A novel automatic algorithm for the segmentation of the lumen of the carotid artery in ultrasound B-mode images

André Miguel F. Santos
Instituto de Engenharia Mecânica e Gestão Industrial,
Faculdade de Engenharia, Universidade do Porto,
Rua Dr. Roberto Frias, s/n, 4200 - 465 PORTO, PORTUGAL
E-mail: andremfs52@gmail.com

Rosa Maria dos Santos
Departamento de Neurologia, Hospital São João,
Faculdade de Medicina, Universidade do Porto,
Alameda Professor Hernâni Monteiro, 4200-319, PORTO-PORTUGAL
E-mail: rosampsants2@gmail.com

Pedro Miguel A. C. Castro
Departamento de Neurologia, Hospital São João,
Faculdade de Medicina, Universidade do Porto,
Alameda Professor Hernâni Monteiro, 4200-319, PORTO-PORTUGAL
E-mail: pedromacc@gmail.com

Elsa Azevedo
Departamento de Neurologia, Hospital São João,
Faculdade de Medicina, Universidade do Porto,
Alameda Professor Hernâni Monteiro, 4200-319, PORTO-PORTUGAL
E-mail: elsaazevedo@netcabo.pt

Luísa Sousa
Instituto de Engenharia Mecânica (IDMEC-Polo FEUP),
Faculdade de Engenharia, Universidade do Porto,
Rua Dr. Roberto Frias, s/n, 4200 - 465 PORTO, PORTUGAL
E-mail: lcsousa@fe.up.pt
ABSTRACT

A novel algorithm is proposed for the segmentation of the lumen and bifurcation boundaries of the carotid artery in B-mode ultrasound images. It uses the image contrast characteristics of the lumen and bifurcation of the carotid artery in relation to other tissues and structures for their identification. The relevant ultrasound data regarding the artery presented in the input image is identified using morphologic operators and processed by an anisotropic diffusion filter for speckle noise removal. The information obtained is then used to define two initial contours, one corresponding to the lumen and the other one regarding the bifurcation boundaries, for the application of the Chan-Vese level set segmentation model. A set of longitudinal ultrasound B-mode grayscale images of the common carotid artery was acquired using a GE Healthcare Vivid-e ultrasound system. The results reveal that the new algorithm is effective and robust, and that its main advantage relies on the automatic identification of the carotid lumen, which overcomes the known limitations of the traditional algorithms.

KEYWORDS: Medical imaging; Ultrasound imaging; Internal and external carotid arteries; Image segmentation; Chan-Vese model.
1. Introduction

The common carotid artery (CCA) is the artery that supplies the human head, specifically the front part of the brain and neck, with oxygenated blood. Like other arteries, it is known for its paired structure: one for left part (with origin in the aortic arch) and another one for the right part of the human body (with origin in the neck). The CCA has a bifurcation in the neck, originating the internal common carotid artery (ICA) and the external common carotid artery (ECA), specifically in the brachiocephalic trunk, and containing a small thoracic portion (Molinari et al., 2007; Rocha et al., 2005, 2010 and 2011). When compared to the ECA, the ICA is characterized by a lower resistance to waveforms and its lateral and posterior position. The ECA extends anteriorly and medially to the ICA, supplying the face, scalp, neck and tongue with blood, being also characterized by its high resistance to waveforms. Alike other arteries supplying blood from the heart, the carotid is in risk of developing several diseases, in particular, atherosclerosis, known as the “hardening of the artery” (Rocha et al., 2005, 2010 and 2011).

Atherosclerosis is an inflammatory disease, dominant in the blood vessels, consequent upon the accumulation of fatty substances, mainly lipoproteins and cholesterol in vessel walls. This accumulation is known as “plaque” and causes the narrowing, i.e., the stenosis, of the vessels, decreasing the blood flow (Finn et al., 2010; Maton et al., 1993). In the case of the carotid artery, the bifurcation and the internal carotid artery are the structures more susceptible to atherosclerosis due to the presence of high hemodynamic forces between them. According to recent studies in clinical manifestations of cardiovascular diseases, atherosclerosis has prevalence in two of three men and one in two women after the age of 40 and is characterized as a potential precursor in approximately 60% of deaths (Jennifer et al., 2009; Latifoglu et al., 2007).

