IVUS SEGMENTATION VIA A REGULARIZED CURVATURE FLOW

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RESUMEN

Cardiac diseases are diagnosed and treated through a study of the morphology and dynamics of cardiac arteries. Intravascular Ultrasound (IVUS) imaging is of high interest to physicians since it provides both information. At the current state-of-the-art in image segmentation, a robust detection of the arterial lumen in IVUS demands manual intervention or ECG-gating. Manual intervention is a tedious and time consuming task that requires experienced observers, meanwhile ECG-gating is an acquisition technique not available in all clinical centers.

We introduce a parametric algorithm that detects the arterial luminal border in *in vivo* sequences. The method consist in smoothing the sequences' level surfaces under a regularized mean curvature flow that admits non-trivial steady states. The flow is based on a measure of the surface local smoothness that takes into account regularity of the surface curvature.

1. INTRODUCTION

Intravascular Ultrasound (IVUS) imaging [2], [3] is a unique tool to analyze the morphology and deformation of arteries and vessels. A study of a single cross-section gives information about the morphology of the vessel, its luminal area, degree of stenosis and plaque composition (soft or hard tissue). It is well known [1] that these features help in the diagnose and treatment of coronary diseases. A 3-D model is useful to study vessel morphology and extract vessel elastic parameters.

In recent years, different algorithms [4]-[10] have been developed to segment different tissues in IVUS images. Sonka et al. [9], [10] use optimal graph techniques to quasi-automatically detect vessel borders in a single frame if some *a priori* information about the 3-D coronary anatomy is known. Birgelen et al. [4]-[5] base their segmentation of electrocardiogram (ECG)-gated sequences on combining short axes image data with two longitudinal image cuts of the artery. More recently, Klingensmith et al., suggest in [7] the use of active contours to adapt the vessel walls in a single image. Although, the authors show that snakes are a straightforward technique compared to the previous ones, the technique requires an accurate initial approximation of the border to be detected.

In this paper, we present a technique based on a minimal surface that recovers a 3-D model of the artery in *in vivo* sequences that keeps information about its morphology and deformations. Our algorithm is based on the distinct dynamical behaviour among the different structures of a vessel. Tissue follows a periodic rotation produced by the heart beat. Blood presents a chaotic movement, seen in the sequence as small quick oscillations of the gray-level, that introduces a lack of smoothness in the level surface that separates blood from tissue. Irregularity of this surface is smoothed by means of a regularized curvature flow (RCF) [12] that penalizes variation of curvature rather than its magnitude. The final surface, prone to be incomplete due to dark areas produced by the guide wire and side branches, is interpolated using active contours.

2. REGULARIZED CURVATURE FLOW

A theoretical analysis of recent filtering techniques [12] points that if an image smoothing operator is to be robust against strong noisy images, it should be independent of image intensity. Essential advantage in this context is represented by geometric flows. Curvature based flows penalize high curvature regardless of their regularity. Notice that descriptors of shapes depend significantly on the extreme values of the curvature of the contours. Only points lying in a neighborhood of high variability in the curvature are prone to be consequence of noise and should be smoothed. Hence, an operator design with shape recognition purposes should include a term penalizing irregularity in the curvature rather than its magnitude. We propose a geometric flow that includes a function that measures the degree of local irregularity present in the curve. The associated evolution equation admits piece-wise curves, as fixed points that keep significant curvature extrema, thus producing a more reliable smooth model of shapes.

2.1. A Measure of Shape Irregularities

We model noise or lack of regularity in a curve or surface by means of the variability of its normal unit vector

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$\overrightarrow{n}$ around each point. We compute this variability as the projection of the unit normal onto a robust mean of the unit normal in a neighborhood of each point. In order to obtain a robust mean of the normal unit vector we use the structure tensor, J_ρ [14]. In the absence of noise, the scalar product between the unit normal and the eigenvector of maximum eigenvalue, v_1, is close to one. In the planar case, $v_1 = (\cos\psi, \sin\psi)$, can be compute in terms of the coefficients of J_ρ as:

$$A := \tan 2\psi = \frac{2a_{12}}{a_{11} - a_{22}} \tag{1}$$

The measure of irregularity for curves we propose is:

$$g(\varphi) = ||v_1 \times \overrightarrow{n}||^2 = \sin^2(\psi - \varphi) \tag{2}$$

where $v_1 \times \overrightarrow{n}$ denotes the vector product and φ the angle of the unit normal with a fixed direction.

We propose a curvature flow such that its steady states are the minima of the energy functional:

$$E(\gamma) = \int_I g(\varphi)\sqrt{\dot{x}^2 + \dot{y}^2}du$$

for $\gamma(u) : I \subset \mathbb{R} \to \mathbb{R}^2$, a curve embedded in $\mathbb{R}^2$.

