See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/287236936>

Atherosclerotic Carotid Plaque Segmentation in Ultrasound Imaging of the Carotid Artery

Article · July 2013

DOI: 10.1007/978-1-4614-7425-8_19

CITATIONS

0

READS

51

2 authors:

Christos P Loizou

University of Cyprus

156 PUBLICATIONS 1,847 CITATIONS

[SEE PROFILE](#)

Marios Pantzaris

Cyprus Institute of Neurology and Genetics

176 PUBLICATIONS 2,147 CITATIONS

[SEE PROFILE](#)

Some of the authors of this publication are also working on these related projects:

Stroke Risk Prediction Based on Ultrasound Carotid Plaque Image Analysis [View project](#)

Motion Analysis of the Carotid Artery [View project](#)

Christos P. Loizou and Marios Pantzaris

Abbreviations

2D	Two-dimensional
3D	Three-dimensional
4D	Four-dimensional
ACSRS	Asymptomatic carotid stenosis and risk of stroke
AS	Automated segmentation
ATL	Advanced Technology Laboratories
CCA	Common carotid artery
DsFlsmv	Despeckle filter linear scaling mean variance
F	Effectiveness
FNF	False-negative fraction
FPF	False-positive fraction
GT	Ground truth
GVF	Gradient vector flow
IMT	Intima-media thickness
IVUS	Intravascular ultrasound
KI	Kappa index
MR	Magnetic resonance
MRI	Magnetic resonance image
P	Precision
ROC	Receiver operating characteristics
Sp	Specificity

TIA	Transient ischemic attack
TNF	True-negative fraction
TPF	True-positive fraction

1 Introduction

Carotid artery atherosclerosis is the primary cause of stroke and the third leading cause of death in the USA. 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 size arteries, and it is characterized by plaque formation due to progressive intimal accumulation of lipid, protein, and cholesterol esters in the blood vessel wall [1], which reduces blood flow significantly. The risk of stroke increases with the severity of carotid stenosis and is reduced after carotid endarterectomy [2]. The degree of internal carotid stenosis is the only well-established measurement that is used to assess the risk of stroke [3]. Indeed, it is the only criterion at present used to decide whether carotid endarterectomy is indicated or not [4]. The objective of this study was to propose an integrated system for the segmentation of the atherosclerotic carotid plaque in ultrasound imaging.

Several studies investigated the segmentation of atherosclerotic carotid plaque in ultrasound imaging, intravascular ultrasound (IVUS) imaging, and magnetic resonance (MR) imaging. An overview of these techniques is given in Table 19.1. Zahalka et al. [5] applied a geometrically deformable model on two 3D ultrasound images of the carotid artery to detect the blood borders in the carotid artery. Hamou et al. [6] proposed a method, which was based on the Canny edge detector to detect the plaque regions in longitudinal carotid artery ultrasound images. A morphological-based approach for the carotid contour extraction was proposed in [7] for longitudinal ultrasound images of carotid artery, incorporating speckle reduction filtering, contour quantization, morphological contour detection, and a contour enhancement stage. Mao et al. [8]

Credit/copyright notice: Based on "An integrated system for the segmentation of atherosclerotic carotid plaque," by C.P. Loizou, C.S. Pattichis, M. Pantziaris, A. Nicolaides, which appeared in *IEEE Trans. Inf. Biomed.*, vol. 11, no. 6, pp. 661–667, ©2007 IEEE.

C.P. Loizou (✉)
Department of Computer Science, School of Sciences and Engineering, Intercollege, 92 Ayias Phylaxeos Street,
P.O. Box 51604, 3507 Limassol, Cyprus
e-mail: loizou.c@lim.intercollege.ac.cy; loizou.christos@ucy.ac.cy

M. Pantzaris
The Cyprus Institute of Neurology and Genetics, P.O. Box 23462,
1683 Nicosia, Cyprus
e-mail: pantzari@cing.ac.cy

Table 19.1 An overview of atherosclerotic carotid plaque segmentation techniques

Study	Segmentation method	2D/3D	AIC	<i>N</i>
<i>Ultrasound imaging</i>				
Zahalka et al. [5]	Deformable models	3D	No	69
Hamou et al. [6]	Canny edge detection	2D	No	–
Abdel-Dayen et al. [7]	Morphological based	2D	No	–
Mao et al. [8]	Discrete dynamic contour	2D	No	7
Abolmaesumi et al. [9]	Kalman filtering	2D	No	1
Gill et al. [10]	Balloon	3D	No	2
Delsanto et al. [11]	Deformable parametric model	2D	No	45
Loizou et al. [12]	Snakes	2D	Yes	80
Guerrero et al. [13]	Star–Kalman algorithm	2D	No	–
Golemati et al. [14]	Hough transforms	2D	No	56
Slabaugh et al. [15]	Region-based active contour	2D	No	–
<i>IVUS imaging</i>				
Zhang [16]	Optimal graph searching	2D	No	20
Cardinal [17]	Fast-marching method	2D	No	200
Brusseau [18]	Statistical approach	2D	Yes	15
Olszewski [19]	Knowledge based	3D	No	21
<i>Magnetic resonance imaging (MRI)</i>				
Xu [20]	Mean shift	2D	Yes	22
Adams [21]	Snakes, GVF	2D	No	20
Yang [22]	Dynamic programming	2D	Yes	62

