

# Automatic construction of a statistic model of calcified aorta areas

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**Abstract** In this article, we report on automatic construction of a statistic model of calcified aorta areas. For the model construction, we developed a method for accurately detecting aorta areas and calcified ones from noncontrasted X-ray CT images. The proposed method firstly extracts the medial line of aorta in a given image by means of the active contour. Secondly the method extracts the wall of the aorta accurately by means of the Tensor Voting. Our method thirdly extracts calcified areas in the extracted aorta, and finally integrates the extracted areas in an aorta model.

**Key words** CT, CAD, image recognition

## 1. Introduction

In recent years, medical images become to play seriously important role in diagnosing, and many kinds of medical pictures are daily captured in hospitals. Consequently, the size of a medical image database in each hospital continuously increases. The goal of our study is to gain new medical knowledge by statistically analyzing a medial image database.

In this article, we report on a statistical analysis of X-CT images to gain statistical distribution of calcified areas in an aortic wall. Given a set of X-CT images of a whole body, we extract the aorta and its calcified areas from each of the images and map the locations of the calcified areas onto an aorta model.

Our method firstly extracts the aorta from a given non-contrasted X-CT image. For this extraction, we employ the active contour method[1]. The proposed method secondly detects the wall of the aorta by means of the tensor-voting[2]. Finally, the calcified areas are detected by binarizing the inside of the aorta.

## 1.1. Previous works

A large number of methods have been proposed for the aorta area extraction. Those methods can be classified into two typical types. One typical methods extract the aorta by the region tracking [3,4]. These methods work well for high-resolution CT images. However we did not employ those methods because we should analyze low-resolution CT images in this study (the resolution is  $0.98 \times 0.98 \times 4.25$ [mm<sup>3</sup>/voxel]).

The other typical methods fit the model of aorta medial line (AML) to a given CT images [5,6]. Those methods can detect the AML in a low-resolution X-CT image well, and we employed one of those methods for identifying the location of the aorta in the image.

After the AML detection, we detect the aortic wall around it. Because the input X-CT images are not contrasted in this study, some parts of the wall are missing and many false edges are detected around the wall. Hence, we employ the tensor voting method[2], which is useful for finding smoothly connected edges in a

noisy image.

## 2 . Detection of Aortic Wall

### 2.1. Body shape normalization

As described in the previous section, we firstly fits the AML model to the given image in order to identify the location of the aorta. For this fitting, we need to normalize the shape of each patient's body. For this normalization, all ribs in the image are detected and their convex hull is computed. Additionally, the bronchial bifurcation is detected as a landmark because the aorta runs around it. Using the normalized shape of the convex hull and the normalized position of the bifurcation as landmarks, we deform the image by means of the thin plate spline[7].

### 2.2. Extraction of Aorta medial line

We constructed the model of aorta, which represents its shape by using a spline curve. For this construction, we manually extracted the aortas from ten X-CT images and computed their mean shape.

The shape of a spline curve can be represented by the coordinates of its control points. Let  $q_i$  ( $i=1,2,\dots,N$ ) denote the  $i$ -th control point and let  $(x_i, y_i, z_i)$  denote its coordinates. Then the  $3N$ -vector  $\mathbf{Q}=(x_1, y_1, z_1, x_2, \dots, z_N)$  represents the shape of AML.

The purpose here is to compute  $\hat{\mathbf{Q}}$  that minimizes the cost function  $E$ :

$$E = \alpha \|\hat{\mathbf{Q}} - \bar{\mathbf{Q}}\|^2 + \|\hat{\mathbf{Q}} - \mathbf{Q}_f\|^2, \quad (1)$$

where  $\bar{\mathbf{Q}}$  and  $\mathbf{Q}_f$  correspond to the mean shape of the AML and the shape fitted to the image, respectively. The latter shape is obtained from the distance map, in which each voxel value shows the shortest distance to the detected edges in the image. Because the shortest distance becomes larger near the center of the aorta,  $\hat{\mathbf{Q}}$  should be computed so that the corresponding curve runs through the local maximum points of the distance map. This requirement corresponds to the second term of the right

hand side of the equation (1).

The distance map, though, is disturbed by image noises, hence the first term of (1) is introduced for the regularization.

