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Interactive Visualization of Statistical Shape Models

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1. Introduction

Statistical Shape Models (SSMs) [CTCG95] have many applications in medical computing, including segmentation, shape analysis and surface extrapolation [HM09]. A set of training shapes is described by a set of n point coordinates, such that all points with coordinate i in different shapes correspond to each other. Point coordinates of a single shape are concatenated to a shape vector, and the SSM is built by applying Principal Component Analysis to the set of training shape vectors. The set of shapes deemed *plausible* by the SSM is $\mathcal{S} = \{x(b) \mid x(b) = \bar{x} + Pb, -B \leq b \leq B\}$, where $\bar{x} \in \mathbb{R}^{3n}$ is the mean shape, $P \in \mathbb{R}^{3n \times t}$ is the matrix containing the t eigenmodes (or simply modes) and $B > 0$ is a vector of bounds for the shape parameters $b \in \mathbb{R}^t$. We call $\mathcal{S}$ the shape space of the model.

The quality of an SSM depends on several factors, for instance the number of training examples and the quality of the point correspondence. Although quantitative measures have been proposed to assess the quality of SSMs, especially in the context of point correspondence [DTT08], researchers can benefit from visualization to gain a better understanding of an SSM. The most frequent technique for the visualization of a mode i is to sample three or five equidistant values for the mode parameter b_i ranging from $-B_i$ to B_i, and to plot the shapes corresponding to these parameters side by side in a scatter plot [CTCG95, DTCT10] (compare also to figure 2). Typically, the first two or three modes of an SSM are shown, because they capture most of the model's variability. To give a continuous impression of a mode, one can use animation [LST*04] or visualize a *trajectory* through $\mathcal{S}$ using silhouettes [BBP10]. However, these visualizations are very restrictive, because they do not account for arbitrary linear combinations of modes. We propose an interactive visualization tool which helps to explore the shape space of an SSM and to compare different models. It can be used to prove or disprove model hypotheses, to find artifacts in the model like folding triangles and to refine model parameters such as the number of modes t or the bounds B.

2. Our approach

Our tool consists of a main view, which displays the current shape, and a control view which is used to modify the shape. Using sliders, one for each mode, the model can be interactively modified. This interaction allows the user to explore the complete shape space, and to prove or disprove that the model only generates plausible looking shapes.

If desired, the point-wise distance of a shape to a reference shape, for example the mean shape, can be visualized, as illustrated in figure 1. This is done by mapping the Euclidean distances between corresponding points in deformed and reference shape to colors. We use a colortable for sequential data taken from `www.colorbrewer2.org` ranging from light orange to red, where red corresponds to large distances. In order to provide a range for the colortable, we compute the upper bound

$$u = \max_{j \in \{1,\ldots,n\}} \sum_{i=1}^{t} \|p_{ij}\| B_i$$

for the maximal movement of a point in the model, where $p_{ij} \in \mathbb{R}^3$ is the displacement vector of point j in mode i.

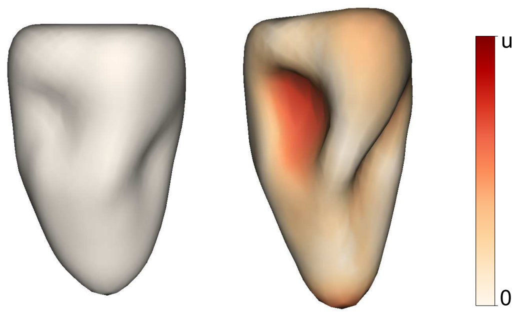

Figure 1: *Mean shape of a left ventricle (left) and a deformed shape (right). The pointwise distance of the deformed shape to the mean shape is visualized using a colortable.*

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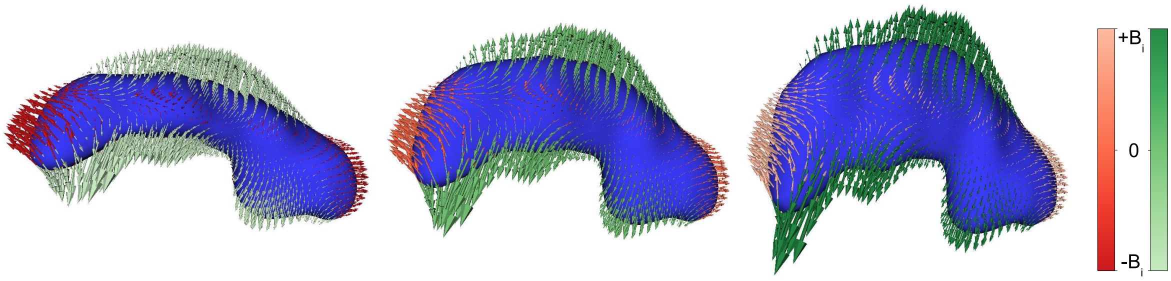

Figure 2: *First mode of variation of an SSM of the hippocampus. The parameter b_1 corresponding to the first mode is set to $-B_1$ (left), 0 (middle), and B_1 (right), respectively. Depending on the value of b_1, the arrows have a strong or weak saturation.*

Our tool also supports the visualization of individual modes using arrow glyphs. In order to visualize mode i, we associate two arrows with each point j: A green arrow points in the direction of p_{ij}, a red arrow points in the opposite direction. To give a visual clue for the magnitude of the point displacement, the arrows are scaled proportionally to $\|p_{ij}\|$. The saturation of the arrow encodes the shape parameter b_i for mode i of the current shape, which is illustrated in figure 2. If b_i is set to its lower bound $-B_i$, the red arrows are maximally saturated, while the green arrows appear pale. When b_i moves towards B_i, the saturation of the green arrows increases, while the saturation of the red arrows decreases. The mode visualization helps to understand and to interpret individual modes, and can be combined with point-wise distance visualization (see figure 3).

In order to compare two different shape models, for example models learned from different subsets of the training set, the user can start two application instances and select one of the instances as *slave* application. The camera position of the slave application window is automatically updated whenever the user changes the camera position in the master application window.

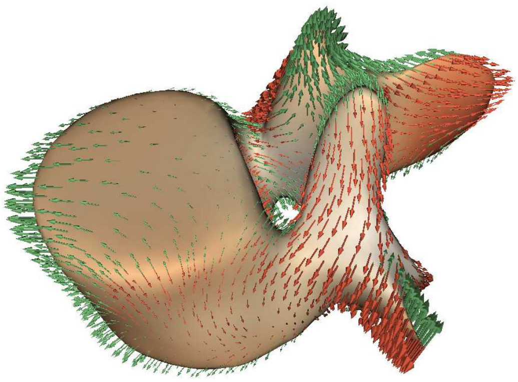

Figure 3: *Visualization of a vertebra model, combining point-wise distance and mode visualization.*

3. Summary

We presented an interactive tool for the visualization of SSMs. Our tool allows for interactive exploration of the complete shape space of a model. Point-wise distances to reference shapes as well as individual modes can be visualized. Moreover, the comparison of different models is supported.

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