Early Detection of Aortic Aneurysm Risk from 4-D MR Image Data

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Abstract

A computer-aided diagnosis method is reported that allows to objectively identify subjects with connective tissue disorders from sixteen-phase 4D (3D+time) aortic MR images. Our automated segmentation method combines level-set and optimal surface segmentation algorithms so that the final aortic surfaces in all 16 cardiac phases are determined in a single optimization process. The resulting aortic lumen surface is registered with an aortic model followed by calculation of modal indices of aortic shape and motion. The modal indices reflect the differences of any individual aortic shape and motion from an average aortic behavior. Support Vector Machine (SVM) classifier is used for classification of normal and connective disease disorder subjects.

4D MR image data sets acquired from 30 normal and connective tissue disorder subjects were used to evaluate the performance of our method. The automated 4D segmentation result produced accurate aortic surfaces in all 16 cardiac phases, covering the aorta from the left-ventricular outflow tract to the diaphragm, yielding sub-voxel accuracy. The computer aided diagnosis method distinguished between normal and connective tissue disorder subjects with a classification correctness of 96.7 %.

1. Introduction

Aortic aneurysms and dissections are the 15th leading cause of death in the US, representing 0.7 % of all deaths in 2004 [1]. Subjects with certain congenital connective tissue disorders, such as Marfan's Syndrome and Familial Thoracic Aortic Aneurysm Syndrome are at increased risk for development of aortic aneurysm and dissection. Therefore, early diagnosis of connective tissue disorders is increasingly important.

Many aortic segmentation techniques were developed in 3D using computed tomography (CT) and MR images. Rueckert [2] used Geometric Deformable Models (GDM) to track the ascending and descending aorta. Behrens [3] obtained a coarse segmentation using Randomized Hough Transform (RHT). Bruijne [4] introduced an Adapting Active Shape Model (ASM) for tubular structure segmentation. Subasic [5] utilized a level-set algorithm for segmentation of abdominal aortic aneurysms.

Several authors have proposed techniques for tracking the cardiac movement in 3D+time cardiac images. Bardinet [6] presented an algorithm for tracking surfaces in 3D+time cardiac images based on a parametric model. Chandrashekara [7] built a statistical model derived from the motion fields in the hearts of several healthy volunteers to track the movement of the myocardium. Dimitrios [8] constructed a 3D+time statistical atlas to describe the cardiac anatomy and how the cardiac anatomy changes during the cardiac cycle. McInerney [9] built a dynamic finite element surface model for segmentation. Montagnat [10] presented a 3D+time cardiac segmentation by introducing time-dependent constraints to the deformable surface framework.

2. Methods

The reported CAD method consists of two main stages – aortic segmentation and connective tissue disorder diagnosis. Surface segmentation of the aortic lumen is obtained with an automatic 4D segmentation method. Next, a quantitative method to detect the differences of the aortic 4D function between normal and tissue disorder patients is employed to provide quantitative descriptors used in a disease classification step.

2.1. Segmentation

A N phases 4D (spatial-temporal) image I can be viewed as a discrete set of N volumetric images defined at N temporal instants $\{I_t(\mathbf{x},\mathbf{y},\mathbf{z})\}_{t\in[0,N-1]}$. The 4D aortic surface can be viewed as a sequence of surfaces $\{S_t\}_{t\in[0,N-1]}$. Let $\{appS_t\}_{t\in[0,N-1]}$ be a set of approximate surfaces for the 4D image I. During the segmentation stage, the 4D segmentation algorithm consists of the following steps:

• *Aortic surface presegmentation:* A 4D fast marching level set method simultaneously yields approximate 4D aortic surfaces $\{appS_t\}_{t\in[0,N-1]}$.
• *Centerline extraction:* Aortic centerline is determined from each approximate surface by skeletonization.
• *Accurate aortic surface segmentation:* Accurate 4D aortic surface $\{S_t\}_{t\in[0,N-1]}$ is obtained simultaneously with the application of a novel 4D optimal border detection algorithm [11].

2.2. Disease detection

The disease detection method is directly based on the analysis of the 4D segmentation result. First, a Point Distribution Model (PDM) is built representing the aortic shape and its motion during the cardiac cycle. Then, the modal indices of the PDM are used as input to a Support Vector Machine (SVM) classifier.

2.2.1. Point distribution models

Building the PDM consists of two stages: 1) Automatic generation of aortic landmarks representing the segmented aorta in 4D. 2) Capturing the shape variation by performing principal component analysis (PCA) on the 4D shape vectors of the aorta.

