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Assessment of intracoronary stent location and extension in intravascular ultrasound sequences

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(Received 16 February 2018; revised 11 October 2018; accepted for publication 12 October 2018; published 14 December 2018)

Purpose: An intraluminal coronary stent is a metal scaffold deployed in a stenotic artery during percutaneous coronary intervention (PCI). In order to have an effective deployment, a stent should be optimally placed with regard to anatomical structures such as bifurcations and stenoses. Intravascular ultrasound (IVUS) is a catheter-based imaging technique generally used for PCI guiding and assessing the correct placement of the stent. A novel approach that automatically detects the boundaries and the position of the stent along the IVUS pullback is presented. Such a technique aims at optimizing the stent deployment.

Methods: The method requires the identification of the stable frames of the sequence and the reliable detection of stent struts. Using these data, a measure of likelihood for a frame to contain a stent is computed. Then, a robust binary representation of the presence of the stent in the pullback is obtained applying an iterative and multiscale quantization of the signal to symbols using the Symbolic Aggregate approxXimation algorithm.

Results: The technique was extensively validated on a set of 103 IVUS of sequences of in vivo coronary arteries containing metallic and bioabsorbable stents acquired through an international multicentric collaboration across five clinical centers. The method was able to detect the stent position with an overall F-measure of 86.4%, a Jaccard index score of 75% and a mean distance of 2.5 mm from manually annotated stent boundaries, and in bioabsorbable stents with an overall F-measure of 88.6%, a Jaccard score of 77.7 and a mean distance of 1.5 mm from manually annotated stent boundaries. Additionally, a map indicating the distance between the lumen and the stent along the pullback is created in order to show the angular sectors of the sequence in which the malapposition is present.

Conclusions: Results obtained comparing the automatic results vs the manual annotation of two observers shows that the method approaches the interobserver variability. Similar performances are obtained on both metallic and bioabsorbable stents, showing the flexibility and robustness of the method. © 2018 American Association of Physicists in Medicine [https://doi.org/10.1002/mp.13273]

Key words: IVUS, malapposition, stent, ultrasound

1. INTRODUCTION

An intraluminal coronary stent is a metal mesh tube deployed in a stenotic artery during percutaneous coronary intervention (PCI) in order to restore blood flow. The assessment of the stent location and extension along the vessel axis is relevant for PCI planning, implantation, and patient follow up. In order to have an effective deployment, a stent should be optimally placed with regard to anatomical structures such as bifurcations and stenoses. The deployment of a stent in an incorrect location may lead to restenosis or bifurcation side branch occlusion.

Although the current reference image modality for verifying the correct positioning of a stent is intravascular optical coherence tomography (OCT), a potential alternative is intravascular ultrasound (IVUS). IVUS is a catheter-based imaging technique that provides the sequence of tomographic images (pullback) of the internal vessel morphology [see Fig. 1(a)]. The stent placement can be deduced by the position of its struts, [see Fig. 1(b)]. The main advantage of OCT over IVUS is that the resolution is 10-fold higher, easing the visualization of the stent for the physician. However, OCT remains inferior to IVUS in matters of depth of penetration.
FIG. 1. Example of IVUS pullback containing a stent (a). In (b) and (c), two examples of IVUS frames in Cartesian coordinates, and belonging to the pullback (a), are depicted. The frame (b) corresponds to the green vertical line in (a), and it does not contain a stent, while (c) corresponds to the vertical line in (a), and it contains a stent. The green circles and the green dotted line in (c) and (d) represent the estimated position of struts and stent shape obtained using the technique. The classification map (d) of the IVUS frame (c) is used to guide the struts and stent estimation. [Color figure can be viewed at wileyonlinelibrary.com]
The coupling of new strategy for the assessment of stent location and extension of intracoronary stent with the previous published methods provides a complete framework for detection of intracoronary stents aimed at assisting intraoperative diagnosis.

Instead of our approach on a reduced dataset was presented in Ref. [24]. This paper extends by focusing on an extensive validation using a set of 103 IVUS sequences of in vivo coronary arteries containing metallic and bioabsorbable stents, which are acquired through an international multicentric collaboration across five centers. Precision, Recall, F-measure, and Jaccard scores along with the distance between detected and reference frames are reported, and compared against inter- and intraobserver measurements of two experts.

