Segmentation and Deformation Analysis of the Aorta in Gated CTA sequences in a MDL Framework

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Abstract. We propose an automated method to quantify the deformation patterns of the aortic arch surface in gated computed tomography angiography sequences. The vessel is detected and segmented by an active surface approach that accurately identifies the lumen in all frames of the sequence. The vessel wall deformation is modeled autonomously based on this data by means of a minimum description length criterion. The approach builds a model from the sequence of volumes, and results in correspondences for a set of landmarks on the vessel surface. The resulting dynamic model enables us to measure global and local deformation properties of the aorta wall during the cardiac cycle and to compare them across different patients and during ongoing therapy. It is targeted at assisting surgeons in planning and evaluating invasive or non-invasive procedures to repair the vessel, like vessel transposition and stent-graft placement. We report qualitative results of the deformation description and a validation of the registration precision for 6 data sets.

1 Introduction

In this paper we propose a method for the modeling of the aorta wall deformation during the cardiac cycle from ECG-gated computed tomography angiography (CTA) sequences. The patient-specific model represents the deformation behavior of the aorta, and in particular the movement of the aortic arch. This is of high relevance in the preparation, planning and follow-up assessment during the treatment of aneurysms. Physiological deformation patterns of the aortic wall are severely altered by aneurysmatic dilatation and again by subsequent treatment, consisting of either surgical or endovascular repair. Nevertheless, no risk stratification score exists for patients suffering from aortic arch pathologies [1]. In order to predict outcome and ultimately avoid complications after different treatment options, it is crucial to quantify changed aortic movement, pulsatility and shear stress of the aneurysm wall.

Segmenting blood vessel systems has been an active area of research ever since appropriate imaging techniques have been available. The work in the field can roughly be grouped into two approaches. For one, a substantial amount of work has been put forward concerned with modeling complex vessel trees such as in the lung [2]. On the other hand, specific vessels and their movement have been analyzed in more detail. To our knowledge, the proposed measures are based mostly on the centerline of the vessel [3]. There exists a substantial amount literature on the dynamics of vessel walls originating form the biomechanics community [4]. Our work is aimed at bridging the gap between these biomechanical models and patient specific observations and analysis. We tackle the deformation analysis in a model building framework. There exists a body of work regarding the question of automatic model building or equivalently that of establishing correspondences over landmark positions in a set of images. Examples are [5] where the temporal continuity of image sequences is used to determine correspondences. Given a set of manual continuous contour annotations in [6–8] landmarks are placed automatically along contours or surfaces that are mapped to a circle or a sphere using minimum description length (MDL). The reference manifold limits the approach to a topological class. Even-though these purely shape based approaches provide good landmark positions for constructing a compact shape model, in [9] the authors conclude that the lack of texture information poses a limitation hampering the capturing of *true* correspondences, like anatomical landmarks, and in [10] an approach for the model learning from discrete point sets based on a shape model, and local features was proposed. The approach proposed in this paper is most closely related to this method.

We propose a method for the autonomous generation of a dynamic model of the aorta wall. The main features of the model building method are a robust center-line estimate, a segmentation of the lumen allowing for anatomical analysis

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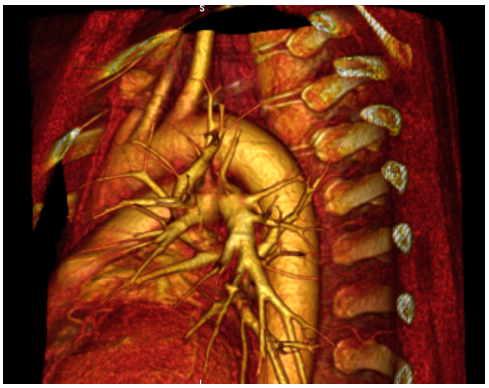

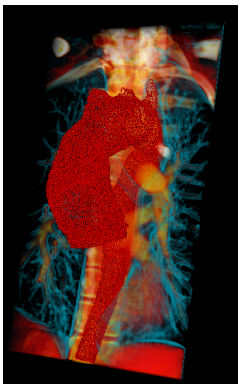

Figure 1. (a) The aortic arch with the three supraaortic branches and the descending aorta. The deformation behavior is relevant to predict intervention outcome, and to assess changes caused by the intervention. (b) The segmentation of the aortic arch.

and a precise registration of points on the vessel wall. We can use this model to measure dynamics of the aorta and changes induced by healthy and pathological deformations.

2 Method Outline

The method is roughly divided into three steps. First the aorta is detected and segmented in each of the CT volumes acquired during the cardiac cycle. Based on this segmentation, correspondences on the vessel surface are established by group-wise registration of the surface data. The resulting model serves as basis for the quantitative assessment of the deformation behavior.

