Automatic Bifurcation Detection in Coronary IVUS Sequences

Marina Alberti, Simone Balocco, Carlo Gatta, Francesco Ciompi, Oriol Pujol, Joana Silva, Xavier Carrillo, Petia Radeva

Abstract—In this paper, we present a fully automatic method which identifies every bifurcation in an IVUS sequence, the corresponding frames, the angular orientation with respect to the IVUS acquisition and the extension. This goal is reached using a two-level classification scheme: firstly, a classifier is applied to a set of textural features extracted from each image of a sequence. A comparison among three state-of-the-art discriminative classifiers, AdaBoost, random forest, and support vector machine is performed to identify the most suitable method for the branching detection task. Secondly, the results are improved by exploiting contextual information using a multi-scale stacked sequential learning scheme. The results are then successively refined using a-priori information about branching dimensions and geometry. The proposed approach provides a robust tool for the quick review of pullback sequences, facilitating the evaluation of the lesion at bifurcation sites. The proposed method reaches an F-Measure score of 86.35%, while the F-Measure scores for inter- and intra-observer variability are 71.63% and 76.18% respectively. The obtained results are positive. Especially considering that the branching detection task is very challenging, due to high variability in bifurcation dimensions and appearance.

Index Terms—Intravascular Ultrasound, coronary bifurcations, texture analysis, contextual classification

I. INTRODUCTION

Atherosclerosis is a disease affecting the arterial walls, evolving towards the formation of multiple plaques inside the arteries. Atherosclerotic plaque can grow, leading to a significant reduction of the blood flow. In addition, atherosclerotic plaque can become fragile, potentially leading to clinical complications, such as angina, myocardial infarction, stroke, and sudden cardiac death [1], [2]. Both, plaque growth and rupture, preferentially involve specific vessel sites, such as vascular bifurcations, also named vessel branchings. Bifurcations can be defined as the sites where an artery diverges into two daughter vessels, the main branch and the side branch. Bifurcations are critical vascular locations from the clinical point of view: it has been shown that arterial hemodynamics plays a relevant role in the progression of atherosclerosis [3]; in particular, the sites of abnormal and disturbed flow, such as vessel branching, are key regions for plaque evolution [4]. Asakura et al. [5] found that wall thickenings and plaque formation in coronary arteries are frequently localized on the outer wall of one or both daughter vessels at major bifurcations. Additionally, the rupture of vulnerable plaque may depend on anatomic parameters, such as the proximity of bifurcations and the axial bending during the cardiac cycle. In particular, the presence of a bifurcation before and especially after the lesion is a marker of an increased risk of plaque rupture and subsequent thrombosis [6]. This connection with disease formation is confirmed by the fact that a large number of bifurcation lesions undergo percutaneous coronary intervention (PCI) [7].

The detection of vascular bifurcations is particularly important in clinical applications, such as the diagnosis of vessel stenosis, surgical planning, and medical image registration, in which branching points can be used as landmarks. In several studies, bifurcations have been identified as a means to segment and reconstruct the entire coronary tree. For instance, in a study on chest CT images [8], the AdaBoost learning technique is used for an automatic detection of bifurcations, aimed at improving the segmentation of vascular structures. In another paper, Wette et al. [9] extend the Corkscrew segmentation algorithm to identify bifurcations in a CT dataset. Similarly, Merle et al. [10] and Koehler et al. [11] address the problem of extraction and analysis of the coronary tree from X-ray angiographies by means of bifurcation identification.

So far, the specific task of bifurcation identification has never been addressed in Intravascular Ultrasound (IVUS). However a few papers [12], [13] previously proposed general frameworks aimed at the simultaneous segmentation of various structures in IVUS images, in which side branches were identified too. In particular in [13], the maximum smoothed intensity for every column of the polar IVUS image is used as a feature, and a simple threshold is applied to identify the branches. In [12], a multi-agent image interpretation system is applied to IVUS images, in which interacting agents are provided manually with a set of rules. The performance of side branch detection is not evaluated. Additionally, both studies consider single image frames neglecting the 3-D context.

IVUS is an intra-operative imaging tool for the quantification and characterization of coronary plaque, used for diagnostic purposes and for planning and validation of PCI, enabling the visualization of high resolution images of internal vascular structures. The procedure for the acquisition of an IVUS sequence consists in inserting an ultrasound emitter, carried by a catheter, into the arterial vessel and dragging the probe from the proximal to the distal position (pullback). The standard IVUS image is a 360-degree tomographic cross-sectional view of the vessel walls, denoted as short-axis view,
which allows an accurate assessment of vessel morphology and tissue composition [14]. Given an angular position on the short-axis view (indicated in Figure 1-b by a line), the corresponding longitudinal view can be generated by considering the gray-level values of the sequence along the diameter at the chosen angle. This longitudinal image approximates the morphology of the vessel section according to the selected scan orientation. A typical branching appearance in both views is illustrated in Figure 1-b, -c. It is worth mentioning that in the short-axis view, in presence of bifurcations, the vessel lumen changes its shape with respect to non-bifurcation transversal sections and the blood region tends to an elliptical profile with higher eccentricity than in other frames (Figure 1-a, -b). Moreover, the texture in the radial direction changes considerably in correspondence to bifurcations. In the longitudinal view, bifurcations appear as lateral ramifications of the vessel (Figure 1-c).

Figure 1. Short-axis view of a vessel showing (a) a non-bifurcation and (b) a bifurcation frame and (c) longitudinal view of the pullback. The lines in (b) and (c) indicate the angular and longitudinal bifurcation localizations, respectively. The regions displayed in red in (b) and (c) correspond to the angular and longitudinal branching extension, respectively.

