

# Three-dimensional labeling of vulnerable regions in carotid plaques using Graph-Cuts

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**Abstract**— Carotid plaque morphology assessed through high resolution ultrasound is nowadays an important diagnostic approach in the evaluation of stroke risk. The literature describes several methods for the characterization of plaque echogenicity and texture by using overall statistics across the carotid plaques. However, this averaged indicators may not be enough for a correct diagnosis of plaque instability. Therefore, it has been suggested that a local characterization of plaque morphology, where the extension and location of vulnerable regions inside the plaques is taken into account, could lead to significant improvements in the assessment of stroke risk.

In this paper, a new method to characterize the morphology of carotid plaques in three-dimensions (3D) is proposed. The local characterization of carotid plaques is performed by using a 3D *Graph-Cuts* (GraphC) robust labeling method. This methodology allows to binary segment the data by minimizing an energy function that uses spatial correlation among neighboring pixels/voxels in order to remove small misclassified regions. The method is efficient since it is able to find the global minimum of the energy function in a very short time interval.

Results show that this labeling procedure is less noisier and favors clustering, being more meaningful from a clinical point of view than the one obtained with simple thresholding. This paper shows that the use of GraphC may improve the 3D morphological characterization of carotid plaques, namely by providing a more appropriate identification of unstable foci inside the plaque.

## I. INTRODUCTION

Apart from classical indicators such as the degree of *stenosis*, plaque morphology is recently being considered relevant to evaluate the stroke risk in the scope of the carotid atherosclerotic disease.

The benefit of surgical intervention for plaque removal, called *endarterectomy*, is clearly demonstrated for patients presenting high degree of *stenosis* (more than 60%) [1]. However, it was also shown that patients on medical treatment remained free of symptoms for a long-time period despite the presence of considerable stenotic lesions. This suggests that the degree of *stenosis* alone is not enough for assessing the carotid plaque risk and that other factors should be taken into account [2,3].

High resolution ultrasound is a widely used imaging tool to assess the degree of *stenosis* as well as the plaque morphology. The two most important parameters to characterize the plaque morphology are its echogenicity and texture. The echogenicity is evaluated from the image intensities. A region is called *hypoechoogenic* if it appears dark in the image

and *hyperechogenic* if it appears bright. Plaque texture may be homogeneous or heterogeneous.

Several studies were pursued to statistically characterize the morphology of carotid plaques in 2D ultrasound images [4] by using, for instance, a stratified *Gray-Scale Median* (GSM) analysis and color mapping of the plaque [5]. The GSM is one of the most important indicators considered on plaque diagnosis and is generally used to classify plaques as hypoechoogenic (GSM < 32) or *hyperechogenic* (GSM > 32) [2]. The total percentage of *hypoechoogenic* pixels (P40), defined as the percentage of pixels with gray levels below 40, is also an important measure for the characterization of plaque echogenicity. In fact, multiple regression analysis [4] has revealed that the GSM and the P40 are the most significant variables related with the presence of disease symptoms. Recently, an activity index aiming at quantifying the stroke risk [2] has been proposed. This overall index merges several indicators, such as, plaque overall texture, degree of *stenosis*, global *echogenicity* and location of *hypoechoogenic* sites across the plaque.

A vulnerable plaque is associated with thinning of the fibrous cap and infiltration of inflammatory cells that lead to plaque rupture. Studies which established a correlation between quantitative analysis based on ultrasound B-mode images and histology [3] have suggested that *hypoechoogenic* regions have more lipid and hemorrhage, indicating inflammatory activity and therefore instability. Conversely, *hyperechogenic* regions are associated with the presence of stable components. Therefore, the location and extension of vulnerable regions throughout the carotid plaque could be a sensitive and relevant marker of stroke risk. Analysis of global information about plaque morphology, despite its unquestionable usefulness, may not be accurate enough in many cases, namely, when plaques are *heterogeneous* or present significant *hypoechoogenic* regions. An overall measure of *echogenicity* or texture is incomplete and does not reveal unstable *foci* inside the plaque which may be threatening.

