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Automatic Detection of Intima-Media Thickness in Ultrasound Images of the Common Carotid Artery Using SVM

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Abstract: **Atherosclerosis is the leading underlying pathologic process that results in cardiovascular diseases, which represents the main cause of death and disability in the world. The atherosclerotic process is a complex degenerative condition mainly affecting the medium- and large-size arteries, which begins in childhood and may remain unnoticed during decades. The intima-media thickness (IMT) of the common carotid artery (CCA) has emerged as one of the most powerful tool for the evaluation of preclinical atherosclerosis. IMT is measured by means of B-mode ultrasound images, which is a non-invasive and relatively low-cost technique. This paper proposes an effective image segmentation method for the IMT measurement in an automatic way. With this purpose, segmentation technique based on machine learning and statistical pattern recognition to measure IMT from ultrasound CCA images. The pixels are classified by means of support vector machine (SVM) to identify the IMT boundaries. The suggested approach is tested on a set of 60 longitudinal ultrasound images of the CCA by comparing the automatic segmentation with four manual tracings.**

Keywords: **Automatic Detection, Ultrasound Images, (IMT), Common Carotid Artery, (SVM).**

1. INTRODUCTION

Cardiovascular diseases (CVD) are the leading cause of death and disability in the world [16]. In 2008, about 17.3 million people died from CVD representing 30 % of all global deaths. An important part of these were premature deaths and could have largely been prevented. Over 80 % of CVD deaths take place in low and middle income countries and occur almost equally in men and women.

Atherosclerosis is responsible for a large proportion of CVD [16]. It is a chronic degenerative disease characterized by the accumulation of fatty material and cholesterol at the arterial walls. Therefore, atherosclerosis causes thickening and the reduction in elasticity in the arterial walls. Therefore, atherosclerosis causes thickening and the reduction in elasticity in the arterial walls. Although this pathology may remain unnoticed for decades, atherosclerotic lesions (plaques) could even lead to a total occlusion of the blood vessels. This is the major underlying cause of heart attacks and strokes. For this reason, an early diagnosis and treatment of atherosclerosis are crucial to prevent patients from suffering more serious pathologies. In this sense, the intima-media thickness (IMT) of the common carotid artery (CCA) is considered as an early and reliable indicator of this condition[12,22]. By studying IMT, a specialist can detect subclinical atherosclerosis and analyze the drug response.

The IMT is measured by means of a B-mode ultrasound scan, which is a non-invasive and low-cost technique that allow a short-time examination. The use of different protocols and the variability between observers is a recurrent problem in the measurement procedure[23]. The repeatability and reproducibility of the process are of great significance to analyze the IMT[1,9]. For these reasons, IMT should be measured preferably on the far wall of the CCA within a region free of plaque[17]. The optimal measurement section (1 cm long) is located at least 5mm below the carotid bifurcation, where a double – line pattern corresponding to the intima-media-adventitia layers can be clearly observed. As can be seen in Fig.1, the IMT is the distance between the lumen intima (LI) interface and the media-adventitia (MA) interface. Usually, delineations of the CCA are manually performed by medical experts. By means of image segmentation algorithms it is possible to reduce the subjectivity and variability of manual approaches and detect the IMT throughout the artery length. In the last two decades, several solutions have been developed to perform the carotid wall segmentation in ultrasound images [7]. Most of the proposed methods are not completely automatic and they require user interaction to start the algorithm, such as [2,5,11,6,18]. However, some fully automatic approaches were recently published [19,20,21,8,14]. In this work, a automatic detection technique based on Machine Learning and Statistical Pattern Recognition is proposed to measure IMT from ultrasound CCA images. Firstly, a given image is pre-processed to detect the region of interest (ROI) by using watershed transform. Then, pixels belonging to the ROI are classified by means of support vector machine to identify the LI and MA interfaces. Finally, the obtained results are post- processed to extract the final contours for the IMT measurement. The automatic measures of the IMT have been compared with the values obtained from different manual segmentations and the statistical analysis of this comparison shows the accuracy of the proposed method. The remainder of this paper is structured as follows: sect.2.1 describes the set of tested ultrasound images and the manual segmentation procedure, respectively. In sect.2.2, the proposed segmentation method is