In the clinical practice, physicians report the presence of bifurcations in terms of both frame localization and angular extension. Moreover, when analyzing a pullback, the angular position of a bifurcation (i.e., its orientation) with respect to the IVUS acquisition, represented in Figure 1-b by a line, allows the visualization of the corresponding longitudinal view in which the whole branching is best visible (Figure 1-c).

In this paper, we present a study on bifurcation detection in IVUS based on the preliminary approach recently presented in [15]. The algorithm identifies every bifurcation in a pullback, the corresponding frames, the angular orientation with respect to the IVUS acquisition and the extension, enabling the quick navigation of the pullback only focusing on branches. The goal of bifurcation detection is reached by means of a pattern recognition approach, in which a set of features provides a representation of IVUS data in a multidimensional space, where a classifier is trained to solve the binary “bifurcation vs. non-bifurcation” problem. The most suitable set of features for bifurcation detection is obtained by analyzing textural features proposed in IVUS imaging studies [16], [17], [18] for characterizing, detecting and quantifying vessel structures. The results of three discriminative state-of-the-art classifiers (AdaBoost, random forest, and support vector machine) are compared. The choice of the best suited classification method for the proposed branching detection framework is discussed in the paper, along with the selection of the most relevant features. After a first classification phase, a multi-scale stacked sequential learning scheme is used, exploiting contextual information [19]. By introducing the spatio-temporal context, the continuity of the bifurcation regions is considered for the refinement of the results. Finally, the classification results are further refined by exploiting a-priori information on branching dimensions and geometries. The proposed method is validated on 22 in-vivo IVUS sequences from coronary arteries acquired from 22 patients.

The main contributions of our study are the following: a complete and thoroughly automatic scheme for bifurcation detection in IVUS is proposed; a subset of optimal features with respect to a large initial feature set, describing the appearance of vessel branching is identified; a deep analysis of state-of-the-art discriminative classifiers is performed and a two-level contextual classification scheme is introduced, where the first level is a basic classifier which is integrated, in the second level, in a contextual classifier. Moreover, a new visualization map for IVUS sequences is presented, summarizing the vessel characteristics in a compact representation and allowing an easy and fast analysis.

The paper is organized as follows: Section II describes in detail the proposed method for bifurcation detection. Experimental results are reported in Section III and a discussion is shown in Section IV. Finally, we present our conclusions in Section V.

II. BIFURCATION DETECTION METHOD

Figure 2. Block diagram of the proposed approach. Three main stages compose the workflow: 1) preprocessing for motion artifacts compensation, 2) classification of the angular sectors of each image frame, and 3) refinement of the obtained classification maps based on contextual information.
The method is divided into three sequential stages, as illustrated in Figure 2. First, the IVUS sequence is compensated for the artifacts due to motion. Subsequently, each angular sector in the sequence is classified as bifurcation or not, leading to a new visualization of IVUS pullbacks (Figure 2, bottom-left). The sequence is organized in a bidimensional representation in the space \((\theta, t)\), where \(\theta\) is the angular position (orientation) with respect to the IVUS acquisition in the short-axis view and \(t\) is the longitudinal (temporal) position along the pullback. Finally, the spatial neighborhood relation among samples is exploited to refine the classification results.

### A. Compensation of Artifacts due to Motion

During the acquisition of an IVUS sequence, the catheter is affected by several artifacts due to the heart motion, interfering with the visualization, the interpretation and the analysis of the acquired sequence. The most relevant artifact is caused by the heart beating, which generates a repetitive oscillation of the catheter (swinging effect) along the axis of the vessel, resulting in possible multiple sampling of the same vessel positions. In order to obtain a unique reconstruction for the transversal sections of the artery, one possible solution is the selection of the frames belonging to the same phase of the cardiac cycle, having similar rotation. Such task can be addressed by using a gating technique, either by exploiting the electrocardiogram (ECG) signal (when it is available) [20] or by image-based gating algorithms, such as the one used in this study [21]. A second undesired artifact is represented by the variations in the position of the catheter with respect to the center of the vessel, causing a spatial misalignment of consecutive frames. In this case, the arterial axis undergoes in-plane translations. In order to align the vessel center with the center of the image, we apply an IVUS registration method [22] consisting in a rigid translation of subsequent frames of the gated sequence. Figure 3 illustrates the results of the two successive stages of the applied artifact compensation. The swinging effect present in Figure 3-a is compensated in Figure 3-b and in Figure 3-c the center of the vessel is aligned with the center of the pullback representation.

### B. Angular Sector Classification

In order to address the bifurcation detection task, we define a binary classification problem aimed at distinguishing between bifurcation and non-bifurcation angular sectors. The most intuitive analysis of an IVUS frame, inspired by the visual inspection performed by physicians, consists in the study of textural changes along the radial direction of each frame. For this reason, we choose to extract features computed along each angular sector of the image.

Our approach relies on a pattern recognition technique, in which a binary classifier is firstly trained on a dataset of IVUS sequences, previously labeled by physicians (training phase). Then it is used to identify the presence of bifurcations in new sequences (test phase). For each IVUS sequence, the ground-truth, consisting in a reliable dataset of labeled samples (separating bifurcation and non-bifurcation samples), is created. Numeric information describing each angular sector is computed by feature extraction. During the training phase, a learning algorithm learns the characteristics of the training data by analyzing the extracted features and the corresponding labels and it produces a function (defined as classifier) which can analyze new sequences and generate their label maps.

