J. Hagenah*, M. Scharfschwerdt, A. Schlaefer, and C. Metzner

A machine learning approach for planning valve-sparing aortic root reconstruction

Abstract: Choosing the optimal prosthesis size and shape is a difficult task during surgical valve-sparing aortic root reconstruction. Hence, there is a need for surgery planning tools. Common surgery planning approaches try to model the mechanical behaviour of the aortic valve and its leaflets. However, these approaches suffer from inaccuracies due to unknown biomechanical properties and from a high computational complexity. In this paper, we present a new approach based on machine learning that avoids these problems. The valve geometry is described by geometrical features obtained from ultrasound images. We interpret the surgery planning as a learning problem, in which the features of the healthy valve are predicted from these of the dilated valve using support vector regression (SVR). Our first results indicate that a machine learning based surgery planning can be possible.

Keywords: aortic root reconstruction; transesophageal ultrasound; surgery planning; support vector regression; machine learning

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1 Introduction

The aortic valve is an important structure located in the aortic root to provide the right direction of the blood flow in the human body. However, the functionality of the valve can be restricted, which can finally lead to a heart insufficiency. One reason for such a restriction is the dilatation of the aortic root wall. In this case, the geometry of the valve is distorted while the shape of the valve leaflets stays unchanged [1]. This distortion causes a valve insufficiency, which happens especially in patients with the Marfan-syndrome [2].
For these patients, the valve-sparing aortic root reconstruction is an alternative to valve replacement. The basic idea of this technique is to remodel the healthy shape of the aortic root using a prosthesis [4]. The patients leaflets are attached to this prosthesis. The advantages of this method are the natural valve leaflets much better mechanical properties and the longer durability compared to artificial valve prosthesis'. Fig. 1 shows the aortic root in the healthy, the dilated and the reconstructed state.

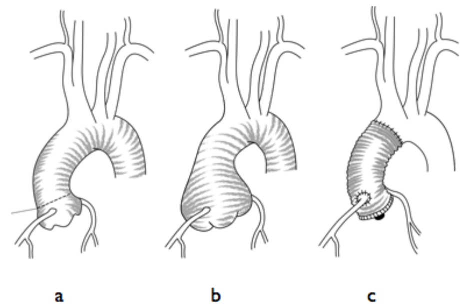

Figure 1: The aortic root. a) healthy state b) dilated state c) reconstructed state [3].

However, the estimation of the actual valve geometry and the determination of the optimal prosthesis size and shape are difficult tasks. During surgery, the heart is not pressurized, which limits the possibilities of detecting the actual root geometry. One further problem is that one can only obtain the root geometry in the dilated state, so the optimal prosthesis shape can only be estimated based on this distorted geometry. Performing this estimation before the treatment could improve the method significantly.
Previous approaches are aiming at finite element based simulation to evaluate the individual valves mechanics as well as the bloodflow through the valve with different prosthesis sizes virtually [5]. One problem of these approaches are the complex, non-isotropic biomechanical properties of the valve leaflets, which are not yet completely understood [6], making it very hard to find biologically reasonable constraints for the model parameters. Furthermore, three-dimensional image acquisition of the valve leaflets can be quite intricate [7] and the models are computational expensive. The simulation of the blood flow raises additionally raises the complexity.
In this paper, we present a new machine learning based

***Corresponding Author: J. Hagenah:** Institute for Robotics and Cognitive Systems, University of Lübeck, E-mail: hagenah@rob.uni-luebeck.de
M. Scharfschwerdt: Department of Cardiac Surgery, University Hospital Schleswig-Holstein, Lübeck, E-mail: michael.scharfschwerdt@web.de
A. Schlaefer: Institute of Medical Technology, Technical University Hamburg-Harburg, E-mail: schlaefer@tuhh.de
C. Metzner: Institute for Robotics and Cognitive Systems, University of Lübeck, E-mail: metzner@rob.uni-luebeck.de

approach to solve this problem avoiding biomechanical uncertainties.

2 Material and methods

The basic idea of the approach is to use a geometric description (so-called *features*) of the pathologically dilated valve in order to estimate the geometry of the optimal prosthesis.

In our experiments, we obtained healthy and dilated features of porcine aortic roots, which results in a *(dilated features, healthy features)* tupel for each examined valve. Accordingly, the problem of finding the optimal prosthesis can be described as a learning problem: the aim is to calculate the features in the healthy state based on the individual features in the dilated state. This problem can be solved using *Support Vector Regression* (SVR) where the obtained tupels *(dilated features, healthy features)* serve as training data.