Non-invasive ultrasound imaging has been widely used in the diagnosis of cardiovascular diseases, especially for the evaluation of the intima-media thickness, by assessing the distance between the lumen of the carotid artery, i.e., where the blood flows, and the inner boundary of the adventitia. This measure, and consequent diagnosis of some cardiovascular diseases, particularly atherosclerosis, is performed acquiring B-mode ultrasound images, which requires the detection in these images of not only the lumen boundaries, but also of the near and far adventitia (Stein, 2008; Hanbay, 2009; Serna-Morales et al., 2012). Therefore, it has been an increasing interest in the automatic and robust
segmentation of the adventitia and lumen boundaries in ultrasound B-mode images of the common carotid artery. According to Halenka (1999), the carotid adventitia appears in this type of images as two almost parallel lines, known for their echogenic characteristics and separated by a hypoechogenic region, known as the “double line” pattern.

Ultrasound B-mode imaging is the most widely used technique in image-based cardiovascular diagnosis due to the fact of the carotid being a superficial artery and quite suitable for this type of imaging. However, it presents several difficulties, specifically regarding the segmentation of the structures imaged, due to typical image characteristics, such as low contrast, speckle noise, echo shadows and artifacts, which usually lead to images of very poor quality and require the interaction of an expert user for their analysis (Wagner et al., 1983; Dutt et al., 1994). In ultrasound imaging, the speckle noise is presented in echogenic regions in the form of granular texture, and its intensity is related to the scanned tissue. Some works found in the literature have been using different statistical distributions, like, for example, the Rayleigh and K distributions (Wagner et al., 1983; Sarti et al., 2005; Dutt et al., 1994; Molthen et al., 1993), in order to attenuate this granular speckle noise in non-compressed signals. However, most of the signals actually acquired in ultrasound imaging and analyzed in medical practice are log-compressed signals, which are unsuitable for the application of statistical distributions due to their reduced intensity range. In 2006, Noble and co-workers (Noble et al., 2006) described the success of texture segmentation techniques in the classification of breast masses and of liver and kidney tissues in ultrasound images. However, the segmentation of the common carotid artery tends to be more difficult due to the extremely low perception of this structure in usual ultrasound B-mode images.

Ultrasound imaging represents extreme and complex challenges to the automatic segmentation algorithms, as for the reasons aforementioned, but also for the amount of boundary edges that may be omitted in the acquired images, leading to gaps in the computer identified, i.e., segmented, boundaries. Additionally, the scan device may respond differently to dissimilar anatomical structures and reveal distinguished anatomic features and, due to their shape variability among subjects, a model-based segmentation procedure is not appropriate for their successfully segmentation (Rocha et al., 2005, 2010 and 2011). Despite these difficulties, as mentioned before, there has been an increasing interest in ultrasound imaging-based medical diagnosis, as a consequence of the technological advances verified in this imaging modality, especially regarding its non-invasive characteristic and affordability.
The segmentation of common arteries in usual ultrasound B-mode images can be achieved by two main steps: i) the definition of a region of interest (ROI) regarding the carotid artery in the input image; and ii) the detection of the boundaries of the artery lumen, intima and adventitia in the ROI defined. For this reason, we may consider that these two steps are strongly interconnected, since the correct detection of the artery walls is strictly dependent on the suitable definition of the ROI.

The first approaches for the segmentation of carotid boundaries in ultrasound B-mode images occurred between 1992 and 1994 (Touboul et al., 1992; Gariepy et al., 1993; Chan, 1993; Selzer et al., 1994; Gustavsson et al., 1994). At this epoch, the computing and image processing and analysis techniques were not as advanced as today, reason for why all these works include a previous manual segmentation of the carotid boundary in order to achieve the final segmentation that was accomplished based on only local image characteristics: echo and gradient intensities. Despite their importance, these segmentation approaches present disadvantages: firstly, the amount of time required, mainly because of the required initial manual segmentation; secondly, the identification of the carotid boundaries cannot be correctly achieved based on a single image characteristic, since it can be strongly affected by speckle noise, low contrast and discontinuities in the carotid boundaries (Molinari et al., 2007; Rocha et al., 2005, 2010 and 2011).