Additionally, applying the framework to each IVUS-gated frame allows to estimate the lumen and stent contours. Using such information it is possible to compute the stent malapposition for each angular sector of the frame along the pullback. As a result, a map indicating the distance between the lumen and the stent in each angular section of the pullback is created and the angular sector of the pullback displaying malapposition is identified.

2. MATERIALS AND METHOD

The three steps of the framework are detailed in the following sections.

2.A. Gating

Let us define an IVUS pullback as a sequence of frames \( I = \{f_i\} \) where \( i \) is the frame number of the sequence. We first preprocess the pullback by applying an image-based gating procedure. Gating allows to reduce the swinging and roto-pulsation effects affecting the reliable identification of luminal area, which is an important factor for the strut detection. In our pipeline, a sequence of gated frames \( G = \{g_j\} \) is obtained by applying the method presented by Gatta et al. to the IVUS pullback. 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. Strut detection

The detection of stent struts was performed by applying the strut detection method proposed by Ciompi et al. to each gated frame independently. The method identifies the stent struts by contemperaneously considering the textural appearance of the stent and the vessel morphology. The strut detection system uses the Multi-Scale Multi-Class Stacked Sequential Learning (M²SSL) classification scheme to provide a comprehensive interpretation of the local structure of the vessel. In the classification problem, the class \textit{Strut} is considered as one of the six considered classes (defined as Blood area, Plaque, Calcium, Guide-wire shadow, Strut, and external Tissues). For semantic classification purposes, tailored features used for classification to the problem are used.

As a result, for each pixel \( p(x, y) \) of a gated IVUS image, a classification map \( M \) is obtained [see Fig. 1(d)]. A curve approximating the stent shape \( S_{\text{shape}} \) is initially estimated considering vascular constrains and classification results. For each region of \( M \) labeled as stent \( M_{[S]} \), a strut candidate is considered. The selected struts \( p(x, y) \) were selected among the candidates, considering both local appearance and distance with regard to the stent shape \( S_{\text{shape}} \). Consequently false-positive candidates were discarded, and the regions containing a selected strut \( M_{[S]}^{*} \) are a subset of \( M_{[S]} \).

2.C. Stent presence assessment

The frames of the pullback corresponding to the vessel positions where the stent begins and ends can be identified by analyzing the extracted struts. We model the presence of stent as a rectangular function \( \Gamma(t) \), where the variable \( t \) indicates the temporal position in the pullback (see Fig. 1). We estimate the binary signal \( \gamma(t) \) by processing a real-valued signal \( \gamma(t) \), which we define as stent presence, corresponding to the frame-based likelihood of finding a stent in each frame of the IVUS sequence. The value of \( \gamma(t) \) for each position \( t \) in the sequence is computed by considering both the number of struts and their area, thus negatively weighting small strut areas of the images which have an high probability to be incorrect detections.

\[
\gamma(t) = \sum_{p \in M_{[S]}^*} p_{|p \in M_{[S]}^*} \tag{1}
\]

where \( p_s \in M_{[S]}^* \) indicates the pixels of the IVUS frame labeled as strut containing an selected strut. An example of signal \( \gamma(t) \) is depicted in Fig. 2(c).

The signal \( \gamma(t) \) may contain several transitions between low and high amplitudes, due to the variability in the number of struts visible in consecutive frames and to suboptimal strut detection. For this reason, we filter the \( \gamma(t) \) signal by considering its local statistics applying the SAX algorithm. SAX is a symbolic representation algorithm that estimates a quantization of the time series based on global signal measurements and on local statistics of subsequent neighbor samples. Given the signal \( \gamma(t) \) and a window size \( w \), the algorithm calculates a Piecewise Aggregate Approximation (PAA) \( \gamma(t) \), which is obtained by computing the local average values of \( \gamma(t) \) over \( n_v \) segments \( w \)-wide. Each average value is then normalized over the signal \( \gamma(t) \). The procedure firstly computes a vector \( \overline{\gamma}_i = (\overline{\gamma}_1, \ldots, \overline{\gamma}_n) \) where each of \( \overline{\gamma}_i \) is calculated as follows:

\[
\overline{\gamma}_i = \frac{1}{w} \sum_{j=w(i-1)+1}^{w(i)} q_j, \tag{2}
\]

where \( i, j \in \mathbb{N} \). The quantified signal amplitudes \( \hat{q}_i \) are obtained by normalizing \( \overline{\gamma}_i \) by the mean \( \mu_i \) and standard deviation \( \sigma_i \) of the signal \( \gamma(t) \):
Then, in another example (c), the SAX algorithm is applied to a signal using \( n_w \) obtained from an IVUS pullback. In this case, the signal to separate the area below the Gaussian curve in the SAX algorithm, a Piecewise Aggregate Approximation of a synthetic curve, not related to the area of the Gaussian curve.