In this article, we restrict the deformation of the aorta model  $\bar{\mathbf{Q}}$  to the affine transformation as follows:

$$\hat{\mathbf{Q}} = \mathbf{W}\mathbf{X} + \bar{\mathbf{Q}}, \quad (2)$$

where  $\mathbf{X}$  is a 12-vector that represents the affine transformation, and  $\mathbf{W}$  is a  $3N \times 12$  matrix constructed from the AML model  $\bar{\mathbf{Q}}$  (see [1]). Given the AML model and the distance map, the active contour method can compute  $\mathbf{X}$  in (2) that minimizes  $E$  in (1).

## 2.3. Extraction of the aortic wall

### 2.3.1. Tensor Voting

As mentioned above, we identify the location of the AML and then detect the aortic wall around it.

An edge detector detects many edges at the regions other than the aortic wall. Hence, we need to select appropriate edges from the detected ones that correspond to the aortic wall. To achieve this purpose, we enhance the edges of which alignment is circular around the detected AML in each slide by means of the tensor voting[2].

Let  $P_i$  denote a detected edge point, and let  $\nabla I_i$  denote the gradient of the image at  $P_i$ . As shown in Fig.1, given  $P_i$ ,  $\nabla I_i$  and  $P_{j \neq i}$ , we can determine a unique circle  $C$  that runs through both  $P_i$  and  $P_j$  and that is orthogonal to  $\nabla I_i$  at  $P_i$ . Let  $\mathbf{n}_j$  denote a normal vector of  $C$  at  $P_j$ . Then,  $P_i$  vote  $\mathbf{n}_j$  for  $P_j$ . Representing a vector  $\mathbf{v}$  by using a tensor  $\mathbf{v}\mathbf{v}^T$ , the method aggregates the voted vector for  $P_j$  as follows:

$$S_j = \nabla I_j \nabla I_j^T + \sum_{i \neq j} DF_i(s, k, \sigma) \mathbf{n}_j \mathbf{n}_j^T, \quad (3)$$

where  $DF_i(s, k, \sigma)$  is the saliency decay function defined as

$$DF_i(s, k, \sigma) = \exp\left\{-\frac{s^2 + K(k - k_0)^2}{\sigma^2}\right\}, \quad (4)$$

where  $s$  is the length of the arc  $P_i P_j$ ,  $k$  is the curvature of  $C$ ,  $k_0$  is the average curvature of the aorta wall,  $K$  is a

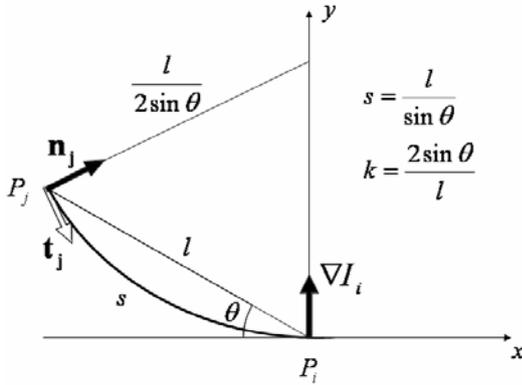
constant that controls the decay with high curvature and  $\sigma$  is a scale. The value of  $DF_i(s, k, \sigma)$  increases  $P_j$  becomes closer to  $P_i$  and when the curvature of  $C$  becomes closer to the average one of the aorta.

Now we obtain  $2 \times 2$  matrix  $S_i$  of each edge point  $P_i$ . Let  $\lambda_1$  and  $\lambda_2$  denote the eigenvalues of  $P_i$ . Then we calculate  $w_i$  defined as

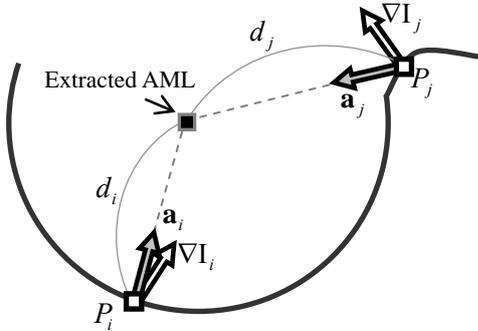
$$w_i = -(\mathbf{a}_i \cdot \nabla I_i) \exp\left\{-\frac{d_i^2}{R^2}\right\} \left(1 - \frac{2\lambda_1\lambda_2}{\lambda_1^2 + \lambda_2^2}\right), \quad (5)$$

as shown in Fig.2, where  $d_i$  is the distance between  $P_i$  and extracted AML,  $\mathbf{a}_i$  is a directional vector in  $P_i$  to the extracted AML and  $R$  is a constant. The value of  $w_i$  becomes larger under the following conditions:

