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Statistical shape modelling of the left ventricle and mitral valve

MEASURING AND AUTOMATION TECHNOLOGY
MAGNETOFLUIDDYNAMICS

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Introduction

Cardiovascular research and medical engineering are vital for combating cardiovascular diseases (CVD). This diploma thesis highlights the use of simulation engineering, high-performance computing, and machine learning to understand blood flows and to improve diagnostics and therapy planning. Standardizing workflows to handle data properties from different imaging procedures is crucial. Statistical shape modelling (SSM) is used to analyze patient-specific datasets, compare healthy and diseased geometries, and create synthetic cohorts.

The thesis focuses on statistical shape analysis of the left ventricle (LV) and the mitral valve (MV) using patient-specific datasets. One major pre-processing step is the alignment of grids and the generation of a common topology. Various SSM variants are compared for the LV and MV.

The human heart (Fig. 1) is structured in the right- and left-hand half. Moreover, one cardiac cycle consists of an expansion phase of the LV (largest volume) in the diastolic state and a contracting phase (smallest volume) in the systolic state. As the focus is only on the geometry outline of the anatomical structures, the two extreme states are of interest. Regarding the MV, the valve is open in the diastolic state and closed in the systolic state.

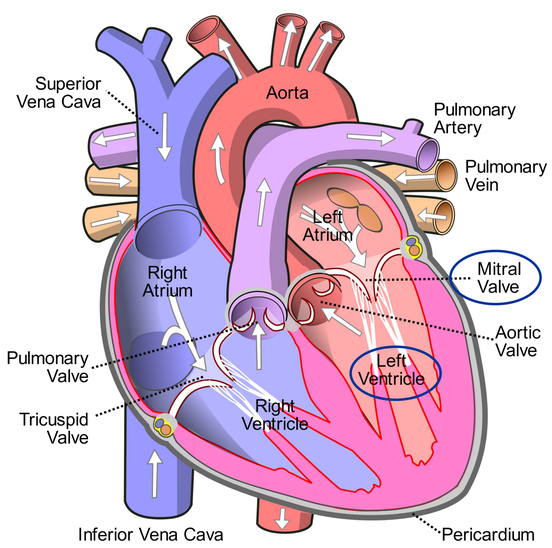

Fig. 1: Structure of the human heart [1].

Methods

After the acquisition of the patient-specific data from medical images, the obtained meshes tend to have different modalities. To conduct a statistical analysis of a cohort (multitude of geometries of one anatomical structure) the geometries and their surface representation are required to have equal grid topologies. Specifically, the number of vertices must be equal.
The statistical shape analysis is a method, which uses principal component analysis to analyze geometry variations. In the linear method, the shape matrix S (1) is constructed to represent multiple shapes with point-to-point correspondence. The mean shape is obtained by averaging the rows of the shape matrix. The correlation between shapes and their coordinates is computed using the correlation matrix (2). The eigenvectors of the correlation matrix represent shape modes, and their eigenvalues correspond to the variance [2].

By combining the mean shape with the eigenmodes and a shape parameter b, a coordinate representation of each mode can be computed (3). The maximum number of modes is determined by the size of the correlation matrix. The SSM can also be set up in a non-linear space to obtain a different behavior of the mode excitation. In the non-linear SSM, mode excitation does not result in a linear exaggeration of shape variation due to curved deformations in the mean shape. Transforming the coordinates into a Riemannian shape space, a different variant of the SSM is obtained [3]. In contrast to the linear SSM in the Euclidean space, the non-linear method promises to handle complex deformations more sophisticated.

$$S_{i,j} = \begin{pmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,m} \\ y_{1,1} & y_{1,2} & \dots & y_{1,m} \\ z_{1,1} & z_{1,2} & \dots & z_{1,m} \\ x_{2,1} & x_{2,2} & \dots & x_{2,m} \\ y_{2,1} & y_{2,2} & \dots & y_{2,m} \\ z_{2,1} & z_{2,2} & \dots & z_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \dots & x_{n,m} \\ y_{n,1} & y_{n,2} & \dots & y_{n,m} \\ z_{n,1} & z_{n,2} & \dots & z_{n,m} \end{pmatrix} \quad (1)$$

$$C_S = \frac{1}{m-1}\left(S^T \cdot S\right) \quad (2)$$

$$\hat{S}_i = \bar{S} + b_i \phi_i \quad (3)$$

Results

The workflow developed in this thesis consists of three main stages:

1. Acquisition of patient-specific data from medical images
2. Preprocessing of the geometrical data
   i. Alignment of shapes
   ii. Generation of meshes with equal topology (nodal correspondence)
3. Setup of statistical shape modelling framework
   i. Linear SSM
   ii. Non-linear SSM

The first phase also includes the segmentation of the medical images, which was not part of the thesis. As a preprocessing step towards the statistical analysis, the cohort of anatomical shapes needs to be aligned in space and all meshes are required to have a nodal correspondence within each other. The SSM method, either the linear or the non-linear variant, is applied on the generated shape matrix to construct the different modes. To compare the different types of statistical analysis, the modes, also called shape variances, are visualized. The shape variance is a statistical representation of typical variations in the shapes of the cohort.
Figure 2 shows the visualization of the first two shape variations of a cohort of left ventricles. The linear variant is compared against the non-linear method. As seen in the figure, the modes have a comparable form (upper and corresponding lower shape), yet the behavior is different. The first mode represents a volume alteration, whereas the second mode shows more detailed shape variations.