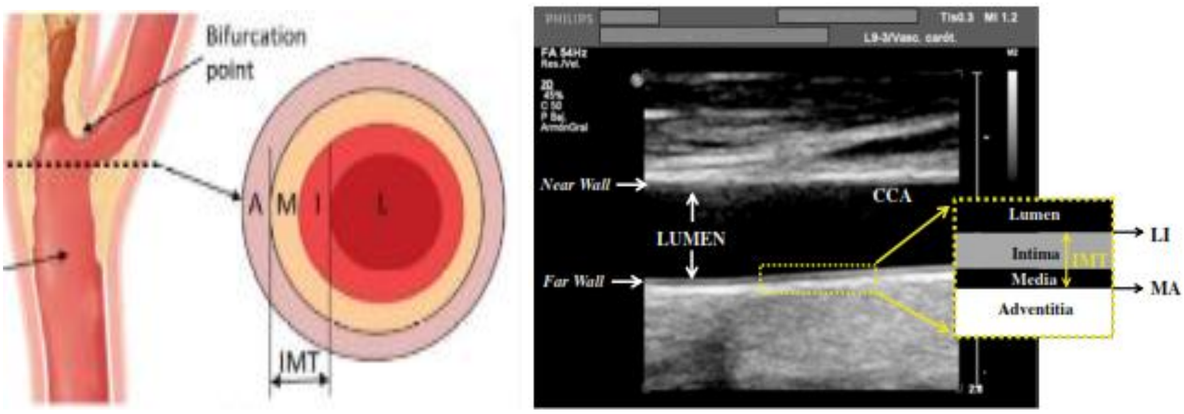

Fig.1 Diagram of the artery wall (left) and longitudinal view of the CCA in a B-Mode ultrasound image(right)

2. METHODS

2.1 Image acquisition:

A set of 60 longitudinal B-mode ultrasound images of the CCA have been used in this work. All of them were provided by the Radiology Department of Hospital Universitario Virgen de la Arrix- aca (Murcia, Spain). Fig. 1 (right) shows an example of the tested ultrasound images. Ultrasound scans were acquired using a Philips iU22 Ultrasound System by means of three different ultrasound transducers (L12-5, L9-3 and L17-5) and recorded digitally with 256 gray levels. The spatial resolution of the images ranges from 0.033 to 0.066 mm/pixel, with mean and standard deviation equal to 0.051 and 0.015 mm/pixel, respectively. The parameters of the scanner were adjusted in each case by the radiologist. Some blurred and noisy images, affected by intraluminal artifacts, and some others with partially visible boundaries are included in the studied set.

To assess the performance of the proposed segmentation method and the accuracy of the obtained IMT measurements, it is necessary to compare the automatic results with some indication of reference values (ground-truth, GT). In this case, the GT corresponds with the average of four different manual segmentations for each ultrasound image. In particular, two experienced radiologists delineated the 60 images twice, with a mean period of two months between tracings. Each manual segmentation of a given ultrasound image includes tracings for the LI and MA interfaces on the far carotid wall.

2.2 Segmentation method:

Fig 2 shows an overview of the proposed IMT segmentation methodology. Firstly, a given ultrasound CCA image is pre- processed to automatically detect the region of interest (ROI), which is the far wall of the blood vessel. As result of this stage, a cropping of the input ultrasound image is obtained (ROI image). Then, a windowing process takes place on the ROI image in order to construct the intensity pattern corresponding to each pixel (intensity values from a neighbourhood). After this, different auto- encoders provide compressed representations of these intensity patterns in a lower dimensional feature space. The new features are classified by means of support vector machine to separately detect the LI and MA interfaces. Finally, classification results are post-processed to extract the final contours on which the IMT is measured.

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2.2.1 Pre-processing stage:

In the carotid ultrasound images (see Fig. 1), the lumen corresponds to a dark region (low echogenicity) delimited by the arterial walls. Over the lumen in the picture, at less depth, it is observed the echo corresponding to the near wall. The far wall, where the IMT is Measured, is located below the lumen, and it constitutes the region of interest (ROI).

