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Fully Automated Intima Media Thickness Measurement of Posterior Wall in Longitudinal Ultrasound B-mode Scans

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Abstract

The robust measurement of the intima media thickness (IMT) of longitudinal common carotid artery (CCA) has an important clinical value because clinicians often use it as an important predictor to assess the possibility of potential cardiovascular events. The purpose of this study was to develop a fully automated algorithm to measure the IMT in the longitudinal ultrasound B-mode images. A completely automated algorithm for identification and calculation of IMT is proposed in this paper. Based on signal analysis, the algorithm can be divided into four steps. The first step is to automatically identify the lumen-intima (LI) interface points of posterior wall. Starting from the detected LI interface points, the second step uses the gradient-based method to locate the candidate media-adventitia (MA) interface points. The third step applies the canny edge detector to remove the outliers from the candidate points. The last step is to calculate the IMT from the final available points. On 35 ultrasound video sequences of the common carotid artery (CCA) taken from 13 healthy subjects, the results generated by the proposed method were compared to the manual annotated data. The proposed method yielded an IMT of 0.61 mm ± 0.085 (mean ± standard deviation) whereas the corresponding result yielded by the manual annotated ground truth data is 0.60 mm ± 0.1. The proposed method eliminates the need of manual initialization, and measures the IMT of the longitudinal CCA with high precision similar to the ones observed in the manual segmentations. It has the potential to be a suitable replacement for manual segmentation and measurement of the IMT.

Keywords: *intima media thickness; image segmentation; common carotid artery; ultrasound*

1. Introduction

By 2030 more than 23 million people will die annually from cardiovascular diseases (CVDs), as reported by the World Health Organization (WHO) [1]. Atherosclerosis, one of the main CVDs, is characterized by arteries' hardening or the increment of the thickness between the intima and media arterial layers. M. W. Lorenz, *et al.,* [2] had shown that the increment of IMT is one of the signals of an ongoing atherosclerotic process. So the precise measurement of the intima media thickness (IMT) provides clinicians a valuable tool to evaluate the potential risk of the atherosclerosis.

Ultrasound medical imaging system provides an inexpensive, safe, convenient and noninvasive medical diagnostic way to assess CVDs. Ultrasound medical imaging machines also allow real-time visualization of arterial walls. Unfortunately, it is well known that ultrasound images suffered from lower signal-to-noise (SNR) as compared to other medical imaging modalities (such as Magnetic Resonance Imaging).

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Figure 1 presents the typical longitudinal ultrasound image of a healthy common carotid artery (CCA) with a normal IMT. It can be observed that LI and MA run like two quasi-parallel lines and IMT is the distance measured from the lumen-intima (LI) interface to the media-adventitia (MA) interface.

The reference values for carotid diameter [3] and the IMT are [4]:

Carotid diameter in men: 6.52 ± 0.98 mm;

Carotid diameter in women: 5.11 ± 0.87 mm;

IMT – Normal: IMT < 1.0 mm;

IMT – Thickening: 1.0 mm < IMT < 1.3 mm;

IMT – plaque: IMT > 1.3 mm.

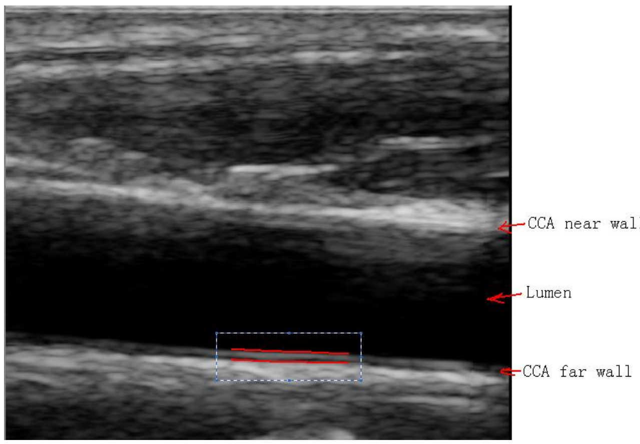

Figure 1a. A Longitudinal Section of Common Carotid Artery (CCA)