The SAX algorithm is iterated \( N_{\text{sax}} \) times, until converging to flat intervals along the signal \( \gamma(t) \). The maximum iteration number \( N_{\text{sax}} \) is achieved when the difference between subsequent iterations of SAX is zero. Figure 2(c) illustrates the iteration of the SAX algorithm over an exemplar signal \( \gamma(t) \). The other parameters of the SAX algorithm is the number of quantized values assigned to the signal \( L_{\text{sax}} \). The iterative SAX algorithm is described by the following equation:

\[
\gamma(t)_{k+1} = \text{SAX}(\gamma(t)_k, \sigma_k^{\text{train}}, \mu_k^{\text{train}}, L^{\text{train}}) 
\]

where \( k = 1 \ldots N_{\text{sax}} \) and \( \sigma_k^{\text{train}} \) and \( \mu_k^{\text{train}} \) are the mean and standard deviation computed on the training set at the iteration \( k \), and the number of quantized values \( L_{\text{sax}} \) is a constant that has been optimized by cross-validation using the training set, as described in the validation section. When the SAX algorithm reaches the maximum iteration number \( N_{\text{sax}} \), the binary signal indicating the stent presence of the stent is obtained as \( \gamma(t)_{N_{\text{sax}}} > \mu_{N_{\text{sax}}}^{\text{train}} \).

3. VALIDATION

3.A. Material

A set of 103 sequences of IVUS images was collected through a multicenter study (see Table 1). In this study, we are interested in assessing the performance of the method at detecting the presence of stent along the pullback. For this reason, pullbacks acquired before and after stent deployment were used, therefore considering also sequences with the absence of stent. The dataset includes nine pullbacks acquired before the stent deployment. The remaining 94 pullbacks contain one or more metalic (met) or bioabsorbable (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 and the IVUS system had a 30 frames per second frame rate. The model of the metallic and bioabsorbable stents were “Promus Coronary Stent, Boston Scientific, MN” and “Absorb Biodegradable Vascular Scaffold (BVS), Abbott, IL”, respectively.

Two experts (one clinician and one experienced researcher in IVUS imaging) manually annotated the beginning and the end of the stent in each sequence. They were asked to scroll the pullback back and forward, looking at the short-axis view only, and analyzing adjacent frames in order to identify the frames defining the stent boundaries. More than one annotation per pullback was allowed when several stents were implanted in subsequent segments of the same artery. Two separate test sets were defined (\( test_{\text{met}} \) and \( test_{\text{abs}} \)), corresponding to pullback containing metallic or bioabsorbable stents, respectively. When sequences containing a metallic stent were the training was performed using pullbacks having a metallic stent (\( train_{\text{met}} \)). Instead when sequences containing bioabsorbable stent were analyzed, the training was performed separately using metallic (\( train_{\text{met}} \)) or bioabsorbable (\( train_{\text{abs}} \)) frames. Since the number of sequences containing a bioabsorbable stent was low, we expect that the stent detection performance might increase when the system is trained on a larger dataset. When pullbacks of the same dataset were used for test and training, a 10-fold cross-validation strategy was used to compute the results, while all the metallic pullbacks (\( train_{\text{met}} \)) were used for training purposes when the test was performed over \( test_{\text{abs}} \) dataset.

3.B. Experiments on stent presence assessment

The assessment of stent presence is based on the analysis of the mono-dimensional signal \( \gamma(t) \). In order to evaluate the performance, the manual annotations of the beginning and end of the stent were converted into binary signals \( \gamma_{\text{obs}}(t) \) indicating the presence of the stent in the pullback. Sequentially, the signals \( \Gamma(t) \) indicating the segments of the pullback in which a stent is likely to be present, were compared against the sections indicated by the observers \( \gamma_{\text{obs}}(t) \). The performance was evaluated by measuring the Precision (P), Recall (R), F-Measure (F), and Jaccard-index (J). The first three indices are typically used to evaluate a detection problem, while the forth index evaluates the overlap between the ground-truth and the automatically detected signals. Additionally, the distance between the automatic and the manual detection expressed as the number of gated frames, in \( mm \), and as percentage of the stent length.
TABLE I. Detailed description of the datasets used in this study.