In 1996, Kozich proposed a new approach based on the minimization of a cost function by dynamic programming. Unlike the segmentation algorithms proposed by Touboul et al. (1992), Gariepy et al. (1993), Selzer et al. (1994), Kozich (1996), Abdel-Dayem et al. (2005 and 2005a). The Kozich’s approach integrates multiple image characteristics into a cost function. Thus, not only the echo and the gradient intensities were taken into account in the segmentation, but also a local constraint was included in order to originate smoothed segmented carotid boundaries. Each image characteristic and the constraint addressed in Kozich’s work is represented by a cost term, usually a constant expressing the importance or, in other words, the weight of each image characteristic or constraint in the evaluation of the segmentation contour. Because of these cost terms, when in comparison with the solutions developed in previous studies, the one proposed by Kozich led to more robust segmentations with much lower human intervention and consequently, considerably less time consuming. However, it also presents certain disadvantages: its performance is directly affected by the presence of plaques, and therefore, is unsuitable for the correct detection of the carotid boundaries in patients with atherosclerosis; also, with this type of approached, some human intervention is frequently needed to improve the segmentation obtained especially when the input image is of low quality. Besides, it is also
required a demanding search for the optimal weights of each image characteristic and constraint, as they have often to be tuned differently for input images acquired using distinct ultrasonic imaging devices or image acquisition parameters.

More recent studies have attained considerable improvements using deformable models that overcome some of the aforementioned problems. These models are focused on the optimization of a cost function in the search of a compromise among the solutions proposed by Kozich (1996), Selzer et al. (1994), Gariepy et al. (1993) and Touboul et al. (1992), which typically consists in the definition of the smoothness and continuity of the segmentation contour at adjacent points of the model by means of internal forces with the combination of external forces that attract the contour towards the boundaries of the desired structures. Deformable models can be divided into main two classes: parametric models, comprising the active contours, also known as snakes; and geometrical models, usually known as level set models (Ma et al., 2010 and 2011).

There are studies, especially those developed by Cheng et al. (1999 and 2002), Schmidt et al. (2001), Jiaoying et al. (2011), Matsakou et al. (2011), Izquierdo et al. (2011) and Yang et al. (2011), for the segmentation of the common carotid artery based on active contours. However, the application of these models can also be found in the segmentation of other structures in ultrasound imaging, such as the bladder and liver, as well as in other imaging modalities, like magnetic resonance imaging and computerized tomography (Ma et al., 2010). Despite the success cases, usual parametric snakes are not the best choice for an automatic and accurate segmentation of the carotid artery wall, particularly, because the propagation forces of these models are based on image intensity gradient information, often stuck in regions associated to local minimal solutions, and are not robust to speckle noise, false edges or boundary patches at which the image intensity gradient is extremely low or even null (Cheng et al., 1999 and 2002; Ma et al., 2010 and 2011). Also, parametric snakes normally require manual initialization, with the definition of an initial contour closest to the carotid boundaries, and constant human intervention to improve the segmentation results (Cheng et al., 1999 and 2002; Loizou et al., 2007; Ma et al., 2010 and 2011).

On the other hand, geometrical models present several advantages in relation to parametric models: simple generalization when are transformed from two spatial dimensions to three or even higher dimensions; easy handling of topological changes in the propagating fronts, as in cases where occur split and merge of contours. There are also several works for the segmentation of the common carotid artery based on geometrical models of which it can be referred those addressed by Petroudi et al.
Petroudi et al. (2011) developed an algorithm that uses parametric snakes, combined with active contours without edges, also known as the Chan-Vese geometrical deformable model, in order to detect the intima-media boundary of the carotid. On the other hand, Cheng et al. (2011) accomplished a comparison among three different geometric models in the detection of atherosclerosis carotid plaques: the geodesic active contour (GAC) model, the Chan-Vese model and the localizing region-based active contour model. From this comparison, it was concluded that when the initial contour of the deformable model was close to the boundary of interest, the localizing region-based model was the most efficient. The works of Petroudi et al. (2011) and Cheng et al. (2011) confirm that geometric models are able to detect the carotid wall boundaries proficiently, not only in images of healthy patients, but also in images of patients with atherosclerotic plaques. The segmentation time required by this type of approach is significantly lower than the one required by the parametric snakes, making it appropriate for medical diagnosis routine.

In this paper, a novel computational algorithm is proposed for the automatic identification of the lumen region and consequent segmentation of the lumen boundaries in longitudinal ultrasound B-mode images of the right carotid artery. The algorithm searches for the hypoechogenic characteristics, i.e., for the image pixels with low contrast, of the lumen region of the CCA in the input image, based on the mean and standard deviation of the pixels’ intensity. Afterwards, the lumen and bifurcation boundaries of the CCA are identified using the Chan-Vese geometrical model. The algorithm is robust to speckle noise, does not require human interaction and adjusts adequate the segmentation contours to the lumen boundaries represented in the input B-mode ultrasound images.