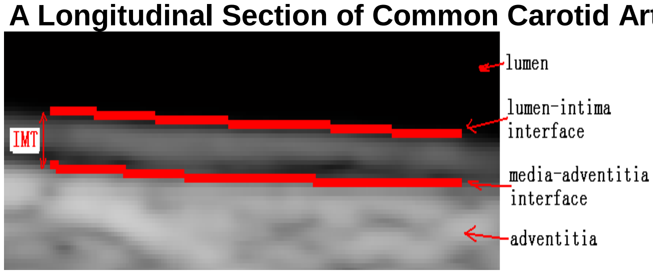

Figure 1b. Detail Show of the Selected Part in (1a)

Figure 1. An illustration of Intima Media Thickness in the Longitudinal Section of the CCA

Manual assessment of IMT generally yields the most accurate measurement, but the process of manual annotation is highly labor intensive and the result suffers from the intra-operator and inter-operators variability. To address this clinical need, many studies have dedicated to develop a semi- or fully-automatic method for IMT measurement. Since the CCA layers often take on a straight line look in longitudinal projection and Hough Transform is good at detecting lines, Golemati, *et al.*, [5] applied Hough Transform to detect the carotid artery wall. The two dominant lines corresponding to the LI and MA interfaces were independently traced and their distance was calculated as IMT. Although the method is simple and computation efficient, it suffers when dealing with curved vessel. Lee, *et al.*, [6] applied dynamic programming method to obtain a global minimum search of image features extracted by a directional Haar-like filter which takes the slope of the boundary into consideration. The proposed method first used the cost terms, which are the image feature term obtained by the horizontal Haar-filter rotated through angles in the range [-45°, 45°] and a geometrical force term, to define a cost function. Then it used dynamic programming method to find the poly line that minimizes the given cost functions. The advantages of the method are the low sensibility to speckle and high efficiency when dealing with sloppy vessels. Molinari *et al.*, [7] showed an approach that integrates two algorithms, *i.e.*, the CULEXsa [8] and the CALEXia [9], to measure IMT. CULEXsa is based on the signal analysis and CALEXia is based on the integrated approach. The authors found that CALEXsa performs better on locating the LI interface while CALEXia performs better on locating the MA interface. So they tried to maximize the benefits of the combination of CULEXsa and CALEXia using a greedy strategy. Molinari, *et al.*, [10] also proposed a completely automated robust edge snapper, which is called CARES 2.0, for IMT measurement. CARES 2.0 is divided into two stages. Stage-I uses an intelligent image feature extraction and line fitting to locate the posterior adventitia border. In stage-II, an improved heuristic search method, cooperating with the bi-directional first order absolute moment (FOAM), is used to locate the LI and MA peaks. Other studies by application of active contours [11], gradient-based method [16], cubic spline and RANSAC methods [12] and Nakagami Mixture Modeling and Stochastic Optimization [13], were also reported in the literature.

In this work, we proposed a fully automated intima media thickness measurement algorithm, called FAIMTM, to measure the IMT of the longitudinal ultrasound CCA images. FAIMTM can be divided into four steps. The first step is to making use of a prior knowledge of the average diameter of the CCA to automatically identify the LI interface points of posterior wall. Starting from the detected LI interface points, the second step uses the gradient-based method to locate the candidate media-adventitia (MA) interface points. The third step applies the canny edge detector as a checker to remove the outliers from the candidate points. At the last step, the IMT is calculated from the final available points.

2. Material and Methods

Thirteen healthy volunteers aged 24-45 with no history of cardiovascular disease, were involved in this study. The common carotid arteries of the right sides of their necks, 2-3 cm proximal to the bifurcation, were scanned by an expert. A total of 35 ultrasound image sequences, consisting of 210 images, were obtained using Saset iMago C21 system (SASET Healthcare, San Francisco, CA) with a 10 MHz linear transducer. The capturing resolution of the images was 0.04×0.04 mm^2. Except for a few cases, the sonographic setting remained unchanged throughout the process of data acquisition.

2.1. Step-1 Lumen-Intima (LI) Interface Recognition

In our study, we chose to use the enveloped IQ data rather than B-mode image data because we found that enveloped IQ data has a higher edge contrast than B-mode image, which is more helpful to locate the LI and MA interface.

