EVALUATING DEFORMATION PATTERNS OF THE THORACIC AORTA
IN GATED CTA SEQUENCES

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ABSTRACT

Cardiovascular interventions in the region of the aortic isthmus such as stent-grafting and vessel transposition introduce substantial changes in the deformation properties of the affected vessels. The changes play a fundamental role in the long-term prognosis for any such treatment, but are only poorly understood to date. We explore a fully automated method to quantify the deformation patterns of the thoracic aorta in gated computed tomography sequences. The aorta is segmented by a level set approach that accurately identifies the vessel lumen in each frame of the sequence. Consequently, landmarks on the vessel wall in each frame are registered using a probabilistic method. This allows for the measurement of global and local deformation properties. We evaluate our method on synthetic datasets and report first results of its application on real world data.

Index Terms— registration, deformation, vessel, cardiovascular

1. INTRODUCTION

In the prognosis for many cardiovascular diseases the vessel movement and wall deformation are of considerable interest [1]. In particular arteriosclerotic and other vascular pathologies and their subsequent treatment - either surgical or endovascular - severely affect the deformation properties especially of bigger, and dynamic vessels such as the thoracic aorta. However, most work on the underlying hemodynamics is based on static models of the vessel system. On the other hand, analysis of vessel dynamics is often limited to measurements on the vessel centerline [2].

We propose a method to automatically build a dynamic model of the whole aorta surface from electro-cardiogram-gated computed tomography sequences (ECG-CTA). This model allows for the computation of a variety of deformation measures on the vessel surface and centerline alike that can be used to quantitatively assess changes caused by pathology and treatment.

ECG gated computed tomography angiography (ECG-CTA) is an imaging modality that enables the visualization of heart and vessel dynamics. A CTA sequence consists of \( n \) volumes representing discrete moments of a heartbeat identified by the phase of a co-observed ECG signal. As it is physically impossible to acquire a complete scan during a fraction of a heartbeat, a series of scans is performed. The data is then matched according to the phase of the patients ECG and the discrete frames reconstructed accordingly. Recent developments allow both high temporal and spatial resolution, making the study of detailed surface deformations possible.

State of the art and related work The automatic segmentation and analysis of blood vessels has been the subject of intensive study for a considerable time. A comprehensive review of the methods is given in [3]. In the following we point out the most closely related approaches.

Even in contrast-enhanced imaging modalities, blood vessels often exhibit low contrast and are hard to discern from surrounding tissue or touching structures. Most notably, level sets have been applied to overcome these problems as they allow for the inclusion of statistical properties of the segmented regions [4]. These segmentations are either computed directly in 3D on the whole volume of interest or iteratively on planes orthogonal to a pre-determined centerline.

Whereas level sets have become the quasi-standard in vessel segmentation, no such consensus exists for the problem of registering vascular structures. This is in large part due to the considerable variability exhibited by the vascular system. One commonly discerns landmark- and intensity-based methods for image registration. The presented method falls into the first category. It is closely related to the work of Langs et al. [5]. More recently, Suinesiaputra et al. proposed a method to automatically generate a model able to quantify heart wall deformation based on Procrustes alignment [6]. An interesting example of intensity-based registration can also be found...
in Zhang et al. [7]. Here, the pulsation of pathological cerebral vasculature is estimated by mapping multiple 2D projections to the underlying 3D volumetric image using mutual information. This approach is however not applicable for the problem at hand due to differences in the underlying image acquisition process. Instead of a global registration scheme the proposed method restricts the tracking to the deformable surface of the vessel, and performs a probabilistic registration of the corresponding discrete samplings.

2. PROPOSED METHOD

The proposed method tracks the deformation of the vessel wall during the cardiac cycle. Three steps are necessary to enable a quantitative analysis of vessel movement from a sequence of CT scans. First, the vessel under consideration is segmented in every frame $I_i$, $i = 1, \ldots, n$ of the ECG-CTA sequence. Consequently, correspondences between points $B_j$, $j = 1, \ldots, m$ of the segmentation must be established between these frames. Based on the resulting motion model local deformation features are extracted for the analysis and comparison of the aortic behavior. Due to space constraints we will focus on the segmentation and deformation analysis of the vessel.

2.1. Segmentation of the Aorta

In this section, we will present a fully automatic slice-wise tracking procedure that allows for the simultaneous extraction of the centerline and lumen of the aorta.