<table>
<thead>
<tr>
<th>Dataset type</th>
<th>Number of pullbacks</th>
<th>Stent deployment</th>
<th>% of stent frames</th>
<th>Training</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metallic</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>#1</td>
<td>80</td>
<td>Deployed</td>
<td>Roughly 50%</td>
<td>trainmet</td>
<td>testmet</td>
</tr>
<tr>
<td>#2</td>
<td>1</td>
<td>Deployed</td>
<td>Roughly 50%</td>
<td>trainmet</td>
<td>testmet</td>
</tr>
<tr>
<td>#3</td>
<td>5</td>
<td>Deployed</td>
<td>Roughly 50%</td>
<td>trainmet</td>
<td>testmet</td>
</tr>
<tr>
<td>Bioabsorbable</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>#4</td>
<td>4</td>
<td>Deployed</td>
<td>Roughly 50%</td>
<td>trainmet</td>
<td>testmet</td>
</tr>
<tr>
<td>#5</td>
<td>1</td>
<td>Deployed</td>
<td>Roughly 50%</td>
<td>trainmet</td>
<td>testmet</td>
</tr>
</tbody>
</table>

In our experiments, we estimate $\sigma_k^{\text{train}}$, $\mu_k^{\text{train}}$, and $L_{\text{train}}$ by optimizing the F-measure score by varying $L_{\text{max}}$ between 3 and 50. When the optimal value of $L_{\text{max}} = 36$ is set, $\sigma_k^{\text{train}}$, $\mu_k^{\text{train}}$ are estimated automatically by the SAX algorithm.

The quantitative results for the pullback-wise analysis for the three experiments are reported in Table II. In the first experiment, the system is trained and tested using metallic pullbacks. In the second and the third, the test is performed over bioabsorbable frames, and the training is obtained using metallic and bioabsorbable data, respectively. As IVUS is highly challenging to interpret, the two observers sometimes disagree as shown in Table II (rows 5, 8, and 11).

In the case of bioabsorbable stents, the performance metrics are obtained when the framework is trained using metallic frames. All the performance metrics (except the Precision) of the second experiment, that is, training using metallic frames (rows 6, 7), are higher with respect to the results obtained in the third experiment, that is, training using bioabsorbable frames (rows 9, 10). In particular, a 10% of difference between the Recall and Jaccard measure of the two experiments can be noticed. This confirms that the bioabsorbable dataset is too small for training purposes.

If we focus on the first two experiments (rows 3–8), in both datasets, the precision approaches the interobserver variability, while the recall is in general between 10% and 20% lower than the results of the manual annotation. The obtained F-measure and the Jaccard measure of the automatic performance show satisfactory results when compared with manual annotations (about 5% and 7% lower than the ground truth score).

Such results are confirmed by analyzing the distance between the boundary assessed with our method and the manual annotations, as illustrated in the last two columns of Table II. In the case of metallic stents, the error in the boundary assessment ranges between 4 and 5.3 gated frames (about 2 and 2.5 mm, respectively). It is interesting to note that such errors correspond in average to 4.2% and 5.8% of the stent length. In the case of metallic stents, the error in the boundary assessment is about 3.4 gated frames (about 1.5 mm). In this case, such an error corresponds in average to 10% of the stent length, given that the length of the bioabsorbable stents composing our dataset was in general smaller than the metallic ones.

The results shown in Table II illustrate that the method is flexible and can be applied to a pullback containing either metallic or bioabsorbable stents with similar results.

In order to analyze if the scores obtained by the automatic method were statistically different from the performance of the manual annotation, an ANOVA test was performed over the results reported in Table II. As can be observed in Table III, the performances of the method were particularly satisfying, since in the case of metallic stent the automatic method approaches the performances of one observer. The error of boundary detection committed by the automatic method was found to be comparable with respect to the errors committed by the first observer, and the difference of F-measure and Jaccard scores committed by the automatic method with respect to the manual annotation, was statistically weak (0.01 < $P$ < 0.05). On the other hand, the results were found to be statistically different ($P < 0.01$) when the automatic method was compared against the manual annotation of the second observer.

