Model-based Postoperative Modeling of Stent-Based Devices from CT: Application to TAVI

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Abstract. As cardiac minimally invasive interventions are progressively substituting conventional surgical procedures, a constantly increasing number of stent-base devices are being implanted. Hence, tools for postoperative assessment and monitoring, which can provide a high-level of information about in-vivo structural and mechanical characteristics of devices, are becoming essential. We propose a novel method to automatically extract a model of stent-based implants from 3D CT volumes that combines data-driven machine learning methods with physically geometrical constraints. The Marginal Space Learning framework is used to estimate the position of a stent from an input cardiac image. A robust detector is introduced, which localizes stent struts crossing from an unfolded volumetric representation parameterized by the local coordinate system of the detected device. The model of a stent-frame is determined by computing its realistic deformation subject to internal forces that emulate mechanical behavior. The method was evaluated on post-operative CT volumes of 28 patients that received CoreValve devices during TAVI procedures. Results demonstrated a speed of 10.2 second per volume and average accuracy of 1.27 mm.

1 Introduction

Last decade has seen a tremendous development of minimally invasive techniques and interventional procedures for cardiac treatment substituting conventional open-heart surgery. An immediate effect of this global trend is a constantly increasing number of implanted devices in lieu of surgical repairs and sutured prosthesis. Hence, the postoperative assessment and monitoring of devices as well as a better understanding of their motion characteristics and in vivo behavior has become essential.

Inaccurate deployment can result in poor hemodynamic performance with severe paravalvular leakages and/or high gradients of pressure and suboptimal effective orifice. Wrong implant sizing may require re-operation or can damage
the vessel tissue and cause catastrophic events as arterial dissection or rupture. A misplaced implant, for instance in the aortic valve, can block the coronary ostia, thus inducing a life threatening ischemic condition. Long term stress during the life time of the implant may cause defects in the device and necessitates periodic evaluation [1]. Therefore, a model that captures a high level of information about a stent-based device would be valuable to analyze and gain insights into its in vivo behavior.

Several methods have been proposed for the segmentation of the wire frame of the stent grafts from CT data, which further underlines the importance for assessment tools for stent-based devices. Recently in a work by Lang et al. [2], the stent’s frame is found using a statistical model by simultaneously learning structural and shape information from a training set. In Klein et al. [3], graph processing is proposed to determine connections between seed points and further refine the segmentation output for the stent in the form of an undirected graph. Since these methods are purely data-driven, performance may suffer in the presence of noise and motion artifacts as well as calcifications.

We propose a novel method to automatically extract a model of stent-frames from 3D CT volumes, which combines data-driven statistical methods with physically-meaningful geometrical constraints. We specifically address an emerging procedure of high-interest, namely the Transcatheter Valve Interventions (TAVI), performed using a Medtronic CoreValve Device (Minneapolis, MN, USA) [4]. In a first step, the device type and global position are computed using the Marginal Space Learning framework. A robust learning-based algorithm is introduced to estimate the probability of strut crossing points in an unfolded volumetric representation of device parameterized by cylindrical coordinates. The final parameters of the stent-frame are determined by computing its realistic deformation subject to internal forces that mimic the mechanical behavior of the device. The proposed method was evaluated on 28 post-operative CT volumes of CoreValve TAVI procedures demonstrating an average accuracy of 1.27 mm and a speed of 10.2 second per volume.

2 Methodology

The process of estimating a personalized model is divided in three stages (Fig 1) that combine the discriminative power of machine learning approaches with the prior knowledge about the device and its geometrical properties: i) estimation of global rigid parameters, ii) identification of stent strut crossing locations and iii) model-based fitting. While the method is generic enough to be applied to other device types, this work focuses without loss of generality on two types of implants of the CoreValve Revalving System by Medtronic (Minneapolis, MN, USA), which are the models CRS-P3-640 and CRS-P3-943.

2.1 Estimation of Global Rigid Parameters

In this step the global position parameters

\[ \Phi = \{(C_x, C_y, C_z), (\alpha_x, \alpha_y, \alpha_z), (S_x, S_y, S_z)\} \] (1)
Fig. 1. Diagram depicting the personalized model estimation. See text for details.

Fig. 2. (a) Diagram showing the correlation function between the middle diameter of the stent and the average $\mu_{S_x, S_y}$ of the bounding box size $S_x$ and $S_y$ measured in mm, the regression line (red line) and its R-Squared value, (b) Cylindrical coordinate system using the estimated parameters $\Phi$ are estimated defining a bounding box around the stent device, where $(C_x, C_y, C_z)$, $(\alpha_x, \alpha_y, \alpha_z)$, $(S_x, S_y, S_z)$ are the position, orientation and scale parameters respectively, and the type $T_1 = CRS - P3 - 640, T_2 = CRS - P3 - 943$ of a device from an input CT volume $I$. A probabilistic boosting tree (PBT) with Haar-like features [5] is trained to estimate the posterior probability $p(\Phi|I)$. The optimal parameters of $\Phi$ are then determined by efficiently scanning the search space using Marginal Space Learning [6].