3 Aorta Segmentation

As a first step we robustly segment the aorta in each frame of the CTA sequence. For this, we propose a strategy that extracts the centerline, the lumen, and consequently local properties of the vessel wall. The approach accounts for the potentially severe pathological changes of the morphology (Fig. 3), that preclude standard vessel detectors.

Initialization and tracking During the gated CT acquisition contrast agent is applied, thus the contrast enhancement (i.e. an increase of Hounsfield units) can be used to robustly locate a point of the first slice of the CTA volume lying inside the *aorta descendens*. Starting in vertical direction at that point, we can derive a first estimate of the vessel by morphological operations on the thresholded slices perpendicular to the vessel axis. This allows for a tracking of the vessel until the aortic valve.

Once a rough estimate of the vessel centerline is computed, we apply simple Fourier-space based smoothing [3] to eliminate higher frequencies of the trajectory. We traverse the volume again following this smoothed centerline. At each sampling point of the trajectory, a slice of the plane perpendicular to the trajectory is extracted from the volume. On this slice, we locate the vessel lumen using a gradient vector flow field (GVF) based active contour model [11, 12] with strong internal forces. This results in a better estimate of the vessel centerline and contour.

Segmentation The two preceding steps result in a robust estimate of the vessel centerline. It is used to perform a fine segmentation of the aorta in the whole CTA volume. To eliminate irregularily sampled regions, the smoothed centerline is interpolated at positions dependent on its local curvature. At each of these, a GVF based active contour model is fitted to the local orthogonal plane, and converges to the interior vessel wall. This segmentation is used as the initialization of a second, balloon gradient-based active contour model [13] which converges to the outside of the gradient induced by the contrast agent (Fig. 2).

4 A dynamic model of the aortic arch deformation

Based on the segmentation of the aorta surface, we now have to establish correspondences for a set of points on the surface across the entire sequence. The approach to register the surfaces is related to the model learning methods proposed in [10, 14] . In contrast to other more differentiated anatomical structures, the aortic surface does not exhibit

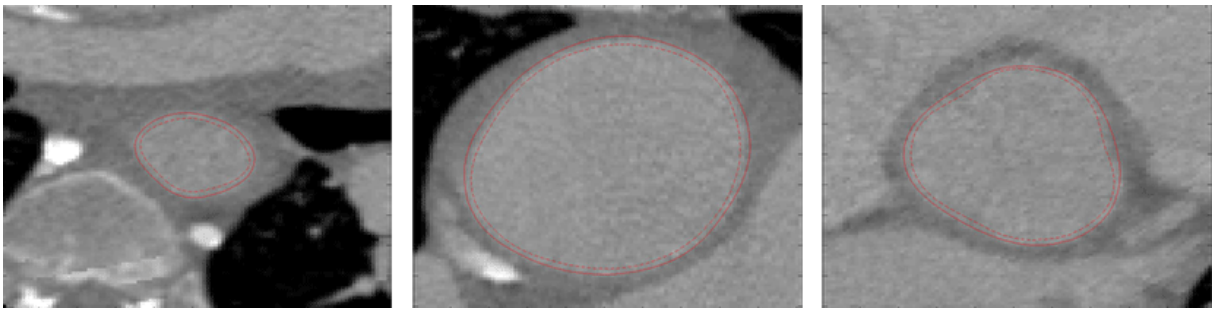

Figure 2. Segmentations of multiplanar 2D slices in (a) the descending aorta, (b) within an aneurysm and (c) at the aortic valve.

clear anatomical landmarks. Thus we derive correspondences by an *emerging shape and appearance prior*, i.e. by learning a shape and local appearance model of the aorta surface and its deformation during the cardiac cycle.