In this paper it is proposed a novel method to characterize the echo-morphology of carotid plaques in 3D. The method binarizes the plaque according to several statistical criteria related with the *echogenicity* or texture in a local basis. This binarization is performed in a Bayesian framework where spatial correlation among neighbors is considered in order to reduce the spurious misclassifications due to the noise. This is done by minimizing an energy function in a binary  $n$ -dimensional space,  $\{0,1\}^n$ , which corresponds to a huge combinatorial optimization problem that may be exactly solved by using GraphC [6] in a short time period.

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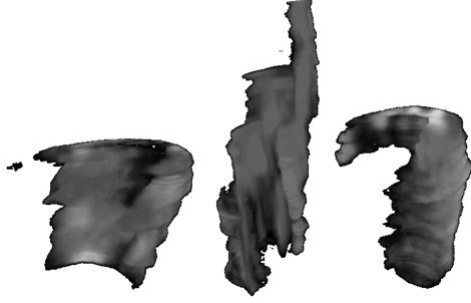


Fig. 1. 3D reconstructed carotid plaques used in the labeling procedure.

## II. METHODS

Volume reconstruction of carotid plaques is needed to make its 3D morphological characterization. In this paper, a reconstruction algorithm proposed by the authors [7] is used. In this method, an image acquisition protocol is used which does not require any special equipment but the common ultrasound scanner available in most medical facilities. The method provides a surface reconstruction of the carotid in the bifurcation region and a volume reconstruction of the plaque. The volume reconstruction is performed from the noisy pixel observations extracted from the segmented plaques. The reconstruction is performed in a Bayesian framework where the observations are described by a Rayleigh distribution to model the speckle noise which corrupts the US images [8] and a *Total Variation* (TV) based Gibbs distribution to regularize the solution. This prior distribution is used to fill the inter-plane gaps, if they exist, and interpolate the observed data to attenuate the speckle noise and the discontinuities that arise during image acquisition. The data used in this paper consists in 3 sets of  $n = 100$  nearly parallel cross-sections of the middle region of the carotid artery near the bifurcation, where plaque formation is more frequent, acquired from different patients.

Traditionally, plaque characterization is based on statistics computed from the observed noisy pixels. Here, the characterization is based on statistical estimators depending on the estimated scalar function,  $f(x) : R^3 \rightarrow R$ , corresponding to the Rayleigh parameters throughout the continuous plaque volume (Fig. 1) [7].

The echogenicity and texture measures, computed from the continuous volume,  $f(x)$ , are the mean ( $\mu$ ), standard deviation ( $\sigma$ ), median ( $v$ ) and percentile 40 (P40) estimators derived from the Rayleigh distribution, used to model *speckle* noise corrupting the ultrasound images (see Table I).

## III. LABELING

In this section a local based characterization labeling approach is described. The goal is to use the statistical estimators (see Table I), depending on the continuous function  $f(x) : R^3 \rightarrow R$  describing the acoustic properties of the carotid plaque, to locally assess the risk of plaque rupture. This local characterization, as already referred, is crucial from a clinical point of view. It is expected by using this method to identify

TABLE I  
STATISTICAL ESTIMATORS USED TO ASSESS CAROTID PLAQUE  
MORPHOLOGY

$f_{\mu}(x)$	$\sqrt{\frac{\hat{f}(x)\pi}{2}}$
$f_{\sigma}(x)$	$\sqrt{\frac{4-\pi}{2}\hat{f}(x)}$
$f_v(x)$	$\sqrt{2\log(2)\hat{f}(x)}$
$f_{P40}(x)$	$1 - e^{\frac{-40^2}{2\hat{f}(x)}}$

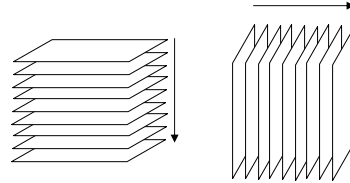


Fig. 2. Labeling process in a plane by plane basis in two steps, along the vertical (left) and horizontal (right) directions.

sites of the plaque, whose features (hypoechoogenicity and heterogeneity) point toward potentially *foci* of vulnerability/rupture.