2.1.1. Initialization

As a first step, by averaging the intensity values $I_i(P_j)$ at the locations $P_j = (x_j, y_j, z_j)$ of strong response (e.g., 95 quantile) of a vesselness filter [8], we compute an estimate $\hat{h}$ of the Hounsfield value corresponding to contrast-enhanced blood inside the vessels. This rough approximation allows for the computation of a point $P_0$ in the descending aorta at which to begin the segmentation. The approximate location of the heart is found from lateral and dorsal projections to serve as a termination point $P_{end}$ for the tracking process.

2.1.2. Vessel tracking

The centerline is initialized in caudal direction ($N_0 = (0, 0, 1)$) at the point $P_0$ in the aorta descendens (see Fig. 1). A section of the plane $L_i$ orthogonal to the centerline at this location is extracted from which the vessel lumen will be segmented. For better readability, we will omit the index $i$ denoting the frame of the CTA sequence in the remainder of this section. It will be reintroduced for the discussion of the registration process. The extracted slice $L$ is pre-processed to remove spurious edges while maintaining salient image features using a two-part diffusion process. For this, two representations are computed from the raw slice (Fig. 1). Thresholding $L$ at the known intensity value $\hat{h}$ of the contrast agent results in a rough binary segmentation $L_T$. To account for edge information, the log-gradient $L_E = \log (1 + \| \nabla L \|$ is used. Whereas the segmented image can be subjected to any smoothing method (we used a Perona-Malik type diffusion), a coherence enhancing diffusion [9] is applied to the edge-image. This corresponds to the computation of

$$\delta_t L_E = \nabla \cdot \left( (R^T \begin{pmatrix} c_1 & 0 \\ 0 & c_2 \end{pmatrix} R) \nabla L_E \right)$$

There, the columns of $R$ are to the eigenvectors of the structure tensor

$$S = \begin{pmatrix} L_{E_x} I_{E_x} + G_u & L_{E_x} I_{E_y} + G_u \\ L_{E_x} I_{E_y} + G_u & L_{E_y} I_{E_y} + G_u \end{pmatrix}$$

in which $L_{E_x}$ and $L_{E_y}$ are the partial derivatives of $L_E$ and $G_u$ are gaussian filters at scale $u$.

This process (Fig. 1) aims at regularizing the segmentation while connecting detached edges. The two diffused images can be recombined and normalized to yield an edge-enhanced homogeneity score for every pixel of the slice. Experimentally, this score proved to be reliable even in ambiguous regions such as touching vessels. Combining this measure with the original grey-level slice results in an image exhibiting strong contrast between blood-filled regions and surrounding tissue.

A level-set segmentation is now computed on the scored slice. Experiments on the extended Kalman filter allows for the robust estimate of the vessels trajectory and thus the extraction of the next slice $L_{P_i N_i}$, defined by the estimated center $P_i$ of the vessel and its direction $N_i$.

There, the mentioned segmentation process recommences.

Fig. 1. Tracking and diffusion processes
2.1.3. Surface reconstruction

The tracking process results in a sequence of circular segmentations. From this, a surface mesh can be extracted by triangulating the underlying point cloud. However, due to irregularly spaced or missing samples, computing such a triangulation is a non-trivial problem. We therefore use that fact that we are operating on a cylindrical structure, and map the point cloud to a 2D space. For this, we define a boundary to the embedding, ideally representing some true outline of the object.

Every surface point \( B \) can be associated with a slice \( L_m \equiv L_{P_m,N_m} \) of the volume and thus with the discrete tracking step \( m \) it originates from. This information can be used to compute a cut \( C \) running along the vessel wall. Starting at \( L_{P_0,N_0} \) and following the estimated centerline, \( C \) contains a pair of neighboring surface points \( C_m = (B^1_{L_m},B^2_{L_m}) \) of every slice. By fixing the embedding of the points \( B_{L_0},B_{L_{N_m}} \) and \( C \), we map the point cloud representing the vessel to 2D using the minimally distorting measure presented in [10].

The coordinates of the embedded points are then interpolated and triangulated using a standard method such as [11] to yield a dense, regular surface mesh. In our experiments the proposed method did not introduce holes or fold-overs. The analysis of this property is subject of ongoing research.