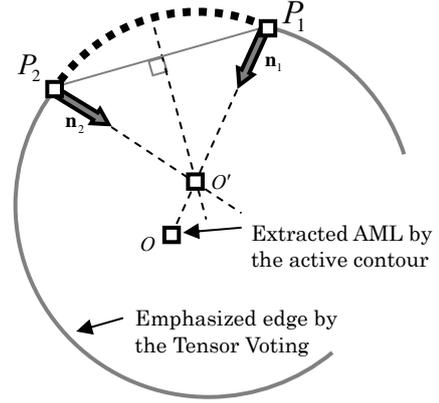
- $P_i$  is close to the extracted AML.
- The gradient vector  $\nabla I_i$  and  $\mathbf{a}_i$  are parallel.
- The curvature  $k$  is similar to  $k_0$ .
- $P_i$  is aligned with other edge along the smooth curve.



**Fig.1** The Tensor Voting method:  $P_i$ ,  $P_j$  and  $\nabla I_i$  determine a circle  $C$ .  $P_i$  votes for  $P_j$  a vector  $\mathbf{n}_j$  that is orthogonal to  $C$  at  $P_j$ .



**Fig.2** Weighting factors of the voting.



**Fig.3** Interpolation of the missing part  $P_1P_2$  using a circular arc.

### 2.3.2. Interpolation of missing parts

Because no edge point is detected from some parts of the aortic walls, we need to interpolate such parts for detecting the entire parts of the aortic wall after the tensor voting.

As shown in Fig.3, we interpolate a missing part by using a circular arc. Let  $P_1$  and  $P_2$  denote the end points of the missing part and let  $\mathbf{n}_1$  and  $\mathbf{n}_2$  denote their normals, respectively. We compute the intersection  $O'$  of  $\mathbf{n}_1$  and  $\mathbf{n}_2$  and set it as the center of the circle.

### 2.3.3. Extraction of Calcified Areas

After the missing parts are interpolated and the entire parts of the aortic walls are detected, then our method binarizes the inside of the aorta and detects the calcified areas. Because the input image is not contrasted, it is not difficult to determine appropriate threshold for the binarization.

### 2.4. Aggregation of Detected Areas

We aggregate the detected calcified areas in order to construct a statistical model of the locations of the calcified areas. For the aggregation, we should represent the location of each detected area by using an identical coordinates system. We, hence embed a cylindrical coordinates system to each detected aortic wall.

The origin of the coordinates system is set by referring to the location of the boundary between the aorta and the heart and to the direction of the body axis. The scale is normalized by the length of the AML between the boundary with the heart and the surface of the diaphragm. Once the coordinates of each detect area is obtained, it is easy to statistically analyze the locations of the calcified areas.

### 3 . Experimental results and discussion

We used 169 non-contrasted X-CT images of different cases for our experiments. The resolution of these CT images is  $0.98 \times 0.98 \times 4.25$  [mm<sup>3</sup>/voxel].

#### 3.1. Extraction of Aorta Medial Line

Examples of the result of the AML extraction are shown in Fig.4 and Fig.5. The extracted AML overlaid on the original images as white line in Fig.4. Fig.5 shows examples of the resultant curves  $\bar{Q}$ ,  $Q_r$  and  $\hat{Q}$  that minimize the cost function  $E$  in (1). As shown in Fig.5, the AML  $Q_r$  are perturbed by false edges and by missing ones.

On the other hand, the resultant AML  $\hat{Q}$  has smooth shape and is successfully regularized.

We applied the proposed method of the AML extraction to the 169 images and evaluated its performance. We valued the resultant AML as success if the entire resultant AML was included in the aorta and otherwise it was evaluated as failure. Then, 156 of 169 results were valued as success (92.3%). Our method failed to extract the AML correctly when the location of the correct AML is far from the AML model despite that the body shape was normalized. Fig.6 shows an example of the failed extraction.

