SEGMENTATION OF THE CAROTID ARTERY IN ULTRASOUND IMAGES USING FREQUENCY-DESIGNED B-SPLINE ACTIVE CONTOUR


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ABSTRACT

Atherosclerosis is a cardiovascular disease very widespread into population. It is characterized by a thickening of the arterial walls, which affects blood flow. The intima-media thickness (IMT) has emerged as a reliable early indicator of this pathology.

Nowadays, the IMT is still measured by the physician using images acquired with a B-scan ultrasound. This can lead to several problems such as the variability between observers, or the obtainment of a minimum few points along the entire length of the arterial walls. Image segmentation can detect the IMT throughout the artery length as well as statistics such as the maximum, the minimum or the average IMT.

The segmentation method proposed in this work is based on active contours, consisting of two parametric curves that are adjusted adaptively to the existing edges in the image. It allows getting measurements similar to those of a specialist, but with minimal user interaction.

Index Terms—Segmentation, carotid artery, ultrasound image, active contours, intima-media thickness

1. INTRODUCTION

Atherosclerosis may progress throughout life being unnoticed or it can lead to serious cardiovascular diseases such as heart attack or stroke. Hence, it is of vital importance to diagnose and treat this disease early. One of the most reliable indicators to detect the thickening of the arterial walls is the intima-media thickness (IMT) of the common carotid artery (CCA) [1]. The main advantage of the IMT analysis lies in the nature of its measurement, achieved by means of a B-mode ultrasound scan, which is a non-invasive technique that allows studying IMT in a short time on a large number of patients.

As it can be seen in Figure 1, the IMT is the distance between the lumen-intima interface and the media-adventitia interface of CCA’s far wall. The doctor measures the IMT by setting manually only two points, which may distort the results depending on whether these points are taken properly or not. By segmenting with active contours, two parametric curves will delineate I5 and I7 interfaces (see Fig. 1), which leads to better and more useful results.

Since Gustavsson [2] began working on the automatic measurement of IMT, various solutions have emerged from the image processing field: snake-based methods [3], dynamic programming methods applied to vertical image cuts [2, 4], or combination of both [5]. In this paper, an efficient frequency-based implementation of a B-spline active contour is proposed. Results show the ability of these curves to measure the IMT in ultrasound images and are also compared with measurements taken by the doctor.

2. ACTIVE CONTOURS

Active contours or snakes were initially proposed by Kass et al. [6] and are a computer vision tool based on the minimization of an energy functional. According to Liang et al. [7], a snake represents a time-variant parametric curve \( \mathbf{v}(s, t) = [x(s, t), y(s, t)]^T \) lying on the image plane, where \( x \) and \( y \) are the coordinate functions which depend on time \( t \) and the indexed domain \( s \).

The shape of the snake is governed by an energy functional containing internal and external components:

\[
E(\mathbf{v}) = \int_0^L \alpha(s) \left( \frac{\partial y}{\partial s} \right)^2 + \beta(s) \left( \frac{\partial^2 y}{\partial s^2} \right)^2 ds + P(\mathbf{v}) \tag{1}
\]

The internal energy \( S(\mathbf{v}) \) controls the elasticity and stiffness of the contour through the \( \alpha \) and \( \beta \) parameters respectively. The term of external energy \( P(\mathbf{v}) \) is usually calculated by means of image processing (e.g. computing the gradient) and attracts the contour to certain features or details in the image. The minimum energy is thus obtained when the contours reach the edges of interest.

In practice, the contour is assembled with \( N \) piecewise polynomials, each one built with a space-independent shape function, such as a B-spline [8], weighted by the node parameters. Based on this discrete spatial parameterization, the equations of motion that lead to the minimization of the energy functional (1) correspond to the Euler-Lagrange partial

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This work is supported by the Spanish Ministerio de Ciencia e Innovación, under grant TEC2009-12675/TEC.
where $u(t)$ is the vector containing the $N$ nodes, $M$ is the mass matrix, $C$ the damping matrix, $K$ the stiffness matrix, and $q$ is the vector with the external forces [7].

The equations of motion (2) are solved by replacing time derivatives with their discrete approximations and discretizing time as $t = \xi \Delta t$, $\Delta t$ being the time-step and $\xi$ the discrete time, which results in the following matrix difference equation:

$$F \xi u = A_1 u_{\xi-1} + A_2 u_{\xi-2} + q_{\xi-1},$$

where

$$A_1 = 2M/(\Delta t)^2 + C/\Delta t,$$

$$A_2 = -M/(\Delta t)^2,$$

$$F = A_1 + A_2 + K.$$

The numerical evaluation of (3) requires high computational cost due to the calculation of the inverse of $F$. Weruaga et al. proposed in [10] an alternative formulation based on the translation into frequency of the energy functional (1). This efficient implementation avoids matrix inversion since it becomes a pointwise inversion in the frequency domain. This formulation is initially valid only for closed contours, however, it can be applied to open contours by using hidden extensions. The frequency domain implementation of open active contours (and the core of the iterative process), by space-invariant linear filtering, is the following:

$$z_{\xi} = a_1 u_{\xi-1} + a_2 u_{\xi-2} + q_{\xi-1},$$

$$d_{\xi} = \Gamma (z_{\xi}),$$

$$[u_{\xi} e] = \text{IDFT} \left\{ \text{DFT} \left\{ [z_{\xi} d_{\xi}] \right\} \cdot \hat{n}_{\xi} \right\},$$

where $u_{\xi}$ is the vector with the $N$ snake nodes, $q_{\xi-1}$ is a vector with the external forces, $\eta$ is the global mass, $\Gamma \{ \}$ implements the hidden snake rule (see eq. (28) from [10]), $d_{\xi}$ is the $N$-node snake extension, $e$ is a $N$-length dummy residual vector and $\hat{n}_{\xi}$ is the discrete Fourier transform (DFT) of a low pass filter which is the pseudo-inverse of the filter that implements the spatial derivatives of $K$ [10].

