CAPSU: a Completely Automated Method for Carotid Plaques Segmentation in Ultrasound Images

Francesca Galluzzo[1], Cristiana Corsi[1], Carmela Morizzo[2], Luca De Marchi[1], Nicola Testoni[1], Nicolò Speciale[1], Guido Masetti[1]

[1]DEI-Department of Electrical, Electronic and Information Engineering, "Guglielmo Marconi", University of Bologna, Bologna, Italy

[2]Department of Surgical, Medical, Molecular Pathology and Critical Care, University of Pisa, Pisa, Italy

Abstract

The accurate carotid plaques segmentation (CPs-S) is essential in the ultrasound (US)-guided carotid atherosclerosis diagnosis. In this work, we propose CAPSU: a completely automated method for CPs-S in US images. The core of the method is an innovative initialization procedure that exploits carotid wall motion analysis to automatically initialize a level-set segmentation algorithm. A strain analysis is also used to improve the initialization procedure. CAPSU performance with and without the strain analysis were evaluated on US data from 8 patients and compared with manual contouring from an expert sonographer. Results show the CAPSU effectiveness as accurate and reliable tool for fully automated CPs-S in US images.

1. Introduction

Carotid atherosclerosis diagnosis (CA), usually guided by ultrasound (US) imaging, is based on the assessment of the stenosis degree due to the presence of carotid plaques (CPs) and on CPs composition study. Accurate CPs segmentation (CPs-S) is a prerequisite for these evaluations and it is usually performed manually by experienced sonographers. However, US data characteristics make this task complicated and extremely operator-dependent. In this context, the need exists for automated CPs-S methods to speed up the CPs-S process and increase its reproducibility. Although some CPs-S methods have been proposed most of them are not fully automated and the task remains particularly challenging [1].

It has been shown that the analysis of tissue motion estimated from longitudinal carotid US imaging is useful to understand correlations between the carotid wall (CW) dynamics and the presence of diseases [1]. Moreover, CPs motion study has received increasing attention, and motion-based strain imaging methods have been proposed to study CPs vulnerability [2, 3].

In this work, we propose CAPSU: a completely automated method for CPs-S in US images. It is based on level-set (LS) segmentation, with an innovative initialization procedure that makes the approach completely user-independent. Basing on the studies highlighting CWs motion alterations in presence of diseases, this procedure exploits the motion analysis of longitudinal carotid US sequences, to differentiate image portions belonging to CPs from ones belonging to CWs or blood, and produce the LS initialization. Accumulated strain measurements are also used to improve the CPs/CWs differentiation. Section 2 describes the CAPSU workflow focusing on the innovative initialization procedure. CAPSU performance are evaluated in section 3. Finally, section 4 concludes the paper.

2. Methodology

2.1. Data collection

2D US longitudinal image sequences of the carotid artery from 8 patients were acquired using a ULtrasound Advanced Open Platform for experimental research (ULA-OP) [4]. The used transducer was a 46 mm, $4-13$ MHz linear array (LA523, Esaote s.p.a.). The dataset comprises subjects of different sex, age and pathological conditions. Each US sequence consists in a cineloop of the carotid artery of about 5s with a frame rate of 62.5 fps. For each patient the acquisition was focused on a specific CP (target CP). Dataset CPs differ in composition and position in the carotid artery. US data were acquired after the IQ demodulation stage.

2.2. Overview of the proposed approach

As shown in Figure 1, CAPSU comprises three main stages. The preprocessing consists in the envelope detec-

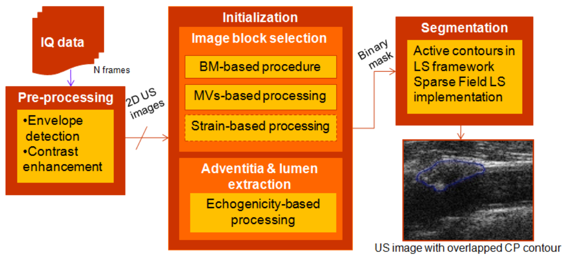


Figure 1: CAPSU workflow.

tion and logarithmic compression of the acquired IQ data. The resulting frame sequence constitutes the input of the initialization procedure, that exploits a motion and strain analysis of the US sequence and image echogenicity to produce the binary mask constituting the initialization of a LS segmentation stage.