AIC automatic initial contour, *N* number of cases investigated

proposed a discrete dynamic contour model for extracting the carotid artery lumen in 2D transversal ultrasound images, whereas Abolmaesumi et al. [9] introduced an algorithm based on the star algorithm improved by Kalman filtering, for extracting the carotid artery boundaries from transversal carotid ultrasound images. A semiautomatic method for tracking the progression of atherosclerotic plaque in 3D images of the carotid artery using the Balloon model introduced in [23] was proposed by Gill et al. [10]. In [11], Delsanto et al. proposed a user-independent plaque characterization and intima–media thickness (IMT) segmentation method, based on area of interest identification stage, gradient segmentation stage, and a contour refinement stage, using deformable parametric model. The overall accuracy of the system determined as normalized error was overall to 8%. Loizou et al. [12] proposed an integrated system for the segmentation of the atherosclerotic carotid plaque on ultrasound images based on initial contour estimation and speckle reduction filtering. It was also shown that normalization and speckle reduction filtering improve the outcome of the plaque segmentation. The user was able to interact and correct the segmentation results manually. A limitation of the proposed method includes the presence of acoustic shadowing together with strong speckle noise, which hinders the visual and automatic analysis in ultrasound images. Furthermore, only vessels without atherosclerotic plaques were segmented in this study. In [13], a method based on a Star–Kalman algorithm was used to determine vessel contours and ellipse parameters using an extended

Kalman filter with an elliptical model. The segmentation and tracking were implemented in real time and validated using simulated ultrasound data with known features and real data, for which expert segmentation was performed. Results indicate that mean errors between segmented contours and expert tracings are on the order of 1–2% of the maximum feature dimension, and that the transverse cross-sectional vessel area as computed from estimated ellipse parameters as determined by the algorithm is within 10% of that determined by experts. Hough transforms were used in [14] to perform the segmentation of 2D longitudinal and cross-sectional ultrasound images of plaques. Slabaugh et al. [15] presented an ultrasound-specific segmentation approach that addressed both the spatial correlation of the data as well as its intensity distribution. The image is first decorrelated and then a region-based active contour whose motion is derived from an appropriate parametric distribution for maximum likelihood image segmentation was applied. A zero-mean complex Gaussian, Rayleigh, and Fisher–Tippett flows were considered, which were designed to model fully formed speckle in the in-phase/quadrature, envelope detected, and display (log compressed) images, respectively. The effectiveness of the method was compared with other parametric and nonparametric active contours.

Furthermore, a number of studies investigated the use of IVUS imaging of the carotid artery. Although, IVUS provides better quality images when compared with ultrasound images, it poses a certain risk to the patients due to the insertion of a catheter in the patient's artery. A graph-searching

approach to detect the wall and plaque borders from IVUS images of the carotid artery was documented in [16]. A semi-automatic segmentation method for IVUS images based on gray-scale statistics of the image was proposed in [17], where the lumen, IMT, and the plaque were segmented in parallel by utilizing a fast marching method. In [18], an automated luminal contour segmentation method based on a statistical approach was introduced, whereas in [19] IVUS images were segmented using knowledge-based methods.

Several studies also investigated the automated segmentation in MRI of the carotid artery. Xu et al. [20] applied a mean shift density estimation algorithm to segment 22 multiple transversal MRI's of the carotid artery. Adams et al. [21] attempted to segment the carotid plaque by using snakes based on the GVF method, in order to detect the artery, lumen, and plaque borders, where the initial contour was placed manually by the expert. The results showed a good accuracy of the segmentation algorithm. Yang et al. [22] proposed a dynamic programming approach to detect the plaque borders in each MRI frame where seed points were placed by the expert for estimating the initial plaque contour.

As shown in Table 19.1, different methods were investigated for the segmentation of the atherosclerotic carotid plaque, however, these studies were evaluated on a limited number of subjects for ultrasound imaging (although this is not the case for IVUS, see study [17]). Therefore, the need still exists for the development, implementation, and evaluation of an integrated system enabling the automated segmentation of ultrasound imaging carotid plaque. In this chapter, we propose and evaluate such a system based on normalization, speckle reduction filtering, and snakes segmentation. Four different snake methods were investigated, namely (1) the Williams and Shah [12, 24], (2) the Balloon [23], (3) the Lai and Chin [25], and (4) the GVF [26]. Preliminary results of this study were also published in [27].