The developed algorithm is described in the next section. Afterwards, experimental results are presented and discussed, including the validation of the results obtained by our algorithm. Finally, the conclusions are presented and future work perspectives are pointed out.

2. Algorithm developed

Our new computational algorithm starts by detaching the ultrasound image data to be analyzed from the other image features, such as interface menus, logos and patient data. Then, it calculates two bi-dimensional histograms (2D Histograms) representing for each image pixel the mean and standard deviation (SD) values of the neighbor pixels’ intensity. Afterwards, a Gaussian low-pass filter is applied for speckle noise reduction, and the smoothed image and the two 2D histograms are used to
identify the lumen region of the carotid artery based on its hypoechogenic characteristics. The algorithm output is the detection of the pixels of the lumen and bifurcation structures represented in the input image. The main steps of our algorithm are described in detail in the following sections.

2.1. Identification of the image area

In the first step of our algorithm we intend to eliminate any possibility of detecting image features that are not part of the ultrasound data to be analyzed. This procedure also reduces the time required in the posterior steps of image processing and segmentation.

The adopted procedure in this step consists in the definition of a rectangular area involving the carotid artery (Golemati et al., 2007). Hence, four points are identified by accomplishing: (i) Morphological opening of the input image, using a circular structuring element to reduce unwanted objects such as characters; (ii) Image binarization with the first 15% of the histogram width, as such, the areas outside the region of the ultrasound data are discarded; (iii) The points corresponding to the first and last nonzero lines and columns are identified in the binarized image. These points are the vertices of the rectangular area in which all the further tasks of image processing and segmentation are performed.

Figure 1 shows an example of this first step of our algorithm and one can observe an example of a rectangular area enclosing the ultrasound image data that was automatically detected for further analyzed.

<insert Figure 1 around here>

2.2. Lumen region identification

The procedure adopted in this step is based on the study performed by Molinari et al. (2007) to develop a computer-based tracing of the carotid artery. According to these authors, the characteristics of the carotid in ultrasound images can be addressed using a model of variable intensity distributions over the carotid structure. It is precisely this idea that is used here for the automatic identification of the lumen of the carotid artery: pixels belonging to the lumen region of the carotid artery are those characterized by low mean intensity and also low standard intensity deviation.
In order to accomplish the lumen region identification in the input image, two bi-dimensional histograms are built: For each pixel of the image to be analyzed, it is calculated the mean and standard deviation intensity values within a neighborhood; both values are then normalized and grouped into a set of classes equally spaced. A row-wise intensity distribution is built for each column of the input image to be analyzed so the pixels corresponding to the carotid artery can be identified. However, the image must be previously processed for speckle noise removal and attenuation of the high intensity noisy pixels.

As mentioned previously, pixels belonging to the lumen region of the carotid artery are characterized by their low mean intensity and standard deviation values. Having this into consideration, those pixels are identified in the intensity distribution built as those corresponding to the minimum values. These values are frequently between the local maxima and the one corresponding to the near and far adventitia layers, or to the walls of the ICA and ECA; alternatively, in the interval between these two structures, if it is considered a column of the image containing pixels belonging to the carotid bifurcation.

Based on Molinari et al. (2007) approach, the identification process starts from the bottom of the image to be analyzed, i.e. at the highest row index, moving upwards along the rows in order to identify the first pixel of the first maxima that possibly corresponds to the far adventitia of the carotid, usually associated to the brightest structure in the ultrasound image of the carotid artery. Having this first pixel estimated as possibly belonging to the far adventitia, the algorithm continues the lumen identification moving upwards and searching for a pixel possible belonging to the lumen region. Taking into account the row of the pixel that corresponds to the far adventitia, the pixel possibly belonging to the lumen is the closest minima after the far adventitia pixel. Also, its neighborhood mean intensity and standard deviation intensity values must match the chosen criteria for the calculation of the two bi-dimensional histograms.

