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Fully Automated Ultrasound Common Carotid Artery Segmentation Using Active Shape Model

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Abstract

B-mode measurement of the contour of the common carotid artery (CCA) has an important clinical value. The purpose of this study was to develop a fully automated ultrasound common carotid artery segmentation method using active shape model (ASM). An image database with 90 images was used to train the ASM model during the offline training phase of ASM. When it came to the online segmentation phase, a knowledge-based seed point detection method was first used to locate the centroid of the CCA. Then the trained ASM model automatically produced an exact contour of the CCA. The proposed method yielded a Dice Metric of 90.5% ± 4.35% and a Hausdorff Distance of 9.28 ± 5.2 pixels in a database of 40 ultrasound images. The segmentation result of upper and bottom part of the CCA was better than that of lateral part of the CCA. The proposed method eliminates the need of manual initialization, and identifies the contour of the CCA with high precision. It has the potential to be a suitable replacement for manual segmentation of the CCA.

Keywords: *active shape model; image segmentation; common carotid artery; ultrasound*

1. Introduction

The common carotid artery (CCA) is a blood vessel that delivers blood from the heart to the head. It is a paired vessel, i.e. left and right CCA, run side by side in the neck. Right CCA ascends from brachiocephalic and left CCA from arch of aorta. Each subsequently splits at the bifurcation to form the internal and external carotid arteries, with the internal carotid artery carrying oxygenated blood for the brain and the external carotid artery carrying oxygenated blood for the head and neck. The measurement of the variation in arterial diameter of CCA may yield useful clinical insights, such as the mechanical properties of the arterial wall which may indicate a sign of atherosclerosis, hypertension or heart failure [1]. So the segmentation of the contour of CCA has an important clinical value.

Ultrasound medical imaging system provides an inexpensive, convenient and noninvasive medical diagnostic way to imaging human organs, such as human heart, CCA, *etc*. But it also should be noted that automated ultrasound image processing is difficult due to the inherent problems with ultrasound imaging, such as low resolution, the presence of speckle, signal dropouts, *etc*. Many researchers have tried to develop semi-automatic or fully automatic segmentation methods to meet this challenge. Mao *et al.*, [2] proposed to handle this problem with a discrete dynamic model approach, in which the model is driven by an internal force and an external force that are calculated from both the geo-metrical properties of deformed contour and the image gray level features. P. Aolmaesumi [5] proposed to track the center of lumen-intima border (LIB) using the Star algorithm and estimate the carotid artery boundary using a modified spatial Kalman filter. In [6], David C. Wang et al. tried to single out CCA and the internal jugular vein (IJV) by fitting ellipse to all the regions that look like major

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arteries or veins in B-mode ultrasound image. They claimed that their method has achieved 100% accuracy in a group of 38 healthy subjects. Ukwatta *et al.*, [7] used a level set method and a combination of a prior knowledge to segment the media-adventitia boundary (MAB) and LIB separately. After several anchor points on the boundaries were chosen by the operator, the proposed algorithm outlined the MAB using edge- and local region-based energies and an energy that attracts the boundary to the anchor points. Then a constraint regulating a boundary separation between the MAB and LIB, combined with local energy and anchor point-based energy, was used to segmenting LIB.

Active Shape Model (ASM) is a statistical approach for shape modeling, which was proposed by Cootes *et al.*, [3, 4]. ASM algorithm first trains a set of training samples with labeled points. Then it uses Principal Component Analysis (PCA) to construct the shape and textual model. Finally the trained Point Distribution Model (PDM) is used to actually segment the targeted structure in an image. Since its publication, ASM has been widely used to analyze images of faces and medicine images. However, the performance of ASM is known to very sensitive to the initial position, which means ASM model fails to find the correct contour when the initial position is too far away from the targeted structure.

In this work, we proposed a novel method to make use of a prior knowledge of the average diameter of the CCA to locate the center of the CCA automatically, which in turn provides an ideal initial position for the trained ASM. After the seed point is determined, ASM is being used to segment the LIB accurately and robustly.

