Automatic Segmentation of Artery Wall in Coronary IVUS Images: a Probabilistic Approach

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Abstract

Intravascular ultrasound images represent a unique tool to analyze the morphology of arteries and vessels (plaques, restenosis, etc). The poor quality of these images makes unsupervised segmentation based on traditional segmentation algorithms (such as edge or ridge/valley detection) fail to achieve the expected results. In this paper we present a probabilistic flexible template to separate different regions in the image. In particular, we use elliptic templates to model and detect the shape of the vessel inner wall in IVUS images. We present the results of successful segmentation obtained from patients undergoing stent treatment. A physician team has validated these results.

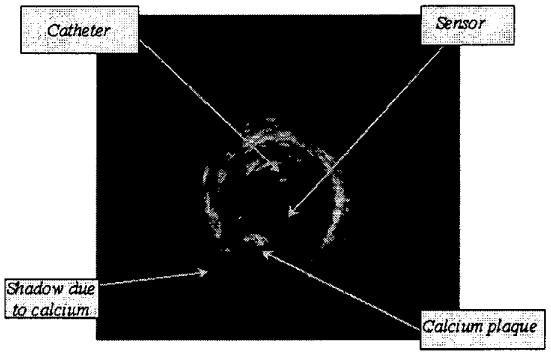

Figure 1. Slice of artery obtained by intravascular ultrasound

1. Introduction

1.1. Intravascular ultrasound sequences

Intravascular Ultrasound (IVUS) imaging is a relatively new medical tool which consists of placing a catheter, with a sensor on its tip, inside the artery. This sensor rotates as it emits pulses of ultrasound. When it receives the echoes the tissues return, it generates an image like the one shown in figure 1. Dark zones correspond to the artery lumen, light zones to the artery wall and the brightest parts with a dark shadow behind, to calcium plaque.The circle in the center of the image is the catheter. The sensor can be seen in some images as a bright spot beside the catheter followed by a dark shadow.

1.2. Previous research

Due to the amount of information they carry ([1], [2]), IVUS images are increasing their role in the diagnosis and treatment of several diseases. Manual segmentation is slow and lacks of objectivity. Consequently, automatic segmentation and tracking of the vessel inner wall in IVUS images has been approached in several recent works ([3], [4]). The poor quality of the images suggests the use of techniques such as probabilities [5] or fuzzy logic [3] guiding an active contour to adjust the inner wall. F. Escolano proposed in [3] the use of circular deformable models guided by a function which had an added term to cope with noise. The rigidity of the shape prevented the template from being mislead by dark shadows.

In this paper, we suggest the use of elliptic templates guided by the global statistics of the image. On one hand, the use of probabilities is a good way of reducing the impact of noise. On the other, using such a restricted deformable shape makes the model more stable under the presence of artifacts such as shadows due to calcium plaque and the sensor. We use an elliptic shape instead of a circle to better adjust the model to the inner wall and because this shape also gives a direct estimation of the maximum and minimum diameters of the lumen. The only assumption made is that lumen and tissue appear in the image as gray-level pixels generated by two distinct normal distributions.

2. Description of the method

An image can be thought of as a function, $i(x, y)$, of two variables. Let us suppose that the origin of our coordinate system is at the center of the image. Notice that this center

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coincides with the catheter's center.

The key idea of the method is to compute a first approximation of an elliptical model which has a high probability of being close to the inner wall. This initial ellipse is obtained by means of a binarized image obtained with a fixed threshold. We, then, refine this ellipse using an adaptive threshold computed for each image. The refining algorithm is based on the search of a minimum of a cost function that discriminates different tissues and uses the simplex method [7].

2.1. The initialization problem

As in any iterative procedure we need to give an initial ellipse for the first frame of the sequence to be analyzed. It is well known that a bad initial point could lead the iterative method to a wrong minimum.

For the initialization process we work with the polar transform of the image (see figure 3), which will be also denoted by i.

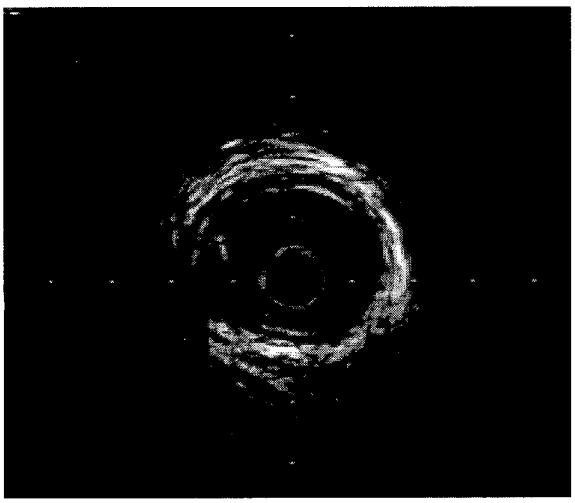

Figure 2. Frame of an IVUS sequence

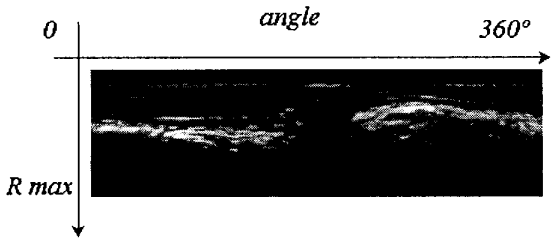

Figure 3. polar transform of the IVUS of figure

We consider the image of the means i_m. That is, for each pixel (x_0, y_0),

$$i_m(x_0, y_0) = \frac{1}{25} \sum_{(x,y) \in B_{(x_0,y_0)}} i(x, y)$$

Where $B_{(x_0,y_0)}$ is a square neighborhood (of 5×5 in our case) centered at (x_0, y_0).