Figure 2 demonstrates an example of the identification of the lumen region of the CCA in an ultrasound image of the carotid artery achieved by our algorithm. Figure 2a shows the cropped image after the application of the Gaussian low-pass filter (using a kernel size of 40x40 pixels and $\sigma=10$). All the possible candidates for the lumen region of the CA are represented in white in the binary image presented in Figure 2b.

<insert Figure 2 around here>
2.3. **Lumen edges identification**

Having obtained the correct identification of a group of pixels belonging to the lumen of the carotid artery in the previous step, the definition of a suitable mask for a posterior level set-based segmentation is possible. However, some processing techniques must be applied on the image in order to assure the robustness of the segmentation process. Hence, an anisotropic diffusion filter is applied on the image to attenuate the high amount of speckle noise that is commonly present; the filter proposed in Perona and Malik (1990) with a 2D network structure of 8 neighboring nodes for diffusion conduction was chosen to accomplish such attenuation. Then, it is applied a morphological closing operator in order to merge small “channels” and “gaps”. Afterwards, an image threshold is performed using an intensity value that is defined based on the image histogram width. This threshold results in a binary image on which is then applied the Sobel gradient operator in order to identify the edge pixels. The binary image obtained combined with the information relevant to the pixels that belong to the lumen region of the carotid allow the identification of the edge pixels corresponding to the superior and inferior walls of the carotid of the carotid artery.

Figure 3 demonstrates this step of our algorithm in the identification of lumen edge pixels: Figure 3a illustrates the cropped image in grayscale, here with pixel intensities varying from 0 (zero - black) to 255 (white), and Figure 3b shows the same image after the application of the anisotropic filter proposed by Perona and Malik (1990) for speckle removal. After the application of a threshold with a value correspondent to the first 15% of the histogram width, the image illustrated in Figure 3c was obtained. In Figure 3d, the pixels identified as belonging to the superior and inferior walls of the CA and to its bifurcation in the binary image resultant from the Sobel edge detector are represented in green. Finally, Figures 3e and 3f illustrate the two masks that define the initial contours for the posterior Chan-Vese level set model-based segmentation.

<insert Figure 3 around here>

2.4. **Segmentation of the lumen and bifurcation boundaries**

The Chan-Vese level set model is used here to detect the lumen boundaries of the carotid artery starting with the two masks built in the previous step as the two initial contours. As already mentioned, this
model is well known for its high flexibility, accuracy and robustness. Besides, as a region-based model not based on gradient information, it is advantageous in cases with boundary gaps, as usually occur in ultrasound B-mode images of the carotid artery.

The segmentation performed by our algorithm of both the lumen and bifurcation boundaries is based on the scheme developed by Lanktom and Tannenbaum (2008), which defines a local-based framework wherein the segmentation contours move according to the internal energy defined in the Chan-Vese approach using a constant intensity model. The framework starts with an initial contour, here, one of the two masks defined in the previous step, and the definition of a signed distance function $\phi$ defined as:

$$\phi = E_d(m) - E_d(1-m) + \left(m - \left(\frac{1}{2}\right)\right),$$

where $m$ represents the initial contour, and $E_d$ is the Euclidean distance transform of the considered binary image, assigning for each pixel the distance to the nearest nonzero value.

Let $C$ be a closed contour as the zero level of $\phi$, i.e., $C = \{x \mid \phi(x) = 0\}$, which its interior is defined as:

$$H\phi(x) = \begin{cases} 1, & \phi(x) < -\epsilon \\ 0, & \phi(x) > \epsilon \\ \frac{1}{2} \left[1 + \frac{\phi}{\epsilon} + \frac{1}{\pi} \sin \left(\frac{\pi \phi(x)}{\epsilon}\right)\right], & \text{otherwise} \end{cases}$$

Similarly, the exterior of $C$ can be defined as:

$$G\phi(x) = \left[1 - H\phi(x)\right].$$

Having $x$ and $y$ as independent variables representing a single point in the domain $\Omega$ of an image, the following equation represents a function used to mask local regions of interest (ROI), assuming the value 1 (one) when the point $y$ is within a ball of radius $r$ and centered at $x$ and assuming the value 0 (zero) otherwise:

$$B(x,y) = \begin{cases} 1, & |x - y| < r \\ 0, & \text{otherwise} \end{cases}$$

Using Equation (4), the energy functional can be defined as:

$$E(\phi) = \int_{\Omega_1} \delta\phi(x) \int_{\Omega_2} \delta\phi(y) B(x,y) F(1(y),\phi(y)) dy dx,$$
where $\delta \phi(x)$ prevents the development of new contours by ensuring that $C$ does not undergo sudden changes in its shape. On the other hand, it will allow certain parts of the contour $C$ to separate or combine within each other. Each point $x$ in this term is masked to $B(x, y)$, ensuring that only the local information surrounding $C$ is used. Equation (5) includes also a generic internal energy function $F$ that assures the connectivity of adjacent contour points.

