Atherosclerotic Carotid Plaque Segmentation

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Abstract—Atherosclerosis is the major cause of heart attack and stroke in the western world. In this paper we present a computerized method for segmenting the atherosclerotic carotid plaque form ultrasound images. The method uses the blood flow image to detect the initial contour for the plaque, followed by despeckle filtering and snakes to deform the initial contour to fit as close as possible the plaque boundaries. The accuracy and the reproducibility of the computerized method was tested on 35 longitudinal ultrasound images of the carotid artery and compared with the manual delineations of an expert. Results showed that the proposed segmentation method is accurate and no manual correction is needed in most of the cases, with true positive fraction TPF=86.44%, true negative fraction TNF=84.03%, false negative fraction FNF=8.5% and false positive fraction FPF=7% respectively. The present plaque segmentation approach is one of the first steps towards the non-invasive assessment of plaque vulnerability in atherosclerotic subjects.

Keywords—segmentation, carotid plaque, snakes, ultrasound image.

I. INTRODUCTION

Carotid atherosclerosis is the primary cause of stroke and the third leading cause of death in the United States. Almost twice as many people die from cardiovascular disease than from all forms of cancer combined. Atherosclerosis is a disease of the large and medium sized arteries, that is characterized by progressive intimal accumulation of lipid, protein, and cholesterol esters which significantly reduces blood flow. Atherosclerosis may be present in different sites of the body, which includes the coronary arteries, the superficial femoral artery, the infrarenal aorta, and the carotid arteries at the area of the common carotid bifurcation. Atherosclerotic plaque formation initially causes compensatory enlargement of the vessel with little or no compression of the lumen. Traditionally the degree of artery stenosis, or narrowing, has been targeted as the marker of a vulnerable plaque (plaque with high risk to rupture), and considered to cause either a complete arterial occlusion or ischemic event in the brain. The risk of stroke increases with the severity of carotid stenosis and is reduced after carotid endarterectomy. The degree of internal carotid stenosis is the only well established measurement that is used to assess the risk of stroke. Indeed, it is mainly the current criterion used to decide whether carotid endarterectomy is indicated or not.

Development and testing of new methods for non-invasive assessment of plaque vulnerability will help the clinical assessment of the subject. Furthermore, non-invasive assessment of plaque characteristics will help the way in which atherosclerotic disease is diagnosed, monitored and treated.

Some researchers have attempted to segment the carotid plaque from vascular magnetic resonance images, where active contours have been used for the detection of the artery lumen and plaque localization and dynamic programming to detect the optimal borders in each MRI frame. Some other researchers used graph-searching approach to detect the wall and
plaque in intravascular ultrasound images [8]. There is currently no method reported for estimating the plaque borders in ultrasound longitudinal images of the carotid artery.

In this paper, we present a system for the segmentation of the arterial plaque from ultrasound images of the carotid artery.

In the following Section, snakes segmentation is introduced. In Section III the methodology for segmenting the plaque in carotid artery images is proposed whereas Sections IV and V present the results and concluding remarks respectively.

II. SNAKES

A snake contour may be represented parametrically by \( v(s) = [x(s), y(s)] \), where \((x, y) \in \mathbb{R}^2\) denotes the spatial coordinates of an image, and \( s \in [0,1] \) represents the parametric domain. The snake adapts itself by a dynamic process that minimizes an energy function defined as follows [9]

\[
E_{\text{snake}}(v(s)) = E_{\text{int}}(v(s)) + E_{\text{image}}(v(s)) + E_{\text{external}}(v(s)) = \int_s \left( \alpha(s)E_{\text{cont}} + \beta(s)E_{\text{curv}} + \gamma(s)E_{\text{image}} + E_{\text{external}} \right) ds
\]  

(1)

At each iteration step, the energy function is evaluated for the current point in \( v(s) \), and for the points in an \( m \times n \) neighborhood along the arc length \( s \) of the contour. Subsequently the point on \( v(s) \) is moved to the new position in the neighborhood that gives the minimum energy. The term \( E_{\text{int}}(v) \) in (1) denotes the internal energy derived from the physical characteristics of the snake and is given by the continuity \( E_{\text{cont}}(v) \) and the curvature term \( E_{\text{curv}}(v) \). It controls the natural behavior of the snake. The internal energy contains a first-order derivative controlled by \( \alpha(s) \), which discourages stretching and makes the model behave like an elastic string by introducing tension and a second order term controlled by \( \beta(s) \), which discourages bending and makes the model behave like a rigid rod by producing stiffness. The weighting parameters \( \alpha(s) \) and \( \beta(s) \) can be used to control the strength of the model’s tension and stiffness, respectively. Altering the parameters \( \alpha, \beta \) and \( \gamma \) may control the operation of the snake. The second term in (1) \( E_{\text{image}}(v) \), represents the image energy due to some relevant features such as the gradient of edges, lines, regions and texture [9]. It attracts the snake to low-level features such as brightness and edge data. Finally the term \( E_{\text{external}}(v) \) is the external energy of the snake, that is user defined and is optional. In our study we used a modification of the greedy algorithm as presented in [9].

