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Automatic quantitative analysis of in-stent restenosis using FD-OCT in vivo intra-arterial imaging

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Purpose: A new segmentation technique is implemented for automatic lumen area extraction and stent strut detection in intravascular optical coherence tomography (OCT) images for the purpose of quantitative analysis of in-stent restenosis (ISR). In addition, a user-friendly graphical user interface (GUI) is developed based on the employed algorithm toward clinical use.

Methods: Four clinical datasets of frequency-domain OCT scans of the human femoral artery were analyzed. First, a segmentation method based on fuzzy C means (FCM) clustering and wavelet transform (WT) was applied toward inner luminal contour extraction. Subsequently, stent strut positions were detected by utilizing metrics derived from the local maxima of the wavelet transform into the FCM membership function.

Results: The inner lumen contour and the position of stent strut were extracted with high precision. Compared to manual segmentation by an expert physician, the automatic lumen contour delineation had an average overlap value of 0.917 ± 0.065 for all OCT images included in the study. The strut detection procedure achieved an overall accuracy of 93.80% and successfully identified 9.57 ± 0.5 struts for every OCT image. Processing time was confined to approximately 2.5 s per OCT frame.

Conclusions: A new fast and robust automatic segmentation technique combining FCM and WT for lumen border extraction and strut detection in intravascular OCT images was designed and implemented. The proposed algorithm integrated in a GUI represents a step forward toward the employment of automated quantitative analysis of ISR in clinical practice. © 2013 American Association of Physicists in Medicine. [http://dx.doi.org/10.1118/1.4803461]

Key words: optical coherence tomography, image segmentation, fuzzy C means clustering, wavelet transform local maxima, in-stent restenosis, quantification

I. INTRODUCTION

In vivo dynamic visualization, recognition, and quantification of vascular networks represent a very interesting methodological requirement for the evaluation of peripheral endovascular revascularization procedures. Optical coherence tomography (OCT) is a catheter-based intravascular imaging method that employs near-infrared light in order to produce high-resolution cross-sectional images of the vessel lumen and wall.\(^1\)

OCT technology provides a higher axial resolution (around 10 μm) compared to IVUS (range: 100–150 μm), while the recently developed frequency-domain interferometry analysis OCT system (FD-OCT) allows for faster image acquisition (up to 20 mm/s) and greater scan depths that enable its application in large caliber vessels. Consequently, FD-OCT is today the preferred intravascular imaging modality for the in vivo atheromatous plaque characterization, and post-stenting assessment in patients with coronary disease.\(^2\) The safety and feasibility of in vivo intravascular imaging of the femoropopliteal and infrapopliteal arteries in patients with peripheral arterial disease (PAD) undergoing angioplasty and stenting using FD-OCT, has been recently reported.\(^3,4\) These studies highlight the role of FD-OCT in peripheral arterial wall characterization, as well as in the quantification and pathophysiological depiction of infrarenal in-stent restenosis (ISR). Moreover, in vivo OCT plaque characterization in cases of carotid artery atheromatous disease and its ability to detect in-stent neatherosclerosis following infrapopliteal stenting could influence the therapeutic plans of peripheral arteriopathy.\(^4,5\) As a result, these novel investigational possibilities raise the issue of the clinical implication of the accurate ISR detection and quantification.

