi, R. Hua, S. Balocco, M. Alberti, O. Pujol, C. Caus, J. Mauri, and P. Radeva, “Learning to detect stent struts in intravascular ultrasound,” in Pattern Recognition and Image Analysis (Springer, 2013), pp. 575–583; available at http://link.springer.com/chapter/10.1007/978-3-642-38628-2_68.

F. Ciompi, S. Balocco, C. Caus, J. Mauri, and P. Radeva, “Stent shape estimation through a comprehensive interpretation of intravascular ultrasound images,” in Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013 (Springer, 2013), pp. 345–352; available at http://link.springer.com/chapter/10.1007/978-3-642-40763-5_43.

S. Balocco, C. Gatta, F. Ciompi, O. Pujol, X. Carrillo, J. Mauri, and P. Radeva, “Combining growcut and temporal correlation for IVUS lumen segmentation,” in IPIBIA, LNCS 6699/2011 (Springer, 2011), pp. 556–563; available at http://link.springer.com/chapter/10.1007/978-3-642-21257-4_69.

C. Gatta, S. Balocco, F. Ciompi, R. Hemetsberger, O. Rodriguez-Leor, and P. Radeva, “Real-time gating of IVUS sequences based on motion blur analysis: Method and quantitative validation,” in MICCAI 2010, LNCS 6362/2010 (Springer, 2010), pp. 59–67; available at http://www.ncbi.nlm.nih.gov/pubmed/20879299.

M. Alberti, S. Balocco, C. Gatta, F. Ciompi, O. Pujol, J. Silva, X. Carrillo, and P. Radeva, “Automatic bifurcation detection in coronary IVUS sequences,” IEEE Trans. Biomed. Eng. 59(4), 1022–2031 (2012).

R. Schapiro, “The boosting approach to machine learning: An overview,” in MSR Workshop on Nonlinear Estimation and Classification (Berkeley, CA, 2001); available at http://link.springer.com/chapter/10.1007/978-3-642-8037-8-15792-9.

T. G. Dietterich and G. Bakiri, “Solving multiclass learning problems via error-correcting output codes,” J. Acad. Ind. Res. 2, 263–286 (1995).

C. Gatta, O. Pujol, O. Rodriguez-Leor, J. Mauri, and P. Radeva, “Fast rigid registration of vascular structures in IVUS sequences,” IEEE Trans. Inf. Technol. Biomed. 13, 1006–1011 (2009).

S. Balocco, C. Gatta, F. Ciompi, A. Wahle, P. Radeva, S. Carlier, G. Unal, E. Sanidas, J. Mauri, X. Carrillo, K. Tornvok, C.-W. Wang, H.-C. Chen, T. P. Exarchos, D. I. Fotiadis, F. Destrempes, G. Cloutier, O. Pujol, M. Alberti, E. G. Mendizabal-Ruiz, M. Rivera, T. Askoy, R. W. Downe, and I. A. Kakadiaris, “Standardized evaluation methodology and reference database for evaluating IVUS image segmentation,” Comput. Med. Imaging Graph. 38, 70–90 (2014).