First of all Watershed transform [13] is applied to the morphological gradient of the image. The transformed image consists of a large number of watershed regions. A binary image with the same dimensions as the input ultra- sound image is built using the obtained watershed lines (borderlines of the watershed regions). Thus, we obtain an initial mask in which only the limits of the water- shed regions are white pixels. Then, closed regions in the mask are filled by means of mathematical morphology; in particular, the algorithm is based on morphological reconstruction [10]. Only those objects with largest areas are kept in the mask, whereas the remaining objects are removed. Hereafter, an object in a binary image will refer to a set of white pixels connected by considering a 2D 8-connected neighbourhood. In this way, we avoid undesirable intra and extra luminal artifacts which can lead into error As result of these steps, we obtain the final binary mask (Fig. 4a) to locate the carotid lumen in a simple manner. In the final binary mask, the largest black area connected to the biggest white object identifies the carotid lumen in the ultrasound image (see Fig.4a & b). Once the lumen has been located, we focus on its

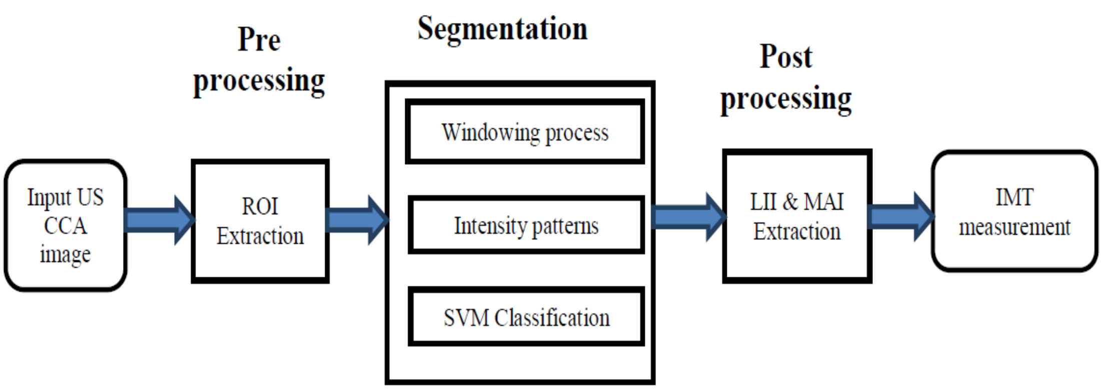

Fig.2 Overview of the proposed method for carotid wall segmentation and IMT measurement

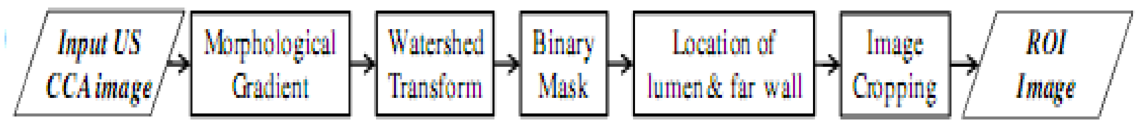

Fig 3. Diagram of the pre – processing stage

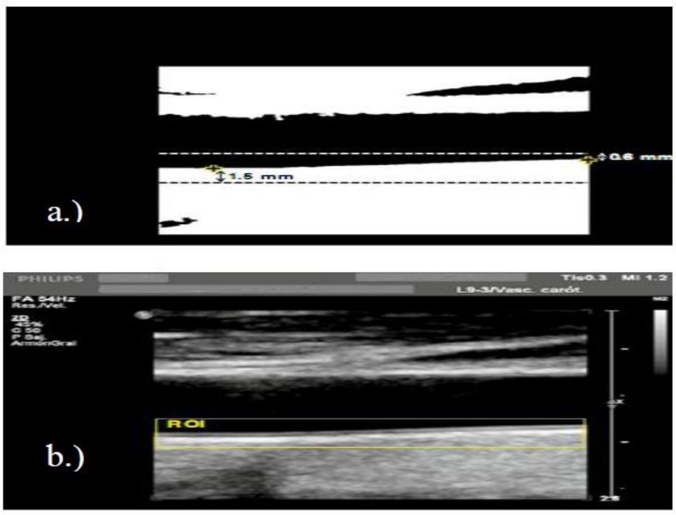

Fig. 4 a.) final binary mask with reference points of the far wall and limits of the ROI;b.) original image with the selected ROI

lower limit corresponding to the posterior wall of the CCA, and the boundaries of the ROI are established. The superior boundary is fixed to 0.6 mm above the uppermost point of the far wall detected in the binary mask, whereas the bottom boundary is fixed to 1.5 mm below the lowest point. Thus, the size of the ROI is related to the carotid artery appearance in the ultrasound image.