Several attempts have been made toward OCT image segmentation. Tanimoto et al.\(^1\) proposed a semiautomatic method that employs a combination of an edge detection filter and a smoothing operator so as to acquire the lumen area boundary in intracoronary arteries. In their study, the strut detection procedure is fully manual. Interobserver variability between two expert observers was employed by means of intra-class and interclass correlation coefficients and the reliability coefficients.\(^6\) Sihan et al.\(^7\) also proposed an edge detection technique in order to acquire the vessel lumen border for in vivo human coronary vessels. A despeckling filter is utilized at first in order to reduce speckle-noise and normalize gaps and shape irregularities in the vessel lumen interface.
Subsequently, the Canny filter is implemented iteratively using a binary search, until the desired percentage of image pixels are classified as edge pixels. Finally, a classification procedure is employed toward discrimination between contour edges and the edges caused from noise or other structures within the OCT image. Throughout the past few years, new methods that provide endothelialization and neointimal hyperplasia (NIH) quantification in follow-up OCT images were also proposed. Bonnema et al. introduced a fully automatic method to detect covered and uncovered struts and establish a percent cellular coverage for a volumetric OCT dataset. The algorithm proposed, was evaluated in tissue-engineered human blood vessels. At first, the luminal surface is identified based on its bright surface reflection. Covered and uncovered struts are detected based on distance between the luminal surface and the bright strut surface reflection, their concentrated energy and the dark shadow underneath the strut. Gurmer et al. proposed an automatic stent implant follow-up in intravascular OCT images. A new spline contour evolution for delineating the lumen and strut area was employed. The strut detection procedure is based on the fact that struts are blocking the penetration of the infrared light and leave a dark shadow in the far field of the image domain.

Kauffmann et al. suggested an automatic and supervised lumen and strut detection algorithm to evaluate re-endothelialization in OCT images. Binarization of the OCT image, morphological segmentation, and an active contour model were employed in order to extract the lumen inner contour. The strut detection procedure takes place via a gradient-based shadow detection algorithm and gray level radial profiles analysis. Unal et al. recommended an automatic segmentation method in OCT images. The lumen segmentation is applied, in previously denoised images, throughout an active contour framework, whereas the strut detection is also based in shadow detection by analyzing angular intensity energy distribution in the lumen area. A semi-automated strut detection algorithm was also developed based on an adapted K-nearest neighbor method by Bruining et al. Struts are identified with a modified K-nearest neighbor (mKNN) algorithm. Five manually selected frames are employed in the mKNN as a priori information so as to detect most of the struts.

Tsantis et al. proposed a segmentation technique for automatic lumen area extraction and stent strut detection in intravascular OCT images for the purpose of quantitative analysis of NIH. A clinical dataset of frequency-domain OCT scans of the human femoral artery was analyzed. First, a segmentation method based on the Markov random field (MRF) model was employed for lumen area identification. Second, textural and edge information derived from local intensity distribution and continuous wavelet transform (CWT) analysis were integrated to extract the inner luminal contour. Finally, the stent strut positions were detected via the introduction of each strut wavelet response across scales into a feature extraction and classification scheme in order to optimize the strut position detection. Lu et al. developed a highly automated method for detecting stent struts and measuring tissue coverage. A bagged decision trees classifier was employed to classify candidate struts using image extracted features.

The study herein introduces a novel fully automatic method for the accurate quantitative analysis of intravascular OCT images. The automatic detection algorithm begins with an image segmentation method based on fuzzy C means (FCM) clustering and wavelet transform (WT) integrating local intensity distribution and edge information toward inner lumen border segmentation. After OCT image segmentation, an edge detection procedure is utilized that analyzes the properties of each wavelet response local maxima in order to optimize the strut position detection. After OCT lumen border delineation and strut detection, a quantitative analysis toward the assessment of the re-endothelialization procedure is employed.

II. MATERIALS AND METHOD

II.A. Materials

II.A.1. OCT clinical dataset

FD-OCT imaging was performed using the C7-XRTM OCT intravascular imaging system (Lightlab Imaging, Inc., Westford, MA). Data acquisition was performed as previously described. In brief, an ipsilateral antegrade puncture of the common femoral artery (CFA) was performed and a standard 5 Fr arterial sheath was positioned to secure the access. A standard 0.014" guide-guide wire was advanced through the stented arterial segment to prior to the introduction of the OCT catheter. During OCT image acquisition, 50 ml dextrose saline flush (glucose 5% w/v) at a rate of 10 ml/s and a maximum pressure of 400 psi was administrated through the arterial sheath using an automated injector pump and manual obstruction of the CFA. The FD-OCT system uses an automatic pullback device that enables data acquisition of a maximum vessel length of 54 mm. These data were exported from the main OCT unit in Digital Imaging and Communications in Medicine (DICOM) format. Four OCT in vivo sequences of the human femoral artery (each scan visualizing 54 mm of vessel lumen in 271 consecutive frames; 1080 frames analyzed in total) were included in the study for the vessel lumen border extraction algorithm. Stent struts, because of previous stent placement, were identified in all four femoral OCT sequences. However, individual stent struts were present in 300 frames from all sequences and were further included in the strut detection study. Prior to image acquisition, the specific OCT unit performs either automatic or manual calibration using as reference an element of known size, such as the size of the catheter. As images were exported in DICOM all necessary calibration information needed for the quantitative results were also available at hand. In case of nonsatisfactory initial calibration, further recalibration of the images before the initiation of the quantitative analysis, was performed. OCT data acquisition parameters are analytically reported in Table I.

