



Cover Page



LUMEN BOUNDARY ESTIMATION FOR PLAQUE DETECTION IN INTRAVASCULAR ULTRASOUND IMAGES BY SHAPE FORMATION APPROACH WITH HAUSDORFF DISTANCE MEASUREMENT

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ABSTRACT

Intravascular Ultrasound (IVUS) image segmentation is an important problem for many applications in study of characteristics of plaque, properties of the coronary artery wall, and its measurements such as lumen size, lumen radius, and wall radius. This paper presents a shape-formation approach to segmentation of the Lumen, Adventitia boundaries from intravascular ultrasound images in the rectangular domain. The proposed work developed a method for boundary estimation of intravascular ultrasound images that identifies the internal and external properties and the plaque-lumen interface. Results of this new IVUS image model agree very well with vessel wall contours. Moreover, Boundary estimation is less sensitive to initialization with average distance between segmentation performed with different initializations <0.85 % and Hausdorff distance <2.6%. Finally, the performance of the proposed method is evaluated by comparing the results to those manually traced borders by an expert on 12 different IVUS images obtained from online databases. The statistical analysis of the results validates based on Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy and K value for media-adventitia border detection with enough consistency in the leakage and calcification regions in IVUS images.

Keywords: IVUS Image, Segmentation, Sensitivity, Specificity, NPV, PPV.

1. INTRODUCTION

IVUS technique is used to analyzing a sequence of video images recorded with an ultrasound transducer device. Transducer device is attached to a catheter which is inserted into the vessel. The images are recorded while the catheter is being pulled out [1]. Manual analysis of these images is very slow and it doesn't provide a global vision of the vessel under study. Therefore, it is necessary to use automatic or semi-automatic methods to speed up the analysis process. The automatic and semi-automatic methods are normally based in computing algorithms whose aim is to detect the regions of interest in each video frame, usually the media-adventitia contour and the intima/plaque-lumen contour as shown in Fig. 1. Several studies on how to solve this problem have been carried out [2-4]. Most of them are based in the minimization of cost functions applied to the regions of interest. Once the regions of interest have been detected the next step is the three-dimensional reconstruction of the vessel. The specialist can use this reconstruction to take measures of area, volume and length, as well as to get a first estimation of plaque severity and a fast access to any region of interest.

Medical IVUS image segmentation algorithms are almost always hampered by noise, stents, shadowing due to calcium deposits and have weak or missing boundaries of structures. The prior models are proved to be useful in aiding the segmentation process. In fact, Active Shape Models (ASMs) have become a popular tool in various segmentation applications for prostate, heart structures such as the left ventricle, and brain structures such as the corpus callosum [5-7]. The contours or shapes in a training dataset are first aligned to build an average shape, and Eigen modes or Eigen shapes obtained through Principal Component Analysis describe the variations from the mean shape. Implicit shape representations are now more popular since they solve the correspondence problem between shapes during the alignment stage [7-10]. Our contribution in this paper is a shape formation approach to IVUS segmentation. Hence, this work constrains the lumen and media-adventitia contours to a smooth, closed geometry, which increases the segmentation quality without any tradeoff with a regularize term, yet with adequate flexibility. This greatly enhances our segmentation method.

2. REVIEW OF LITERATURE

Hassen Lazrag et al [11], presented the fuzzy c-mean with spatial constraint algorithms used to efficiently extract the Region of Interest information from the IVUS image.

Ashok Kumar, and P.Rajendran [12] explained the statistical level parameters, namely mean, standard deviation and CV% and the correlation. The above said technique evaluates the performance of the automated method.

V, Gogas BD et al [13] discussed the two different kinds of measurements, namely qualitative and quantitative for the analysis of dynamic behavior of the anatomical structure in ultrasound images. This research says various ultrasound image segmentation methods. But do not concentrate of the feature enhancement and accuracy.

3. METHODOLOGY

The proposed method consists of five steps (Figure 1): acquiring an image, preprocessing of the image using a median filter, mask creation process, contour estimation and detection of the regions of interest using active contours models for the media–adventitia border, finally, a shape formation/ segmentation.