Figure 2 presents a typical profile of the enveloped IQ intensity of a column of the longitudinal CCA. From Figure 2b, we can observe that the lumen area of CCA is corresponding to a non-stop section of low intensities and LI interface is the pixel right after this non-stop section. Combining this observation and the prior knowledge that the average diameter of the CCA for adult males and females is 6.52 mm and 5.11 mm respectively, we designed the following method to detect LI interface:

For every column of the image, iterates

Step 1.1 Sort the intensities of enveloped IQ data in ascending order and select the 30th percentile as the threshold, denoted as thre_blood, to distinguish blood pixels from non-blood pixels.

Step 1.2 Check the original column to see if there is a non-stop section whose length is within the range of [4 mm, 8 mm] and the intensities of all pixels within this section are all lower than thre_blood. If this section is not found, this column is labeled as void; else this column is labeled as the candidate column and the pixel right after the non-stop section is labeled as LI interface point

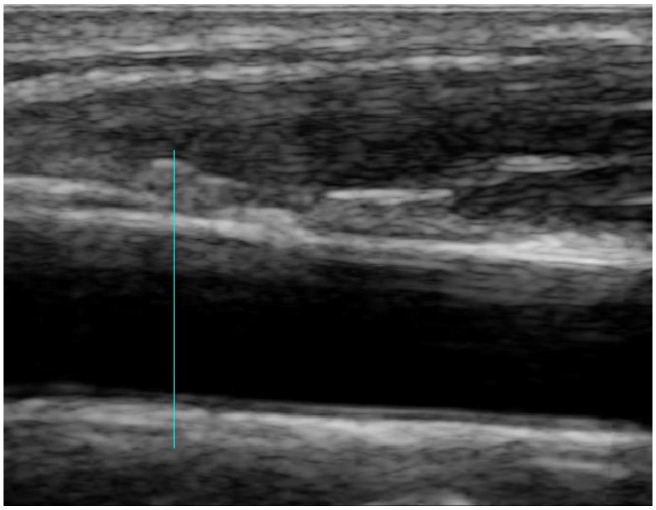

Figure 2a. A Longitudinal Section of Common Carotid Artery (CCA)

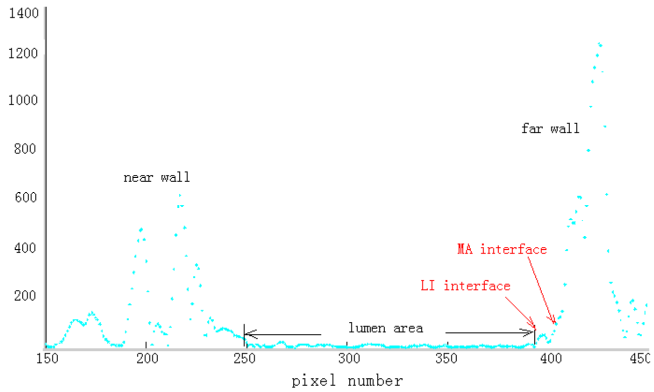

Figure 2b. The Corresponding Profile of the ROI in (2a)

Figure 2. The Typical Profile of the Intensities along the Column of the Longitudinal CCA

2.2. Step-2 Media-Adventitia (MA) Interface Recognition

As can be seen from Figure 2b, there is a obvious valley-shaped signal flow between MA interface and LI interface and MA interface. Let's denote the peak of the signal flow as P. Then MA interface is the first pixel whose intensity of enveloped IQ data is higher than that of P. This observation inspired us to design the following method to detect MA interface:
For every candidate column, iterates

Step 2.1 Starting from LI interface point, check if there is a valley-shaped signal flow right after it. If this signal flow is not found, this column is labeled as void; else jumps to step 2.2.

Step 2.2 Locate the first pixel whose intensity of enveloped IQ data is higher than that of the peak of the signal flow. Denote that pixel as MA interface point.

However, it is well known that real clinical images are not noiseless. Consequently LI and MA interfaces are not always well defined as shown in Figure 2b. The direct effect of the noise is that some detected LI and MA interface points may deviate far way from the 'real' position and we call these deviated points as outliers. To ensure the reliability of the IMT measurement, we must find an intelligent and robust way to remove these outliers.