1) Feature Extraction: In most of the frames, the lumen has a pseudo-elliptical shape in the short-axis view, which typically, in the presence of bifurcations has higher eccentricity than in non-bifurcation frames, as shown in Figure 1-a, -b. The radial extension of the blood region usually increases in correspondence to bifurcation angular sectors, as it happens, for instance, along the line in Figure 1-b. We exploit this property by extracting characteristics of the image texture computed along each radius of the IVUS frame. Since the applied rigid registration technique has aligned the center of the vessel with the center of the image (Figure 4), we can extract homogeneous radial features. For this purpose, we replace the region occupied by the catheter circular “ring down” artifact with a portion of lumen texture extracted from a frame of the sequence, as shown in Figure 4-b, -d. Each of the normalized images \(I(x, y) \in [0, 1]\), which constitutes the sequence \(S(x, y, t) \in [0, 1]\), is first converted into polar coordinates:

\[
\tilde{I}(\rho, \theta) = I(\rho \cdot \cos \theta, \rho \cdot \sin \theta) ,
\]

where \(x\) and \(y\) are the horizontal and vertical coordinates in the cartesian system, \(\rho\) and \(\theta\) are the radial and angular coordinates in the polar system, \(t\) is the longitudinal (temporal) coordinate along the pullback.

Following similar approaches of texture analysis applied to IVUS data [16], [18], [23], a set of \(N_T\) texture descriptors is defined. Each descriptor specifies a mapping function:

\[
F: \tilde{I}(\rho, \theta) \rightarrow M_j(\rho, \theta) ,
\]
Figure 4. Short-axis view of a bifurcation frame before the registration phase (a) in the cartesian coordinate system and (b) in the polar representation. View of the same frame after the registration phase and the “ring down” artifact compensation, (c) in cartesian and (d) in polar coordinates. The dotted curves represent an approximation of the typical geometry of the blood region contour in the bifurcation case.

where $M_j(\rho, \theta) \in \mathbb{R}$ is the parametric feature map according to the $j^{th}$ textural descriptor, $j = 1, 2, \ldots, N_T$. Successively, in order to extract information on the extension and eccentricity of the blood region, we consider the statistics related to each column $\theta$ of the obtained parametric maps. For each angular sector (column in Figure 4), basic statistical features: (i) standard deviation, (ii) mean value, (iii) median value, (iv) maximum value, (v) radial position of the maximum value, and (vi) histogram (10 bins) are computed. To this aim, a second mapping function $D$ is applied:

$$D : M_j(\rho, \theta) \rightarrow f_i(\theta),$$

where $f_i(\theta) \in \mathbb{R}$, $i = 1, 2, \ldots, N_D$, and $N_D$ is defined as the total number of statistical descriptors.

We apply two families of texture descriptors, of which the first has demonstrated its capability to characterize the tissue in IVUS images [24], [17], while the second has been used to characterize the blood region [25], [26]. The first group ($M_j(\rho, \theta)_{\text{tissue}}$) is composed of five maps including Gabor filters and local binary patterns:

- Gabor filters [27] can extract the textural properties of the image according to a particular filter orientation.
- Local binary patterns (LBP) [28] are used to detect uniform texture patterns in circular neighborhoods, with any quantization of angular space and spatial resolution and invariant to brightness variations.

The second group ($M_j(\rho, \theta)_{\text{blood}}$) consists of six maps including autocorrelation and cross-correlation:

- Autocorrelation and cross-correlation are introduced to exploit the low correlation expected in the blood region with respect to the tissue due to the flow motion [25], [26]. Each of them is used at three scales: 6, 12, and 18 pixels representing 1/3, 2/3, and the size of the speckle on the IVUS image, respectively.

The gray-level image $\tilde{T}(\rho, \theta)$ is considered as one of the feature maps, as well, leading to a total of 12 main maps. On the seven parametric maps $\tilde{T}(\rho, \theta)$ and $M_j(\rho, \theta)_{\text{blood}}$ two additional transformations are applied [18], leading to the computation of fourteen additional maps $A_{ej}(\rho, \theta)$, and $A_{ij}(\rho, \theta)$ for a total number of 26 parametric maps. The map $A_{ej}$ can be related to a quantification of the blood accumulation in the range $[\rho, \rho_{\text{MAX}}]$, where $\rho$ represents the radial depth, while the map $A_{ij}$ gives information about the amount of blood accumulated in the range $[1, \rho]$:

$$A_{ej}(\rho, \theta) = \frac{\sum_{m=m-\rho}^{\rho_{\text{MAX}}} M_j(\rho, \theta)}{\rho_{\text{MAX}} - \rho}$$

$$A_{ij}(\rho, \theta) = \frac{\sum_{m=1}^{\rho} M_j(\rho, \theta)}{\rho}$$

where $\rho_{\text{MAX}}$ is the maximum value of the radius.

The computation of statistical features $f_i(\theta)$ on all the parametric maps ultimately provides information about the presence of a bifurcation. For instance, the position of the maximum value in the gray-level image usually corresponds to the distance between the vessel center and the vessel border and it increases with the vessel eccentricity; at the same time, the standard deviation and the mean value along the radius typically decrease, due to the presence of external vessel tissue (adventitia) with bright appearance (see Figure 4). Each angular sector $\theta$ is described by a feature vector $x(\theta) = [x_1(\theta)\ x_2(\theta)\ \ldots\ x_{N_F}(\theta)]$, where $N_F = 253$ is the total number of considered features.

2) Classification: In the proposed framework, a supervised learning approach is chosen, given the availability of ground-truth data and the consequent possibility of learning from examples. A discriminative classification method is applied in order to avoid the need to formulate hypotheses on the feature space. A comparison among the results of three state-of-the-art discriminative classifiers (AdaBoost, random forest, and support vector machine) is provided, in terms of performance and computational cost.

The AdaBoost algorithm [29] creates a strong classifier as a linear combination of simple weak classifiers (base learners). An interesting quality of AdaBoost, when the base learner is a decision stump, is its ability to assign a weight to the features during training, which can be related to the feature relevance and can be used to perform feature selection. Random forest [30] grows an ensemble of classification trees, where each tree votes for a class. The output of random forest is the mode of the classification tree outputs. Random forest can robustly handle a very large number of input features. Like AdaBoost, random forest can measure the relevance of the features. The SVM classifier [31] performs binary classification by constructing a $N$-dimensional hyperplane, which optimally separates the samples into categories. Although SVM is considered an efficient classifier, the training phase in cases of large cardinality of the training set usually suffers from high memory usage and computational complexity.