2 Materials and Methods

2.1 Recording of Ultrasound Images

A total of 80 B-mode and blood flow longitudinal ultrasound images of the common carotid artery (CCA) bifurcation were selected at random representing different types of atherosclerotic plaque formation with irregular geometry typically found in this blood vessel. The images were acquired by the ATL HDI-3000 ultrasound scanner (Advanced Technology Laboratories, Seattle, USA) [28] and were recorded digitally on a magneto optical drive, with a resolution of 768×576 pixels with 256 gray levels. Digital images were resolution normalized at 16.66 pixels/mm (see Sect. 2.3). This was carried out due to the small variations in the number of pixels per mm of image depth (i.e., for deeply situated carotid arteries, image depth was increased and therefore

digital image spatial resolution would have decreased) and in order to maintain uniformity in the digital image spatial resolution [28, 29]. The images were recorded at the Saint Mary's Hospital, Imperial College of Medicine, Science and Technology, UK, from 32 female and 48 male symptomatic patients aged between 26 and 95 years old, with a mean age of 54 years. These subjects were at risk of atherosclerosis and have already developed clinical symptoms, such as a stroke or a transient ischemic attack (TIA).

2.2 Manual Plaque Segmentation and Classification

An expert manually delineated the plaque borders, between plaque and artery wall, and those borders between plaque and blood, on 80 longitudinal B-mode ultrasound images of the carotid artery, after image normalization and speckle reduction filtering (see Sects. 2.3 and 2.4), using MATLAB software developed by other researchers from our group. The procedure for carrying out the manual delineation process was established by a team of experts and was documented in the asymptomatic carotid stenosis and risk of stroke (ACRSRS) project protocol [4]. The correctness of the work carried out by a single expert was monitored and verified by at least another expert. Usually the plaques are classified into type I–type V as documented in [4, 12]. In this study the plaques delineated were of type II, III, and IV because it is easier to make a manual delineation since the fibrous cap, which is the border between blood and plaque, is more easily identified. If the plaque is of type I, borders are not visible well. Plaques of type V produce acoustic shadowing and the plaque is also not visible well.

2.3 Image Normalization

Brightness adjustments of ultrasound images were carried out in this study based on the method introduced in [30]. It was shown that this method improves image compatibility by reducing the variability introduced by different gain settings, different operators, different equipment and facilitates ultrasound tissue comparability [30]. Algebraic (linear) scaling of the image was manually performed by linearly adjusting the image so that the median gray level value of the blood was 0–5, and the median gray level of the adventitia (artery wall) was 180–190 [30, 31]. The scale of the gray level of the images ranged from 0 to 255. Thus the brightness of all pixels in the image was readjusted according to the linear scale defined by selecting the two reference regions. It is noted that a key point to maintaining a high reproducibility was to ensure that the ultrasound beam was at right angles to the adventitia, adventitia was visible adjacent to the plaque and that for image normalization a standard sample consisting of the half of the width of the brightest area of adventitia was obtained.

Fig. 19.1 Plaque initialization using the blood flow image: (a) original ultrasound B-mode image of a carotid artery with plaque at the far wall, (b) blood flow of the image in (a), (c) initial blood flow edge contour with the area for the initial contour selected by the user, (d) sampled

initial snake contour, (e) Williams and Shah snakes segmentation of plaque, and (f) manual segmentation of plaque. Source [12], © IEEE, 2007

2.4 Speckle Reduction Filtering

In this study, a linear scaling filter (DsFlsmv—*Despeckle filter linear scaling mean variance*) utilizing the mean and the variance of a pixel neighbourhood was used. This filter was introduced in [32] and evaluated on ultrasound imaging of the carotid giving best results in [33]. The DsFlsmv filter may be described by a weighted average calculation using subregion statistics to estimate statistical measurements over 7×7 pixel windows applied for five iterations [31–33].

2.5 Plaque Contour Initialization

In most of the cases a plaque is visualized in a B-mode longitudinal ultrasound image and its size confirmed in transverse section using color blood flow imaging. However, uniformly echolucent plaques are not obvious on B-mode, and color flow imaging is needed. These echolucent plaques are seen as black filling defects. PW Doppler is used to measure velocity in order to grade the degree of stenosis and

blood flow can be detected at a specific depth by selecting the time interval between the transmitted and received pulses.

In this work the blood flow image was used, in order to extract the initial snake contour for the plaque borders in the carotid artery. The plaque snakes contour initialization procedure, carried out using both the blood flow and the B-mode images, may be described as follows (see also Fig. 19.1):

1. The blood flow area is extracted from the blood flow image (Fig. 19.1b) by searching to find all color pixels (i.e., if the red, green, and blue pixel values are different). Otherwise, pixels belong to a grayscale area. All color pixels are (set to zero) in the blood flow image. The resulting image is then cross-correlated with the B-mode image (Fig. 19.1a) so that the blood flow edge is mapped on the B-mode image.
2. Dilate the extracted blood flow edge image to eliminate small gaps and remove small-undesired regions.
3. From the dilated edge blood flow image, detect the blood flow edge contour (see Fig. 19.1c). Mark a region of

interest on the edge contour (a task carried out by the user of the proposed system, illustrated by a rectangle in Fig. 19.1c) where the lower or the upper boundary of plaque is covered. This is used as an initial snake contour.