The smoothness of the contour $C$ is assured through the application of a regularization term that penalizes the arc length. The weight of this penalty term is controlled by the parameter $\lambda$ in the equation of the energy functional:

$$E(\phi) = \int_\Omega \delta \phi(x) \int_\Omega B(x, y) F(I(y), \phi(y)) dy dx + \lambda \int_\Omega \delta \phi(x) \nabla \phi(x) dx.$$  \hspace{1cm} (6)

Lanktom and Tannenbaum (2008) tested the introduction of specific energies into the generic framework, including the Chan-Vese energy that is expressed as:

$$E_{CV} = \int_\Omega H\phi(y)(I(y) - u)^2 + (1 - H\phi(y))(I(y) - v)^2 dy,$$  \hspace{1cm} (7)

where $u$ and $v$ are the global mean intensities of the inner and outer regions of $C$ given as:

$$u = \frac{\int_\Omega H\phi(y)I(y) dy}{\int_\Omega H\phi(y) dy},$$  \hspace{1cm} (8)

$$v = \frac{\int_\Omega (1 - H\phi(y))I(y) dy}{\int_\Omega (1 - H\phi(y)) dy}.$$  \hspace{1cm} (9)

The corresponding Chan-Vese internal energy function can be expressed in terms of the local mean intensities $u_x$ and $v_y$, instead of $u$ and $v$, resulting:

$$F_{CV} = H\phi(y)(I(y) - u_x)^2 + (1 - H\phi(y))(I(y) - v_y)^2,$$  \hspace{1cm} (10)

$$u_x = \frac{\int_\Omega B(x, y)H\phi(y)I(y) dy}{\int_\Omega B(x, y)H\phi(y) dy},$$  \hspace{1cm} (11)
\[
\nu_x = \frac{\int_{\Omega} B(x,y)(1-H\phi(y))I(y)\,dy}{\int_{\Omega} B(x,y)(1-H\phi(y))\,dy}.
\]

Equation (10) can be substituted into the energy functional of the framework given by Equation (6) defining a localized energy. However, to obtain the curvature flow regularization term, Equation (10) needs to be derivated:

\[
\nabla_{\phi(y)} F = \delta \phi(y) \left( \left( I(y) - u_x \right)^2 - \left( I(y) - v_x \right)^2 \right),
\]

\[
\frac{\partial \phi(x)}{\partial t} = \delta \phi(x) \int_{\Omega} B(x,y) \nabla_{\phi(y)} F(I(y), \phi(y))\,dy + \lambda \delta \phi(x) \text{div} \left( \frac{\nabla \phi(x)}{\sqrt{\nabla \phi(x)}} \right) \Leftrightarrow \delta \phi(x) \int_{\Omega} B(x,y) \delta \phi(y) \left( \left( I(y) - u_x \right)^2 - \left( I(y) - v_x \right)^2 \right)\,dy + \lambda \delta \phi(x) \text{div} \left( \frac{\nabla \phi(x)}{\sqrt{\nabla \phi(x)}} \right). \tag{14}
\]

The Chan-Vese energy function has its minimum value, when the inner and outer regions of \( C \) are closer to the global mean intensities \( u \) and \( v \); while in the localized version, the minimum value is obtained when they are closer to the local mean intensities \( u_x \) and \( v_x \).

For the segmentation of the bifurcation boundaries, a mask as the one illustrated in Figure 3e is chosen as the initial contour. The level set model must be enough flexible in order to reach the limit of the bifurcation walls. On the other hand, for the segmentation of the lumen boundaries, a mask as illustrated in Figure 3f is defined as initial contour and the development of the contour \( C \) has to be properly controlled and somehow attenuated in order to prevent its development towards other structures near the carotid artery. The circular ROI used in the model has also to be chosen narrow in order to prevent larger intensity variations during the contour development along the Chan-Vese energy minimization process.

