ROBUST COMMON CAROTID ARTERY LUMEN DETECTION IN B-MODE ULTRASOUND IMAGES USING LOCAL PHASE SYMMETRY

José Rouco and Aurélio Campilho

INEB - Instituto de Engenharia Biomédica, Porto, Portugal
Faculdade de Engenharia, Universidade do Porto, Rua Roberto Frias, 4200-465, Porto, Portugal
{jrouco, campilho}@fe.up.pt

ABSTRACT

This paper presents a new method for automatic common carotid artery detection in B-mode ultrasonography. The proposed method is based on the location of phase symmetry patterns at apropriate scale of analysis. The local phase information is derived from the monogenic signal and isotropic log-normal band-pass filters, and the resulting common carotid artery is located using a dynamic programming optimization algorithm. The experiments show that the proposed method is more robust to noise than previous approaches, although additional research is required for robust common carotid artery detection on the more complicated cases.

Index Terms— biomedical image processing, ultrasonography, dynamic programming, carotid artery detection, monogenic signal

1. INTRODUCTION

Ultrasonography of the common carotid artery (CCA) has become widely used in clinical practice for the diagnosis of atherosclerosis and associated diseases, as it is a high-resolution, non invasive, low cost and readily available medical imaging technology. From a longitudinal B-mode ultrasound image of the CCA (figure 1), it is possible to measure the intima-media thickness (IMT), the lumen diameter, or the identification of the atheroscletotic plaques [1].

Several accurate and automatic IMT measurement algorithms have been proposed in the last few years [2, 3, 4, 5]. Most of the existing methods require some kind of user interaction to locate a region of interest (ROI) in the image containing the carotid artery walls. Some other algorithms, usually referred to as fully-automatic, incorporate a CCA detection algorithm as a previous step for ROI location [2, 5, 6, 7, 8, 9]. These algorithms can either provide information about the lumen [2, 6, 5], which is the area of the vessel where the blood flows, or a more detailed ROI that include approximations of the artery walls [7]. In either case, the objective is to locate the vessel structure whithin the image so that the posterior IMT segmentation and measurement process does not get confused with other similar structures in the image. The objective of this paper is to derive a method for robust CCA lumen centerline detection.

A robust method for CCA detection should take into account the usual difficulties in ultrasonic image analysis, that include the presence of speckle noise and local changes of intensity and contrast. The CCA appears in the image as an oriented, nearly horizontal and bent low echogenicity region (the lumen), surrounded by two bright bands (the artery walls) [6]. Fortunately this structure is large and high contrasted enough for not being significantly affected by the speckle noise. However, the shape of these regions may vary depending on the subject anatomy and the imaging plane, and may also be affected by the presence of atherosclerotic plaques. Even more, for some insonation planes, other anatomical structures with similar shape to that of the CCA, such as the jugular vein or the sternocleidomastoid muscle, may appear in the image. The concrete echogenicities of the CCA lumen and walls do not only depend on their tissue composition, but also on

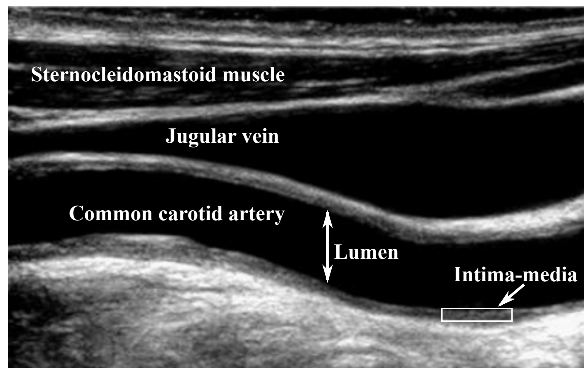

Fig. 1. Structures of interest in a longitudinal B-mode ultrasonography of the common carotid artery.