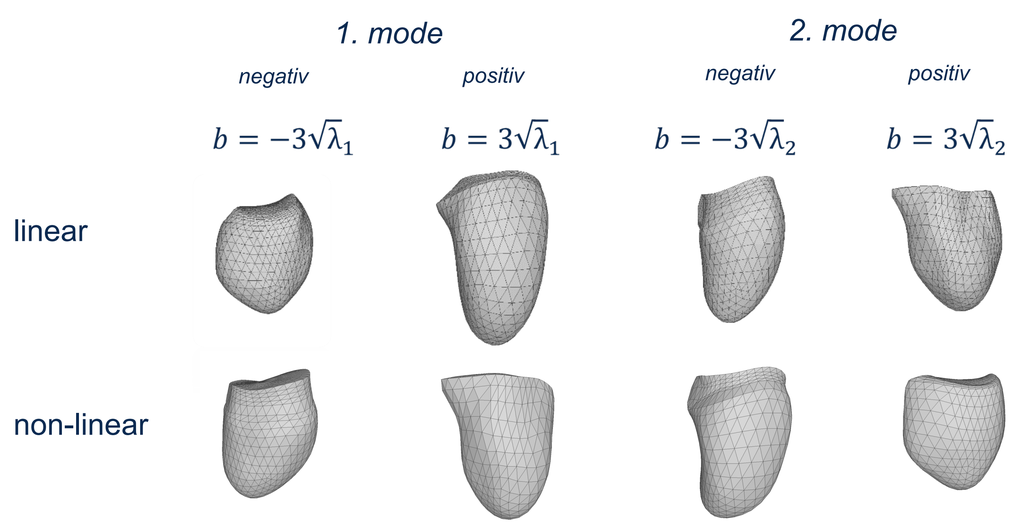

Fig. 2: Visualisation of the first and second mode of the LV using linear and non-linear SSM.

Conclusion and Outlook

The aim of this research is to overcome the limitations of acquiring large-scale anatomical datasets and facilitate the development of robust computational models for various applications in medical imaging, computer-aided diagnosis, and surgical planning. These statistical models capture the underlying anatomical variability, which can be expressed as a low-dimensional shape space.
The SSM gives the opportunity to construct synthetic shapes in a similar range of geometrical representations as the input data. Using the eigenvalues and the normalized eigenvectors, new shapes with a statistical representation of metric parameters can be created. By randomly selecting shape variations, a diverse range of anatomical instances can be created, resembling the real anatomical structures while preserving their statistical properties.

The shape parameter b is the scaled eigenvalue regarding each mode. A typical procedure to construct new realistic geometries is the usage of a normal distribution for the shape parameters and combining multiple significant modes together as Eq. (4) implies. Figure 3 visualizes a sample of synthetic reconstructed left ventricles. The synthetic cohort has a high variability in the curvature and size of the ventricles. Through filtering metrics of anatomical thresholds and characteristics the output of a realistic cohort can be ensured. A typical method uses defined metrics and compares the distribution of the metrics on the original and the synthetic data.

$$S_{new} = \bar{S} + \sum_{i=1}^{m} b_i \phi_i \quad (4)$$

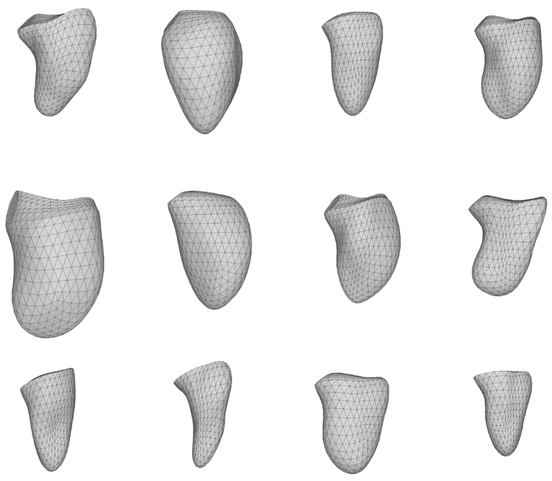

Fig. 3: Synthetic reconstruction of left ventricles using SSM.

In conclusion, the generation of synthetic anatomical data using statistical shape analysis offers a powerful tool for advancing medical imaging and computational modeling. The poster emphasizes the significance of this approach in addressing data scarcity, facilitating algorithm development, and ultimately enhancing patient care and treatment outcomes.

References

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