Beyond the classifier labeling, an additional output provided by the above mentioned classifiers is the classification margin.
\( \text{mar} \in [-\infty, +\infty] \), representing, in the feature space, the distance from a sample to the decision boundary.

C. Contextual Information

1) Multi-Scale Stacked Sequential Learning: In the learning system described so far, the classification is based on the assumption that each angular sector of the IVUS images is independent of the others. However, the continuity of the branchings in pullback sequences can be additionally taken into account to enhance the classifier capabilities. We apply a multi-scale stacked sequential learning (MSSL) scheme [19], consisting in a contextual meta-classifier in which the first stage of classification is included, as a way of capturing and exploiting sequential correlations extended over multiple spatial scales. As depicted in the block diagram of Figure 5, the MSSL scheme makes use of the feature set used in the previous classification and of the classification margin provided as an output by the first classifier.

Figure 5. Block diagram representing the MSSL scheme.

For each pullback, the classification margin values are converted into an estimate of the likelihood that a sample belongs to the bifurcation class and organized in a bidimensional pseudo-probability map, \( p_b(\theta, t) \in [0, 1] \), being \( \theta \) the angular polar coordinate and \( t \) the longitudinal (temporal) position (Figure 6-a). The representation of an IVUS sequence in the space \( (\theta, t) \) is introduced to exploit the spatial coherence of neighboring pixels. In the MSSL scheme, the pseudo-probability map is represented according to a multi-scale (multi-resolution) decomposition. Given \( p_b(\mathbf{q}) \) the likelihood at position \( \mathbf{q} = (\theta, t) \), the multi-resolution decomposition \( \Phi \) is defined as following:

\[
\Phi(\mathbf{q}, s) = p_b(\mathbf{q}) * G(0, \gamma^{s-1}),
\]

where \( s \in \{1, 2, \ldots, S\} \) represents the scale, \( G \) is a bidimensional Gaussian with zero mean and \( \sigma = \gamma^s \) and \( \gamma \) is the “step” of the decomposition. The multi-resolution decomposition is sampled to obtain a set of features. Wrap-around issues are handled by using a circular padding in the horizontal dimension of the map and by setting the values of the extended set outside the map to 0 in the vertical dimension as the most conservative choice. An extended feature set is created, by joining the original feature set and the additional features from the sampling. Finally, the extended set is analyzed by a second classifier and final classification labels are produced. The two classifiers are trained separately and after training they can be applied to new sequences inside the same scheme. The multi-resolution decomposition allows to recover the homogeneity and regularity of the bifurcation regions at different scales, if such properties are present in the training samples. In Figure 6, the binary classification output before (b) and after (c) sequential learning is illustrated for a sequence, together with the corresponding pseudo-probability map (a). We can notice an increase in the homogeneity of the classified regions and a decrease in the presence of false positive errors after the second stage of classification.

Figure 6. (a) Pseudo-probability map for a pullback, in which the gray-level expresses the likelihood of bifurcation presence. Corresponding binary label maps, after (b) the first and (c) the second classification stages of the MSSL scheme. The detected bifurcation regions are represented in red. The horizontal and vertical axes represent the angular position with respect to the IVUS acquisition \( \theta \) and the longitudinal position \( t \), respectively.

2) A-priori Map Refinement: After the classification stage, we refine the results, by taking advantage of a-priori knowledge about the geometry of the coronary branchings and the characteristic dimensions of the vessels. Different artifacts, such as the guidewire shadow, might be confused with bifurcation regions, since their appearance in the short-axis view may be similar. However, since the textural pattern of the guidewire shadow is repeated along several frames of the sequence, we are able to discriminate between the two structures by discarding from the classification maps the regions in which the longitudinal dimension is much more extended than the angular dimension. The regions forming an angle with respect to the \( \theta \)-axis, which is superior to a given threshold \( \tau \) are removed. Subsequently, in order to make the results more homogeneous and exclude regions that are too small to be bifurcations, we perform a morphological filtering with a rectangular structuring element of size \( [n_D n_F] \), where \( n_D \) is the number of angular degrees and \( n_F \) is the number of frames. A cross-validation process is applied to tune the model parameters \( \tau, n_F, \) and \( n_D \).

III. RESULTS

A. Materials: Reference Data

A set of 22 in-vivo pullbacks from human coronary arteries has been acquired from 22 patients by means of iLab IVUS Imaging System (Boston Scientific), available in the Hospital “Germans Trias i Pujol”, Badalona (Spain), using a 40 MHz catheter Atlantis SR 40 Pro (Boston Scientific). The dataset has been chosen randomly without any exclusion criteria from the hospital database. 14 patients have been monitored preoperatively, and 8 after PCI. The patient population is composed of 18 men and 4 women ranging in age from 31 to 81 (median 54); there are 4 diabetic patients.
In order to validate our approach, ground-truth bifurcation labels have been created by manual segmentation performed by two medical experts. The physicians selected the angular sector comprising the bifurcation in the short-axis view, taking care to choose the smallest extension possible, thus ensuring the correctness of the training samples for the bifurcation class, and the initial and final branching frames in the longitudinal view. The intersection between the two segmentations has been used as ground-truth, hence making the most conservative choice. The most experienced of the two observers performed the segmentation of the whole dataset twice, to allow the computation of intra-observer variability.