The local characterization method is an extension of the global analysis of plaque morphology described in literature [9], where, the GSM, P40, Mean and others, are computed, not averaging the noisy observed pixels corrupted by speckle noise, but only the specific value of  $f(x)$  at each location. Each location is binary labeled by comparing the statistics  $s(f(x))$  (Table I) with a threshold defined by the clinician. This is done for every voxel to build a 3D map of labels describing the classification across the plaque with respect to each one of the statistical indicators.

The simpler approach is to use a local thresholding in a voxel by voxel basis without taking into account the neighboring nodes. This strategy gives rise to small regions or isolated labels not morphologically supported but resulting from imperfections on the reconstruction volume,  $f(x)$ .

Here, a more sophisticated and accurate method is used where the labeling procedure takes into account, not only, the intensity value of the statistic function at location  $x$  but also its neighborhood values. The goal is to introduce spatial correlation in the labeling process to reduce the misclassification rate by assuming that the plaque is composed by homogeneous regions separated by abrupt transitions. This assumption is acceptable from an anatomical point of view and is usually adopted in the general algorithms for denoising and deblurring on medical imaging.

The scalar continuous function  $f(x)$  is defined as a linear combination of basis functions  $f(x) = \sum_k f_k \phi_k(x)$ , where  $f_k$  are the coefficients estimated in the volume reconstruction step and  $\phi_k(x)$  is the  $k^{th}$  basis function centered at the  $k^{th}$  node of a 2D regular grid (the index  $k \in N^2$ ). The basis functions are chosen in order to make  $f(\mu_k) = f_k$  where  $\mu_k$  is the location where  $\phi_k(x)$  is centered, a node of the 2D regular grid.

The label maps,  $\mathcal{L}_\tau$  with  $\tau = \{\mu, \sigma, v, P40\}$ , are performed in a plane by plane basis, where each plane is labeled independently of the others. The segmentation is binary which means  $\mathcal{L}(k) \in \{0, 1\}$  where  $\mathcal{L}(k)$  is the  $k^{\text{th}}$  node of the labeled volume. The labeling procedure of the whole volume is performed in three steps:

- 1) all stacked planes along the vertical direction are independently labeled (see Fig.2-left).
- 2) all stacked planes along the horizontal direction are independently labeled (see Fig.2-right).
- 3) both volumes obtained,  $\mathcal{L}_v(k)$  and  $\mathcal{L}_h(k)$ , are fused by making  $\mathcal{L}(k) = \mathcal{L}_v(k) \otimes \mathcal{L}_h(k)$  where  $\otimes$  denotes the boolean product or AND operator.

The labeling process of each plane is performed by solving the following optimization problem

$$\mathcal{L}_\tau = \arg \min_{\mathcal{L}} E(F, \mathcal{L}), \quad (1)$$

where the energy function is

$$E(F, \mathcal{L}) = \sum_k (f_{\text{thrs}} - f_k)(2\mathcal{L}(k) - 1) + \alpha \sum_k [V(\mathcal{L}(k), \mathcal{L}(k_v)) + V(\mathcal{L}(k), \mathcal{L}(k_h))] / \tilde{g}_k, \quad (2)$$

where  $\mathcal{L}(k) \in \{0, 1\}$ ,  $\alpha$  is a parameter to tune the strength of smoothness,  $f_{\text{thrs}}$  is the threshold,  $\tilde{g}_k$  is the normalized ( $\epsilon \leq \tilde{g}_k \leq 1$ ) gradient of  $f(x)$  at the  $k^{\text{th}}$  node,  $\epsilon = 10^{-6}$  is a small number to avoid division by zero and  $\mathcal{L}(k_v)$  and  $\mathcal{L}(k_h)$  are the labels of the causal vertical and horizontal neighbors of  $\mathcal{L}_k$ .  $V(l_1, l_2)$  is a penalization function defined as follows

$$V(l_1, l_2) = \begin{cases} 0 & l_1 = l_2 \\ 1 & l_1 \neq l_2 \end{cases}. \quad (3)$$