2.2.2 Classification stage:

Carotid artery disease diagnosis greatly depends upon accurate artery image segmentation and classification of the segmented images. Segmented images are classified into normal or abnormal. In this study, we have used SVM classifier for classification of the carotid artery images. Four different features are extracted from the IMT values obtained from carotid artery segmented images to train and test the SVM classifier.

Feature Extraction:

The following four commonly used statistical features are extracted from IMT measurements of the segmented carotid

artery image. These features are normalized in the range of [0 1] and then used as input to the SVM classifier. Classification accuracies are observed to be the best using these features for the given dataset. Mathematical description of each feature is

as under:

$$Average = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad (1)$$

Where {x1, x2,…, xn}are the observed values and n is the total number of observations.

$$Var(X) = \frac{1}{N}E[(X_i - \mu)^2] \qquad (2)$$

Where {x1, x2,…, xN} are the observed values, μ is the mean of the observed values, and N is the total number of observations.

$$SD = \sqrt{(\frac{1}{N}E[(X_i - \mu)^2])} \qquad (3)$$

Standard deviation is the square root of the variance defined in Eq. 2

$$Skewness = E[(\frac{X_i - \mu}{\sigma})^3] \qquad (4)$$

Where μ shows the mean of x and expected value of quantity is represented by E.

SVM Classifier:

The SVM classifier is a supervised learning algorithm, which successfully being used for classification and analysis of data. It is a binary classifier, but with kernel method, it can be utilized for multi-class problem as well. For instance, to classify data in two classes, SVM finds a new hyper plane with the help of support vectors and margins. SVM selects the hyper plane having maximum separation between the classes.

Quadratic optimization is used to solve the classification problem. Classification error is minimized at each new training example to find the optimal linear hyper plane [4, 15].Different kernel functions are available for SVM to classify the data. In the current research, we have used SVM radial basis function for classification of the segmented images into normal or diseased. LIBSVM 3.11 toolbox is used to train and test SVM [3]. For training and testing the SVM classifier, we have used tenfold cross-validation.

Classification performance measurement:

In statistical prediction, to check the effectiveness of the method, different types of cross-validation techniques are in practice. Among the cross-validation methods, jackknife is a popular one. It gives unique results for a given dataset. It is being used by the analysts to validate the accuracy of prediction. In our work, we have also used jackknife validation technique to examine the quality of the classifier. According to jackknife test, N−1 samples are used for training and one of the data sample is used for testing. The class of the test pattern is predicted by the classifier based on the N−1 training samples. The sampling process is repeated for N times and the class of each sample is predicted. The true positive (TP) and true negative (TN) are the number of correctly classified positive and negative classes. The false positive (FP) and false negative (FN) are those images which are incorrectly classified. To evaluate the performance of the classifier, the following measures are used.

Accuracy:

This measure is used to assess the overall usefulness of the classifier. Accuracy can be determined by the following expression:

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$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \quad (5)$$

Sensitivity

Sensitivity is used to check the ability of a classifier to recognize the positive class patterns. The following equation is used to calculate the sensitivity of the classifier:

$$Sensitivity = \frac{TP}{TP+FN} \quad (6)$$

Specificity

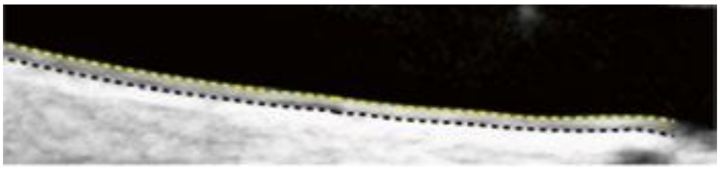
It is used to check the ability of a classifier to recognize the patterns of negative class. It can be calculated using expression (7)