Each IVUS frame is composed of 360 angular sector samples, corresponding to angular degrees and to columns in the polar representation, leading to an average 32,645 data samples per gated sequence. The ground-truth contains a total amount of 72 bifurcation regions, with an average 3.2 bifurcations per sequence. Given that the amount of samples and the variety of bifurcation structures and sizes are large, the dataset can be considered as representative of the possible range of vascular branchings.

The classification performance is assessed by means of Leave-One-Patient-Out (LOPO) cross-validation technique over \( N_p = 22 \) folds. LOPO can be considered as a special case of \( N \)-fold cross-validation, where each fold contains all the data from one patient. Further details about LOPO technique can be found in [14]. For each fold, the training is performed on samples from all the other folds and the trained classifier is tested on the fold itself. The performance is evaluated as an average of the results over the \( N_p \) folds in terms of:

\[
\begin{align*}
\text{Accuracy:} & \quad A = \frac{TP + TN}{TP + TN + FP + FN} \\
\text{Sensitivity:} & \quad S = \frac{TP}{TP + FN} \\
\text{Specificity:} & \quad K = \frac{TN}{TN + FP} \\
\text{Precision:} & \quad P = \frac{TP}{TP + FP} \\
\text{False Alarm Ratio:} & \quad FAR = \frac{FP}{TP + FN} \\
\text{F-measure:} & \quad F = \frac{2PS}{P + S}
\end{align*}
\]

where \( TP = \text{True Positive} \), \( TN = \text{True Negative} \), \( FP = \text{False Positive} \), and \( FN = \text{False Negative} \).

The positive and negative classes are strongly unbalanced, since the positive class represents 1% of the total amount of samples. In order to achieve a good generalization in the training phase, all the bifurcation samples are used, together with an equal number of randomly selected negative samples. In the test phase, a normalization of the confusion matrix is applied for the computation of all the performance scores with the exception of the accuracy.

It is worth noticing that in a detection problem, the two most significant parameters are sensitivity \( S \) and precision \( P \), since in this case \( S \) (true positive rate) expresses the proportion of actual bifurcation samples, which are correctly identified as such, and \( P \) (positive predictive value) represents the proportion of samples assigned to the bifurcation class which are correctly classified. Therefore, the F-measure can be used as a single score to assess the overall performance of the method, since it is defined as the harmonic mean of precision and sensitivity.

**B. Bifurcation Classification**

1) AdaBoost vs. Random Forest: The AdaBoost, random forest, and SVM classifiers are compared in the bifurcation vs. non-bifurcation classification. Since, among the three methods, AdaBoost and random forest are able to handle efficiently a large training set and a high-dimensional feature space, the two classifiers are firstly compared. Once the best performing classification algorithm between the two is identified, the method is compared with SVM using a selected subset of the most relevant features.

To ensure its convergence, AdaBoost has been trained up to \( N_{iter} = 110 \) iterations and the classifier has been noticed to converge after around 80 iterations. The parameters of random forest are set to a number of trees \( N_{trees} = 1,000 \) and a number of input variables determining the decision at each node of the tree \( M_{try} = \log_2(N_F) + 1 \), as suggested by [30]. In order to corroborate the statistical significance of the achieved results, the Wilcoxon signed-ranks test [32] is performed. With a significance level \( \alpha = 0.05 \), the null hypothesis that the mean values of the two distributions are equal can be rejected if \( z < -1.96 \), where \( z \) is the value of the Wilcoxon statistics. The last two columns in Table I illustrate, for every comparison, the difference between the average performance scores of AdaBoost and random forest and the value of the \( z \) statistics, respectively. The presence of the asterisk in the fifth column denotes statistical significance. For each performance measure, the score of the technique which performs better is typeset in bold.

<table>
<thead>
<tr>
<th>Performance of the AdaBoost and Random Forest Classifiers.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A )</td>
</tr>
<tr>
<td>( S )</td>
</tr>
<tr>
<td>( P )</td>
</tr>
<tr>
<td>( K )</td>
</tr>
<tr>
<td>( FAR )</td>
</tr>
<tr>
<td>( F )</td>
</tr>
</tbody>
</table>

Random forest is superior to AdaBoost for most of the considered performance scores (Table I) and has an excellent performance in terms of accuracy (94.85%). However, the sensitivity is lower (63.50% for random forest when compared with 76.97% for AdaBoost) leading to a significantly lower F-Measure score. Moreover, the computational complexity of AdaBoost with decision stumps is lower, since it is \( O(T_{nm}) \) in training and \( O(T) \) in test, while for random forest it is \( O(TnM_{try}) \) in training and \( O(Tn) \) in the worst case, \( O(T\log n) \) in average in test, where \( T = N_{iter} \) for AdaBoost and \( N_{trees} \) for random forest, \( n \) is the number of training samples, \( m \) is the number of features, and \( M_{try} < m \) is the random subspace dimensionality. Considering this, we can state that the AdaBoost classifier is the most suited for the proposed task.

2) Feature Selection by Weight Analysis: A feature selection study is performed, with the aim of reducing the computational cost of the learning algorithm and possibly enhancing the generalization capability of the classifier. Different learning
algorithms may perform better with different feature sets, since there cannot be a unique concept of relevant features [33]. For this reason, we perform feature selection based on the used classification algorithm. We exploit the embedded property of AdaBoost with decision stump of assigning a weight to each weak classifier (feature) at each training iteration. Such weights can be used to evaluate the feature relevance. Let us define $N_F$ the number of features, $N_P$ the number of initial features, $k = 1, 2, \ldots, N_F$ the index of each feature and $\alpha_k^p$ the weight assigned to the $k$th feature at the $p$th LOPO validation fold, corresponding to the $p$th pullback. The normalized weight assigned by AdaBoost to each feature $w_k$ can be expressed as:

$$w_k = \frac{1}{N_P} \sum_{p=1}^{N_P} \max\{\alpha_1^p, \ldots, \alpha_{N_F}^p\} \tag{7}$$