4. Sample the initial snake contour at 20–40 consecutive points to construct an interpolating B-spline.
5. Connect the first and the last snake points on the initial contour to form a closed contour.
6. Perform image normalization (see Sect. 2.3) and speckle reduction on the B-mode image by the DsFlsmv filter described in Sect. 2.4.
7. Map the initial plaque contour on the B-mode image (see Fig. 19.1d).
8. Deform the initial contour by the snake to accurately locate the plaque–blood borders (see Sect. 2.6).
9. Save the final plaque contour and display it on the B-mode image (see Fig. 19.1e).

2.6 Snake Segmentation

Four different snake segmentation methods were investigated in this study, namely (1) the Williams and Shah [12, 24], (2) the Balloon [23], (3) the Lai and Chin [25], and (4) the GVF [26]. Preliminary results of this study were also published in [27]. The parameter values for the four different snakes segmentation methods were the same in all experiments. For the Williams and Shah snake, the strength, tension, and stiffness parameters were equal to $\alpha_s = 0.6$, $\beta_s = 0.4$, and $\gamma_s = 2$, respectively. For the Lai and Chin, the regularization parameter, λ_π , was varied as documented in [25]. For the GVF snake, the elasticity, rigidity, and the regularization parameters were, $\alpha_{GVF} = 0.05$, $\beta_{GVF} = 0$, and $\mu_{GVF} = 0.2$, respectively [26].

2.7 Evaluation of the Segmentation Methods

ROC analysis [34] was used to assess the specificity and sensitivity of the four segmentation methods by the true-positive fraction, TPF and false-positive fraction, FPF [34]. The TPF is calculated when the expert detects a plaque (when a plaque is present) and the computerized method identifies it as so, whereas the FPF is calculated when the expert detects no plaque and the computerized method incorrectly detects that there is a plaque present. The TNF fraction is calculated when the expert identifies no plaque and the computerized method identifies it as so (absent), whereas the FNF is calculated when the expert identifies plaque presence and the computerized method incorrectly identifies plaque absence. Ratios of overlapping areas can also be assessed by applying the similarity kappa index, KI, [35] and the overlap index [36]. These indices were computed as follows:

$$\begin{aligned} TPF &= \frac{|AS \cap GT|}{|GT|}, \quad FPF = \frac{|AS| - |GT|}{|GT|}, \\ TNF &= \frac{|AS \cap GT|}{|AS|}, \\ FNF &= \frac{|AS| - |GT|}{|AS|}, \quad KI = 2 \frac{|GT \cap AS|}{|GT| + |AS|}, \\ \text{and } overlap &= \frac{|GT \cap AS|}{|GT \cup AS|} \end{aligned} \quad (19.1)$$

where $||$ denotes the magnitude, $\cap$ denotes the intersection (the number of common pixels in the manual and the snakes-segmented areas), and $\cup$ the union (the number of all pixels defined by the manual and the snakes-segmented areas where the common pixels are considered only once). GT , denotes the number of pixels defined by the segmented area, representing ground truth delineated by the expert, $\overline{GT}$, its complement, and AS the number of pixels belonging in the area, obtained by the snakes segmentation method. The intersection gives the probability that both AS and GT occur and the union is the probability that either AS or GT occur. The specificity, $Sp = 1 - FPF$, the precision, P , and the effectiveness measure, $F = 1 - E$, [34] were also calculated to describe the ROC characteristics of the segmentation methods.

2.8 Univariate Statistical Analysis

The Wilcoxon matched-pairs signed rank sum test was used in order to detect if for each metric, TPF, TNF, FPF, FNF, KI, overlap index, Sp , P , and F , a significant difference or not exists between all the segmentation methods at $p < 0.05$. The test was applied on all 80 segmented plaques for all different segmentation methods.

3 Results

3.1 Examples of Plaque Segmentation

Figure 19.2 illustrates the original longitudinal ultrasound B-mode image of a carotid plaque with a manual delineation made by the expert in (a), and the results of the William and Shah segmentation in (b), the Balloon segmentation in (c), the Lai and Chin segmentation in (d), and the GVF segmentation in (e). Figure 19.2f shows the superimposition of the segmentation contours computed in Fig. 19.2b, e. As illustrated in Fig. 19.2f, both the manual and the snakes segmentation contours are visually very similar. It could be noted that the despeckle filter DsFlsmv [31, 33] with a moving sliding window of $[5 \times 5]$, was iteratively four times applied on all images before segmentation.

