Real Time IVUS Segmentation and plaque characterization by combining Morphological Snakes and Contourlet Transform

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Abstract – After the principal custom of the technics of intravascular ultrasound (IVUS) as an imaging technique for the coronary artery system 70th century until nowadays, the segmentation of the arterial wall boundaries and plaque characterization still an imperative problem. Much research has been done to give improved segmentation result for better diagnostics, therapy planning and evaluation. In this paper we present a new segmentation technics by combining Contourlet transform and Morphological Snakes which developed by Luis Alvarez used for IVUS segmentation followed by plaque characterization. The morphological snakes associate the morphological and differential operators used in the standard PDE based snake models. Results are presented and discussed in order to demonstrate the effectiveness of this approach in IVUS segmentation.

Keywords: Contourlet transform, IVUS Segmentation, Morphological Snakes, Plaque characterization

I. Introduction

From its improvement in the 1970s [1], Intravascular Ultra Sound (IVUS) has become a precious technique for diagnosis and the treatment of coronary artery diseases [3][5]. Intravascular Ultra Sound (IVUS) is a catheter-based system that give 2D cross sectional images of the coronary[14][16] arteries and offers information concerning the lumen and the vessel wall. In a typical IVUS image[4], we compare three regions: the lumen, the vessel wall, consisting of the adventitia and the intima layers and the media plus surroundings [3]. Characterization of the plaque composition remains difficult. Studies have exposed the advantage of IVUS in applications where precise quantification and visualization of atherosclerotic plaques[8] is required [6][7], such as assessing stent deployment or plaque progression – regression studies of lipid-lowering medical therapy.

Despite the good susceptibility determination, IVUS has the difficulty that manual analysis of the huge amount of images is problematic, time-consuming, and subjective. Thus, there is a huge interest for the development of automatic segmentation technics for IVUS images. This present a challenge due to image quality and the noise.

Much of research [23][24][25] on this question has been done using different technics and algorithms like live wire, active contours, shape-driven. In this study, a new algorithm developed by combining Morphological snake, the so-called Morphological snake and the contourlet transform, this technic is employed to detect Lumen, Media /Adventitia [2] contours and plaque characterization. We used this new snake in a traditional segmentation pipeline: first, the preprocessing of the image, then, catheter circle detection and finally Snakes initialization.

II. Preprocessing

IVUS images are quite noisy, so to perform the segmentation [15] in an easier way, denoising it is a necessary step to apply filters. Many different types of filters where tested, wavelet transform, Curvelet transform and contourlet transform. Finally we have chosen the Contourlet transform which gave the best result.

Recently Do and Vetterli proposed an efficient directional multi resolution image representation called the contourlet transform. Contourlet transform has better performances in representing the image such as lines, edges, contours [18] and curves than wavelet and curvelet transform because of its directionality and anisotropy. The contourlet transform consists of two steps which is the sub band decomposition and the directional...
transform. A Laplacian pyramid is first used to capture point discontinuities then followed by directional filter banks to link point discontinuity into lineal structure. The overall result is an image expansion using basic elements like contour segments thus the term Contourlet transform being coined [26].

![Fig. 1. The Contourlet transform framework](image)

This Fig. shows a flow diagram of the Contourlet transform.

![Fig. 2. The Contourlet filter bank](image)

Fig. 2. The Contourlet filter bank [27]

III. The Morphological Snake

Many technics were used like level set, active snakes, live wire [10-16] to detect the media-adventitia contour [2]. In our case we propose a solution based on morphological snake.

This algorithm developed by Alvarez [17] and his colleagues uses a morphological discretization of the Partial Differential Equations of curve evolution of the geodesic active contours in a level set framework. The main steps of this algorithm are:

1- The contour is represented in an implicit form included as the level set of an embedding function calculating the contour signed distance function [21] [22].

2- Solving the Partial Differential Equations in a contour narrow band.

3- Keeping the stability of the algorithm by reinitializing of the distance function and the contour [17].

Let \( C \) a parameterized 2D curve; \( C : [0,1] \rightarrow \mathbb{R}^2 \) and \( I : \mathbb{R}^2 \rightarrow \mathbb{R} \). Under the effect of the scalar field \( F \) the curve is deformed along its inwards normal vector, in other word \( C_t = N \cdot F \).