The normalized weights $w_k$ are used to perform feature selection, by keeping only the features whose cumulative weight represents a percentage of the total cumulative weight set to 75%. For this reason, the initial set of $N_F = 253$ features $x = [x_1 \ x_2 \ \ldots \ x_{N_F}]$ is ordered from the most to the least relevant descriptor, creating a sorted set $x_{SORT} = [x_{1S} \ x_{2S} \ \ldots \ x_{N_F}]$ with corresponding normalized weights $w_{SORT} = [w_{1S} \ w_{2S} \ \ldots \ w_{N_F}]$. Subsequently, the feature subset $x_{SORT} \subseteq x_{SORT}$, $\overline{x}_{SORT} = [x_1' \ x_2' \ \ldots \ x_{N_S}']$, with corresponding normalized weights $w_{SORT} = [w_1' \ w_2' \ \ldots \ w_{n_S}']$ is selected, comprising the most relevant $N_S$ features in $x_{SORT}$ whose partial cumulative weight $c_{wS} = \sum_{j=1}^{N_S} w_k'$ sums up to 75% of the total cumulative weight:

$$N_S : \sum_{k=1}^{N_S} w_k' = 0.75 \cdot \sum_{k=1}^{N_F} w_{kS} \tag{8}$$

resulting in $N_S = 40$ selected features.

![Figure 7. Analysis of the normalized weight for each feature. The descriptors are organized into different categories: (a) gray-level image, (b) Autocorrelation, (c) Cross-correlation, (d) Gabor, (e) LBP, (f) shadow transformations on the gray-level image, shadow transformations on the (g) Autocorrelation and (h) Cross-correlation maps.](image)

In Figure 7, the normalized weight $w_f$ for each feature in $x$ is represented, together with a summarized description of the feature categories. Among the most relevant descriptors, we find: the radial position of the maximum value, both in the gray-level image and in its parametric representations, features computed from the Gabor parametric maps, features computed from the gray-level image and features from the cross-correlation maps.

### Table II

<table>
<thead>
<tr>
<th></th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\delta_k^\alpha$</th>
<th>$z$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>(89.82 ± 4.51)%</td>
<td>(89.79 ± 4.49)%</td>
<td>-0.03%</td>
<td>-0.23</td>
</tr>
<tr>
<td>$S$</td>
<td>(76.97 ± 11.94)%</td>
<td>(81.24 ± 11.48)%</td>
<td>+1.27%</td>
<td>-2.56</td>
</tr>
<tr>
<td>$F$</td>
<td>(85.57 ± 4.69)%</td>
<td>(89.08 ± 4.47)%</td>
<td>+0.51%</td>
<td>-2.06</td>
</tr>
<tr>
<td>$R$</td>
<td>(89.90 ± 4.55)%</td>
<td>(89.90 ± 4.55)%</td>
<td>-0.06%</td>
<td>-0.82</td>
</tr>
<tr>
<td>$FAR$</td>
<td>(10.04 ± 4.55)%</td>
<td>(10.10 ± 4.55)%</td>
<td>+0.06%</td>
<td>-0.82</td>
</tr>
</tbody>
</table>

The AdaBoost algorithm is applied on the extracted subset $F_{SORT}$, using $N_{iter} = 110$ iterations. In Table II, we can observe an overall improvement in the performance after feature selection. In particular, the statistical analysis proves that the sensitivity, precision and F-Measure scores, which are the most relevant for the considered application, significantly increase. Moreover, the computational complexity in training $O(Tnm)$ decreases.

### 3) AdaBoost vs. SVM:

The training set cardinality and the feature space dimensionality imply a high computational cost for the classification. We choose not to reduce the number of training samples because of the imbalance between the two classes. However, we can accelerate the SVM by applying it after feature selection, reducing the feature space dimensionality. Hence, we compare the performance of AdaBoost and SVM using the $N_S = 40$ selected features. A Radial Basis Function (RBF) kernel is used and the parameters $\gamma$ and $C$ are tuned as indicated in [34] and in this way set to $\gamma = 0.001$ and $C = 10$. The results of the SVM classifier are compared in Table III with the results of AdaBoost after feature selection.

As it can be observed, the SVM classifier is superior to AdaBoost in terms of sensitivity, but it is significantly inferior in terms of the accuracy, precision, specificity, false alarm ratio scores. The overall performance is comparable, as shown by the F-measure scores. However, the computational complexity of SVM is higher, since it varies between $O(n^2)$ and $O(n^3)$ in training, depending on the number of support vectors and it is $< O(nm)$ in test. Additionally, the accuracy of a SVM model largely depends on the selection of the kernel parameters, which have to be tuned implying a high computational cost during training. By considering these results, we conclude that the AdaBoost classifier is the most appropriate technique for the addressed task.

### Table III

<table>
<thead>
<tr>
<th></th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\delta_k^\alpha$</th>
<th>$z$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>(89.79 ± 4.49)%</td>
<td>(87.46 ± 5.01)%</td>
<td>-2.33%</td>
<td>-3.23</td>
</tr>
<tr>
<td>$S$</td>
<td>(81.24 ± 11.48)%</td>
<td>(83.26 ± 12.09)%</td>
<td>+2.02%</td>
<td>-1.23</td>
</tr>
<tr>
<td>$F$</td>
<td>(89.08 ± 4.47)%</td>
<td>(87.12 ± 5.34)%</td>
<td>-1.96%</td>
<td>-2.77</td>
</tr>
<tr>
<td>$R$</td>
<td>(89.90 ± 4.55)%</td>
<td>(87.53 ± 5.57)%</td>
<td>-2.37%</td>
<td>-3.23</td>
</tr>
<tr>
<td>$FAR$</td>
<td>(10.10 ± 4.55)%</td>
<td>(12.47 ± 5.57)%</td>
<td>+2.37%</td>
<td>-3.23</td>
</tr>
<tr>
<td>$F$</td>
<td>(84.56 ± 6.84)%</td>
<td>(84.71 ± 6.87)%</td>
<td>+0.15%</td>
<td>-0.17</td>
</tr>
</tbody>
</table>
4) Bifurcation Map Refinement: After the classification of angular sectors as independent samples, a refinement of the results is performed in two stages. First, the contextual information is exploited using the MSSL approach. Then, the guidewire artifact and the small detected regions are removed using a-priori information.