II.B. Lumen wall delineation

A specifically designed detection algorithm was implemented to identify the vessel-lumen border. From this
The FCM algorithm assigns pixels to two or more clusters by using fuzzy memberships. It is considered as an iterative optimization that minimizes a cost function when pixels close to the centroid of their clusters, are assigned with high membership values. This membership function represents the probability that a pixel belongs to a specific cluster. Let $V = \{v_1, v_2, \ldots, v_N\}$ denote an image with $N$ pixels to be partitioned into $c = 2$ number of clusters (i.e., the lumen and the hyperplasia area) clusters, where $u_i$ represents the feature value. The cost function is defined as follows:

$$Q_{\text{fcm}} = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^{m} \|v_j - \mu_i\|^2 \quad 1 \leq m < \infty \quad (5)$$

subject to

$$\sum_{i=1}^{c} u_{ij} = 1, \quad u_{ij} \in [0, 1], \quad 1 \leq j \leq n, \quad 1 \leq i \leq c,$$

where $m \in (1, \infty)$ controls the fuzziness of the resulting partition, $u_{ij}$ and $d_{ij} = \|v_i - \mu_j\|^2$ represent the membership of pixel $v_i$ in the $j$th clustering, and the distance between the pixel $v_i$ and the cluster center $\mu_j$, respectively. In image clustering, the most commonly used feature is the gray-level value, or intensity of image pixel. Thus, the FCM cost function is minimized when high membership values are assigned to pixels whose intensities are close to the centroid of their clusters and low membership values are assigned when the point is far from the centroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain. The membership function and cluster centers are updated by the following equations:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \frac{u_{ik}^m}{d_{kj}^2}}, \quad (7)$$

$$\mu_i = \frac{\sum_{j=1}^{n} u_{ij}^m v_j}{\sum_{j=1}^{n} u_{ij}^m}, \quad (8)$$

Starting with an initial guess for each cluster center, the FCM converges to a solution for $\mu_i$ representing the local minimum or a saddle point of the cost function. Convergence can be detected by comparing the changes in the membership function or the cluster center at two successive iteration steps. The FCM algorithm determines the centroids and membership function pixel-by-pixel while it is employed for image clustering. In addition, FCM is considered as a local search optimization algorithm, and because of this it is very sensitive to the initial centroid. If the initial centroid is randomly generated, it is possible that the convergence of the algorithm will become time-consuming, turning out to be impractical for image clustering purposes. So, to avoid the blindness of random evaluation and processing time increment, CWT analysis provides the initial centroids in order to minimize the number of iteration steps. This initialization step provides edge information into the FCM clustering algorithm by selecting the initial
In this study, the 2D CWT was implemented employing the “Mexican hat” wavelet filter
\[ \psi(t) = \frac{2}{\sqrt{3\sigma^2}} \left(1 - \frac{t^2}{\sigma^2}\right) e^{-t^2/2\sigma^2}, \tag{10} \]
which is the normalized negative second derivative of a Gaussian function [equivalent to the Laplacian of Gaussian (LOG) function]. The 2D wavelet coefficients \( W_f(a_1, a_2, b_1, b_2) \) of an image \( f(t_1, t_2) \) are defined as
\[
W_f(a_1, a_2, b_1, b_2) = |a_1 a_2|^{-1} \int_{-\infty}^{+\infty} f(t_1, t_2) \cdot \psi \left( \frac{t_1 - b_1}{a_1}, \frac{t_2 - b_2}{a_2} \right) dt_1 dt_2. \tag{11}
\]
Due to the wavelet transform initialization, the average number of iterations was approximately 3. The fuzziness value was set at \( m = 2 \) in this study to further reduce the computation time (the power functions are replaced by squares). Choosing the value of the fuzziness parameter degree in FCM is usually heuristically conducted using a performance-based criterion.\(^{22}\) It is typically suggested to use values in the 1–3 interval, with values around 1.5 bearing the best results in terms of obtained error rates and generalization capacity of the trained models.\(^{23}\) It is furthermore found that increases in the level of fuzziness beyond the upper boundary value identified in this analysis do not provide additional information, since the membership values do change in a counterintuitive manner, and at the same time increase the processing time.\(^{24}\)