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the insonation angle, the tissue attenuation, and on the ultrasound gain parameters. Some common consensus on carotid IMT measurement include B-mode image acquisition guidelines that aim to standardize the overall aspect of the CCA [1]. These guidelines recommend to adjust the overall gain to avoid most of lumen noise, and the time gain compensation to achieve similar brigthness of both artery walls. That is why some intensity-based methods have been succesfully used for CCA detection [7, 5], regardless of not being specifically well suited for ultrasound image analysis. Nevertheless, these ultrasound settings are ultimately stabilished according to the subjective judgement of the operator, and it may not be possible to achive homogeneous imaging along the whole CCA. Thus, a robust CCA detection algorithms should be able to tolerate the presence of lumen noise and intensity variations.

2. RELATED WORK

The existent CCA detection algorithms can be classified in two main strategies. The first strategy consists on performing a column-wise vertical analysis of the image to locate candidate points at the CCA lumen or walls, which are then classified and connected into line segments [6, 7, 8, 9]. The second strategy uses a dynamic programming (DP) algorithm to find a path, from one image border to the other, by optimizing a global evaluation function that points the interesting image locations [2, 5]. The proposed method in this paper follows this second strategy, as it provides an appropriate framework to integrate fuzzy low level image features and criteria that do not only consider the vertical direction. Regardless of the strategy, the CCA detection process may be based on vessel wall shape detection [6, 7, 8, 9], or based on lumen region features as the average echogenicity [7, 5], gray level variability [6, 7] or lumen diameter [6, 5].

The automatic CCA detection and ROI selection is often relegated as preprocessing step of minor importance within a global methodology for automatic IMT measurement. The proposed methods are often heuristic and may sometimes contain parameters that are set ad-hoc for the testing database without further analysis or discussion on the method limitations. Thus, in general, the lack of experimental evaluation and adequate algorithm details complicates the method comparison. There are, however, two works focused on the topic of CCA detection [6, 7], both of them performing column-wise analysis. Rossi et al. [6] propose a real-time method for lumen centerline detection on ultrasound video sequences which is robust to noise and variation of gain settings. They report that their main source of failures is due to a very low signal-to-noise ratio (SNR) or due to the presence of long segments of jugular vein. Differently, Molinari et al. [7] proposed a method to detect both CCA lumen and walls. They report high performance results on images acquired with several commercial ultrasonographers. However, the method performance may be severly affected by some parameter settings, which are empirically selected. Their method do not correctly detect the CCA in images with high levels of lumen noise and artifacts.

Among the methods using DP, Liang et al. [2] propose the use of a multiscale processing to first broadly locate the vessel walls and subsequentially refine the segmentation of the IMT boundaries. However, the initial location of the CCA was based on minimum location on the horizontal projection of the image, which is not suitable for images containing similar structures and for highly sloping or bent CCAs. In addition the proposed DP gain functions contain several parameters which are adjusted through training. Differently, Rocha et al. [5] propose to use a triangle histogram thresholding algorithm to segment the dark regions of the image. Then, the vertical distance transform to these region boundaries is computed and the local maxima in the distance map which value is in the interval of valid lumen radii are selected as points of lumen symmetry axis, are used to guide the DP process. An additional heuristic procedure that selects the deepest adequate DP local maximum reduces the missdetections due to similar structures in the image.

In this paper, as in [5], the symmetry information of structures of appropriate size is used for lumen centerline detection using DP. However, as shown by Kovesi [10], it is possible to contruct a contrast invariant symmetry measure that does not require any prior recognition or segmentation of objects using the local phase information. Thus, in this work a local phase symmetry measure that point the CCA lumen in longitudinal B-mode ultrasonographies of the carotid is computed using signal processing methods. In order to estimate the local phase, the monogenic signal [11] is used to compute log-normal isotropic filters in quadrature.