It is worth noticing that the MSSL scheme is independent of the classification methods chosen for the two classification stages. The multi-scale decomposition is applied using 5 scales, by setting the decomposition parameters to $\sigma = 2e^{(s-1)}$ and $s = \{1, 2, \ldots, 5\}$ and using a 9 element neighborhood. The sampling leads to 45 additional features, for a total 85 features composing the extended feature set. The AdaBoost classifier is applied to the extended feature set, performing $N_{iter} = 160$ iterations. The parameters of the a-priori refinement $n$, $n_D$, and $n_F$ are tuned by exhaustive search by maximizing the F-Measure score using LOPO cross-validation technique. The parameters are tuned on reasonable ranges of values chosen according to physiological a-priori. In particular, the threshold $n$ ranges between 25 degrees and 50 degrees, while the horizontal and vertical distances of the structuring element $n_D$ and $n_F$ range between 5 and 20 degrees and 1 to 5 frames, respectively. The obtained optimized parameters are $n = 30$ degrees, $n_D = 10$ degrees and $n_F = 1$ frame.

In Table IV, the overall incremental results for the successive stages of the method are illustrated, together with inter-observer and intra-observer variability. We can notice a steady improvement of the performance for consecutive phases of the workflow (rows from $[a]$ to $[e]$), which is reflected into the increase in the F-Measure score. The second classification stage of the MSSL scheme is apparently in counter trend because the F-Measure slightly decreases. At the same time, the computational complexity additionally includes both (1) the complexity for the multi-scale decomposition + sampling $O(SN_{map}\log N_{map} + 9SN_{map})$, where $S$ is the number of scales, $N_{map}$ is the size of the map, and 9 is the size of the sampling neighborhood, and (2) the complexity for the second classification stage. However, this step produces a significant decrease in the false alarm ratio score (row $[c]$). The a-priori refinement improves the performance (rows $[d]$, $[e]$) without being computationally expensive, since the computational complexity is $O(R)$ for the first stage, where $R$ is the number of connected branching regions, and $O(n_Dn_FN_{map})$ for the second stage, where $N_{map}$ is the size of the map, and $n_D$, $n_F$ are the two dimensions of the structuring element.

The automatic method reaches an accuracy of 95.21%, a sensitivity of 80.66%, a precision of 94.60% and an F-Measure of 86.35%. It can be noticed that the sensitivity score, which is critical in a detection problem, is low for inter-observer variability (57.05%): the task of evaluating bifurcation location and extension is particularly challenging also for trained physicians and the results suffer from substantial variability depending on the observer. The F-Measure score reached by the automatic method is higher than for both the intra- and inter-observer variability (+10.17% and 14.72% respectively), showing that the algorithm successfully reaches a compromise between the two segmented ground-truths.

The performance of the method significantly decreases if only the first classifier is used (rows$[i]$, $[j]$), because the MSSL scheme helps to find connected regions on which the first stage of refinement is based.

IV. DISCUSSION

A. Results Analysis

The identification of vascular bifurcations in IVUS images is considerably challenging due to the high variability in branching dimensions and appearance. Portions of the vessel may appear like bifurcations. Additionally, shadows can hide bifurcations, making the images with deployed stent more difficult to classify. The images in Figure 8(a-c) illustrate some challenging frames in which the existing bifurcations are correctly identified. In most cases, the errors of the automatic method can be ascribed to a specific vessel morphology. False positive errors are localized most frequently in correspondence to deployed stents (Figure 8(d-f)), in vessel sections close to the ostium (Figure 8(g-h)) and when a vein is visible close to the inspected vessel (Figure 8(i-j)). Veins might be confused with the extreme frames of the branches where two lumen regions are separated by adventitia. False negative errors are mostly found in case of small bifurcations, such as the one represented in Figure 8-k. Finally, the method rarely fails in large bifurcation frames. It is worth mentioning that in several cases the method performs better than the manual labeling, since in some cases one or both experts did not label a branching which is actually present in the sequence, as illustrated in Figure 8-l. Indeed, the physicians confirmed the presence of a bifurcation a-posteriori, given the algorithm detection.

Figure 8. Analysis of bifurcation detection results. The convex angles in green and red correspond to the angular extension of the bifurcation as identified by the algorithm, in case of correct detection and false positive error, respectively.

B. Clinical Applicability: Evaluation per Regions

For a clinical use of the proposed method, the main concern for physicians is that a minimum amount of branching regions...
incremental performance of the automatic method, in rows [a] to [e]: ([a]) before feature selection, ([b]) after feature selection, ([c]) at the second classification stage of the MSSL scheme, ([d]) refinement based on region orientation, ([e]) refinement using morphological filtering, ([f]) inter-observer and ([g]) intra-observer variability. Refinement performance by applying only the first classification stage: ([h]) refinement based on region orientation, ([i]) refinement using morphological filtering.

