AUTOMATIC SEGMENTATION IN TRANSVERSE ULTRASOUND B-MODE IMAGES OF THE CAROTID ARTERY

SEGMENTAÇÃO AUTOMÁTICA DE IMAGENS DOPPLER TRANSVERSAIS MODO-B DA BIFURCAÇÃO CAROTÍDEA

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ABSTRACT

Ultrasound imaging is extremely important for the assessment of disease severity in the carotid arteries. The high complexity of irregular structures in transverse ultrasound images of abnormal bifurcation of the common carotid artery brings tremendous difficulty to segmentation and identification of vulnerable atherosclerotic plaques. Automatic algorithms for image segmentation provide results minimizing the variability caused by subjective decisions and different operators. The proposed algorithm for automatic segmentation of B-mode transverse images of the carotid bifurcation facilitates structure selection for further analyses and provides an evaluation performance of the methodology and a means for comparing different algorithm settings. Patient-specific Doppler imaging is used to illustrate the new developed methodology.

Keywords: Doppler ultrasound, carotid artery bifurcation, B-mode transverse image, segmentation algorithm, filters applications.

RESUMO

O exame Doppler das carótidas é extremamente importante para a avaliação da severidade da doença arterial obstrutiva. O registo de imagens ultrassom em modo-B da bifurcação da artéria carótida comum permite guardar informação pertinente para avaliação futura. Algoritmos automáticos de segmentação de imagem fornecem resultados minimizando a variabilidade causada por decisões subjetivas e operadores diferentes. As imagens transversais de artérias obstruídas apresentam estruturas irregulares de elevada complexidade introduzindo dificuldades acrescidas quer na segmentação do lúmen quer na identificação das placas ateroscleróticas vulneráveis à rotura. A proposta de um algoritmo inovador para segmentação automática de imagens transversais em modo-B da bifurcação carotídea permite a identificação dessas estruturas permitindo a construção de modelos arteriais para análise futura. A comparação de diferentes configurações de algoritmo e o seu desempenho são avaliados utilizando um registo de imagens ultrassom em modo-B de um exame Doppler das carótidas.

1. INTRODUCTION

Image segmentation is a particular procedure for achieving feature identification and identification of structures in medical images is crucial, due to the facility brought by automatisms of technological improvement. In fact, segmentation of images representative of the bifurcation of the common carotid artery allows a better identification of certain anomalies, such as atherosclerosis and other cardiovascular diseases [1], which affects people's lives, drastically. Recent studies have being presented, in particular, for analyzing the transverse representation of this bifurcation, but this can be seriously complicated, due to the irregularity of atherosclerotic plaques, provoking non-circular shapes for lumen transverse representation and to low image quality. Despite of this situation, it is possible to review some aspects that medical specialists use for fastest identification, and 'tips' that images leave, according with the manner how they are produced, which can be apply incorporated in the methodology to address these problems.

The study presented here complements an initial proposal of a methodology for the segmentation of the lumen and bifurcation boundaries of the carotid artery in B-mode ultrasound images [1]. Artery segmentation as opposed to vessel segmentation considers the arterial wall resistance to collapse. The new methodology for automatic segmentation of B-mode transverse images of the carotid bifurcation introduces a new index methodology (circularity, irregularity and centrality) in the segmentation process aiming better accuracy in the selection of the correct artery structure as compared with previously published developments.

2. METHODOLOGY

For the image segmentation, it was applied a binary methodology based on a luminance limit value. Binary images contain only black and white pixels. The output of an image segmentation algorithm is often based on a binary image, where the white pixels represent the object of interest and the black pixels represent the background. Therefore, after reading the original input image, or posteriorly, after the possible filter application, a new binary image is built assigning a value 0 (black) to all pixel grey ton values higher than that limit value and, logically, assigning value 1 to all other cases, this value 1 is converted to value 255 (white), on the occurrence of grey scale. The segmentation on the original image consists in marking, with a different ton value, within other possible values of the gray scale, the pixels making the separation between all regions with 0 and all regions with 255 of the black and white image. Different methods have been proposed for selecting the luminance limit value, such as making a histogram with all pixel values, and selecting a percentile 5 limit as an objective value.

Assuming images are grey toned, the segmentation method consists in memorizing pairs of pixels that assure the connection, in terms of immediate neighborhood, between all regions with 0 and all regions with 255 of the black and white image, respectively. Starting from pixels of maximum value (white pixels), every neighbor pair is scrutinized. If this pair has different colors (one black and one white) segmentation is performed and the black pixel becomes a reference pixel. Figure 1 details such a process. Then the analysis continues repeating the described process by scrutinizing the next neighbor pair of the previous white pixel. The process is repeated for all white pixels of the image.