III. METHODOLOGY

A. Recording of Ultrasound Images

A total of 35 blood flow (PW Doppler) and B-mode longitudinal ultrasound images of the common carotid artery were selected representing a range of atherosclerotic disease with irregular geometry typically found in this vessel. In this study the ATL HDI-5000 ultrasound scanner [10] was used. Images were recorded digitally on a magneto optical drive, with a resolution of 768x756 pixels with 256 gray levels. The image resolution was 16.66 pixels/mm.

The ATL HDI-5000 ultrasound scanner is equipped with an 256-element fine pitch high-resolution 50 mm linear array, a multi element ultrasound scan head with an extended operating frequency range of 5-12 MHz and real spatial compound imaging. The scanner increases the image clarity using SonoCT imaging by enhancing the resolution and borders, and interface margins are better displayed.
Traditionally, suspected plaque formation is confirmed with color blood flow image. PW Doppler is used in order to detect blood flow at a specific depth. By selecting the time interval between the transmitted and received pulses, it is possible to examine vessels at a specific depth. In this work we used the blood flow image as an initial snake contour estimation. The limitations of this approach i.e. using the blood flow image to locate the blood borders are the following: a) the blood sometimes covers areas of the tissue (verbarations), and b) the colour does not always fill up places where the blood has a low speed.

Plaques may be classified into the following types: type I: uniformly echolucent (black), where bright areas occupy less than 15% of the plaque area, type II: mainly echolucent, where bright echoes occupy 15-50% of the plaque area, type III: mainly echolucent, where bright echoes occupy 50-85% of the plaque area, type IV: uniformly echogenic, where bright echoes occupy more than 85% of the plaque area, type V: calcified cup with acoustic shadow so that the rest of the plaque cannot be visualized. In this study the plaques delineated were of type II, III and IV. If the plaque is of type I, borders are not well visible. Plaques of type V produce acoustic shadowing and the plaque is also not well visible. Plaques of type I and V were therefore not delineated in our study.

B. Image Normalization

The images were normalized manually by linearly adjusting the image so that the median gray level value of the blood was 15-20, and the median gray level of the adventitia (artery wall) was 180-200. The scale of the gray level of the images ranged form 0-255. This normalization using blood and adventitia as reference points was necessary in order to extract comparable measurements in case of processing images obtained by different operators or different equipment.

C. Manual Delineation of Plaque

One vascular specialist delineated the plaques on all 35 B-mode ultrasound images of the carotid artery after image normalization. The expert defined the outline of the plaque by marking 20 to 40 consecutive points on the plaque border on the B-mode image. The physician was guided by the blood flow image, which indicated the possible plaque-blood borders, in order to delineate the plaque on the B-mode image. Plaque outline was performed on the far wall (posterior) of the common carotid artery (CCA) because there, the intima media complex and the neighboring tissues are better visible. Delineations taken from the near wall are less accurate, caused by overlap of echo pulses, and therefore less reproducible than those taken from the far wall.

D. Despeckling

Speckle is a form of multiplicative noise, which corrupts medical ultrasound imaging making visual observation difficult. In a recent study we have shown that despeckle filtering improves the physicians optical perception. Many researchers refer to speckle as the major difficulty in analyzing and segmenting US images. In this study, the linear filter was used, which may be described by a weighted average calculation using sub region statistics to estimate statistical measures over 7x7 pixel windows. The filter is based on first order statistics and was applied 5 times iteratively on each image. It assumes that the speckle noise model has the following multiplicative form with \( i, j \in N \), where \( g_{i,j} \) represents the noise pixel in the middle of the moving window, \( f_{i,j} \) represents the noise-free pixel and \( n_{i,j} \) is a Rayleigh distributed noise on pixel. Hence the algorithms in this class may be traced back to the following equation.
where $f_{i,j}$ is the new estimated pixel, $g_{i,j}$ is the old pixel in the middle of a moving window, $\bar{g}_{i,j}$ is the local mean value of a $N_1 \times N_2$ region, $k_{i,j}$ is a weighting factor with $k \in [0..1]$, and $i,j$ the absolute pixel coordinates. The factor $k_{i,j}$ is a function of the local statistics in a moving window and is derived as $k_{i,j} = \sigma_n^2 / (\sigma_n^2 + \sigma_i^2)$, where $\sigma_n^2$ and $\sigma_i^2$ the variance in the moving window and the variance of noise in image respectively. The variance of noise for the logarithmic compressed image is $\sigma_n = g_{i,j} / \sigma_i^2 [13]$.}

E. Snake Contour Initialization

It is important to position the initial snake contour as close as possible to the area of interest otherwise the snake may be trapped into local minima or false edges, and converge in a wrong location. We have therefore developed an initialization procedure where the outline of the blood flow is used to detect the initial contour placement. The initialisation procedure may be described as follows (see also Fig. 1 at the Results Section): a) Cross correlate the blood flow image with the B-mode image and extract the blood flow area. b) Dilate the extracted blood flow area to close small gaps and remove small regions. c) From the dilated blood flow image, detect the blood flow edge contour. d) Mark a region of interest on the edge contour (task carried out by the expert), where the lower or upper boundary of plaque is covered to use it as initial snake contour. e) Sample the initial snake contour at 20 to 40 consecutive snake points to construct an interpolating B-spline. f) Connect the first and the last snake points on the initial contour to form a close contour. g) Despeckle the B-mode image by the lsmv filter. h) Map the initial plaque contour on the B-mode image. i) Deform the initial contour by a snake to accurately locate the plaque-blood borders and j) Save the final plaque contour and display it on the B-mode image.