In order to evaluate the clustering performance of the proposed method, a comparative study was held between the clustering results and the “ground truth” derived from an expert physician who manually delineated the lumen area, by means of overlap degree between the two sets. Overlap is defined as the ratio of intersection over the union of the two clustered areas.\(^{18}\) The value of overlap is bound to values between zero (no overlap) and one (exact overlap). Additionally, the proposed method was compared by means of mean distance difference in mm in the polar coordinates and in mm\(^2\) in the Cartesian coordinates with the expert’s manual assessments.

**II.C. Stent strut position detection**

In OCT images, stent struts do not have a constant appearance. They often give a bright reflection and usually appear as small line segments or spots depending on the light reflection angle. In some cases, they also produce a shadow zone behind the bright echo. The proposed algorithm approaches the strut position detection as a blob detection procedure in which blobs are considered as the maximum response of the LOG filter in the CWT analysis. All wavelet local maxima values that correspond to various structures within the OCT image are considered as candidate strut positions (Fig. 4).

In cases where most of the strut is visible, the corresponding wavelet local maxima can be discriminated from other structures within the OCT image. However, in most cases the transmission-reflection light path is not perpendicular and
produces a shortened line segment or a small blob with lower brightness values. This is due to refraction of the incident light beam. This complexity of OCT images enhances the strut pattern variability, which in turn constitutes the edge information provided by the wavelet coefficient values as insufficient information toward accurate strut detection. In order to overcome the aforementioned limitations, a new map was built that incorporates the edge properties provided by the wavelet local maxima value combined with spatial and regional properties of the strut.

Although the wavelet values are similar, there are spatial (size of the structure) and regional (adjacent structural environment) properties that can distinguish the correct strut positions. A thorough examination was made in order to quantify these properties so as to discriminate the strut responses from the other candidate positions. The candidate strut positions are located either in the interface between lumen and vessel area or within the hyperplasia area. The alteration of size and neighborhood of each candidate maxima position consequently transforms the size and behavior of each wavelet response (Fig. 5).

Two metrics have been employed toward the new mapping; (a) the full width at half maximum—$U_1$ (FWHM) that represents the spatial resolution properties of each strut and (b) the relation between the corresponding wavelet signal transitions starting at a local minimum, followed by the local maximum and ending again at a local minimum—$U_2$ (Fig. 6)

$$U_1 = \text{FWHM},$$

$$U_2 = \frac{\max - \min_2}{\max - \min_1}.$$

The FWHM metric provides the size differentiation of each candidate maxima. Apparently, struts are thinner than the other structures providing smaller FWHM values. Also $U_2$ metric due to the bilateral signal transition from the maxima.
provides the symmetry response, thus, revealing the homogeneity environment around the strut positions within the hyperplasia. A symmetrical (value close to 1) response suggests a strut positioned within hyperplasia.

Each wavelet local maxima is transformed into the new mapping value with the following equation:

\[ U = U_2 \times \frac{\text{Local maxima value}}{U_1}. \] (14)

The new map values are utilized to the FCM membership function providing high membership values for strut wavelet responses and low memberships values for the rest of the wavelet responses (Fig. 7).