Definition 2.1 *The* **Regularized Geometric Heat Equation** *we suggest is the geometric flow defined in standard form as:*

$$\gamma_t = g(\varphi)\kappa\overrightarrow{n} \tag{3}$$

with the function $g(\varphi)$ given by formula (2) and κ denoting the mean curvature.

RCF can be adapted to smooth curves on surfaces by replacing in equation (3) the mean curvature, κ, by the normal curvature, κ_n, of the curve and computing the roughness measure, g, as the vector product between the normal to the curve and its robust mean. In any case, the magnitude of the roughness measure, g, provides the technique with a stop criterion [12] that stabilizes the evolution at non-trivial steady states.

2.2. Segmenting Blood from Tissue

An IVUS sequence can be modeled as a 3-D block: each frame constitutes a $x - y$ plane and the z-axis represents time in the sequence. We base our method on the distinct dynamics of each structure of a vessel. Blood can be separated from tissue by means of its turbulent movement. Turbulence causes irregularities on the level surfaces of the sequence. We study the regularity of the level surfaces of an IVUS sequence in the temporal direction, z, in order to determine a minimum surface segmenting blood and tissue.

We model the surface segmenting blood from tissue as a cylinder, that, in polar coordinates, is given by:

$$\sigma(\theta, z) = (\theta, r(\theta, z), z)$$

The initial surface, σ_0, is computed as the collection of the cross sections, γ_0. The set γ_0 is obtained as union of the longest level curves for the threshold value α, which depends on the frequency of the ultrasound device, that best separates blood from tissue. Notice that by selecting the longest α-curves we are already removing part of blood turbulence (fig. 3(b),(c)). Only blood turbulence near the intima stays in the form of irregularities in the longitudinal curves, $\theta = \theta_0$, of the surface.

Following the criterion of the former section, we detect shape irregularity by means of the smoothness of the normal vector, $\overrightarrow{n}$, to the curves $\theta = \theta_0$. In order to remove it, we search for the minimum of:

$$\int_\sigma g(\overrightarrow{n})||\sigma_z||d\theta dz \tag{4}$$

with initial condition σ_0. Since $\overrightarrow{n}$ is a planar vector, we compute the roughness measure g by means of the formula (1).

The level sets formulation [15] we integrate is:

$$u_t = \sqrt{u_x^2 + u_y^2 + u_z^2}\, g(u_y, u_z)\kappa_n \tag{5}$$

with initial condition the signed distance map to σ_0 and κ_n computed as:

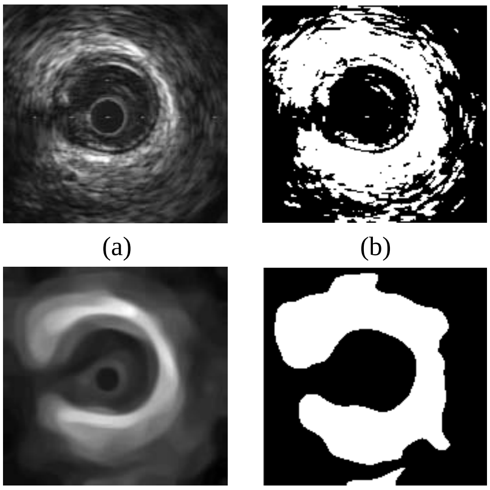
$$\kappa_n = \frac{(-2(u_z u_y^3)u_{yz} + u_{yy}u_z^2 u_y^2 + u_{zz}u_y^4)}{(u_y^2 + u_z^2)\sqrt{u_x^2 + u_y^2 + u_z^2}}$$

Following [11], we remove points of discontinuity and lying on the guide wire from the zero level surface of the steady state of equation (5). Finally, we use a classical snake ([13]) parameterized as a cubic B-spline to smoothly interpolate the intima.

3. RESULTS

We have tested our segmentation algorithm in sequences obtained *in vivo* at constant pull-back speed with two different ultrasound devices at $40Mhz$. The sequences were carefully chosen in order to cover the largest variety of morphology (side branches, stenosis intrastent, calcium and blood turbulence) and artifacts (speckle noise, intensity drop out, sensor guide wire and incompleteness of vessel wall) present in IVUS images. We have applied RCF to, both, the original images and to distance maps to the level surface segmenting blood and tissue. Following [10], [7], in order to determine the accuracy of the segmenting algorithm we computed the positioning error between automated segmented and observer defined borders. We have considered two different kinds of error, the average distance and the maximum distance to the manual detected border. Distances were computed as the radial disagreement between the two borders.

