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, etc). The poor quality of these images makes traditional segmentation algorithms (such as edge 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. The use of elliptic templates forces a global probabilistic approach, that makes use of image statistics inside regions. We present the results of successful segmentation obtained from 12 patients undergoing stent treatment. A physician team has validated these results.

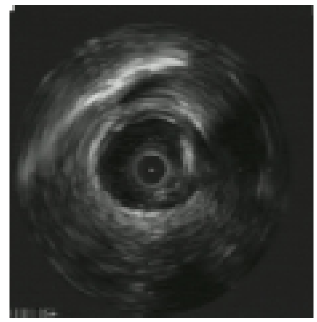

Figure 1. Slice of artery obtained by intravascular ultrasound

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.

1.2. Previous Research

Due to the amount of information they carry ([5], [4]), IVUS images are increasing their role in the diagnosis of several diseases. Consequently, segmentation and tracking from IVUS images of the vessel inner wall has been approached in several recent works ([2], [7]). The poor quality of the images suggests the use of techniques such as probabilities [1] or fuzzy logic [2] guiding an active contour to adjust the inner wall. In the case of coronary images one has the additional problem of the dark shadows that the calcium plaque produces. That makes probabilistic approaches taking into account only the statistics in a neighborhood of the model border [1] fail to obtain good results. F. Escolano proposed in [2] 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.

*This work was supported by TIC98-1100 .

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2. Description of the method

The image will be always thought of as a function, $i(x, y)$, of two variables. The origin of our coordinate system will be supposed to be at the center of the image.

The first step is to select the region of interest in the image. Notice that since the outer part of any IVUS is completely dark, dealing with the whole of the image may induce some errors, specially during the selection of the threshold α (see next paragraph). Denote by $\mathbb{D}_r$ the disk of radius r centered at the origin and by P the probability of having a dark gray-level inside $\mathbb{D}_r$. Let us consider the function $g(r) = P(i(x, y) < 0.2)$. Notice that if one takes disks of increasing radius, the global minimum of g indicates the point we stop having significant echoes. From now on, whenever we talk about the image we will be thinking of this selected part.

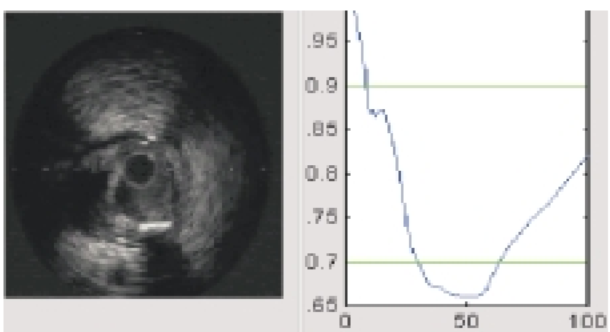

Figure 2. Right: original image. Left: graphic of the function g(r)

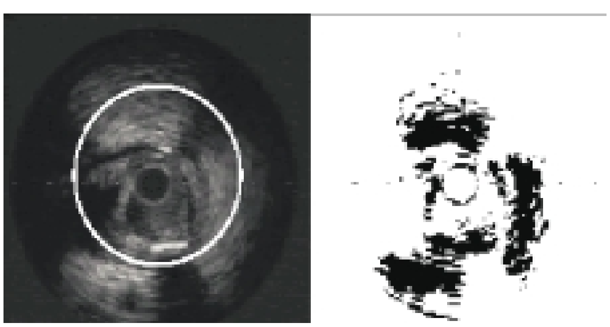

Figure 3. Right: area of interest. Left: pixels under threshold $\alpha = 0.26$

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 separates both distributions. We compute it automatically by means of the method described in [6]. The threshold is obtained taking into account the histogram of the area of interest. Once this parameter α has been fixed, we proceed to the deformation of the ellipse as follows.

Let $\mathcal{E}_{int}$ denote the interior of the deformable ellipse and $\mathcal{E}_{ext}$ its complement in the image. Then, to segment the lumen we search for the ellipse that maximizes the following 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.

Notice that an ellipse is defined by five parameters (a, b, σ, x_0, y_0). The pair (x_0, y_0) are the coordinates of the center, σ is the angle of rotation and the parameters a and b are the lengths of the principal axes [see figure below].

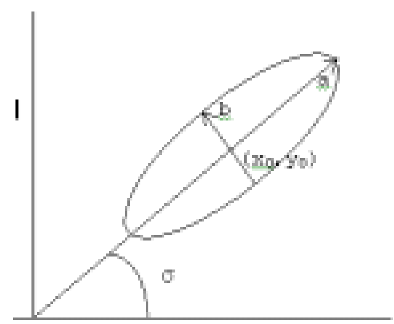

Figure 4. representation of the five parameters of an ellipse

The problem, then, reduces to maximize a function, $F = F(a, b, \sigma, x_0, y_0)$, of 5 variables. Its maximum is obtained by the steepest descent method [3].

Consider the following change of variables

$$\begin{pmatrix} \tilde{u} \\ \tilde{v} \end{pmatrix} = \begin{pmatrix} a\cos\sigma & b\sin\sigma \\ -a\sin\sigma & b\cos\sigma \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} + \begin{pmatrix} x_0 \\ y_0 \end{pmatrix}$$

In these new variables $(\tilde{u}, \tilde{v})$, the function in (1) can be written as

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$$F(a,b,\sigma,x_0,y_0) = \frac{\int_{\mathbb{D}} abI(\tilde{u},\tilde{v})dudv}{Area\ of\ \mathcal{E}_{int}} + \\ + (1 - \frac{\int_{\mathbb{D}^c} abI(\tilde{u},\tilde{v})dudv}{Area\ of\ \mathcal{E}_{ext}})$$

where $\mathbb{D}$ is the disk of radius one centered at the origin and $\mathbb{D}^c$ is its complement.