3. METHODOLOGY

Kovesi [10] proposes a normalized symmetry measure that is based on local frequency analysis. The symmetry measure varies almost linearly with phase deviation, and achieves maximum values at 0 and π phases, which point the location of the symmetry axes of light and dark regions respectively. Differently, but with analogous implications, the following local symmetry function, which points symmetry axes of dark regions, is proposed in this work:

$$Sym(\boldsymbol{x}) = \frac{|\phi(\boldsymbol{x})|}{\pi} \, . \tag{1}$$

where $\boldsymbol{x} = (x_1, x_2)^\top$ denotes an image location, with $\top$ being the transpose operation, and $\phi(\boldsymbol{x}) \in [-\pi, \pi)$ the local phase at $\boldsymbol{x}$.

The local phase information is derived from monogenic signal analysis [11]. The monogenic signal is an isotropic generalization of the analytic signal to two dimensions, that uses the Riesz transform instead of the Hilbert transform. The monogenic signal $f_M(\boldsymbol{x})$ of a given signal $f(\boldsymbol{x})$ is given by:

$$f_M(\boldsymbol{x}) = f(\boldsymbol{x}) - (i,j)\boldsymbol{f}_R(\boldsymbol{x}) \ . \tag{2}$$

where i and j denote imaginary units, and $\boldsymbol{f}_R(\boldsymbol{x})$ corresponds to the Riesz transform of $f(\boldsymbol{x})$, which in the frequency domain is given by:

$$\boldsymbol{F}_R(\boldsymbol{u}) = \frac{i\boldsymbol{u}}{||\boldsymbol{u}||}F(\boldsymbol{u}) \ . \tag{3}$$

where $\boldsymbol{u} = (u_1, u_2)^\top$, and $F(\boldsymbol{u})$ is the Fourier transform of the input signal $f(\boldsymbol{x})$.

The monogenic signal allows the estimation of the local amplitude, the local orientation and the local phase of the signal. The local phase $\phi(\boldsymbol{x})$ is obtained as:

$$\phi(\boldsymbol{x}) = atan2(||\boldsymbol{f}_R(\boldsymbol{x})||, f(\boldsymbol{x})) \ . \tag{4}$$

where $atan2(\cdot) \in [-\pi, \pi)$. For a complete local phase estimation it would be necessary to add a sign factor that depends on the direction of $\boldsymbol{f}_R$. However, in the case of this work, the sign factor is not necessary as the polarity of the antisymmetric phases is not taken into account in equation (1). The monogenic signal estimates the local phase in the direction of the locally strongest intrinsically one-dimensional signal. This phase is suitable for longitudinal B-mode CCA ultrasound image analysis as their structures of interest are usually arranged in locally parallel layers.

Moreover, the analysed signal $f(\boldsymbol{x})$ is a band-pass filtered version of the input image. The used band-pass filter is a radial log-normal filter which transfer function in frequency domain is defined as:

$$B_{\omega_0,\kappa}(\boldsymbol{u}) = \exp\left(-\frac{(log(||\boldsymbol{u}||/\omega_0))^2}{2(log(\kappa))^2}\right) \ . \tag{5}$$

where ω_0 is the centre frequency of the filter, and κ is the parameter controlling the bandwidth. Log-normal filters allow arbitrarily large bandwidth with a zero DC component.

The ω_0 and κ parameters of the band-pass filter allows to select the size of the structures of interest. In this case, it is assumed that the possible CCA diameters are within the interval $[D_{min}, D_{max}]$, thus the filter parameters are selected according to the following equations:

$$\omega_0 = \frac{1}{\sqrt{D_{max}D_{min}}} \ . \tag{6}$$

$$\kappa = e^{-\frac{\sqrt{2}}{4\sqrt{log(2)}}log(\frac{D_{max}}{D_{min}})} \ . \tag{7}$$

so that the half-response cutoff frequencies of the filter correspond to D_{max}^{-1} and D_{min}^{-1}.