Figure 4 demonstrates the results of this step of our algorithm starting with the initial contours defined by the masks shown in Figures 3e and 3f: Figure 4a shows the segmentation obtained for the bifurcation of the carotid artery boundaries, and Figure 4b reveals the segmentation obtained for the lumen boundaries.

<insert Figure 4 around here>
2.5. Smoothing of the final contours

The smoothing of each final contour is done projecting all the contour’s points onto local regression lines: For each point of the contour, 8 neighboring points lying on the contour are chosen of each side and the regression line is computed. Posteriorly, the point is projected on this line. This procedure is repeated for all points of the contour.

3. Experimental results

A set of 15 longitudinal B-mode images of the CCA was acquired in 256 gray levels using a GE Healthcare Vivid-e ultrasound system (GE Healthcare, United Kingdom). All the images include part of the CCA and the bifurcation that separates the CCA into the ICA and ECA. In order to achieve high robustness in the acquisitions, i.e., images with high contrast and low speckle noise, the parameters of the scanner were adjusted according to the characteristics of each case under evaluation. The parameters of the proposed algorithm were defined on an experimental basis and maintained constant along the experimental image set.

Figure 5 shows the smoothed contours obtained by our algorithm for the lumen and bifurcation boundaries for 6 of the 15 B-mode ultrasound images randomly chosen. From a visual based analysis, one can conclude that the segmentation results of our algorithm are very good.

<insert Figure 5 around here>

For a quantitative assessment about the quality of the segmentation results obtained by our algorithm, the same set of 15 B-mode ultrasound images was manually segmented by a specialist on this medical exam. This manual segmentation consisted in the definition of a set of border points on the lumen and bifurcation of the carotid artery in each image under evaluation. From the points manually defined, the correspondent contour of the carotid artery was defined by cubic interpolation and then smoothed, Figure 6. Afterwards, the evaluation of the our algorithm was performed adopting two different procedures: one focused on area-based metrics, by comparing the area enclosed by the contour obtained by the computational algorithm with the one obtained by the manual segmentation; and the second one focused on a distance-based metric of the maximum distance from the points that were defined by the specialist with the closest ones in the contour obtained by the algorithm, through the definition of the normal lines that intersect the correspondent points in the contour manually defined.
The used area-based metric procedure is based on the approach proposed by Guo et al. (2011), according to which the evaluation is achieved by performing a pixel-analysis of true positives ($TP$), false positives ($FP$), true negatives ($TN$) and false negatives ($FN$), and computing the parameter related to the area overlapped ($AO$) by the two contours:

$$Area\ Overlapped\ (AO) = \frac{TP}{TP + FP + FN} \times 100.$$  \hspace{1cm} (15)

As such, the parameter $AO$ is proportional to the area within the contour obtained by the computational algorithm that is correctly identified relatively to the one within the manual segmentation. The values found for this parameter regarding the images under study are shown in Table 1. From the values presented in this table, one can conclude that the values of $AO$ vary between 94.64% and 98.89%, being the mean value equal to 96.78%.

Concerning the distance-based metric, firstly, it is found the number of points that are coincident on the two contours: the one resultant by the automatic segmentation and the one manually defined. Then, for each non-coincident point of the manual contour, it is defined the straight line and passes through that point and is normal to the contour. The definition of this line facilitates the identification of the correspondent point in the related contour obtained by our computational algorithm, and the consequent calculation of the distance between correspondent points, i.e., the distance error ($e_i$). With this approach, the maximum and mean errors can be determined, Figure 7 and Table 1.

4. Discussion

The proposed computational algorithm provides the fully automatic segmentation of the arterial lumen and bifurcation sections of the carotid artery in longitudinal ultrasound B-mode images. Its main advantage relies on the automatic identification of the carotid lumen based on its hypoechogenic characteristics, which overcomes the limitations of the traditional computational solutions. In our experimental data set, the algorithm demonstrated to be highly efficient, robust and accurate.
As can be verified in Figure 4b, the application of the anisotropic diffusion filter proposed by Perona and Malik (1990) is satisfactory, allowing the correct distinction of the carotid artery from other near vessels and small features, which greatly facilitates the posterior detection of the carotid boundaries for the definition of the initial contours to be used in the application of the Chan-Vese-based geometrical segmentation model. In all tested images, all these initial contours were successfully defined, i.e., the contours were always defined very close to the true lumen and bifurcation boundaries of the carotid artery, which is an advantage of the proposed algorithm, as the robustness of the posterior segmentation process is significantly increased.