2. Main Principle of ASM

In 1994, Cootes *et al.*, [4] proposed a statistical shape model, ASM. The working mechanism of the model can be divided into two phases, *i.e.*, offline training phase and online segmentation phase. During the offline training phase, a set of training images, each labeled with n feature points, is used to construct a mean shape and a matrix P. The core model equation is defined by

$$S = \overline{S} + P * b \qquad (1)$$

where $P = (P_1|P_2|\ldots|P_t)$ contains t eigenvectors corresponding to the t largest Eigen values λ_i derived from the covariance matrix, and b is a vector of t elements, computed by

$$b = P^T * (S - \overline{S}) \qquad (2)$$

When fitting the model to a set of points, b is constrained to the range $\pm m\sqrt{\lambda_i}$, and the value of m is usually between two and three. During the online segmentation phase, an iterative approach, which utilizes the already trained ASM model, is used to matching model points to target points. The main principle of the iterative approach can be described as follows: (a) Look for a better position for each target point; (b) Calculate the changes in the pose and shape parameters resulted from (a); (c) Update the model parameters to enhance the match between target image and the trained model so that the final contour should be consistent with the training set.

3. Material and Methods

3.1. Data Acquisition

Three healthy volunteers aged 27-40 with no history of cardiovascular disease, were involved in this experiment. The common carotid arteries of the right sides of their necks, 2-3 centimeters proximal to the bifurcation, were scanned by an expert. A total of 130 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 0.07×0.07 mm^2. Except for a few cases, the sonographic setting remained unchanged throughout the process of data acquisition.

3.2. Offline Training Phase of ASM

The training set consists of 90 contours from the ultrasound CCA images of three healthy persons. The images were chosen to cover a broad range of LIB shapes and none of the training set images were used in the online segmentation phase. The landmark points annotation rule is detailed as below.

Step 1. The expert estimated the centroid of the CCA with his eyes.
Step 2. The border point right above the centroid was labeled as the first landmark point.
Step 3. Other ten landmark points were labeled equally spaced clockwise.

After all the eleven landmark points were annotated, the centroid of these 11 landmark points, denoted as C, was calculated. We then cropped from the training image a 181×181 (in pixels) rectangular area centered at C, and out-put it for ASM training. Since the sonographic setting remained the same and the CCA always take on a circular appearance, additional alignment operations, such as rotating and scaling, were not applied in this case. We adopted traditional gray-level appearance model with normalized first derivative of profiles centered at each landmark that run perpendicular to the object contour and found out that it achieved high segmentation performance in this dataset. Figure 1 shows an example of the annotation of the 11 land-mark points on the LIB boundary labeled by the expert.

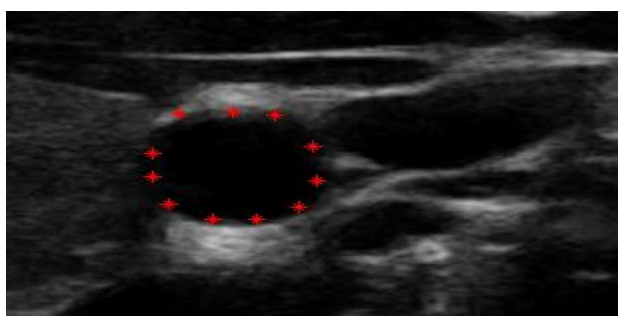

Figure 1. The Eleven Landmark Points used to Model the LIB shown as Red Stars

3.3. Initial Position Optimization

As we mentioned before, the performance of ASM is sensitive to the initial position. The best initial position for segmenting the CCA we think is the center of the CCA. So we have developed a novel, knowledge-based method to automatically detect the center of the CCA.

After considering the characteristics of the intensity of blood: (a) it is different at different depths; (b) it is always the lower as compared to that of non-blood pixels, we experimentally choose 20th percentile intensity of all pixels at the same depth, i.e. row, as the blood threshold for that particular depth. First, the depth-adaptive thresholding method is being used to transform the gray-scale image into a binary image. Then the connected component areas in the binarized image are labeled and the horizontal diameter (hd) and vertical diameter (vd) of each connected component area are calculated. After applying the knowledge that CCA is always of circular appearance and the average diameter of the CCA for adult males and females is 6.52 mm and 5.11 mm respectively [9], we claim that the connected component area whose hd is between 4 mm and 10 mm, vd is between 4 mm and 10 mm, and abs(hd – vd) <= 1 mm is the CCA we pursued. The center of that connected component area is selected as the initial position for the online segmentation of ASM. Figure.2 shows an example of the process of detecting initial position. Figure 2a shows the result after the depth-adaptive threshold is applied. For the sake of comparison, we plot both the calculated initial position (red) and the center point (blue) of the CCA drawn by the expert in Figure 2b. It can be seen that these two points are very close.

Figure 2a. The Blood Area (White) and Non-blood Area (Black) Emerged after the Depth-Adaptive Threshold is Applied.