Fig. 19.2 Plaque segmentation results on a longitudinal ultrasound B-mode image of the carotid artery: (a) manual, (b) Williams and Shah, (c) Balloon, (d), Lai and Chin, (e) GVF snake, and (f) superimposition of segmentation contours computed in (b)–(e). Source [12], © IEEE, 2007

Table 19.2 ROC analysis based on TNF, TPF, FNF, FPF, KI, overlap index, Sp, P , and $F = 1 - E$, for the four different plaque snakes segmentation methods on 80 ultrasound images of the carotid artery

Segmentation method	System detects	Expert detects no plaque	Expert detects plaque	KI (%)	Overlap index (%)	Sp	P	$F = 1 - E$
Williams and Shah	No plaque	TNF = 77.59 %	FNF = 19.64 %	78.86	67.60	0.935	0.926	0.862
	Plaque	FPF = 6.50 %	TPF = 81.76 %					
Balloon	No plaque	TNF = 77.12 %	FNF = 13.90 %	77.87	67.79	0.946	0.927	0.888
	Plaque	FPF = 5.40 %	TPF = 80.35 %					
Lai and Chin	No plaque	TNF = 80.89 %	FNF = 15.59 %	80.66	69.30	0.942	0.934	0.885
	Plaque	FPF = 5.86 %	TPF = 82.70 %					
GVF	No plaque	TNF = 79.44 %	FNF = 14.90 %	77.25	66.60	0.937	0.926	0.883
	Plaque	FPF = 6.30 %	TPF = 79.57 %					

Bolded values show best performance

Source [12], © IEEE, 2007

3.2 Evaluation of Plaque Segmentation Methods

Table 19.2 tabulates the results of the ROC analysis based on TNF, TPF, FNF, FPF, KI, overlap index, Sp, P , and F , for the four different plaque snakes segmentation methods on 80 longitudinal ultrasound images. Although all methods demonstrated similar performance with nonsignificant

differences (see Sect. 3.3), the best overall performance was demonstrated by the Lai and Chin segmentation method. Bolded values in Table 19.2 show best performance. The results showed that the Lai and Chin method agrees with the expert by correctly detecting no plaque (TNF) in 80.89 % of the cases, by correctly detecting a plaque (TPF) in 82.70 % of the cases, disagrees with the expert by detecting no plaque

Fig. 19.3 ROC curve analysis based on the TPF and FPF fractions for the four snakes segmentation methods. Source [12], © IEEE, 2007

(FNF) in 15.59 % of the cases, and by detecting a plaque (FPF) in 5.86 % of the cases. The similarity kappa index KI, and the overlap index, for the Lai and Chin snakes segmentation method were the highest, equal to 80.66 % and 69.3 %, respectively. The best FPF and FNF fractions were given by the Balloon, with 5.4 % and 13.90 %, respectively. The GVF gave the worst results with the lowest similarity kappa index, KI, (77.25 %), and the lowest overlap index (66.6 %). The best specificity, Sp, was given by the Balloon (0.946), followed by the Lai and Chin (0.942) snakes segmentation method. The Lai and Chin gave the best precision, P , (0.934), whereas the best F , was given by the Balloon (0.888), followed by the Lai and Chin (0.885) snakes segmentation method.

Figure 19.3 shows the ROC curves for the four snakes segmentation methods, based on the TPF and FPF fractions with 95 % confidence margins. The area below the ROC curve was 0.90, 0.83, 0.79, and 0.67 for the Lai and Chin, GVF, Balloon, and Williams and Shah snakes segmentation method, respectively. It is clear that the largest area under the ROC curve was obtained by the Lai and Chin snakes segmentation method.

3.3 Univariate Statistical Analysis

The Wilcoxon matched-pairs signed rank sum test was performed to check if significant differences exist between the different segmentation methods at $p < 0.05$ for the measures TPF, TNF, FPF, FNF, KI, the overlap index, Sp, P , and F . There were no significant differences between the four segmentation methods for all measures, except for the case of the FNF between the Balloon and the Lai and Chin snake segmentation methods.

4 Discussion

The comparison of the four different snakes segmentation methods proposed in this chapter showed that the Lai and Chin gave slightly better results, although these results were not statistically significant when compared with the other three snakes segmentation methods.

4.1 Normalization and Speckle Reduction Filtering

To the best of our knowledge no other study carried out ultrasound image normalization as described in this study, prior to segmentation of the atherosclerotic carotid plaque. However, in [6], histogram equalization was performed on carotid artery ultrasound images for increasing the image contrast. The normalization method used in this study was documented to be helpful in the manual contour extraction as well as in the snake's segmentation of the IMT [37, 38]. Moreover, this method increased the classification accuracy of different plaque types as assessed by the experts [38].

In this chapter, speckle reduction filtering was used as a preprocessing step based on our previous work [33, 38]. More, specifically, in [38], it was shown that image normalization followed by speckle reduction produces better quality images, whereas the reverse (speckle reduction followed by normalization) might produce distorted edges. Speckle reduction filtering of the carotid was also proposed by [12, 37, 39], where it was shown that this improves the image quality and the visual evaluation of the image. However in

other segmentation studies for extracting the carotid artery plaque borders in IVUS imaging, speckle was used as useful information [16–19].