A statistical test on the blood's gray-level mean (μ) of the type: $H_0 : \mu \geq \alpha_0$, shows with a significant level of 0.05 that this mean μ is under a fixed threshold α_0 (which for images taken at 40 Mhz is $\alpha_0 = 0.23$). Notice that this threshold depends on the frequency of the ultrasonic signal. The higher the frequency is, the more details one gets in the image. This means that blood is detected in the image as a sort of texture, for instance in images at 40 Mhz. This fact makes the threshold α_0 increase. One should comment that blood-pixels above this fixed threshold are mainly due to blood backscatter. Since this phenomena appears near the inner wall, the center of our initial guess is close to the inner wall barycenter. We will see in the next section that this fact is relevant in the refinement process, which justifies the use of a fixed threshold in the first stage.

We consider the binary image, I, associated to the threshold α_0, that is

$$I(x, y) = \begin{cases} 1 & , if\ i(x, y) \leq \alpha_0 \\ 0 & , otherwise \end{cases}$$

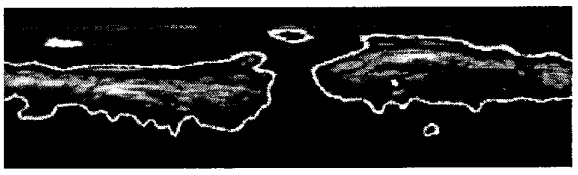

Figure 4. Edges of the binary image

We then apply ASF (Alternative Sequential Filter) on I with a 3×3 square structural element and compute its edges (figure 4). Afterwards, we take, for each angle, the edge of minimum radius (figure 5) . And finally, we eliminate those points lying on the sensor and discontinuities (see figure 6)

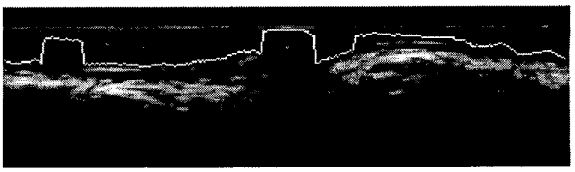

Figure 5. Set of points selected by minimum radius

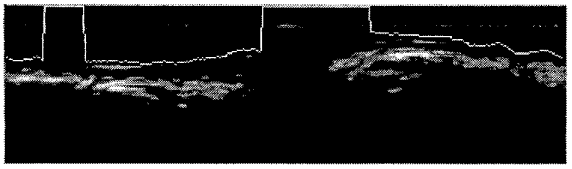

Figure 6. Final set of points to be approximated by a circle

Then, the circle approximating the set of points obtained gives us an ellipse close enough to the inner wall as to use it as initial point for the iterative algorithm.

For the rest of the sequence, we take as initial ellipse the one segmenting the lumen of the previous frame.

2.2. Improvement of the initial ellipse

The method we propose is based on the assumption that lumen and tissue appear in the image as gray-level pixels generated by two distinct normal distributions. Let α be the value that best separates both distributions. We compute it automatically by means of the method described in [6]. Notice that since the outer part of any IVUS is completely dark, dealing with the whole of the image may induce some errors. Thus, the first step is to select a region of interest in the image. We do it automatically as follows. Denote by $\mathbb{D}_r$ the disk of radius r centered at the initial ellipse and by P the probability of having a dark gray-level inside $\mathbb{D}_r$. To be precise, we consider the function $g(r) = P(i(x,y) < 0.2)$. If one takes disks of increasing radius, the global minimum of g indicates the point we stop having significant echoes. This minimum is highly dependent on the center of the disks $\mathbb{D}_r$, especially in images with an eccentric catheter position. From now on, whenever we talk about the image we will be thinking of this selected part.

Once this parameter α has been fixed, we proceed to the deformation of the ellipse.

Let $\mathcal{E}_{int}$ denote the interior of the deformable ellipse and $\mathcal{E}_{ext}$ its complement in the image. Then, the ellipse segmenting the lumen is the global maximum of the function:

$$F = \frac{\int_{\mathcal{E}_{int}} I(x,y)dxdy}{Area\ of\ \mathcal{E}_{int}} + (1 - \frac{\int_{\mathcal{E}_{ext}} I(x,y)dxdy}{Area\ of\ \mathcal{E}_{ext}}) \quad (1)$$

where

$$I(x,y) = \begin{cases} 1 & , if\ i(x,y) \leq \alpha \\ 0 & , otherwise \end{cases}$$

The first term represents the probability that the gray level of the inner points of the ellipse belong to the probabilistic distribution corresponding to the lumen. The second one represents the probability of having an outside gray level belonging to the distribution which corresponds to the tissue.