As previously stated, in a practical finite elements formulation a snake is defined by a few nodes and a shape function. Using B-splines as the shape function, the final solution is smoother [7], and in addition fewer calculations are performed in each update of the contour. Cubic B-splines have been chosen because they have the best performance-execution time ratio [11]. Therefore, node parameters $u$ are interpolated using cubic B-spline basis in order to obtain the active contour $v$ in the image plane.

### 3. DESCRIPTION OF THE APPLICATION

The main goal is to obtain the IMT semi-automatically from a set of images in DICOM format provided by the radiology department of “Hospital Universitario Virgen de la Arrixaca” (Murcia, Spain). With this purpose, an application for Matlab® has been developed. The steps of the application are listed and explained below (see figure 2):

1. Read the image from a DICOM file (images are usually 1024x768 RGB) and convert it to grayscale.
2. Preprocessing step to facilitate the segmentation.
3. Manual initialization of snakes by the user.
4. Segmentation process with two frequency-implemented B-spline snakes.
5. Show measurements and report.

The application begins by reading a DICOM file. Once the image has been extracted (converted to grayscale if needed), gradients on main directions are enhanced to further processing, which in this case corresponds to the calculation of the laplacian as an external force. Since derivatives are very sensitive to noise, a low pass Gaussian filter (7x7 window, $\sigma = 0.8$) is previously applied to reduce the noise. At this point the gradient is calculated from the resultant image. Only positive values in the descending vertical direction are taken from the gradient, because our interest is focused on the black to white transitions at interfaces I5 and I7 (see Fig. 1). In addition, morphological filtering is performed with a small structuring element to remove traces of characters that may remain in the gradient image.

Taking advantage of the fact that images show the arterial walls in relatively horizontal position, morphological filtering is also used to clean the image highlighting only the relevant information. The orientation of the structuring elements (it takes more than one, as it may appear more than one head tilt) is obtained by using the Hough transform. Afterwards, the laplacian is calculated and used as an external force. To speed up the process (Hough transform is computationally expensive), at each stage, black edges of the image are ignored since they do not provide useful information.
After preprocessing, the resulting image is shown, and the user is prompted to mark four points (two per *snake*) to indicate the slope of the initial contours (straight lines along the width of the image are used as initial *snakes*).

Afterwards, the iterative process consists of evaluating the equations (7)-(9) until the process reaches the end condition of the algorithm: reaching 1000 iterations or that the curves remain almost stationary. However, two issues must be controlled: *snakes* would remain motionless if they are initialized in areas where external forces are null (i.e. zero laplacian regions), and keep them from crossing. To solve the first problem in the first iterations, a small gravity force is added to the upper *snake*, and a take-off force to the lower *snake* (since gradient vector flow [12] does not work properly in this case).

To tackle the second problem the algorithm detects, column by column, if there is a bimodal profile in the gradient image: a peak for I5 interface and another for I7 interface. Whenever it is found, the program moves the corresponding node to each peak of the bimodal profile; if not, the less attracted node (lower gradient value at the position of the node) would be repelled.

Measurements are obtained by multiplying the vertical distance of the curves by the centimeters-per-pixel ratio (taken from the DICOM file). Since the curves are displayed along the entire width of the image (only in the image after preprocessing), it is likely that not all values are valid to compute the IMT and its statistics. Therefore, only the columns with a bimodal profile are considered valid to measure the maximum and minimum IMT, as well as its average and variance. Finally, two images are shown to the user, the first is the initial image with the *snakes* in their final position; the second image shows a close-up of the *snakes* (which can help the doctor to determine if the segmentation was correct) and the evolution of the measured IMT, highlighting the area(s) labeled as valid in thick line.

4. RESULTS

Figures 3 and 4 show the result of applying the whole procedure to two patient’s studies. The measurements related to these images under study are shown in Table 1. As can be noticed from Table 1, the IMT shows no substantial difference with the IMT extracted manually by the specialist. Also note that in the images there are markers used by the doctors to make their manual measurements which make the detection of the interfaces more difficult.

<table>
<thead>
<tr>
<th>Image</th>
<th>IMT (centimeters)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Doctor</td>
</tr>
<tr>
<td>#1 (Fig. 3)</td>
<td>0.079</td>
</tr>
<tr>
<td></td>
<td>0.072</td>
</tr>
<tr>
<td>#2 (Fig. 4)</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>0.095</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

This paper proposes a segmentation method of the carotid artery based on frequency implementation of B-spline active contours. With this procedure, the segmentation of the ultrasound images under study is accomplished. The use of mathematical morphology allows the enhancement of arterial walls, as well as the automatic selection of the region of interest containing only the ultrasound image. *Snakes* achieve the extraction of the wall interfaces. Besides, the use of cubic B-splines provides smooth edges and removes the characteristic rough texture in ultrasound images.

When compared to similar solutions like [3], the proposed algorithm presents some improvements such as the simultaneous detection of both intima and adventitia layers; whereas Ceccarelli’s approach uses a particularization of zip-lock *snake* to detect the adventitia layer, after finding intima layer via constrained segmentation.

The authors are working on an exhaustive validation process, including more images (without doctor markers) and patients, in order to verify these preliminary results. Moreover, the inclusion of a robust detection of the lumen for an automatic initialization of *snakes* is being developed.
Fig. 3. Image under study #1.

6. REFERENCES