2.3. Step-3 Outliers Removal

The basic assumption behind the design of step 3 is that the candidate LI and MA interface points should be or close to an edge point detected by the Canny edge detector.

Step 3.1 Extract the region of interest (ROI) that is barely contained all the candidate LI and MA interface points. Apply the Canny edge detector to this ROI. In our study, the sigma value of the canny edge detector is experimentally set as 0.3.

Step 3.2 For each candidate column, denote the location of LI interface point as L, check whether there is any edge point detected by Canny edge detector in the range of [L-1, L+1]. If there is not any, label this column as void.
The same is applied to the MA interface points.

Step 3.3 Compute the least square regression line that is best fit all the LI interface points of the candidate columns, points that are farther from the line than a given threshold (3.5 pixels) are discarded and the corresponding columns are labeled as void.
The same is to the MA interface points.

2.4. Step-4 Calculation of the IMT

Step 4.1 Divide the candidate LI and MA interface points into groups using distance metric, *i.e.,* in the same group the distance of neighboring points is less than a given threshold (20 pixels). If the number of points within the group is less than a given threshold (4 points), this group is discarded.

Step 4.2 For each group, apply the cubic spline interpolation algorithm to the LI interface points and MA interface points respectively. Calculate the IMT between the LI interface line and MA interface line.

3. Results

To illustrate the performance of the proposed method, Figure 3 shows the IMT segmentation results for the first frames in three randomly chosen longitudinal CCA ultrasound sequences. For the sake of clarity, only the region of interest (ROI) is displayed. It can be observed that the IMT is only detected in part of the longitudinal CCA, labeled as red in Figure 3. After analyzing the data, we found that other part of the longitudinal CCA, in which the IMT can not be detected, is a bit of too noise to have a well defined LI and MA interface.

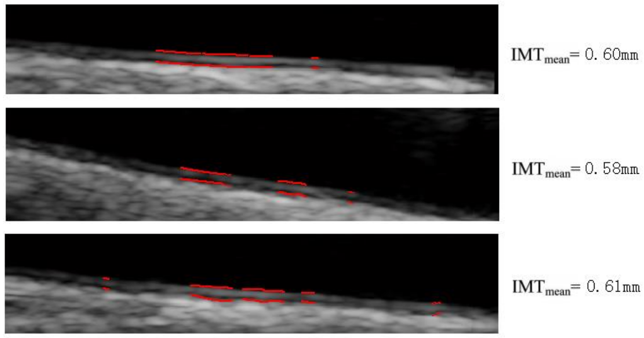

Figure 3. An Illustration of the Mean IMT Value Measured by FAIMTM

If the image is too noise, it may be impossible to measure the IMT. For our case, FAIMTM failed to find the LI and MA interfaces in 4 of the 140 analyzed images.

By comparing the results returned by the proposed method with the ground truth data manually annotated by an expert, two validation metrics have been used to quantify the performance of the proposed method in our study. The first metric concerns about the overall border deviation errors for LI and MA interface points. The second concerns about the mean IMT value.

The first metric is measured by computing two set of Euclidean distance. The first set is the Euclidean distance between the LI interface line returned by FAIMTM and the corresponding LI interface line returned by the ground truth data. The second set is the Euclidean distance between the MA interface line returned by FAIMTM and the corresponding MA interface line returned by the ground truth data. Figure 4 depicts the measurement of the overall deviation errors using the box plot () function from Mat lab. It reveals that MA interface line is more error-prone than LI interface line as for the task of border detection.

The second metric is measured by comparing the mean IMT values that are determined by FAIMTM and the ground truth data respectively. Figure 5 depicts the box plot of the calculated mean IMT values from our test data. IMT mean_FAIMTM stands for the mean IMT value returned by FAIMTM and IMT mean_GT stands for the mean IMT value returned by the ground truth data. The proposed method yielded an IMT of 0.61 mm ± 0.085 (mean ± standard deviation) whereas the corresponding result yielded by the manual annotated ground truth data is 0.60 mm ± 0.1.