4.2 Plaque Contour Initialization

Initial contour estimation using the blood flow image was proposed in this work where the limitations of this method based on the color imaging were outlined in Sect. 2.5. Initial contour estimation was also proposed in [18], which was derived from the polar image by combining information extracted from the probability function of the contour position, and more specifically from the function maximum location and the first zero crossing of its derivative. Then, starting from the initial contour, a region of interest was automatically selected and the process iterated until the snake contour evolution could be ignored. In [19], a cost function was calculated and used as an input to the segmentation algorithm. In [10], a dynamic balloon model [23] represented by a triangular mesh was applied for detecting the plaque borders on two 3D ultrasound carotid images where the initial contour was placed manually. In all of these studies as well as in the present study, the significance of the initial contour placement was not investigated in order to estimate how this influences the final segmentation result.

4.3 Plaque Segmentation

The four different snakes segmentation methods presented in this study gave very satisfactory results, with the best performance obtained by the Lai and Chin. Snakes were only investigated by other researchers, for segmenting 3D ultrasound images of the carotid artery in a small number of cases with very promising results [10, 19]. Additional effort, for segmenting the atherosclerotic carotid plaque, was made on IVUS images [16], where the insertion of a catheter in the patients artery for acquiring the IVUS images posed a certain risk to the patient. This method was based on graph searching, which required that the expert must provide the initial plaque border contour. Furthermore, a time consuming methodology based on the Balloon snake [23] was proposed in [10] for 3D ultrasound carotid artery images, by triangulating the image in a finite element mesh. The method proposed in [9], for longitudinal images of the carotid artery, was time consuming and results were not that satisfactory as the lumen borders of the carotid artery were not that accurately found. Furthermore, in a recent study [6], where morphological processing was applied, the results were not in agreement with the manual delineations of an expert, and the expert had no interaction with the system. In [17] a semiautomatic segmentation method for IVUS images, based on gray-scale statistics of the image was proposed, where the

lumen, IMT and the plaque were successfully segmented in parallel by utilizing a fast-marching model. The performance of the segmentation methods proposed above was not compared with other different segmentation methods, nor was investigated under different preprocessing conditions, such as normalization and speckle reduction filtering, as in this study.

The evaluation of the four plaque snakes segmentation methods based on ROC curves (see Fig. 19.3) showed that the best ROC curve was obtained for the Lai and Chin snakes segmentation method. The area under this curve was larger than the others.

Some attempts were made from other researchers to segment the carotid plaque in MRI by using the GVF field [21], snakes [21], and dynamic programming [22]. In all of the above studies, the initial snake contour was placed manually, and a smaller number of images compared with this study were tested. More specifically, a segmentation method for the arterial walls and plaque in transversal MRI images based on dynamic programming was proposed in [22]. In [20], the plaque borders in transversal MRI carotid images were segmented based on the mean shift density estimation algorithm. In [21], a snakes segmentation method was applied on MRI transversal carotid images to detect the lumen and the outer wall boundaries of the artery by using the GVF force field [26].

There are some limitations in the proposed methodology which are summarized as follows: (a) The color flow sometimes overlaps with areas of the tissue wall or the plaque. (b) The color does not always fill up places where the blood flow velocity is very low. Therefore the contour initialization estimation may not be that accurate. The contour initialization can be improved by using a statistical approach to initialize and train the snake about blood flow [40]. (c) The snake contour may be some times attracted by local minima and converge to a wrong location. (d) Cases of plaque type I and type V (see Sect. 2.2) were not considered for segmentation.

5 Concluding Remarks and Future Directions

The method presented in this study proposes an integrated system for plaque segmentation in longitudinal ultrasound images of the carotid artery. Such a system cannot only reduce significantly the time required for the image analysis but also it can reduce the subjectivity that accompanies manual delineations and measurements. The method will be further evaluated on a larger number of ultrasound images and using multiple experts. In this chapter, the cases of totally occlusive dissections and side-branches, as well as cases of plaque type I and type V (see Sect. 2.2) were not considered for segmentation. Future work will focus on

improving the segmentation procedure, such that it can process satisfactorily these special cases and difficult to segment images, taking for example into consideration a statistical approach to initialize and teach the snake about the blood flow and plaque area [40]. Furthermore, the segmentation system proposed in this study will be incorporated into a computer-aided diagnostic system that supports the texture analysis of the segmented plaque, as documented in [41], providing an automated system for the early diagnosis and the assessment of the risk of stroke.

The majority of plaque image analysis studies are focused on the development of 2D ultrasound systems. In general these studies present effective methods for image segmentation, image de-speckling, and texture feature extraction. Due to the large number of parameters involved, we can see many variations in the results. Thus, even for 2D systems, there will always be an interest in developing more robust segmentation methods, new multiscale texture features, and the application of innovative classification techniques. Some of the most interesting challenges are associated with emerging studies [42]. These methods can be used in order to focus on new 2D problems associated with early plaque formation.

The extraction of 3D shape and structure information can be used to further our understanding of carotid plaque morphology. We believe that research will continue in establishing 3D volumetric changes and their associations with atherosclerosis.

Plaque motion analysis holds significant promise as well. The relative motion among different plaque components should be investigated [43]. The future development of very accurate 3D/4D systems will also help with the development of accurate motion analysis systems. Finally, in [44] a method for the segmentation of plaques in video sequences of ultrasound images of the internal carotid artery was presented. The method was formulated in a Bayesian framework.