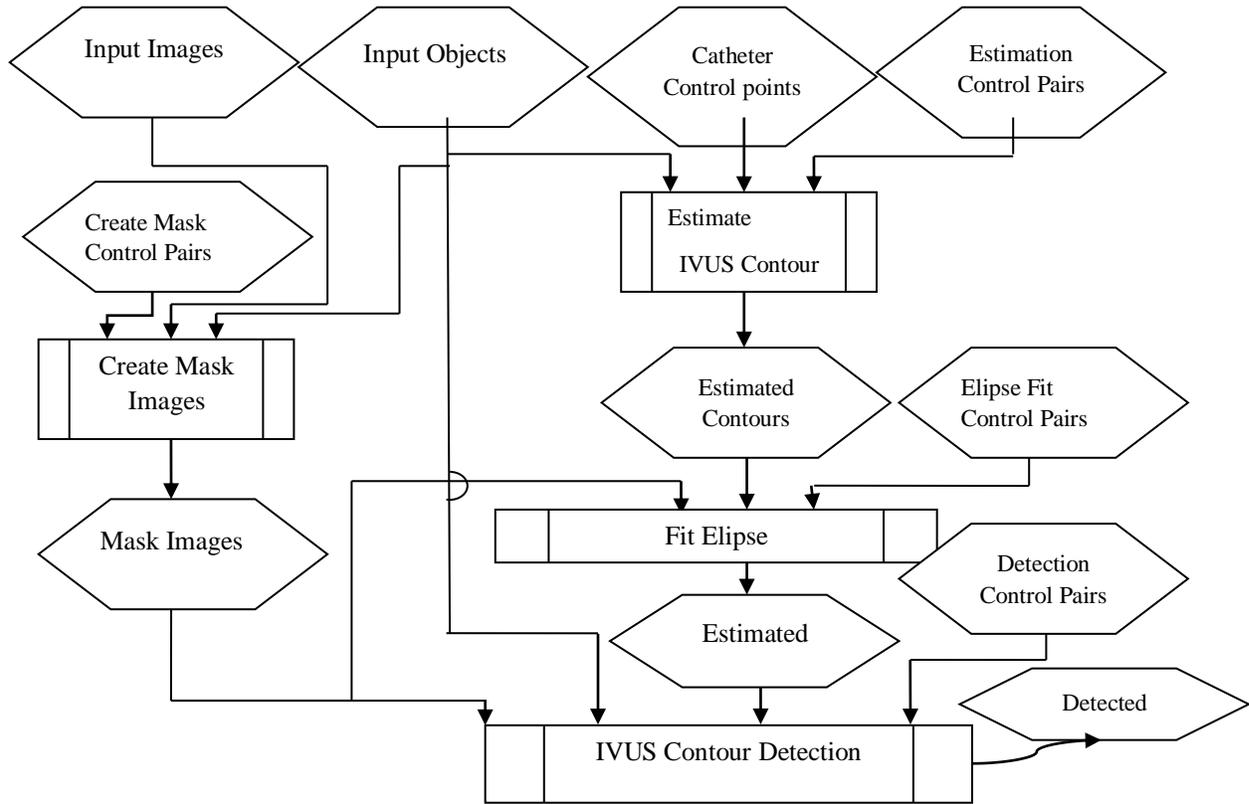
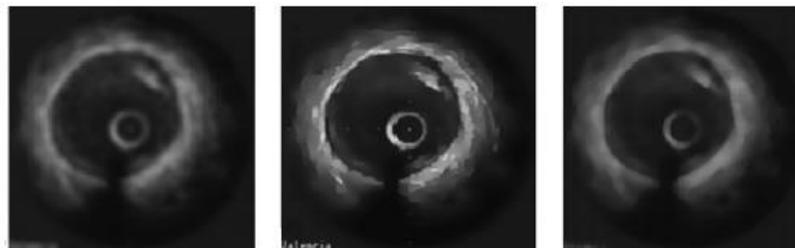


Figure 1: Shape Formation Approach (Geometric boundaries extracted)

3.1 Preprocessing

The first step of our methodology consisted in determining the image zones where our regions of interest may be choosing a squared region of interest (ROI). IVUS images are quite noisy, so a noise reduction filtering was considered. Because next step is border detection, it was necessary for the filter to be noise reductor and edge-enhancer. Three different types of filters were studied: Gaussian filter, anisotropic filter and median filter.

A median filter of size 7 was finally used because its good results for noise reduction and edge enhancement and also because it was relatively fast in comparison to the other evaluated filters. Comparison of the three types of filters evaluated for our IVUS images is shown in figure 2.