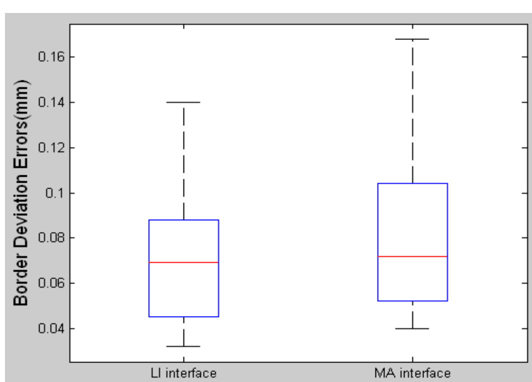

Figure 4. Illustration of the Overall Border Deviation Errors for the LI and MA Interfaces Returned by FAIMTM with Respect to that of the Ground Truth Data

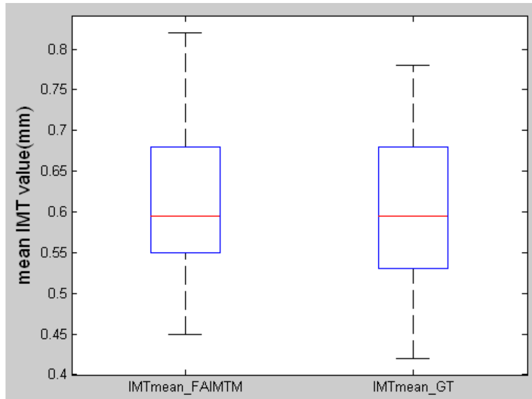

Figure 5. Illustration of the Mean IMT Value Returned by FAIMTM with Respect to that of the Ground Truth Data

Implemented in Mat lab 7.6 (The Math Works, Natick, MA), the computation time required to calculate the IMT of a 512×976 frame is about 0.85 second in a desktop computer with 2G memory and Intel Celeron 2.5 GHz CPU inside.

4. Discussion

The measurement of IMT has long been used by clinicians as a useful tool to assess the risks of possible vascular alternations. And the IMT measured from the manual segmentation of the CCA is accepted as the golden standard at present. However, the manual approach suffered from two limitations. The first limitation is the inter-operators and intra-operator variance. The second is that manual measurement is time-consuming and labor-intensive.

The method reported here is fully automated and real-time, which has important clinical meanings. For example, the real-time capability of the proposed system enables the clinician to tune the imaging parameters of the ultrasound system so as to acquire better image quality when the IMT measurement is still on going. It also eliminates the possibility of inter-operators and intra-operator variance occurred in manual approach. Meanwhile, the result returned by the proposed method shows good agreement with the ground truth data. So the proposed method can be considered as a valid alternative to the manual measurements.

The innovative aspects of our FAIMTM technique are: (1) introducing a knowledge-based technique to automatically locate the posterior LI interface; (2) using the enveloped IQ data to search the edge of LI and MA interface; (3) applying the canny edge detector as the checker to avoid false border points.

Here we present some other reported results from the literature for comparison. In [14], Ilea, *et al.*, tested their IMT segmentation and tracking method on 40 ultrasound video sequences of the CCA and they reported that the measured IMT is 0.60 mm ± 0.10 (mean ± standard deviation) whereas the manual annotated IMT is 0.60 mm ± 0.11. The computational time required to segment the first frame in the video sequence is in the range of 6 to 14 seconds. Applying CALEXia method on a database of 200 images, Molinari, *et al.*, [15] reported that the average error for LI and MA interface tracings were 0.091 ± 0.093 mm and 0.025 ± 0.055 mm respectively when comparing the results from the proposed method with the manual annotated results. It should be noticed that this kind of direct comparison may not reasonable due to the difference in experimental data set and evaluation methods. Nonetheless, we can observe that our results are comparable to those of the two above-mentioned works.

5. Conclusions

In summary, the proposed method described in this paper provides a simple and accurate way to segment and calculate the IMT of the longitudinal ultrasound CCA images. It has the potential to be an alternative for the labor-intensive manual annotation of the IMT. The future work will be focused on evaluating our method on patients who are suffered from advanced cardiovascular conditions, such as those with atherosclerosis plaque.

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