It would be interesting to develop noninvasive, multi-modality plaque image analysis systems. The advancement of 3D ultrasound will help these efforts. Basically, high-resolution 3D ultrasound reconstructions will be much easier to fuse with 2D slices from other modalities. To do this, we would need to register the geometric features of the 2D slice to the 3D volume or to use a mutual information registration method. It would also be interesting to examine how 2D histological studies match 3D ultrasound reconstructions.

References

1. Zarins CK, Xu C, Glagov S (2001) Atherosclerotic enlargement of the human abdominal aorta. *Atherosclerosis* 155(1):157–164
2. ACAS Clinical Advisory (1994) Carotid endarterectomy for patients with asymptomatic internal carotid artery stenosis. *Stroke* 25(12):2523–2524
3. Executive Committee for the Asymptomatic Carotid Atherosclerosis study (2002) Endarterectomy for asymptomatic carotid stenosis. *J Am Med Assoc* 273:1421–1428
4. Nicolaides A, Sabetai M, Kakkos SK, Dhanjil S, Tegos T, Stevens JM (2003) The asymptomatic carotid stenosis and risk of stroke study. *Int Angiol* 22(3):263–272
5. Zahalka A, Fenster A (2001) An automated segmentation method for three-dimensional carotid ultrasound images. *Phys Med Biol* 46:1321–1342
6. Hamou A, El-Sakka M (2004) A novel segmentation technique for carotid ultrasound images. In: International conference on acoustic speech and signal processing ICASSP, vol 521, p 524
7. Abdel-Dayen AR, El-Sakka MR (2004) A novel morphological-based carotid artery contour extraction. *Can Conf Electr Comput Eng* 4:1873–1876
8. Mao F, Gill J, Downey D, Fenster A (2000) Segmentation of carotid artery in ultrasound images: method development and evaluation technique. *Med Phys* 27(8):1–10
9. Abolmaesumi P, Sirouspour MR, Salcudean SE (2000) Real-time extraction of carotid artery contours from ultrasound images. In: Proceedings of IEEE international conference on computer based medical systems, pp 181–186
10. Gill JD, Ladak HM, Steinman DA, Fenster A (2000) Segmentation of ulcerated plaque: a semi-automatic method for tracking the progression of carotid atherosclerosis. In: World congress on medical physics and biomedical engineering, pp 1–4
11. Delsanto S, Molinari F, Liboni W, Giustetto P, Patalamenti S, Suri JS (2006) User-independent plaque characterization and accurate IMT measurement of carotid artery wall using ultrasound. In: Proceedings of 28th annual international conference IEEE EMBS, pp 2404–2407
12. Loizou CP, Pattichis CS, Pantziaris M, Nicolaides AN (2007) An integrated system for the segmentation of atherosclerotic carotid plaque. *IEEE Trans Inf Technol Biomed* 11(6):661–667
13. Guerrero J, Salcudean SE, McEwen SE, Masri JA (2007) Real-time vessel segmentation and tracking for ultrasound imaging applications. *IEEE Trans Med Imaging* 26(8):1079–1090
14. Golemati S, Stoitsis E, Sifakis G, Balkis T, Nikita KS (2007) Using the Hough transform to segment ultrasound images of longitudinal and transverse sections of the carotid artery. *Ultrasound Med Biol* 33(12):1918–1932
15. Slabaugh G, Unal G, Wels M, Fang T, Rao B (2009) Statistical region-based segmentation of ultrasound images. *Ultrasound Med Biol* 35(5):781–795
16. Zhang X, McKay CR, Sonka M (1998) Tissue characterization in intravascular ultrasound images. *IEEE Trans Med Imaging* 17(6):889–899
17. Cardinal MR, Meunier J, Soulez G, Therasse E, Cloutier G (2003) Intravascular ultrasound image segmentation: a fast-marching method. In: Proceedings of MICCAI LNCS 2879, pp 432–439
18. Brusseau E, De Korte CL, Mastick F, Schaar J, Van der Steen AFW (2004) Fully automatic luminal contour segmentation in intracoronary ultrasound imaging – a statistical approach. *IEEE Trans Med Imaging* 23(5):554–566
19. Olszewski ME, Wahle A, Vigmostad SC, Sonka M (2005) Multidimensional segmentation of coronary intravascular ultrasound images using knowledge-based methods. In: Proceedings of SPIE medical imaging: image processing, vol 5747, pp 496–504
20. Xu D, Hwang J-N, Yuan C (2001) Atherosclerotic plaque segmentation at human carotid artery based on multiple contrast weighting MR images. In: IEEE ICIP, pp 849–852
21. Adams GJ, Vick GW, Ballantyne CM, Insull W, Morrisett JD (2002) Estimation of carotid atherosclerotic plaque volume in vivo magnetic resonance images. In: Proceedings of EMBS/BMES conference, pp 1072–1073