(a) Gaussian Filter (b) Anisotropic Filter (c) Median Filter

Figure 2: Comparison Results of three kinds of filter

3.2 Media–adventitia contour Estimation

Contour estimation and detection, were used to detect the media–adventitia contour. In these models the energy function to minimize is

$$E_{\text{Contour}}(Z) = \sum_{i=1}^n (E_{\text{int}}(z_i) + \kappa E_{\text{ext}}(z_i, I)) \quad \text{Eq. 1}$$

where $Z = [z_1, \dots, z_n]$ defines the contour points, $z_i = (x_i, z_i)$, x_i and z_i are the coordinates of the contour, κ is a weight factor, E_{contour} the total energy associated to the contour, E_{int} is the energy that is associated to the contour in itself and E_{ext} is the energy associated to both the contour and the characteristics of the image I .

3.3 Lumen Border Estimation

The use of intensity information readily available from the IVUS image $I(r, \theta)$ after the preprocessing stage is a common approach to contour initialization, since intensity is the simplest form of information that can be used for detecting the lumen boundary (Algorithm 1). The lumen boundary, when travelling from the center of the catheter towards the image borders on a radius R (i.e. for $\theta = \text{const}$) is typically denoted by an increase of intensity from $I(r, \theta) < c'$, c' being a small constant, to $I(r, \theta) >> c'$ (e.g. Figure. 3); assuming the presence of no artifacts (noise) in the lumen area, inequality $I(r, \theta) < c'$ should hold for all pixels belonging to the lumen area.

$$I_{\text{image}}(r \text{ radial}, \theta \text{ tangential}) \quad \text{Eq. 2}$$

3.4 Media, Adventitia and Lumen contour detection

The internal energy is determined from the characteristics of the present contour. This means that an initial contour must be manually defined prior to let the contour deform to search the minimum energy function. For the rest of frames, the previous contour was taken as initial contour for the current frame. The shape formation approach (Figure4) uses a number of parameters which determines how the contour will internally behave, i.e. its elasticity, rigidity, viscosity and pressure force weight, without considering yet the image characteristics.

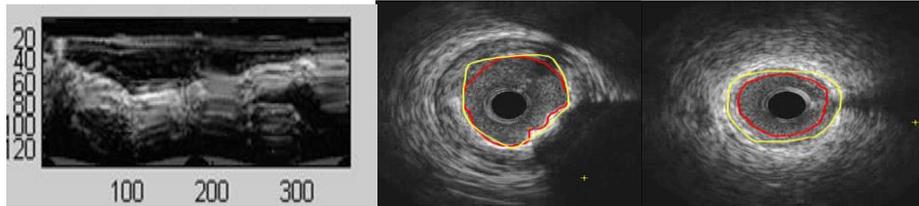


Figure3: Internal behavior of the image

Contour Detection

Mask creation process
Iterative Level Analysis

Inputs: In 2D image

Initialize the mask
Initialization (1 = foreground, 0 = background)
Maximum_iter Number of Iterations to be taken.
Weight calculation Higher = smoother term is taken into account.
default = 0.1 to 0.2 (threshold value chosen)
displ(optional) displays
intermediate outputs (obtained) default = true

Outputs: segm

Final mask image (Segmented / Extracted)
(1=foreground,0=background)

Figure 4: Algorithm for Shape Formation Approach Description

In this phase, Hausdorff distance measurement also used for computing the geometric shape boundaries in Intravascular ultrasound images. Geometric boundaries of images are like circle and ellipse and quatrefoil etc. So, it is used to the compute the vertex points in counter clockwise and clockwise and then compute the distance between two sets(A, B) of geometric boundaries.