The presented method can be separated into four steps: the experimental data acquisition, the feature extraction, the model training and the feature prediction. These steps are visualized in Fig. 2 and are described in the following paragraphs.

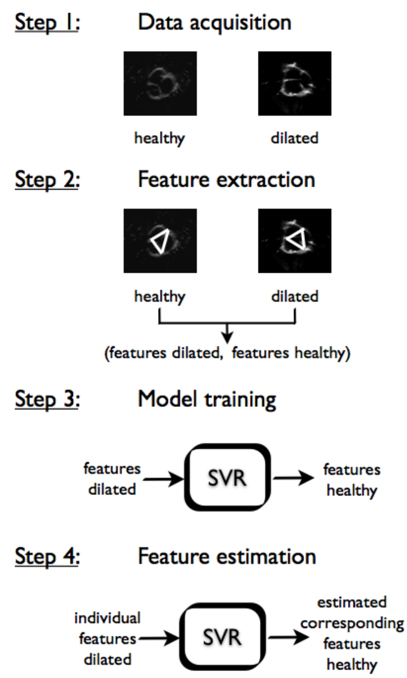

Figure 2: The main steps of the presented method. At first, ultrasound images are acquired. Then, geometrical features are extracted to get tupels of features in the healthy and dilated state. With these tupels, an SVR-model is trained. This model allows feature estimation.

2.1 Data acquisition

To obtain features of an aortic root, a suitable imaging modality is needed. Due to its fine structure and its fast movement during the cardiac cycle, the detailed leaflet geometry is hard to extract from typical volumetric images like CT or MRI. Because of this reason, we previously proposed the use of transesophageal ultrasound (TEE) [8], given its high temporal resolution. Further benefits of this modality are its low examination costs (compared to CT and MRI) and its availability in clinical practice.

We designed a setup to conduct a TEE-examination on ex-vivo porcine aortic roots [8]. In this setup, a porcine aortic root is pressurized by a constant diastolic pressure created by a water head. The ultrasound images are taken sequentially while the imaging plane is rotating. After that, a three-dimensional reconstruction is done by transforming the image data to a Cartesian coordinate representation. The result is a volumetric image frame of the aortic root.

As mentioned above, we examined ex-vivo porcine aortic roots. To get information about the root geometry before and after the pathological dilatation, we studied each aortic root in two different states: the *healthy* state and the *dilated* state. To examine the healthy state, we took volumetric ultrasound images of the unchanged root. To simulate the dilated state, the root wall was manually enlarged by adding additional aortic tissue into cuts in the root wall. After that, we acquired three-dimensional image data of the dilated root. The result are three-dimensional images of the root in both states.

2.2 Feature extraction

The aim of this step is to generate tupels of features that describe the geometry of the valve in the healthy and the dilated state. The extracted features were the three commissure distances k_1, k_2 and k_3, the effective height h_{eff} and the leaflet-specific characteristic parameters F and α, described in more detail below. The effective height is defined as the height difference between the commissure plane, where the leaflets are attached to the root wall, and the coaptation plane, where the three leaflets meet each other. It has a high influence on the functionality of the valve [5]. The leaflet-specific parameter F describes the area of the triangle formed by the two commissure points of the leaflet and the coaptation point (cf. Fig. 3). Hence, F

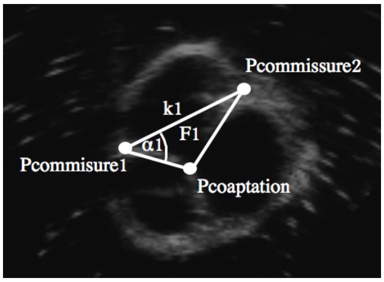

Figure 3: Ultrasound image of a porcine aortic root. For one leaflet, the commissure points $P_{commissure1}$ and $P_{commissure2}$, the coaptation point $P_{coaptation}$ and the geometrical features k_1, F_1 and α_1 are shown.

measures the size of the leaflet. α is one of the angles of the same triangle and describes the leaflets sheering. Both F and α affect the performance of the valve [9]. The commissure distances are defined as the distances between pairs of the three commissure points, respectively (cf. Fig. 3). The features were manually obtained from the ultrasound images using the open-source image analysis tool *3dSlicer* (Harvard Medical School, Boston, USA).

At the moment, the prostheses used in clinical practice are shaped as a tube, so we aimed to estimate the optimal prosthesis diameter. This diameter can be calculated based on the three commissure distances as the diameter of the circumcircle of the triangle formed by the commissure points. Hence, the commissure distances k_1, k_2 and k_3 are very important and the focus of this paper lies on a good estimation of them.