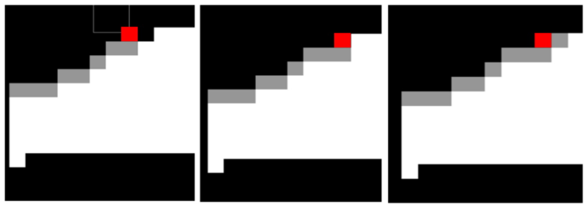

Fig 1 - Segmentation process: the red square identifies the black reference from the previously analyzed pair.

This methodology of pixel reference is really important due to the possibility of regions separated by only one pixel. However, multiple scenarios have to be taken into account, like for example, the possibility of non-existence of pairs connecting white and black regions. This can only occur if all pixels in the neighborhood are black or all white. In case of a white pixel with all pixels in the neighborhood being black this means that the segmented region is constituted just by one pixel, so this pixel is segmented and it can pass to another region. On the other hand, white ones in the middle of other non-black pixels, then whites are inside a white region and it cannot be accounted for the segmentation procedure. Besides, previously analyzed pixels that have to be accounted for a black region inside a white one, they are turned to white again and the process is the same. So, what really counts are the black references.

The application of Gaussian filters introduces advantages due to the significant reduction of image noise. Filter application is just efficient if the parameters, kernel and standard deviation, are chosen correctly. Nevertheless, the segmentation result will be different if filters are applied beforehand. Figure 2 points toward result differences using an image without or with filtering prior to the segmentation process.

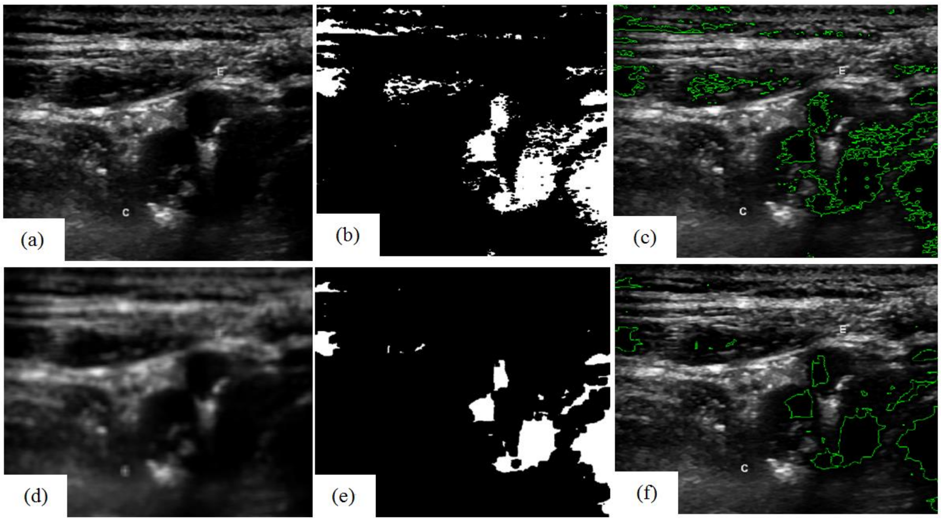

Fig 2 - Image segmentation without and with previous filter aplication. Top sequence (a), (b) and (c): original image, binary image and segmentation; bottom sequence (d),(e) and (f): original image after aplication of filter with kernel [30 30] and standard deviation 10, binary image and segmentation.

Some B-mode transverse images are really complicated to analyze, due to the level of high irregularity for specific regions, the bad definition of arteries walls and the low quality of the images. Arguments for poor artery segmentation results are not always the same and for the specific purpose of improving automatic carotid image segmentation some generally accepted issues are:

- Doppler principles for image construction are the same for all images, where generally the top of the images is brighter, and bottom of the image is darker;
- All blood structures present the lowest values for luminance and these values generically are almost always close to 0;
- Healthy arteries are circular and even with arteriosclerosis the artery wall keeps a high degree of circularity;
- Artery walls and artery lumen presents a non-disruptive smooth structure;
- Most of the time, medical specialists performing ultrasound carotid examinations, try to keep the artery as close as possible to the image center what it is not so easy to do depending on the specific person's neck.

Specifically based on the last three issues, and in order to automatically identify and segment the correct intended artery (not just any blood vessel) mathematical indexes capable of keeping the segmentation process in the correct track have been proposed, namely [2]: Circularity index, *MR*, Irregularity index, *Ir*, and Centrality index, *Id*.