Algorithm 1: Shape Formation in boundary detection using the distance measures

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double HausdorffDistance (A, B)
1. From a1, find the closet set point b1 and compute d1 = d (a1, b1)
2. H(A, B) = d1
3. for each vertex ai of A
4. if ai+1 is to the left of aibi
5. find bi+1, scanning B counterclockwise with
6. CheckForClosePoint from bi
7. If ai+1 is anywhere on aibi
8. bi+1 = bi
9. di+1 = d (ai+1, bi+1)
10. h(A, B) = max(h (A, B), di+1)
11. return h(A, B)

```

**4 RESULTS AND DISCUSSION**

The Proposed IVUS shape formation method is tested to the update equations (1) and (2), which are used to extract the lumen and media/adventitia contours and they typically converge after 5 to 50 iterations. Figure 5 demonstrates our results for several frames. This system found that the shape formation method works very well when there are no very strong features such as a large calcification or a large side branch opening. With minor calcification and side branches, the segmentation is fairly successful due to the nicely constrained shape space in which our segmentation takes place. Because of this, even if there are openings, noise or other artifacts, the contour stays as a closed smooth contour, and can achieve meaningful results. Table. 1 depicts the percentage of true positive pixels, false positive pixels, Positive Predictive value, Negative Predictive value, Accuracy and Kappa. It can be observed that proposed method achieved a 98.8% correct classification for the lumen contour and the comparative results are reported in Figure 6.

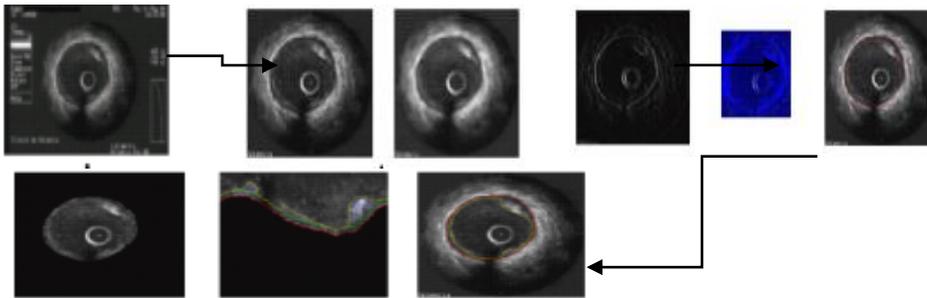


Figure 5: Contour extraction in Lumen, Media and Adventitia borders in IVUS Image

Table 1: Evaluation of Parameters

| Methods                                    | Sensitivity % | Specificity % | PPV % | NPV % | Accuracy % | K    |
|--------------------------------------------|---------------|---------------|-------|-------|------------|------|
| Snake Method                               | 85.3          | 94.8          | 86.6  | 94.2  | 92.1       | 0.84 |
| Energy Minimization                        | 95.7          | 98.7          | 99.4  | 91.7  | 96.7       | 0.92 |
| Proposed Method (Shape Formation approach) | 93.3          | 99.5          | 96.6  | 99.1  | 98.8       | 0.94 |

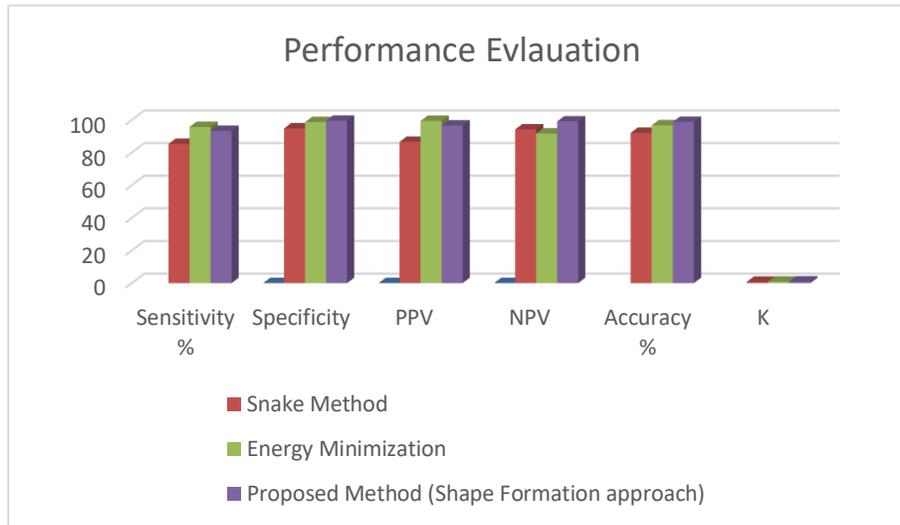


Figure 6: Performance analysis of Contour extraction process in IVUS image layers (Lumen, Media and Adventitia borders)

### CONCLUSION

The shape formation approach for the detection of lumen media and adventitia borders in IVUS images is presented, based on the results of texture analysis and use of Iterative analysis procedure. The experiments conducted with the various combinations of contour initialization and contour estimation methods proposed in this work. First results are promising and they demonstrate the method accuracy in determining Media–adventitia contour detection depends highly on the quality of the images so a better reconstruction and a more accurate set (98.8%) of results depend directly on the strategy followed for the contour detection.

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