2.3 Model training

The surgery planning method aims at estimating the healthy features only based on the knowledge of the dilated features. In the previous steps we have obtained tupels *(dilated features, healthy features)*. Using this data set we train a support vector regression (SVR) algorithm to learn the mapping between the dilated and the healthy states. The SVR is a machine learning method that performs regression without initial knowledge of the underlying model [10]. In this paper, we used the so called ϵ-SVR with a *Gaussian radial basis function* kernel (RBF) using the *MATLAB*-implementation of the open-source library *libsvm* [11].

As mentioned above, the focus of this paper lies on a good estimation of the commissure distances. To find the best parameter combination for reaching this goal, we implemented a nonlinear simplex optimization method that minimizes the sum of absolute differences between the healthy commissure distances and the estimated commissure distances.

With this parameter set, we can train our SVR-model with the *(dilated features, healthy features)* tupels.

2.4 Feature estimation

After the training, the model is ready to reconstruct the healthy features of a valve from the individual dilated features. We obtained tupels of the healthy and dilated features of six aortic roots using the method previously described. We trained the SVM-model with five of the tupels and estimated the healthy features of the sixth valve with it. To evaluate the accuracy we compared all estimated features to the reference by calculating relative distances. Additionally, we calculated the root diameter based on the estimated features and the reference.

This evaluation was performed six times, each time estimating the healthy features of another valve while the other five valves where used for training (leave-one-out).

3 Results

We examined six porcine aortic valves using the method described in chapter 2. Accordingly, we estimated the healthy features of each of the six valves using an SVR-model trained with the other five valves' features, respectively. Table 1 shows the relative distances between the estimated features and the reference as well as the mean difference for each feature. As mentioned in section 2.2, our aim is to calculate the optimal prosthesis diameter based on the commissure distances. For this purpose, this diameter was calculated for the estimated healthy features as well as the reference features. The resulting prosthesis sizes are presented in Table 2. As the commonly used prostheses are produced with even-numbered diameters, we rounded our results appropriately.

4 Discussion

Table 1 shows particular differences between the estimated and the reference features. Some parameters for some valves are estimated good, others depict a high discrepancy. This is mainly due to the fact that the regression was performed with only five training samples. This is obvi-

Table 1: Relative differences in percentage between the estimated features and the reference for the six examined valves.

Feature	Valve 1	Valve 2	Valve 3	Valve 4
k_1	23,07	14,10	3,76	1,38
k_2	21,00	16,89	1,81	9,02
k_3	10,96	24,68	77,64	27,63
h_{eff}	50,901	69,77	9,30	38,65
α_1	8,81	47,18	54,85	6,31
α_2	16,24	26,18	4,48	2,18
α_3	0,87	3,41	1,24	16,76
F_1	38,22	50,70	17,64	27,40
F_2	26,64	85,92	110,83	33,21
F_3	38,77	39,02	100,82	18,00

Feature	Valve 5	Valve 6	Mean
k_1	18,61	2,73	10,61 ± 9.23
k_2	7,42	17,18	12,22 ± 7.28
k_3	4,52	4,94	25,06 ± 27.56
h_{eff}	29,93	10,13	34,78 ± 23.58
α_1	45,82	5,25	28,04 ± 23.51
α_2	3,04	12,20	10,72 ± 9.41
α_3	41,00	48,68	18,60 ± 21.24
F_1	51,06	18,06	33,85 ± 15.18
F_2	27,44	23,81	51,31 ± 37.42
F_3	80,71	27,72	50,84 ± 32.52

ously not enough information to produce reliable feature estimations.

However, Table 2 depicts that in two cases, the calculated prosthesis diameter fits to the diameter of the healthy valve. In three other cases, the difference is only one prosthesis size step. Hence, even with this small data set, an estimation of the best prosthesis diameter is possible.

Further work should aim for the enlargement of the training data set. This would likely enhance the accuracy of the SVR-model. Additionally, a greater number of training samples would allow for a higher dimensional regression, i.e. the estimation of one feature could be based on all other features.

Another interesting point is the further processing of the estimated features. If the features could be translated to a geometric model of the aortic root, it would be possible to produce patient individual prosthesis' with the specific shape of that patients aortic root in the healthy state. Estimating the prosthesis diameter could be just the beginning of individualization of cardiovascular implants.

Table 2: Estimated and reference prosthesis diameters in mm.

Valve	Reference	Estimated
1	24	26
2	18	20
3	16	20
4	28	28
5	20	20
6	22	24

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Author's Statement

Conflict of interest: Authors state no conflict of interest. Material and Methods: Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use has been complied with all the relevant national regulations, institutional policies and in accordance the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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