For the correct assignment of the carotid artery, an objective function combining the three indexes has been under discussion:

$$E = MR + Ir + Id \qquad (1)$$

Circularity index, *MR*, can be used to decide how circular the contour of certain region is. In a perfect circle, there is only one radial distance to the center. In the presence of a deformable region, radial distance discrepancies are found from the contour to the center of the region. Considering circularity index varying from 0 (non-circular) to 1 (perfect circle), Ritter and Cooper [3] present the index:

$$MR = \frac{1}{P}\sum_{i=1}^{P}\frac{\bar{r}}{|r_i-\bar{r}|+\bar{r}} \tag{2}$$

where P is the total number of contour pixels, r_i is the value of each individual radius that can be calculated by the distance between coordinates of the region center ($\bar{x}$,$\bar{y}$) and the coordinates (x_i,y_i) for each contour pixel i, $r_i = \sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}$, and $\bar{r}$ is the mean radius:

$$\bar{r} = \frac{1}{N}\sum_{i=1}^{N} r_i \tag{3}$$

The assigned values for the region center, in terms of approximation, can be obtained by calculating the arithmetic mean of all pixels coordinates of the region. This type of approximation although not the unique way to obtain it, can be considered a good approximation presenting the lowest execution time. Other expressions allowing calculating the referred indexes have been presented in the literature, but their possible theoretical values do not present the same variability interval. For instance, for irregularity index [4]:

$$Ir = P * \left(\frac{1}{d}-\frac{1}{D}\right) \tag{4}$$

being d and D the minimum and the maximum diameter found for the selected region, respectively. These values are higher as higher is the difference between the diameters or higher is the size of the region. In order to include the irregularity index in equation (1) giving a certain equilibrium to the three terms, the inverse of the distance between the center of image and the center of the region might be considered. In the work presented here, images are to be analyzed with the application of an irregularity index:

$$Ir = \sqrt{\frac{\bar{r}}{r_{image}}} * \left(1-\frac{1}{d}+\frac{1}{D}\right) \tag{5}$$

where r_{image} is a reference radius for the image. The full image is rectangular and the reference radius was taken as half the shortest side of the rectangle. As a side comment, for smooth contours, the number of pixels is related to the mean radius of region, the larger the region the larger the number of contour pixels, and r_{image} is the maximum radius that is possible to obtain from a specific image. As for the centrality index previous authors have proposed:

$$Id = \frac{1}{D_{region}} \tag{6}$$

being D_{region} the reference distance from the analyzed region center to the image center. This expression is controversial since it can take values as high as infinity. Considering D_{image} the reference diameter of the full image, new proposals for associated centrality indexes, varying within a range 0 to 1, are

$$Id = 1-\frac{D_{region}}{D_{image}} \tag{7}$$

and

$$Id = \left(1-\frac{D_{region}}{D_{image}}\right)^2 \tag{8}$$

The square in equation (8) is important since it induces a stronger selection of the central region, but not so exposed as being the inverse of the center distance.

3. RESULTS

A set of Doppler images from specific patient with severe carotid disease was acquired by a qualified medical technician using a new ultrasound system Philips Affiniti 50G with a broadband linear array L12-4 transducer. The new algorithm for image processing and analysis was developed using Matlab 2018a.

Methodology was applied to images with and without the previous use of a Gaussian filter. Main results on the analysis behavior of Gaussian filter parameters, kernel and standard deviation, for the circularity parameter, *MR*, and with selection of larger artery on the image is presented in Figure 3. Curiously, it is possible to conclude that kernel common values do not influence the circularity parameter, and only standard deviation influences the higher or lower values, depending on the irregularity of the selected region.

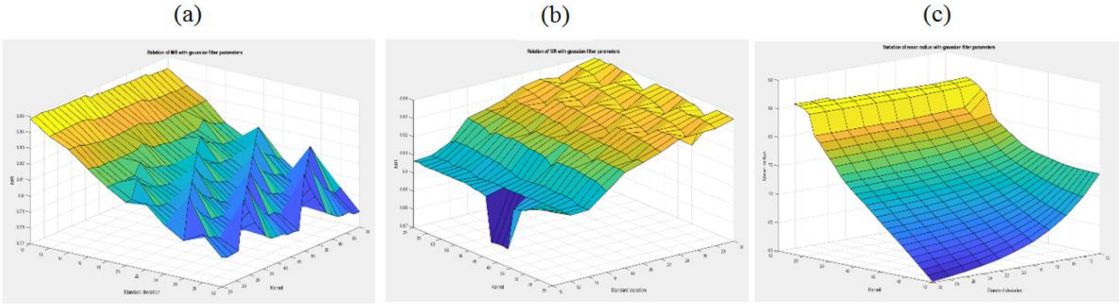

Fig 3 - Selecting different Gaussian filter parameters. (a) decrease of MR value with the increase of standard deviation; (b) increase of MR value with the increase of standard deviation; (c) relating of first region mean radius with filter parameters.