II.D. Hyperplasia estimation

In order to approximate the strut contour, a double fitting scheme with a feedback procedure is employed toward the hyperplasia quantification. All wavelet local maxima clustered as struts from the previous procedure are employed in the double fitting procedure that utilizes a gradient-weighted algebraic fitting algorithm so as to decide whether the struts points form a circle or an ellipse.

The circle algebraic fitting algorithm is based on the minimization of the sum of squares of algebraic distances from the circle with center \((a, b)\) and radius \(R\) to the \(N\) data points \(x_i\).\(^{25}\)

The circle objective function \(F\) with the natural parameters is given

\[ F(a, b, R) = \sum_{i=1}^{n} [(x_i - a)^2 + (y_i - b)^2 - R^2]^2, \] (15)

where \(a \neq 0\) and \(b, c \in \mathbb{R}^2\).

The parameterized form is given by

\[ F(A, B, C, D) = \sum_{i=1}^{n} (A z_i + B x_i + C y_i + D)^2, \] (16)

where \(A = 1\), \(z_i = x_i^2 + y_i^2\), \(B = -2a\), \(C = -2b\), and \(D = a^2 + b^2 - R^2\), under the constraint \(B^2 + C^2 - 4AD = 1\).

Every circle will correspond to a unique quadruple \((A, B, C, D)\) and vice versa. In order to approximate the local maxima points clustered as struts, the implicit polynomial function \(P(x, y) = 0\) that describes a circle is minimized. The coefficients of the polynomial are equivalent with the aforementioned parameters. The gradient weighted algebraic fit is based on minimizing

\[ F_g = \sum_{i=1}^{n} \frac{[P(x_i, y_i)]^2}{\nabla [P(x_i, y_i)]^2}, \] (17)

where \(P(x, y) = A(x^2 + y^2) + Bx + Cy + D\).

The ellipse fitting algorithm considers the implicit quadratic polynomial function that represents a general conic\(^{17}\)

\[ F(A, X) = A \cdot X = ax^2 + bxy + cy^2 + dx + ey + f, \] (18)

where \(A = [abcdef]^T\) and \(X = [x^2, xy, x, y, 1]^T\). \(F(A; X_i)\) is called the algebraic distance of a point \((x, y)\) to the conic \(F(A; X_i) = 0\). The fitting is approached by minimizing the sum of squared algebraic distances

\[ D(A) = \sum_{i=1}^{N} F(X_i)^2. \] (19)
FIG. 8. Double fitting procedure with feedback toward hyperplasia quantification. (a) The fitting procedure adds in the strut group four additional points (white full rectangles) misclassified by the FCM clustering whereas removes a false classified point as strut (white full circle) in polar coordinates. (b) The fitting algorithm in Cartesian coordinates.

The best fit between the two aforementioned algorithms is considered as the curve with the minimum distance between the approximated curve points and the local maxima points. A feedback algorithm is also employed toward the optimization of the strut detection procedure. All local maxima points (struts and not struts) are reinserted in the best fitting curve computed from the preceding step to check any possible misclassifications from the FCM clustering. Any misclassified point of either cluster that fits the approximated curve (circle or ellipse) is classified to the correct group (Fig. 8).

The fitting procedure besides the hyperplasia quantification increases the specificity of the proposed method by reducing the number of false maxima classified as struts combined with the sensitivity increment by adding in the struts cluster any maxima that was misclassified from the FCM algorithm.

III. RESULTS

As regards the inner vessel lumen segmentation accuracy, the results provided by the proposed method are at first compared with manual segmentation by an expert physician in terms of overlap degree between the two sets. The proposed automatic segmentation had an average overlap value of 0.917 ± 0.065 for all OCT images included in the study. Moreover, the mean difference by means of vertical distances in the polar coordinates was 0.089 ± 0.75 mm and in terms of area in the Cartesian coordinates was 0.09 ± 0.80 mm².

Table II gives a detailed account of the strut detection accuracies obtained by the proposed method. The accuracy values presented in Table II are calculated after the double fitting algorithm employment. The corresponding values before the fitting algorithm were 89.77% as overall accuracy, with sensitivity and specificity values of 66.00% and 94.07%, respectively. These results are highly indicative of the effectiveness of the proposed method toward an accurate strut detection procedure. The mean difference in terms of area values between the strut contours acquired from the proposed algorithm and that from the struts depicted by the expert was 0.06 ± 0.5 mm².