4.1 Registering the vessel wall by learning a model

The registration is based on the assumption that both the shape of the aorta and the local anatomical structure changes in a systematic manner during the cardiac cycle. We formulate the registration problem as the question of learning a model that captures both the shape and local structure variation in a compact manner. The segmentation of the aorta at each time point serves as a set of candidate points. For a set of landmarks we learn correspondences across the entire cardiac cycle. From the set of n volumes $\mathbf{I}_i$, $i = 1, 2, \ldots, n$ of the aortic arch acquired during a cardiac cycle the segmentation results in n (very large) sets of m_i vessel wall points i.e., the segmentation. Initial correspondences for a subset of k of these points are established by pairwise matching of subsequent frames. The k initial landmarks are chosen randomly, and k is chosen so that the landmarks cover the vessel wall with a certain density. This results in initial correspondence estimates for k landmarks $\{l_1, \ldots, l_k\}$, which can be encoded in a $k \times n$ matrix $\mathbf{G}$. Each column represents an example volume, and the entry $\mathbf{G}_{ji} \in \{1, \ldots, m_i\}$ with $j \in \{1, \ldots, k\}$ is the index of the interest point in volume $\mathbf{I}_i$, at which the landmark l_j is positioned. Starting from these correspondence estimates we minimize a criterion function that captures the compactness of the model comprising the local variation of landmark positions and local feature variation at the landmark positions. By minimizing the criterion we aim at improving the correspondences, so that the final trajectories capture the true deformation of the aorta surface. The points on the vessel surface are treated as landmark candidates. Each point (i, q) with $q \in \{1, \ldots, m_i\}$ is assigned its coordinate information $\mathbf{p}(i, q)$ and local features $\mathbf{f}(i, q)$ - in our case: the local gradient behavior at the point position. By assigning $\mathbf{G}_{ji} = q$ the landmark l_j in image $\mathbf{I}_i$ has position $\mathbf{p}_{ij} = \mathbf{p}(i, q)$ and feature vector $\mathbf{f}_{ij} = \mathbf{f}(i, q)$. During model building we minimize the criterion function, resulting in *optimal* positions for each landmark in each image. In the following we will briefly explain the two main terms of the criterion, capturing the *shape variation*, and the *local appearance variation*.

The local shape model constraint We use a standard linear multivariate Gaussian model [15] to represent the shape variation of local sets of landmarks. Each of n shapes is represented by the set of k landmarks in the corresponding volume. Each of the n shapes in the training set can then be represented by a $3k$ dimensional vector $\mathbf{x}_i$ generated by concatenation of the 3-dimensional coordinates of the points. The shape is modelled by a multivariate Gaussian with model mean $\bar{\mathbf{x}}$ and covariance matrix Σ. During the optimization we build a local shape model for each landmark i, that consists of the u closest neighbouring landmarks in each iteration. The local shape examples are aligned, and the covariance matrix of the landmark coordinate values is used to calculate the shape cost term C_S^i, which is the corresponding Mahalanobis distance to the resepective distribution of the landmark position.

Local data constraint In addition to the pure shape term we use the local CTA data to guide the registration. Each of the landmark candidates on the vessel surface is associated with local gradient behavior at its position. In the resulting data criterion two local gradient values corresponding to a landmark are modeled as a Gaussian. Analogously to the shape model, we use the mahalanobis distance C_D^i to determine the most fitting candidate point to be assigned the landmark identity in each iteration.

The criterion The optimization iteratively optimizes the joint criterion $C^i = C_S^i + C_D^i$ for each landmark, and converges at landmark positions for each of the time points in the gated CT sequences. These positions capture the deformation of the aorta wall, and define a global deformation field, that allows for a study of the motion patterns on the aortic wall.

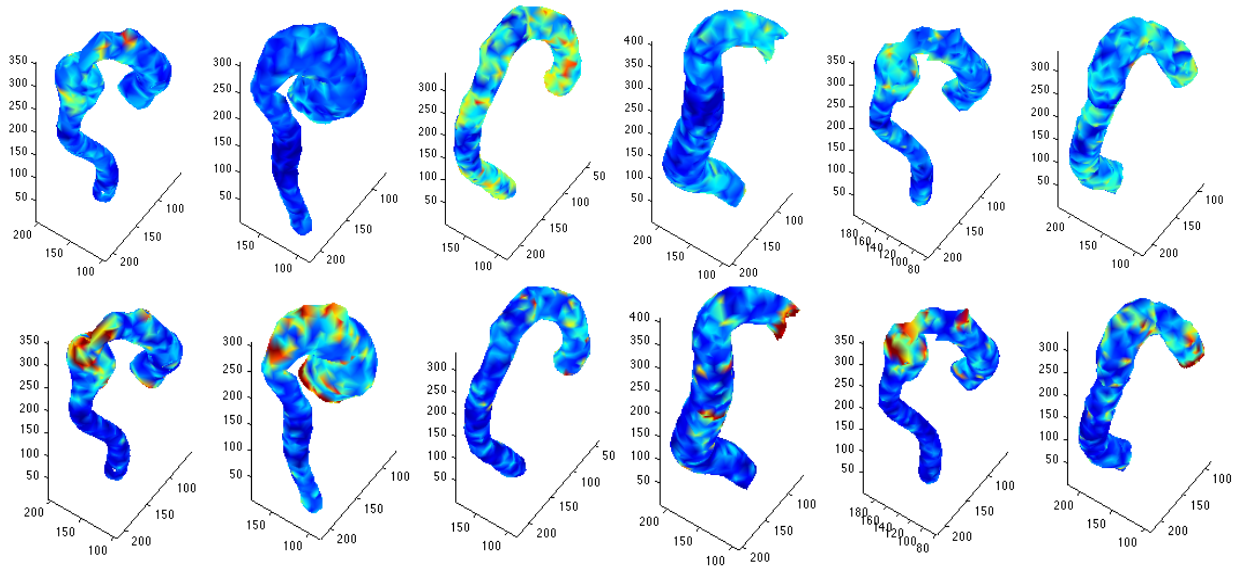

Figure 3. Mean bending (a - upper row) and stretching (b - lower row) of the vessel surface.