2.2.2. Discrimination model

With each 4D aortic instance represented by the principal components describing the observed shape and motion variations, an efficient classification algorithm was developed for pattern recognition using support vector machines (SVM) [12, 13]. The classifier is used to classify 4D aortic instances into classes of normal and connective tissue disorder subjects. Given M input training samples $x \in \Re^n$ with class labels $y \in \{-1, 1\}$, the SVM maps sample x into a high-dimensional space using a kernel function $K(x, x_i)$ and constructs an optimal hyperplane separating the 2 classes in this space. The optimal hyperplane is identified as such a hyperplane which maximizes its distance from the training samples (maximal margin in the high dimensional space). The decision function given by the SVM is of the form

$$f(x) = sign\left(\sum_{i=1}^{M} \alpha_i y_i K(x, x_i) + b\right) \quad . \qquad (1)$$

Here, $\alpha = \{\alpha_1, \alpha_2, ...\alpha_n\}$ is determined by optimizing the quadratic programming problem

$$\begin{aligned} \underset{\alpha}{Min} \quad & \tfrac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} \alpha_i\alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{M} \alpha_i \\ \text{subject to} \quad & \sum_{i=1}^{M} y_i\alpha_i = 0, 0 \le \alpha_i \le P, i = 1, ..., l \end{aligned} \qquad (2)$$

where P is a predefined parameter controlling the amount of admissible errors.

3. Results

The algorithm was evaluated in a set of 30 MR image sequences acquired from 30 subjects (20 normal, 10 diseased). Each sequence was composed of 16-25 cardiac phases covering one cardiac cycle. For each subject, both the candy cane view and left ventricular outflow tract (LVOT) view are captured with voxel sizes ranging from $1.5 \times 1.5 \times 3.0$ mm^3 to $2.0 \times 2.0 \times 6.0$ mm^3. The diseased subjects were selected due to their family history of connective tissue disorder. Yet, all the diseased subjects had "normal looking" aortic MR exam with no presence of a developed aortic aneurysm.

To obtain 4D image data that would have the same number of cardiac phases for all subjects and consisted of isometric voxels, the number of phases was normalized to 16 and the LVOT and candy-cane view image data were registered using a mutual information registration algorithm and interpolated using B-splines. For some images, the aortic information that is not present in the candy can view is available in the LVOT view. Fig. 1 shows the image data after the registration.

To assess the accuracy of the automated 4D segmentation, aortic luminal surfaces were compared with the expert traced independent standard. The independent standard was defined by manual tracing in 5 randomly selected MR slices in each of 21 subjects (7 patients and 14 normal subjects, total of 105 manually traced slices). Surface positioning errors were defined as the shortest distances between the manually traced and computer-determined surfaces in the 4D aortic images. Signed and unsigned surface positioning errors are expressed as mean$\pm$standard deviation in voxels and millimeters.

To assess the diagnostic performance of the aortic shape and motion PCA indices derived from 16-phase 4D segmentation, six most significant principal components of shape and motion were used for classification. Expert-defined disease status derived from the clinical records formed the binary prediction output (normal/abnormal). Leave-one-out validation method was used to evaluate the predictive classifier performance. Performance was assessed in terms of the overall classification correctness and expressed in percent.

All 21 4D aortic MR images were successfully segmented by our 4D segmentation algorithm. Comparison of computer-determined and expert-traced surfaces showed good agreement. Fig. 2 summarizes the signed positioning errors obtained for each 4D image.

For the sixteen-phase 4D image data, all cardiac phases were considered a single shape/motion instance and

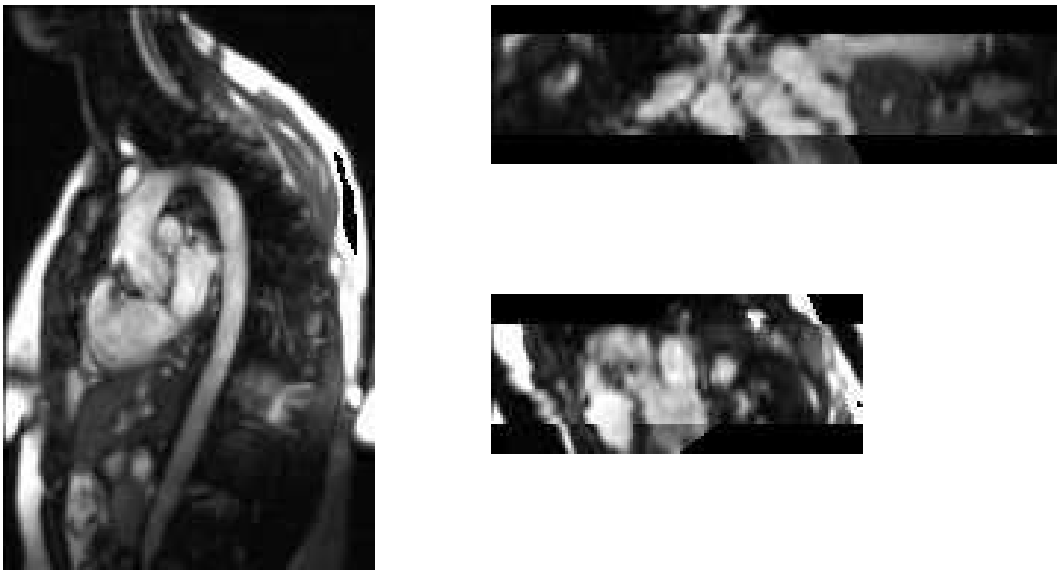

Figure 1. A registered 3D image resulting from merging the LVOT and candy–cane image data, shown in three standard orthogonal views.