In the case of bioabsorbable frames trained using metallic pullbacks, comparable results were found only in the relative boundary errors, while in the other cases the results...
between automatic and manual detection was considered statistically different. Finally, in the case of bioabsorbable frames trained using bioabsorbable pullbacks, all the tests reported a statistical difference between the automatic and the manual detection.

3.C. Malapposition analysis

Malapposition happens when at least one stent strut is separated from the intimal surface of the arterial wall and it is generally computed as the distance between the malapposed struts and the vessel wall, and the area is measured.

In particular, the thresholds of malapposed struts depends on the stent type and brand\(^{28}\) ranging from 100 \(\mu\)m to 160 \(\mu\)m. In the case of the Boston Scientific brand, we consider the stent malapposed when the distance to the lumen is higher than 130 \(\mu\)m. The frame-wise analysis obtained by applying the framework to each IVUS-gated frame allows to estimate the lumen and stent contours. Using such information, it is possible to compute the stent malapposition for each angular sector of the frame along the pullback. As can be seen in Fig. 3 (top) an exemplar IVUS pullback is analyzed. The framework provides a map indicating the distance between the lumen and the stent in each angular section of the pullback. Then a plot, as shown in Fig. 3 (middle), illustrates the maximum amplitude of the distance along the pullback. Finally, a third plot indicates the percentage of the stent displaying malapposition (bottom).

4. RESULTS

4.A. Metallic stents

Examples of processed signals for the detection of a metallic stent in the IVUS frame are depicted in Fig. 4. In Figs. 4(a1) and 4(b1), both the initial and final frame of the sequence are accurately identified. The result is not obvious since in (a) the amplitude of the signal \(\gamma(t)\) is almost null in two sections of the pullback. However, the SAX algorithm allowed to detect the presence of a stent, based on the statistics of the frames in the neighborhood. On the other hand, in Fig. 4(a2), the central section of the pullback where \(\gamma_{\text{auto}}(t)\) is almost null is correctly classified by the SAX algorithm as the absence of stent. This is coherent with the manual annotation of the two observers, where two stents are labeled. It must be noted that in this paper no constrain on the minimum length of the stent is applied. In 4(b2), we observed a case in which the absence of the stent is correctly identified. Indeed, observing 4(b2), it can be noticed that the quantification of the signal is below the global threshold \(T_{\text{global}}\). In Fig. 4(a3) and 4(b3), regions of high signal separated from the main stent have been identified as a secondary implanted stent. It might be noticed that this error happens only when a strong spike in the signal is present, for instance when a calcified plaque is mistaken for a deployed stent. In Figs. 4(a4) and 4(b4), the initial and final frame of the stent are incorrectly identified since the amplitude of \(\gamma(t)\) is low and comparable with the noise at the proximity of the stent area.
4.B. Bioabsorbable stents

Examples of processed signals for the detection of a bioabsorbable stent in the IVUS frame are depicted in Fig. 5. In Figs. 5(a1) and 5(b1), we observe two cases of accurate stent detection. In the rest of cases the performance of the stent detection decreases. In Figs. 5(a2), 5(b2), 5(a3), the stent detection is incorrectly classified. In Fig. 5(a3), it is interesting to note how the algorithm is able to recover the whole stent longitude at the right side of the image, even if the signal amplitude is low at the middle of the stent area. Finally, Figs. 5(b3), 5(a4), 5(b4) show a pullback not containing a stent in which short but intense peaks in the signal are misclassified.

5. DISCUSSION

In this paper, for the first time, a framework for the automatic identification of stent presence along the pullback (location and extension) has been presented.

The methodology described in the paper is based on three main steps (1) a gating technique and (2) a stent strut detection technique used to obtain a measure of likelihood for a frame to contain a stent. The paper introduces (3) a new strategy for obtaining a robust binary representation of the presence of the stent in the pullback using the SAX algorithm. The stages (1) and (2) of the pipeline, can be computed using similar method proposed in the state of the art. However, since the reliability of the strut detection is a critical step of the pipeline, the influence of using a method less reliable might have a negative impact over the performances of the whole framework.