2.1. Dynamics of the parameters

Following the steepest descent method, the dynamics of the parameters are obtained by means of the partial derivatives of F.

The iterative procedure needs an initialization of the ellipse. As initial ellipse for the first frame, we take a circle centered at the origin of a radius close to the one of the sensor. Indeed, any ellipse contained in the inner wall would do. Since the sensor always lies inside the lumen, this is the initial shape we consider. Sometimes, though, when the center of the lumen is far away from the origin, it is highly recommended to start with a circle centered at the lumen. If one wanted the method to be completely automatic, a global minimization method (such as simulated annealing) for the first frame should be used. At each new frame, we take as initial ellipse the one segmenting the lumen of the former image.

Sometimes, the method fails to converge to the inner wall. We detect these failures by comparing two consecutive ellipses. If the Euclidean norm between the two sets of parameters is high, we reject the segmentation result.

3. Results

The method has been used to segment and track the inner wall of coronary arteries in short sequences (up to 30 frames at a rate of 12 frames per second) extracted from IVUS made to patients undergoing stent treatment. We have tested the method on a set of 270 frames from twelve different patients. The results obtained have been validated by a medical team. According to experts the method detects the inner wall in 80% of the cases if the lumen is not completely obstructed by proliferation. Some of the ellipses obtained are shown in the figures below. They illustrate four different kinds of IVUS images.

Images in figure 5 have got shadows due to the sensor. The one on the left, at the right inferior quadrant. The other, at the left inferior quadrant. Figure 6 (left) presents a shadow due to calcium plaque that occupies most of its right side. While figure 6 (right) shows a stent, which appears as bright spots around the lumen. A typical binary image we work with is the one of figure 7 (left). The white area inside the lumen corresponds to the sensor.

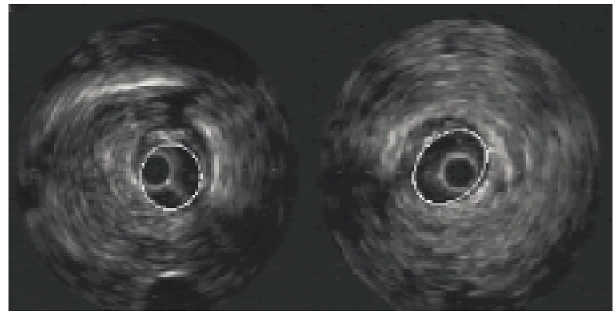

Figure 5.

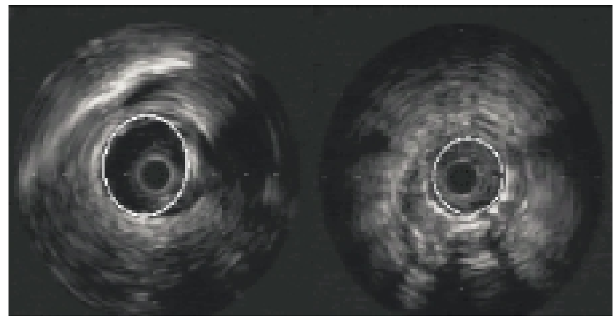

Figure 6.

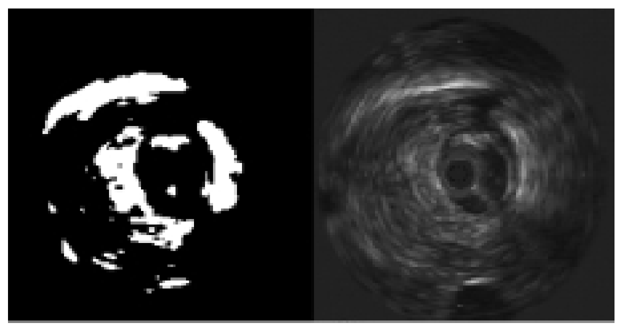

Figure 7. Right:original image. Left:pixels above threshold α

Results obtained using other methods are shown in figure 8. The use of probabilities only in a neighborhood around the border of the template kept the ellipse in figure 8 (left) from absorbing the sensor. The ellipse on the right was guided taking into account the total number of inner points with gray level under α and the total number of outer points with gray level above this threshold. The dark echoes due to the small upper plaque mislead the template.

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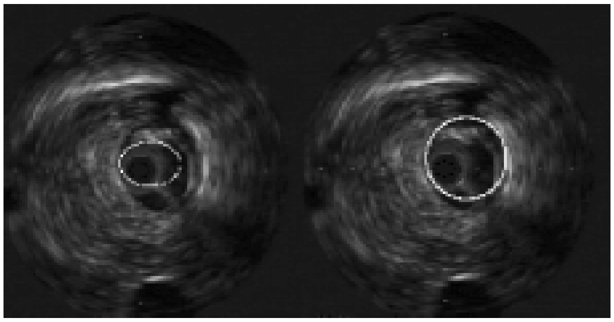

Figure 8. ellipses obtained using other methods

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.

The tracking of the inner wall in IVUS sequences is one of the first steps to obtain a faithful 3-D reconstruction of the coronary tree. This is vital to decide whether a patient can go under stent treatment or not. It can also help to estimate the heart dynamics. There is the hypothesis that heart and artery dynamics may be a way of evaluating heart tissue damage after a coronary stroke. Our future work will focus on both 3-D artery reconstruction and estimation of heart dynamics.

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