After algorithmic application toward detection of the lumen area and stent struts in each one of the four femoral OCT datasets, the following parameters indicated as clinically significant were calculated in every OCT frame as already described in a previous study of our group:14 maximum stent diameter ($D_S$; corresponding to lumen diameter immediately after stent placement), maximum lumen diameter ($D_L$; corresponding to the maximum patent lumen diameter at the time of the OCT acquisition after development of NIH), late lumen loss ($D_{LLL}$; corresponding to the maximum thickness of NIH), stent area ($A_S$; corresponding to cross-sectional vessel area immediately after stent placement), and lumen area ($A_L$; corresponding to cross-sectional patent lumen area at the time of the OCT acquisition after development of NIH).

Quantitative data on the predetermined morphological variables in the four individual clinical datasets are outlined in detail in Table III. Maximum stent diameter ($D_S$) ranged from 3.34 to 6.04 mm, maximum lumen diameter ($D_L$) from 1.97 to 2.86 mm, and late lumen loss ($D_{LLL}$) was variable ranging from 0.39 to 0.75 mm. A wide range of vessel stenosis on diameter or area basis (%Dstenosis ranged from 15.75% to 20.69%, while %Astenosis ranged from 35.32% to 45.75%, respectively) was found in all analyzed vessel segments. NIH had developed diffusely in all femoral arteries and its respective area ranged from 1.45 to 5.01 mm².

All case studies have been evaluated by means of a special designed graphical user interface (GUI) program that depicts both lumen and strut contours. The implemented GUI has already been applied into the daily clinical practice of our hospital and it is being continuously updated during a feedback procedure between the researchers and the physicians utilizing it. It performs distinct functions, including initially loading the OCT images, providing the...
inner lumen contour and subsequently depends on the user, who can further identify struts and strut contours. All results are available both on screen for visual assessment and saved for future evaluation. During the strut detection procedure and before the double fitting algorithm is applied, the user has the ability to interact with the interface and manually correct the results by adding or removing any additional or unwanted detected struts in a relative low processing time of approximately 4.5 s per OCT frame. The developed algorithm has been checked on a Windows 7 PC with a Dual Core AMD 64 Athlon processor running at 2.8 GHz and 4 GB of RAM.

### IV. DISCUSSION

In the present study, an improved methodology has been proposed toward vessel lumen border segmentation and stent strut detection so as to assess the degree of ISR using OCT images. As to the vessel lumen segmentation accuracy, the proposed algorithm exhibited equal or better results compared to previous studies. The proposed method had a 0.09 ± 0.80 mm² mean difference between the algorithm’s and expert’s contours and an average overlap value of 0.917 ± 0.065, whereas Tanimoto et al. showed 0.11 ± 0.33 mm², Sihan et al.'s 0.11 ± 0.67 mm², and Tsantis et al.'s 0.937 ± 0.045 average overlap value.

Regarding strut detection accuracy, the proposed method also presented superior overall accuracy value of 93.8% with sensitivity and specificity values 77.74% and 96.35%, respectively. The mean difference between stent areas. In the study of Bonnema et al., 0.065, Sihan et al. demonstrated 0.11 ± 0.70 mm², and Tsantis et al. had 0.937 ± 0.045 average overlap value.

The proposed double fitting algorithm enhances the accuracy of the proposed strut detection method by reducing the number of the false positive maxima and adding any missing maxima that were initially misclassified by the clinical user.

In this study, an improved method is introduced compared to Tsantis et al. It presents superior segmentation and strut detection accuracies and significant lower processing time up to five times faster. In addition, the implemented algorithm is part of a sophisticated GUI program that provides lumen, strut contours as well as quantitative information about NIH.