The energy function (2) is composed by two terms: the first called *data term* and the second called *regularization term*. The first forces the classification to be  $\mathcal{L}(k) = 1$  when  $f_k > f_{\text{thrs}}$  because this leads to a decreasing on the term  $(f_{\text{thrs}} - f_k)(2\mathcal{L}(k) - 1)$  when compared with the alternative solution,  $\mathcal{L}(k) = 0$  and the reverse when  $f_k < f_{\text{thrs}}$ . The second term forces the uniformity of the solution because the cost associated with uniform labels is smaller than non uniform ones (3). However, in order to preserve the transitions the terms are divided by the normalized gradient magnitude of  $f(x)$ ,  $\tilde{g}_k$ . Therefore, when the gradient magnitude increases the regularization strength is reduced at that location. The minimization of (2), formulated in (1), is a huge combinatorial optimization problem in the  $\{0, 1\}^{NM}$  dimensional space where  $N$  and  $M$  are the dimensions of the image.

In [6] it is shown that several energy minimization problems in high dimensional discrete spaces can be efficiently solved by using *Graph-Cuts* based algorithms. The authors have designed a very fast and efficient algorithm to compute the global minimum of the energy function. However, the algorithm is not completely general which means that some energy functions can not be minimized with the proposed

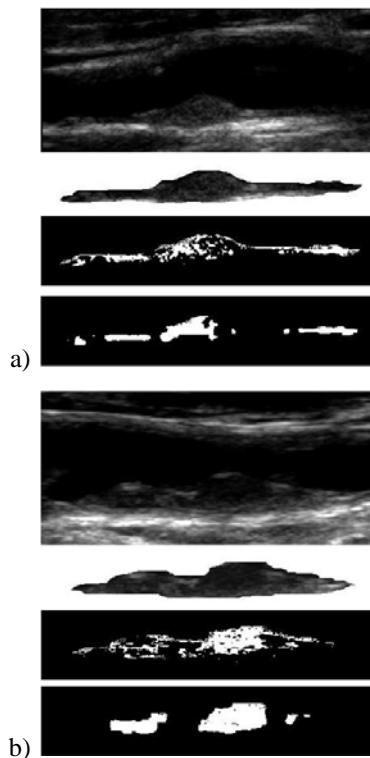


Fig. 3. (a-b) Original images (top) and segmented carotid plaques (middle). (Bottom) Labeling of carotid plaques, using thresholding and graph-cuts methods.

method. In [10] the authors present a wide class of energy functions that may be minimized with the GraphC method. Fortunately, the function (1) belongs to that class. A  $200 \times 300$  pixel image is processed in 0.2 seconds in a Intel Core2 CPU at 1.83GHz with 2GB RAM, which illustrates the small processing time of the method.

#### IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section we present two examples of application of the labeling method in order to locally characterize the carotid plaque morphology.

In the first example, the labeling is performed in two longitudinal ultrasound images showing carotid plaques (Figs. 3(a-b) (top)). The segmented carotid plaques (Figs. 3(a-b) (middle)) were characterized according to the labeling methods based on thresholding and GraphC (see Figs. 3(a-b) (bottom)). In this example the original noisy images were used and a threshold value of 32, in a gray scale (0–255) was used to locally characterize the plaque echogenicity. It is observed that a characterization based on a simple thresholding of the pixel intensity values leads to labeled images with a great amount of noise, which are not realistic from a clinical point of view. In fact, clinicians aim to identify certain regions of vulnerability across the carotid plaques, where isolated or dispersed pixels (here termed outliers) are not expected to occur. It is verified (see Fig. 3(a-b) (bottom)) that the labeling using GraphC is less noisier and favors clustering, being more clinical meaningful than the one obtained with simple thresholding.