22. Yang F, Holzapfel GA, Schulze-Bauer CAJ, Stollberger R, Thedens D, Bolinger L, Stolpen A, Sonka M (2003) Segmentation of wall and plaque in in-vitro vascular MR images. *Int J Cardiovasc Imaging* 19:419–428
23. Cohen LD (1991) On active contour models and balloons. *Comput Vis Graph Image Process Image Underst* 53(2):211–218
24. Williams D, Shah M (1992) A fast algorithm for active contour and curvature estimation. *CVGIP Image Underst* 55(1):14–26
25. Lai KF, Chin RT (1995) Deformable contours-modeling and extraction. *IEEE Trans PAMI* 17(11):1084–1090
26. Xu C, Prince J (1998) Generalized gradient vector flow external forces for active contours. *Signal Process* 71:131–139
27. Loizou CP, Pattichis CS, Pantziaris M, Nicolaides AN (2005) Performance evaluation of active contour models for carotid plaque segmentation. In: EMBEC European medical and biological engineering conference IFMBE on biomedical engineering, Prague, Czech Republic, vol 11, issue 1, pp 1–6
28. A Philips Medical System Company (2001) Comparison of image clarity, SonoCT real-time compound imaging versus conventional 2D ultrasound imaging. ATL Ultrasound Report
29. Kyriakou E, Pattichis MS, Christodoulou C, Pattichis CS, Kakkos S, Griffin M, Nicolaides A (2005) Ultrasound imaging in the analysis of carotid plaque morphology for the assessment of stroke. In: Suri JS, Yuan C, Wilson DL, Laxminarayan S (eds) *Plaque imaging: pixel to molecular level*. IOS Press, Washington, DC, pp 241–275
30. Elatrozy T, Nicolaides A, Tegos T, Zarka A, Griffin M, Sabetai M (1998) The effect of B-mode ultrasonic image standardization of the echodensity of symptomatic and asymptomatic carotid bifurcation plaque. *Int Angiol* 17(3):179–186
31. Loizou CP, Pattichis CS (2008) Despeckle filtering algorithms and software for ultrasound imaging. *Synthesis lectures on algorithms and software for engineering*. Morgan & Claypool, San Rafael, CA
32. Lee JS (1980) Digital image enhancement and noise filtering by use of local statistics. *IEEE Trans Pattern Anal Mach Intell PAMI-2*(2):165–168
33. Loizou CP, Pattichis CS, Christodoulou CI, Istepanian RSH, Pantziaris M, Nicolaides A (2005) Despeckle filtering in ultrasound imaging of the carotid artery. *IEEE Trans Ultrason Ferroelectr Freq Control* 52(2):1653–1669
34. Metz C (1978) Basic principles of ROC analysis. *Semin Nucl Med* 8:283–298
35. Fleiss JL, Cohen J, Everitt BS (1969) Large sample standard errors of kappa and weighted kappa. *Psychol Bull* 72(5):323–327
36. Rosenfield GH, Fitzpatrick-Lins K (1986) A coefficient of agreement as a measure of thematic classification accuracy. *Photogramm Eng Remote Sensing* 52(2):223–227
37. Loizou CP, Pattichis CS, Pantziaris M, Tyllis T, Nicolaides A (2007) Snakes based segmentation of the common carotid artery intima media. *Med Biol Eng Comput* 45(1):35–49
38. Loizou CP, Pattichis CS, Pantziaris M, Tyllis T, Nicolaides A (2006) Quantitative quality evaluation of ultrasound imaging in the carotid artery. *Med Biol Eng Comput* 44(5):414–426
39. Abd-Elmonien K, Youssef A-B, Kadah Y (2002) Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion. *IEEE Trans Biomed Eng* 49(9):997–1014
40. Gil D, Hernandez A, Mauri J, Radeva P (2006) Statistical strategy for anisotropic adventitia modeling in IVUS. *IEEE Trans Med Imaging* 25(6):768–778
41. Christodoulou CI, Pattichis CS, Pantziaris M, Nicolaides A (2003) Texture based classification of atherosclerotic carotid plaques. *IEEE Trans Med Imaging* 22(7):902–912
42. Kyriakou E, Pattichis CS, Pattichis MS, Loizou CP, Christodoulou C, Kakkos S, Nicolaides A (2010) A review of non-invasive ultrasound imaging processing methods in the analysis of carotid plaque morphology for the assessment of stroke. *IEEE Trans Inf Technol Biomed* 14(4):1027–1038
43. Loizou CP, Pantziaris M, Pattichis CS, Kyriakou E (2010) M-mode state-based identification in ultrasound videos of the common carotid artery. In: *Proceedings of 4th international symposium on communications, control and signal processing ISCCSP*, pp 1–6
44. Destrempes F, Meunier J, Giroux M-F, Soulez G, Cloutier G (2011) Segmentation of plaques in sequences of ultrasonic B-mode images of carotid arteries based on motion estimation and a Bayesian model. *IEEE Trans Biomed Eng* 58(8):2202–2210