#### 3.2. Extraction of aortic wall

Examples of the results of the Tensor Voting are shown in Fig.7. As shown in the figure, only the edges on the

aortic walls are successfully enhanced by the tensor voting. It should be noted that edge points of the calcified areas are not emphasized. This improves the aortic wall extraction.

Fig.8 shows examples of the interpolation. As shown in the figure, the missing parts of the aortic walls were appropriately interpolated by a circular arc. Figure 9 and 10 show the final results of the extracted aortic walls and of the detected calcified areas. As shown in the figures, our method successfully detected the aortic walls and the calcified areas.

For validating our method, we manually constructed the grand truce of the aortic wall for fifteen images. Seven of them included some calcified areas and others did not.

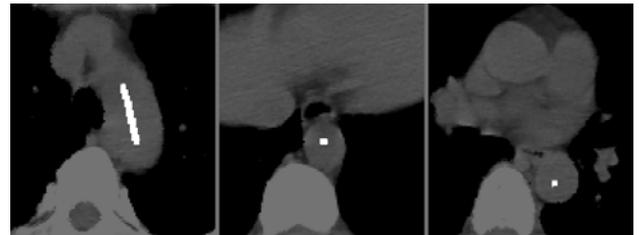


Fig.4 Examples of the extracted results.

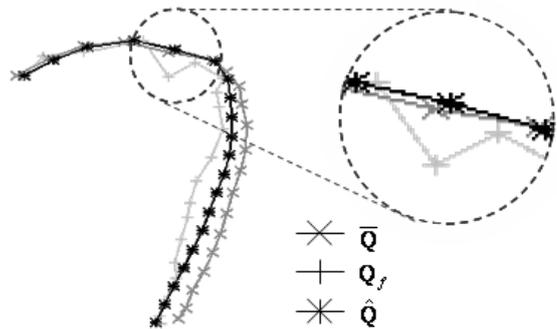
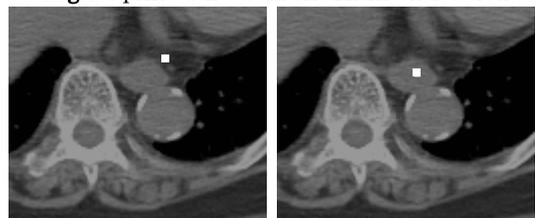


Fig.5 Spline curves in the AML extraction.



(A)

(B)

Fig.6 Examples of the failed results.

(A) the AML model (B) the extracted result

Referring to the gold standard, we computed the concordance rate  $\gamma$  of the resultant aorta as follows:

$$\gamma = \frac{A \cap B}{A \cup B}, \quad (6)$$

where A is the area of the extracted aorta and B is the gold standard area.

Figure 11 shows the concordance rate for each group of cases. Each floating bar shows the minimum, average and maximum of  $\gamma$ . The average of  $\gamma$  for all cases was 90.9[%] and the minimum of that was 87.5[%]. In the figure, the performance of the aorta extraction proposed in [5] is also indicated. This method extracts the aorta basically based only on the distance map. As shown in the figure, the performance of our method was superior to that of [5].

### 3.3. Statistics of the location of the calcified area

Fig. 12 shows the statistical model of the location of the calcified area. This model was constructed from the automatically detected calcified areas from 65 cases, all of which have calcified areas in their aorta.

In the figure, the frequency of the calcification is indicated by the blackness. As shown in the figure, the sidewalls of aortic arch were calcified in many cases. The most calcified point is shown by a black arrow in figure.

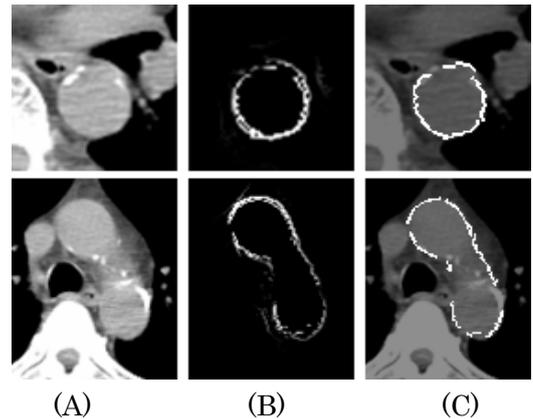
## 4 . Conclusion

In this article, we proposed the automatic construction method of a statistic model of calcified aorta areas.