2.2.1. Segmentation procedure

The active contour segmentation consists in propagating an interface into the image domain in order to detect a target object. When a LS formulation is used, the evolving interface is implicitly represented by the zero LS of a smooth function. The interface propagation is thus controlled by the implicit function ϕ (LS function) evolution according to:

$$\frac{\partial \phi}{\partial \tau} = F \cdot \|\nabla \phi\| \tag{1}$$

where the speed function (SPF) $F(\cdot)$ describes the evolution and is formally derived by the minimization of an energy functional that reflects the target object properties. In literature, several SPFs have been proposed. Among them region-based models drive the contour evolution by taking into account the statistical properties of the foreground and background regions. Since these approaches use global statistics, they may fail when segmenting heterogeneous objects. The local region-based approach proposed by Lankton [5] has proven its effectiveness in handling such situations, as it is the case of US images. Following this approach, hereto we used the localized version of the Yezzi energy functional [6]:

$$\frac{\partial \phi}{\partial t}(\mathbf{x}) = \delta\phi(\mathbf{x}) \int_{\Omega_{\mathbf{y}}} B(\mathbf{x}, \mathbf{y}) \cdot \delta\phi(\mathbf{y}) \left(\frac{(I(\mathbf{y}) - u_x)^2}{A_u} - \frac{(I(\mathbf{y}) - v_x)^2}{A_v} \right) d\mathbf{y} + \lambda \delta\phi(\mathbf{x}) div \left(\frac{\nabla\phi(\mathbf{x})}{|\nabla\phi(\mathbf{x})|} \right) \tag{2}$$

where the mask function $B(\cdot)$ defines the (circular) neighborhood around $\mathbf{x}$ where the local parameter driving the evolution are estimated [5]. To reduce the LS computational time, we used the sparse field (SF) LS method proposed by Whitaker [7], that restricts the LS computation on a one point wide narrow band around the zero LS. When implementing this method an input binary mask is used to initialize ϕ [8].

2.2.2. Initialization procedure

The proposed initialization procedure is based on the observation that, in a carotid US image sequence, image portions corresponding to CPs or CWs move less and slower than the ones corresponding to the blood. Thus they can be considered *almost still* across the sequence. Moreover, it has been shown that the presence of both stenosis and CPs alters the CW motion characteristics [1]. Basing on these observations our initialization procedure uses a motion estimation and compensation procedure, based on the block matching (BM) algorithm, to automatically identify these *almost still regions* discarding the others. Then, the estimated displacement vectors are also used to better distinguish between regions belonging to the CWs from the ones belonging to the CPs. Strain measurements can be also computed from the accumulated displacements to improve this differentiation. Finally, the motion-based procedure outputs are combined with echogenicity information to produce the binary mask for the LS initialization.

Block Matching-based procedure. Basically, the BM algorithm applied to a frames pair works as follows: (i) the current frame is divided into equally sized blocks; (ii) then, each block is associated with a search region in the reference frame (usually constrained up to p pixels on all four sides) where the algorithm searches for the *candidate block* that best matches the original one according to a matching criterion; (iii) the relative distance between the original and the *candidate* blocks constitutes the displacement vector (motion vector) associated to that block. Among the existing matching criteria and searching techniques, the mean absolute difference and the exhaustive search technique [9] were used in this work. To reflect the rectangular shape of the acquired images (size 128x512), we used blocks of size 8x32 pixels, while the search parameter p was equal to 7. While in video coding the blocks movement estimation obtained with the BM is used to compensate motion in the reference frame, in our procedure this information is used to keep trace of that blocks that don't move between two frames (*constant blocks*). This operation is repeated for all frames with a distance of 4 between current and reference frame. Then, the procedure identifies blocks that have been found to be *constant blocks* for the 90% of the total amount of frames (*frozen blocks*), and produces an image where only these blocks are maintained while the others are discarded (*frozen blocks image*, see Fig. 2 (b)).

Motion Vectors- & Strain-based processing. This step of the initialization procedure consists in using the radial component (normal to the vessel axis) of the MVs associated to the *frozen blocks* to further remove some blocks from the image, in order to better isolate the CPs from the CWs. To achieve this goal the mean of the absolute values and the standard deviation of the MVs radial component are computed across the frames, and thresholded to perform the block selection. Additionally, at this point a strain-based processing can be performed to allow a better CPs/CWs blocks differentiation. In particular, lateral (parallel to the vessel axis) and radial displacements are accumulated across the frames. Then, the corresponding accumulated strains are computed as the gradient of the accumulated displacements, by using a two point central difference method. Basically, if local lateral strain is defined by the expression $\epsilon_{xx} = \frac{\partial u_x}{\partial x}$ the corresponding accumulated strain as defined in this work is given by:

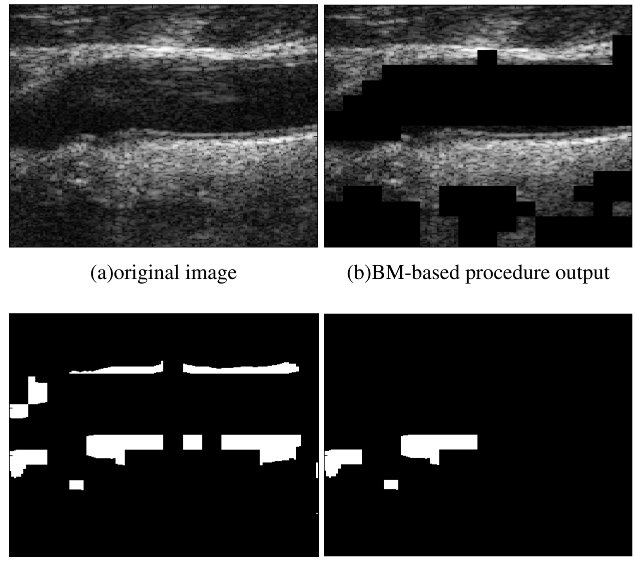
$$\alpha_{xx} = \frac{\partial V_x}{\partial x}, \quad V_x = \frac{1}{n}\sum u_x$$

where V_x denotes the accumulated displacement. Then, both radial and lateral strains are analyzed and thresholded to perform a further blocks selection. This selection is based on experimental observations on the strain patterns exhibited by CPs and CWs. Examples of these observations are that high strain was found at the junction between CPs and the normal vessel or that heterogeneous CPs with calcified regions exhibits low strain in correspondence of calcifications and high strain in their neighborhood. Since dataset CPs differ in composition and position (near and far wall), to handle different situations, strains associated to each block are also analyzed *w.r.t.* their neighbors, and a further block selection is performed basing on conditions that allows to identify strain patterns associable to the CPs.

Echogenicity-based processing. Since image blocks corresponding to regions at the interface between the lumen and CWs can be characterized by similar motion characteristics, this step exploits image intensity distribution to better isolate CPs from the rest of wall. It is based on the observation that CWs, especially the adventitia, and lumen are respectively characterized by high- and low-intensity pixels. At first a median filter is applied to denoise the *frozen blocks image*. Then, the intensity profile is computed column-wise to detect pixels in the $90th$ and $10th$ percentile of the distribution. These information are used to identify the lumen and the adventitia. Finally, basing on geometrical and morphological considerations, the algorithm differentiates between near and far wall, and removes from them pixels that could belong to CPs calcified portions. By combining these information with the output of the previous step, the final binary mask is created.

3. Experiments & results

To evaluate CAPSU performance, without and with the strain analysis, a comparison with manual contouring from an expert sonographer was performed. In particular, for



(a)original image (b)BM-based procedure output

(c)final binary mask obtained without the strain computation (d)final binary mask obtained with the strain computation

Figure 2: Initialization procedure input and outputs.

each preprocessed US sequence, the sonographer manually segmented the target CP (see subsection 2.1) on a selected frame, and this segmentation was used as reference for method validation. Comparison metrics were the Kappa Index (KI), Sensitivity (SE), and Specificity (SP) [10]:

$$KI = 2\frac{|C \cap C_{man}|}{|C| + |C_{man}|} \quad SE = \frac{|C \cap C_{man}|}{|C_{man}|} \quad SP = \frac{|\bar{C} \cap \bar{C}_{man}|}{|\bar{C}_{man}|}$$

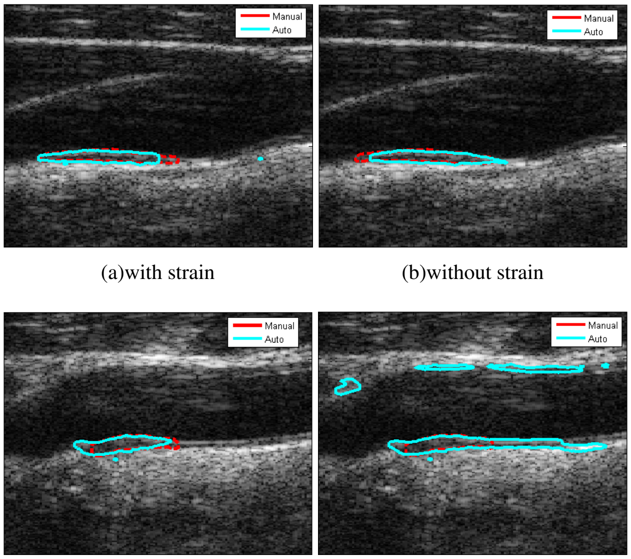
where C and C_{man} respectively indicate the automated and the manual contour. The complement of the segmented region was computed on the smallest rectangle containing both the contours [10]. Since the ground truth is constituted by the manual segmentation of one specific CP for each image, metrics were computed on the target CP contour. The BM-based procedure and the SF LS were developed basing on the open source implementations respectively proposed by Barjatya [9] and Lankton [8]. To allow a fair comparison the two CAPSU implementations were launched with the same segmentation parameters.