The three components of the band-passed monogenic signal are computed in the frequency domain using Fast Fourier Transform (FFT). Thus, in order to avoid periodization effects, a symmetrized border of width $D_{\max}$ is added at image boundaries before the FFT computation, and it is then removed in the resulting filtered images.

Finally, a DP algorithm is used to find the path, from the left to the right borders of the image, that maximizes the gain function G which integrates the local symmetry at the path positions:

$$G = \sum_{t=1}^{N} Sym(\boldsymbol{x}_t) \ . \tag{8}$$

where $\boldsymbol{x}_t$ denote the path positions, and N the number of columns in the image.

4. RESULTS AND DISCUSSION

A set of 50 longitudinal B-mode CCA images was used for testing. The images were acquired with a Philips HDI 5000 ultrasound system, and corresponded to 25 different patients. This same image database was used in [4] and [5]. The pixel size was normalized to 0.09 mm, although this normalization is not necessary for the proposed method if the filter parameters are varied accordingly.

Three different manual segmentations of the intima-media region by medical experts were available. The segmentations consisted of the delineations, for each of the two CCA walls (1 and 2), of the boundaries between the lumen and the intima (LI1 and LI2) and between the media and the adventitia (MA1 and MA2), being the adventitia the outermost layer of the vessel wall. Using this ground truth, a CCA was considered a correct detection if all of the points in the detected centerline contour fell within the LI1 and LI2 contours for all the three expert segmentations, and it was considered a wrong detection ofthherwise. Thus, the performance of the method was evaluated as the percentage of images from which the CCA was correctly detected.

The point-to-point vertical distances from MA1 to MA2 were measured as approximations of the local CCA diameters. These diameter values ranged from 4.12 mm to 13.65 mm for the three expert segmentations and all the images. According to this, the $[D_{min}, D_{max}]$ interval was set to $[4, 14]$ mm. Note, however, that the obtained results do not vary when these parameters are varied up to several milimiters.

Figure 2 depicts examples of application of the proposed method for two different input images. In the first example (figure 2(a)) corresponds to a good result, in which the CCA centerline is smoothly delineated avoiding plaques and a clear maximum appears in the DP gain. Instead, the second example (figure 2(e)), which also corresponds to correct CCA detection, presents an additional significant local maximum in the DP gain, corresponding to the sternocleidomastoid muscle. This, on the one hand, illustrates that the proposed symmetry measure is robust to high contrast artifacts, as it is able to detect the overall symmetric shape of the muscle region regardless of the muscle texture. However, on the other hand, it also evidences that the algorithm might have missdetected the CCA under slightly different anatomy or image conditions.