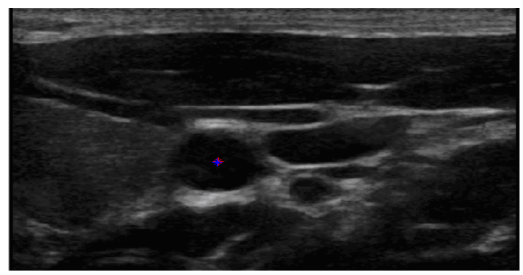

Figure 2b. The Detected Initial Position (Red), the Center Point (Blue) of the CCA Drawn by the Expert

Figure 2. The Process of Initial Position Detection

3.4. Online Segmentation Phase of ASM

A 181×181 (in pixels) rectangular area centered at the initial position, is cropped from the testing image. The ASM model takes the rectangular area as input, and process it as described in section 2. At last, the output of the online ASM segmentation is superposed on the original image for showing.

A total of 40 images were segmented in this phase. Figure 3 shows an illustration of ASM segmentation process and result. One example of ASM segmentation process is shown in Figure 3a and the corresponding segmentation result is shown in Figure 3b.

4. Validation Metrics

4.1. The Validation Metric of Initial Position Optimization

We validate the proposed initial position optimization algorithm based on the distance between the calculated initial position and the center of the contour drawn by the expert. The closer these two points are, the better the initial optimization algorithm is.

4.2. The Validation Metric of ASM Segmentation

The quality of our segmentation method was validated using two measures: 1) Dice Metric (DM) and 2) Hausdorff Distance (HD) [8]. DM evaluates the similarity between two areas. It is defined as

$$DM = \frac{2 * (area1 \cap area2)}{area1 + area2} * 100 \qquad (3)$$

So we know that the more similar two areas are, the higher value DM becomes, and vice verse. And a perfect match would yield a value of 100%.

The HD aims to evaluate the distance between two contours. If two contours are represented by a set of points $A = \{a_1, a_2, \ldots, a_m\}$ and $B = \{b_1, b_2, \ldots, b_m\}$, where each a_i and b_i is an ordered point on the curve. The Distance to the closest point (DCP) for a_i to B is defined as

$$d(a_i, B) = \min_j \| b_j - a_i \| \qquad (4)$$

The HD is defined as

$$HD(A, B) = \max(\max_i \{DCP(a_i, B)\}, \max_j \{DCP(b_j, A)\}) \qquad (5)$$

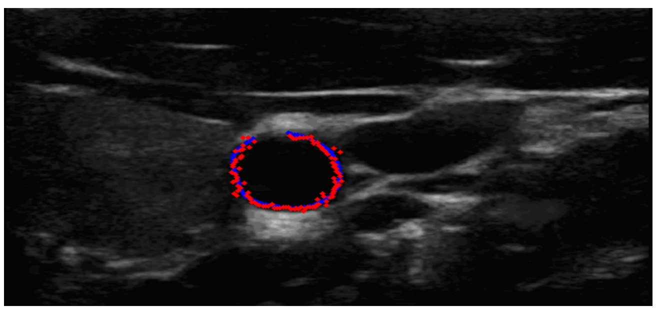

Figure 3a. the process of ASM Online Segmentation

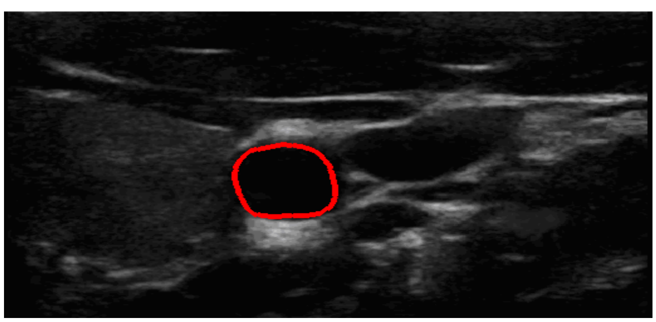

Figure 3b. The Segmentation Result

Figure 3. An Illustration of the Process and Result of ASM Online Segmentation

5. Result

5.1. Validation of the Initial Point Optimization

As for our data set, the distance between the calculated initial position and the center of the contour drawn by the expert is 3.53 ± 1.7 pixels.

5.2. Validation of the Proposed LIB Segmentation Algorithm

The accuracy of the proposed LIB segmentation algorithm was evaluated by comparing the contour resulted from the proposed method with the expert-drawn contours. The proposed method yielded a DM of 90.5% ± 4.35% for the LIB and a HD of 9.28 ± 5.2 pixels in a dataset of 40 ultrasound images. After observing the segmentation results, we noticed that the segmentation result of upper and bottom part of the CCA was better than that of lateral part of the CCA. The observations may result from the fact that the lateral part of the CCA is parallel to the ultrasound beam direction and thus has weaker boundary. Figure 4 illustrates an example of the segmentation result. Figure 4a shows the contour manually drawn by the expert; Figure 4b plots the contour determined by the proposed method and the result of measures (DM, HD) is (0.924, 10 pixels).