Regarding the results of the proposed algorithm (Figure 5), we can consider them to be very satisfactory, as there was a general correct identification of the boundaries of the carotid artery lumen and bifurcation. The best segmentation was achieved in the image in Figures 5a and 6a since, although it is the image with the lumen, intima-media and adventitia boundaries best defined in terms of contrast, hypoechoic characteristics and noise, the obtained contours are highly smoothed and perfectly adjusted to the carotid artery boundaries. The bifurcation was also very well defined in this image. The same was not observed for the carotid in Figures 5d and 6d; in this image, it is clear that the carotid artery bifurcation is poorly contrasted and has considerable noise and gaps. However, although the complexity of this image, the segmentation obtained by our algorithm can be globally considered as satisfactory.

The images tested were manually segmented by an expert (Figure 6), and two quantitative comparisons against the segmentations obtained by the automatic segmentation algorithm were performed (Table 1). The results obtained (Table 1), with a mean area overlapped of 96.73%, and a maximum distance of 9.84 pixels between the non-coincident points of the contours obtained automatically and manually, confirm the good quality of the proposed segmentation algorithm. The overall error regarding the distances between the non-coincident points of the contours automatically and manually obtained was very low, with a maximum value equal to 1.419 pixels, which proves that the contours detected by the automatic segmentation algorithm were very similar to the ones manually defined by the expert.

5. Conclusions and future work

A new carotid segmentation algorithm was developed based on cervical ultrasonography. The main advantage of the algorithm relies on the automatic identification of the carotid lumen, which overcomes the limitations of the traditional solutions.
As future works, our algorithm will be tested in more B-mode ultrasound images, including images of carotid arteries of patients with severe atherosclerosis. Additionally, with additional images acquired by computerized angiography, we expect to build accurate 3D models for representative carotid arteries that can be posteriorly deformed and adjusted to patient’s data previously segmented by our algorithm from the patient’s carotid artery lumen and bifurcation in ultrasound B-mode images. This will allow the achievement of more truthful 3D models for patients’ carotid arteries from B-mode ultrasound images that can be used, for example, in more realistic biomechanical simulations.

Acknowledgments

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References


TABLE CAPTIONS

Table 1: Results of the comparisons performed between the automatic and manual segmentations obtained for the 15 B-mode ultrasound images under analysis.
FIGURE CAPTIONS

Figure 1: Automatic identification and consequent detaching of the ultrasound data to be further analyzed: (a) Original image; (b) Image resultant of the morphological opening; (c) Resultant threshold image overlapped with the rectangular area defined to crop the original image found based on the first and last nonzero pixels in the lines and columns; (d) Resultant image with the desired ultrasound image data.

Figure 2: Automatic identification of the lumen region of the common carotid artery in one B-mode ultrasound image: (a) Image to be segmented after the application of a Gaussian low-pass filter; (b) The pixel candidates for the lumen region of the common carotid artery (in white).

Figure 3: Lumen edges identification: (a) Image to be segmented in grayscale; (b) Resultant image after the application of an anisotropic diffusion filter for noise speckle removal; (c) Image after the application of the Sobel edge detector; (d) Image to be segmented overlapped with the pixels identified in image (c) as belonging to the superior and inferior walls of the carotid artery (in green); (e and f) The two binary images defining the masks found to be used in the level set-based segmentation.

Figure 4: Segmentations obtained using the geometric level set model based on the Chan-Vese energy minimization for: (a) the carotid artery bifurcation boundaries; (b) the carotid artery lumen boundaries;

Figure 5: Segmentations obtained by our algorithm for carotid artery lumen and bifurcation boundaries in 6 B-mode ultrasound images.

Figure 6: Contours obtained by an expert (in green) and our segmentation algorithm (in red) in the 6 B-mode ultrasound images shown in Figure 5.

Figure 7: Example of a non-coincident point and calculation of the associated distance: (a) Contour manually defined draw (in green) and the non-coincident point (in yellow); (b) Definition of the straight line passing at the non-coincident point and normal to the contour manually defined; (c) Difference between the contours manually and automatically obtained at the non-coincident point; (d) Enlargement of the rectangular area identified in red in image (c).
## TABLES

### Table 1

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FIGURES

Figure 1

(a)  
(b)  
(c)  
(d)

Figure 2

(a)  
(b)
Figure 7