The variation between the two devices addressed in this work is mainly characterized by a difference in the smallest diameter and height when completely expanded: 22/55mm and 24/53mm for the CRS-P3-640 and CRS-P3-943, respectively. Knowing that the diameter of CRS-P3-640 cannot be larger than 22 mm. A linear regression model (Fig 2(a)) can be used to estimate the device type directly from the global size parameters $S_x$ and $S_y$ and the measured smallest diameter. The device type $T$ is determined based on $\mu_{S_x, S_y} = (S_x + S_y)/2$, where $T = T_1$ if $\mu_{S_x, S_y} < 35 mm$ and $T = T_2$ otherwise.
2.2 Estimation of Stent Struts Crossings Locations

In this step a set of probable candidates is estimated for the location of stent struts crossings \( C = \{(x, y, z)_1, \ldots, (x, y, z)_n\} \). From the estimated parameters \( \Phi \), a cylindrical coordinate system is defined, that allows for an unfolded volumetric representation of the stent. The original volume \( I \) is reinterpreted and interpolated along radial, circumferential and longitudinal coordinates \((r, \phi, \alpha_z)\), to construct the unfolded volume \( I_u \) capturing the maximum diameter and height of the device (Fig 2(b) and 3 Top Left). The parameterization in the cylindrical coordinates not only facilitates the assessment and annotation of the device but also significantly benefits the subsequent discriminative learning steps by eliminating feature aligning procedures and minimizing the interclass variation [7].

Next, a robust detector is trained using Haar features and the PBT algorithm to model the posterior probability of strut crossing locations \( p(S|I_u) \). As radiation attenuation is much stronger for metallic materials, and hence its Hounsfield units (grey level intensity) is significantly above the tissue intensities, we reduce the search space for training and testing within a binary mask, obtained by image thresholding (\( \geq 1600 \) HU showed best performance in the presence of noise and artifacts), to concentrate the generation of positive and negative locations (Fig. 3 Top Right). A typical probability map for strut crossing locations is given in Fig. 3 Bottom Left.

From the obtained uniform distribution of the final candidates for stent struts crossing locations a subset is extracted by exploiting prior knowledge about the
device geometry and topology. A clustering scheme is applied that is parameterized by the crossing location and size of a strut of an optimally deployed stent in cylindrical coordinate space (Fig 3 Bottom Left). In the spirit of non-maximal suppression for each of the clusters ($N \leq 165$), the top 10 most probable candidates are selected for further consideration.

### 2.3 Model based fitting

In order to address image noise and artifacts following a model based approach, a virtual templates of the target stent is created, which incorporate realistic geometrical properties of the device and mimics its mechanical behavior during the process of fitting the template to the subject specific deformation.

**Device Modeling** The implant consists of two eyelets and 135 cells formed by the struts, which ensues 165 strut crossing locations and 11 parallel ring levels, where the levels are defined by the short axis cuts containing the strut crossings (see Fig. 4(a)). Dimensions were obtained from the design specification and stereolithographic scans of fully expanded implants, namely the strut lengths, the characteristic angles in each cell and circumferences at each ring level. The virtual device is composed of the computational mesh — a 2-simplex mesh, which guides the fitting process — and the stent mesh, which is defined on a subset of points across the computational mesh (see Fig. 4(b)) and captures the device’s geometry [8] and is associated with the measured dimensions.

**Device Deployment** The virtual deployment of the device is modeled by balancing external and internal forces to mimic its mechanical behavior, using iterative optimization methods. Internal stiffness and external attraction to the previously estimated strut crossings are acting on the stent template to enforce subject specific deformation, while preserving characteristic dimensions.
<table>
<thead>
<tr>
<th>stent point-to-mesh</th>
<th>mean (std)</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
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<td>0.77</td>
<td>1.36</td>
</tr>
<tr>
<td>ascending sinususes</td>
<td>1.09 (1.51)</td>
<td>1.06</td>
<td>1.31</td>
</tr>
<tr>
<td>annulus</td>
<td>1.38 (1.21)</td>
<td>1.35</td>
<td>1.75</td>
</tr>
</tbody>
</table>

**Fig. 5.** Estimation accuracy in mm across the whole stent (point-to-mesh) and three levels relative to the aortic valve anatomy ([A], [B], [C]). Values of mean and standard deviation are provided as well as 80 and 90-percentiles.