Since an ellipse is defined by 5 parameters (a, b, σ, x_0, y_0) (see figure 7),the problem reduces to maximize a function, $F = F(a, b, \sigma, x_0, y_0)$, of 5 variables. Its maximum is obtained by the simplex method.

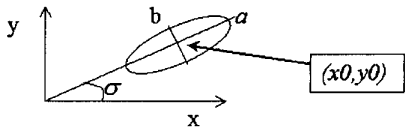

Figure 7. representation of the five parameters of an ellipse

3. Results

The method has been used to segment and track the inner wall of coronary arteries extracted from IVUS made to patients undergoing stent treatment. The sequences were obtained by pull-back at a speed of 0.5 mm/sec and acquisition rate of 25 frames/sec. The digitalized images were 384 x 288. We have tested the method on a total set of 1600 frames extracted from 8 different patients (sequences of 200 frames per pacient).The initialization process was run every 50 frames.

We use the standard L_2-norm for functions to estimate the relative error of our approach. That is, if $\mathcal{E}$ is our ellipse and γ (computed by manual segmentation) is the curve segmenting the inner wall, and both curves are parameterized by the angle, then the relative error made is

$$E_2 = Error(\mathcal{E}, \gamma) = \frac{\int_0^{2\pi} \|\mathcal{E} - \gamma\|^2 dt}{\int_0^{2\pi} \|\gamma\|^2 dt}$$

That means that the real curve is within $(1 \pm E_2)\mathcal{E}$ as it illustrates figure 8

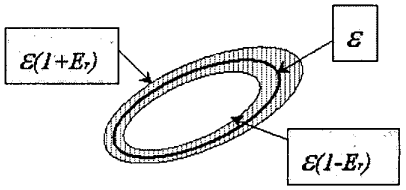

Figure 8. Inner wall lies somewhere inside the stripped area

We have also computed the relative error of the cross-sectional area:

$$E_A = \frac{A_{lumen} - A_{\mathcal{E}}}{A_{lumen}}$$

The results obtained have been validated by a medical team. According to experts, if the lumen is not completely obstructed by proliferation, the L_2-relative error made in $77,4\%$ of the total number of frames is less than 0.1. The mean L_2-error is 0.0571 ± 0.98 and the mean area error of the lumen is 0.15 ± 0.1. The failures were due to the initialization process. The main source of errors in the successful detections were mainly due to blood backscatter (2/3 of the errors approx.) and to bad detection of soft plaque.

In the case of severe restenosis, the final ellipse adapts to the stent. This is due to the way we compute the particular threshold for each image ([6]).

Failures	14% of the total frames
Successful Detection	E_2<0.1 in 90% of successes
	E_A<0.2 in 75% of seccesses

Figure 9. Error in %

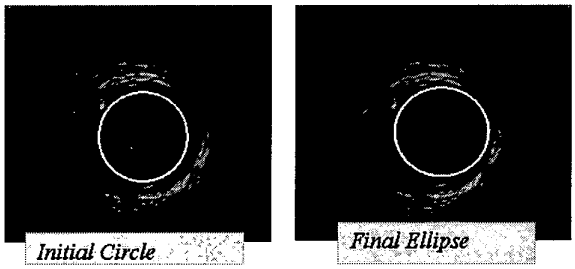

Figure 10. First approach and final ellipse

4. Conclusions and future developments

The method presented in this paper introduces a simple global probabilistic model which behaves well in low quality images. The method detects the inner wall in 80% of the frames when severe restenosis is not observed. We are studying if the problem can be overcome considering gray-level pixels generated by three normal distributions instead of two and taking into account other features such as spatial and temporal coherence in the sequence.

Tracking the inner wall in IVUS sequences is one of the first steps to obtain a faithful 3-D reconstruction of the coronary tree. Furthermore, if one succeeded in distinguishing between blood, tissue and proliferation, one would have a way of determining the grade of occlusion the artery suffers and, thus, the volume of blood that flows through it. All this would help to decide whether it is worthy placing an stent or not.

Besides, modeling the inner and outer wall of vessels by ellipses can help to estimate the vessel movement. On a first approach one models this movement as the best affine transformation that takes one frame to the next one. An ellipse contains all the parameters involved in an affine transformation, that is, the scaling terms a, b, the translation (x_0, y_0) and the angle of rotation σ. Therefore, comparing 2 consecutive ellipses segmenting the outer wall would give us a rough approximation of the affine transformation. The movement appreciated in an IVUS sequence is directly related to the heart movement and there is the hypothesis that heart and artery dynamics may be a way of evaluating heart tissue damage after a coronary stroke.

Our immediate work will be aimed at improving the segmenting algorithm. Further on we will focus on both 3-D artery reconstruction and estimation of heart dynamics.

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