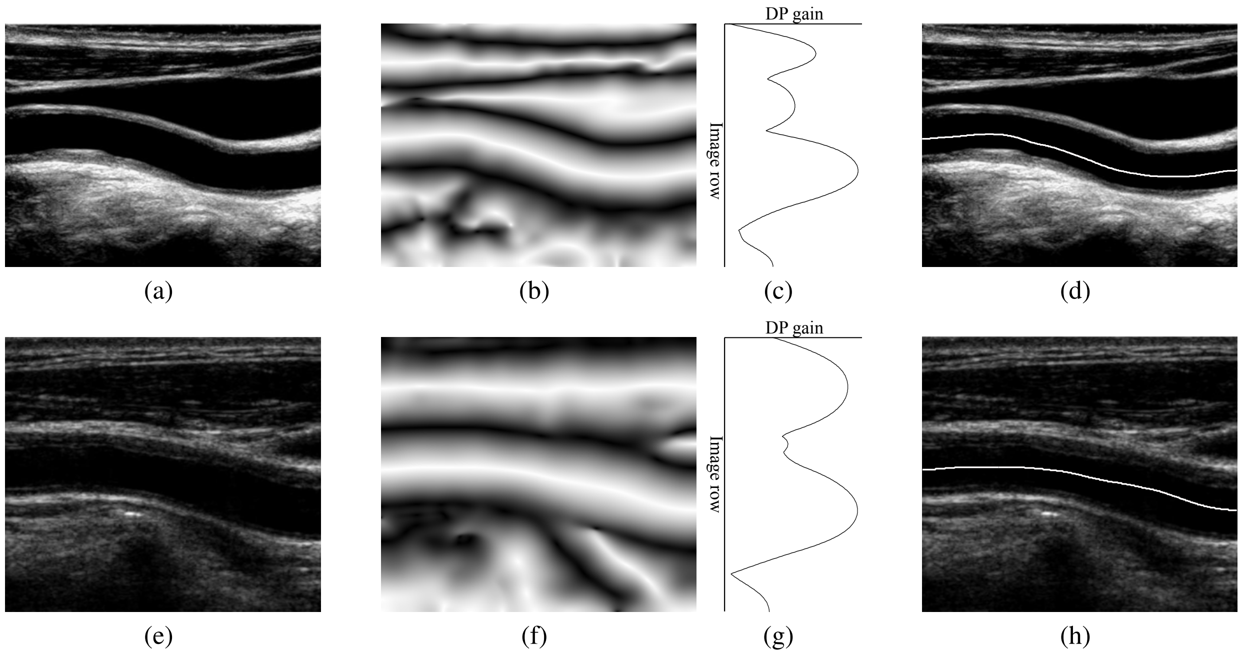

Fig. 2. Result examples. (a)(e) Input images; (b)(f) Local symmetry maps according to equation (1); (c)(g) DP gain of path candidates according to equation (8); (d)(h) Resulting CCA centerlines.

	Additive white Gaussian noise (I_G)						
Proposed	100	100	98	64	54	50	40
Rocha et al. [5]	98	90	44	44	0	4	12
	Additive speckle noise (I_S)						
Proposed	100	100	100	100	100	100	98
Rocha et al. [5]	100	100	98	92	94	92	92
SNR (dB)	30	20	10	0	-10	-20	-30

Table 1. Percentage of correct CCA detections for Rocha et al. [5] and the proposed method with varying noise level.

In order to test the robustness of the method, artificial noise of two different kinds is added to the input images I according to the following noise models:

$$I_G = I + n \,. \tag{9}$$

$$I_S = I + I^{\gamma} n \,. \tag{10}$$

where $n \sim \mathcal{N}(0, \sigma^2)$ is a normally distributed noise factor with zero average. I_G corresponds to additive white Gaussian noise, while I_S corresponds to a model of additive speckle noise, which has been commonly used for modelling the speckle noise on log-compressed ultrasound images with $\gamma = 1/2$ [12].

A performance comparison on CCA detection, for varying levels of image noise, is shown in table 1. It can be observed that, in general, the proposed method outperforms the CCA detection method proposed by Rocha et al. in [5] on images with very high levels of noise. Both methods are less sensible to speckle than to Gaussian noise. This behaviour was expected, as the interesting regions for CCA detection correspond to the lowest image values, and therefore they are less affected by the I_S noise model. Instead, the outperformance of the proposed method is more significant with the images following the additive Gaussian model I_G. In order to understand the relevance of this, note that the ultrasound gain parameters that have been used during the image acquisition were tunned by the ultrasound operator to minimize the noise in the lumen region. The added Gaussian noise can be seen as a simulation of high levels of noise in the lumen region, thus it can be concluded that the proposed method is much less sensible to lumen noise.

5. CONCLUSIONS

A new method for robust CCA centerline detection have been presented in this paper. The method is based on a contrast invariant symmetry measure, which is computed from the local phase information and does not require any prior recognition or segmentation of objects. The experiments show that the method is robust to lumen noise and artifacts. However, additional research is necessary to minimize the confusion with similar structures in the image, which would require the addition of new features, heuristics, and experimentation on larger ultrasound image databases.

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