F. Evaluation of Segmentation Method

To evaluate the performance of the proposed segmentation method, we compared the manually identified borders with the computerized detected borders defined by an expert. The intra- and inter-observer variability caused by multiple experts, was not taken into account in this study. Let $GT$ denote the segmented area representing ground truth, $\overline{GT}$ its complement, and $AS$ the segmented area obtained by the computerized approach. ROC analysis may be used to assess the specificity and sensitivity of the method by the true-positive fraction ($TPF$) and false-positive fraction ($FPF$) detected [15] respectively. The $TPF$, is calculated when the computerized method detects a plaque (plaque is present) and the expert identifies it as so, where the $FPF$, is calculated when the computerized method detects no plaque and the expert incorrectly decides that there is plaque present. The $TNF$ fraction is calculated when the computerized method identifies no plaque and the expert identifies it as so (absent), where the $FNF$ is calculated when the computerized method identifies plaque presence and the expert incorrectly identifies plaque absence. Ratios of overlapping areas, can also be assessed by applying the similarity kappa index ($KI$) [16] and the overlap index [17]. These indices were computed as follows:

$$TPF = \frac{AS \cap GT}{GT}, \quad FPF = \frac{|AS - GT|}{GT}, \quad KI = 2 \frac{GT \cap AS}{GT + AS}, \quad overlap = \frac{GT \cap AS}{GT \cup AS}$$

(3)

where $\cap$ denotes the intersection and $\cup$ the union of the two areas. The intersection gives the probability that both $AS$ and $GT$ occur and the union is the probability that either $AS$ or $GT$ occur.
IV. RESULTS

Figure 1 a) illustrates the original ultrasound image of the carotid artery with a plaque at the far wall, the blood flow image in b), the initial blood flow edge contour and the user selected initial contour (enclosed in the rectangle) in c), the user selected sampled initial snake contour superimposed on the original image in d), the manual segmentation results of the expert in e), and the segmentation results of the proposed snakes method in f) respectively. It is shown that the manual and the computerized segmentation results are optically very similar. This observation suggests that the two segmentation methods can be interchangeable.

Table I shows a comparison of plaque segmentation by an expert and the proposed segmentation method. It is shown that the proposed method agrees with the expert in 84.03% of the cases (\(TNF\)) by correctly detecting no plaque, in 86.44% of the cases (\(TPF\)) by correctly detecting a plaque, and disagrees with the expert, in 7% of the cases (\(FPF\)) by detecting plaque, and in 8.5% (\(FNF\)) of the cases by detecting no plaque.

Ideally, the computerized method should have a 100% score for \(TPF\) and \(TNF\) and a 0% score for \(FPF\) and \(FNF\) for the above measures. The similarity kappa index, \(K_I\), and the overlap index between the manual method and the proposed segmentation method, were 85.5% and 74% respectively, which are considered very satisfactory.

TABLE I

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<tr>
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<th>Expert detects no plaque</th>
<th>Expert detects plaque</th>
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<tr>
<td>System detects no plaque</td>
<td>TNF=84.03%</td>
<td>FNF=8.5%</td>
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<tr>
<td>System detects plaque</td>
<td>FPF=7%</td>
<td>TPF=86.44%</td>
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V. CONCLUDING REMARKS

In recent years, the composition and structure of atherosclerotic plaque has been a primary focus of cardiovascular research, where the aim is to classify the carotid plaque as symptomatic or asymptomatic [18]. This classification will help in enhancing the significance of noninvasive cerebrovascular tests in the identification of carotid stenosis at risk of stroke.

In this study a new method is proposed for the segmentation of atherosclerotic carotid plaque where an initial estimate of the contour is carried out at the PW Doppler blood flow
image that is then mapped on the B-mode image. This initial contour is then deformed using snakes to find the final contour. Results showed that the proposed segmentation method is quite accurate and no manual correction is needed in most of the cases, with true positive fraction TPF=86.44%, true negative fraction TNF=84.03%, false negative fraction FNF=8.5% and false positive fraction FPF=7% respectively. Therefore, the proposed method gives results comparable to the manual delineation procedure.

Concluding, the method presented is to the best of our knowledge the first computerized approach for plaque segmentation from ultrasound images of the carotid artery. The success of the method will greatly depend on the future results, which will have to be performed on a larger number of ultrasound images and on multiple experts’ evaluation. A computerized method not only significantly reduces the time required for the image analysis, but also eliminates much of the subjectivity that accompanies manual measurements. It is expected that the segmentation method will be incorporated into an integrated system enabling the texture analysis of the segmented plaque, providing an automated system for the early diagnosis and the assessment of the risk of stroke.

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