An Automatic Media-Adventitia Border Segmentation Approach for IVUS Images

Matheus Cardoso Moraes¹, Sergio Shiguemi Furuie¹

¹ School of Engineering, University of São Paulo, Brazil

Abstract

In image processing, segmentation is considered one of the most important and hardest operations. The media-adventitia segmentation, in Intravascular Ultrasound (IVUS) images, is one of the first steps for a vessel 3D reconstruction, and it is an important operation for many applications: measurements of its border circumference, area and radius; for studies about the mechanical properties and anatomical structures of vessels; which consequently will infer about therapy plans and evaluations; localization of pathologies. The purpose here is to segment the media-adventitia in IVUS images with high accuracy by combining a set of imaging-processing techniques: Speckle Reducing Anisotropic Diffusion (SRAD), Wavelet, Otsu and Mathematical Morphology. Firstly, SRAD is applied to attenuate the speckle noises. Next, the vessel and plaque features are extracted by performing Wavelet Transform. Optimal thresholding is carried out by Otsu to create a binarized version of these features. Then, Mathematical Morphology is used to obtain an adventitia shape. Finally, this approach is evaluated by segmenting 100 challenging images, obtaining an average of True Positive (TP) = 92.83 ± 4.91, False Positive (FP) = 3.43 ± 3.47, True Negative (TN) = 3.43 ± 3.47, False Negative (FN) = 7.17 ± 4.91, Max False Positive (MaxFP (mm)) = 0.27 ± 0.22, Max False Negative (MaxFN (mm)) = 0.31 ± 0.2. Furthermore, its effectiveness is demonstrated by comparing this result with a recent one in the literature.

1. Introduction

Yearly, over 250,000 lives are lost in USA by atherosclerosis [4]. Intravascular ultrasound (IVUS) is a medical imaging modality, which provides anatomical, morphological, and some pathological information of coronary arteries and plaques. Thus, it is employed in most cardiac procedures [5,7]. Likewise, its image segmentation is not only known to be one of the steps for a vessel 3D reconstruction, yet it can also help health professionals to study vessel and plaques characteristics, mechanical properties, anatomical structures, tissue qualification and volume quantification, internal and external wall perimeter and radius, and location of pathologies. Accordingly, it results in more precise diagnostic, therapy plans and evaluations [2,9,12]. Two different IVUS-image segmentation methods are described in [5,12]; the former is based on Discrete Wavelet Packet Frame (DWPF) [1], k-means and the spline interpolation, while the latter relies on Principal Components Analysis (PCA), and an energy minimization process. Again, a simple, reliable and automatic method to segment the m-a border in IVUS images is proposed herein.

2. Methods

The Material is from the Heart Institute of São Paulo Brazil (InCor), and consists of 100 challenging IVUS images from 24 patients - with different vessel and plaques features. The Method consists in segmenting the media-adventitia borders by accomplishing the following stages: pre-processing, processing, and post-processing, as summarized bellow:

1. Pre-processing:
   (a) Image size and resolution normalization;
   (b) Transducer reflection attenuation;
   (c) Speckle Filtering;
   (d) Conversion to the polar domain.

2. Processing:
   (a) Feature extraction using DWPF;
   (b) Binarization using Otsu;
   (c) Morphological Combination.

3. Post-processing:
   (a) Branch-opening test and correction;
   (b) Return to the Cartesian domain;
   (c) Adventitia-Contour extraction (Segmentation Concluded).

2.1. Pre-processing

The pre-processing stage is shown to make the image ready for being processed, by respectively minimizing and maximizing the undesirable and desirable image features. It begins with a 400x400 Image size and resolution nor-
malization followed by a Transducer reflection attenuation:

\[
I_{NR} = \begin{cases} 
I_O, & \text{if } rad < 41\text{pix} \\
\left(\frac{I_{NR}}{I_O}\right) \cdot (rad - 40), & \text{if } (41 \leq rad < 51)\text{pix} \\
I_D, & \text{otherwise}
\end{cases}
\]

(1)

where \(I_O\) and \(I_{NR}\) are respectively the pixels’ intensities of the original and no reflection image, \(rad\) is the radius to current processed pixel. This procedure does not create new borders. Next, Speckle filtering. “Speckle Reducing Anisotropic Diffusion” (SRAD) [13] takes place to attenuate the Speckle noise, using: Windows size in \(n = 100\) and homogeneous region (\(\Delta t = 0.5s\)). A Conversion to the polar domain, \(I_{Polar}(r, \theta)\) helps the computational process [12], and concludes this section (Figure 1(a)).