In clinical practice, the presented system could be used intraoperatively to perform automatic analysis of the stent position and placement. This would ease the task of physicians, by reducing the burden of manual search and measurements of the deployed stent via inspection of the IVUS sequence. In order to show how the result can be represented in a clinical application, in Fig. 6, two exemplar IVUS long-axis views of the stent detection are depicted, superimposed with vertical lines representing the boundaries of the stent manually labeled by the physician.

The presented framework processes a sequence of gated frames. Due to the catheter swinging effect, nongated frames might be analyzed multiple times along the sequence. Applying gating has the advantage of providing frames that are less affected by motion artifacts, in which the analysis of blood texture can be done in a more robust and reproducible way. Moreover, gating reduces the amount of frames to be analyzed by approximately a factor 30, which also benefits the system in terms of computation time. Using gated frames does not limit the applicability of the proposed system, which can potentially work on nongated frames as well. However, in this case a reduction in performance can be expected.

The analysis of the stent presence signal has been performed using the SAX algorithm which provides an unsupervised classification of the stent location in a fast and statistically robust fashion.

Since the proposed system is meant to be used in an intraoperative fashion, it is important to evaluate the computational cost in order to assess its real impact during clinical practice. For this purpose, we evaluated the computation time of the system. The method has been implemented in Matlab (The MathWorks, Natick, MA, USA, 2011) and the computation time of the pullback analysis is one order of magnitude lower than the time required for detecting the stents. Indeed the pullback-wise analysis took about 4.1 s per pullback vs 0.33 s per frame (around 33 s per pullback) required for a stent detection (measured on a Intel i7 quad-core processor).

6. CONCLUSION

We presented a new strategy for the assessment of stent location and extension of intracoronary stent in intravascular ultrasound sequences. Such a technique, when coupled with previous published methods, provides a complete framework for the intracoronary stents aimed at assisting intraoperative diagnosis. The results obtained from 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.

In the case of metallic stent, the performances have an overall F-measure of 87.4% and 86.4% and a Jaccard score of 76.6% and 75.0% obtained by comparing the automatic results against the manually annotated struts of the two observers, respectively. For bioabsorbable stents, the overall F-measure of 88.6%, and 88.9% was obtained, with a Jaccard score of 77.7% and 78.1% obtained by comparing the automatic results against the manually annotated struts. Such values approached the interobserver variability which corresponded to a F-measure of 92.1% and a Jaccard score of 86.7% in the case of metallic stents, and a F-measure of 99.2% and a Jaccard score of 98.5% in the case of bioabsorbable stents.

With regard to the distance between the automatic and the manual detection, the error in case of metallic stents is of 4.0 and 5.3 gated frames (corresponding to about 2 and 2.5 mm, respectively) from the manually annotated struts of the two observers, while in case of bioabsorbable stents the error is 3.4 and 3.3 gated frames (corresponding to about 1.5 mm). These results are satisfying considering that the interobserver error of the manual annotation is 3.2 and 3.3 gated frames (corresponding to about 1.5 mm).
Future work will be addressed toward comparing the performance of the current pipeline against the assessment of stent location and extension obtained using deep learning (DL) techniques. In particular, artificial neural networks (ANN) might improve the classification on both frame-wise and pullback-wise analyses. ANNs are well known for...
providing state-of-the-art classification performances, however, it should be noted that ANN are currently affected by some limitations: (a) a large dataset (of the order of 10000 samples) is usually required for training purposes. (b) in literature there is not a clear consensus about how to find the optimal parameter for the network fine-tuning. Such limitations

Fig. 5. Qualitative evaluation on testabs dataset. The signal $\gamma(t)$ is illustrated in the first row, while in the second, the result of the SAX quantization is reported. Finally in the third row, three binary signals representing the presence or the absence of the signal are compared: the first corresponds to the automatic results, while the second and the third are the annotations of the two observers. [Color figure can be viewed at wileyonlinelibrary.com]
and, for each frame, only the stent area computed by the automatic method was colored. The pictures illustrate how the results can be represented in a clinical application. [Color figure can be viewed at wileyonlinelibrary.com] should be carefully studied in order to analyze if a deep learning strategy could be successfully applied to IVUS pullbacks.

ACKNOWLEDGMENT

The authors thank Darren Barlow for the English proofread. This work was supported in part by the MICINN Grant TIN2015-66951-C2-1-R, SGR 1219, CERCA, and ICREA Academia 2014. The authors have no relevant conflicts of interest to disclose.

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Medical Physics, 46 (2), February 2019