Since the program is written in Matlab 7.1 (The MathWorks, Natick, MA), an interpreted language, the average running time for segmenting a 512×498 image is about 8.5 seconds in a desktop computer with 2G memory and Intel Celeron 2.5 GHz CPU inside.

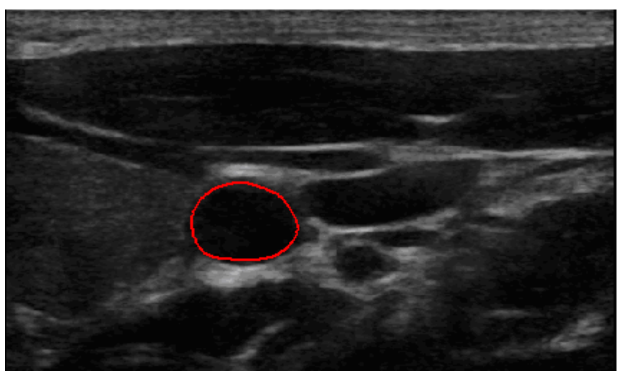

Figure 4a. Contour Drawn by the Expert

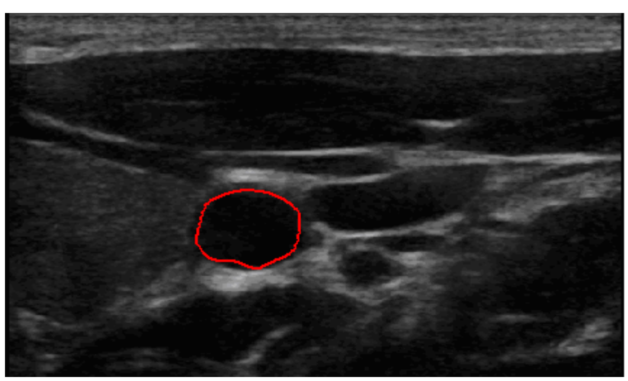

Figure 4b. The Contour Determined by the Proposed Method

Figure 4. An Illustration of the Comparison of the Segmentation Result

6. Discussion

This study has presented an efficient method for automated detection of the contour of LIB in 2D cross section ultrasound image. First, a knowledge-based seed point detection method was utilized to locate the centroid of the CCA. Then the ASM model automatically produced an exact contour of the LIB. An image database with 90 cases was used to train the ASM model and another database with 40 cases was used for evaluation. The proposed method was found to yield satisfactory results which are very similar to expert-drawn contours. It can be concluded that the proposed method can practically segment the contour of LIB from ultrasound images.

The advantage of the current method over the traditional ASM model is the elimination of manual initialization by providing an automatically created initial position. And this improvement of initial position optimization does not degrade the performance of ASM algorithm.

ASM model captures expert prior knowledge in the training examples annotation and applies it to the segmenting objects, since they have strict point correspondence between landmark points. Therefore ASM performs exceptionally well when the objects do not have a clear and continuous boundary, like the CCA.

Although direct comparison is not reasonable, due to the difference in data set and evaluation methods, we still present here some reported segmentation results from the literature. In [10], Sherif G. Moursi and Mahmoud R. El-Sakka proposed a 2D active contour based CCA segmentation method with improved initial contour optimization. A sensitivity of 85.5% to 90.5% with 95% confidence interval, over a set of 25 test images, was reported. In [11], Spyretta Golemati et al. proposed an automatic segmentation to extract the longitudinal and transverse sections of the CCA. An accuracy on average higher than 0.96 for both sections, over 10 normal subjects, was achieved in their work. And we observe that our results are comparable to the two above-mentioned work.

7. Conclusions

The novelty of this paper has two points, 1) the design of a heuristic-based, yet robust, method to automatically detect the initial position of the CCA in the ultrasound images; 2) a way to train the ASM model for the task of detection of LIB boundary and incorporate 1) and 2) together to segment the CCA.

In summary, the proposed initial position optimized ASM-based segmentation algorithm described in this paper provides a simple and accurate way to segment ultrasound images of transverse sections of the CCA. It has the potential to be a suitable replacement for manual segmentation of the CCA. Future work would be focused on (a) including more unhealthy objects, such as those with atherosclerosis plaque; (b) optimizing the proposed method and improves the computing speed.

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