5 Describing the Vessel Wall and its Deformation

The registration of points across the frames of the gated CTA sequence allows us to measure local properties of the surface. We explore two measurements useful in the planning and assessment of surgical interventions in the aorta, in particular in the aortic arch: **1. Change of local curvature** We deduce the amount of bending occuring at specific locations of the aorta from the angular change of their respective normal vectors as illustrated in Fig. 3 (a). This change in local curvature of the aorta can either be measured between consecutive frames or aggregated over the whole cardiac cycle, yielding an estimate of overall bending-stress on the vessel. **2. Surface stretching** We assess the stretching of the surface during the cardiac cycle by measuring the change in distance of every point of the model to its k-nearest neighbours serves as an indicator for the amount of tissue stretching induced by the vessels movement. Fig. 3 (b) shows examples of this deformation measure. Note the increased stretching at the aortic valve and in the aortic arch.

6 Experiments

We performed experiments on a set of 6 gated CTA sequences. The goal of the experiments was to assess the motion features qualitatively, and to validate the precision of the model learning procedure.

Vessel deformation assessment For each of the 6 sequences we performed the model learning, and measured both the bending and the stretching measure at each of 2000 nodes on the surface. In Fig. 3, the value of the deformation in the cardiac cycle is depicted on the mean vessel surface. The colours indicated the strength from blue for low to red for high. Notably, the stretching as well as bending forces are high at the aortic valve and in the aortic arch. Note that in particular positions close to aneurysms (see e.g. round extension in the first column) are subject to higher bending deformations. Column 1 and 5 show data of the same patient at different acquisition sessions. Note that both the bending and stretching are consistent across the acquisitions. The study of specific locations of high strain induced by the vessels movement and their clinical relevance is subject of ongoing research.

Reproducibility To validate the precision of the model learning and registration we perform multiple registrations: First, segmentations of the aorta in 6 CTA sequences consisting of 10 frames each are computed. We then learn 5 models from every sequence based on randomly seleceted interest points distributed evenly on the surface. These are used to compute thin plate spline deformation functions between every two frames of each sequence. These 81 mappings are compared by applying them to a set of 5000 points on the aorta surface. The mean deviation of the resulting positions indicate the reproducibility of the registration.The procedure gives a measure of the reproduciability of the MDL-based registration. Mean and standard deviation of the mapping error for 6 different cases are given in fig. 4. The results show a deviation in mapping of no more than 1.5 voxels, the mean deviation is between 0.414 and 0.555 voxels. This indicates that the model building process is independent of the chosen subset used for registration and captures the vessel shape variation well, given a sufficient number of sample points.

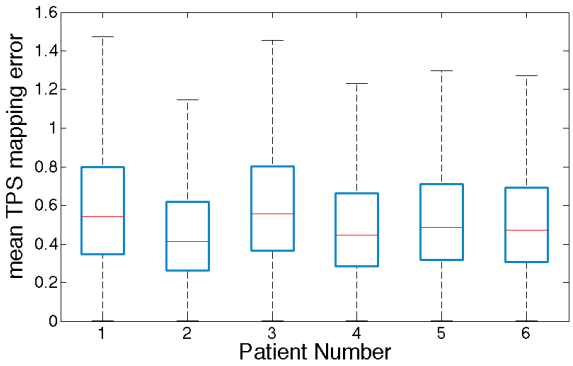

Figure 4. Precision of the registration: standard deviation of deformation fields (in voxels) measured for 5000 points, for 5 repeated registration runs on 6 gated CT sequences.

7 Conclusion

In this paper, we propose a method for the fully automatic segmentation and deformation measurement of the aorta in gated CTA sequences. Dense point clouds generated by a segmentation of the aorta in each frame of the sequence are used as basis to learn a statistical model of the deformation of the vessel. These models are based on a set of landmarks for which correspondences are learnt throughout the sequence. They capture the deformation of the vessel wall, and are used to assess different measures of the dynamics of the vessels movement. These measures are highly relevant in the preparation and risk stratification of intravascular repair. Future work will focus on correlating the observed deformation patterns with the ECGs to obtain time-specific quantitative information of the vessel motion, as well as on the registration of segmentations of pre- and post-interventional sequences.

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