Binarization using Otsu - A binarized version of the resultant wavelets’ coefficients were created, \(cA_{bin}^{1}, cD_{bin}^{1}, cD_{bin}^{-1}\), and \(cD_{bin}^{-1}\) (Figure 1(c)), aiming to improve the known information and estimating the missing ones. Otsu’s [10] was used for optimum thresholding, seeing that the coefficient histograms are quite bi-modal.

Morphological Combination - The \(cA_{bin}^{1}\) is shown to be the binary image that has the most complete plaque and adventitia information (Figure 1(d) in blue and red). Therefore, it will be used to generate the \(APO_{bin}\) (Figure 2(i)), using Mathematic Morphology [3]. This procedure consists in creating and combining three complementary images: Tissue Information \((T_{inf})\) (Figure 2(b)), Adventitia Missing Region Information \((A_{mis})\) (Figure 2(c)) and Skeleton \((Skt)\) (Figure 2(d)). The Complementary Images 1 or \(T_{inf}\) (Figure 2(b)) is obtained by an opening operation between the \(cA_{bin}^{1}\) and a structuring element \((S_{2x50})\) with 2 lines and 50 columns filled by ones.

\[
T_{inf} = cA_{bin}^{1} \circ S_{2x50}.
\]

(2)

The reason of this operation, and this structuring element dimension, is to separate the plaques from the adventitia, so that the first could be removed by area selection in later operations. Complementary Image 2 or \(A_{mis}\) (Figure 2(c)) shows the \(cA_{bin}^{1}\)-adventitia missing information(Figure 2(a) highlighted in yellow). This estimation is obtained by; firstly, applying 10 times a thickening procedure(\(\psi\)) of 1 pixel \((S_{1})\) over \(cA_{bin}^{1}\)

\[
cA_{bin}^{1,\text{Thick}} = \left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi\left(\psi(\psi}\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right)\right).
\]

(3)

next, performing an upward filling procedure at \(cA_{bin}^{1,\text{Thick}}\), where its columns are filled with ones upwardly until the first white pixel.

\[
A_{mis} = Fill_{upward}(cA_{bin}^{1,\text{Thick}}).
\]

(4)

Complementary Image 3 or \(Skt\) (Figure 2(d)) is known to be the structure, which connects only the adventitia objects, for the latter binary selection. This skeleton is created by

\[
Skt = \bigcup_{k=0}^{K} S_k \left( CF_{down} \right),
\]

(5)

where \(S_k\) is a skeleton procedure, and \(CF_{down}\) is given by:

\[
CF_{down} = Fill_{down}(cA_{bin}^{1} \bullet S_{10x100}),
\]

(6)

where Fill_{down} is a downwards filling procedure and \(\bullet\) is a closing operation between \(cA_{bin}^{1}\) and \(S_{10x100}\).

Final Polar Domain Image - The complete adventitia shape in the polar domain \(APO_{bin}\) (Figure 2(g)), is obtained by; firstly, unifying the mentioned three complementary images (Figure 2(e))
\[ U = T_{\text{inf}} \cup A_{\text{mis}} \cup Skt; \]  
(7)

secondly, removing the plaques from the image by using binary area selection, \( B_{\text{selected}} \) (Figure 2(f)), and; finally, the Adventitia Polar Object \( (APO_{\text{bin}}) \) (Figure 2(g)) is obtained using:

\[ APO_{\text{bin}} = (B_{\text{selected}} \cdot S_{\text{circular}(50)}), \]  
(8)

where the structuring element \( S_{\text{circular}(50)} \) is a special matrix that disposes the ones in a circular way with 50 pixel diameter.

2.3. Post-processing

Test and correction of Side Branches - For a signal \( h(\theta_i) \) representing the column height of the \( APO_{\text{bin}} \),

\[ h(\theta_i) = \sum_j APO_{\text{bin}}(r_j, \theta_i), \]  
(9)

and given two derivatives of this signal, higher than a certain threshold. The branch correction is performed by computing an interpolation between these two derivatives; afterwards, this signal goes back to the binary image domain.

Returning to the Cartesian Domain - A Cartesian domain image is generated \( I_{\text{Cartesian}} \) (Figure 2(h)) from the \( APO_{\text{bin}} \).