In order to present the discussion on the applicability of considering different indexes when automatically selecting the artery lumen in an image, the same image with no filtering has been used. The circularity index given in equation (2) is accepted. Irregularity index as given by other authors in equation (4) seems controversial and results are compared to the new proposal for irregularity given by equation (5). As for centrality, index given by equation (6) will be compared with results using equation (7) and equation (8). Image analysis results with different combination of indexes give completely different arterial selections as presented in Figure 4 and Table 1. Three cases, A, B and C, are considered:

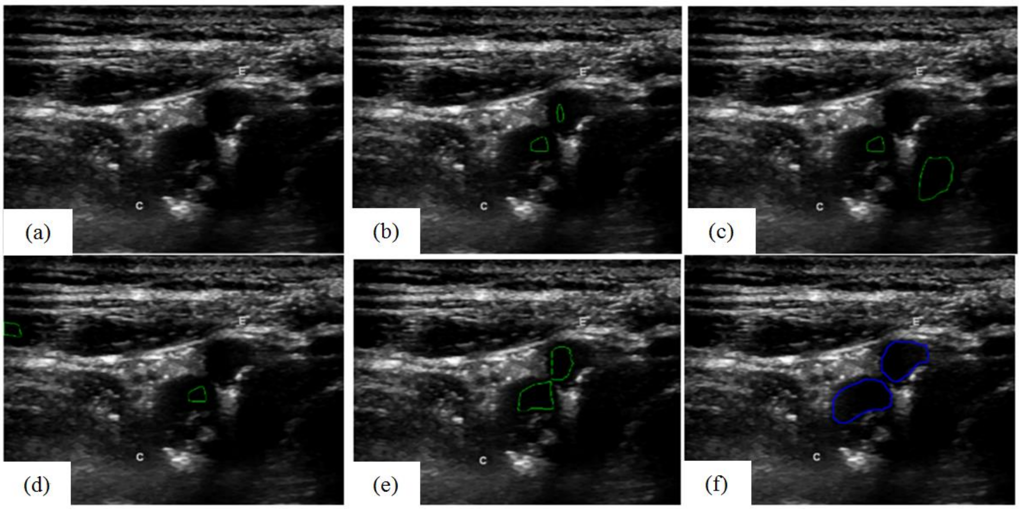

Fig 4 - Selecting arteries: (a) original image; (b) new proposed indexes A; (c) previous indexes B; (d) previous indexes C; (e) expansion of luminance limit value to 1combined with A; (f) expert manual segmentation.

Table 1 - Parameter *E* and index values (*MR*, *Ir* and *Id*) for the three main regions in selected images. D1 and D2 report differences between *E* values of Region 2 and Region 1 and Region 3 and Region 2, respectively.

	Region 1 (*E, MR, Ir, Id*)	Region 2 (*E, MR, Ir, Id*)	Region 3 (*E, MR, Ir, Id*)	$D1=E_1-E_2$ (μ, σ)	$D2=E_2-E_3$ (μ, σ)
A	1.9113 0.9028 0.2474 0.7611	1.5718 0.7692 0.1912 0.6114	1.5599 0.8709 0.3824 0.3660	0.227076 0.0923757	0.140433 0.0940728
B	2.0226 0.9028 0.2474 0.8724	1.8070 0.8709 0.3824 0.5537	1.7423 0.7692 0.1912 0.7819	0.237666 0.0327079	0.149942 0.125694
C	0.9376 0.9028 0.0115 0.0233	0.9017 0.8871 0.0109 0.0037	0.8827 0.8709 0.0051 0.0067	0.025252 0.022004	0.0269722 0.0223863

- A - New proposal for E=adding equations (2), (5) and (8);
- B - Another proposal E=adding equations (2), (5) and (7);
- C - Previously published proposal E=adding equations (2), (4) and (6).

For the analysis of figure 4 and table 1, it is important to refer the obtained differences for the indexes used by different authors. Distance between the two first selected regions is smaller and, definitively, distance is a parameter that is important to have in account.

4. CONCLUSIONS

Image segmentation by luminance limit value is not sufficient. Indexes used as selection criteria help to identify lumen artery. To achieve fully automatic segmentation of B-mode transverse images of the carotid bifurcation, future research developments are in order:

- The developed software is user dependent to inform the number of regions to be selected and segmented, whereas the ideal would be an algorithm to detect, by itself, the number of lumen arterial regions;
- From the increase or decrease of image scale, there is no 'best' Gaussian filter parameters to use in all images; up to now Gauss filter parameters are user dependent;
- Using the lowest values for luminance limit, does not allow lumen extension, in order to keep separation of segmented regions.

The main advantage of the developed methodology is the user-independent ability to indicate the number of regions of interest due to be segmented. This ability indicates the possibility of implementing a fully automatic segmentation algorithm. The basis of success are among others the new geometrical center identification, the correct identification of the two focus of ellipses, the evaluation of shape irregularity and the innovative parameter for circularity. Disadvantages are the difficulty to identifying the correct artery centers for extremely irregular artery shapes. Despite of the better results applying the new proposed index methodology further study is needed to perform selection and segmentation with better accuracy.

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