Figure 1(a) shows a cross section of an IVUS sequence and fig. 1(b) the binary image representing the level surface that separates blood from tissue. The inner border of

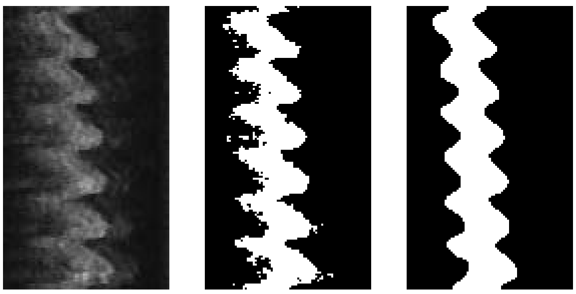


(a) (b)
(c) (d)

Figura 1. Cross Sections of IVUS sequences. Original IVUS images (a) and segmenting surface (b), steady state attained with RCF (c) and the resulting segmenting surface(d).

the largest white shape corresponds to the curve segmenting blood and tissue. Isolated white areas in the interior of the black circle are product of noise. The image achieved by RCF is displayed in fig. 1(c) and the corresponding segmenting binary image in fig.1(d). Notice that small artifacts have been removed while the segmenting curve is preserved.

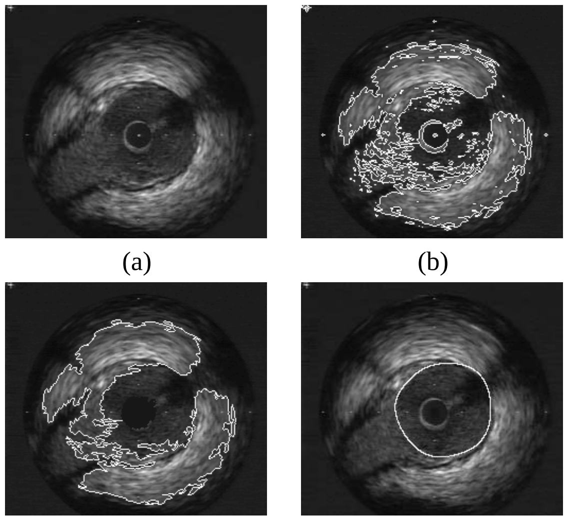
Figure 2 shows a longitudinal section (fig. 2(a)) and the binary segmenting image (fig. 2(c)). The wavy shape, characteristic of IVUS longitudinal cuts, reflects cardiac motion and its of clinical interest, meanwhile small irregularities are caused by blood turbulence. The smoothed curve using RCF is shown in figure 2(c). The model recovered by RCF is a smooth shape that keeps the same number of undulations than the original cut.



(a) (b) (c)

Figura 2. Longitudinal cut of IVUS (a), shape segmenting blood and tissue in (b) the original cut and the smoothed shape with RCF (d).

An example illustrating the segmenting steps of section 2.2 is displayed in fig. 3. The cross section shown in fig. 3(a) is incomplete at the upper right part due to the shadow after the guide wire. Besides the set of all α-level curves (fig. 3(b)) includes several artifacts such as speckled noise, the catheter and, to some extent, blood turbulence and the guide wire of the sensor. By removing short α-level curves (fig. 3(c)), we cope with such isolated artifacts. In this manner, we obtain an automated reliable first approximation to the luminal border based only on the gray-level intensity of the image. This fact is already an advantage over other methods using active contours [7], which require a manual placement of the initial template near the border to be detected. However, this first approximation may be mislead in the presence of blood turbulence and guide wire of the sensor, which are detected as part of the border when located close to the intima. The final model (fig. 3(d)) has succeeded in removing the irregularity at the bottom of the curve of fig. 3(c) and in correctly interpolating the intima at the upper right part of the cross section.



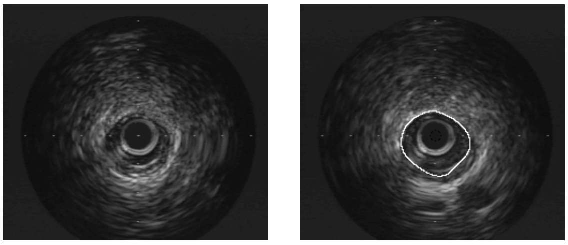
(a) (b)
(c) (d)

Figura 3. Segmentation of intima layer: original image (a), α-level curves (b), longest α-level curves (c) and approximation of the intima (d).

Statistics made on errors yield an average error in the range of 0.1094 ± 0.0388. In the case of the maximum error, in order to get a more realistic estimate, statistics using the jackknife resampling technique will be presented in the final version of the paper.

4. CONCLUSIONS

In this work we present a method to obtain a model of the artery reflecting its geometry by means of a procedure requiring the minimal manual intervention as possible. Artifacts caused by blood flow and the speckled nature of ultrasound images forced some kind of smoothing of the level surfaces.



(a) (b)

Figura 4. Intima detection (b) in the presence of a prominent sensor guide wire (a)

The key ideas that make the method reliable are summarized as follows. A filtering of the images using the shape structure based technique introduced in this paper, provides a good first approximation to the intima border. A temporal analysis of the cube of data, only possible in non ECG-gated sequences, helps to distinct blood and tissue. Finally, the use of snakes allows a robust detection of the intima in those cases where part of the information is lost.

The results obtained show that the method succeeds in recovering a smooth 3-D model of the artery independently of its anatomy, which encapsulates not only the morphology of the vessel but also its deformations.

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