Adventitia Contour Extraction - The segmentation is concluded by extract the \( I_{\text{Cartesian}} \) contour, using:

\[ \beta(I_{\text{Cartesian}}) = I_{\text{Cartesian}} - (I_{\text{Cartesian}} \cdot S_{3 \times 3}), \]  
(10)

where \( \varepsilon \) represents an erosion procedure, and placing it at the \( I_{\text{Original}} \), generating \( I_{\text{Final}} \) (Figure 2(i)):

\[ I_{\text{Final}} = \beta(I_{\text{Cartesian}}) \cup I_{\text{Original}}. \]  
(11)

3. Results

Some visual result from the dataset mentioned in the methodology can be seen in Figure 3 (a), (b) and (c), and its manual segmentation respectively in Figure 3 (d), (e) and (f), made by an expert (Gold Standard). According to [11], we compute the rate of True Positive (TP), False Positive (FP), False Negative (FN), Maximum Positive Deviation (MaxFP) and Maximum Negative Deviation (MaxFN) (Table 1). Nonetheless, in order to compare this result with the one obtained by [12], our index were taken to theirs: Overlap Ratio (OR) \([\text{OR}=\frac{\text{TP}}{\text{TP}+\text{FP}+\text{FN}}]\); False Positive Rate (FPR) \([\text{FPR}=\frac{\text{FP}}{\text{FP}+\text{TN}}]\); False Negative Rate (FNR) \([\text{FNR}=\frac{\text{FN}}{\text{FN}+\text{TP}}]\), and Maximum Distance (MaxDistance) \([\text{MaxDistance}=\max(\text{MaxFP}, \text{MaxFN})]\) (Table 2).

4. Discussion and conclusions

As can be seen, Table 2 (Unal Method 1) provides the best result, as it used a set of images with minor calcification and branch opening, images assumed to be easily segmented. Conversely, in Table 2 (Unal Method 2), the result suffered a degradation, because it used not only the previous dataset, but also some challenging images, with large calcification and branch opening, which represents 34% of the total set. In our dataset, there are images with and without branches, different vessel sizes; moreover, 88% of the images have calcified, fibrotic and lipidic plaques. Therefore, our resulting Table 2 (Proposed Approach), could be fairly compared to the (Unal Method 2), which gives an
advantage to them, respectively, less than 1% and 2% at the OR(%) and FNR(%), yet the proposed approach provides smaller standard deviation and MaxDistance (Table 2). In general, one can say that both methods have similar results. Nonetheless, ours is simpler computationally, since it does not have to compute large covariance and estimation of PDFs.

This paper presented a new segmentation method, the result of which justifies its use, our contribution were: a) Catheter reflection attenuation; b) A combination of techniques (SRAD, DWPF, Otsu) and the optimum parameters, which led to tissue and plaques feature extracted; c) Morphological operations to create a adventitia shape; d) segmentation results of challenging images. For future work, the association of other parameters to segment the Lumen will be investigated.

Acknowledgments

CNPq (National Council of Scientific and Technological Development - Brazil), InCor (Heart Institute of São Paulo - Brazil), LEB-USP (Biomedical Engineering Laboratory of the State University of São Paulo - Brazil).

References


Table 2. Result comparison among the methods and parameters of three different datasets using the index suggested by Unal et al.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Index Used by Unal</th>
<th>OR (%)</th>
<th>FNR (%)</th>
<th>MaxDistance (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unal</td>
<td>92.23</td>
<td>3.39</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>Method 1</td>
<td>±6.27</td>
<td>±7.86</td>
<td>±1.74</td>
<td></td>
</tr>
<tr>
<td>Unal</td>
<td>90.57</td>
<td>5.55</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>Method 2</td>
<td>±10.66</td>
<td>±9.20</td>
<td>±1.78</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td>89.79</td>
<td>7.17</td>
<td>0.31</td>
<td></td>
</tr>
<tr>
<td>Approach</td>
<td>±4.51</td>
<td>±4.91</td>
<td>±0.2</td>
<td></td>
</tr>
</tbody>
</table>

Address for correspondence: 

Names: Matheus Cardoso Moraes

Postal address: Laboratório de Engenharia Biomédica - Departamento de Telecomunicações e Controle - Escola Politécnica da USP - Av. Prof. Luciano Gualberto, Travessa 3, 158 - sala D2-06 CEP 05508-970 São Paulo - SP - Brazil 

E-mail address: matheuscardosomg@hotmail.com

392