On the issue of processing time, the proposed algorithm takes approximately 4.5 s to give quantitative results for every OCT frame. This processing time includes the preprocessing procedure of bright rings removal, the segmentation, and strut detection procedure along with the parameters calculation. The preprocessing procedure can be omitted after the first run of the algorithm since these concentric circles remain identical throughout the complete OCT scan for each patient. In the same manner, the CWT initialization can be utilized only once for the whole OCT scan without affecting the clustering results since the gray level histogram is not significantly altered along the scanned frames. Both these actions further reduce the processing time down to 2.5 s per frame which is critical in the daily clinical use. Considering that each OCT scan is consisted of 271 frames, the proposed method results in a total processing time of approximately 11 min for every OCT scan.

This study is a continuation of the work presented by Tsantis et al. Compared to that, the approach reported herein presents advantages both at performance and processing time, while the vessel lumen delineation accuracy exhibits similar overlap values of 0.917 ± 0.065 against 0.93 ± 0.045 in Tsantis et al. The strut detection was evaluated in a frame by frame manner with very good performance (93.8%) com-

### Table III. NIH quantitative results, values expressed as means (standard deviation).

<table>
<thead>
<tr>
<th>Case</th>
<th>Maximum stent diameter, $D_s$ (mm)</th>
<th>Maximum lumen diameter, $D_l$ (mm)</th>
<th>Diameter stenosis, $D_{st}$%</th>
<th>Late lumen loss, $D_{LLL}$ (mm)</th>
<th>Stent area, $A_s$ (mm²)</th>
<th>Lumen area, $A_l$ (mm²)</th>
<th>Area stenosis, $A_{st}$%</th>
<th>NIH (mm²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>6.04 (0.10)</td>
<td>2.17 (0.25)</td>
<td>20.69 (5.12)</td>
<td>0.52 (0.15)</td>
<td>5.82 (0.41)</td>
<td>3.37 (0.72)</td>
<td>42.04 (3.24)</td>
<td>2.45 (1.08)</td>
</tr>
<tr>
<td>Case 2</td>
<td>3.49 (0.22)</td>
<td>2.83 (0.17)</td>
<td>19.14 (6.2)</td>
<td>0.60 (0.15)</td>
<td>7.91 (1.09)</td>
<td>5.06 (0.58)</td>
<td>35.93 (2.58)</td>
<td>2.84 (1.35)</td>
</tr>
<tr>
<td>Case 3</td>
<td>3.75 (0.09)</td>
<td>2.86 (0.15)</td>
<td>23.88 (5.4)</td>
<td>0.75 (0.08)</td>
<td>10.96 (0.46)</td>
<td>5.95 (0.6)</td>
<td>45.75 (5.51)</td>
<td>5.01 (0.88)</td>
</tr>
<tr>
<td>Case 4</td>
<td>3.34 (0.18)</td>
<td>1.97 (0.16)</td>
<td>15.73 (4.3)</td>
<td>0.39 (0.09)</td>
<td>4.11 (0.5)</td>
<td>2.66 (0.44)</td>
<td>35.32 (3.01)</td>
<td>1.45 (0.86)</td>
</tr>
</tbody>
</table>
pared to the PNN classification procedure that was implemented in the entirety of the OCT data simultaneously. A superior method was also proposed based on the double fitting procedure that approximated with better results the strut contour and consequently the NIH extent. The major advantages of the presented automated quantitative analysis approach are: (a) the very short processing time that can be minimized to 2.5 s for every frame of the OCT dataset, (b) the new detection local maxima mapping by the fuzzy model depending on both regional and wavelet features (bilateral signal transition from the maxima and the FWHM) enhancing the performance of the algorithm, and (c) the implemented sophisticated GUI. These attributes are the main features that impart the value of the proposed approach.

V. CONCLUSION

Conclusively, up to date FD-OCT technology which allows fast image acquisition of even large caliber vessels, has an emerging clinical role in the assessment of endovascular treatment of both coronary and peripheral atheromatous arterial disease. This study reports the design and implementation of a novel, rapid, and accurate automatic segmentation technique combining FCM and WT for lumen border extraction and strut detection in intravascular OCT images. The proposed algorithm integrated in the GUI represents a step forward in the employment of automated quantitative analysis of in-stent restenosis in every day clinical practice.

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