$$Specificity = \frac{TN}{TN+FP} \quad (7)$$

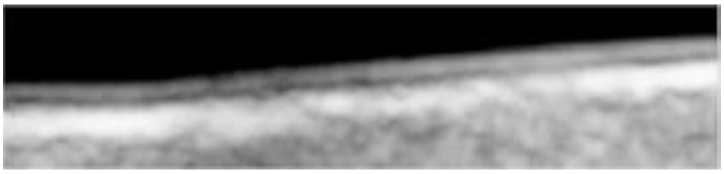
Where TP is the true positive; TN is the true negative; FP and FN are the number of false positive and false negatives, respectively. The network is trained to produce a value of '1' for an input sub-image with a target 'IMT- boundary' at its central position, and '0' otherwise ('non- IMT-boundary') The networks must classify a given pixel as 'IMT-boundary' (class '1', which is considered as a 'positive') or 'non-IMT-boundary' (class '0' or 'negative'). therefore, a 'true positive' is a pixel belonging to the class '1' which is correctly classified as 'IMT-boundary', whereas a 'false positive' is a misclassified 'non-IMT-boundary' pixel. On the other hand, a 'true negative' is a correctly classified 'non-IMT-boundary' pixel, whereas a 'false negative' is a pixel belonging to the class '1' which is misclassified as 'non-IMT-boundary'. Thus, Accuracy represents the success rate (proportion of correctly classified pixels), Sensitivity relates to the ability to identify negative results ('non-IMT-boundary' pixels) and Specificity relates to the ability to identify positive results ('IMT- boundary' pixels).

2.3 Post processing stage

The results of the classification stage should be debugged to extract the final LI and MA boundaries, see central image in Fig. 5. It is necessary to identify and discard, as far as possible, the misclassified pixels. In this sense, the relative position between pixels classified as 'LII-pixels' and those classified as 'MAI-pixels' provides useful information. Moreover, due to the poor resolution of the ultrasound images, thick boundaries are obtained instead of one- pixel contours. This happens because the networks find the searched intensity patterns in all these pixels. In order to solve this drawback, a simple non-linear data-fitting problem is formulated to find the best polynomial approximation for LI and MA interfaces. This is done by minimizing the squared error between the (LII-pixels or MAI- pixels) in the image and the approximated contour. The bottom image in Fig. 5 shows an example of the final boundaries extracted from the classification results (central image).



(a)



(b)

(c)

Fig. 5 Examples of good segmentation: a.) ROI or the ultrasound image in Fig. 1; b.) Binary image obtained at the output of the second classification stage; c.) final LI and MA boundaries obtained after the post-processing stage

3. RESULT

The suggested method was developed and tested under MATLAB, on a PC with an Intel Core i5 processor at 2.8 GHz and 8 GB RAM. The mean total CPU time per processed image is 3.44s. The ROI selection task (pre-processing stage) has showed a high efficiency by spending 0.34 s in mean for each case. Once the networks have been trained, classification results are provided in a fast way, with an average response time of 0.72 s for all the pixels in the selected ROI. On the other hand, given the binary output image of an ultrasound image, the post-processing stage achieves the location of the reliable sections and returns the final IMT boundaries in 2.4 s (mean time).

4. CONCLUSIONS

This paper proposes a fully automatic segmentation method of the CCA far wall based on Machine Learning in order to measure the IMT. Segmentation is treated as a pattern recognition problem. Thus, the main stage of the proposed technique is a classification stage, in which Support vector machine perform a classification of the image pixels to detect the IMT contours (LI and MA interfaces). Networks take as input information only the intensity values from a neighbourhood (13x3) of the pixel to be classified. The system is completed with a pre-processing stage in which ROI (far wall of the CCA) is automatically selected and with a post-processing stage for the extraction of the final contours on which the IMT is assessed.

The proposed configuration has been tested using a set of 60 ultrasound CCA images. The automatic segmentation achieves the correct detection of the LI and MA interfaces in all the tested images. Furthermore, the automatic measurements of IMT have been compared with the values obtained from manual tracings and several quantitative statistical evaluations have shown the accuracy and robustness of the suggested approach.

The main advantage of the CCA segmentation method proposed in this paper is its computational efficiency, with a mean total time per processed image of 1.4 s. This fact together with the high agreement between automatic and manual segmentations makes this method a suitable solution for the clinical evaluation of IMT. Besides, with this average execution time, the method could also be used for the segmentation of ultrasound CCA videos. Future works must study the use of different learning machines (extreme learning machines) to construct the proposed deep networks. However, although the MLP solution used in this work seems to be the simplest, it provides quite satisfactory results.

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