such as strut lengths. Initially centered and oriented using the previously estimated bounding box the fully expanded model represented by a simplex mesh is deformed iteratively according to the following explicit scheme:

\[ p^{n+1}_i = p^n_i + (1 - \gamma)(p^n_i + p^{n-1}_i) + f_{int}(p^n_i) + f_{ext}(p^n_i) + f_{reg}(p^n_i) \]

In this equation, \( p_i \) is a point on the simplex mesh, \( n \) is the iteration number, \( f_{ext}, f_{int} \) and \( f_{reg} \) are the external, internal and regularizing forces, and \( \gamma \) is the weighting parameter. Fig. 4cd show a visual description of each of the forces. In this study we employed the internal and regularizing forces. In particular, the regularizing forces \( f_{reg} \) act on the simplex mesh to provide smoothness while the internal forces \( f_{int}(p^n_i) = f_{length}(p^n_i) + f_{angle}(p^n_i) \) model the intrinsic properties of the stent and enforce the targeted dimensions, that is the strut lengths and characteristic angles observed in the expanded shape.

By integrating the knowledge obtained from the previous estimation step. We model the external forces \( f_{ext}(p_i) \) such that they drive the stent template towards the detected strut crossing points: \( f_{ext}(p_i) = c - p_i \), where \( c_j \) is a detected strut crossing and \( p_i \) is its corresponding crossing on the template. The correspondence is determined automatically, and updated at every iteration, within local bins determined in the cylindrical parameterization of the stent according to the following rule: \((c_j, p_i)\) is paired, if \((c_j - p_i) \cdot t_i < d_i^u \land (c_j - p_i) \cdot t_i < d_i^v\), where \( t_i^u, t_i^v \) are tangents along circumferential and longitudinal directions of the stent mesh at \( p_i \) and \( d_i^u, d_i^v \) are the distances to the neighbors of \( p_i \). The algorithm iterates until convergence is detected by \( \sum_i ||p^{n+1}_i - p^n_i||/N_i < \epsilon \), where \( \epsilon = 0.02 \) showed best results in our experiments.

**3 Experimental Results & Discussion**

The validation of the proposed framework was done on 28 patients with post operative single-phase cardiac CT data. Scans are acquired from different patients with various cardiovascular diseases (including ascending aortic root aneurysm, regurgitation, calcific stenosis and bicuspid aortic valves), using different protocols, resulting in volumes with 80 to 350 slices and 153x153 up to 512x512
Fig. 7. Example results of ground truth stents (a-d) vs. detected stents (e-h) showing color coded point-to-mesh distance measured in mm.

voxel grid resolution and an average spatial resolution of 1 mm. Each data set is associated with an expert annotation used as ground-truth.

The accuracy of the method was obtained using leave-one-out cross validation. The algorithm performed at an average speed of 10.2 seconds on a standard desktop machine (Intel Xeon 2.66Ghz, 2GB RAM). Quantitative evaluation of estimation results is provided in Table 3. The accuracy of the method was analyzed with two metrics computed on estimation result and ground truth annotation: the point-to-mesh distance across the whole stent mesh and the point-to-curve distance among points on three levels of the stent mesh, namely on the level of the ostia, annulus and in the ascending aorta. These levels have been selected as they are most relevant for detecting critical conditions such as blockages of coronary ostia, paravalvular leakages at the annular level or vessel dissection within the ascending aorta (Fig. 6). To guarantee a symmetric measurement, those distances were calculated in both directions, i.e. from estimated result to ground truth annotation and vice versa. The accuracy is close to the mean image resolution of 1 mm and acceptable regarding the fact that CT imaging displays the struts with a diameter of about 2 mm. A selection of estimation results vs. ground truth annotations are displayed in Fig 7, where estimation results are overlayed with color coding of point-to-mesh error.

Fig. 8 highlights the robustness of our method in three cases with heavy calcification and artifacts and displays two-dimensional reformation of the image.
Fig. 8. Estimation results in cases with strong calcifications and image artifacts. The algorithm produces plausible results despite considerable image distortion.

data overlayed with estimation results. Our algorithm still produces plausible results despite the presence of considerable image artifacts, which would harm the performance of purely data-driven approaches.

4 Conclusion
In this paper a framework for postoperative assessment of aortic valve implantation was presented based on a fast and robust estimation of a detailed stent model. Our approach enables precise modeling of the patient-specific stent morphology from clinical images. The validation on 28 patients showed promising within the range of image resolution. Our framework, being automatic, may thus constitute a surrogate tool for quantitative and systematic assessment of deployed stents, potential device migration and defects during long term follow up examinations.

References