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>S</th>
<th>P</th>
<th>K</th>
<th>FAR</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>[a]</td>
<td>(89.82 ± 4.51)%</td>
<td>(76.97 ± 11.94)%</td>
<td>(88.57 ± 4.69)%</td>
<td>(89.96 ± 4.55)%</td>
<td>(10.86 ± 4.55)%</td>
<td>(81.90 ± 7.45)%</td>
</tr>
<tr>
<td>[b]</td>
<td>(89.79 ± 4.49)%</td>
<td>(81.24 ± 11.43)%</td>
<td>(89.08 ± 4.47)%</td>
<td>(89.90 ± 4.55)%</td>
<td>(10.19 ± 4.55)%</td>
<td>(84.56 ± 6.84)%</td>
</tr>
<tr>
<td>[c]</td>
<td>(91.88 ± 3.24)%</td>
<td>(79.40 ± 15.33)%</td>
<td>(90.68 ± 4.33)%</td>
<td>(92.02 ± 3.26)%</td>
<td>(97.98 ± 3.26)%</td>
<td>(84.60 ± 10.05)%</td>
</tr>
<tr>
<td>[d]</td>
<td>(95.42 ± 2.05)%</td>
<td>(77.67 ± 17.08)%</td>
<td>(94.60 ± 2.61)%</td>
<td>(95.62 ± 2.05)%</td>
<td>(94.38 ± 2.05)%</td>
<td>(84.29 ± 11.42)%</td>
</tr>
<tr>
<td>[e]</td>
<td>(95.21 ± 2.28)%</td>
<td>(80.66 ± 14.90)%</td>
<td>(94.60 ± 2.65)%</td>
<td>(95.38 ± 2.29)%</td>
<td>(94.62 ± 2.29)%</td>
<td>(86.35 ± 9.28)%</td>
</tr>
<tr>
<td>[f]</td>
<td>(97.01 ± 1.76)%</td>
<td>(97.05 ± 10.58)%</td>
<td>(97.76 ± 1.31)%</td>
<td>(98.48 ± 0.89)%</td>
<td>(91.52 ± 0.89)%</td>
<td>(71.63 ± 8.6)%</td>
</tr>
<tr>
<td>[g]</td>
<td>(98.05 ± 1.37)%</td>
<td>(62.86 ± 11.84)%</td>
<td>(98.76 ± 0.82)%</td>
<td>(99.01 ± 0.69)%</td>
<td>(99.99 ± 0.69)%</td>
<td>(76.18 ± 9.91)%</td>
</tr>
<tr>
<td>[h]</td>
<td>(93.23 ± 3.76)%</td>
<td>(69.40 ± 24.19)%</td>
<td>(86.83 ± 20.53)%</td>
<td>(93.47 ± 3.77)%</td>
<td>(06.53 ± 3.77)%</td>
<td>(79.59 ± 15.24)%</td>
</tr>
<tr>
<td>[i]</td>
<td>(93.48 ± 4.09)%</td>
<td>(72.69 ± 25.26)%</td>
<td>(87.44 ± 20.74)%</td>
<td>(93.68 ± 4.12)%</td>
<td>(06.32 ± 4.12)%</td>
<td>(81.85 ± 15.77)%</td>
</tr>
</tbody>
</table>

Table IV

Figure 9. Average TPO score for 15 equally spaced ranges of bifurcation angular extension. In the considered dataset, the bifurcation angle ranges between 3 and 72 degrees. The data distribution is approximated as a third-order polynomial, shown in red.

In Figure 10, examples of ground-truth labels and corresponding final result maps are illustrated. In most cases the bifurcation regions which are labeled in the ground-truth are correctly detected, while the main limitation lies in the possible identification of false positive branching regions.

C. Discussion on Methodology

The use of image-based gating cannot assure that the scan line followed over the longitudinal view actually represents the same orientation relative to the vessel. However, the measurements of bifurcation angular extension and position relative to the IVUS acquisition are clinically relevant because they are used by physicians to characterize the branches and their position with respect to the plaque location.

The choice of introducing the 3-D context in the classification domain instead of in the feature domain is motivated by the fact that along the longitudinal (temporal) dimension of the IVUS sequences, bifurcations can significantly change their appearance, so 3-D descriptors would not be coherent. On the contrary, the MSSL scheme does not take into account the appearance, but the pseudo-probability of bifurcations.

V. Conclusion

In this paper, we presented a fully automatic method for identifying the longitudinal and angular bifurcation position and extension in IVUS sequences. This goal is obtained by means of a pattern recognition approach, in which a set of features provides a representation of IVUS data in a multidimensional space where a classifier is trained to solve
the binary “bifurcation vs. non-bifurcation” problem. Although the branching detection task is particularly challenging due to the high variability in bifurcation dimensions and appearance, as demonstrated by the F-Measure scores of 71.63% and 76.18% for inter and intra-observer variability respectively, our approach reaches a F-Measure of 86.35% (sensitivity 80.66% and precision 94.60%) and a TPO of 90.97%. Satisfactory results are obtained in most of the frames, while the performance slightly decreases when stent, vein, ostium and small bifurcation frames are analyzed.

The proposed methodology provides a tool for the quick review of pullback sequences, making the bifurcation inspection more intuitive and facilitating the evaluation of the lesion at bifurcation sites. Future work will be addressed towards the automatic identification of the optimal longitudinal view for each bifurcation, from which the angle of incidence (the angle between the main vessel and the side-branch) is visible. Additionally, the method can be applied in large clinical studies involving the correlation between bifurcation and plaque. Finally, a three-dimensional pullback reconstruction using X-ray and IVUS techniques [35] could contribute to the fluid dynamic analysis of the vessel at bifurcation sites.

ACKNOWLEDGMENT

This work has been supported in part by the projects TIN2009-14404-C02, La Marató de TV3 082131, CONSOLIDER INGENIO CSD 2007-00018, AIB2010SE-00210 of the Spanish Ministry of Science and Innovation (MICINN), SGR00696, and AIB2010SE-00210. A patent application (No. 61510014) was filed on July 20th, 2011 with the U.S. Patent and Trademark Office on behalf of Boston Scientific Corporation.

REFERENCES