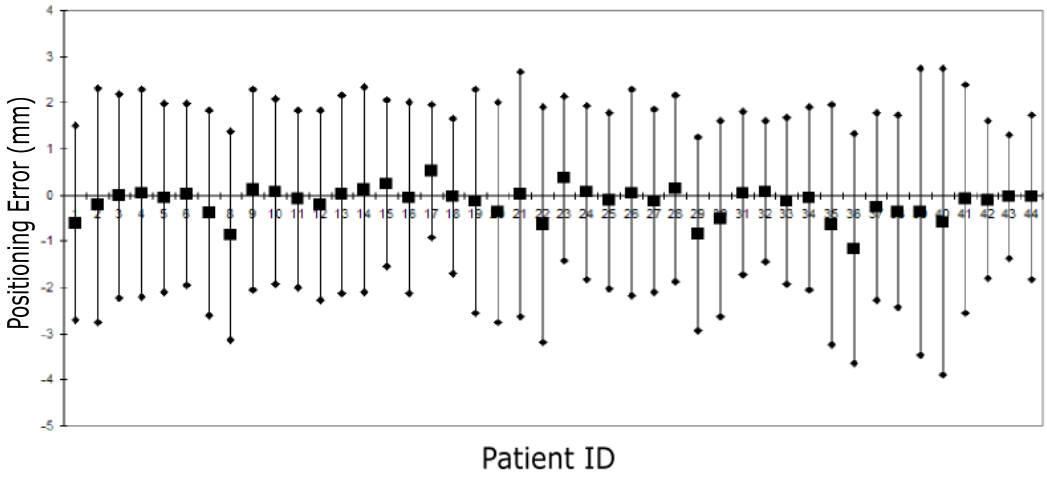

Figure 2. The average signed positioning errors for aortic segmentation.

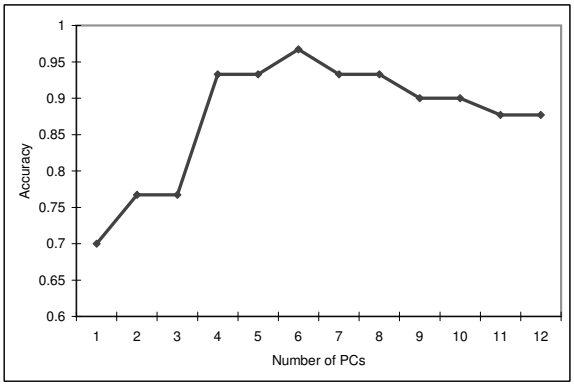

Figure 3. Classification correctness vs. number of PCs selected for SVM classification.

10,713 landmarks were generated. The first 6 principal components were selected as SVM input features. The classifier exhibited correctness of 96.7%.

The achieved results demonstrate that the functional (shape and motion) information is an important contributor to the ability to distinguish between the normal and connective tissue disorder subjects. This shall not be surprising since the aortic motion is considered an important factor in diagnosing the aortic disease. Fig. 3 gives classification correctness assessment as a function of the number of PCs selected for SVM classification. This curve shows that

the best classification result for the sixteen-phase model is reached when 6 PCs are selected.

4. Discussion and conclusions

In this study, a computer-aided diagnostic method to identify subjects with connective tissue disorders from 4D aortic MR images was presented. The use of the 4D fast marching algorithm provides an automated pre-segmentation of the aorta allowing determination of the aortic centerline. Using the centerline, optimal graph-based multiple surfaces detection algorithm generates accurate and robust 4D segmentation surfaces simultaneously on the 4D aortic MR images. This segmentation results also guaranteed a globally optimal segmentation result. The resulting aortic surfaces showed an excellent agreement with the segmentations traced by expert observers.

When comparing the single-phase and 16-phase disease classification acuracy, the classification accuracy generated from the sixteen-phase 4D model was substantially better compared to that obtained by the single-phase model (86.7%). This result demonstrates that the motion information which is captured in the 4D model likely contributes to the classification performance and is therefore related to the connective tissue disorder disease. This motion information is difficult to observe by a human eye but it can apparently be detected by our 4D CAD system.

Our novel approach to objective image-based computer-aided identification of connective tissue disorder subjects offers excellent performance. Our results yield a great promise to focusing on the next step of our research – computer-aided determination of disease status from longitudinal sequences of MR image data.

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