In the geodesic active contours [18][21] : \( F \) is approached by:

\[
F = g(I)k + g(I) \nu \nabla g(I) \cdot N,
\]

where \( k \) is Euclidian curvature \( \nu \) is a real parameter of the balloon force term [22] and \( g(I) \) is a function low at the boundaries of image and selects the region which will attract the contour. In general \( g(I) \) is defined by:

\[
g(I) = \frac{1}{\sqrt{G_2 * I}} \quad (1)
\]

At the boundaries of the image:

\[
g(\partial I) = |G_2 * I| \quad (2)
\]

We define \( u \) as an implicit representation of \( C \):

\[
u : \mathbb{R}^2 \rightarrow \mathbb{R}, \quad C(t) = \{(x, y); u(t, (x, y)) = 0\}.
\]

As illustrated previously, the curve evolution has the form \( C_t = N \cdot F \) so we can see that the evolution of any function \( u(x,y) \) embeds the curve such as one of its level set is:

\[
\partial u/\partial t = F \cdot \nabla u \quad (3)
\]

The curvature parameter \( K \) is calculated with the information on \( u \) : \( k = \text{div}(\nabla u / |\nabla u|) \). Arranging all those equations, the geodesic active contours in a level set frame work became:

\[
\partial u/\partial t = g(I) |\nabla u| (\text{div}(\nabla u / |\nabla u|) + \nu) + \nabla g(I) \cdot \nabla u \quad (4)
\]

The solution of the previous equation can be spitted into in 3 terms : (1) the Balloon force term, (2) the smoothing term and (3) the attraction force term and we will explore those elements separately.
III.1. The Balloon force term

The two known morphological operators erosion and dilatation defined respectively \( (E_h u)(x) = \sup_{y \in h B} u(x-y) \) and \( (D_h u)(x) = \inf_{y \in h B} u(x-y) \) with \( h \) is the operator radius , \( B \) is a disk with radius 1. In terms of morphology continues scale , the defined function \( u_d(t,x) = D_t u_0(x) \) is the solution of the PDE :

\[
\frac{\partial u_d}{\partial t} = |\nabla u_d| \tag{5}
\]

With \( u_d(0,x) = u_0(x) \) , We can deduce that \( D_t \) is the infinitesimal generator of the partial differential equation proved by

\[
\lim_{h \to 0} \frac{D_h u - u}{h} = |\nabla u| \tag{6}
\]

The strength of each segment of the curve is controlled by \( g(I) \) which acts as weight factor : when \( g(I) \) increase , the corresponding segment moves away from target zone and the balloon force should be strong , otherwise , if \( g(I) \) decrease , the corresponding segment approaches from its target and balloon force becomes neglected. In effect, according with the sign and value of \( \nu \) the remaining term \( \nu |\nabla u| \) bring us to the dilatation and erosion PDEs [20] given above. At \( n \) iteration, the balloon force PDE applied over \( u_n \) may be using the morphologic approach [17]:

\[
u^{n+1}(x_i) = \begin{cases} (D_{x_i}u^n)(x_i) & \text{if } g(I)(x_i) > \theta \text{ and } \nu > 0 \\ (E_{x_i}u^n)(x_i) & \text{if } g(I)(x_i) > \theta \text{ and } \nu < 0 \\ u^n(x_i) & \text{otherwise} \end{cases}
\]

With \( E_d \) and \( D_d \) are the discrete forms of dilation and erosion. The structure element is formed with eight neighbors of the pixel. \( E_d \) and \( D_d \) are executed by iterations of 8 or 5 neighborhood minima (or maxima) computation with homogeneous Neumann type borders condition. In our case we used the 5 neighbors version. Additional advantageous option to make evolves this Balloon force term is to use an image interval value:[17-20]

III.2. The smoothing term

Let \( B \) a set of all line segments with length of 2 centered at the origin of \( \mathbb{R}^2 \). We define the morphological line operators as:

\[
(F_B u)(x) = \frac{S_{x-1}u(x)+S_{x+1}u(x)}{2} \tag{7}
\]

The called Koepfler -Catté-Dibos- scheme [19] [17] relates the operator \( F_t \) with the mean curvature motion in the following way:

\[
(F_t u)(x) = u(x) + h^2 \frac{1}{4} |\nabla u| \frac{\partial u}{\partial t} - \frac{h^2}{8} \sum_{i} \left| \nabla u(x_i) \right|^2 \tag{8}
\]

And \( g(I) \) is a weight factor which controls the strength of the smoothing operation at each point . By discretizing it another time by means of a threshold \( t_2 \) the above PDE can be approached by using these line morphological operators in this numerical scheme (approximates mean curvature motion):

\[
u^{n+1} = \begin{cases} (S_{x-1} u^n + S_{x+1} u^n)(x) & \text{if } g(I) \geq t_2 \\ u^n(x) & \text{otherwise} \end{cases} \tag{9}
\]

With \( S_{x-1} \) and \( S_{x+1} \) are discrete forms of the aloft morphological continuous line operators.