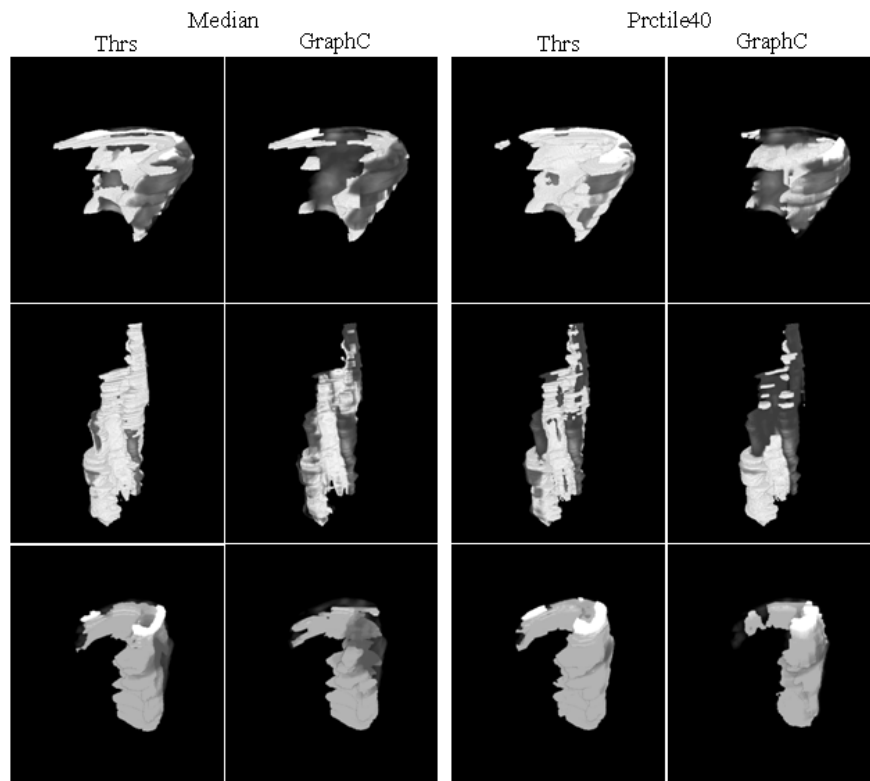


Fig. 4. Comparison of 3D thresholding and GraphC labeling methods in different plaques, using different statistical indicators of echogenicity.

In the second example, 3 reconstructed carotid plaques where locally characterized according to the previously described statistical indicators depending on the estimated parameters of the Rayleigh distribution. The statistical estimators considered in this example are the median and the P40. Published studies [3] in the carotid plaque characterization field suggest that hypoechogenic regions, corresponding to instability *foci*, have  $GSM < 32$  and P40 above 43%.

Fig. 4 displays the labeling of potentially dangerous sites inside the plaque, using the two labeling methods described in this paper (thresholding and GraphC). It is again observed that the labeling using graph cuts allows to better discriminate the regions of interest across the carotid plaques. Volumes labeled with GraphC appear less noisier than by using the threshold method.

This suggests that the use of graph-cuts may improve the characterization of carotid plaques, namely by providing a more appropriate identification and definition of unstable regions across the plaque. As it is pointed out by the most recent literature [2], the degree of extension of these unstable regions as well as their location throughout the plaque should be used as important markers of stroke risk.

## V. CONCLUSIONS

Local and global characterization of plaque echogenicity and texture from ultrasound images are considered to be powerful criteria to be used in the assessment of stroke risk. This paper proposes a new approach to overcome the major limitations of a single global characterization of the plaque by computing local indicators obtained from the noiseless reconstructed volumes containing the plaque. This

method uses a fast computational labeling algorithm based on graph-cuts to improve the segmentation of potential *foci* of instability across the carotid plaques by providing labeled plaques less noisier and more clinical meaningful.

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