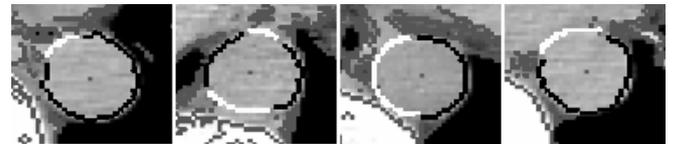
Our method firstly detects the AML and then detects the aortic walls around the detected AML. For accurately detecting the walls, we employed the tensor voting method.

By binarizing the inside of the detected aorta, the method automatically detects the calcified aorta areas. The experimental result of the aorta and calcified areas extraction shows approximately 90% concordance rate. Finally, we constructed a statistical model of the location

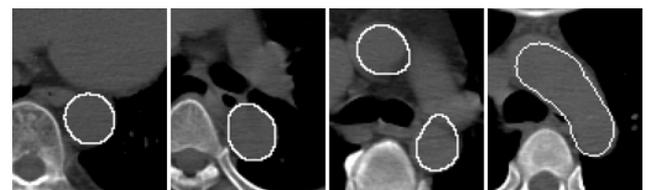
of the calcified areas. To our knowledge, such a statistical model has not been automatically constructed from an image database. The authors believe that such an automatic construction of statistical medical model will become more and more important. Future works include the estimation of the bias of the automatically constructed model.



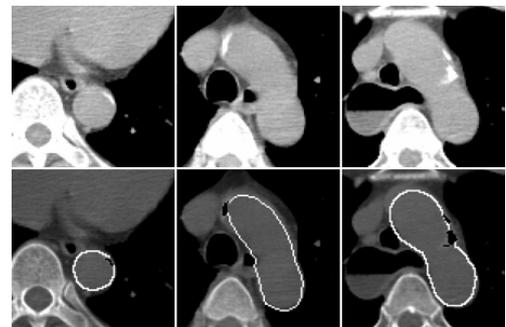
**Fig.7** Enhancement of the aortic walls by means of the tensor voting. (A)Original images. (B) Results of the enhancement. (C) Extracted aortic walls.



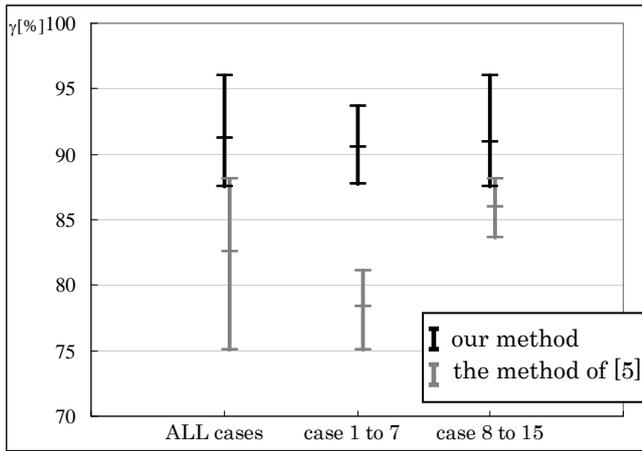
**Fig.8** Examples of the closed curve construction. Black lines show the aortic wall extracted by the Tensor Voting. White lines show the arcs that are interpolating the missing parts



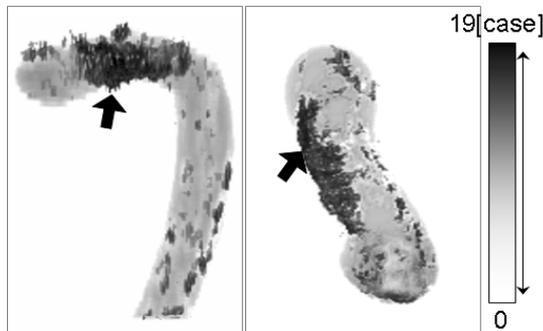
**Fig.9** Examples of the extracted aorta



**Fig.10** Examples of extracted calcified areas. Calcified areas are shown as black regions.



**Fig.11** Concordance rate of the extracted aortas estimated using 15 cases. Case 1 to 7 have calcified areas and 8 to 15 don't have these area.



**Fig.12** The statistic model of calcified areas. Calcified areas are extracted from 65 cases.

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