2.2. Probabilistic Tracking of the Vessel Surface Deformation

A dynamic model of the vessel is obtained by establishing correspondences between sampling points on the vessel surface in consecutive frames of the ECT-CTA sequence. For this, it is not necessary to match every sampling point in every segmentation. Instead, a subset \( B^{(r)}_i \subseteq B_i \) of surface points closest to the interpolated ones is chosen, where \( r \) is their index positions in \( B_i \).

The shape of the Aorta can safely be assumed to vary smoothly during a heart beat. Also, neighboring regions on the vessel surface generally move in a coherent manner. Whereas earlier work [12] focused on the automatic construction of correspondences by MDL, we found that introducing a penalty on the coherence of the motion increased the performance of the method. We thus chose to align each frame in the sequence with the subsequent frame by means of the coherence point drift (CPD) method [13]. CPD is a probabilistic registration method. A mapping between point sets is computed by fitting gaussian mixture models (GMMs) to the points to be registered using a maximum likelihood criterion. The centroids of these GMM are in turn defined by the points being registered upon. The procedure thereby effectively establishes pairwise correspondences. The coherence of the matchings of nearby points is enforced by regularizing the displacement field defined by the registration.

The resulting registration can then be compactly represented as a matrix of indices \( G_{r,i} \), where each column contains the indices \( r \) of the chosen subset of \( B_i \). The rows of \( G \) represent the correspondences between \( B_{1\ldots n} \).

2.3. Deformation measures

We use two measures to characterize the vessel wall deformation at each registered surface point:

Local bending: We define local bending as the change in normal vector direction at a landmark position, thus \( \theta_{r,i} = \hat{n}_{G_{r,i}} \cdot \hat{n}_{G_{r,i+1}} \), \( \hat{n} \) being the local normal vector.

Local stretching: Stretching of the vessel wall \( \sigma \) can be approximated by the mean change in distance between a landmark \( r \) and its \( k \) nearest neighbors \( N_k(r) \) in consecutive frames. Formally, \( \sigma_{r,i} = \frac{\sum_{j \in N_k(r)} \| B_{r,i}(t_j) - B_{r,i+1}(t_{i+1}) \|}{k} \)

The measurements give a quantitative measure of the local deformation properties of the vessel wall during the cardiac cycle.

3. RESULTS

We evaluated our method on two data sets: 1. a set of 10 synthetically generated CTA sequences for which the correspondences are known. 2. For 2 patients we have pairs of ECT-CTA sequences acquired before and after stent-graft placement, for which we evaluated the the deformation measurements during follow-up examinations.

![Fig. 2. Evaluation on synthetic datasets](image_url)

3.1. Synthetic data

We defined deformation fields via sets of discrete control points in synthetic volumes. These were evaluated at the sampling locations of the segmentations using thin-plate splines interpolation. Comparing these expected deformations with the ones achieved by the proposed method on 10 synthetic
datasets yielded a mean registration error of .82 voxel. The results are summarized in fig. 2.

3.2. Clinical data

All data used in this study was acquired using a Phillips Brilliance 64 with a slice thickness of 1.4mm and reconstructed using a 512 matrix. We started evaluating registered sequences acquired pre- and post-treatment by visual inspection. Figure 3 gives an example of the mean bending and stretching for two specific cases before and after stent-grafting in the aortic arc (after supra-aortic rerouting). The change in deformation induced by the intervention can be noted at various points of the vessel surface. First results indicate that bending seems to have increased especially at the extremities of the stent-graft (marked by arrows in fig. 3). On the other hand, stretching has diminished notably in the stented part of the vessel, possibly due to the rigidity of the prosthesis.

4. CONCLUSION

We present a fully automatic method to quantify the changes to vessel wall movement induced by surgical and endovascular interventions. It is based on a probabilistic tracking of the thoracic aorta wall during the cardiac cycle. The framework is the basis for the quantification of deformation changes caused by vessel transposition and stent-graft placement in the thoracic aorta. Future work will focus on the inclusion of a parametric deformation model during the tracking. These measurements and the patterns they exhibit can lead to better understanding of the origin and the prevention of post-interventional complications. Additionally, we will evaluate the possibility of using the knowledge gathered via the presented method for therapy planning and outcome prediction.

5. REFERENCES