Figure 2 shows a US sequence frame for a carotid artery with a CP at the far wall (a), the corresponding BM-based procedure output (b), and the corresponding final binary mask produced by the initialization procedure respectively without (c) and with (d) the strain computation. As it is shown, in both cases CPs image regions are well detected, but the strain computation allows discarding more image blocks that do not belong to the target CP.

Figure 3 shows two different examples (by row) of manual (dashed line) and automated (solid line) CPs-S with (a, c) and without (b, d) the strain analysis. By considering figures 3 (a, b) it can be observed that good agreement be-

Table 1: Quantitative evaluation of CAPSU performance.

segmentation method	# of patients	KI	SE	SP
CAPSU with strain	8	77.20%	70.48 %	90.27%
CAPSU without strain	8	71.16%	71.70 %	85.99%



(a)with strain (b)without strain

(c)with strain (d)without strain

Figure 3: Manual (dashed line) and automated (solid line) CPs-S results for two patients with (a,c) and without (b,d) the strain analysis.

tween CPs-S methods was achieved both with and without the strain analysis. In the case in figure 3 (c, d), instead, the strain analysis introduction allows better CP boundary delineation by discarding regions at the junction with the normal vessel, as well as false positive regions.

Table 1 shows the quantitative results of the evaluation. Namely, the KI, SE and SP values averaged on the whole set of patients are shown for both CAPSU with (first row) and without (second row) the strain analysis. Achieved average KI, SE and SP indicate good agreement between manual and automated CPs-S in both cases (perfect agreement $= 100\%$). A KI improvement of 8.5% confirms that, in many cases, the strain analysis introduction allows better CPs boundaries delineation. Moreover, SP was improved in the range of 5% and SE was almost maintained. These results demonstrate the CAPSU effectiveness in achieving accurate CPs-S. A significant performance improvement was achieved by introducing the strain analysis. CAPSU generalization ability was validated by using a dataset with CPs differing in composition and position.

4. Conclusions

In this work a completely automated method for CPs-S in US images (CAPSU) was proposed. Its core is an innovative initialization procedure that exploits CWs motion and strain analysis to initialize a LS segmentation without requiring any user intervention. By comparison with manual contouring CAPSU was shown to be an accurate and reliable tool for fully automated CPs-S in US images. The strain induced performance improvement suggest to use the CAPSU motion and strain analysis procedure for CPs characterization toward the development of a fully automated support tool for CA diagnosis.

Acknowledgements

This work was partially funded by the Italian Ministry of Education, University and Research (PRIN 2010-2011).

References

[1] Golemati S, Gastounioti A, Nikita K. Toward novel non-invasive and low-cost markers for predicting strokes in asymptomatic carotid atherosclerosis: The role of ultrasound image analysis. IEEE Trans Biomed Eng 2013; 60(3):652–658.

[2] McCormick M, Varghese T, Wang X, Mitchell C, Kliewer M, Dempsey R. Methods for robust in vivo strain estimation in the carotid artery. PMB 2012;57(22):7329.

[3] Shi H, Mitchell C, McCormick M, Kliewer M, Dempsey R, Varghese T. Preliminary in vivo atherosclerotic carotid plaque characterization using the accumulated axial strain and relative lateral shift strain indices. PMB 2008; 53(22):6377.

[4] Tortoli P, Bassi L, Boni E, Dallai A, Guidi F, Ricci S. Ula-op: an advanced open platform for ultrasound research. IEEE TUFFC 2009;56(10):2207–2216.

[5] Lankton S, Tannenbaum A. Localizing region-based active contours. IEEE T Image Process 2008;17(11):2029–2039.

[6] Yezzi Jr A, Tsai A, Willsky A. A fully global approach to image segmentation via coupled curve evolution equations. J Vis Commun Image Represent 2002;13(1):195–216.

[7] Whitaker RT. A level-set approach to 3d reconstruction from range data. Int J Comput Vision 1998;29(3):203–231.

[8] Lankton S. Sparse field methods-technical report. Technical report, Georgia Tech., 2009. http://www.shawnlankton.com/wp-content/uploads/articles/lankton-sfm-TR-2009.pdf.

[9] Barjatya A. Block matching algorithms for motion estimation. IEEE Trans Evol Comput 2004;8(3):225–239.

[10] Destrempes F, Meunier J, Giroux M, Soulez G, Cloutier G. 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 2011; 58(8):2202–2211.

Address for correspondence:

Francesca Galluzzo

University of Bologna-DEI, V.le Risorgimento, 2, 40136, Bologna. francesca.galluzzo@unibo.it