Both \( S_{x-1} \) and \( S_{x+1} \) have their specific form of the set \( B,P \), which is a group of four discretized segments centered at the origin:

![Fig. 4. Some illustrations of the effect of the Sd In those examples where as straight line is found (striking in red), the central pixel remains white ((a)and(b)). When the central pixel don’t belong to a straight line of white pixels, it is made inactive ((c)and(d)).](image)

IV. Implementation

As explained above , the active contour equation (4) is made up of three different components : a smoothing force , a balloon force and an attraction force. And these components may be solved with morphological operators, so the algorithm is very easy, in each iteration we will apply the morphological smoothing, the morphological balloon force and the discretized attraction over the embedded level-set function \( u \).

![Fig. 5. The curve C and it’s embedded level-set binary function u.](image)
The level set function $u$ in different iteration which represent the morphological implementation of the PDE. Just a reminder, the input and the output level set is a binary image in other words, these 3 numerical systems are morphological that they don’t make extra level set values, [17-20]. The snake is initialized automatically by detecting the catheter circle which detected by using Hough transform.

The mentioned algorithm was tested by using LabVIEW with 50 IVUS images were acquired with a 20 MHz mechanical catheter using motorized pullback (1mm/s). Image size was 356 X 356, those images were analyzed by one experienced observer. The observer used a semi-automatic segmentation method to obtain lumen and vessel contours which were then manually corrected where necessary. No images were excluded and different configurations with calcified plaque, shadows, sidebranches, and drop-out regions were present. The pixel size is 27 x 27 µm².

IV.1. Plaque characterization

In standard IVUS gray-scale images, calcified regions of plaque and dense fibrous components usually reflect ultrasound energy well and thus appear bright and
homogeneous on IVUS images. Conversely, regions of low echo reflectance in IVUS images are usually labeled "soft" or "mixed" plaque. However, this visual interpretation has been demonstrated to be very inconsistent in accurately determining plaque composition and does not allow real-time assessment of quantitative plaque constituents. Histogram analysis of the image permits detailed evaluation of plaque composition.

After segmentation, ROI is extracted for plaque classification based on gray level median of echogenicity. The following histogram show the distribution of gray scale intensities within the plaque.

In addition, linear regression analysis revealed that the obtained result was strongly correlated with the reference manual, and yielded the following results for Lumen and Media / adventitia contours respectively: $y = 0.944x + 0.0278, r = 0.9$; $y = 0.616x + 2.564, r = 0.78$. As shown, the performance of the automated segmentation was remarkably high, even in poor quality IVUS images due to artifacts, calcifications, or speckles noise, additional supporting the detection efficiency of our segmentation approach. With respect to the manual segmentation method, the required analysis time for the dataset of 50 selected images reduced by 98% with our method (2 s per image for morphological snakes versus 105 s per image for manual segmentation), suggesting that apart from applicable and reliable, the method we propose is markedly rapid.

**TABLE 1. AREA DIFFERENCES BETWEEN THE AUTOMATIC SEGMENTATION AND THE MANUAL EXPERT SEGMENTATION FOR LUMEN AND MEDIA/ADVENTITIA CONTOURS.**

<table>
<thead>
<tr>
<th></th>
<th>Area Difference (mm²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lumen Contours</td>
<td>-0.04±0.26</td>
</tr>
<tr>
<td>Media/Adventitia contours</td>
<td>-0.04±0.47</td>
</tr>
</tbody>
</table>

**VI. Conclusion**

In this paper we have presented a new approach for IVUS segmentation based on combining Contourlet transform and morphological snakes. The new approach has been applied to IVUS images which were segmented; Lumen and Adventitia /Media contours were detected automatically and compared with expert-corrected contours. Results show good...
correlation between agents and observer for the lumen areas with $r = 0.78$, and good correlation for the vessel areas with $r = 0.74$. In future, we plan to focus on detecting calcifications and branch openings. We will also take advantage of the continuity of images in the IVUS pullback sequences and enhance our algorithm by extending it to 3D.

References


